

M2RI, Parcours Images et Données

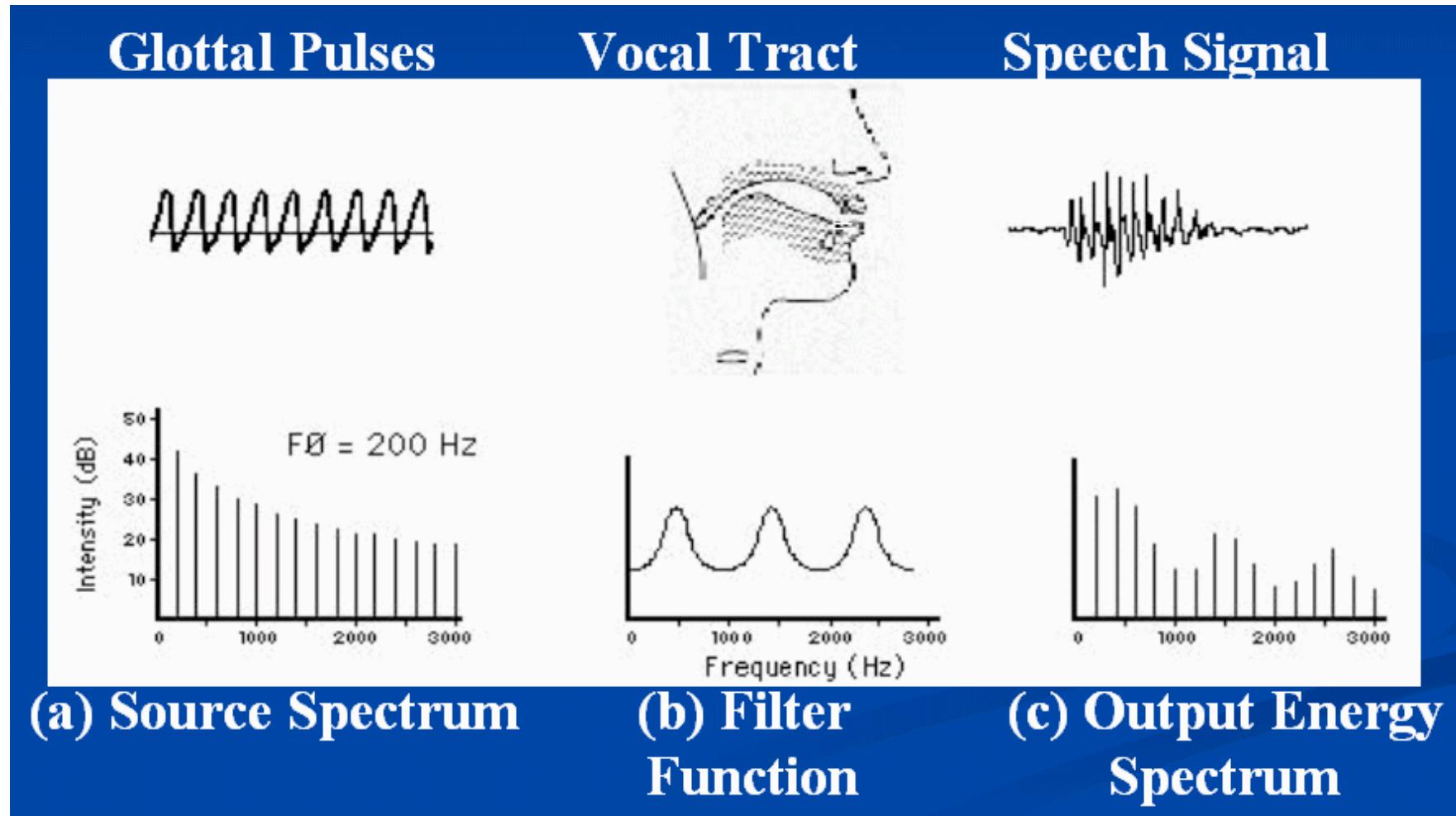
Module Acquisition et Représentation des Données

Extraction de caractéristiques

Features Extraction - 2

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- Human speech production



■ Source + filter model

- ◆ **Time model**

$$x(t) = (h \star s)(t)$$

- ◆ **Frequency model**

$$X(f) = H(f)S(f)$$

$$\log |X(f)| = \log |H(f)| + \log |S(f)|$$

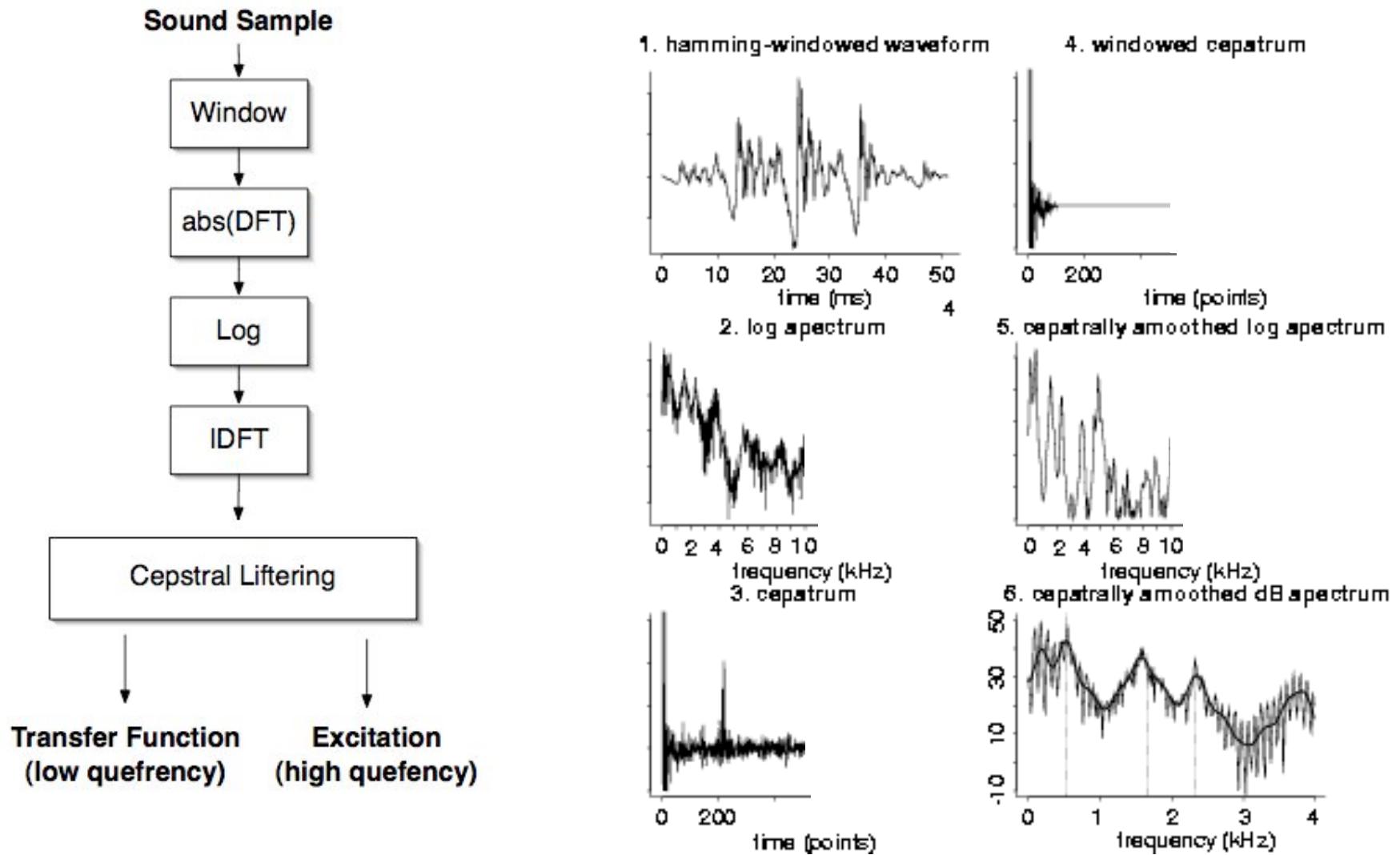
varies slowly varies rapidly

- ◆ **“Quefrency” model**

$$F^{-1}\{\log |X(f)|\} = F^{-1}\{\log |H(f)|\} + F^{-1}\{\log |S(f)|\}$$

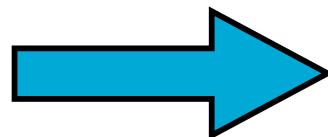
low quefrency high quefrency

■ Cepstrum



■ Use of the Cepstrum in speech analysis

- ◆ Compute the cepstrum on 20 msec. window frames, every 10 msec.
- ◆ N=12 lowest “quefrency” coefficients
- ◆ +1 energy on each frame
- ◆ + first & second time derivatives



3(N+1) dimensional feature vector
every 10 msec.

■ Difficulties of Feature Extraction

- ◆ Segmentation
- ◆ Recognition in Images
- ◆ Recognition in Document Images

■ Feature Extraction/Detection on the whole Signal

- ◆ Global Descriptor
- ◆ Local Descriptor

■ Feature Extraction/Detection on Objects

- ◆ Object Localization / Extraction
- ◆ Object Characterization

■ Interest of Multi-Resolution

■ Using Features

- Stable across images

- ◆ Invariant to small camera transformations
 - ◆ Robust to changes in illumination

- Descriptive

- ◆ Different image patches will be represented differently
 - ◆ Descriptions can be reliably compared

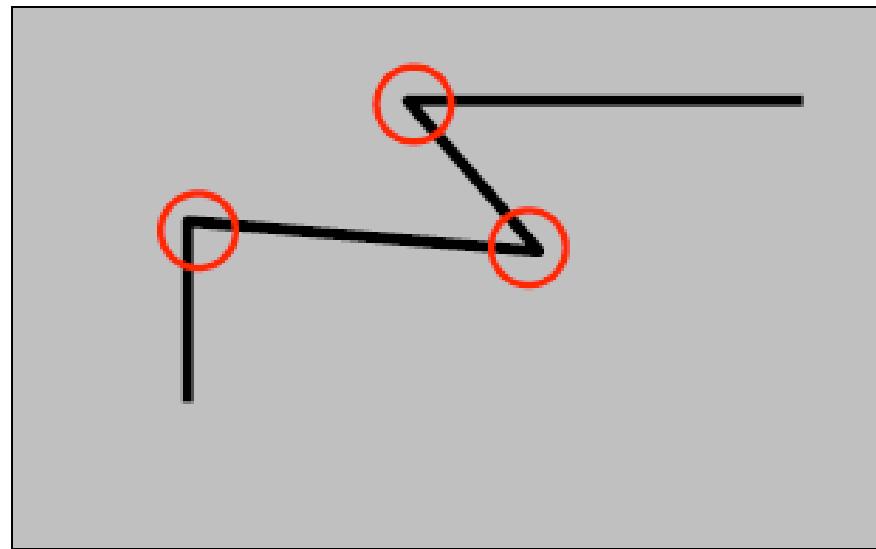
- Interest Point Detector

- ◆ Harris Corner Detector (very popular)

- Feature Descriptor

- ◆ SIFT (best performer)

- Harris corner detector

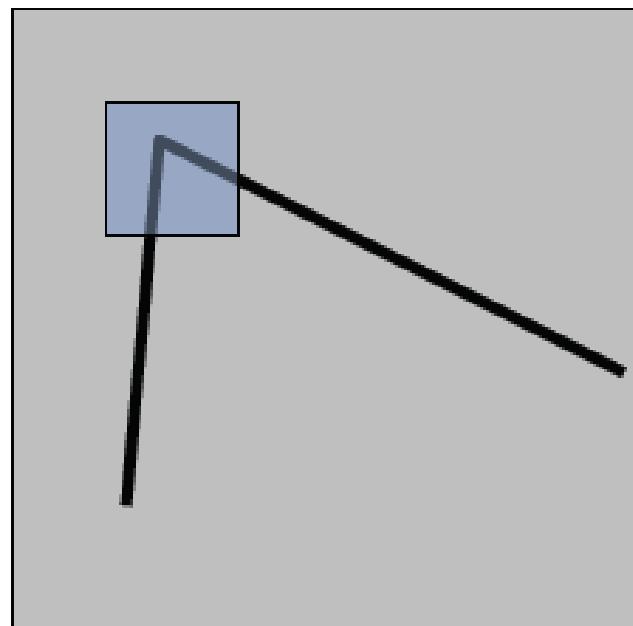


- ◆ C.Harris, M.Stephens. “A Combined Corner and Edge Detector”.
1988

Local Descriptor: Harris

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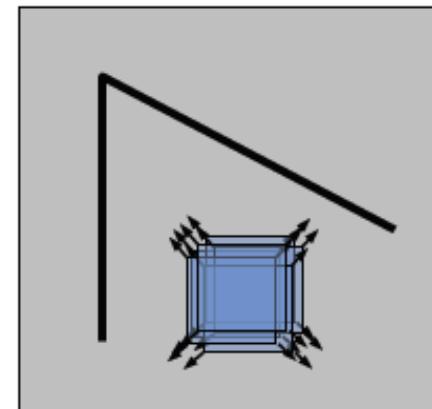
- We should easily recognize the point by looking through a small window
- Shifting a window in any direction should give a large change in intensity



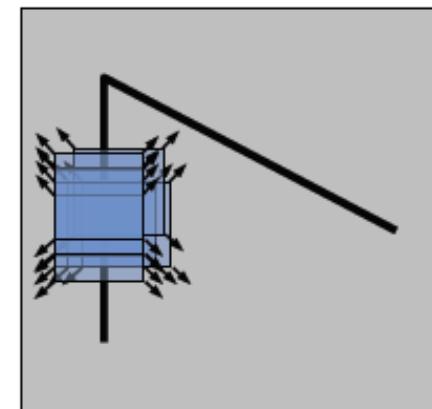
Local Descriptor: Harris

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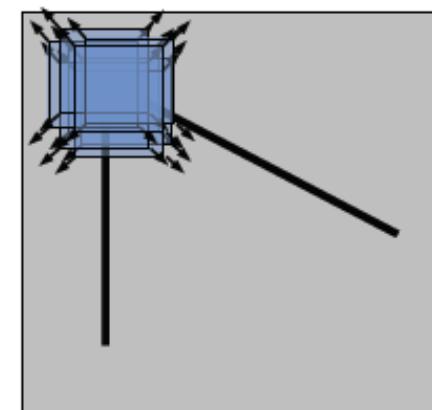
- “flat” region: no change in all directions



- “edge”: no change along the edge direction



- “corner”: significant change in all directions



Local Descriptor: Harris

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Change of intensity for the shift $[u, v]$:

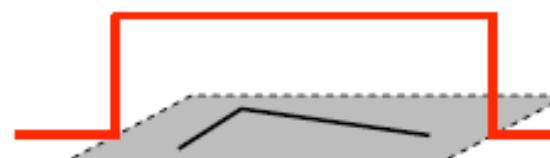
$$E(u, v) = \sum_{x, y} w(x, y) [I(x + u, y + v) - I(x, y)]^2$$

Window
function

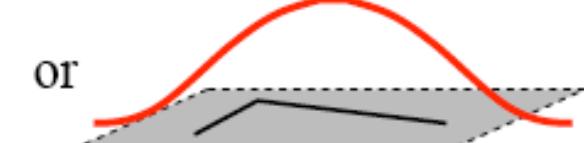
Shifted
intensity

Intensity

Window function $w(x, y) =$



1 in window, 0 outside



Gaussian

$$= \sum_{x, y} w(x, y) [I_x u + I_y v + O(u^2, v^2)]^2$$

For small shifts $[u, v]$ we have a *bilinear* approximation:

$$E(u, v) \cong [u, v] \cdot M \begin{bmatrix} u \\ v \end{bmatrix}$$

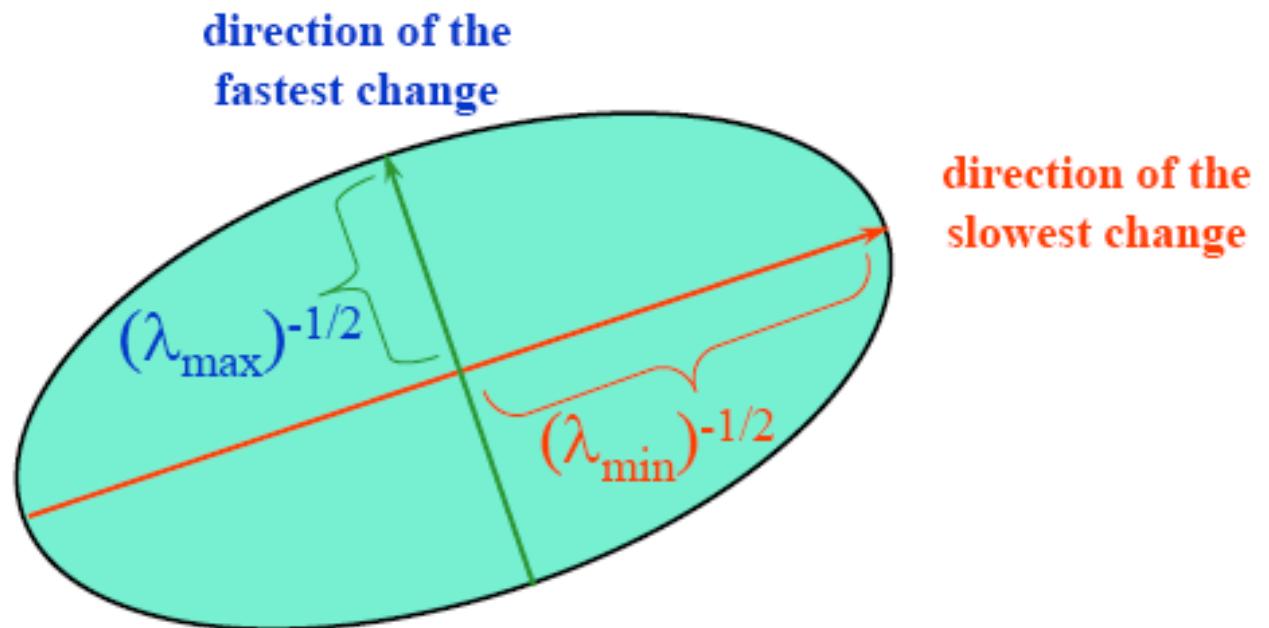
where M is a 2×2 matrix computed from image derivatives:

$$M = \sum_{x,y} w(x, y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

Intensity change in shifting window: eigenvalue analysis

$$E(u, v) \cong [u, v] M \begin{bmatrix} u \\ v \end{bmatrix} \quad \lambda_1, \lambda_2 - \text{eigenvalues of } M$$

Ellipse $E(u, v) = 2$



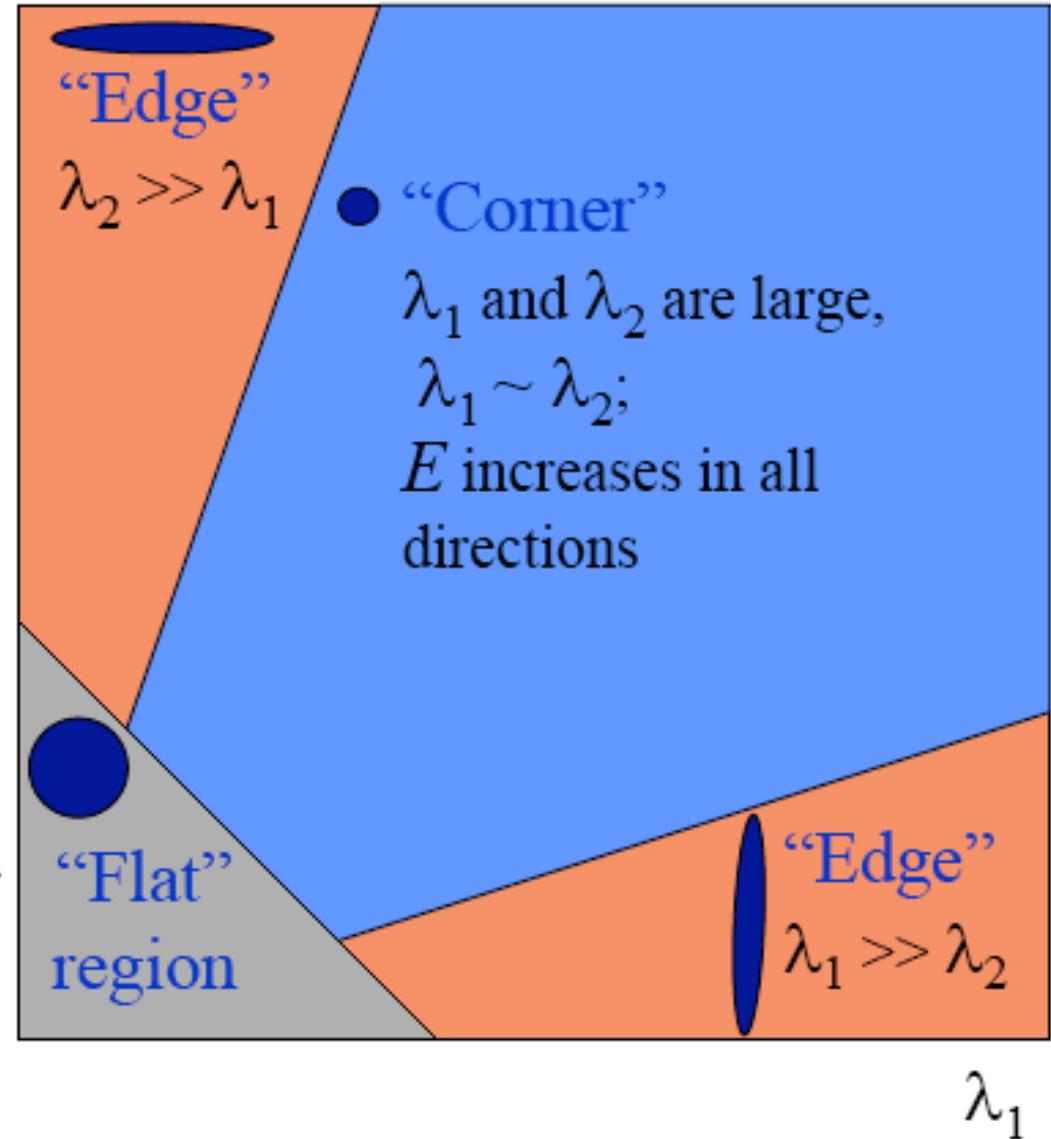
Local Descriptor: Harris

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Classification of
image points using
eigenvalues of M :

λ_1 and λ_2 are small;
 E is almost constant
in all directions

λ_2



Measure of corner response:

$$R = \det M - k (\operatorname{trace} M)^2$$

$$\begin{aligned}\det M &= \lambda_1 \lambda_2 \\ \operatorname{trace} M &= \lambda_1 + \lambda_2\end{aligned}$$

