Fundamentals of Image Processing

▶ Lecture 7: Extraction of image primitives ◀

Master of Computer Science
Sorbonne University

September 2022

Outline

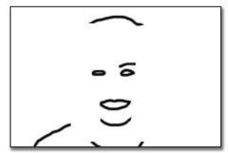
Introduction

Introduction

- What is a primitive in an image?
- Pixel-based approach $\Rightarrow$ Edges $\Rightarrow$ Contours (segments, curves, closed or not)

Introduction

- Pixels
- Edges
- Contours



- Regions from a segmentation

- Regions or Points Of Interest (ROI, POI):

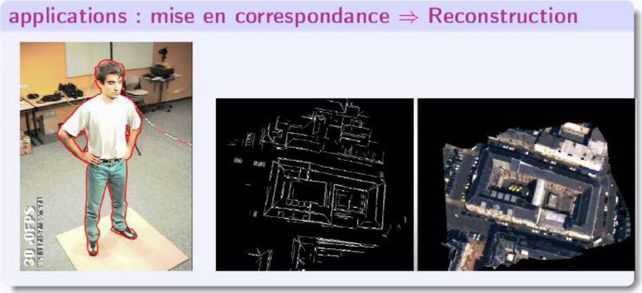
- Points with high contrast
- Corner detector (Harris)
- SIFT
- MSER (region-based)

Introduction

- Why detect features?
  - Useful for image analysis
- Various applications:
  - 3D reconstruction
  - Image analysis, interpretation, object detection
- 2 key steps:
  1. features detection,
  2. features description and characterization.

Introduction

- Back to edge detection:



- Contours frequently used for template matching
- But low robustness: contours are often fragmented

Introduction: issues

- Feature extraction should be reproducible
  - robustness to translation, rotation, illumination...
- Features should be accurate, well localized
- Features should be as exhaustive as possible
  - image domain should be well covered
- Features should contain relevant information
  - in order to be exploitable

Introduction

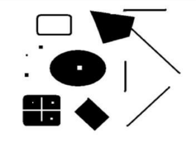
- Edges/contours: discontinuity in one direction
- Points of interest (corners for instance): discontinuity in two directions (first definition)
- Visual saliency: points of interest for human vision (may be based on intensity, color, orientation...)

Points of interest

Points of interest: Hessian detector [Baudet, 1978]

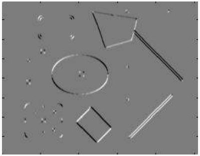
- Principle: threshold the Hessian determinant.
- Hessian: matrix of second derivatives

$$H_I = \begin{pmatrix} \frac{\partial^2 I}{\partial x^2} & \frac{\partial^2 I}{\partial x \partial y} \\ \frac{\partial^2 I}{\partial x \partial y} & \frac{\partial^2 I}{\partial y^2} \end{pmatrix} = \begin{pmatrix} I_{xx} & I_{xy} \\ I_{xy} & I_{yy} \end{pmatrix}$$



I

I_{xx}



I_{xy}

I_{yy}

- Intuition: the critical points of I are points of interest, I viewed as the graph of a function $(x, y, I(x, y))$.

Points of interest: Hessian detector

- Critical points: local extrema, saddle points

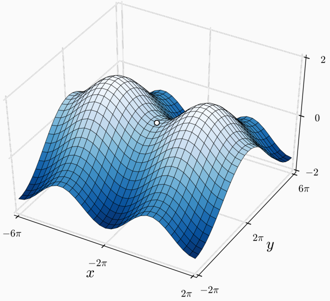


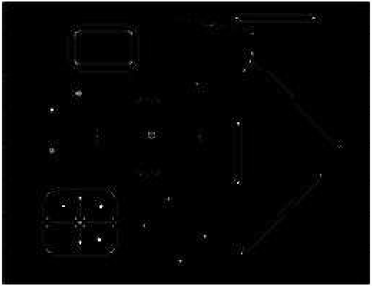
Figure 1: Saddle point between two local maxima

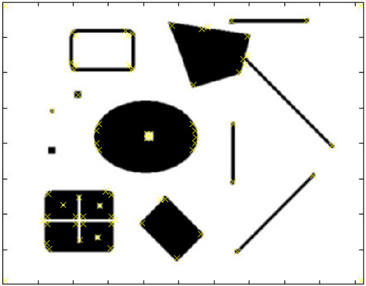
- Critical points are zeros of the Hessian determinant:

$$\det(H_I) = I_{xx} I_{yy} - I_{xy}^2$$

Points of interest: Hessian detector

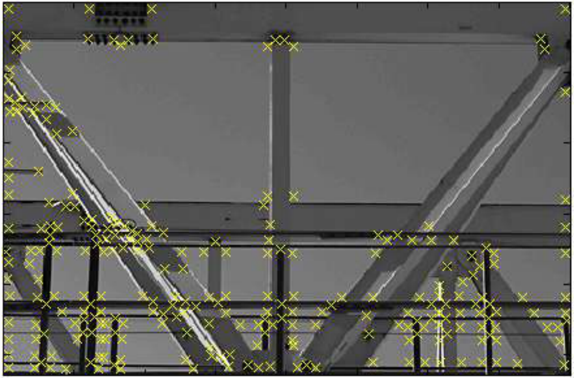
- Map of the determinant and threshold:





Points of interest: Hessian detector

- Features: corners and textured regions



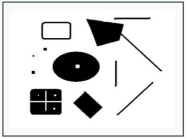
Points of interest: Hessian detector

- Features:

Points of interest: Harris detector [Harris and Stephens, 1988]

- Autocorrelation (see tutorial works):

$$R_I(\sigma) = g_\sigma \star \begin{pmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{pmatrix}$$



- Intuition: in a neighborhood (Gaussian window), looking for variations in two directions.
- $R_I(\sigma)$ is positive definite $\Rightarrow$ two positive eigenvalues

$\Rightarrow$ compute eigenvalues of R_I

Points of interest: Harris detector [Harris and Stephens, 1988]

- Autocorrelation (see tutorial works):

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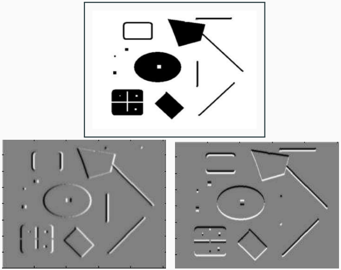
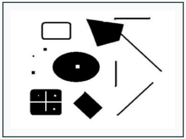


1. Compute derivatives I_x, I_y

Points of interest: Harris detector [Harris and Stephens, 1988]

- Autocorrelation (see tutorial works):



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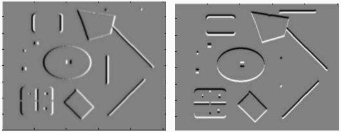
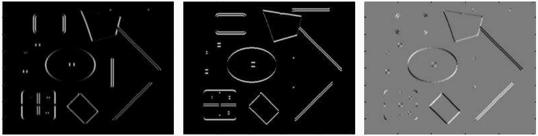


2. Compute squared terms I_x^2, I_y^2, $I_x I_y$



Points of interest: Harris detector [Harris and Stephens, 1988]

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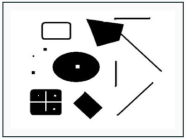

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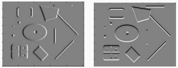

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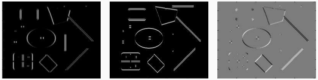
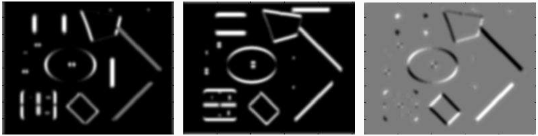


3. Gaussian filtering



Points of interest: Harris detector [Harris and Stephens, 1988]

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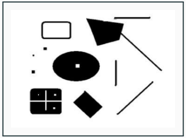

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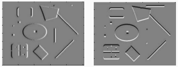

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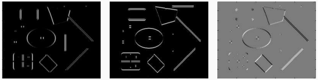

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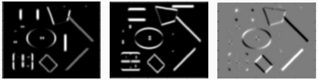


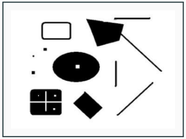
4. Two high eigenvalues if $Har > 0$

$$Har = \det(R_I(\sigma)) - \kappa \,\mathrm{trace}(R_I(\sigma))$$

Points of interest: Harris detector [Harris and Stephens, 1988]

- Autocorrelation:

$$R_I(\sigma) = g_\sigma \star \begin{pmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{pmatrix}$$



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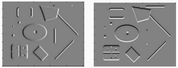

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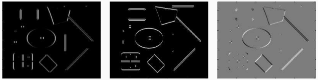

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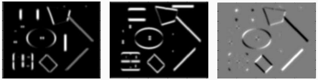
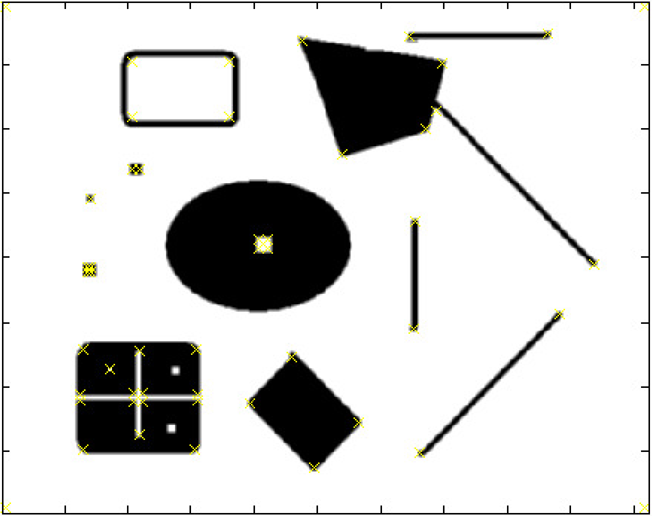


4. Two high eigenvalues if $Har > 0$
5. Suppression of non maxima

Points of interest: Harris detector

- Features extracted by Harris detector



Points of interest: Harris detector

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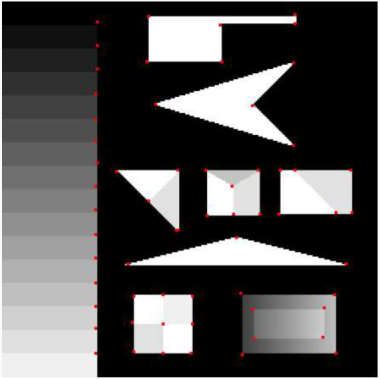


Points of interest: Harris detector

- Reminder on linear algebra: $\lambda_{1,2} \geq 0$ eigenvalues of R_I:

$$\begin{aligned} \det(R_I) &= \lambda_1 \lambda_2 \\ \mathrm{trace}(R_I) &= \lambda_1 + \lambda_2 \end{aligned}$$

