

Digital Image Processing

Image Improvement

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 operation

III. Discrete 2D Processing

- Vector space, Convolution
- Unitary Transformation

IV. Image Improvement

- Enhancement, restoration, geometrical modifications

Image Improvement

- Image improvement denotes three types of image manipulation processes:
 - Image enhancement entails operations that improve the appearance to a human viewer, or operations to convert an image to a format better suited to machine processing
 - Image restoration has commonly been defined as the modification of an observed image in order to compensate for defects in the imaging system that produced the observed image
 - Geometrical image modification includes image magnification, minification, rotation and nonlinear spatial warping

Image Improvement

- Image enhancement
 - Contrast and histogram
 - Noise cleaning
 - Edge enhancement
 - *Color/multispectral image enhancement*
- Image restoration
- Geometrical image modification

Image Enhancement

- Improve the visual appearance of an image or to convert the image to a form better suited for analysis by a human or a machine
- A lot of techniques exist
- There is no general unifying theory of image enhancement at present because there is no general standard of image quality that can serve as a design criterion for an image enhancement processor

Contrast improvement

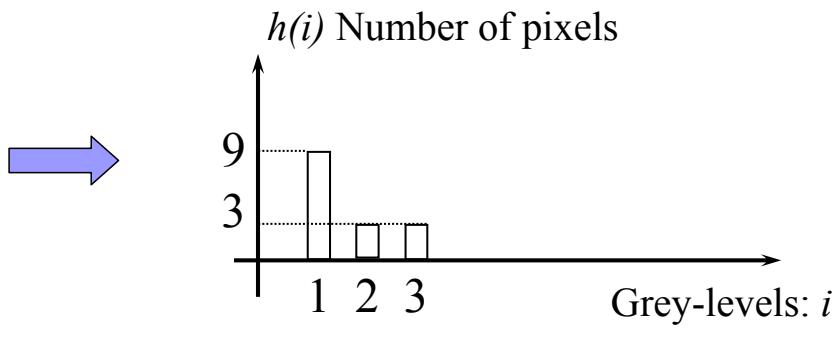
- The most common defects of photographic or electronic images is poor contrast resulting from a reduced, and perhaps nonlinear, image amplitude range
- ➔ Image contrast can often be improved by amplitude rescaling of each pixel
 - ➔ Histogram
 - ➔ Transformation functions

Histogram

- Number of pixels that have a given intensity value

| | | | | |
|---|---|---|---|---|
| 1 | 2 | 1 | 3 | 1 |
| 2 | 1 | 1 | 3 | 1 |
| 1 | 2 | 3 | 1 | 1 |

image

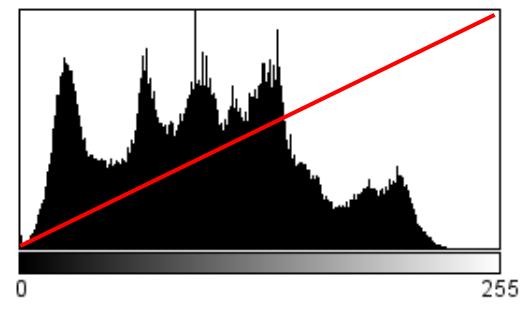


- Similar to the probability density function

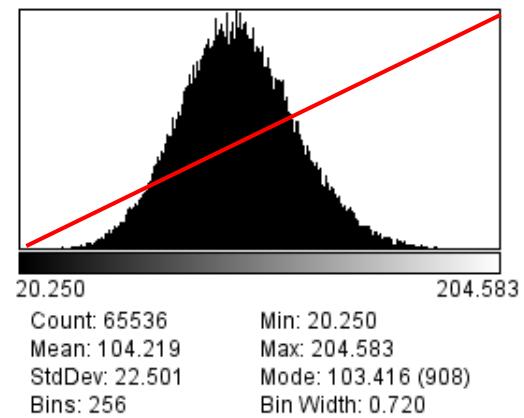
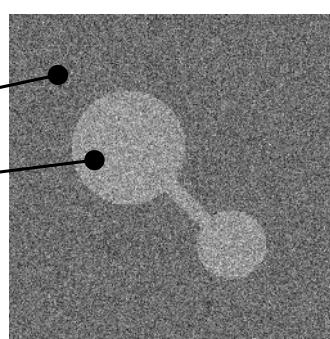
$$p(i) = h(i) / \text{nb_of_pixels}$$

Histogram

- Examples



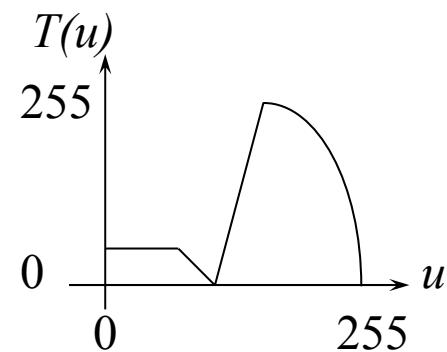
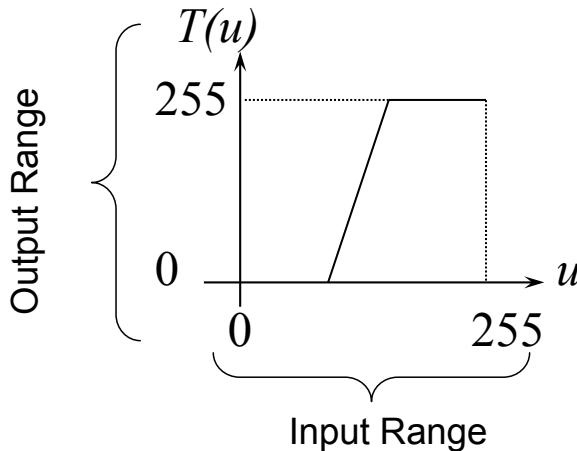
Mean = 100
Mean = 130
 $\sigma = 20$



Histogram manipulation

■ Use a transformation function

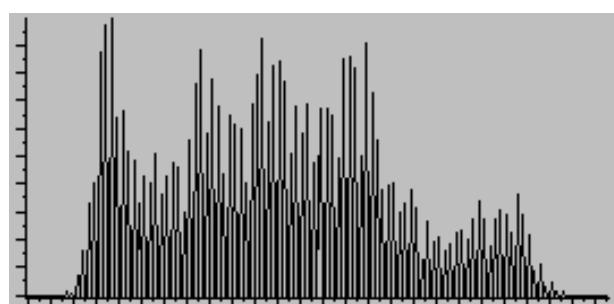
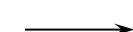
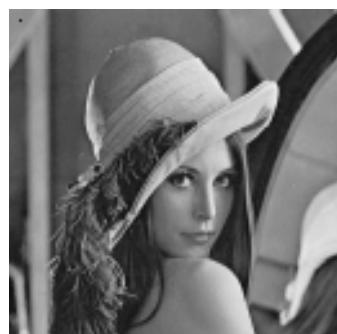
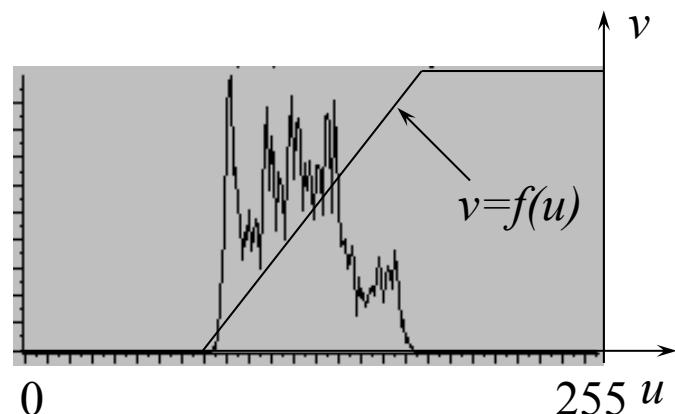
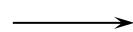
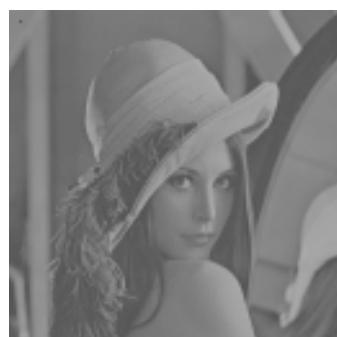
- Try an existing (classical) one
- Build your own!