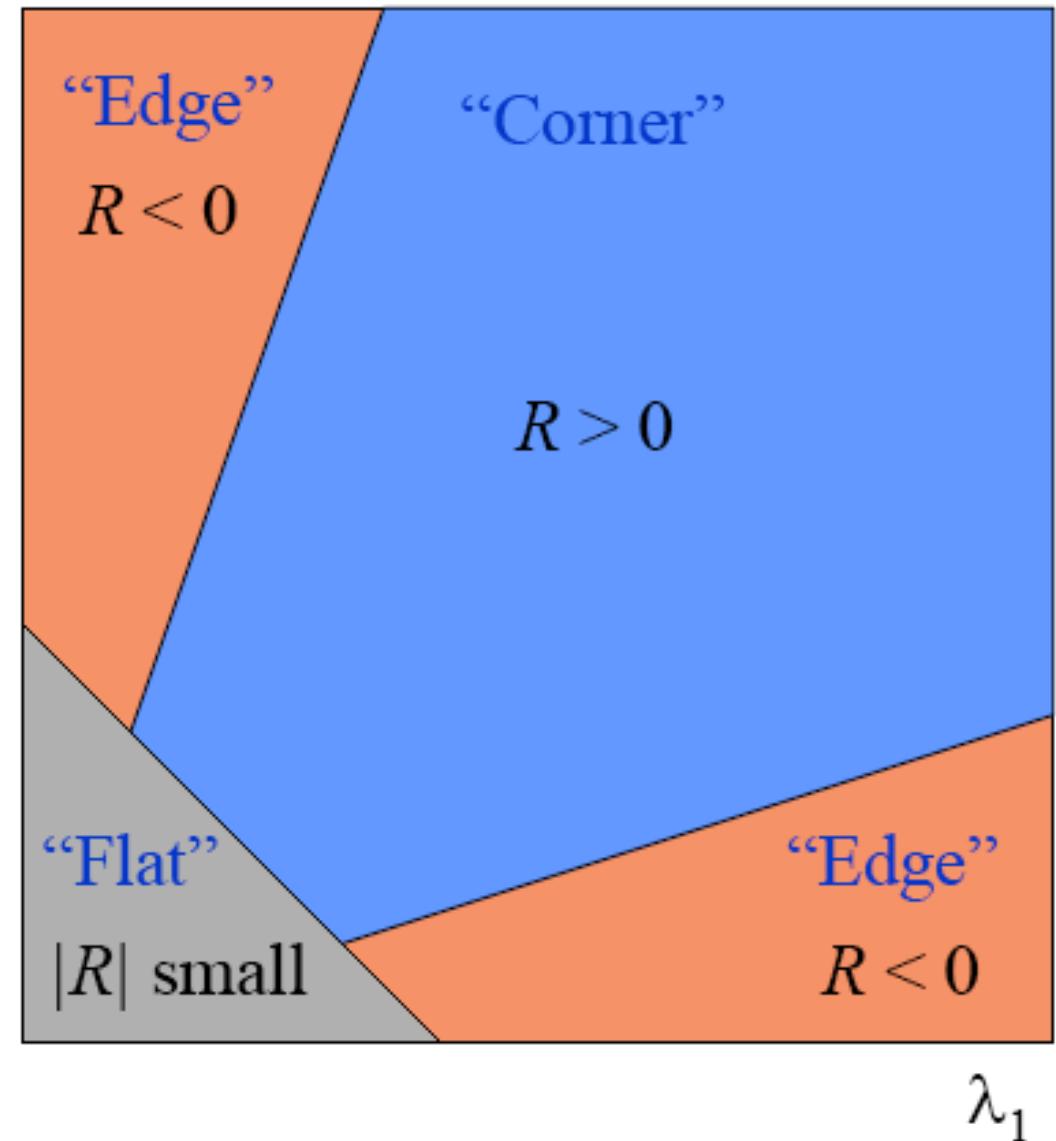
(k – empirical constant, $k = 0.04\text{-}0.06$)

Motivation: computation avoids explicit eigenvalue decomposition

Local Descriptor: Harris

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- R depends only on eigenvalues of M
- R is large for a corner
- R is negative with large magnitude for an edge
- $|R|$ is small for a flat region



■ The Algorithm

- ◆ Find points with large corner response function R
 $(R > \text{threshold})$
- ◆ Take the points of local maxima of R

Local Descriptor: Harris - Example

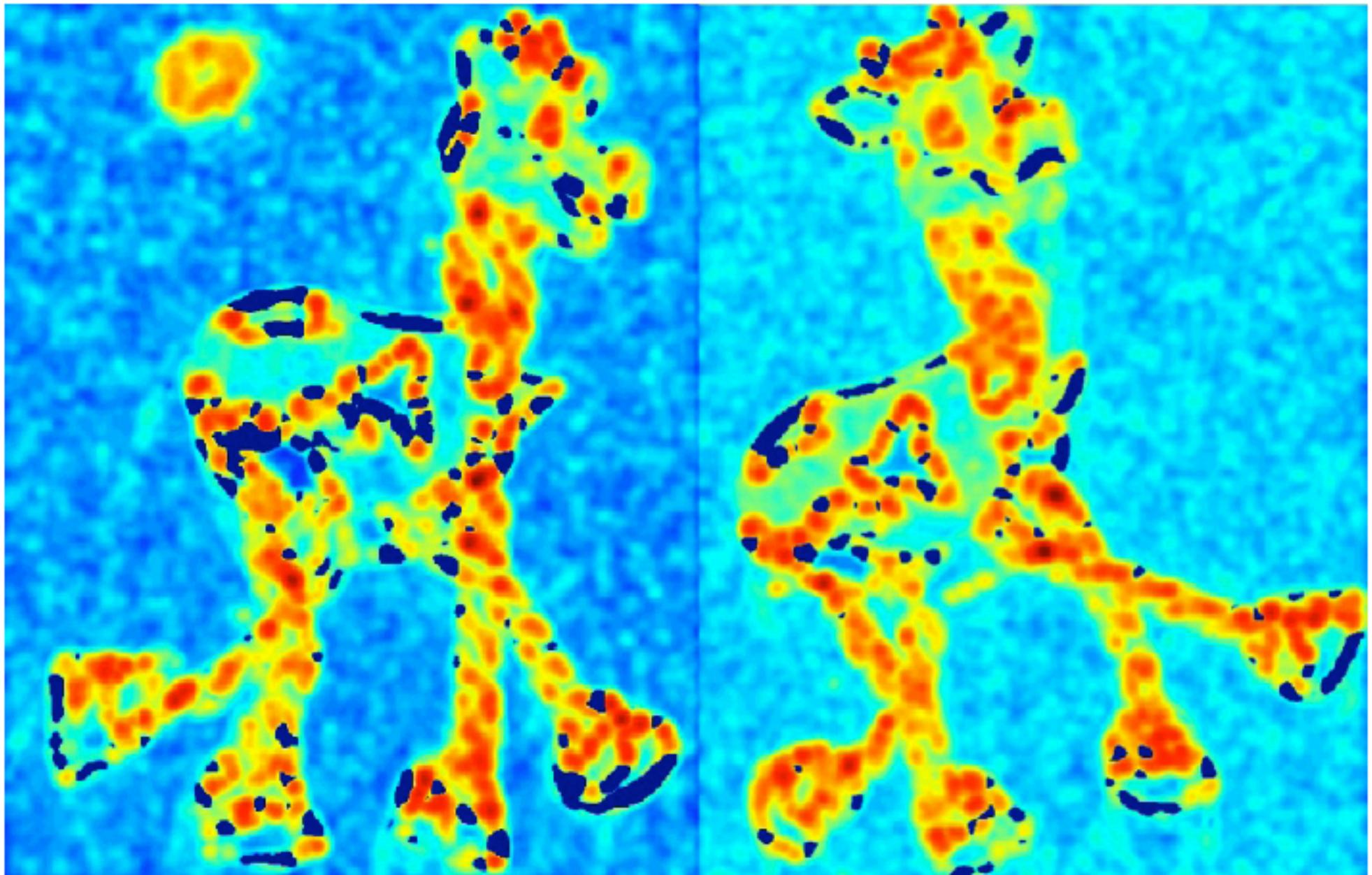
67



Local Descriptor: Harris - Example

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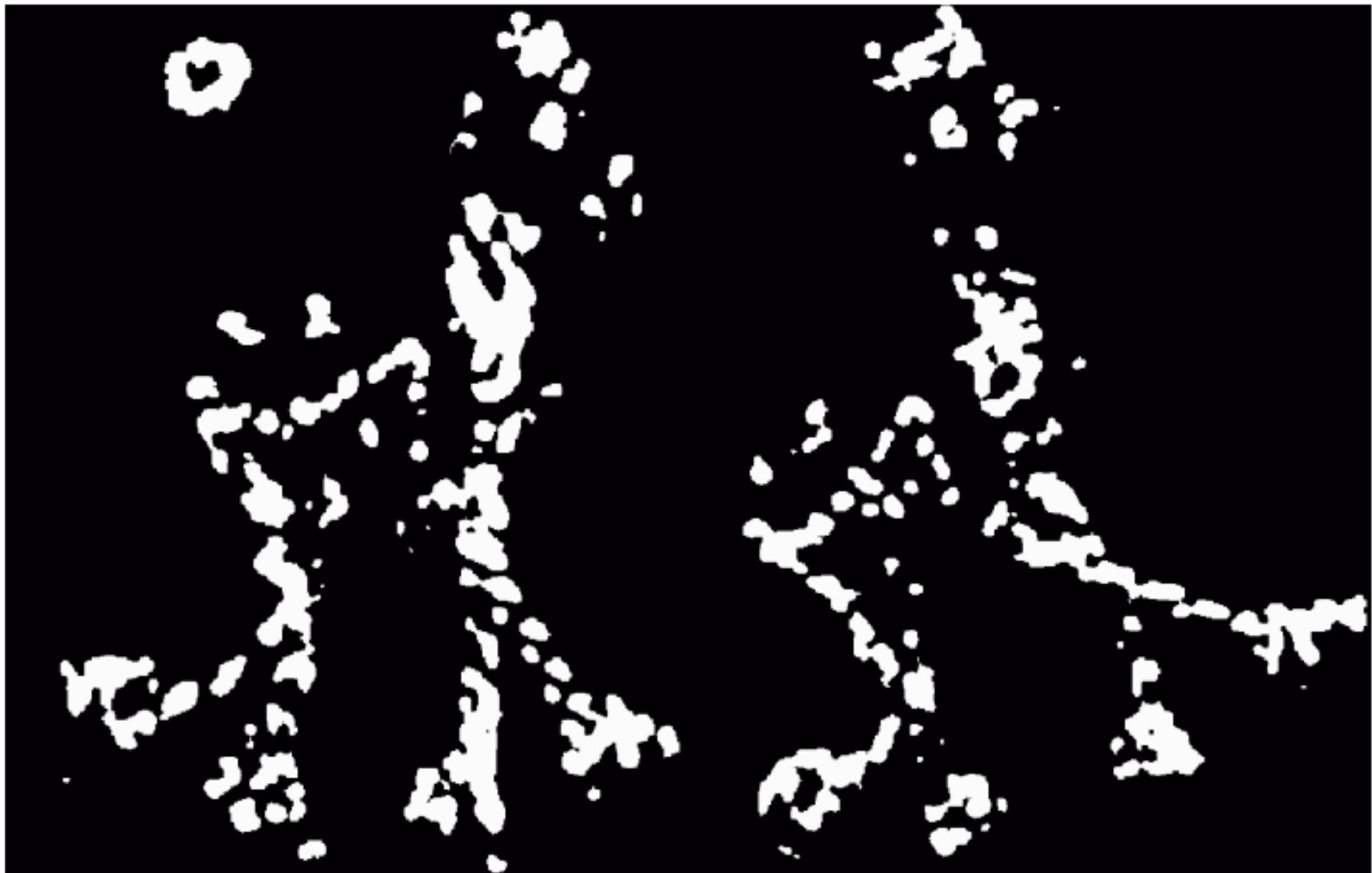
- Compute corner response R



Local Descriptor: Harris - Example

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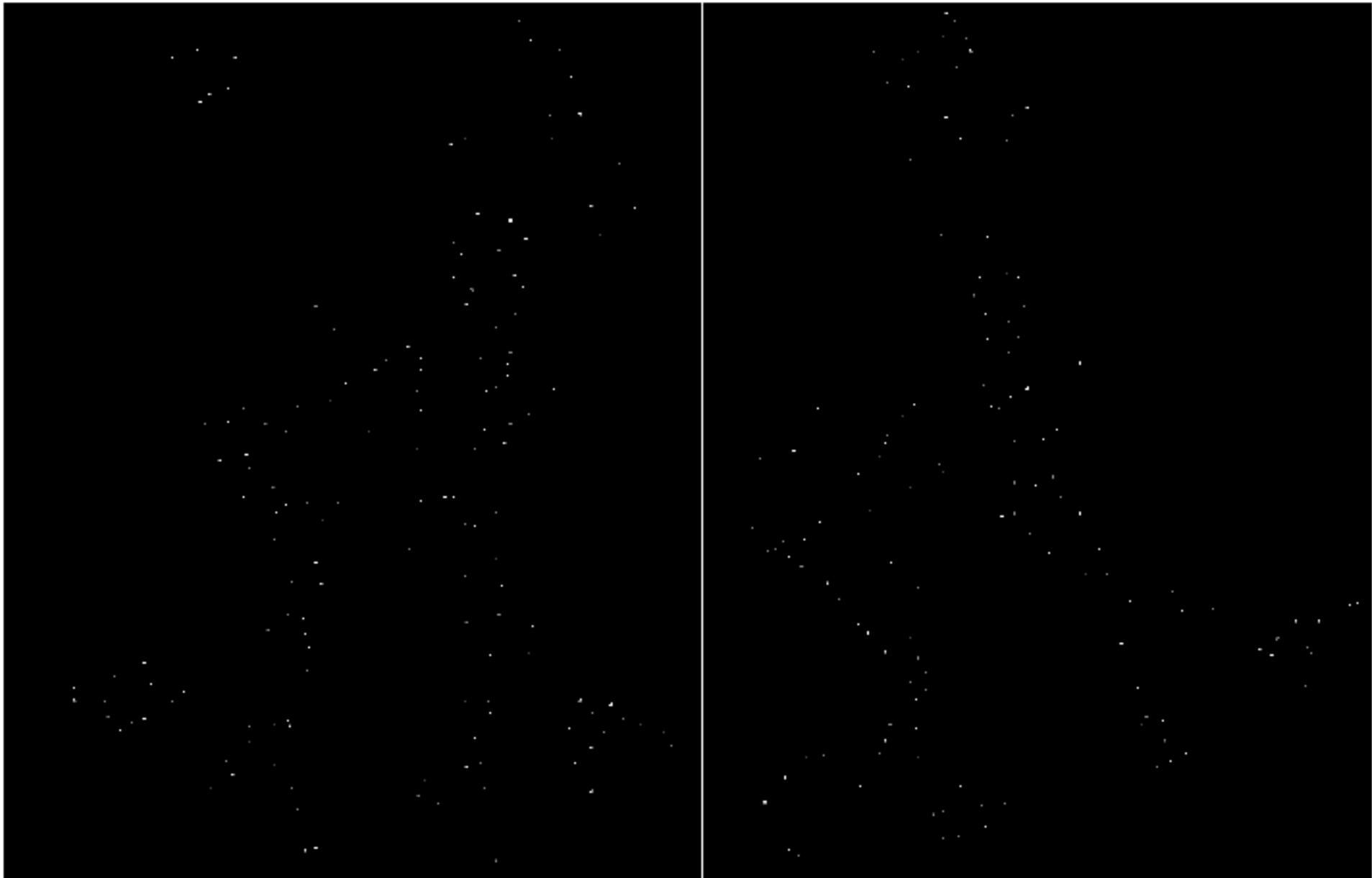
- Find points with large corner response: $R > \text{threshold}$



Local Descriptor: Harris - Example

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- Take only the points of local maxima of R



Local Descriptor: Harris - Example

71



- Average intensity change in direction $[u, v]$ can be expressed as a bilinear form:

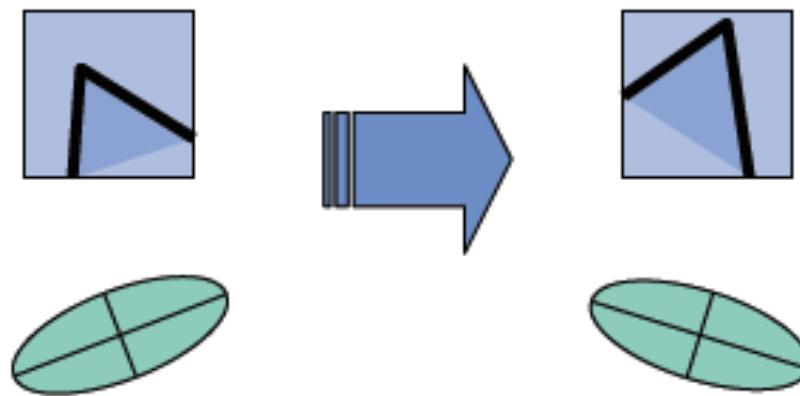
$$E(u, v) \cong [u, v] M \begin{bmatrix} u \\ v \end{bmatrix}$$

- Describe a point in terms of eigenvalues of M :
measure of corner response

$$R = \lambda_1 \lambda_2 - k(\lambda_1 + \lambda_2)^2$$

- A good (corner) point should have a *large intensity change in all directions*, i.e. R should be large and positive

❑ Rotation invariance



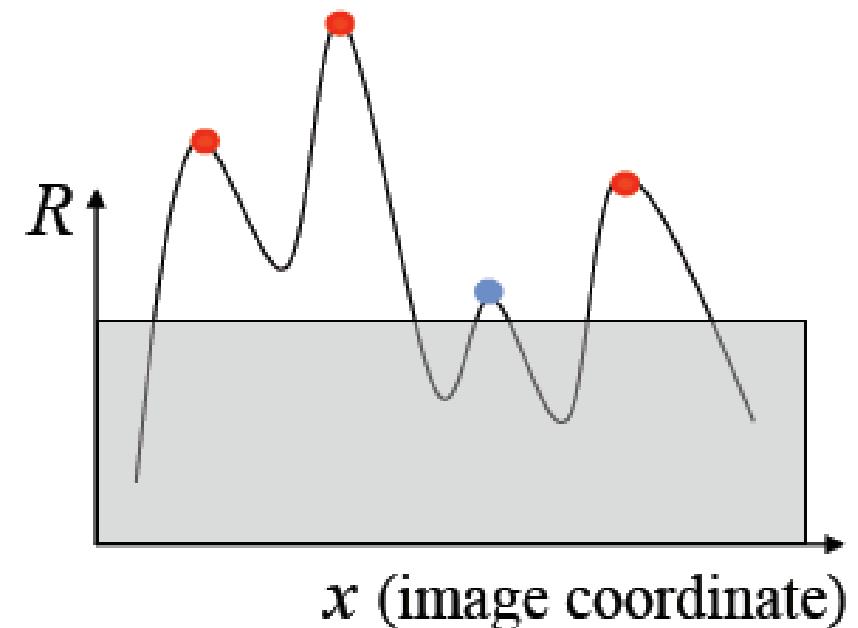
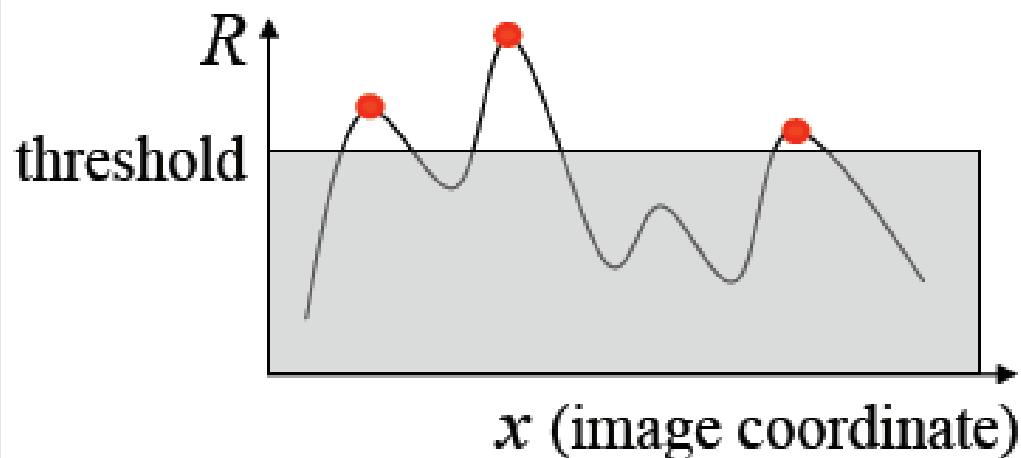
Ellipse rotates but its shape (i.e. eigenvalues) remains the same

Corner response R is invariant to image rotation

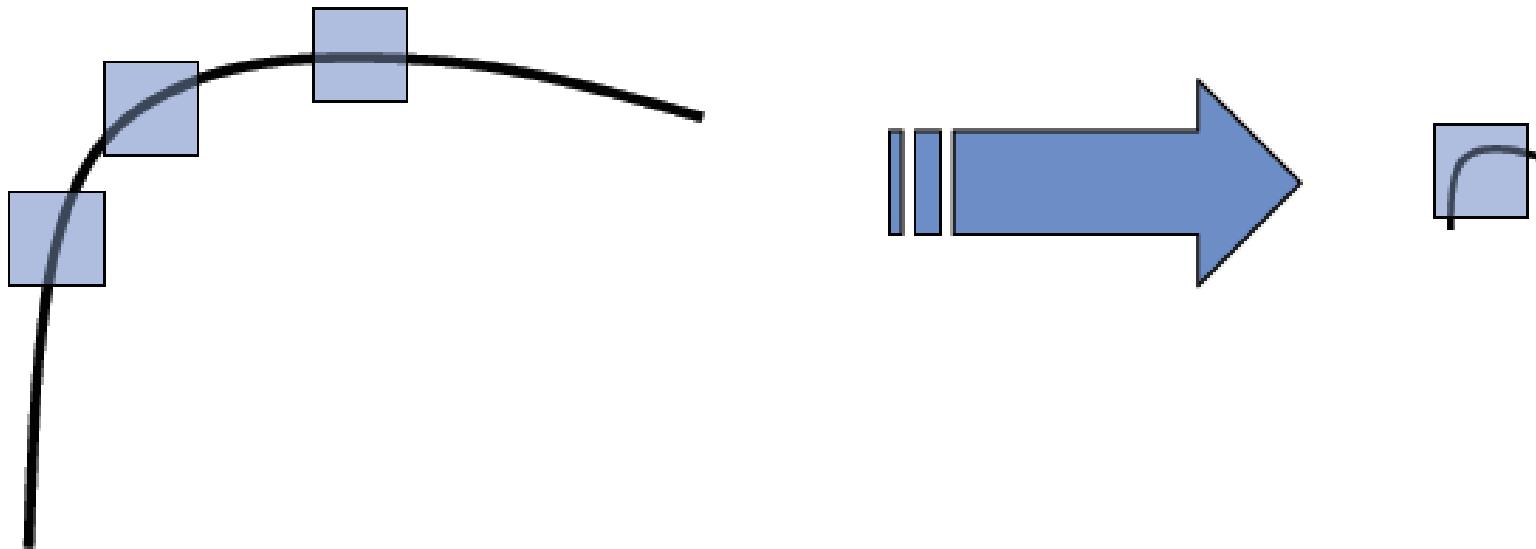
□ Partial invariance to *affine intensity* change

✓ Only derivatives are used => invariance
to intensity shift $I \rightarrow I + b$

✓ Intensity scale: $I \rightarrow a I$



- ❑ But: non-invariant to *image scale*!