- $Har = \lambda_1 \lambda_2 - \kappa(\lambda_1 + \lambda_2)$
- 3 configurations:
  1. homogeneous region: null eigenvalues, $\det = 0, \mathrm{trace} = 0$, $Har = 0$
  2. edge: one null eigenvalue, $\det \approx 0, \mathrm{trace} > 0, Har < 0$
  3. corner: no null eigenvalues, $\exists \kappa > 0 \mid Har > 0$

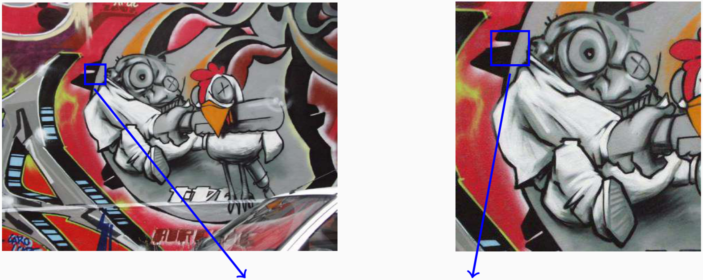
Multiscale detection

Scales in images

- Maar and Hildreth, 1980: detection of a primitive is performed at an optimal scale.

Scales in images

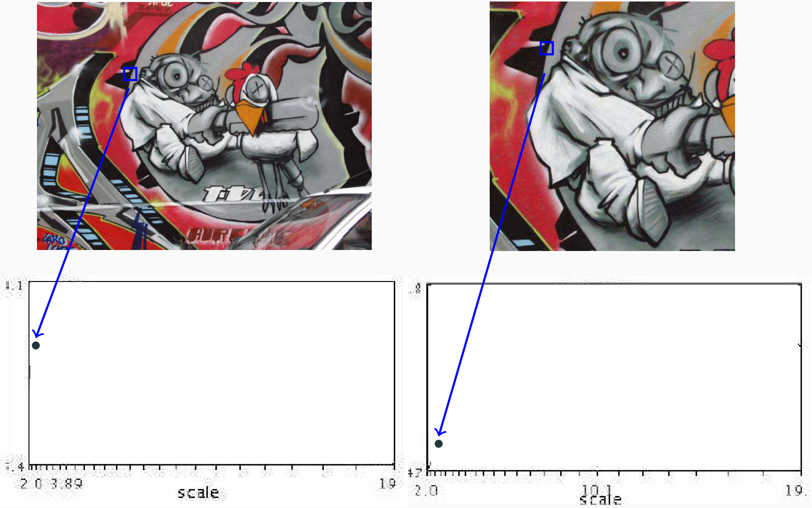
Scales in images



$$f(I_{i_1 \cdots i_m}(x, \sigma)) = f(I_{i_1 \cdots i_m}(x', \sigma')) \quad ?$$

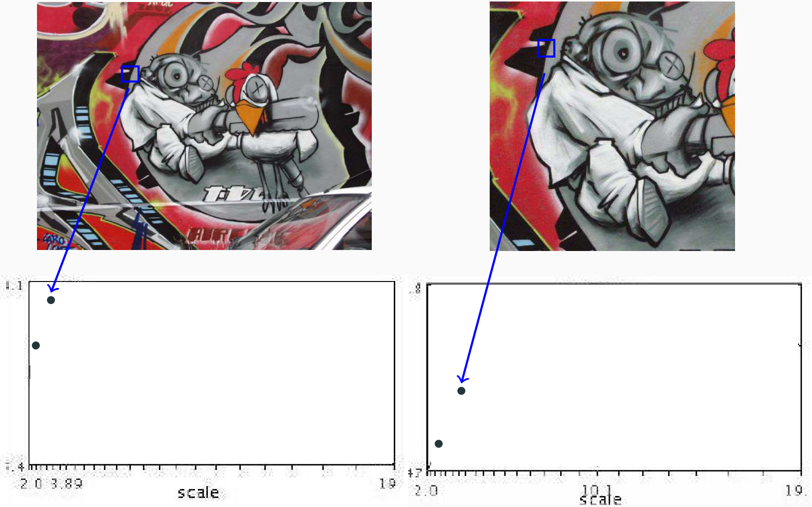
- Let f be an operator acting on image derivatives ($I_{i_1, \cdots, i_m}$ denotes a m-order derivative)
- Can the response of this operator be the same if the analysis windows (patches) contain the same image at a given scale factor?
- How to find the size of the patches?

Automatic scale selection: Function responses for increasing scale (scale signature)



$f(I_{i_1 \dots i_m}(x, \sigma))$ $\qquad$ $f(I_{i_1 \dots i_m}(x', \sigma'))$

Automatic scale selection: Function responses for increasing scale (scale signature)



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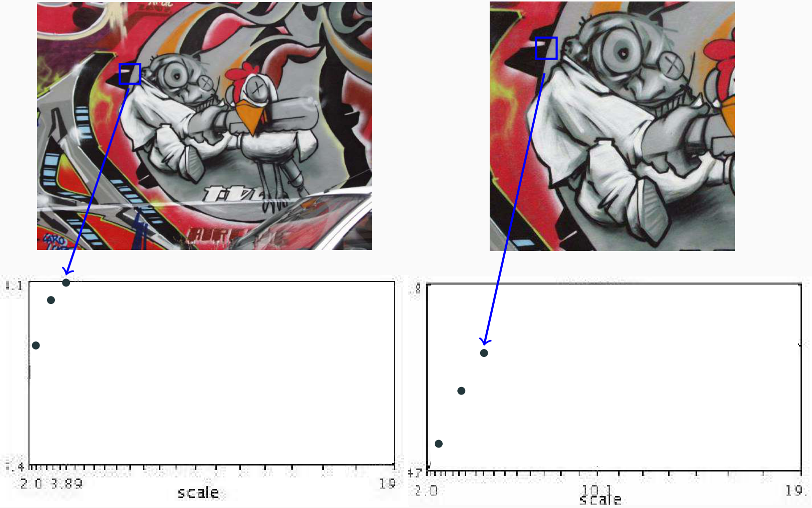