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Histogram manipulation

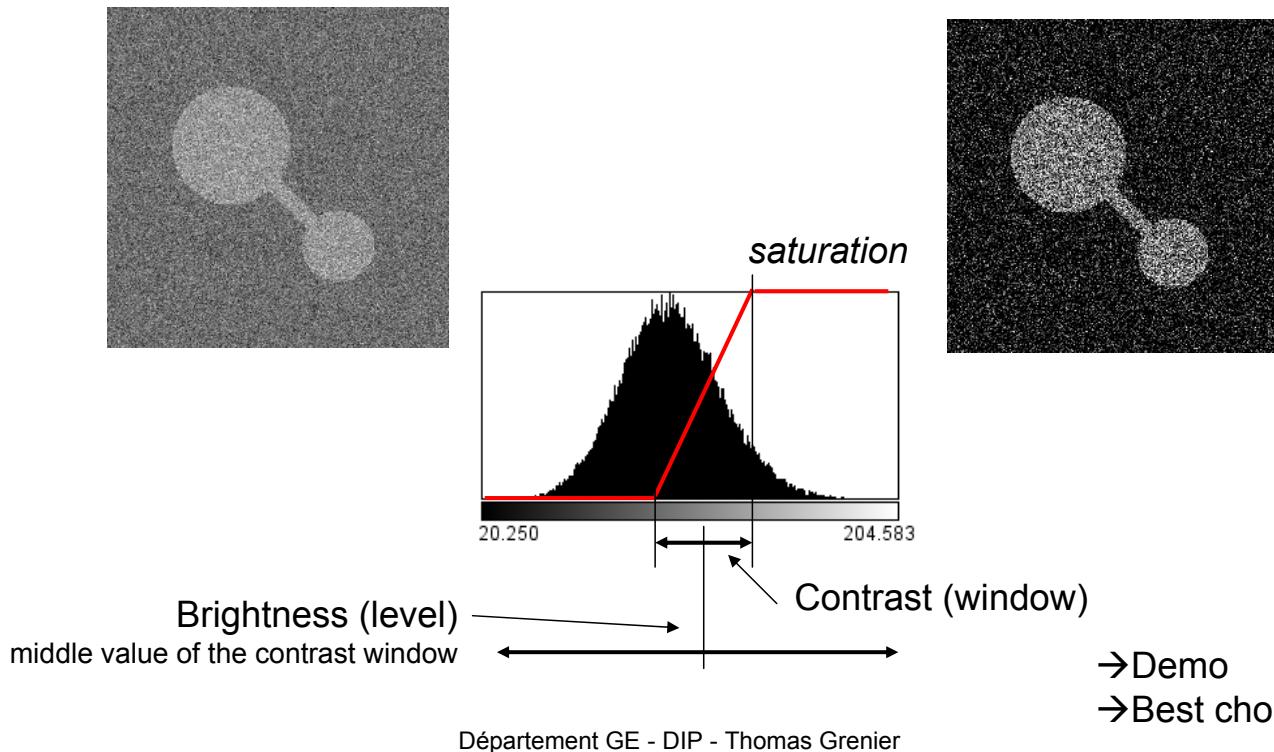


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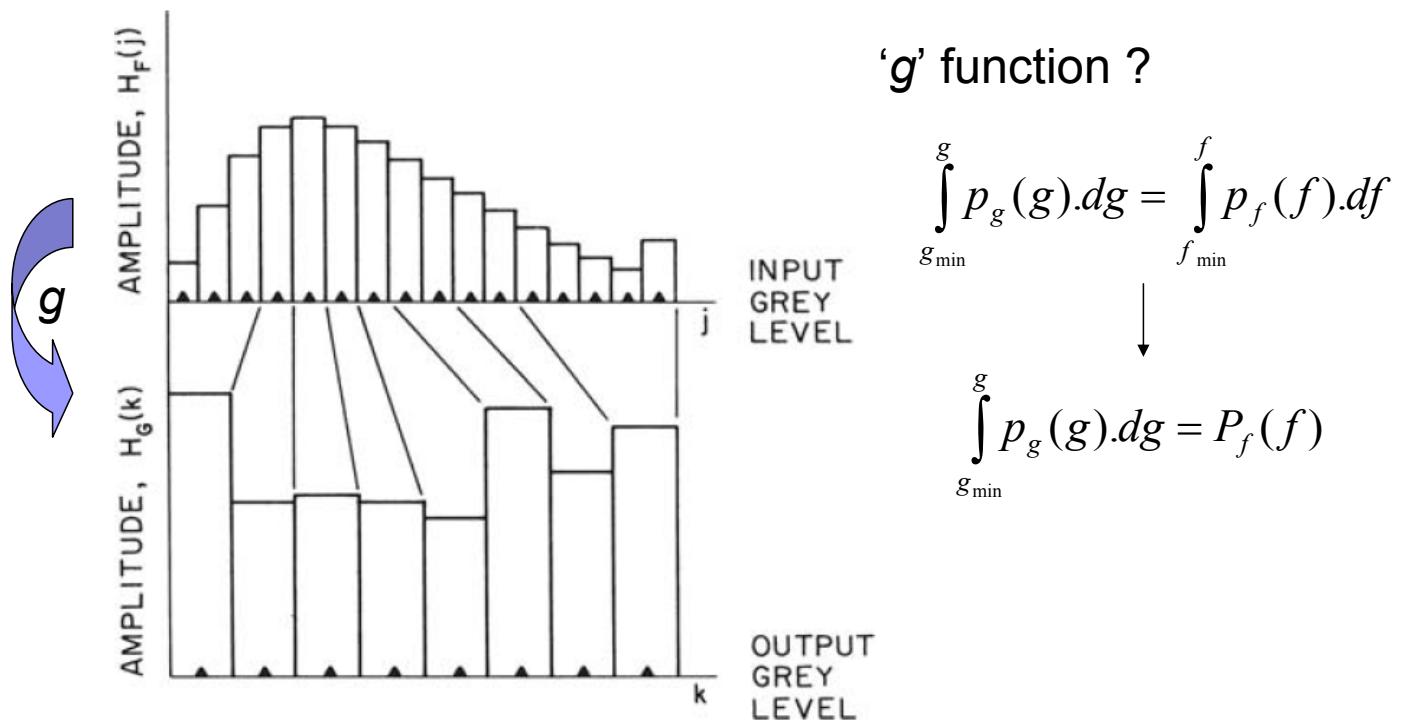
Histogram manipulation

■ Brightness and contrast



Histogram manipulation

■ Grey level histogram equalization



Histogram manipulation

■ Histogram equalization

□ Examples

- The output density is forced to be the uniform density

$$p_g(g) = \frac{1}{g_{\max} - g_{\min}} \quad g_{\min} \leq g \leq g_{\max}$$



$$g = (g_{\max} - g_{\min})P_f(f) + g_{\min}$$

- Other functions for the output density (exponential, logarithmic)

$$p_g(g) = \alpha \exp\{-\alpha(g - g_{\min})\} \quad g \leq g_{\min} \quad \longrightarrow \quad g = g_{\min} - \frac{1}{\alpha} \ln\{1 - P_f(f)\}$$

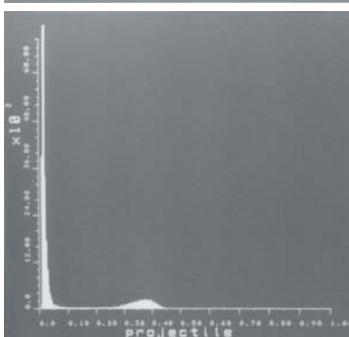
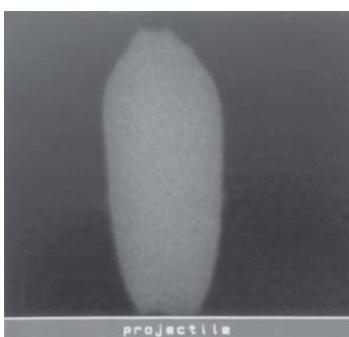
$$p_g(g) = \frac{1}{g[\ln\{g_{\max}\} - \ln\{g_{\min}\}]} \quad \longrightarrow \quad g = g_{\min} \left(\frac{g_{\max}}{g_{\min}}\right)^{P_f(f)}$$

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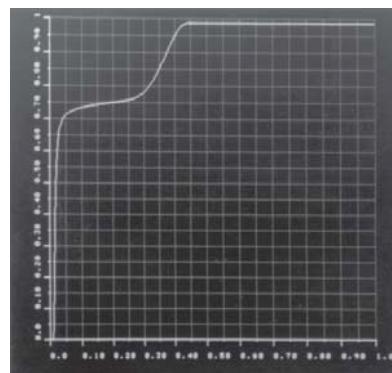
13

Histogram manipulation

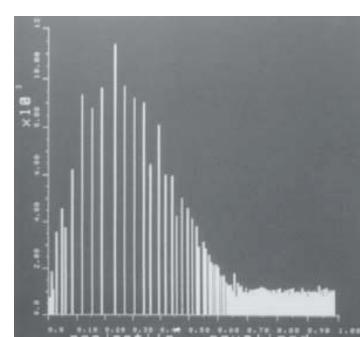
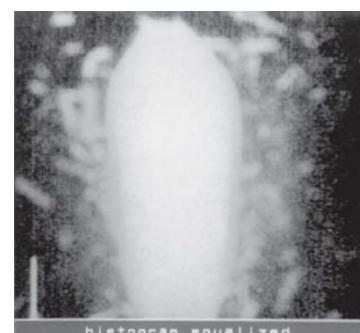
■ Histogram equalization, example



X-ray projectile image
and histogram



Transfer function
($P_f(f)$)



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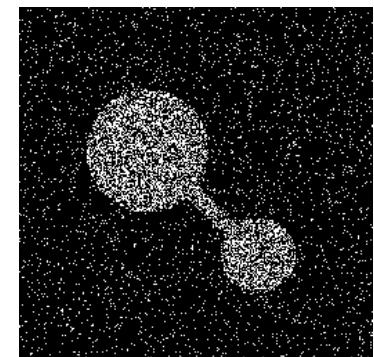
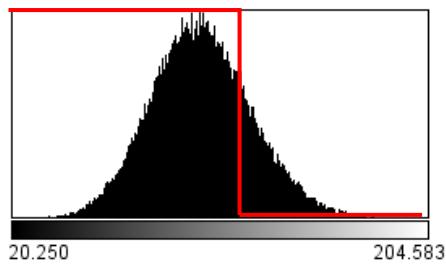
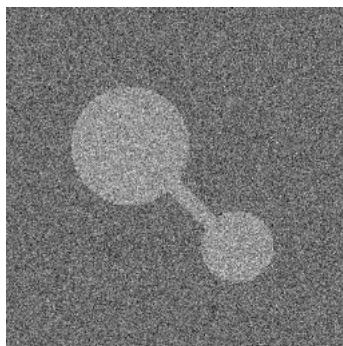
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Histogram manipulation

■ Threshold



binary

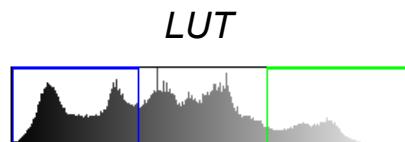


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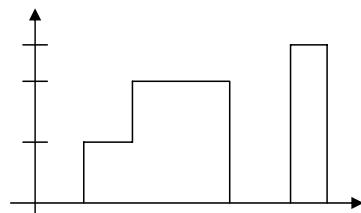
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Histogram manipulation

■ Threshold



n regions



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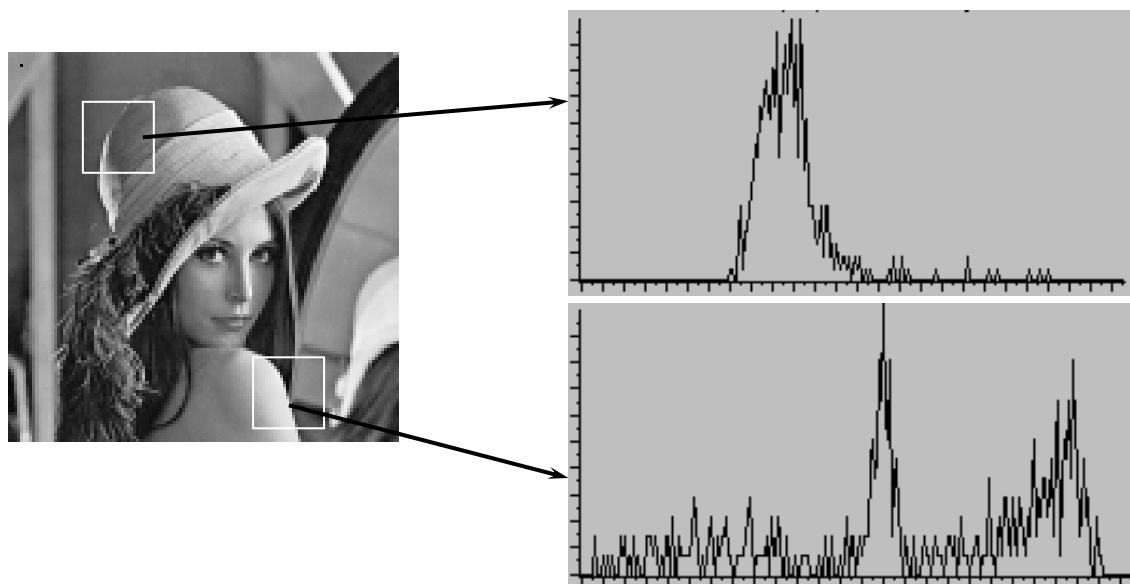
Histogram manipulation

■ Limitations

- Histogram equalization is not well adapted for good quality images
- Histogram threshold is not a noise removing technique!
- Histogram equalization should be adaptive!
 - Some methods exist (local equalization)

Local Histogram analysis

- features measured on the smallest neighborhood (1 pixel)
grey-level (NG), color, quantitative value (Bq/cc, ...) ...
- features measured on a neighborhood → local histogram



Common computed values from the density probability function $p(x)$ (based on histogram, local or not)

- Moments

$$m_i = E[x^i] = \sum_{n=0}^{N-1} x^i p(x)$$

N: number of grey levels

- Centered Moments

$$\hat{m}_i = E[(x - E[x])^i] = \sum_{n=0}^{N-1} (x - m_1)^i p(x)$$

- Entropy

$$H = - \sum_{x=0}^{N-1} p(x) \log_2(p(x))$$

- Absolute moments, median value, max/min value, mode, percentiles, invariant moments (Legendre, ...) ...

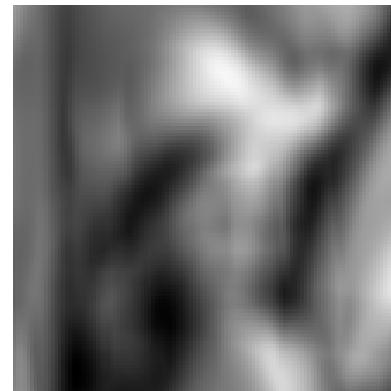


128x128 pixels

Computed on a 16x16 neighborhood



Variance



Mean

Noise cleaning

- Mean filter (linear filtering)
- Median filter (nonlinear filtering)
- Frequency domain filter (LP, HP, band-rejection (*notch*), ...)
- ...

Noise cleaning

- Many types of noise...