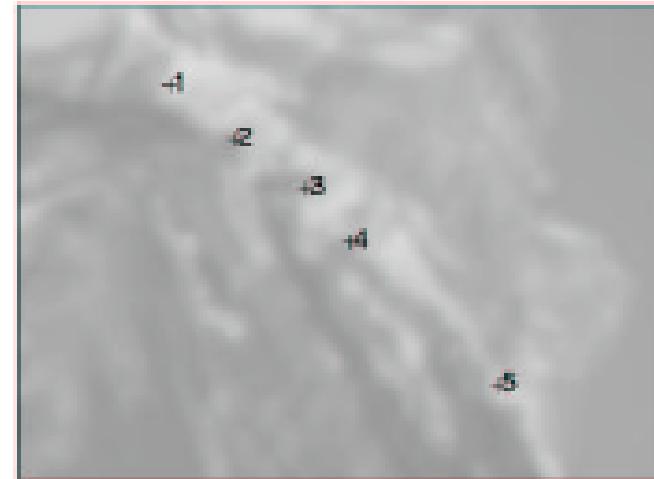
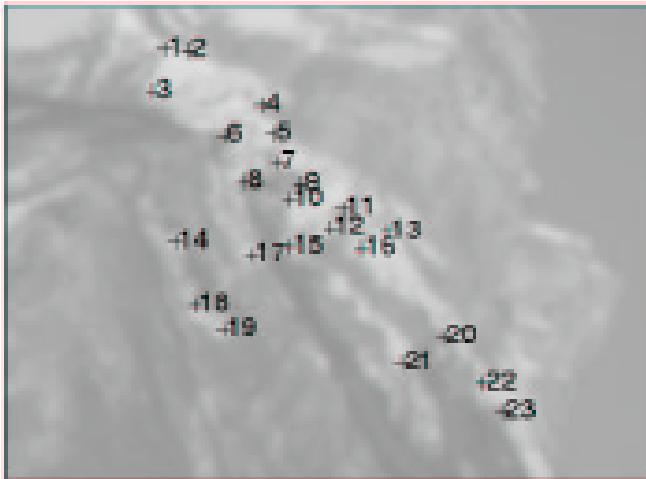
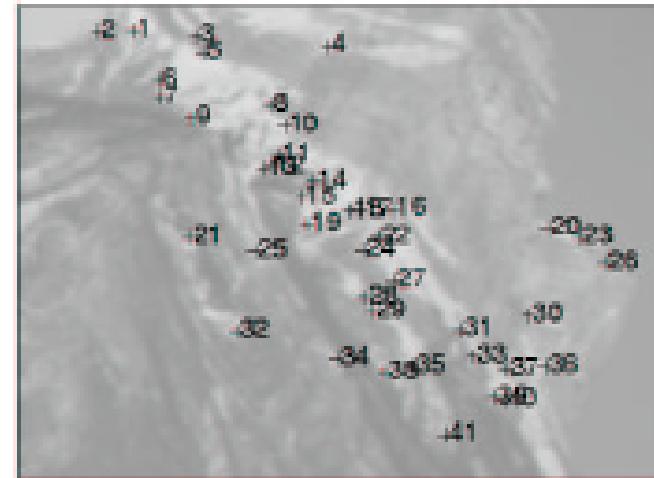
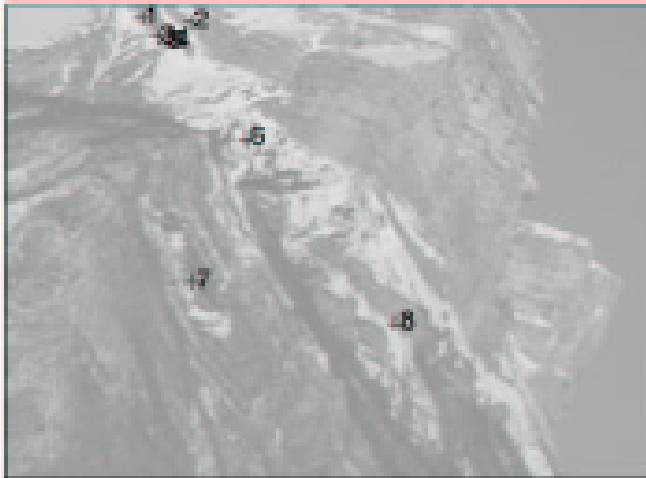
All points will be
classified as edges

Corner !

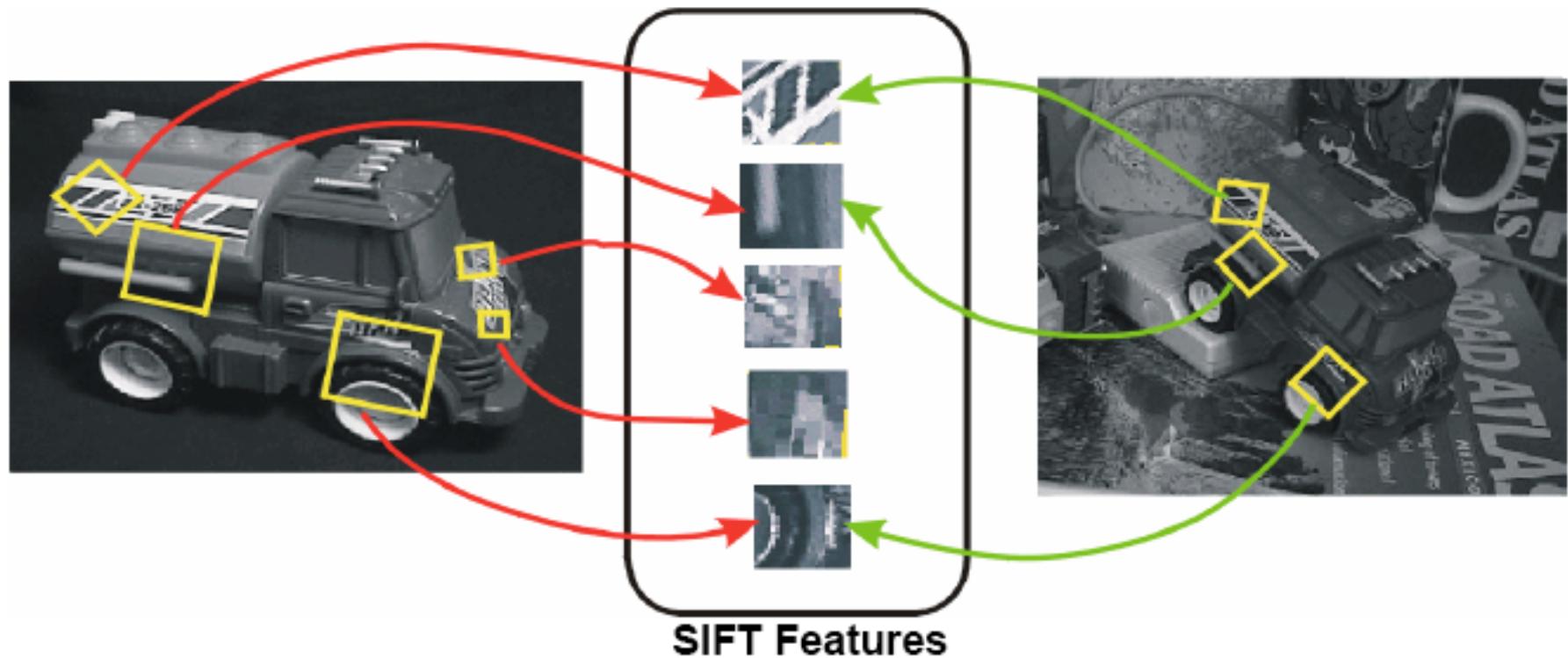
Local Descriptor: Harris

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■ Example of Harris Corner Detector at different scales



- SIFT: Scale Invariant Feature Transform
- Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters



◆ D.G. Lowe, 1999, 2004

- 1) Scale-Space Extrema Detection
 - ◆ **Interest Point**
 - ◆ Local extrema of difference-of-Gaussian filters at different scales
- 2) Keypoint localization
 - ◆ **Removes extrema with low contrast**
- 3) Orientation assignment
 - ◆ **Gradient Orientation**
- 4) Generation of keypoint descriptors

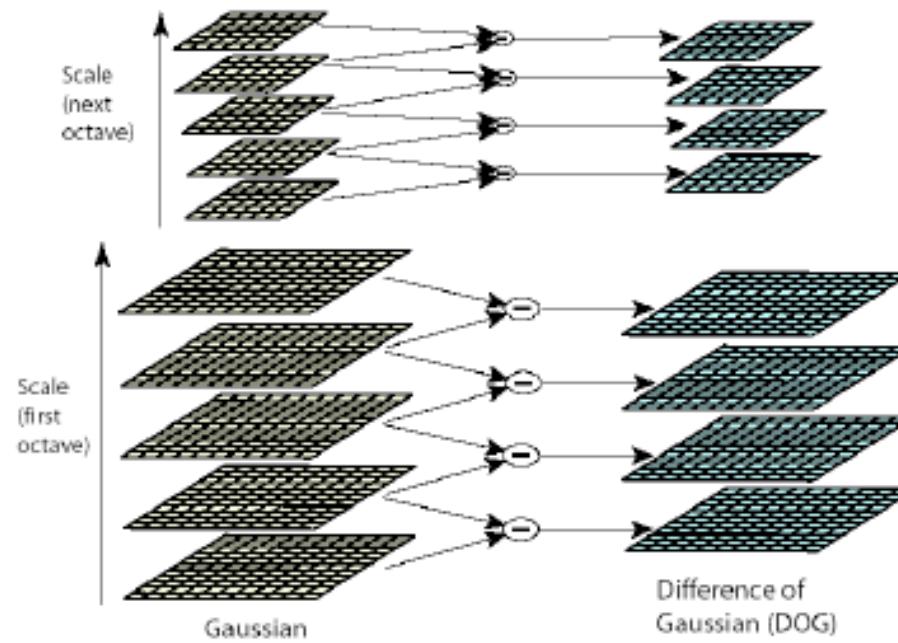
SIFT: 1) Scale-Space Extrema Detection

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From Gaussian scale pyramid --

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$$

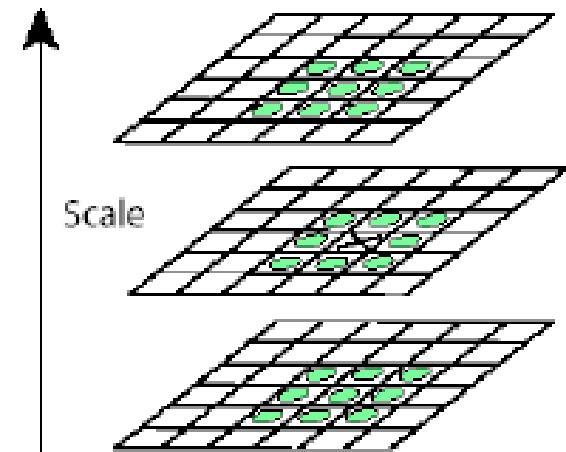
...



create Difference of Gaussian (DOG) images

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y)$$
$$= |x, y, k\sigma| - L(x, y, \sigma).$$

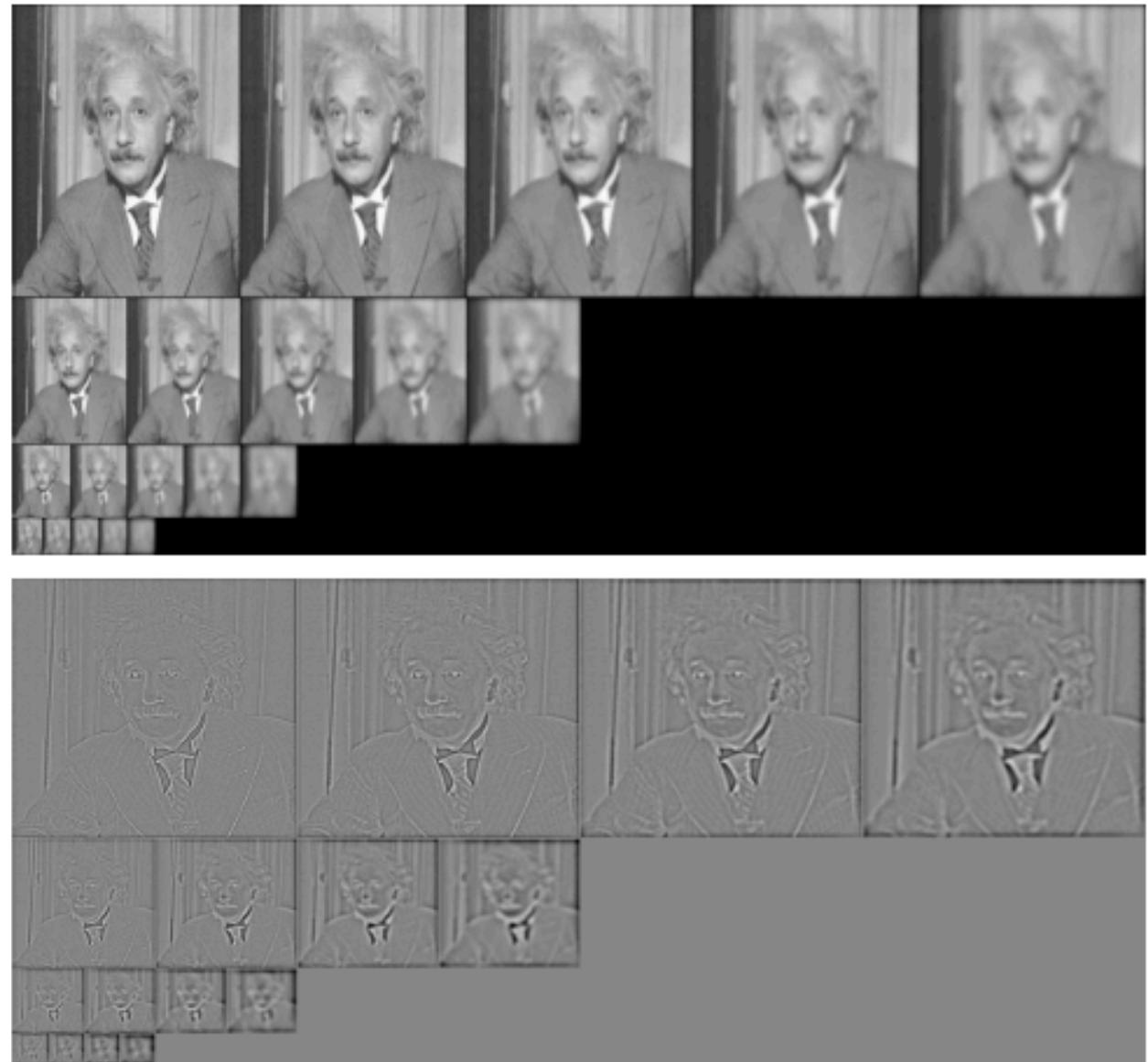
- ◆ Find maximum response over space and scale



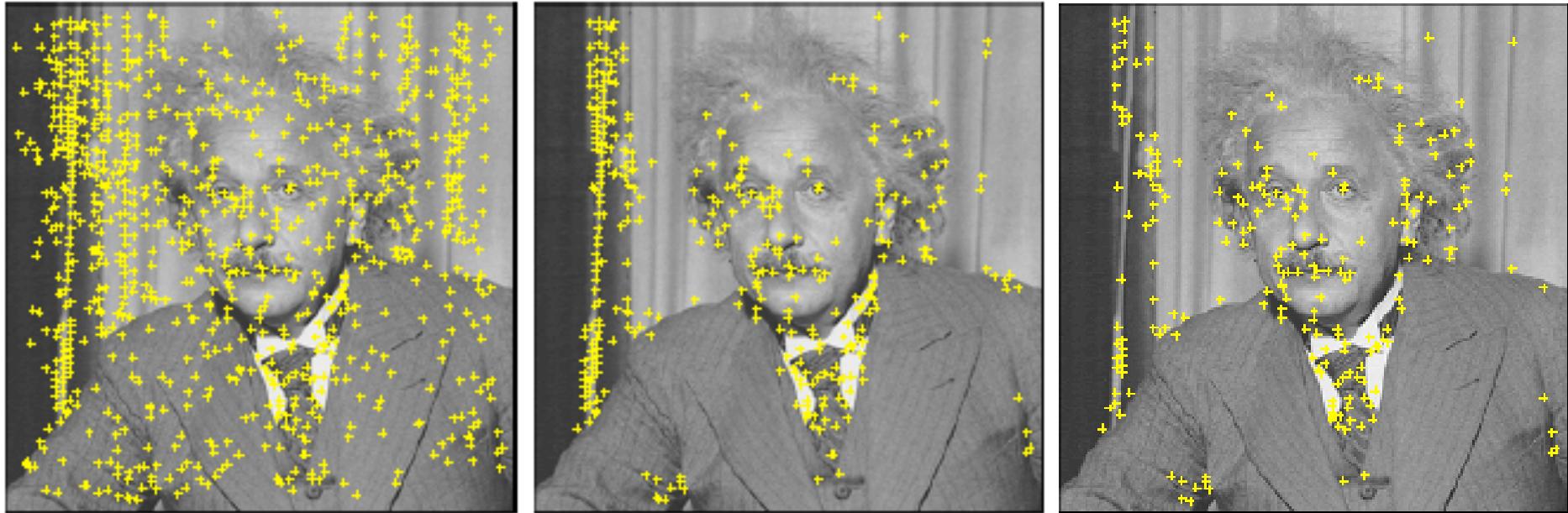
SIFT: 1) Scale-Space Extrema Detection

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- Gaussian blurred images and DoG images grouped by octave



Range: [-0.11, 0.131]
Dims: [959, 2044]

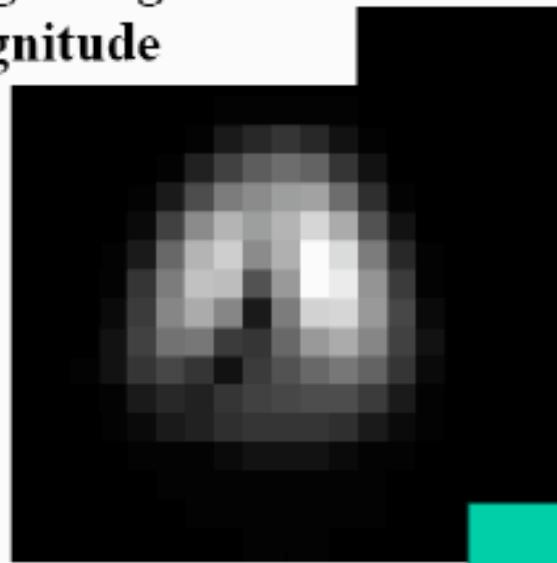


- 1) Scale-Space Extrema Detection
 - ◆ Left: Maxima of DoG across scales
- 2) Keypoint Localization
 - ◆ Middle: Remaining Keypoint after removal of low contrast point
 - ◆ Right: Remaining Keypoint after removal of edge responses

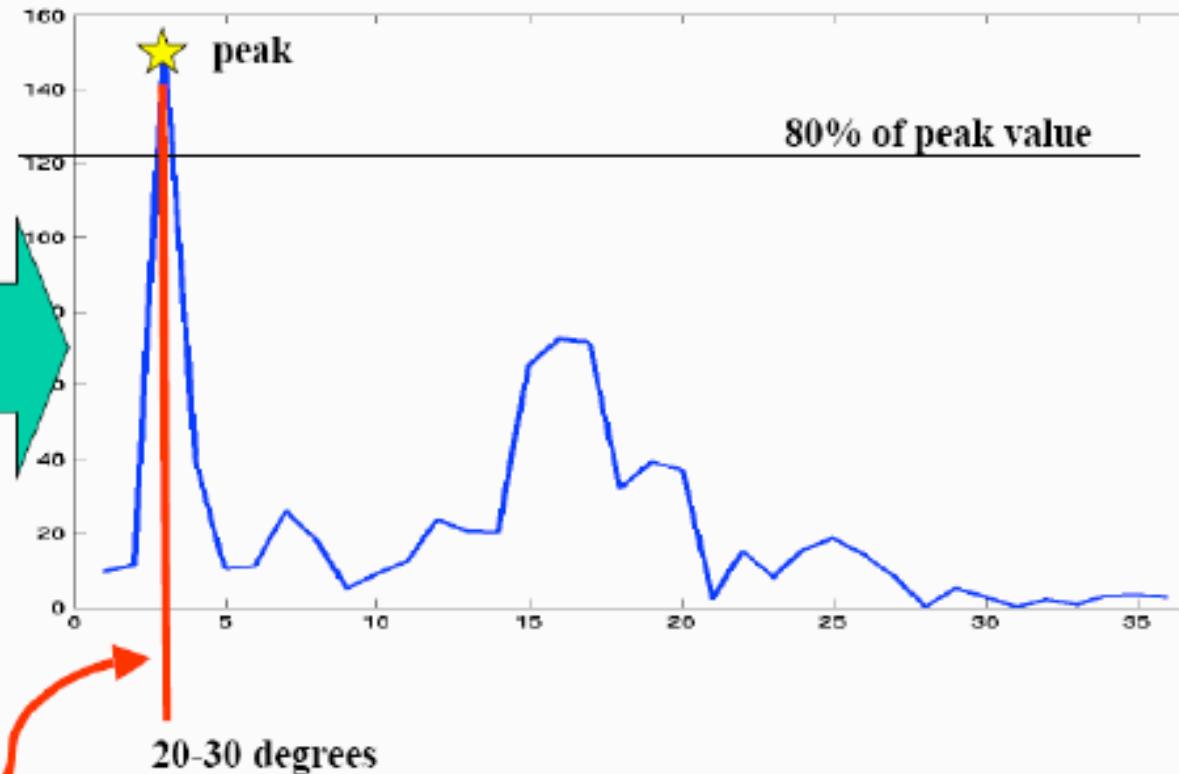
SIFT: 3) Orientation Assignment

82

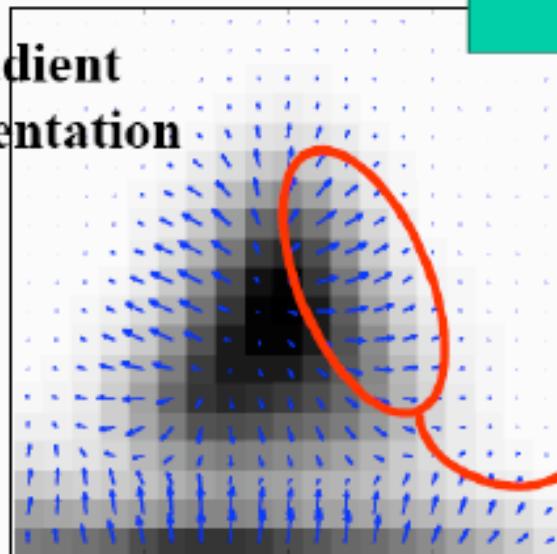
weighted gradient
magnitude



weighted orientation histogram.