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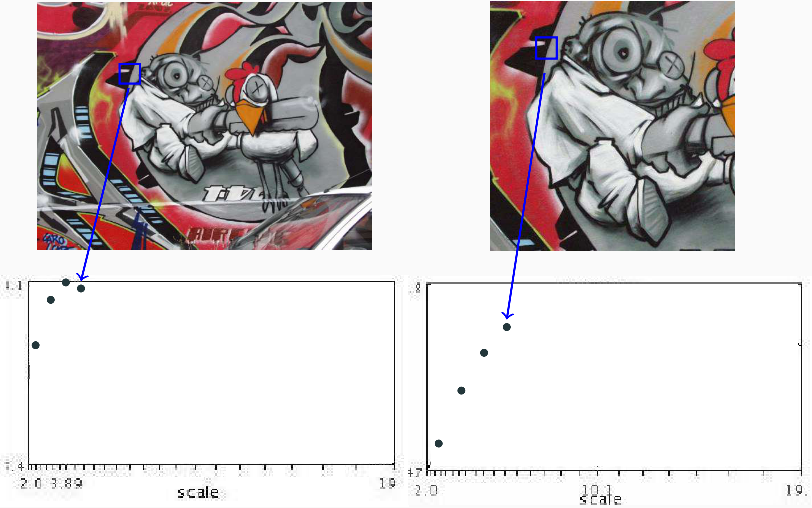
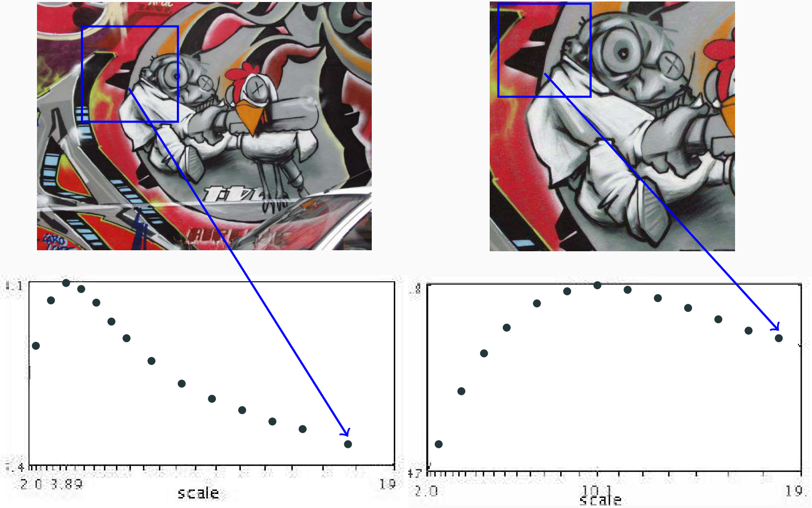


$f(I_{i_1 \ldots i_m}(x, \sigma))$ $f(I_{i_1 \ldots i_m}(x', \sigma'))$

Automatic scale selection: Function responses for increasing scale (scale signature)



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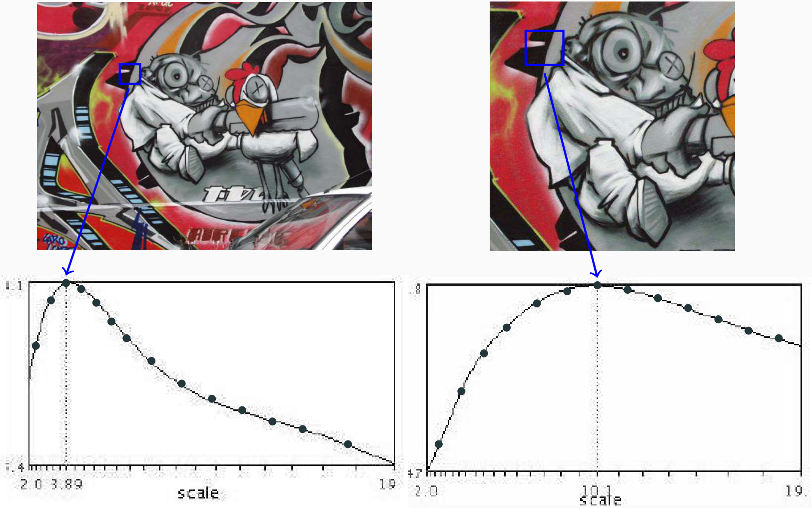
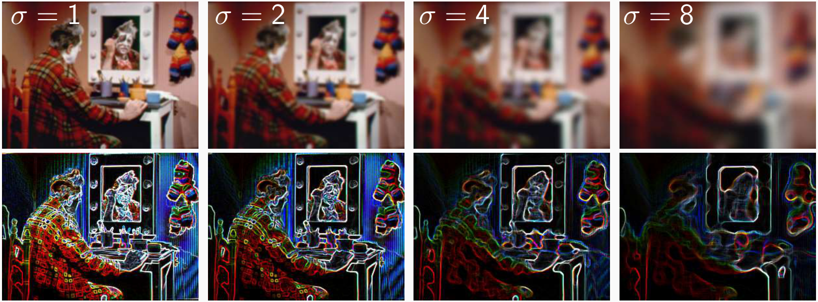
Automatic scale selection: Function responses for increasing scale (scale signature)



$f(I_{i_1 \dots i_m}(x, \sigma))$ $\qquad$ $f(I_{i_1 \dots i_m}(x', \sigma'))$

Scale space analysis [Witkin, 1983]

- How to obtain $I(x, \sigma)$?
- Applying a Gaussian filtering, with high value for σ: it is possible to extract global but simplified patterns.