Gaussian Noise
(sd 25)



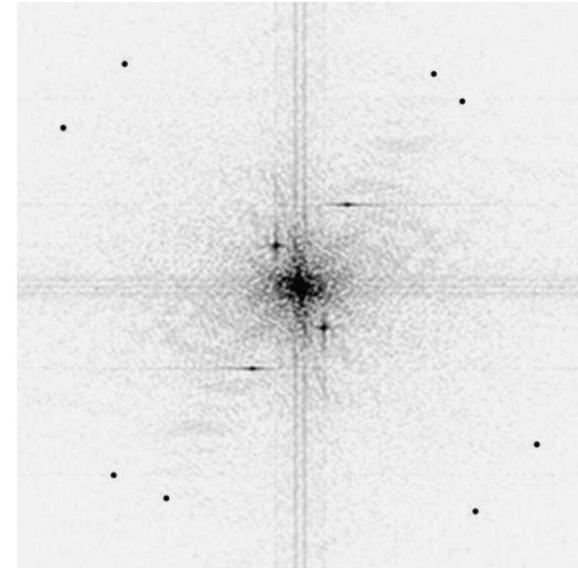
Salt and pepper noise

Noise cleaning

■ Periodic and quasi periodic noise



Quasi periodic noise



Fourier amplitude spectrum

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Linear filtering

■ Mean filter

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

W: 25 neighbors

Result on Gaussian noise

$H=(1/25).I$

Result on Salt & Pepper noise



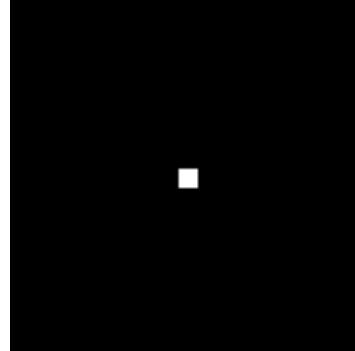
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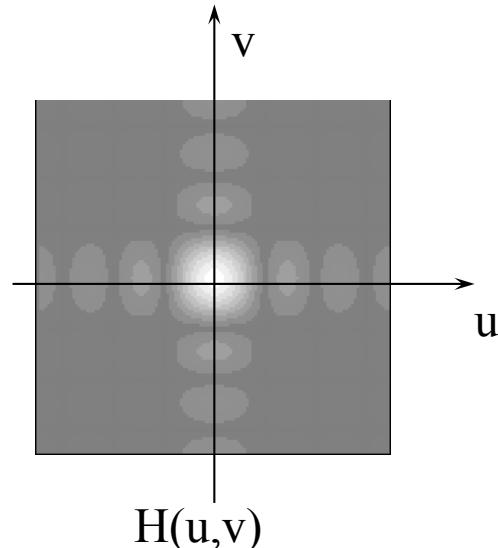
Linear filtering

■ Mean filter and DFT

$N=M=1$: mask 3×3



$h(x,y)$

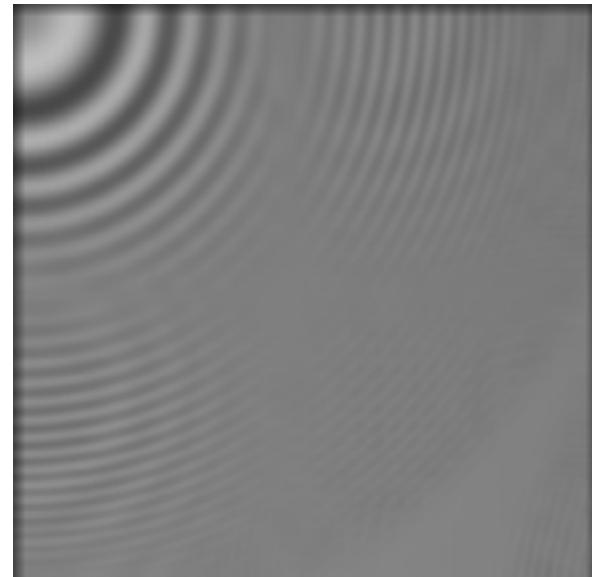
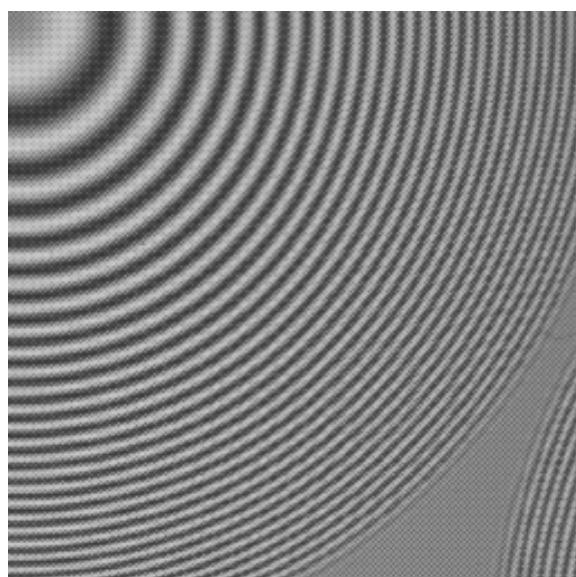


$H(u,v)$

➔ Anisotropic low pass filter with poor selectivity

Linear filtering

■ Mean filter anisotropy, (mask 11×11)



Linear filtering

■ Gaussian Filter

$$h(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

Filter with infinite impulse response! → Approximate the ideal filter by truncating and windowing the infinite impulse response to make a FIR



Isotropic low pass filter with poor selectivity
 $H(u,v)$ is a gaussian

→ Many other types of filter

- high pass, low pass, band-stop, derivative...
- Ideal, Butterworth,...

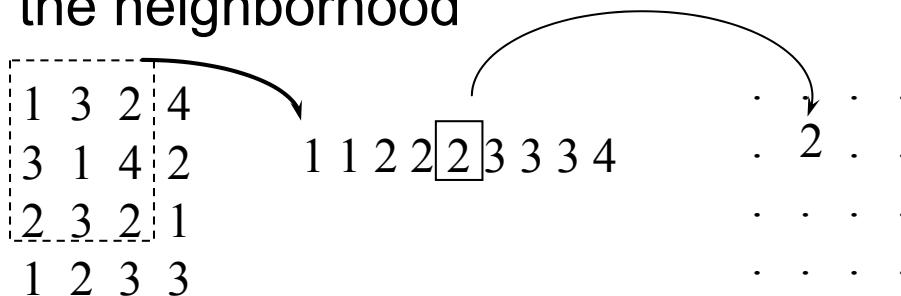
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Non linear filtering

■ Median filter

- Replace the central value by the median value of the neighborhood



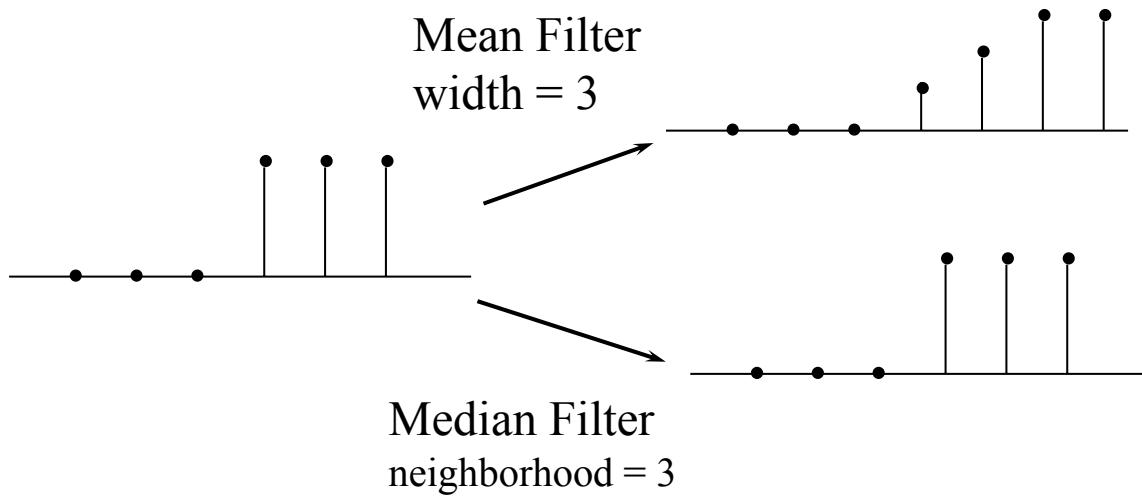
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Non linear filtering

■ Median filter

- Advantage of median filtering over linear filtering:
edges are preserved



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Non linear filtering

■ Median filter

Result on Gaussian noise



W=25

W=9

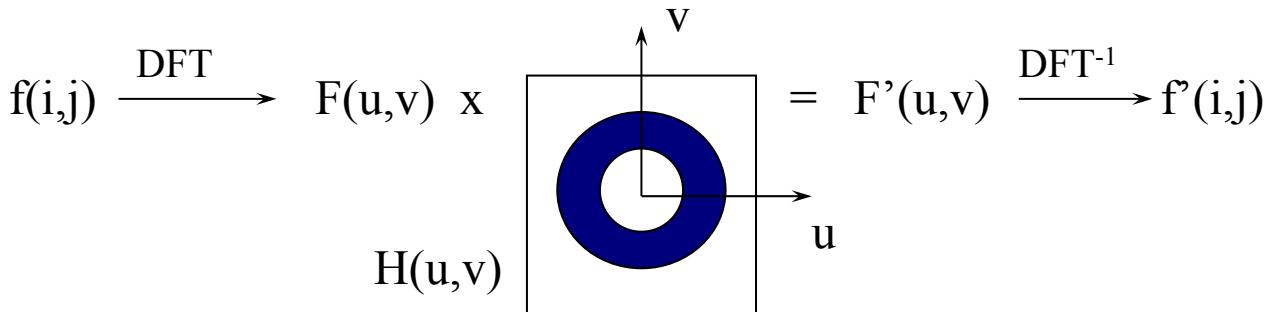
Result on salt & pepper noise



Frequency domain filtering

■ Approach

- Region selection in the frequency space (u,v)



- to keep $f'(i,j)$ real, regions must be symmetric about the origin
- In frequency space (u,v), region boundaries can be
 - Steep (but ... oscillations can appear: Gibbs)
 - Smooth (but less selective)

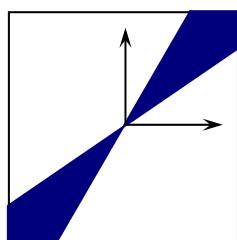
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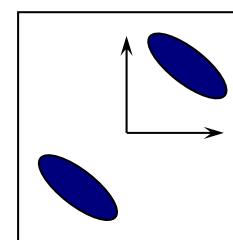
Frequency domain filtering

■ Approach

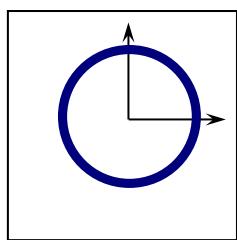
- Many forms for regions



Choice of one direction



Choice of the direction and frequency bands



Choice of frequency bands



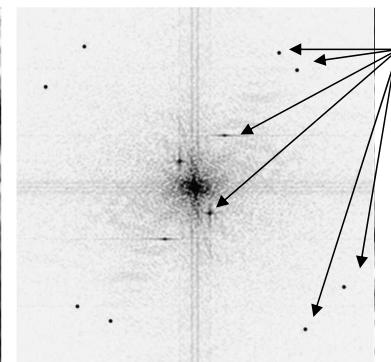
Mix !

- Low-pass filters
- High-pass filters
- Band-pass filters
- Band-reject filters...