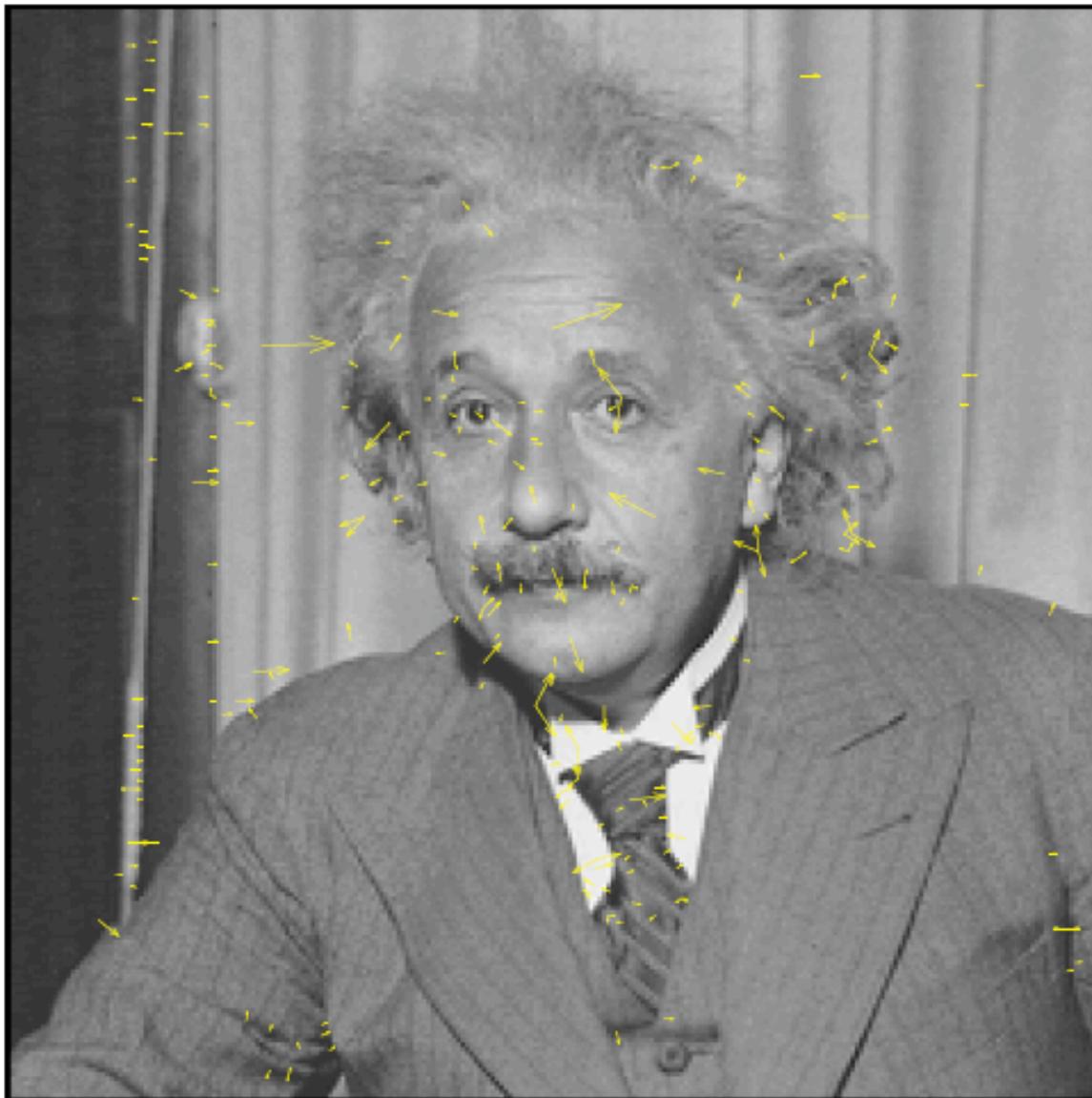
gradient
orientation



Orientation of keypoint
is approximately 25 degrees

SIFT: 3) Orientation Assignment

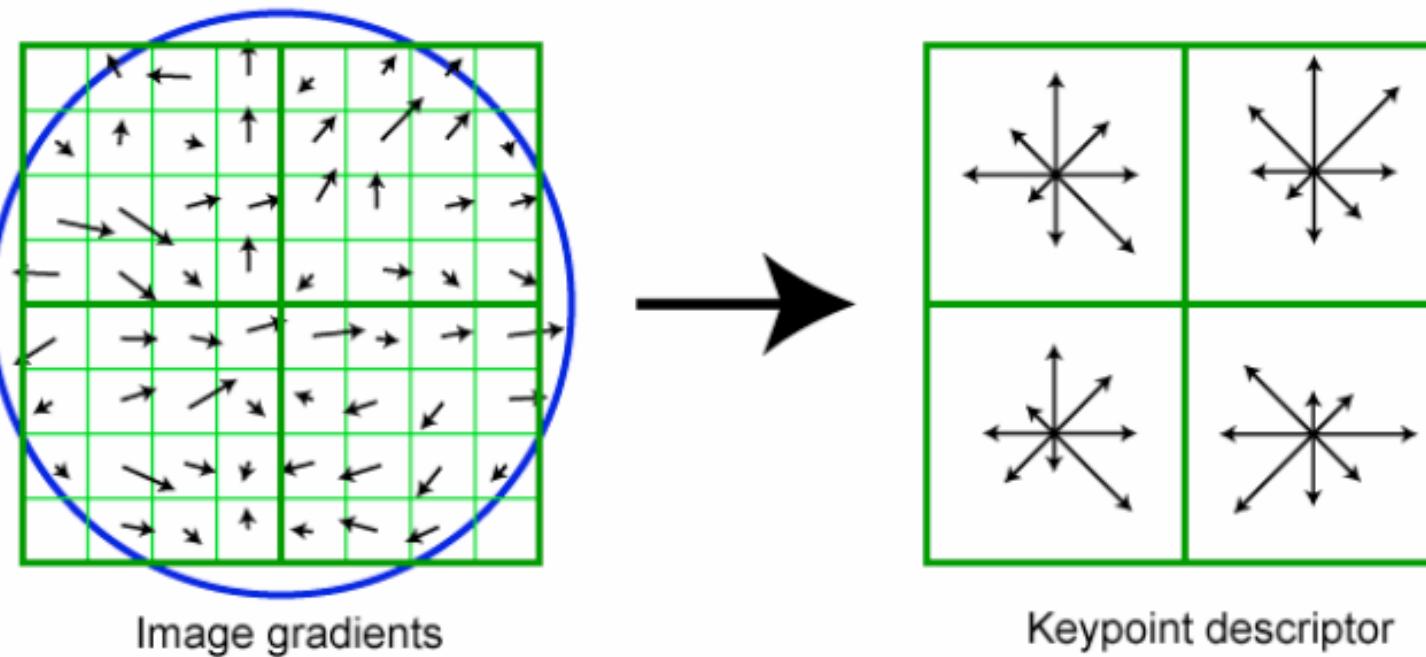
83



SIFT: 4) Keypoint Descriptor

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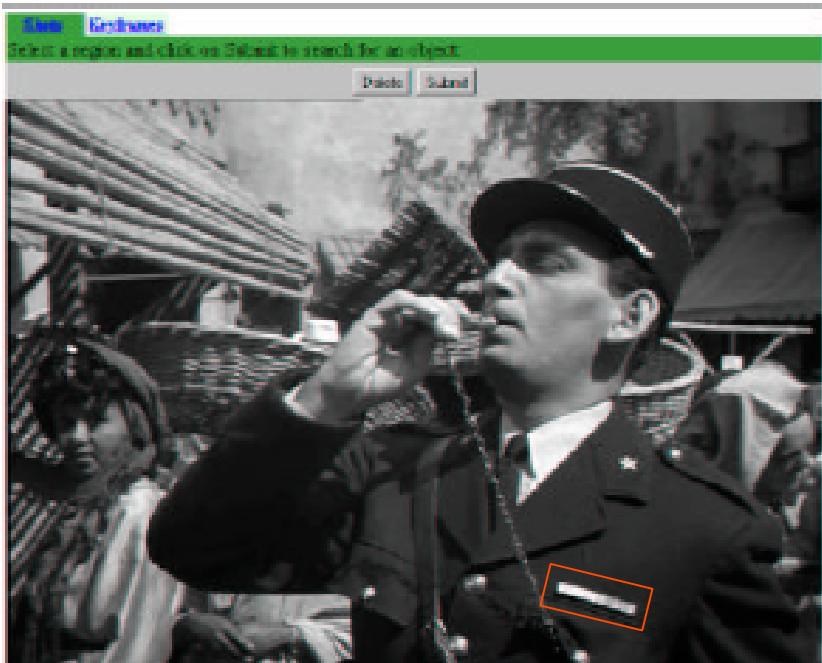
- Thresholded image gradients are sampled over 16x16 array of locations in scale space
- Create array of weighted orientation histograms



- 8 orientations x 4x4 histogram array = 128 dimensions

SIFT: Application

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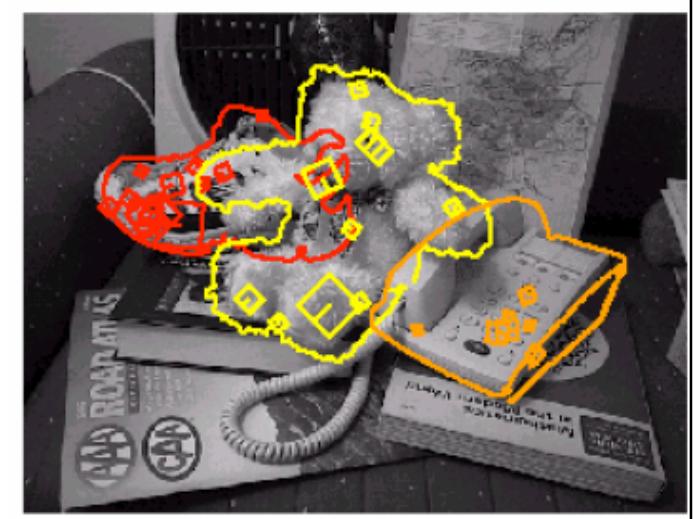
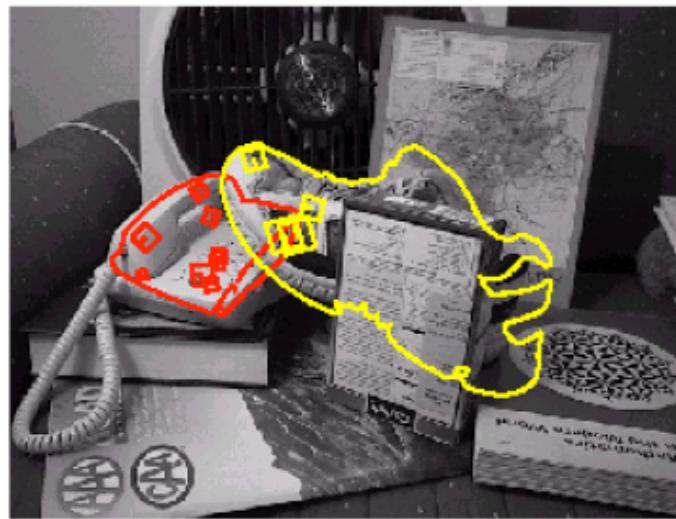
SIFT: Application

86



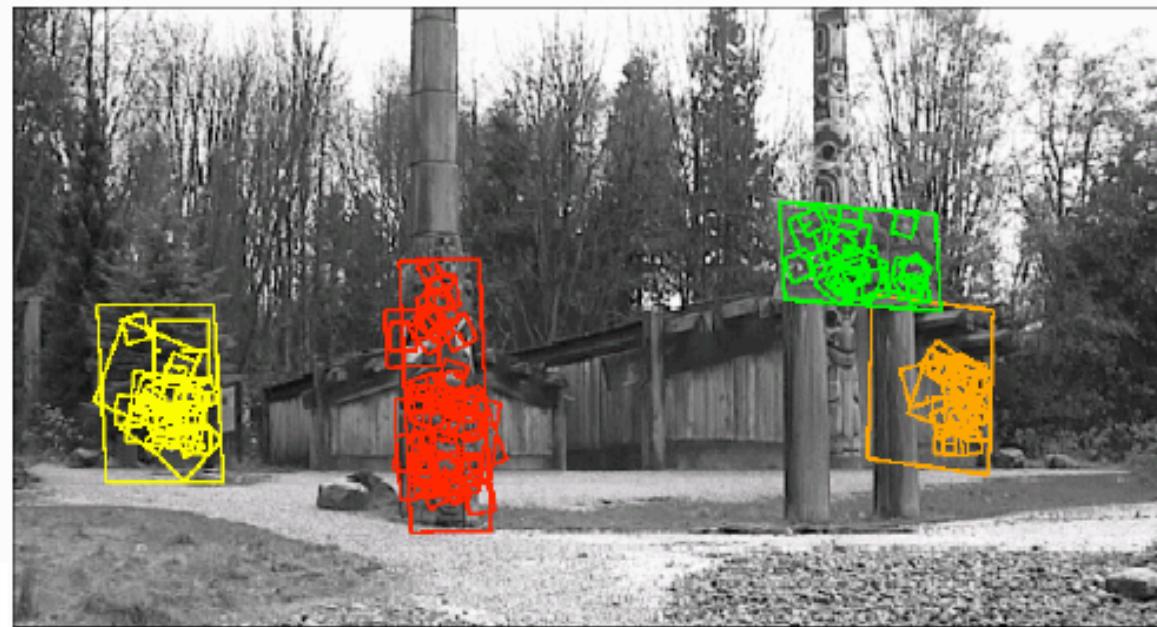
SIFT: Application

87



SIFT: Application

88



❑ Invariances:

- Scaling Yes
- Rotation Yes
- Illumination Yes
- Perspective Projection Maybe

❑ Provides

- Good localization Yes

■ Difficulties of Feature Extraction

- ◆ Segmentation
- ◆ Recognition in Images
- ◆ Recognition in Document Images

■ Feature Extraction/Detection on the whole Signal

- ◆ Global Descriptor
- ◆ Local Descriptor

■ Feature Extraction/Detection on Objects

- ◆ Object Localization / Extraction
- ◆ Object Characterization

■ Interest of Multi-Resolution

■ Using Features

■ Features on Objects

- ◆ Need to detect Objects in Images
 - ◆ Segmentation
 - ◆ Difficult task
 - ◆ Recognize => Segment but Segment => Recognize
 - ◆ See section Segmentation difficulties
- ◆ Object characterization
 - ◆ Features extracted on Segmented Objects

■ Difficulties of Feature Extraction

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■ Interest of Multi-Resolution

■ Using Features

- Difficulties of Feature Extraction
- Feature Extraction/Detection on the whole Signal
- Feature Extraction/Detection on Objects
 - ◆ Object Localization / Extraction
 - ♦ Region Labeling
 - ♦ Edge Detection
 - ♦ Connected Components Labeling
 - ♦ Skeletonization
 - ♦ Handwriting extraction
 - ♦ Line-Segment Detection
 - ◆ Object Characterization
- Interest of Multi-Resolution
- Using Features

- Criteria: Luminosity, Color, Texture...

- ◆ Homogeneous Regions / Criteria
- ◆ Significant Criteria Difference

- Simple Inside, no small holes

- Regular Edges

- Measure Space Partition

- Region Growing

- ◆ Find a Germ
- ◆ Aggregation

- Edge-Region Duality

- ◆ Edge Detection
 - ◆ See next section
- ◆ Fill inside

- Using Time in Image Sequence

- ◆ Object Movement can be detected
- ◆ What Changed from one image to another
- ◆ Follow Object

■ Measure Space

- ◆ Luminosity
- ◆ Color
- ◆ Texture
- ◆ Gradient

■ Measure Space Partition

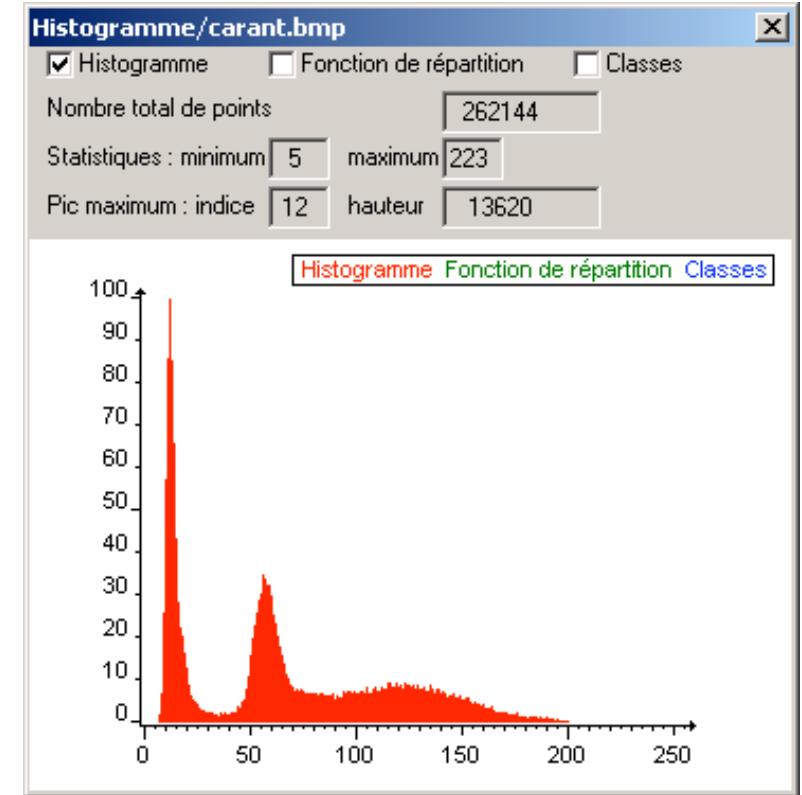
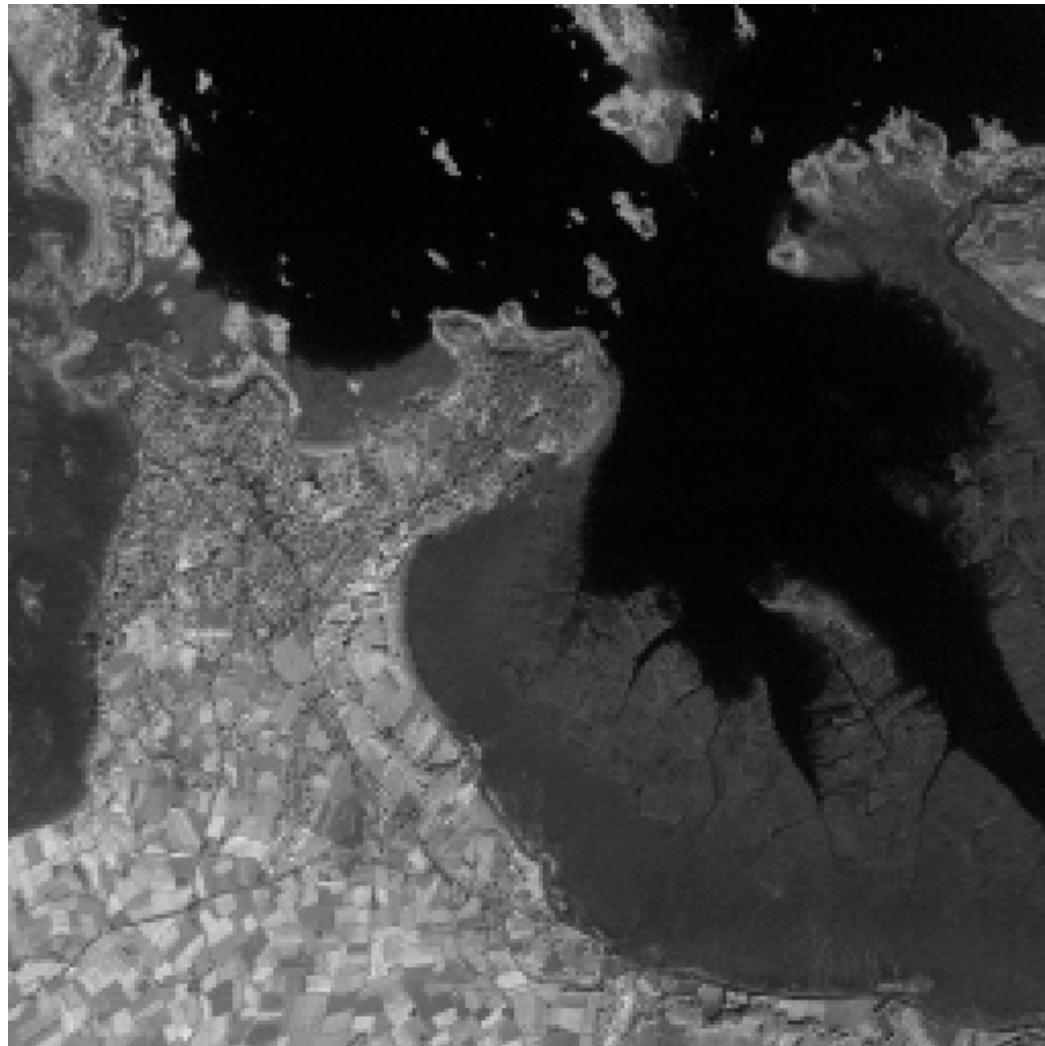
- ◆ For example: black/white

■ Pixel Labeling by a class name

- ◆ Connected Components of the same name

Luminosity Partition

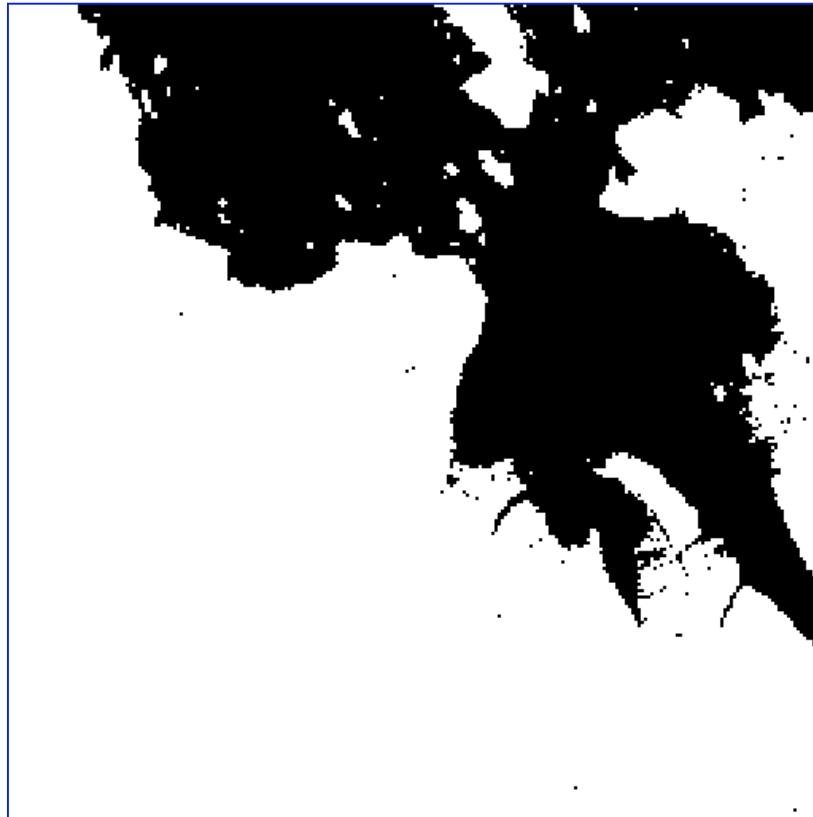
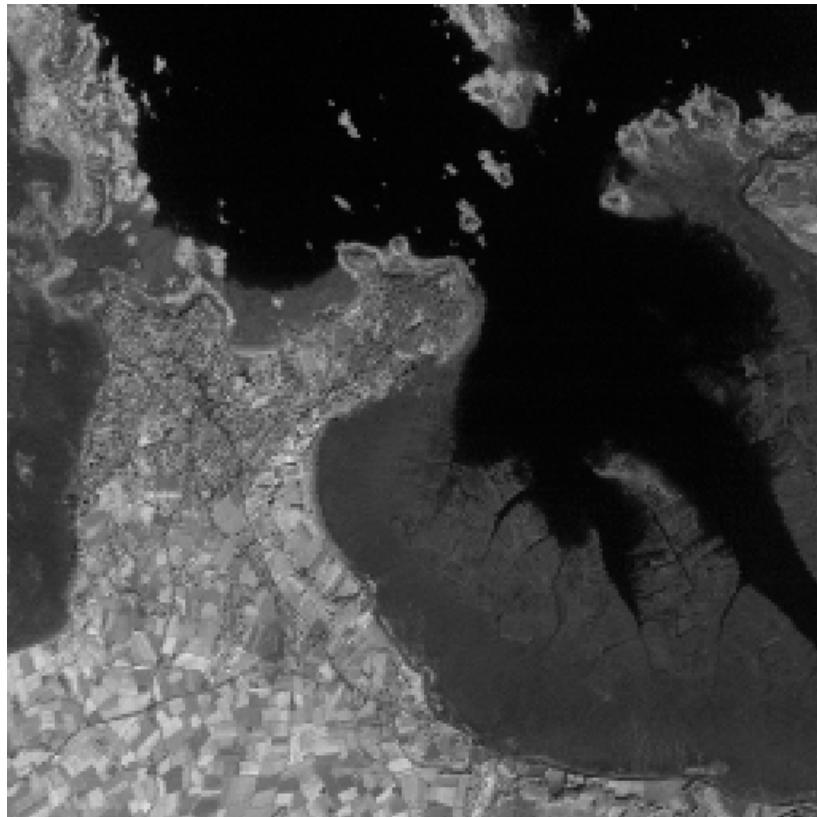
97