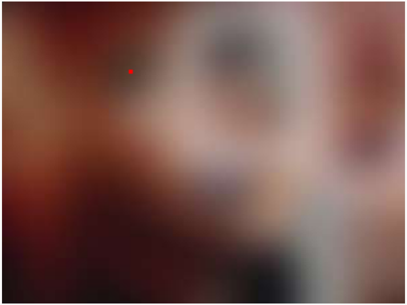


Scale-space analysis

- Consider scale (σ) as a continuous parameter:

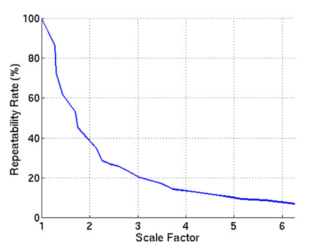
$$\begin{aligned} S(x, y, 0) &= I(x, y) \\ S(x, y, \sigma) &= I \star g_\sigma(x, y), \sigma > 0 \end{aligned}$$

- Detect global patterns at higher scale ($\sigma \gg 0$) and localize them at finer scales.



Harris detector and change of scale

- Behavior of Harris detector when image scale varies?
- Example with a direct application of Harris detector:



- Application at each scale
- Same corners detected?
- At same location?

- Measurement of coherence between detections using the repeatability rate. Repeatability rate: percentage of detected points that are correctly located (given a distance threshold) between any two images.

$\Rightarrow$ Rapid degradation of results, adaptation to scale required.

Normalized derivatives (choice of f)

- Given two views I and I' of a same image at different scales. There exists s such as:

$$I(x, y) = I'(x', y') = I'(sx, sy)$$

- Given the Gaussian kernel for any $s > 0$:

$$g_\sigma(x, y) = g_{s\sigma}(sx, sy)$$

- And its derivatives:

$$\frac{\partial g_\sigma}{\partial x}(x, y) = s \times \frac{\partial g_{s\sigma}}{\partial x}(sx, sy) \text{ (and same for } y\text{)}$$

- **Normalized** derivative:

$$\frac{\partial}{\partial x}\left(I \star g_\sigma\right)(x, y) = I \star \frac{\partial g_\sigma}{\partial x}(x, y) = {\color{red}s} \times I' \star \frac{\partial g_{s\sigma}}{\partial x}(sx, sy)$$

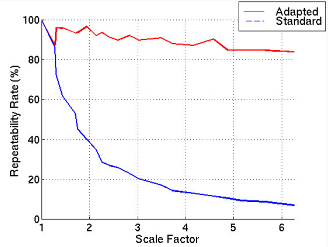
- Generalization: $f(I_{i_1,\cdots,i_m}(x, y, \sigma)) = \sigma^m I_{i_1,\cdots,i_m}(x, y, \sigma)$

Normalized derivatives for Harris detector

- Multiscale Harris detector: auto-correlation matrix becomes:

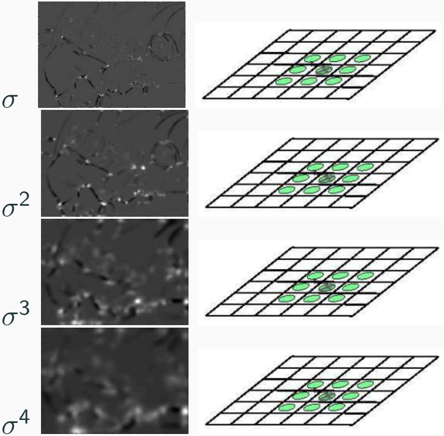
$$R(\sigma_I, \sigma_D) = \sigma_D^2 g_{\sigma_I} \star \begin{pmatrix} I_x^2(\sigma_D) & I_x(\sigma_D) I_y(\sigma_D) \\ I_x(\sigma_D) I_y(\sigma_D) & I_y^2(\sigma_D) \end{pmatrix}$$

  with $I_x(\sigma_D) = I \star \frac{\partial g_{\sigma_D}}{\partial x}$ and $I_y(\sigma_D) = I \star \frac{\partial g_{\sigma_D}}{\partial y}$
- σ_I: integration scale, σ_D: differentiation scale.
- Using normalized derivative allows us to keep a good detection for any scales



Multiscale Harris detector

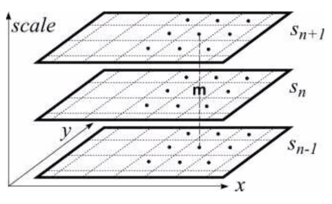
- Procedure: compute multi-scale Harris detector for various scales, and select local maxima (8-neighborhood)

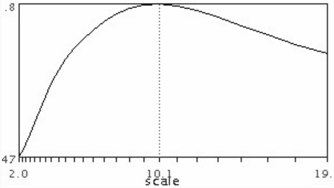


- Issue: detected corners are not spatially stable over scales. How to select the best scale leading to the best localization?