Frequency domain filtering

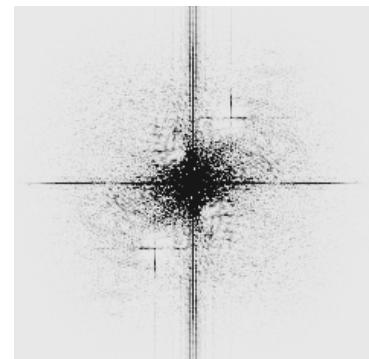
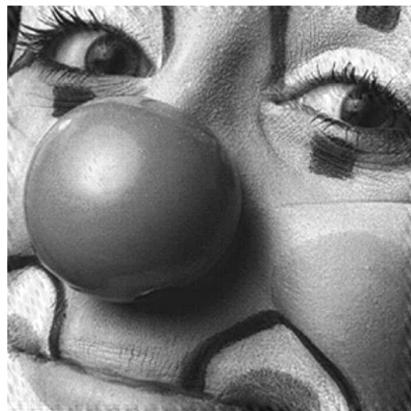
■ Notch filter

Periodic noise



Remove!

Clean dots and lines



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Edge enhancement

- **Edges:** Changes or discontinuities of amplitude in an image
- Edges provide an indication of the physical extent of objects within the image → **Contours**

■ Edge detection

- Differential detection
- Model fitting

■ Edge enhancement filters

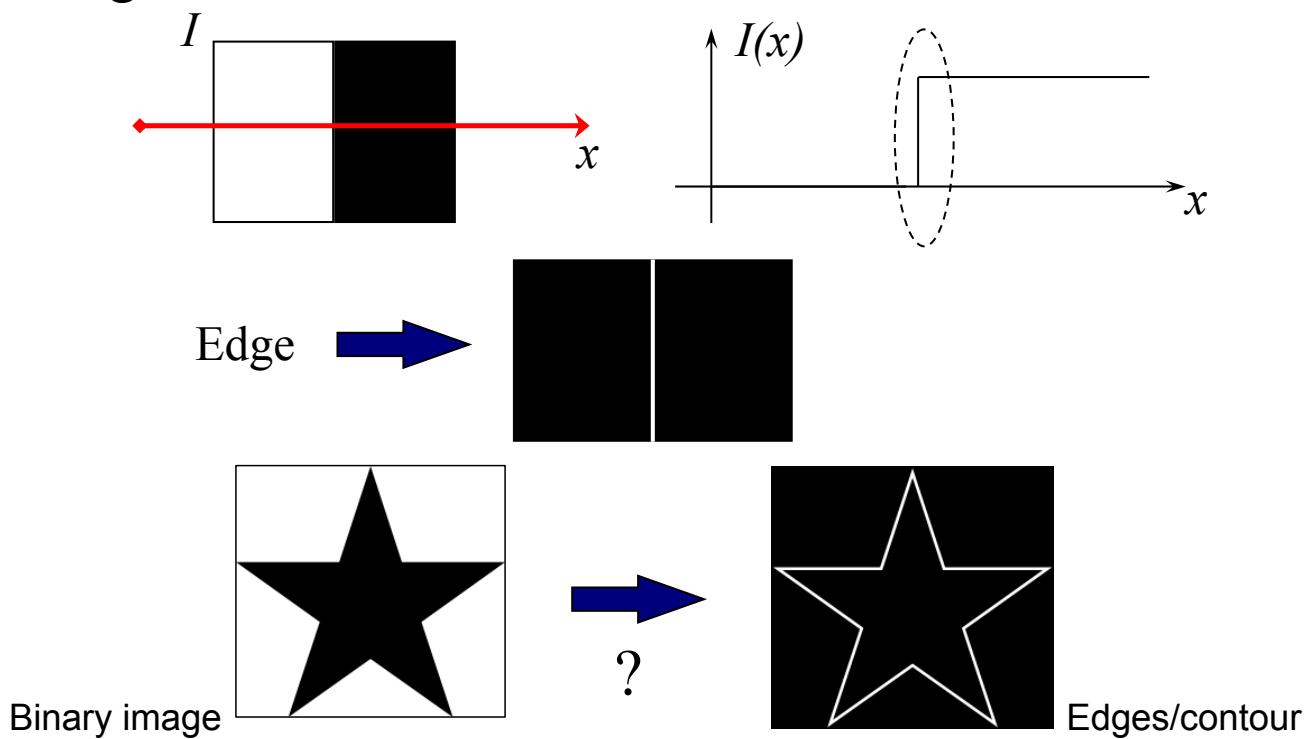


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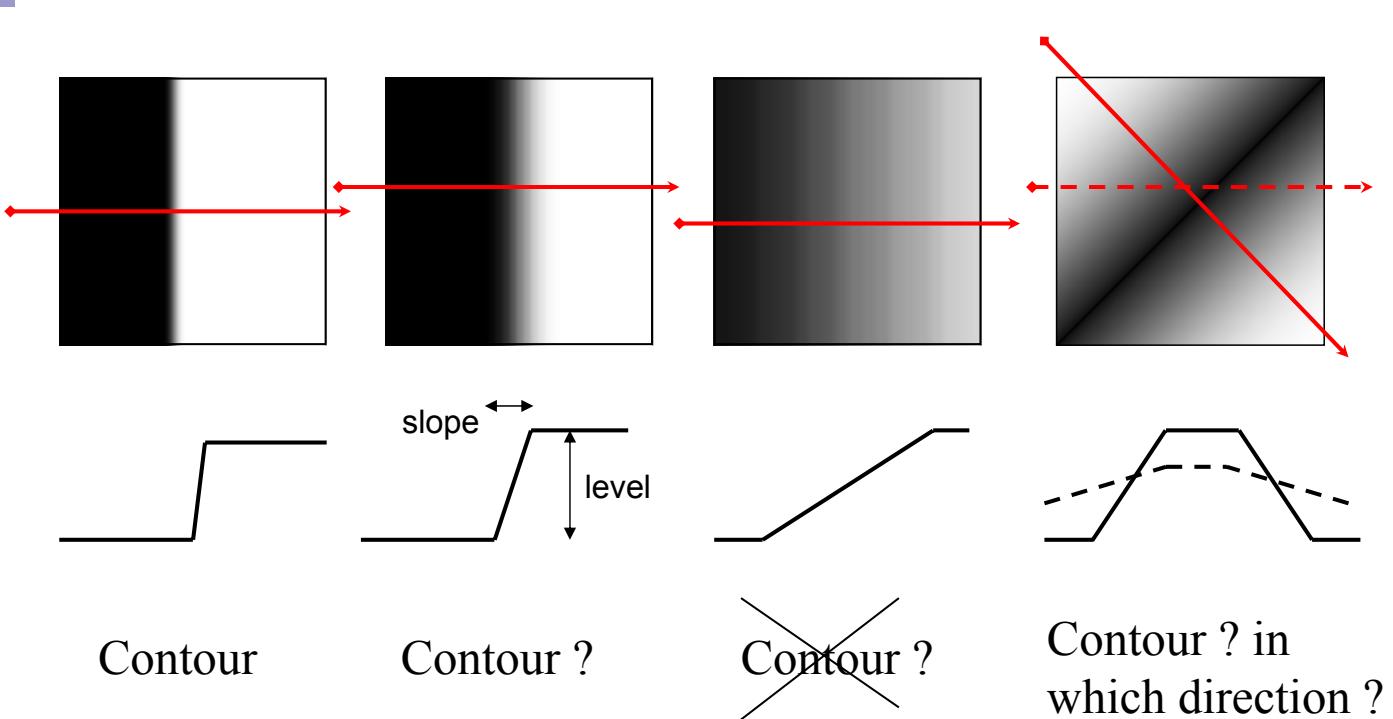
Edge enhancement

■ Edge detection



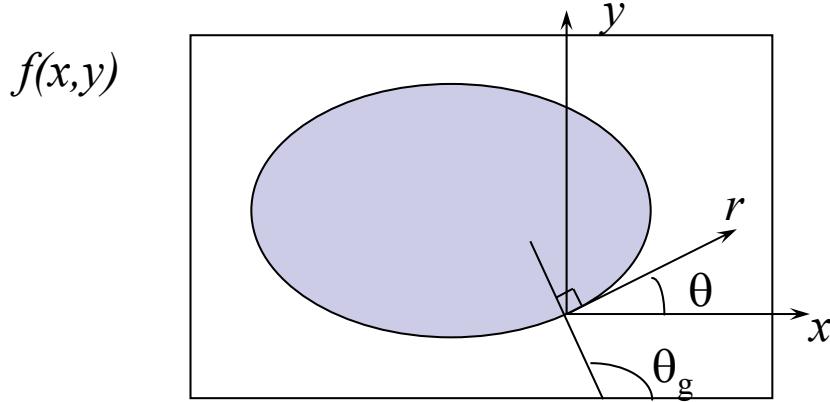
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- ➔ What are a change or a discontinuity ?
- ➔ What about the direction (in image) ?

□ Definition of continuous contour and gradient



Continuous one-dimensional gradient $\mathbf{g}(x,y)$ of $f(x,y)$ along a line normal to the edge slope which is at an angle θ with respect to the horizontal axis:

$$\frac{\partial f(x,y)}{\partial r} \text{ max for } \theta_g = \theta + \frac{\pi}{2} \rightarrow \frac{\partial}{\partial \theta} \left(\frac{\partial f(x,y)}{\partial r} \right) = 0$$

$$\mathbf{g}(x,y) = \nabla f(x,y) = \begin{cases} \frac{\partial f(x,y)}{\partial x} \\ \frac{\partial f(x,y)}{\partial y} \end{cases}$$

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$$\frac{\partial f}{\partial r} = \frac{\partial f}{\partial x} \frac{\partial x}{\partial r} + \frac{\partial f}{\partial y} \frac{\partial y}{\partial r} = \frac{\partial f}{\partial x} \cos(\theta) + \frac{\partial f}{\partial y} \sin(\theta)$$

$$\frac{\partial}{\partial \theta} \left(\frac{\partial f(x,y)}{\partial r} \right) = 0 \rightarrow -\frac{\partial f}{\partial x} \sin(\theta) + \frac{\partial f}{\partial y} \cos(\theta) = 0$$

Direction

$$\theta_g = \arctan \left(\frac{\frac{\partial f}{\partial y}}{\frac{\partial f}{\partial x}} \right)$$

Amplitude

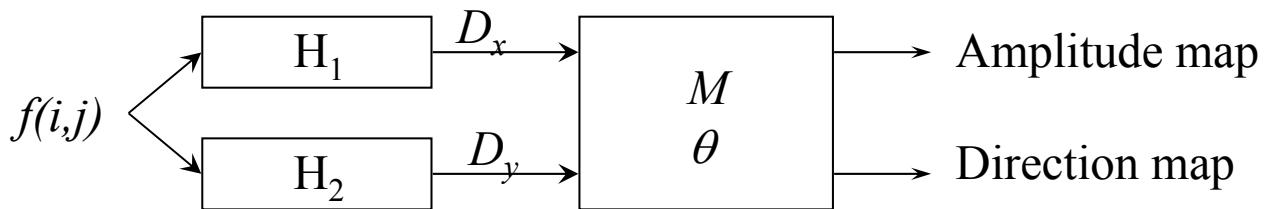
$$\left(\frac{\partial f}{\partial r} \right)_{\max} = \sqrt{\left(\frac{\partial f}{\partial x} \right)^2 + \left(\frac{\partial f}{\partial y} \right)^2}$$

□ Gradient in discrete domain

- For each pixel (i,j): gradient computation in two orthogonal directions $\rightarrow D_x, D_y$

- Gradient amplitude $M = \sqrt{D_x^2 + D_y^2}$

- Gradient direction $\theta = \text{Arctan}\left(\frac{D_y}{D_x}\right)$



- For computational efficiency, the gradient amplitude is sometimes approximated by the magnitudes combination

$$M = |D_x| + |D_y|$$

- If the gradient amplitude M is large enough (i.e., above some threshold value), an edge is deemed present
 → The direction (angle) map is used to follow the contour
 → Many H1 H2 operators exist:

Pixel difference

$$D_x(i, j) = f(i, j) - f(i-1, j) \quad \frac{df(x)}{dx} = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h}$$

$$D_y(i, j) = f(i, j) - f(i, j-1)$$

Separated pixel difference

$$D_x(i, j) = f(i+1, j) - f(i-1, j)$$

$$D_y(i, j) = f(i, j+1) - f(i, j-1)$$

→ Convolution windows!