Seuil manuel
0-40 eau
41-98 estran
>98 terre

Luminosity Partition

98

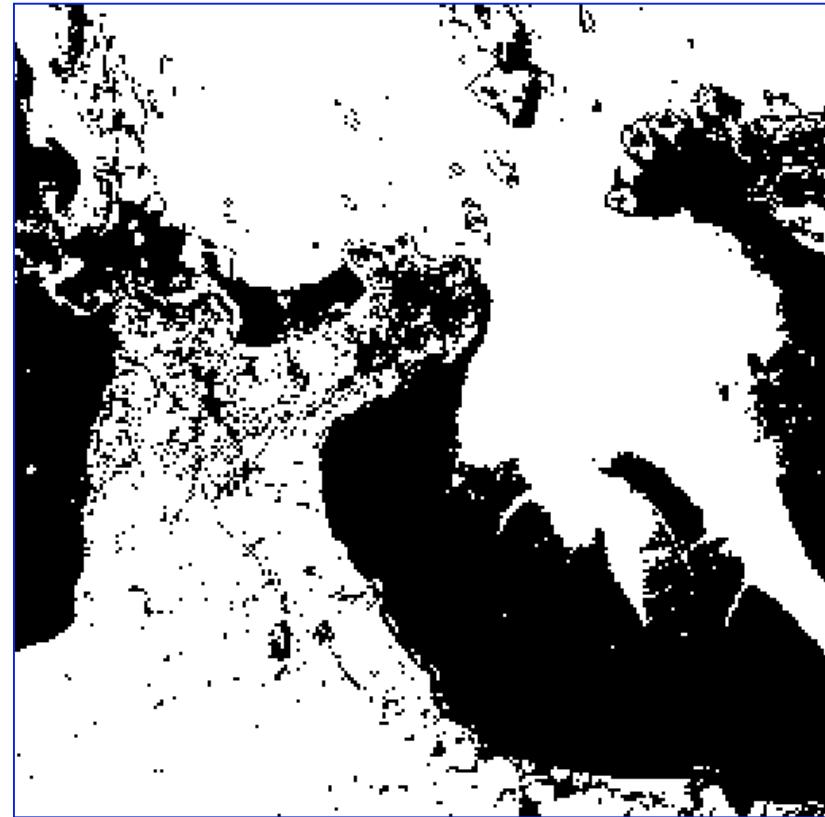
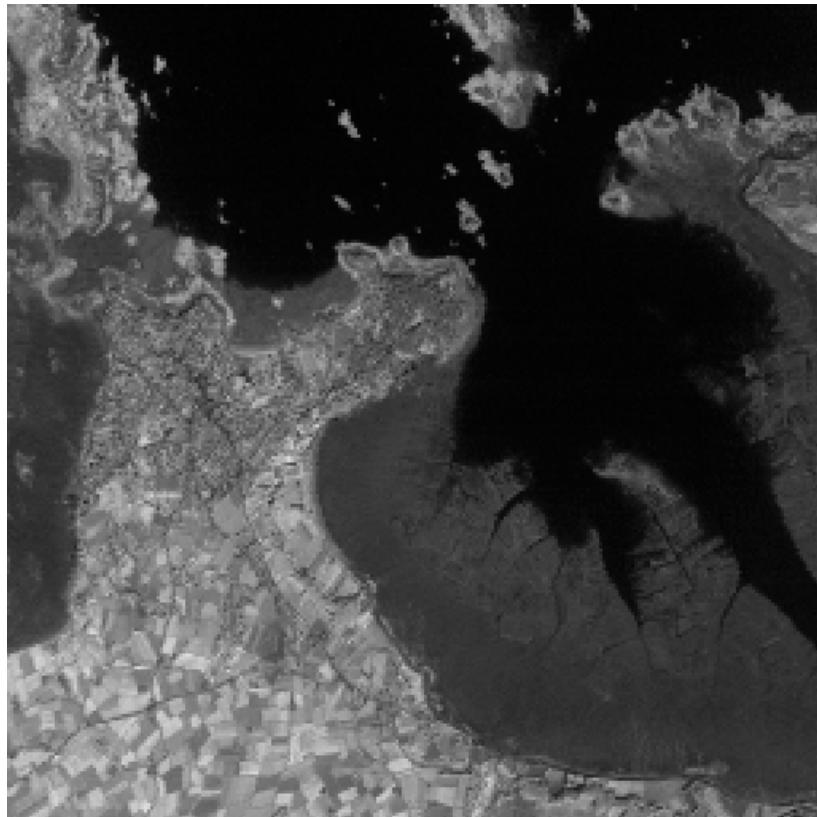


eau < 40

Noter les pixels isolés

Luminosity Partition

99

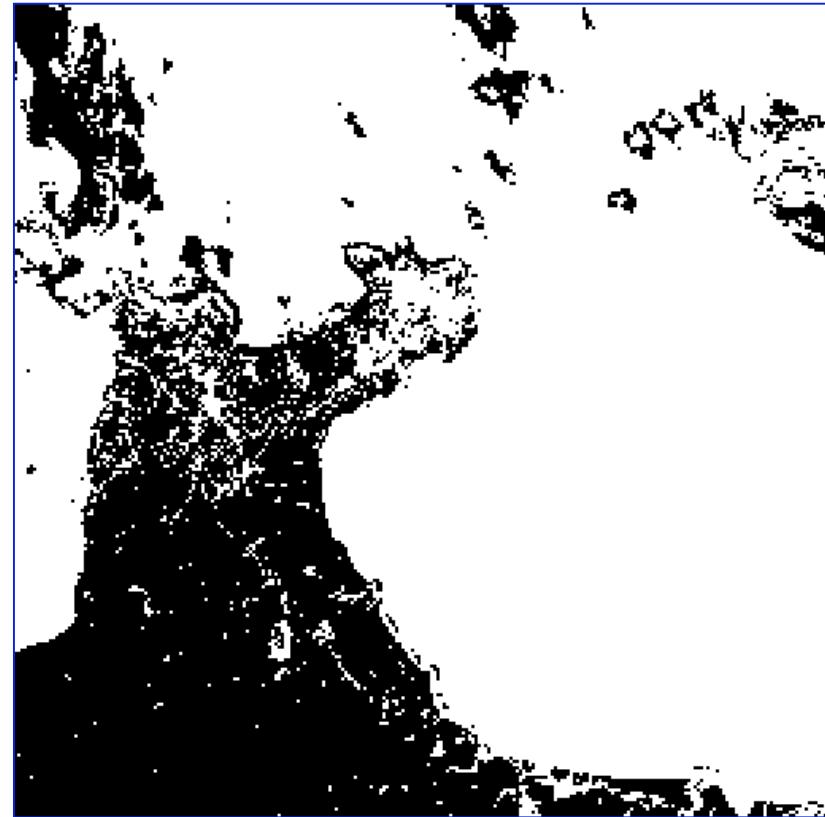
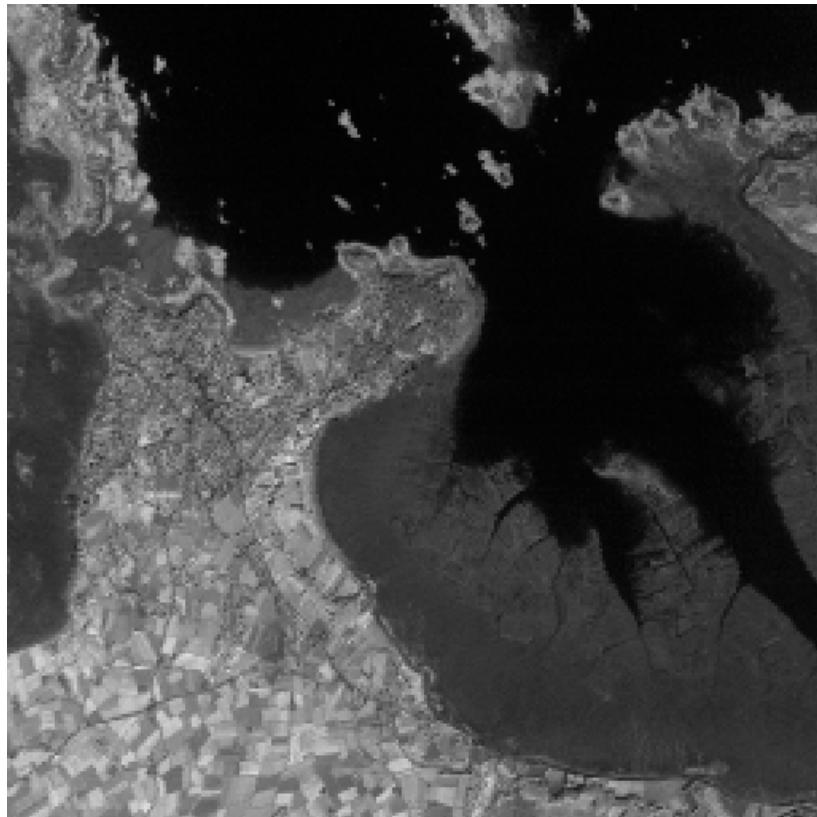


$41 < \text{estr} < 98$

Besoin d'un critère en plus

Luminosity Partition

100

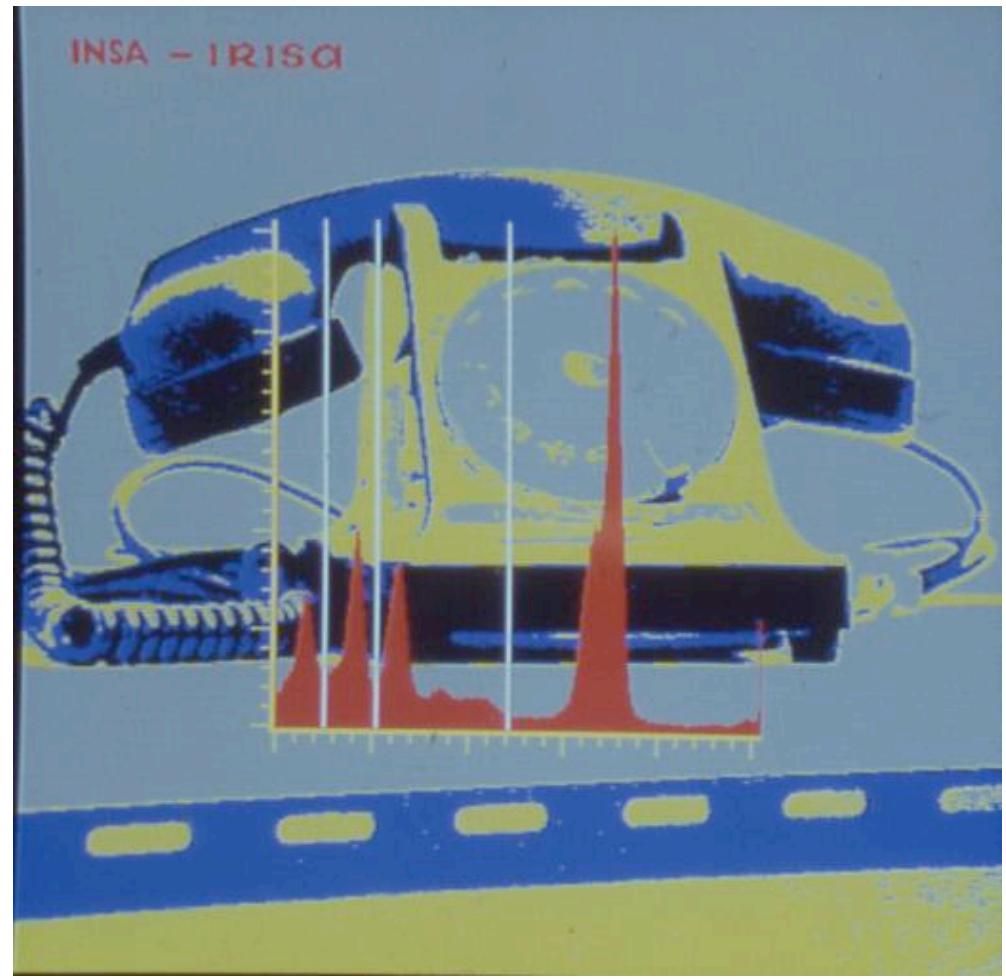
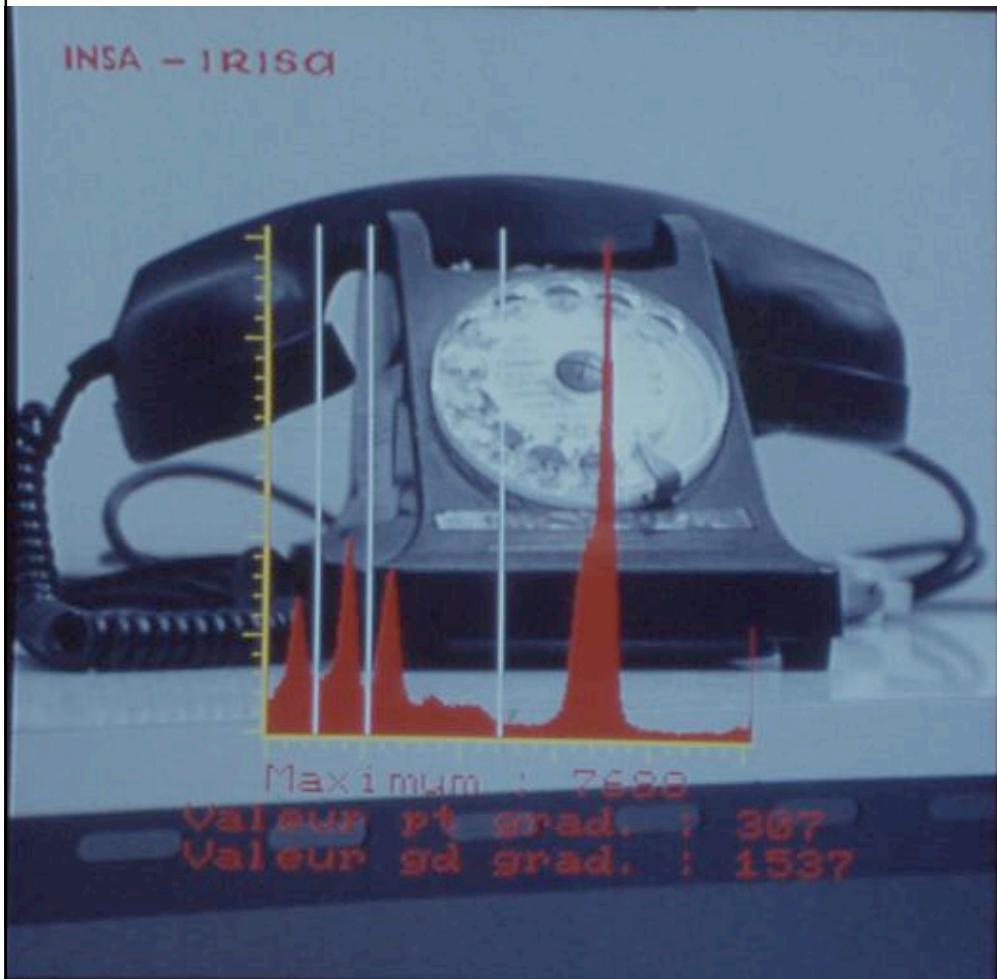


terre > 98

Besoin d'un critère en plus

Multi-Class Luminosity Partition

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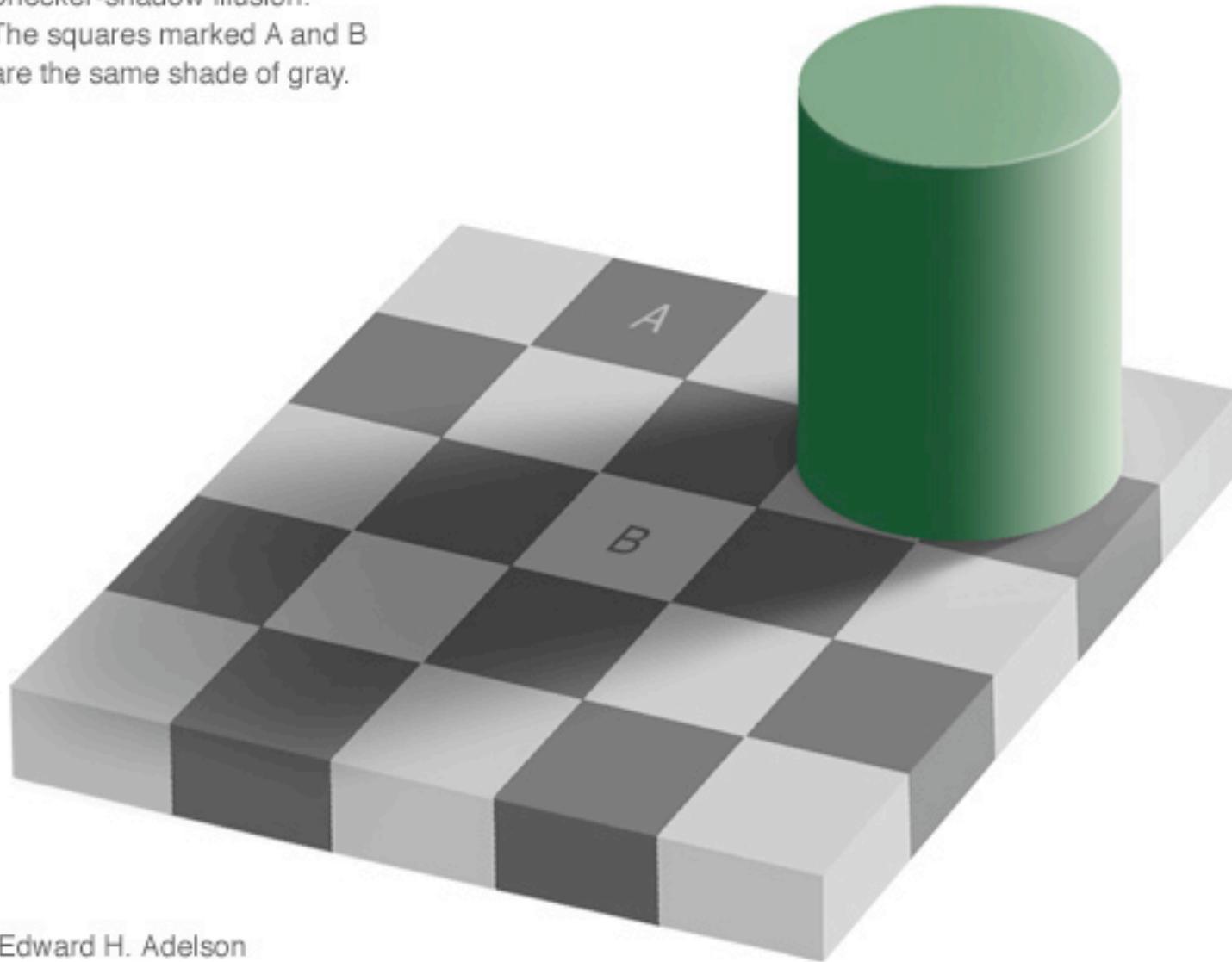


Difficult Task

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Checker-shadow illusion:

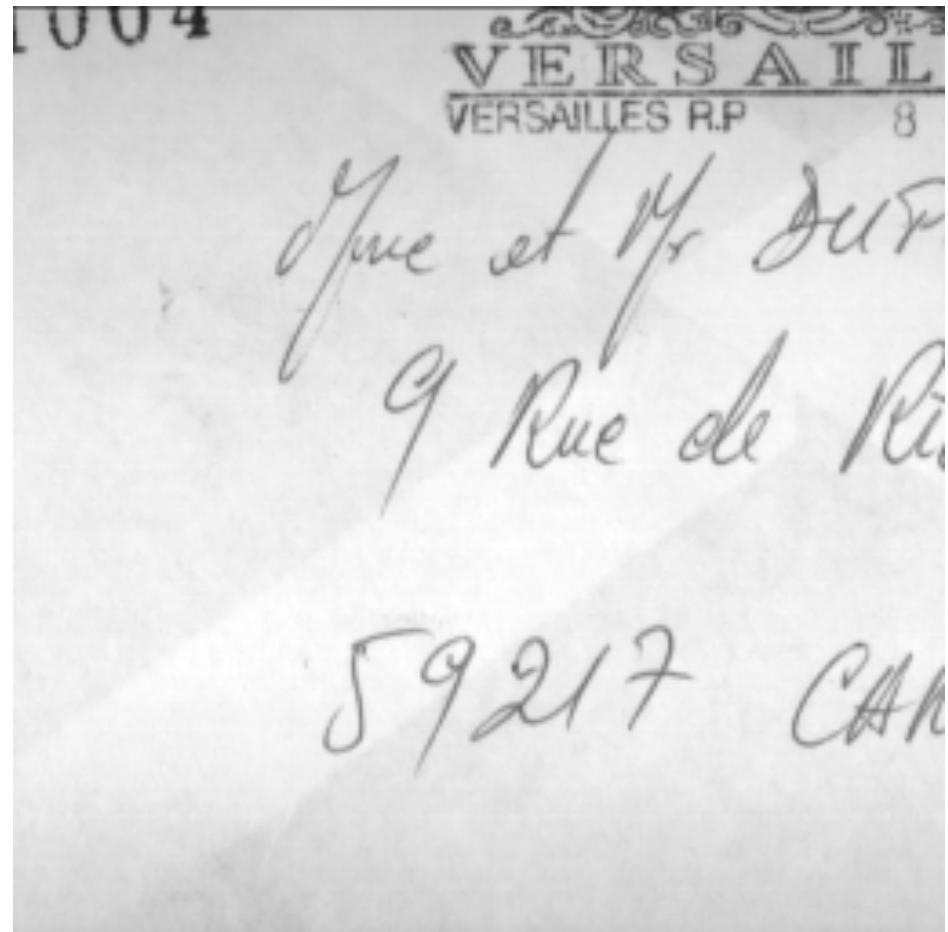
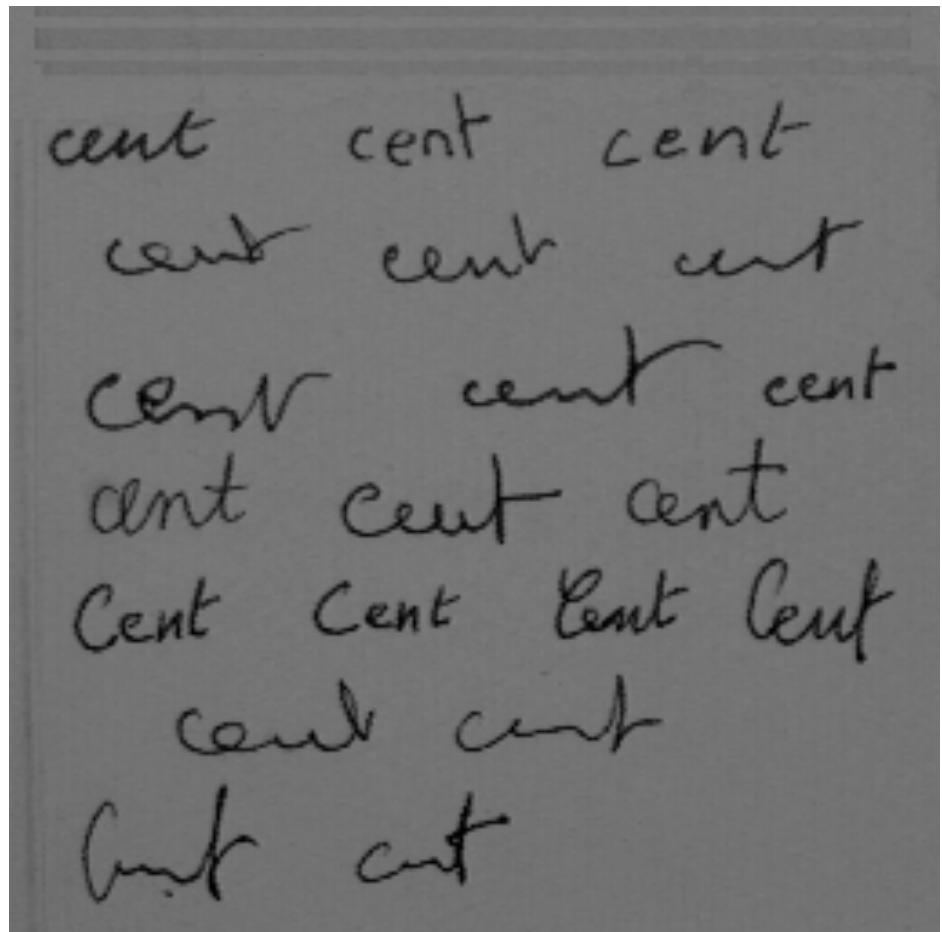
The squares marked A and B
are the same shade of gray.