Multiscale detector scheme

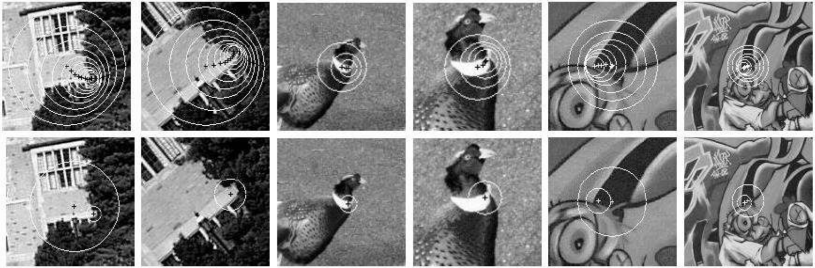
1. Compute edge detector (gradient norm, Laplacian...) for various scales s.
2. Use normalized derivatives. Example for Laplacian: $s^2|I_{xx}(s) + I_{yy}(s)|$
3. Optimal scale: select the scale which gives the highest detector response over space and scale.





Robust scale invariant detector: Harris-Laplace [Mikolajczyk and Schmid, 2001]

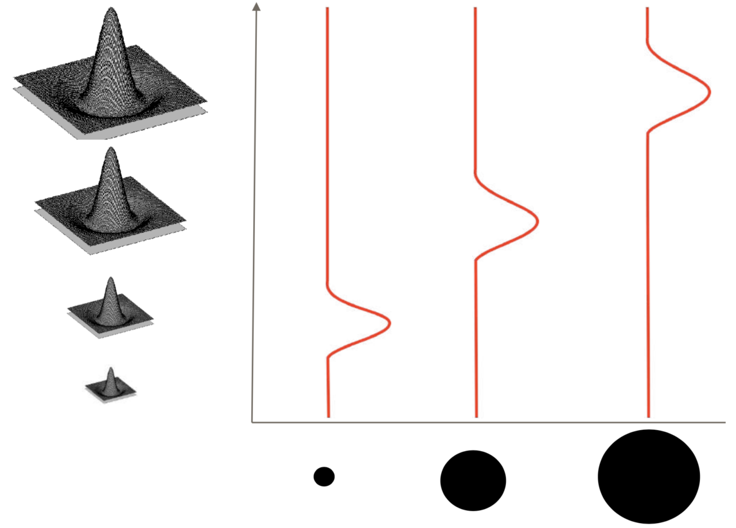
1. Initialization: multi-scale Harris detector for various scales
2. Select corners having a maximal (normalized) Laplacian response over scale



- Same procedure with Hessian detector: Hessian-Laplace

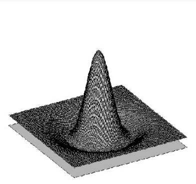
Blobs detector

- Laplacian of Gaussian = “blob” detector



Laplacian of Gaussian (LoG)

$\Rightarrow$ Local maxima of Laplacian of Gaussian over scale [Lindeberg, 1998]