H_1, H_2

Operator

Pixel difference

Row gradient H_1

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & -1 \\ 0 & 0 & 0 \end{bmatrix}$$

Column gradient H_2

$$\begin{bmatrix} 0 & -1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

Separated
pixel difference

$$\begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & -1 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 & -1 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

Roberts

$$\begin{bmatrix} 0 & 0 & -1 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} -1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

Prewitt

$$\frac{1}{3} \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix}$$

$$\frac{1}{3} \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

Sobel

$$\frac{1}{4} \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$

$$\frac{1}{4} \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

Frei-Chen

$$\frac{1}{2 + \sqrt{2}} \begin{bmatrix} 1 & 0 & -1 \\ \sqrt{2} & 0 & -\sqrt{2} \\ 1 & 0 & -1 \end{bmatrix}$$

$$\frac{1}{2 + \sqrt{2}} \begin{bmatrix} -1 & -\sqrt{2} & -1 \\ 0 & 0 & 0 \\ 1 & \sqrt{2} & 1 \end{bmatrix}$$

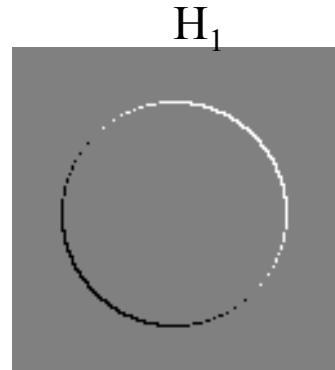
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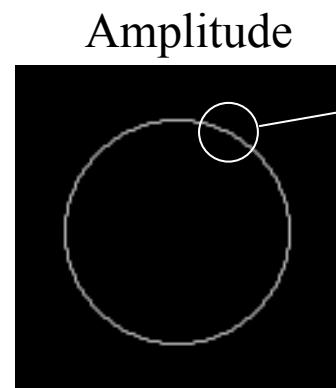
Roberts



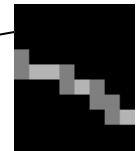
128x128



H_1

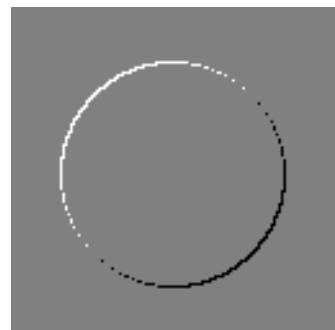


Amplitude

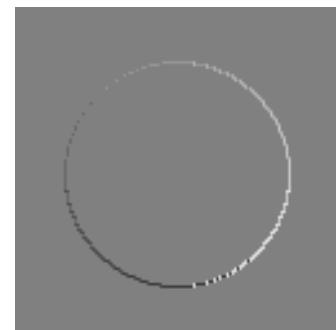


Zoom

(inhomogeneities!)



H_2



Direction

white = $\pi/4$

...

grey = $\pi + \pi/4$

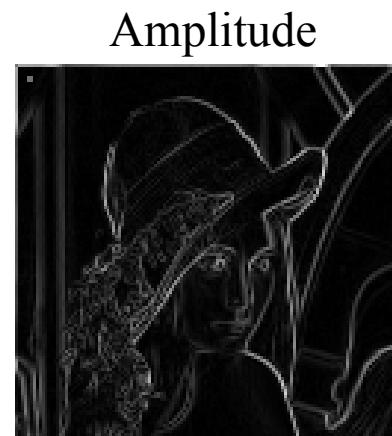
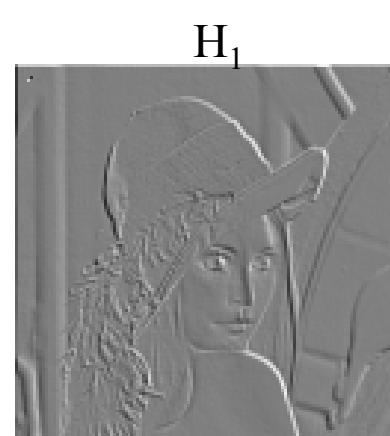
...

black = $2\pi + \pi/4$

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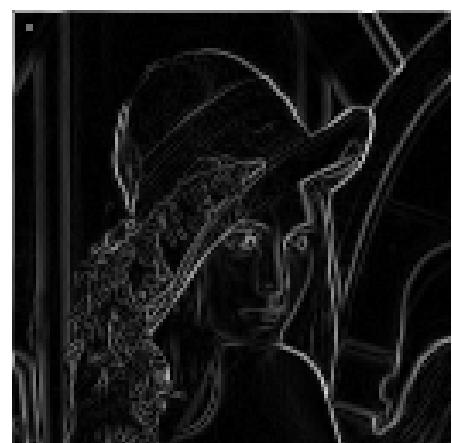
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Roberts



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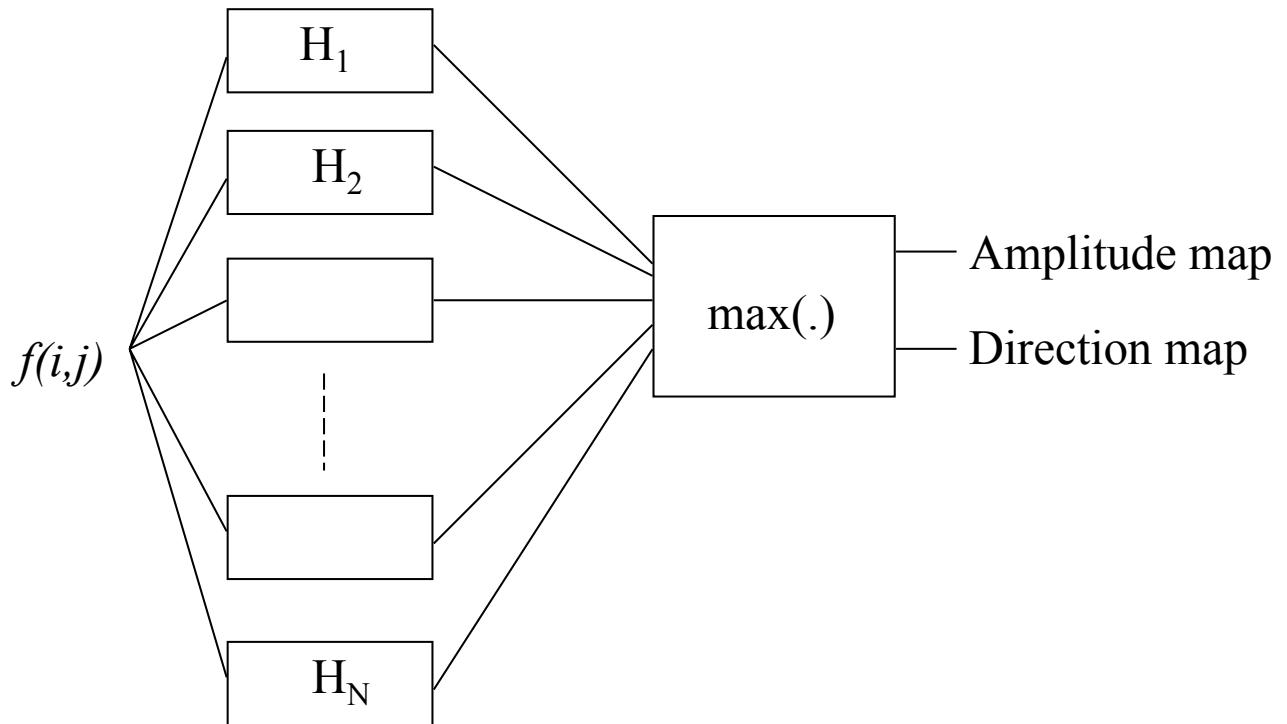


- Increasing the contrast, many edges appear due to noise
- Edge detectors are high-pass filters



□ Compass operator

- Computation of the gradient in N directions
- Selection of the maximum value



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■ Examples

| Gradient direction | Prewitt compass gradient | Kirsch | Robinson 3-level | Robinson 5-level |
|--------------------|-------------------------------------------------------------------------|--------------------------------------------------------------------------|------------------------------------------------------------------------|------------------------------------------------------------------------|
| East H_1 | $\begin{bmatrix} 1 & 1 & -1 \\ 1 & -2 & -1 \\ 1 & 1 & -1 \end{bmatrix}$ | $\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix}$ | $\begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix}$ | $\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$ |
| Northeast H_2 | $\begin{bmatrix} 1 & -1 & -1 \\ 1 & -2 & -1 \\ 1 & 1 & 1 \end{bmatrix}$ | $\begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix}$ | $\begin{bmatrix} 0 & -1 & -1 \\ 1 & 0 & -1 \\ 1 & 1 & 0 \end{bmatrix}$ | $\begin{bmatrix} 0 & -1 & -2 \\ 1 & 0 & -1 \\ 2 & 1 & 0 \end{bmatrix}$ |
| North H_3 | $\begin{bmatrix} -1 & -1 & -1 \\ 1 & -2 & 1 \\ 1 & 1 & 1 \end{bmatrix}$ | $\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix}$ | $\begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$ | $\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$ |
| Northwest H_4 | $\begin{bmatrix} -1 & -1 & 1 \\ -1 & -2 & 1 \\ 1 & 1 & 1 \end{bmatrix}$ | $\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$ | $\begin{bmatrix} -1 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix}$ | $\begin{bmatrix} -2 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 2 \end{bmatrix}$ |
| West H_5 | $\begin{bmatrix} -1 & 1 & 1 \\ -1 & -2 & 1 \\ -1 & 1 & 1 \end{bmatrix}$ | $\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix}$ | $\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$ | $\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$ |
| Southwest H_6 | $\begin{bmatrix} 1 & 1 & 1 \\ -1 & -2 & 1 \\ -1 & -1 & 1 \end{bmatrix}$ | $\begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix}$ | $\begin{bmatrix} 0 & 1 & 1 \\ -1 & 0 & 1 \\ -1 & -1 & 0 \end{bmatrix}$ | $\begin{bmatrix} 0 & 1 & 2 \\ -1 & 0 & 1 \\ -2 & -1 & 0 \end{bmatrix}$ |
| South H_7 | $\begin{bmatrix} 1 & 1 & 1 \\ 1 & -2 & 1 \\ -1 & -1 & -1 \end{bmatrix}$ | $\begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$ | $\begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$ | $\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$ |
| Southeast H_8 | $\begin{bmatrix} 1 & 1 & 1 \\ 1 & -2 & -1 \\ 1 & -1 & -1 \end{bmatrix}$ | $\begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$ | $\begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -1 \end{bmatrix}$ | $\begin{bmatrix} 2 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -2 \end{bmatrix}$ |
| Scale factor | $\frac{1}{5}$ | $\frac{1}{15}$ | $\frac{1}{3}$ | $\frac{1}{4}$ |