Edward H. Adelson

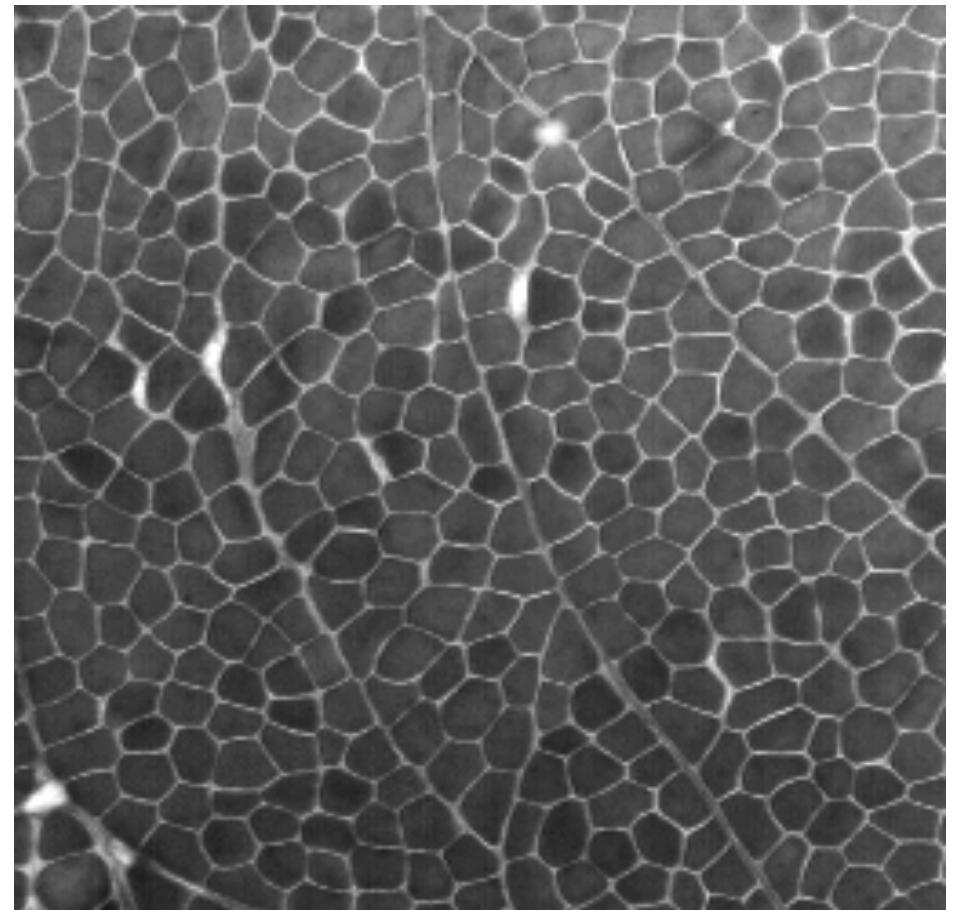
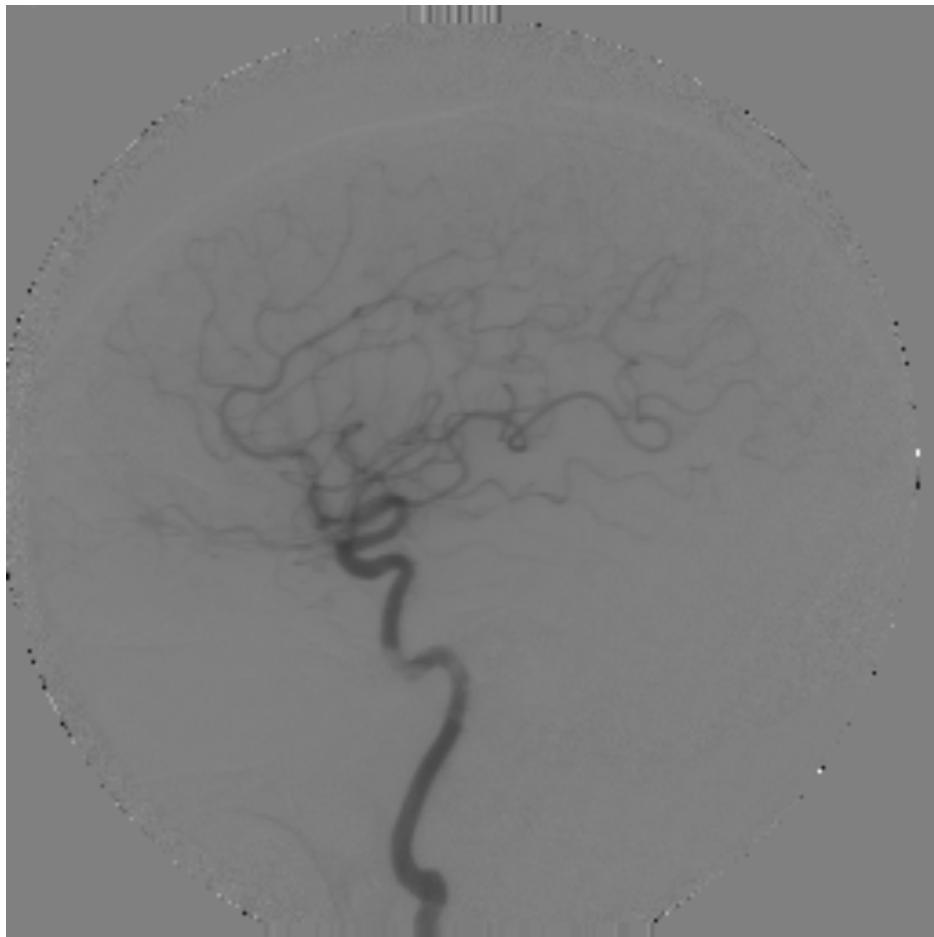
Binarization Possible on Text Images

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Binarization Possible on Bio-Medical Images

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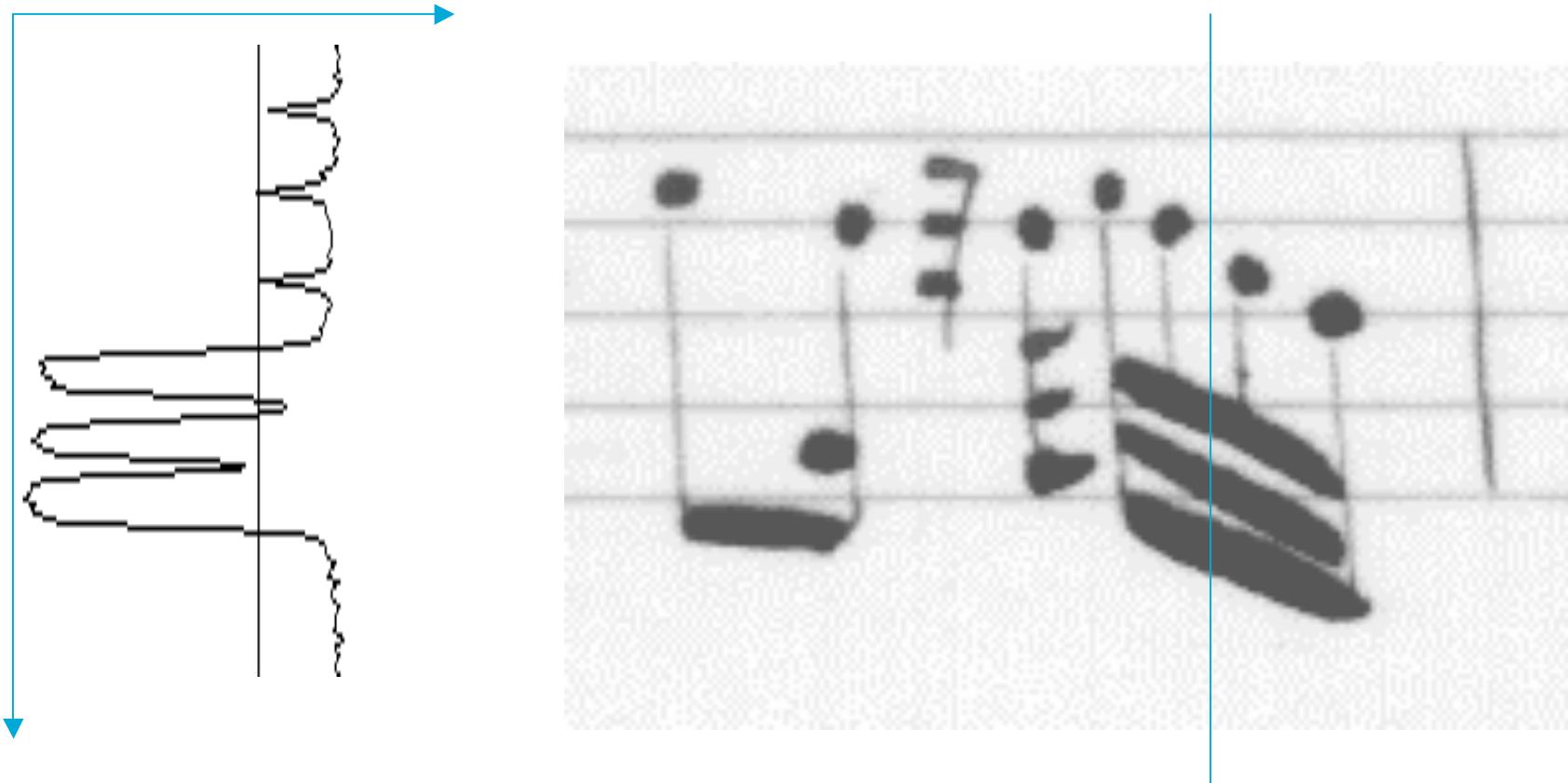


Binarization?

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Luminosité



Threshold

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210



195



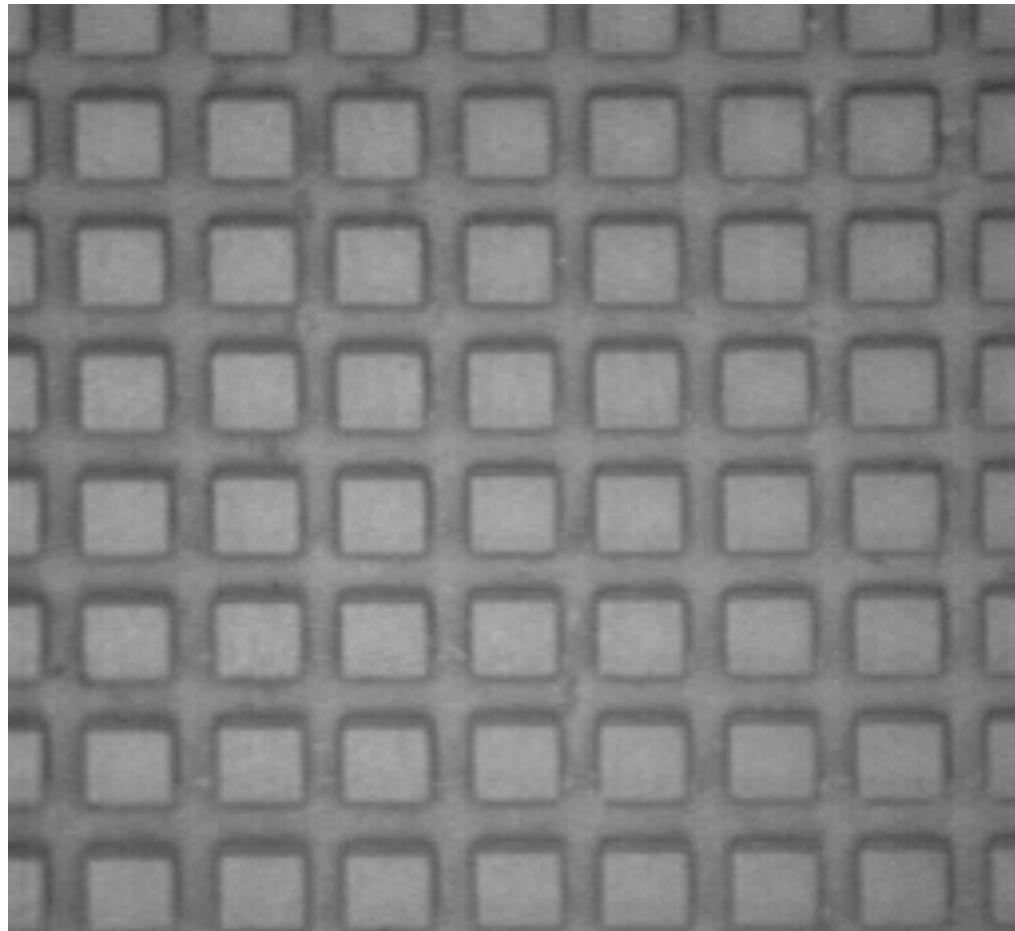
110



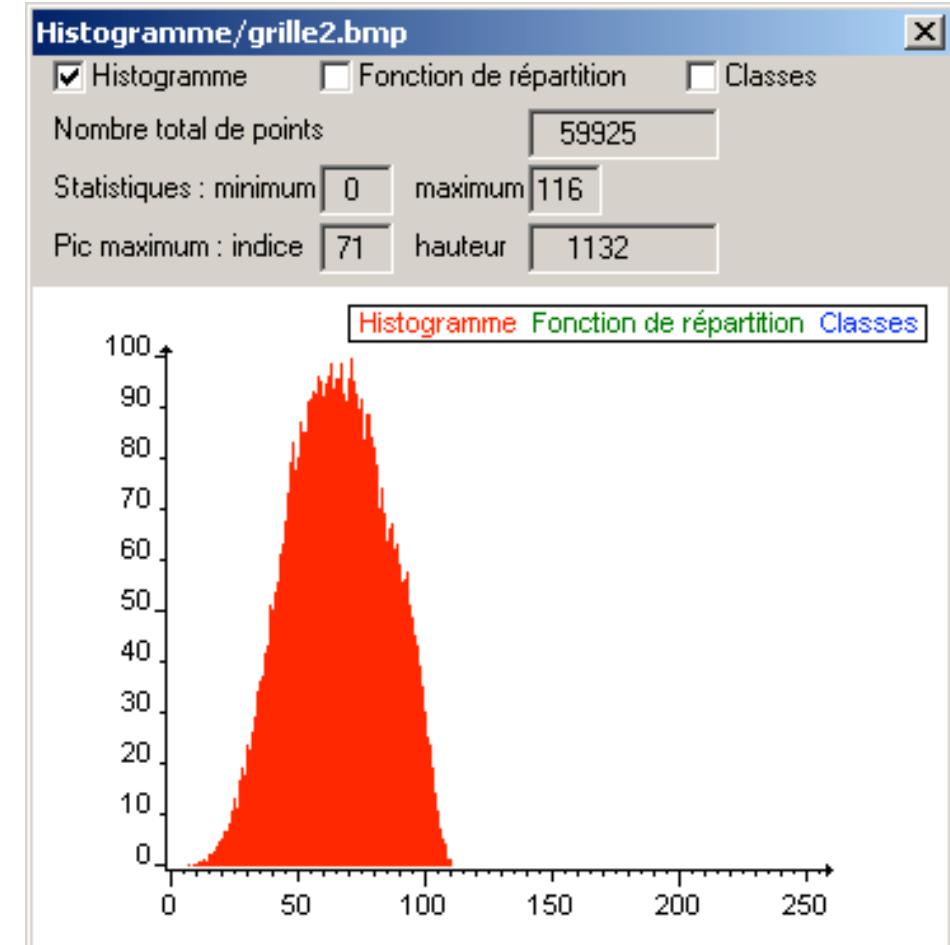
Seuillage adaptatif

Mono-modal Histogram

108



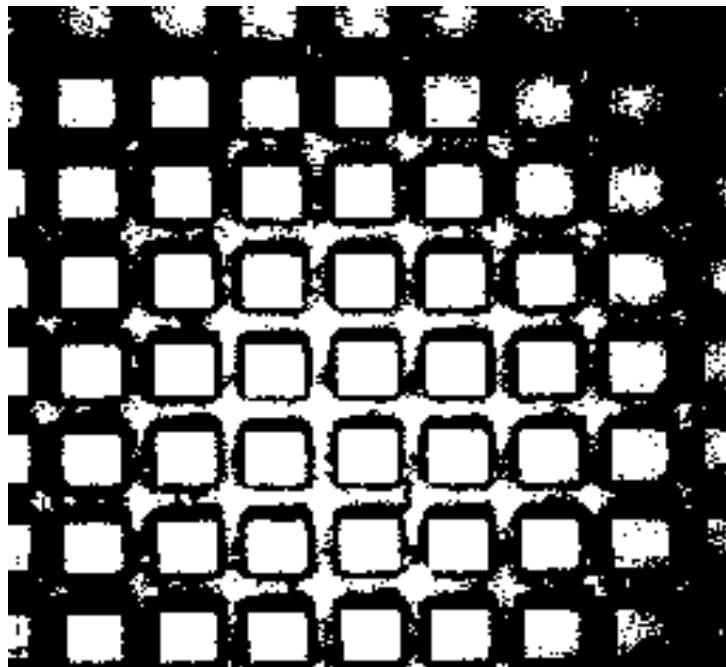
Bi-Modal Image



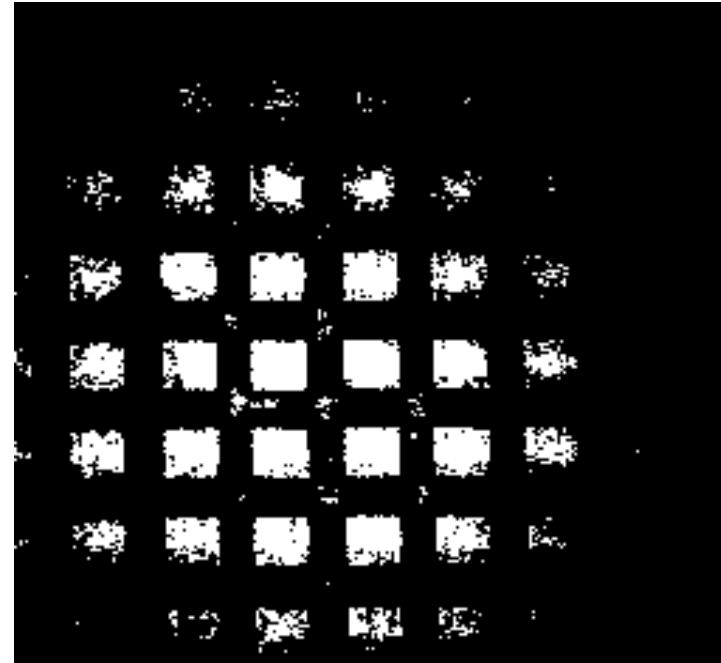
Mono-Modal Histogram

Mono-modal Histogram

109



Threshold at 71, max peak



Too high threshold

Conclusion: non uniform lightning

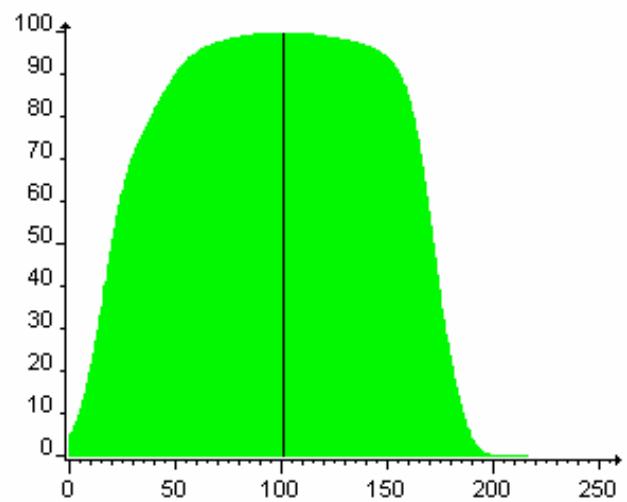
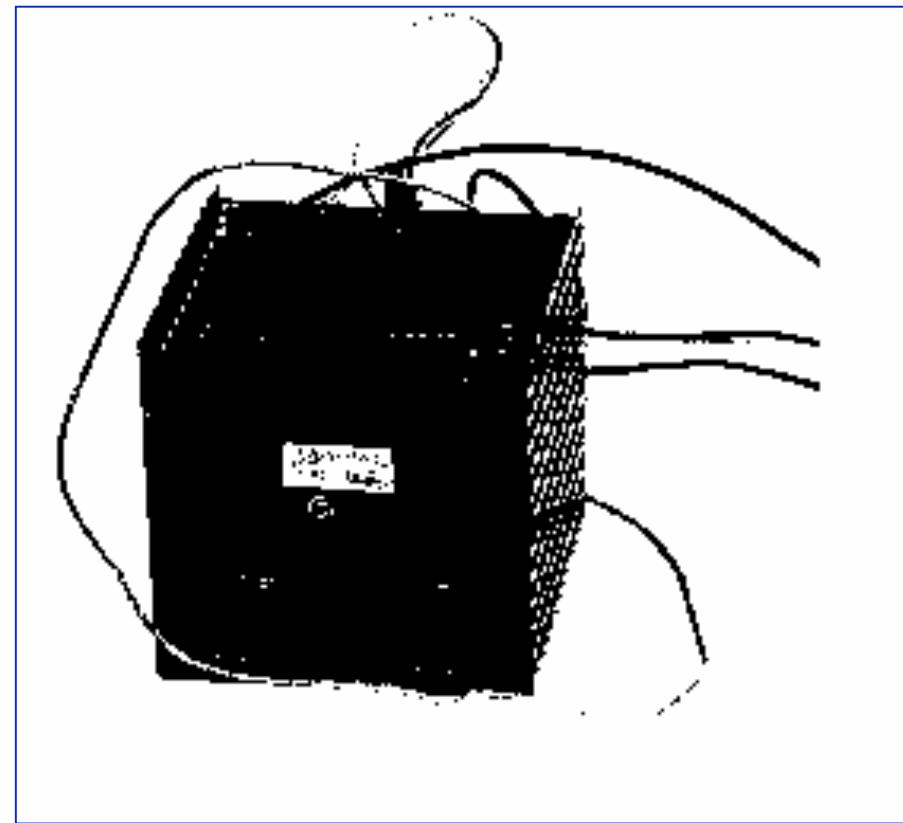
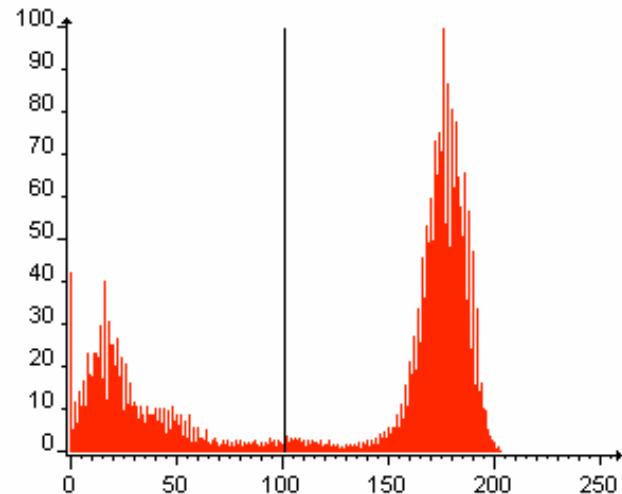
■ Global Methods

- ◆ **Interclasse Variance : Otsu**
- ◆ **Histogram Concavity Analysis**
- ◆ **Entropy : Pun**
- ◆ **Moments**
- ◆ **Histogram Modification: Mason**
- ◆ **Transition Matrix: Deravi**
- ◆ ...