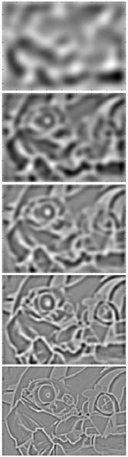
σ^5

σ^4

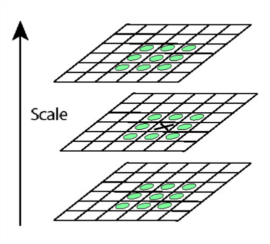
σ^3

σ^2

σ^1

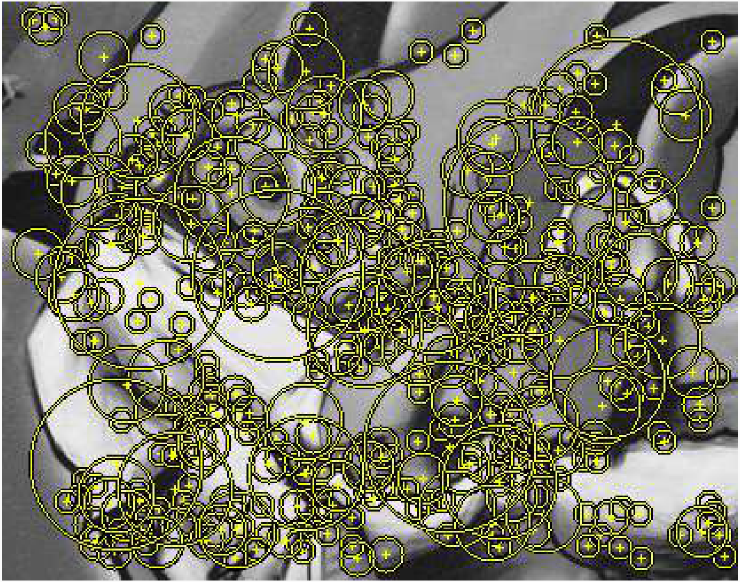


$\sigma^2(I_{xx}(\sigma) + I_{yy}(\sigma))$

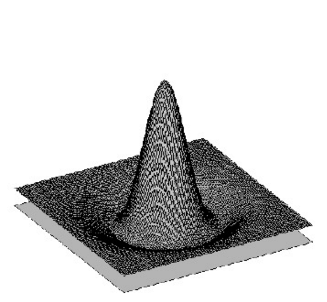


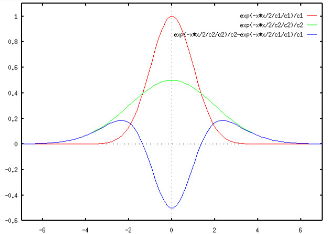
scale selection

Laplacian of Gaussian: Results



- DoG $\approx$ LoG





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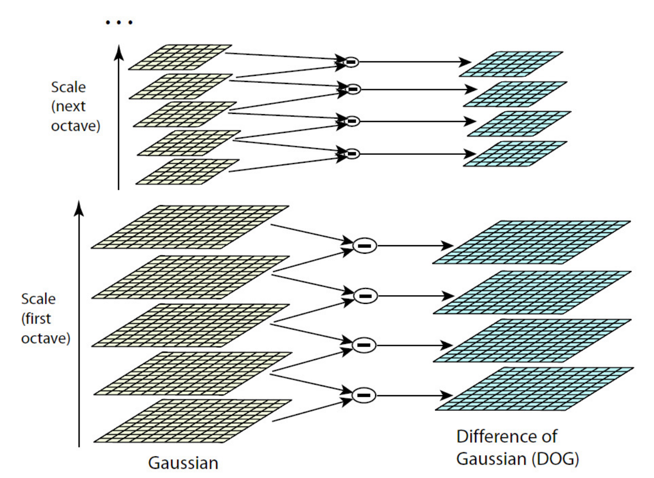
DoG: fast computation

- Pyramid of resolutions: Gaussian convolutions and sub-sampling [Lowe, 1999]

subsampling with step 2, $\sigma^4 = 2 \longleftarrow$

$\xrightarrow{\sigma=2^{\frac{1}{4}}}$

Original image

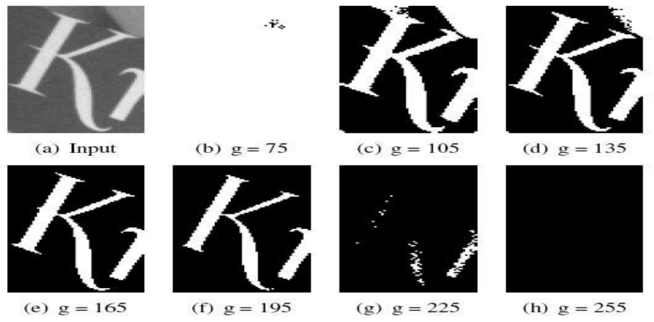


Blobs detection with DoG

Regions of interest

Regions of interest detection: MSER

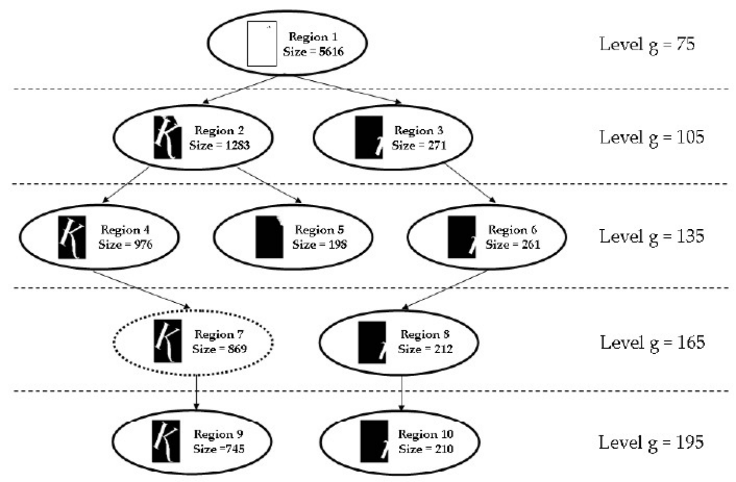
- MSER: Maximally Stable Extremal Region



$$I_{\text{bin}}^{g} = \begin{cases} 1 & \text{if } I_{\text{in}} \geq g \\ 0 & \text{otherwise} \end{cases}$$

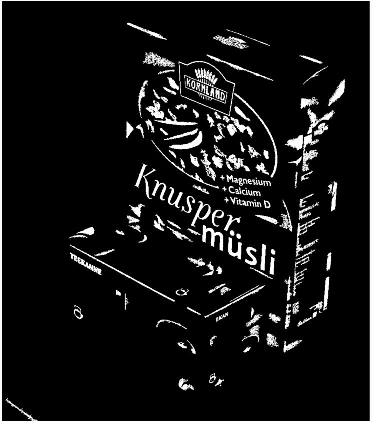
MSER

- Selection of regions that remain stable for a large number of parameter values g.



