Instance-level recognition: Local invariant features

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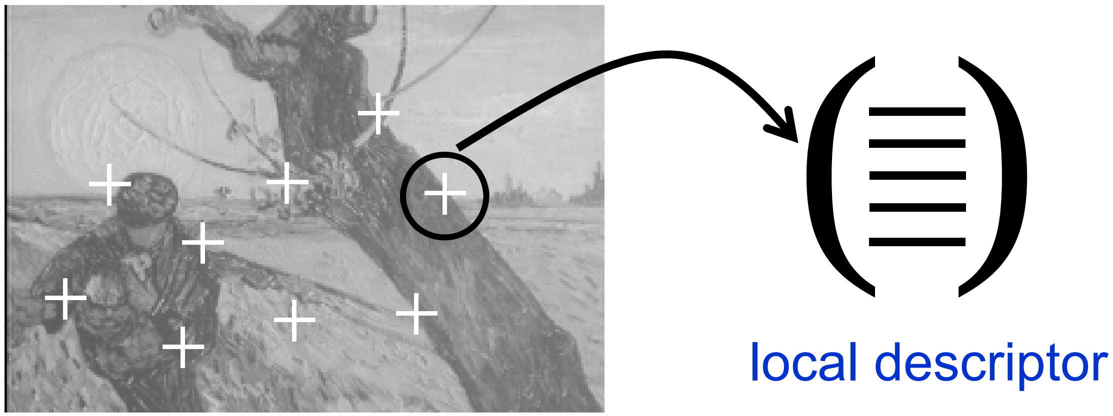
Overview

- **Introduction to local features**
- Harris interest points + SSD, ZNCC, SIFT
- Scale & affine invariant interest point detectors
- Evaluation and comparison of different detectors
- Region descriptors and their performance

Local features



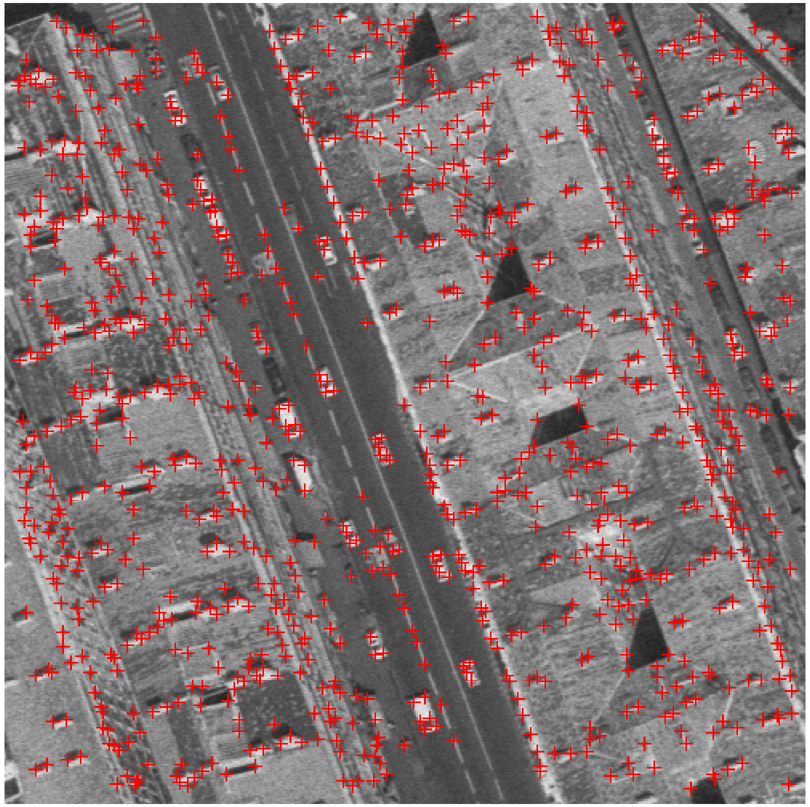
Several / many local descriptors per image