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□ Laplacian

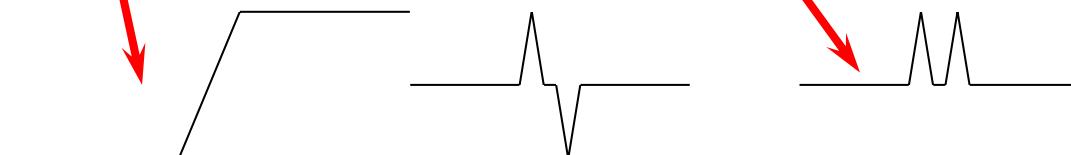
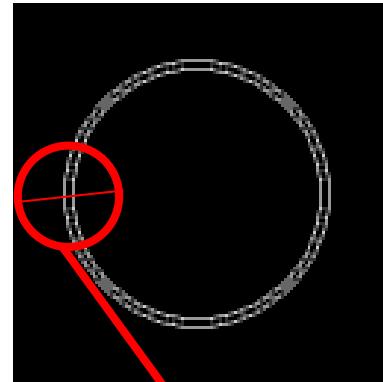
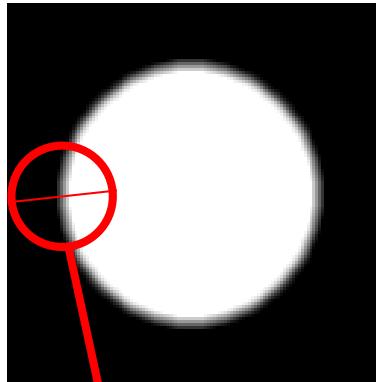
$$\Delta f(x, y) = \nabla^2 f(x, y) = \frac{\partial^2 f(x, y)}{\partial x^2} + \frac{\partial^2 f(x, y)}{\partial y^2}$$

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & -1 \\ 0 & 0 & 0 \end{bmatrix} \otimes \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & -1 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 & -1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \otimes \begin{bmatrix} 0 & -1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\left\{ \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \right.$$

then absolute value



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■ Emphasis filter

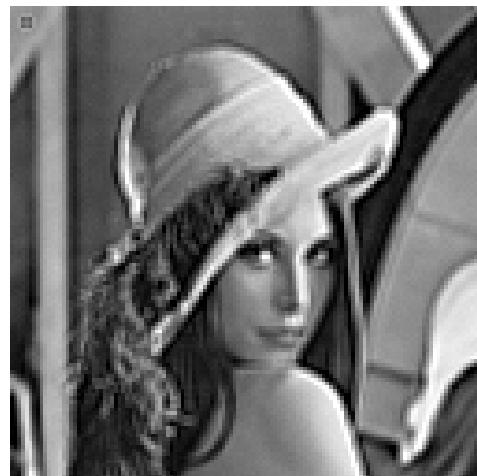
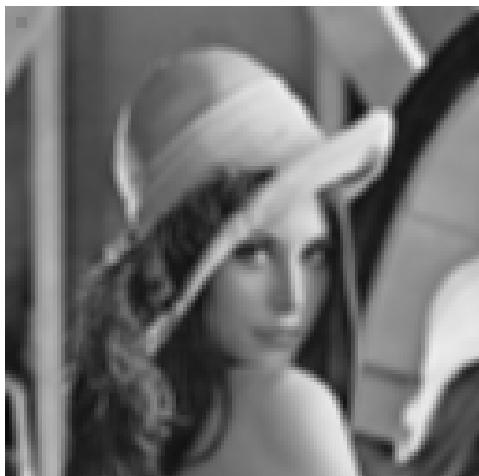
$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \rightarrow$$



= Input Image + Laplacian

→ Enhancement of high frequencies



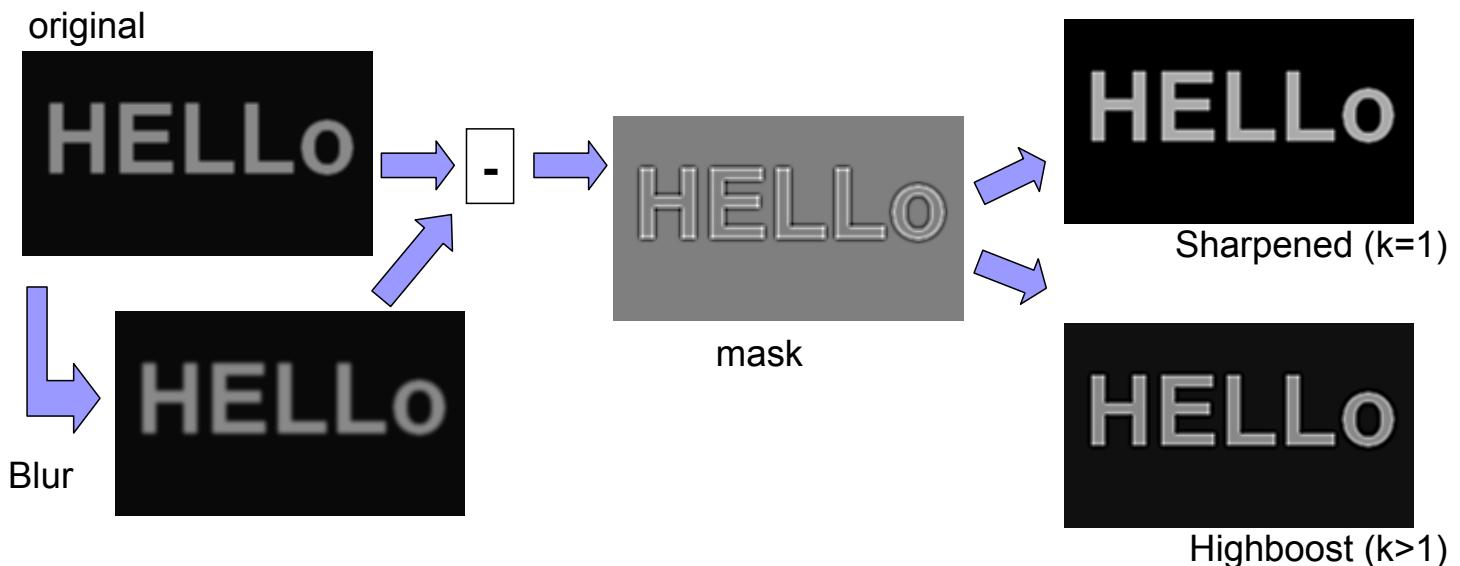
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■ Unsharp masking, Highboost Filtering

- Used by the printing and publishing industry

- 1- Blur the original image
- 2- Subtract the blurred image from the original (the result is called the mask)
- 3- Add the mask (multiplied by k) to the original

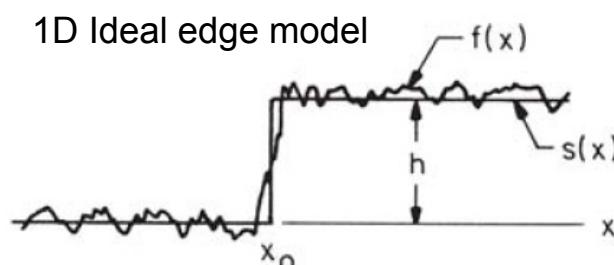


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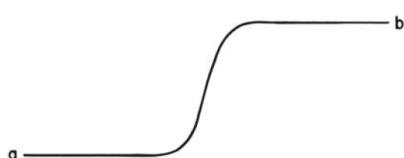
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Edge fitting

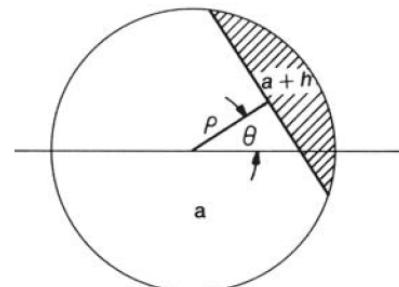
- ### ■ Image data f can be fitted to an ideal edge model s



Hyperbolic Edge model 1D



2D Ideal edge model



→ An edge is assumed present if the Mean Square Error is below a threshold value

$$MSE = \int_{x_0-L}^{x_0+L} [f(x) - s(x)]^2 dx$$

Model+minimization... image restoration

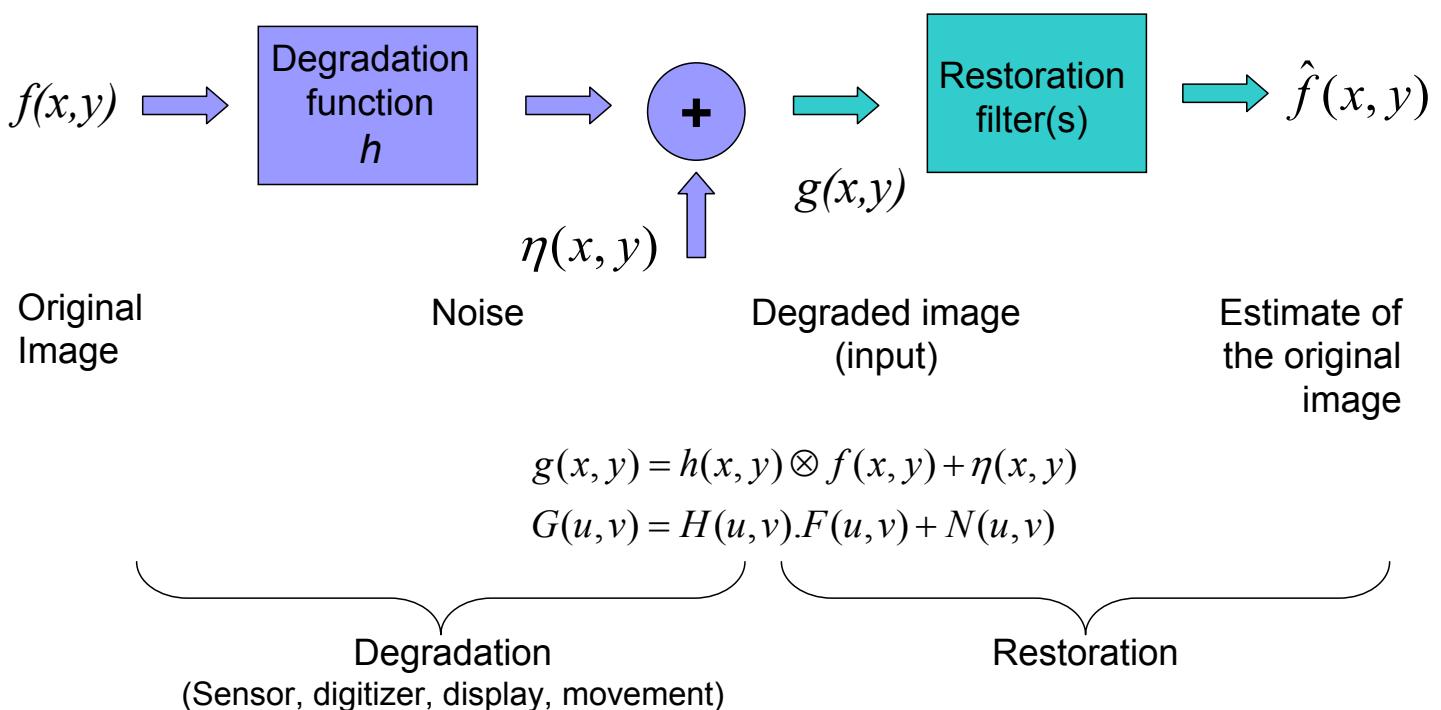
Image Restoration

- Image restoration attempts to recover an image that has been degraded using a priori knowledge of degradation phenomenon
 - Modeling the degradation
 - Applying the inverse process (in order to recover the original image)
- Involves formulating a criterion of goodness that will yield an optimal estimate of the desired result

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- A model of the image degradation/restoration process



■ Noise Models

- Gaussian (normal) noise

$$p(z) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(z-\bar{z})^2/2\sigma^2}$$

- Uniform noise

$$p(z) = \begin{cases} \frac{1}{b-a} & \text{if } a \leq z \leq b \\ 0 & \text{otherwise} \end{cases}$$

- Impulse (salt and pepper) noise

$$p(z) = \begin{cases} P_a & \text{for } z = a \\ P_b & \text{for } z = b \\ 0 & \text{otherwise} \end{cases}$$

- Erlang (gamma) noise

- Rayleigh noise

$$p(z) = \begin{cases} \frac{2}{b} \cdot (z-a) e^{-(z-a)^2/b} & \text{for } z \geq a \\ 0 & \text{for } z < a \end{cases}$$

Restoration: presence of noise only

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

■ Mean filters

- Arithmetic,

$$\frac{1}{m.n} \sum_{i,j \in S_{xy}} g(i, j)$$

- geometric,

$$\left[\prod_{i,j \in S_{xy}} g(i, j) \right]^{\frac{1}{m.n}}$$

- harmonic

$$\frac{m.n}{\sum_{i,j \in S_{xy}} \frac{1}{g(i, j)}}$$

■ Order statistic filters

- Median,

$$\hat{f}(x, y) = \underset{s,t \in S_{xy}}{\text{median}}(g(s, t))$$

- min & max,

$$\hat{f}(x, y) = \underset{s,t \in S_{xy}}{\max}(g(s, t))$$

- midpoint

$$\frac{1}{2} \max + \frac{1}{2} \min$$

$$\hat{f}(x, y) = \underset{s,t \in S_{xy}}{\min}(g(s, t))$$

■ Adaptive filters

- Local noise reduction, adaptive median, ...