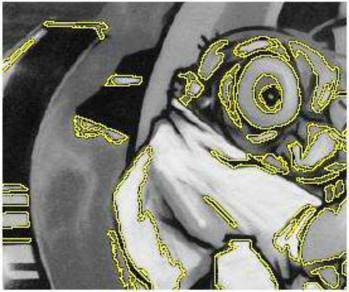
MSER: examples

(a) Original image



(b) MSER detected

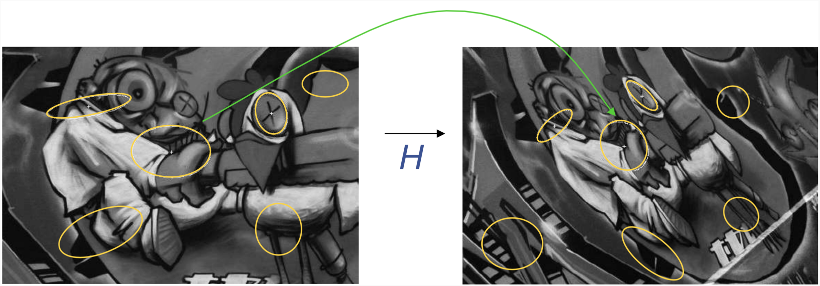
MSER: examples



Evaluation of detection

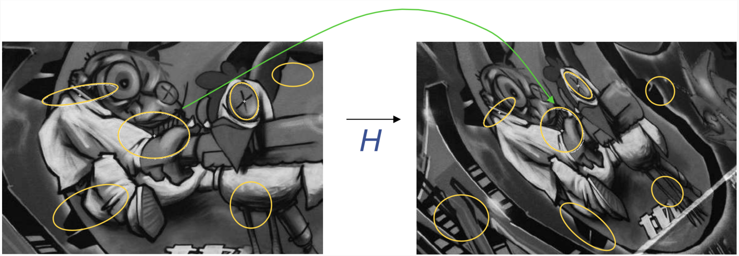
- Quantitative evaluation of the detection of points/regions of interest:
  - points / regions approximately at the same location
- Two points/regions correspond if:
  - low localization error
  - large intersection area
- Repeatability rate: percentage of corresponding points

Evaluation criteria



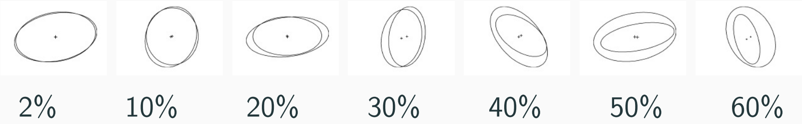
$$repeatability = \frac{\#corresponding\ \ regions}{\#detected\ \ regions} \times 100\%$$

Evaluation criteria



$$repeatability = \frac{\#corresponding\ regions}{\#detected\ regions} \times 100\%$$

$$overlap\ error = \left(1 - \frac{intersection}{union}\right) \times 100\%$$

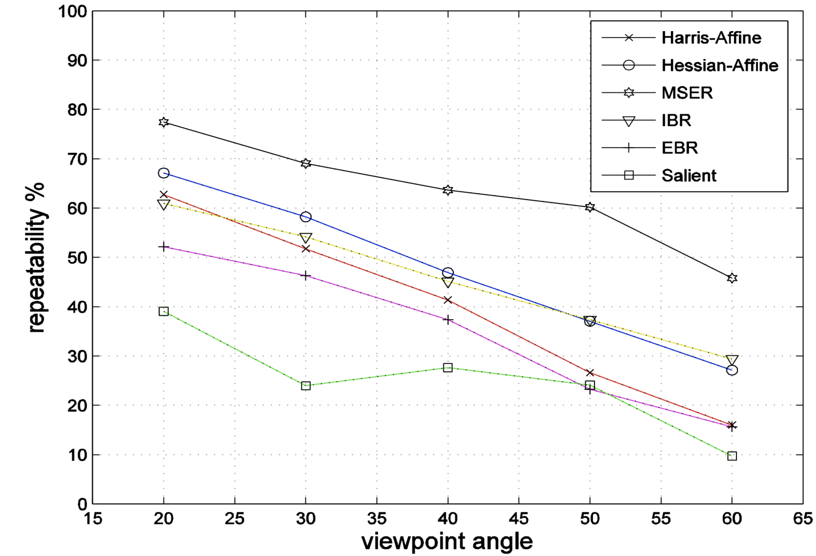


Datasets

- Different types of transformation:
  - Viewpoint change
  - Scale change
  - Image blur
  - JPEG compression
  - Lighting change
- Two types of scenes:
  - Structured
  - Textured
- Transformations within the sequence (homographies)
  - Independent estimation

Viewpoint change (0-60°)

Viewpoint change, structured scenes



Zoom and rotation change

(a) Structured scene

(b) Textured scene

Blur, compression, change of illumination

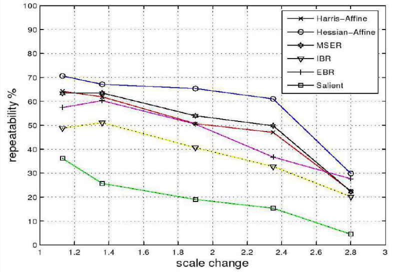
(a) Blur - structured scene

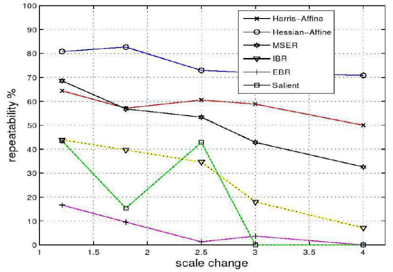
(b) Blur - textured scene

(c) Light change - structured scene

(d) JPEG - structured scene

Scale and rotation change





Conclusion on conventional detectors

- Today there are several POI/ROI detectors that are robust to large changes in scale and viewpoint
- The best choice may depend on the type of deformation
- MSER well suited for structured scenes
- Harris and Hessian well suited to textured scenes
- SIFT (DoG), and high-performance variants such as SURF

- Algorithmic processing chain:
  1. Detection of extrema in scale space with optionally a fine relocation of the POI
  2. Extraction of the region of interest (affine invariance, rotation invariance...)
  3. Descriptor calculation

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