■ Local Methods

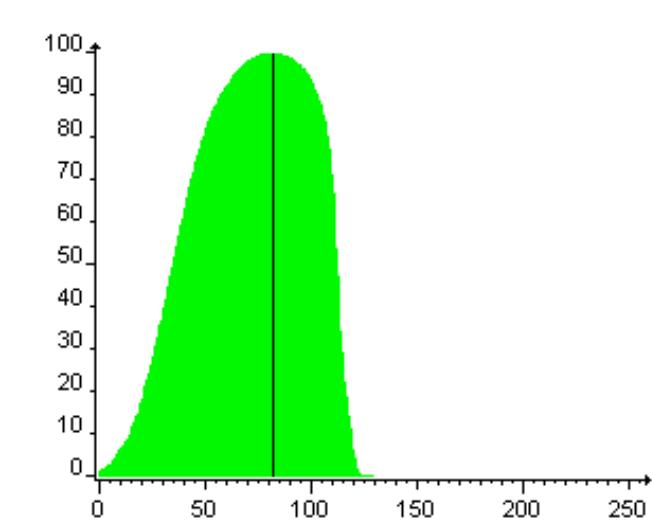
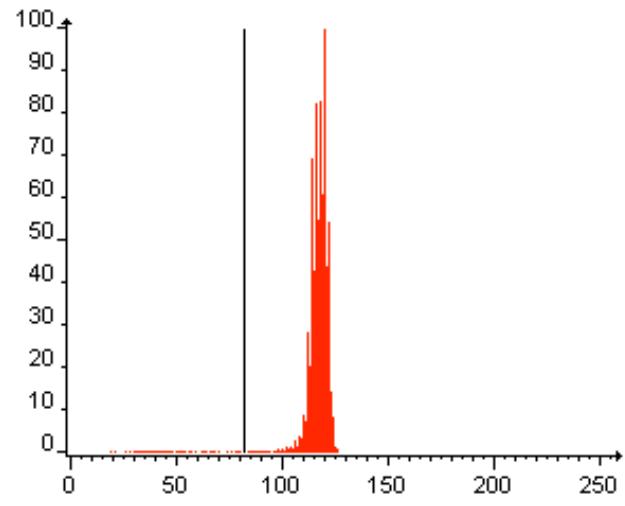
Binarization: Otsu Method

111



Binarization: Otsu Method

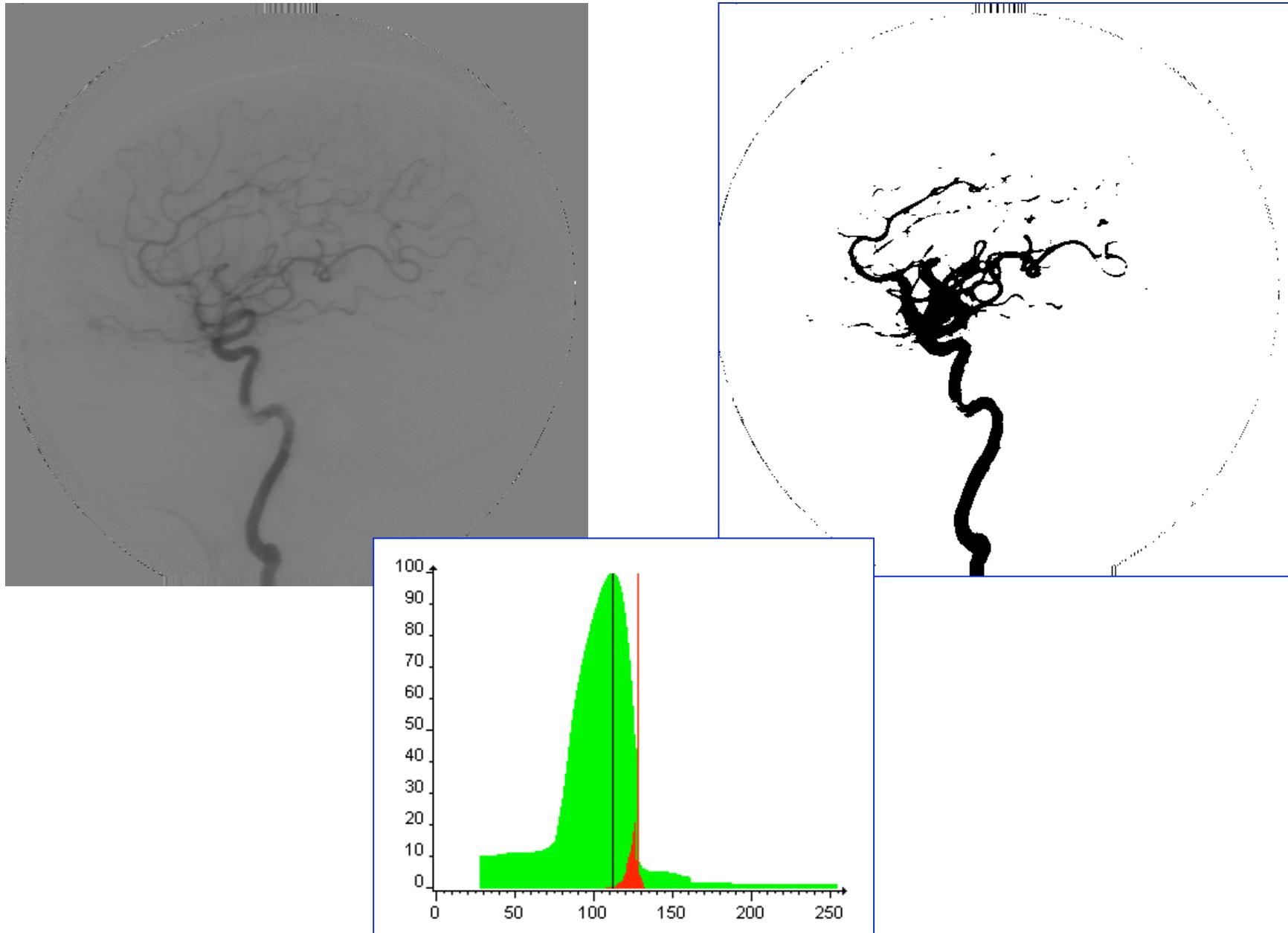
112



cent cent cent
cent cent cent
cent cent cent
cent cent cent
Cent Cent Cent Cent
cent cent cent
Cent Cent Cent Cent

Binarization: Otsu Method

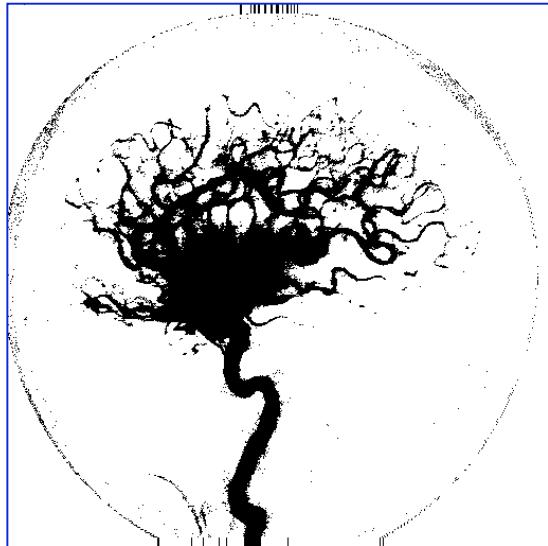
113



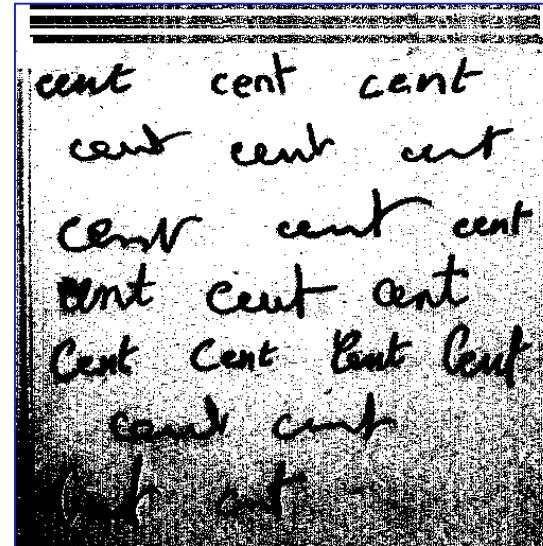
Binarization: PUN Method

114

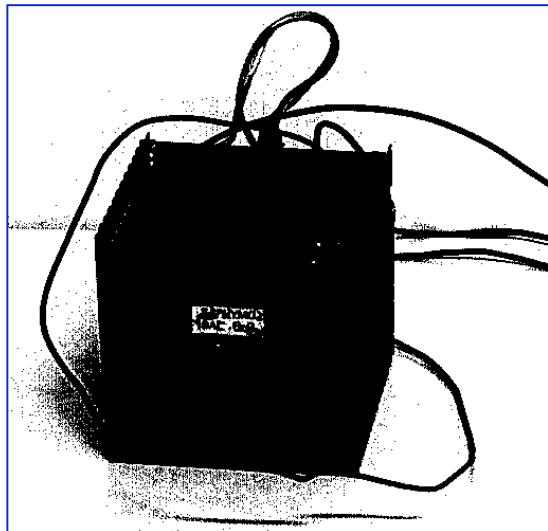
121



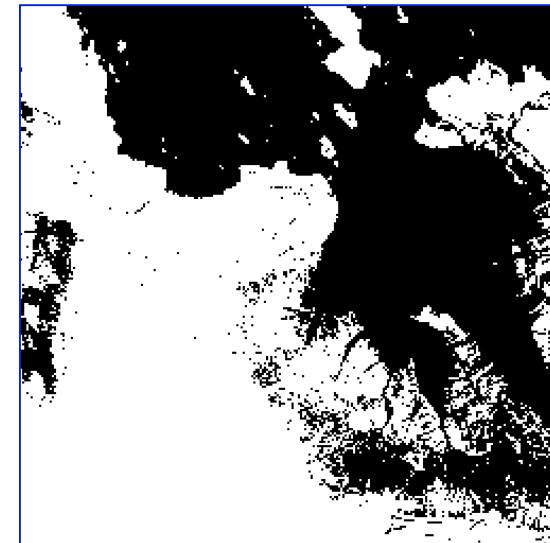
116



157



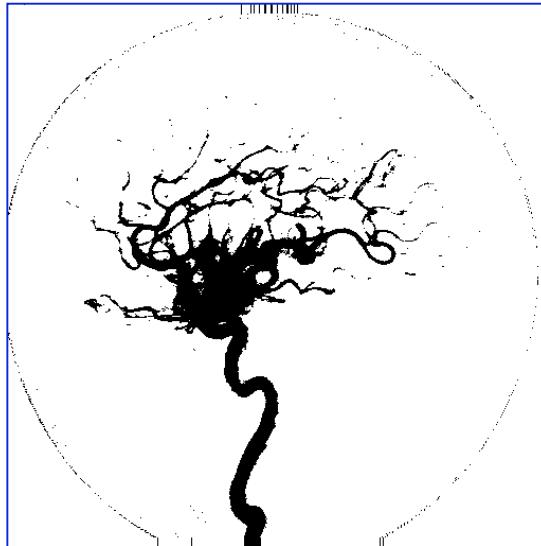
57



Binarization: Moments Method

115

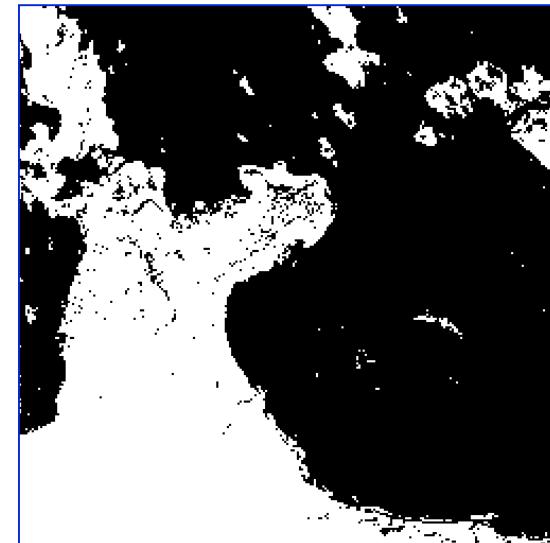
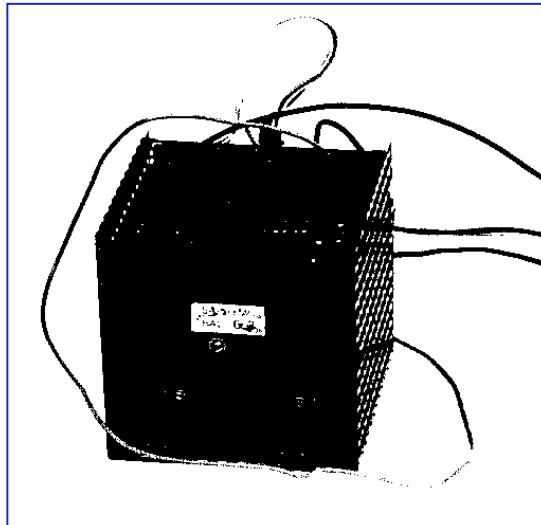
117



cent cent cent
cent cent cent
cent cent cent
cent cent cent
Cent Cent Cent Cent
cent cent
cent cent

85

100

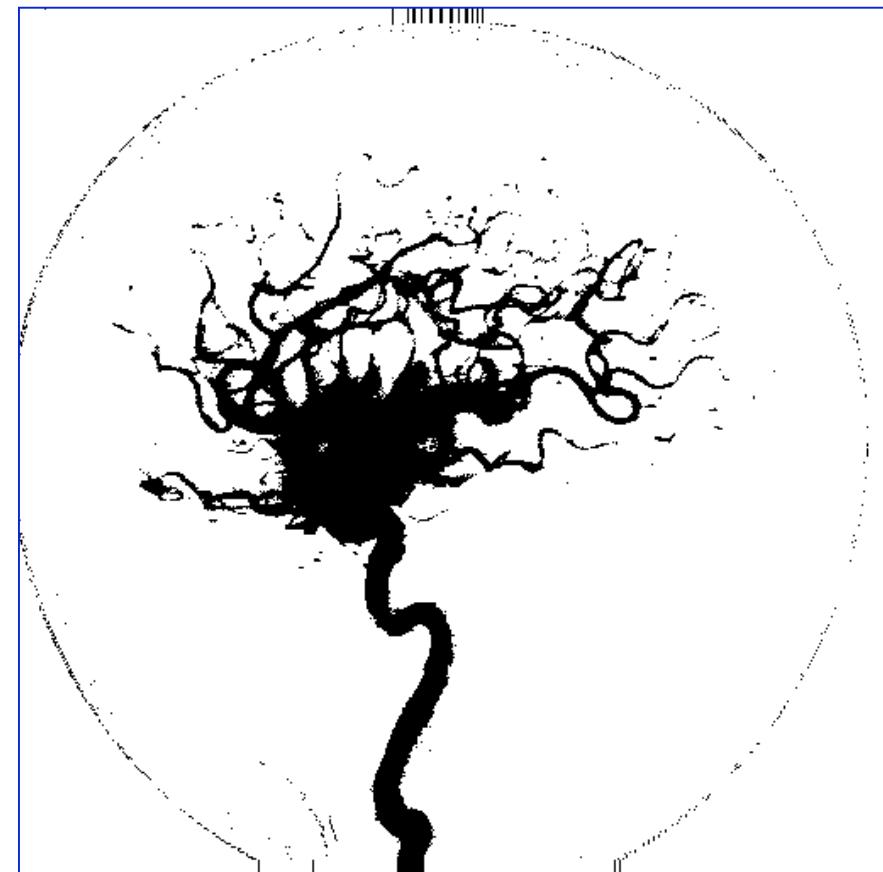


77

Binarization: Deravi

116

cent cent cent
Cent Cent Cent Cent
cent cent
Cent cent



106

119

- Lot of Different Methods

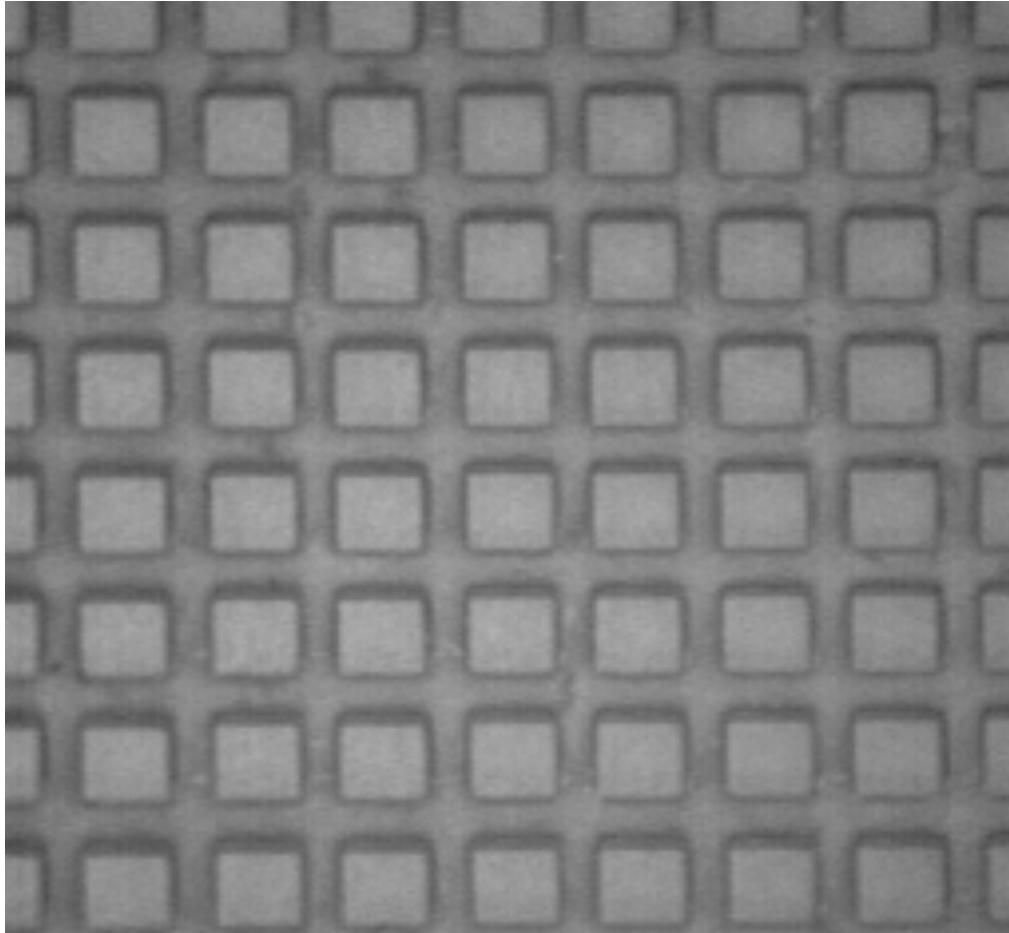
- None really usable

- Problem

- ◆ Global Threshold

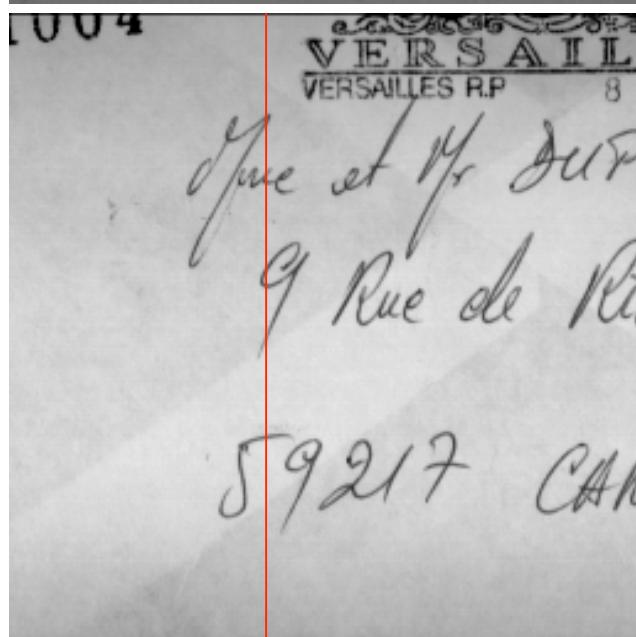
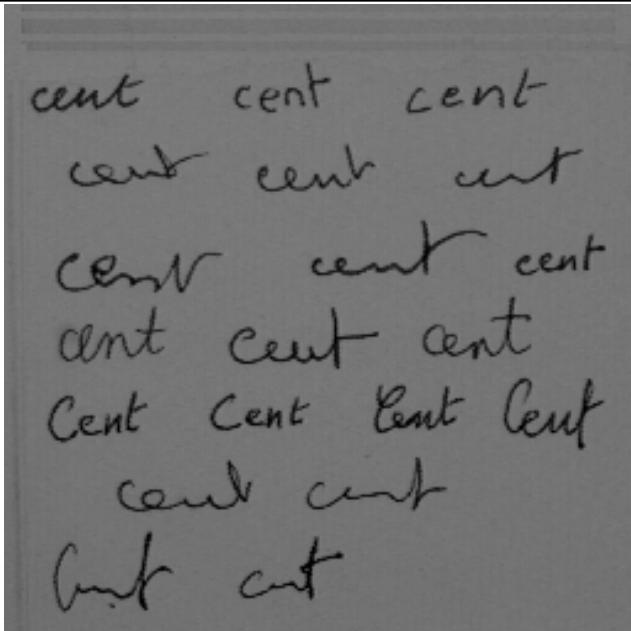
Non-uniform Lightning

118



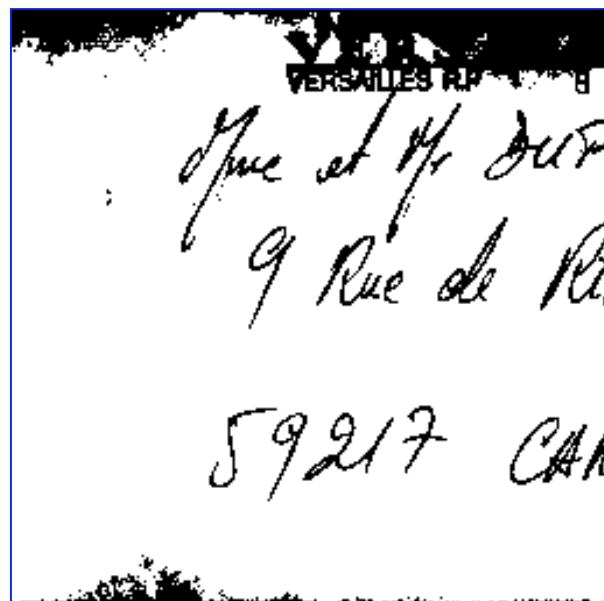
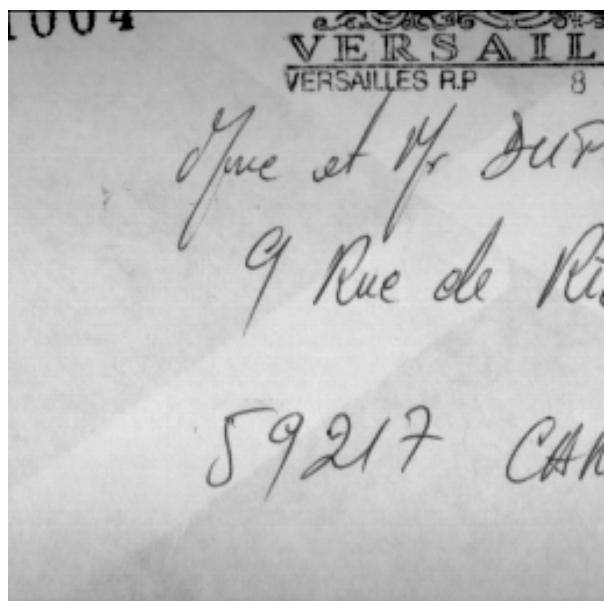
Non-uniform Lightning: Column