■ Adaptive Median Filter

Notations

z_{\min} = minimum intensity value in S_{xy}
 z_{\max} = maximum intensity value in S_{xy}
 z_{med} = median of intensity values in S_{xy}
 z_{xy} = intensity value at coordinates (x,y)
 S_{\max} = maximum allowed size of S_{xy}

Algorithm for a pixel (x,y)

Stage 1 :

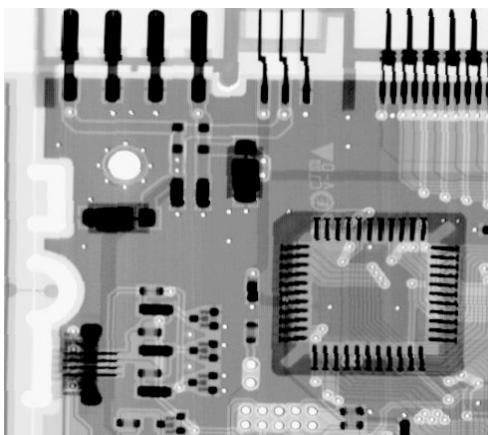
Compute z_{\min} , z_{\max} , z_{med}
 $A1 = z_{\text{med}} - z_{\min}$
 $A2 = z_{\text{med}} - z_{\max}$
if $A1 > 0$ and $A2 < 0 \rightarrow$ stage 2
increase the window size
if window size $< S_{\max} \rightarrow$ stage 1
else output z_{med}

Stage 2:

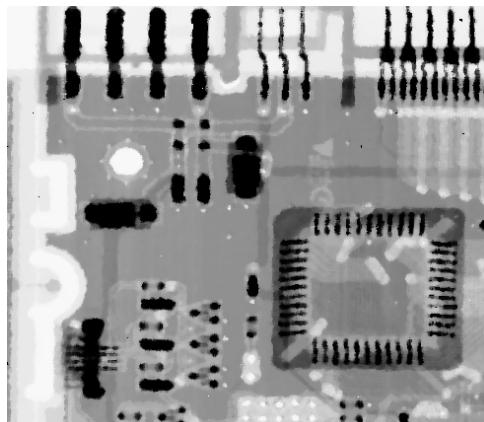
$B1 = z_{xy} - z_{\min}$
 $B2 = z_{xy} - z_{\max}$
if $B1 > 0$ and $B2 < 0$
output z_{xy}
else output z_{med}

□ Result of Adaptive Median filter

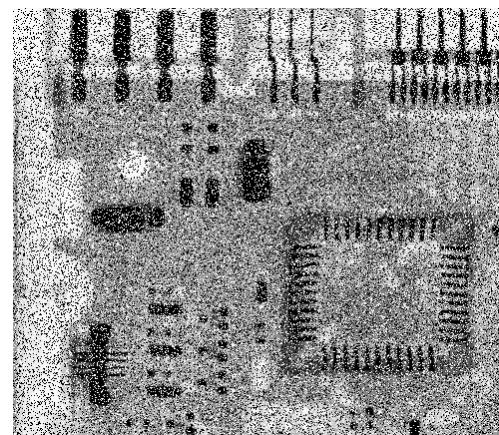
Reference



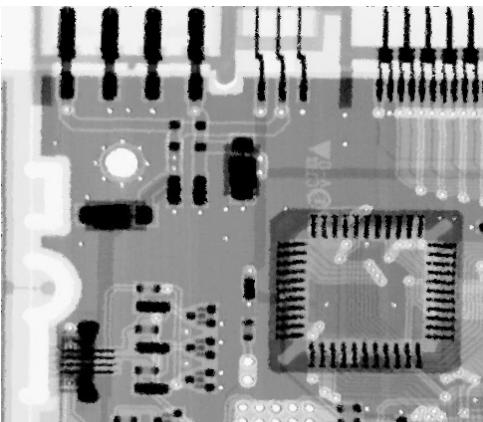
Median Filter (5x5)



Noisy image (S&P, 0.35)



Adaptive Median (S_{\max} 9x9)



Restoration: Periodic noise reduction

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

■ By frequency domain filtering

- Bandreject filter
- Notch filter → optimum notch

Build H_{NP} (Notch Pass) by placing a notch pass filter at the location of each spike.
Interference noise pattern is:

$$\begin{aligned} N(u, v) &= H_{NP}(u, v) \cdot G(u, v) \\ \text{then } \eta(x, y) &= \text{FT}^{-1}[N(u, v)] \\ \text{thus } \hat{f}(x, y) &= g(x, y) - w(x, y) \cdot \eta(x, y) \end{aligned}$$

Estimate of $f(x, y)$ Weighted function (minimizes the effect of components not present in the estimate of η)

→ How to select $w(x, y)$?

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■ $w(x, y)$?

$w(x, y)$ is selected so that the local variance of the estimate of f is minimized (optimum choice of w)

$$\frac{\partial \sigma^2(x, y)}{\partial w(x, y)} = 0$$

$$\rightarrow w(x, y) = \frac{\overline{g(x, y) \cdot \eta(x, y)} - \overline{g(x, y)} \cdot \overline{\eta(x, y)}}{\overline{\eta^2(x, y)} - \overline{\eta}^2(x, y)}$$

→ Prove the validity of this equation

Hints:

→ estimate the variance in a small neighborhood

→ assume that w remains essentially constant over the neighborhood

Restoration: linear, position-invariant degradation

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

- H is linear,

$$H[af_1(x, y) + bf_2(x, y)] = aH[f_1(x, y)] + bH[f_2(x, y)]$$

- If H is position invariant then (for any a and b):

$$H[\delta(x - a, y - b)] = h(x - a, y - b)$$

→ $\mathbf{g(x,y)}$: $g(x, y) = h(x, y) \otimes f(x, y) + \eta(x, y)$

$$G(u, v) = H(u, v) \cdot F(u, v) + N(u, v)$$

Estimating the degradation function

Blind deconvolution

- 3 principal ways

□ Observation

- Small rectangular section containing samples structures (part of an object, background)

$$H_s(u, v) = \frac{G_s(u, v)}{\hat{F}_s(u, v)}$$

□ Experimentation

- Obtain the impulse response of the degradation function by imaging an impulse (small dot of light)

$$H(u, v) = \frac{G(u, v)}{A}$$

□ Modeling

- Mathematical model that take into account environmental conditions that cause degradation
- Derive a mathematical model starting from basic principles

And after ?

■ Inverse filtering

- Without noise

$$\hat{F}(u, v) = \frac{G(u, v)}{H(u, v)}$$

- With noise

- We have to known N!

$$\hat{F}(u, v) = F(u, v) + \frac{N(u, v)}{H(u, v)}$$

- What happen for small values of H(u,v) ?

■ Minimum Mean Square Error (Wiener) Filtering

■ Constrained Least Squares Filtering

■ ...

Geometrical image modification

■ Spatial transformations

- Example

- Shrink image to half its size

$$(x', y') = T\{(x, y)\} = (x/2, y/2)$$

- Affine transform:

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

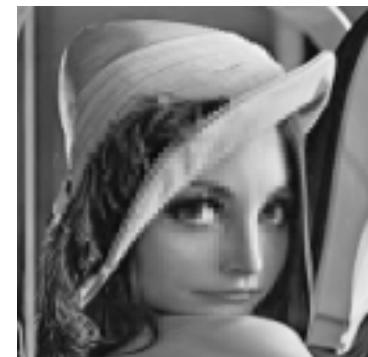
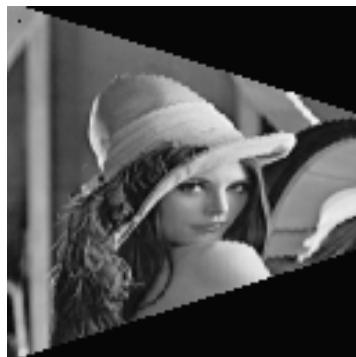
- Higher order

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

→ Estimate (or compute) the inverse matrix

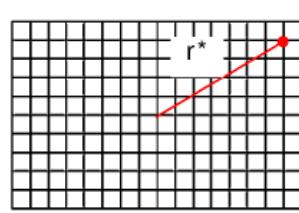
→ If needed, use interpolation

Higher order transforms

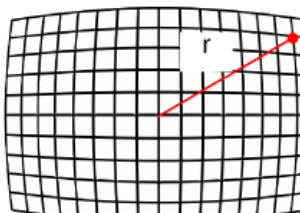


Applications :

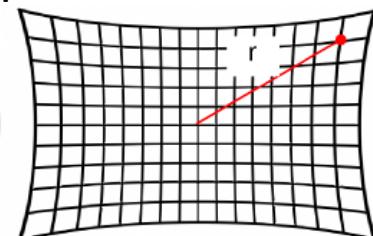
Lens distortion correction, perspective



Orthoscopic
projection



Barrel
distortion



Pincushion
distortion

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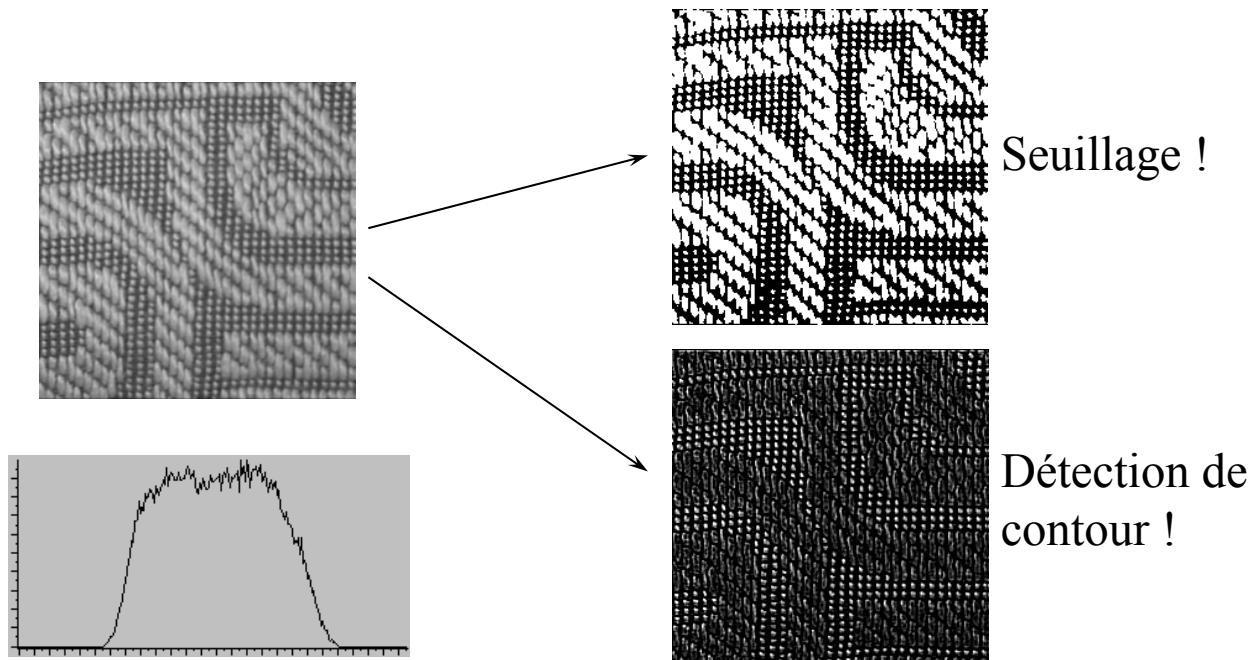
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■ End ...