119

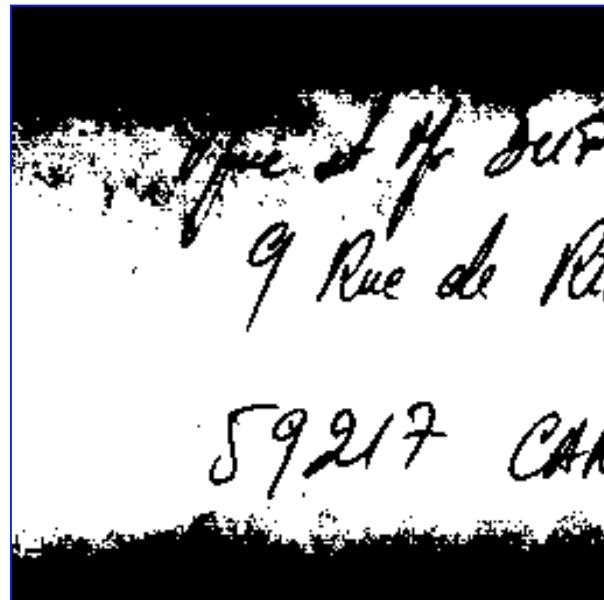
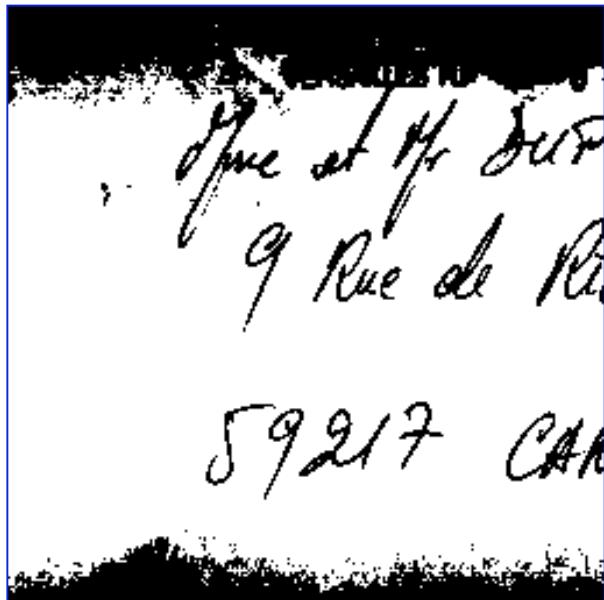


Non-uniform Lightning: Column

120



170



190

- Split Image in Squares

- ◆ Square Size
- ◆ Threshold for each Square

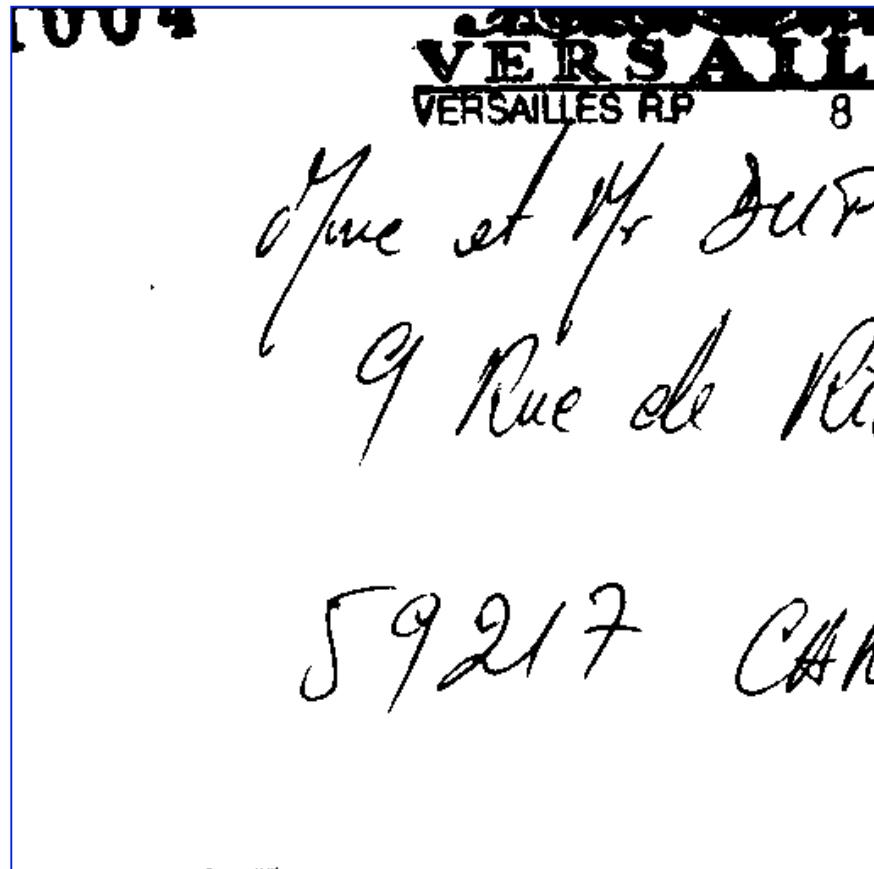
- Using Threshold

- ◆ By Square
- ◆ By Interpolation
- ◆ Overlaping Squares

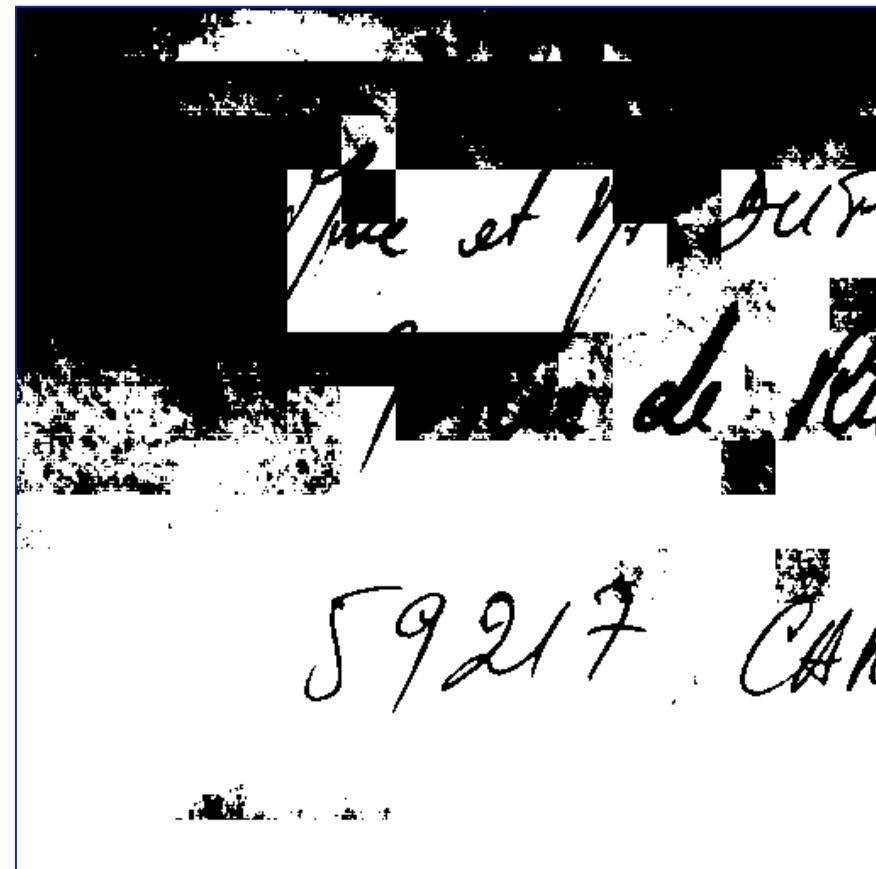
- Variation Lightning Evaluation

Binarization: Local Method

122

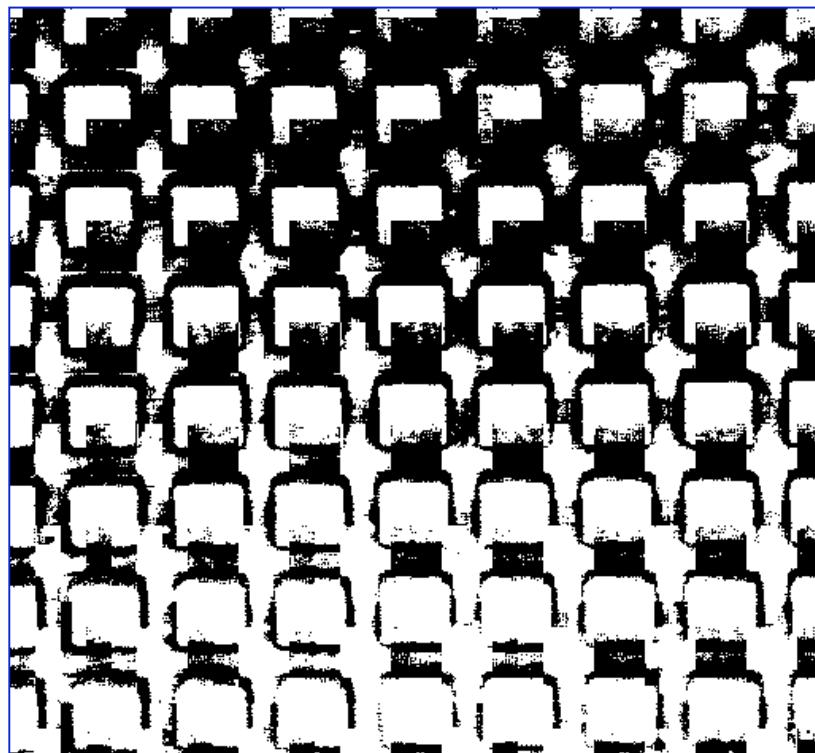


Otsu: Threshold at 188

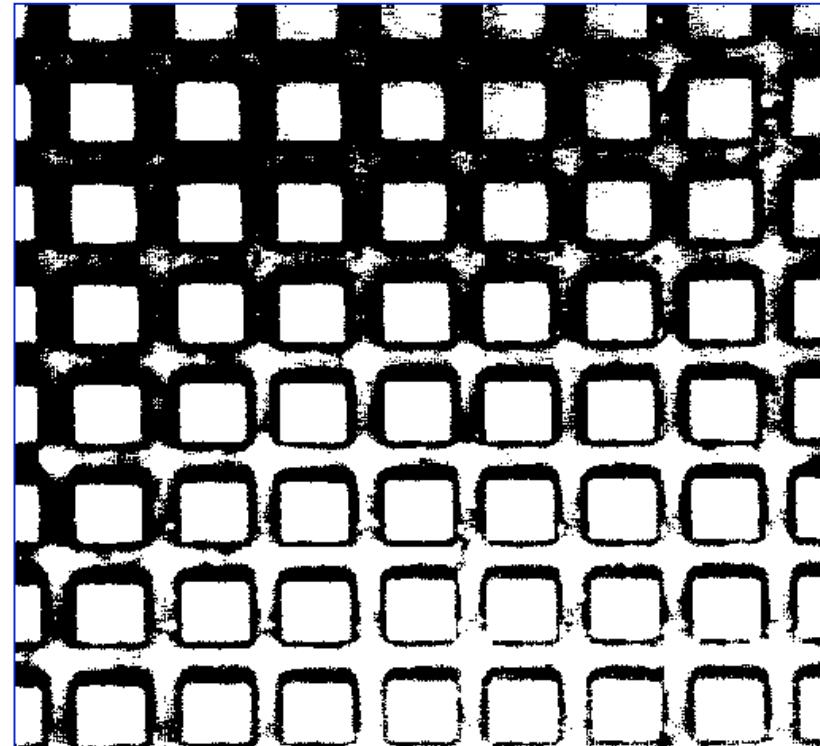


Otsu: 32x32 Squares

Otsu Method in each Square

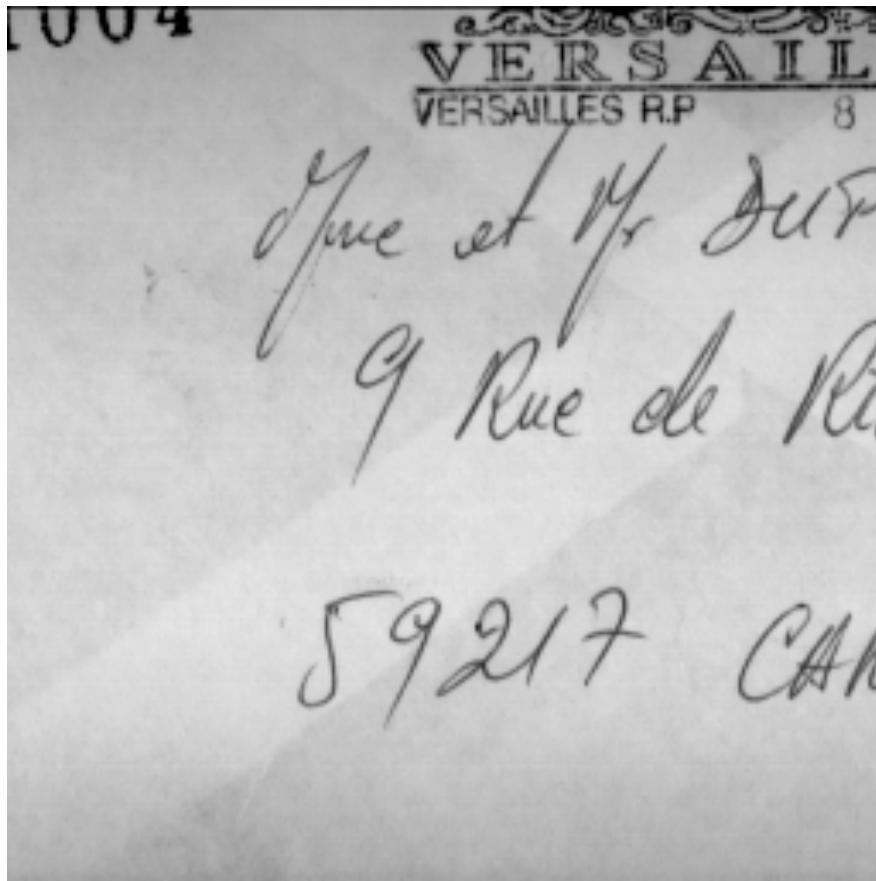


16x16 Square, too small



64x64 Square, good fit

■ Variation Lightning Evaluation



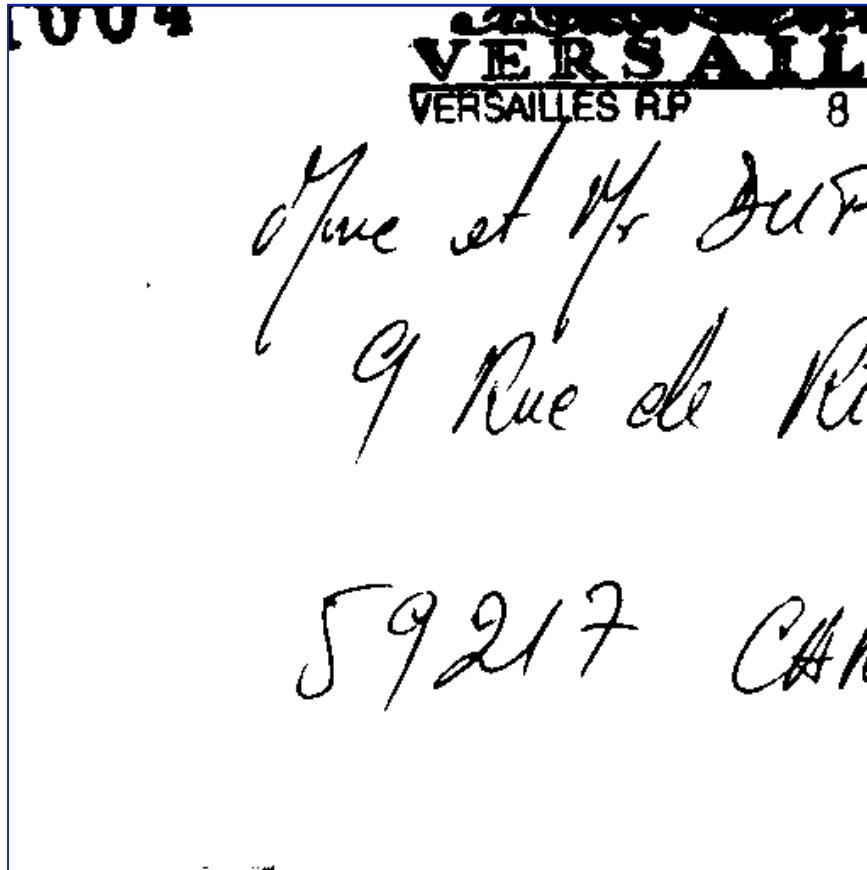
Binarization: Low-Pass Filtering

125

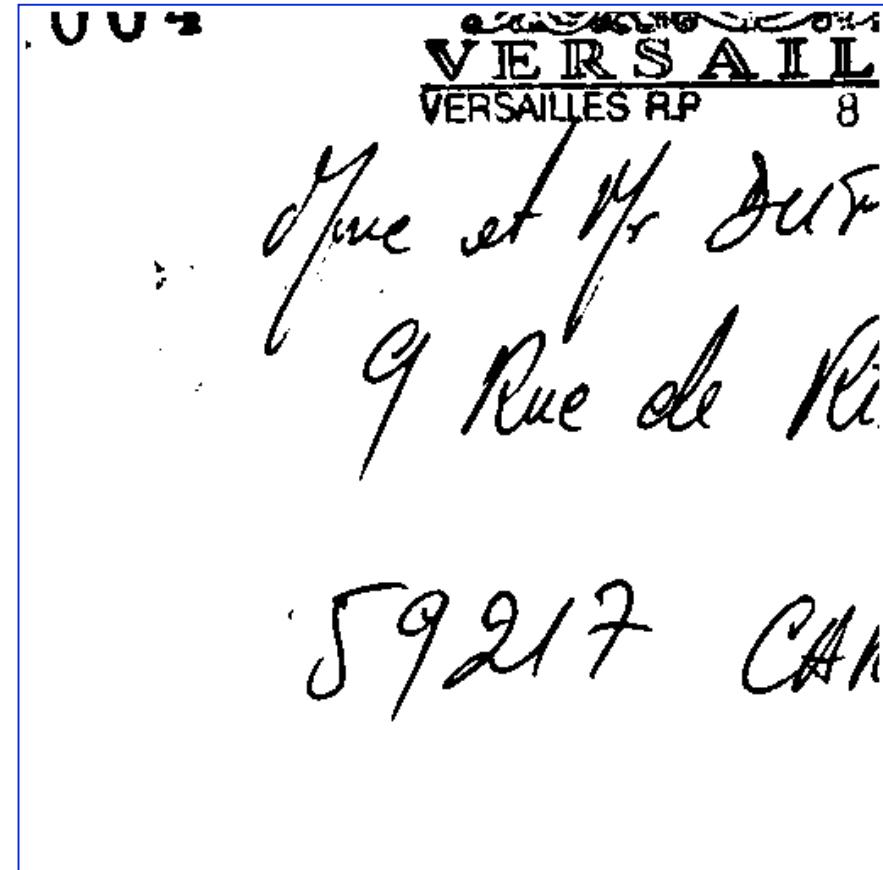


Binarization: Low-Pass Filtering

126



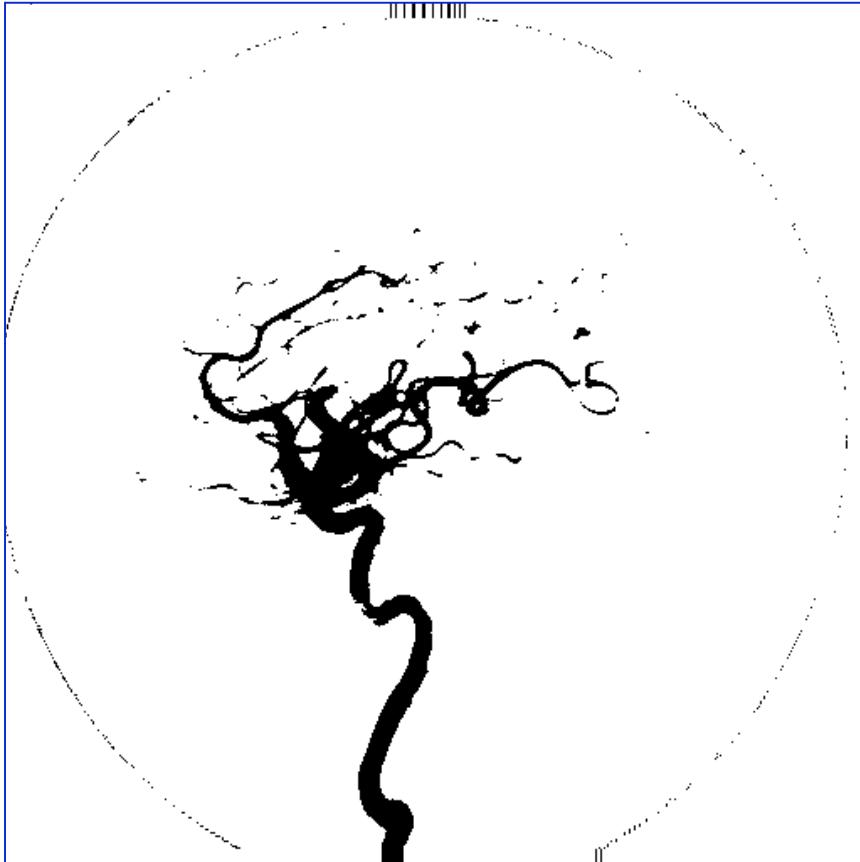
Otsu : seuil à 188



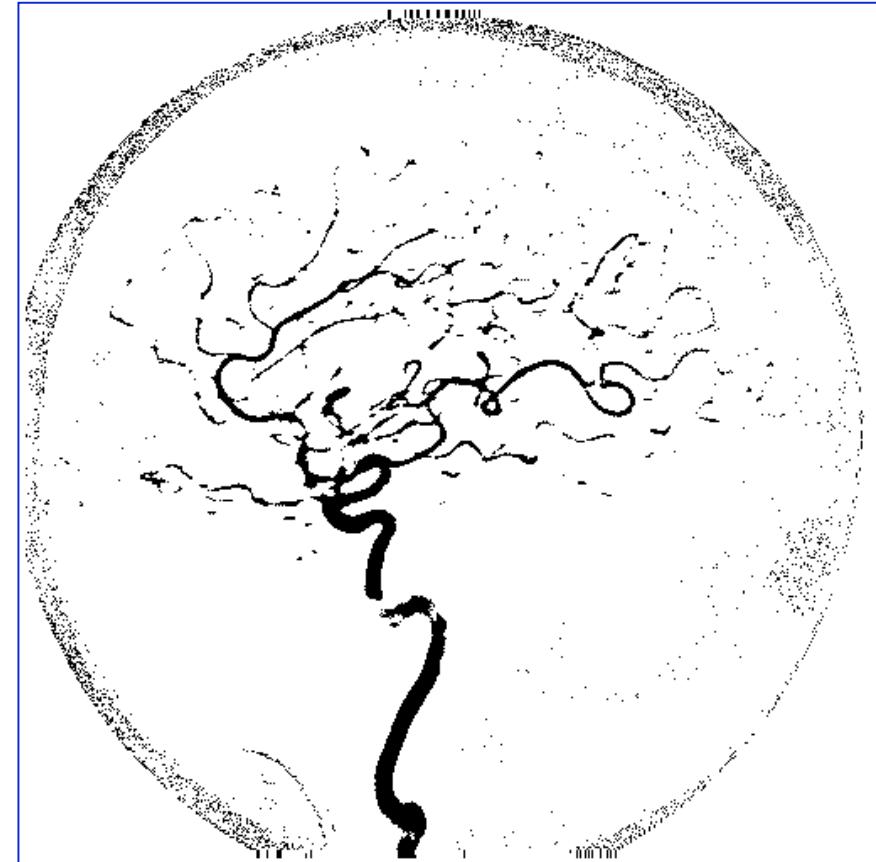
Filtrage passe-bas,
contraste de 10

Binarization: Low-Pass Filtering

127



Otsu : seuil à 109



Filtrage passe-bas,
contraste de 3