Before texture

Analyse de texture

Région \neq zone de NG ou de couleur homogène



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Texture = information visuelle qualitative:

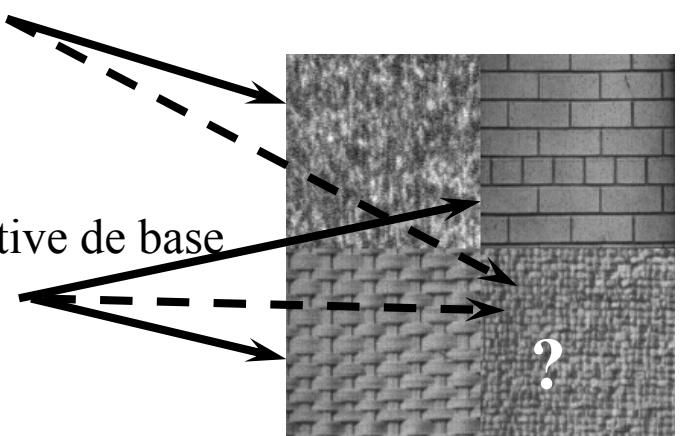
Grossière, fine, tachetée, marbrée, régulière, périodique...

Région homogène: Assemblage plus ou moins régulier
de primitives plus ou moins similaires.

Analyse de texture = formalisation de ces critères

Texture microscopique: Aspect chaotique mais régulier,
primitive de base réduite.

Texture macroscopique: primitive de base
évidente, assemblage régulier.



Méthodes d'analyse de texture:

Structurelles: recherche de primitives de base bien définies et de leur organisation (règles de placement)
Méthodes peu utilisées

Stochastiques: primitives mal définies et organisation +/- aléatoire.

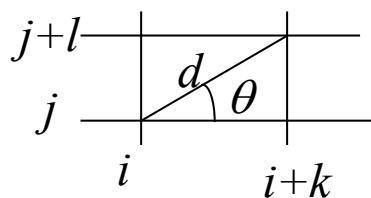
Principe: évaluation d'un paramètre dans une petite région
 (fenêtre de taille dépendant de la texture (!)):
 Analyse fréquentielle, statistiques, comptage
 d'événements, corrélation,....

Pas de modèle général de texture →
 Nombreuses méthodes ad-hoc.

Exemple de méthode: Matrices de co-occurrence

Statistique du second ordre:

$$\text{Pr.}(f(i,j)=a \text{ et } f(i+k,j+l)=b) = p(k,l; a,b) = p(d, \theta; a,b)$$



$$d = 1, \theta = 0^\circ \quad (k=1, l=0)$$

| | | | |
|---|---|---|---|
| 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 2 | 2 | 2 |
| 2 | 2 | 3 | 3 |

| $a \backslash b$ | 0 | 1 | 2 | 3 |
|------------------|---|---|---|---|
| 0 | 2 | 2 | 1 | 0 |
| 1 | 0 | 2 | 0 | 0 |
| 2 | 0 | 0 | 3 | 1 |
| 3 | 0 | 0 | 0 | 1 |

| $a \backslash b$ | 0 | 1 | 2 | 3 |
|------------------|---|---|---|----|
| 0 | 4 | 2 | 1 | 0 |
| 1 | 2 | 4 | 0 | 0 |
| 2 | 1 | 0 | 6 | 1 |
| 3 | 3 | 0 | 0 | 12 |

(en symétrique
 $\theta = 0^\circ, d = 1 \text{ et } d = -1$)

Quelques Paramètres extraits des matrices de co-occurrence

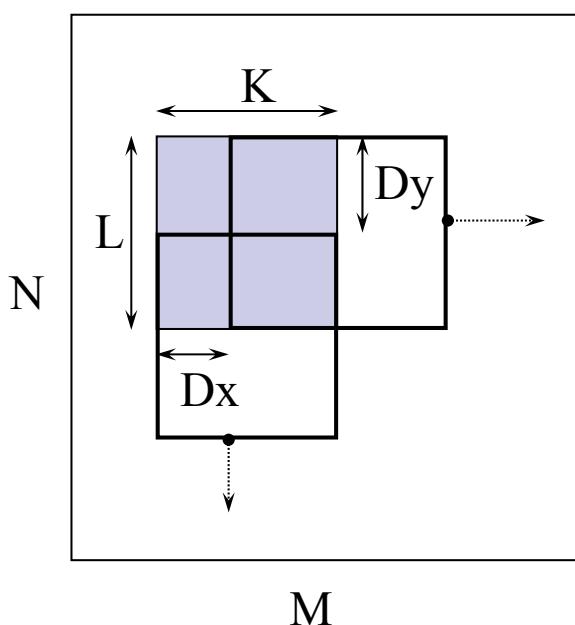
| | | |
|--------------------------------------------------|-----------------------------------------------|-----------------------------------------------------------------|
| Moyenne locale: | $\sum_{i=1}^{NG} \sum_{j=1}^i (i+j)p(i,j)$ | (i,j : ligne et colonne de la matrice de co-occurrence p) |
| Energie ou second moment: | $\sum_{i=1}^{NG} \sum_{j=1}^i p(i,j)^2$ | |
| Inertie ou moment d'ordre deux des différences : | | $\sum_{i=1}^{NG} \sum_{j=1}^i (i-j)^2 p(i,j)$ |
| Autocorrélation: | $\sum_{i=1}^{NG} \sum_{j=1}^i i.j p(i,j)$ | |
| Contraste: | $\sum_{i=1}^{NG} \sum_{j=1}^i (i+j)^2 p(i,j)$ | |

- Il y en a d'autres
- L'interprétation visuelle est difficile.

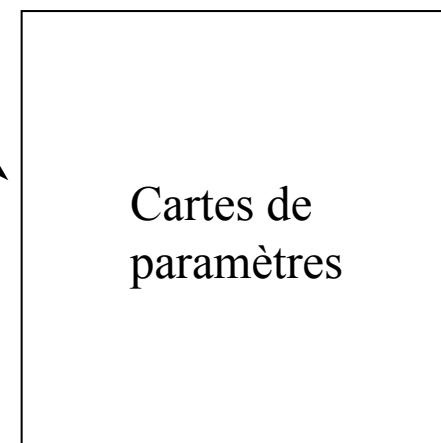
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Application de l'analyse de texture

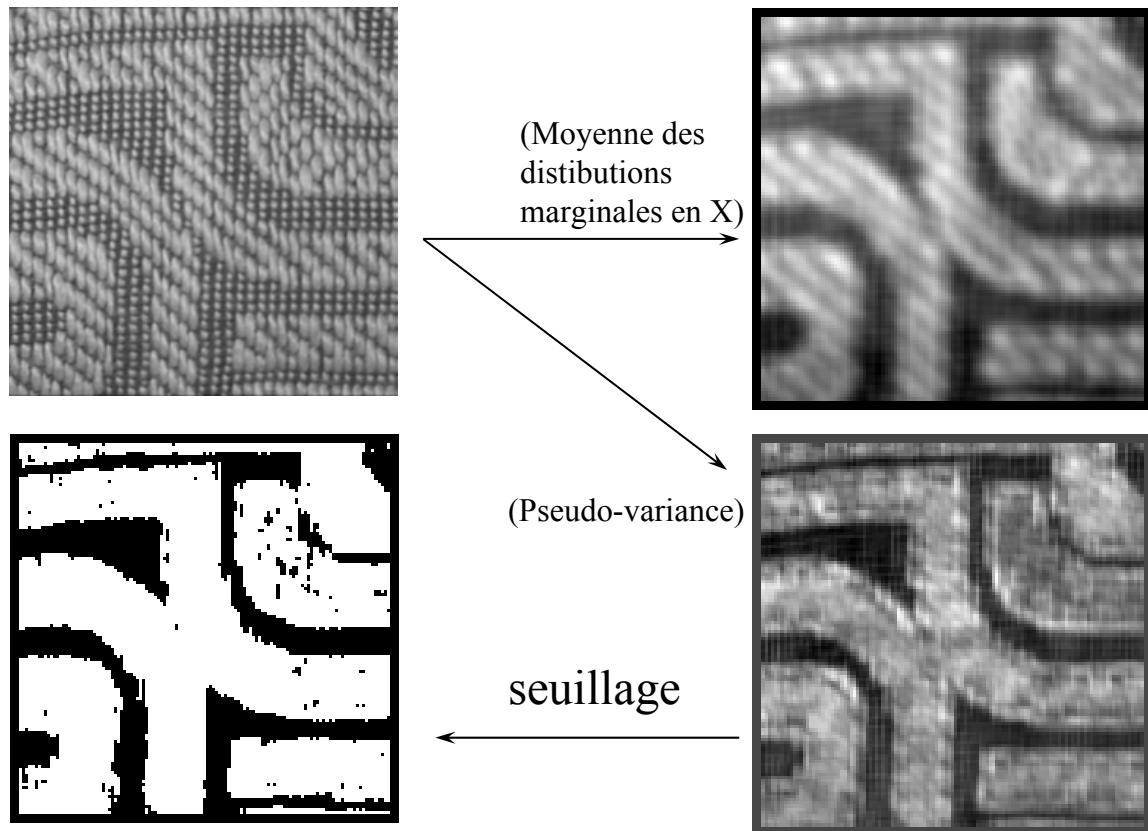


Mesure de paramètres dans une fenêtre de taille K,L
Avec un pas de déplacement Dx, Dy



Application des matrices de co-occurrence

Fenêtre 16x16, pas 2x2, $k=1$, $l=0$



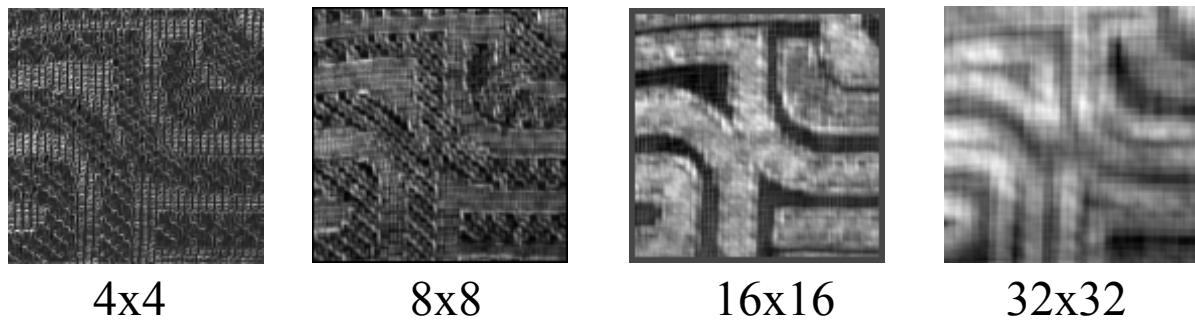
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Influence des paramètres

- Exemple : Choix de la taille de la fenêtre

(Matrice de co-occurrence : Pseudo-variance)



Le choix et les réglages des paramètres sont difficiles. Il faut souvent faire de nombreux essais.

Les paramètres obtenus doivent être pertinents pour l'opération suivante de **segmentation**.