Robust to occlusion/clutter + no object segmentation required

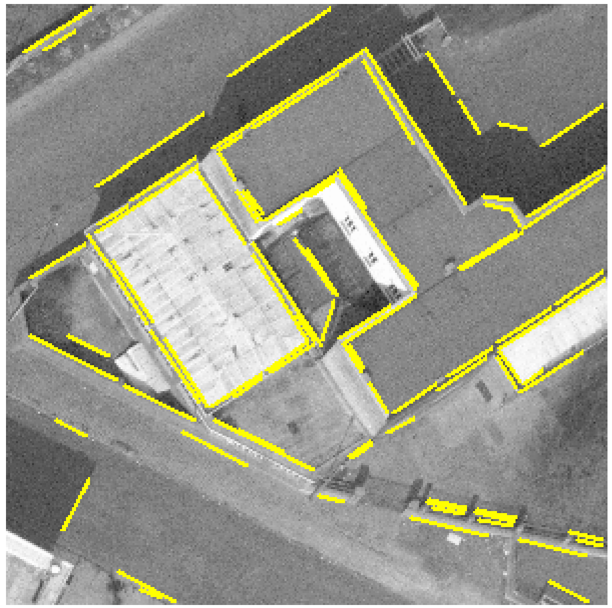
Photometric : distinctive

Invariant : to image transformations + illumination changes

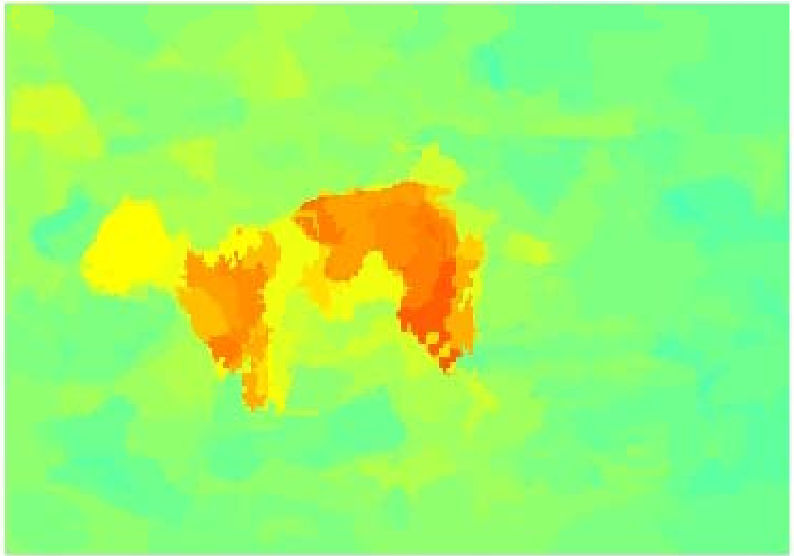
Local features: interest points



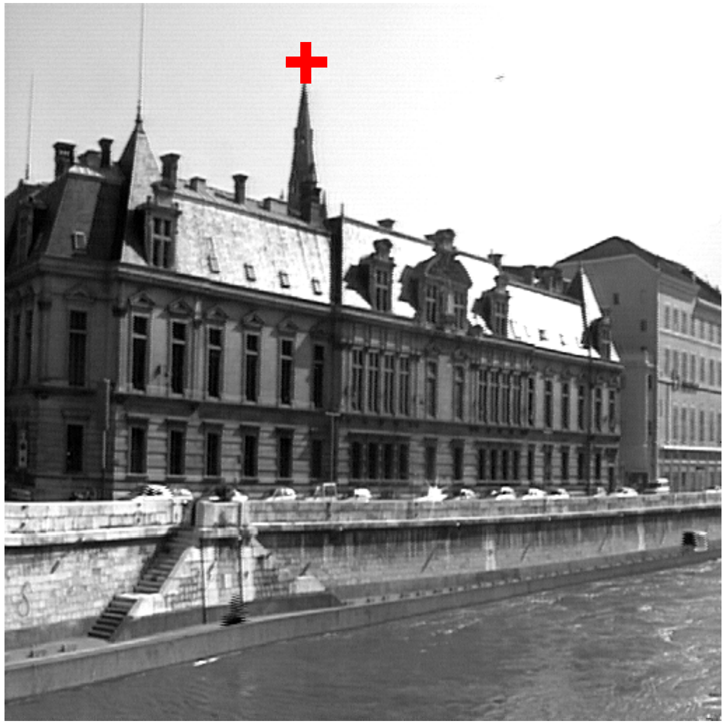
Local features: Contours/segments



Local features: segmentation

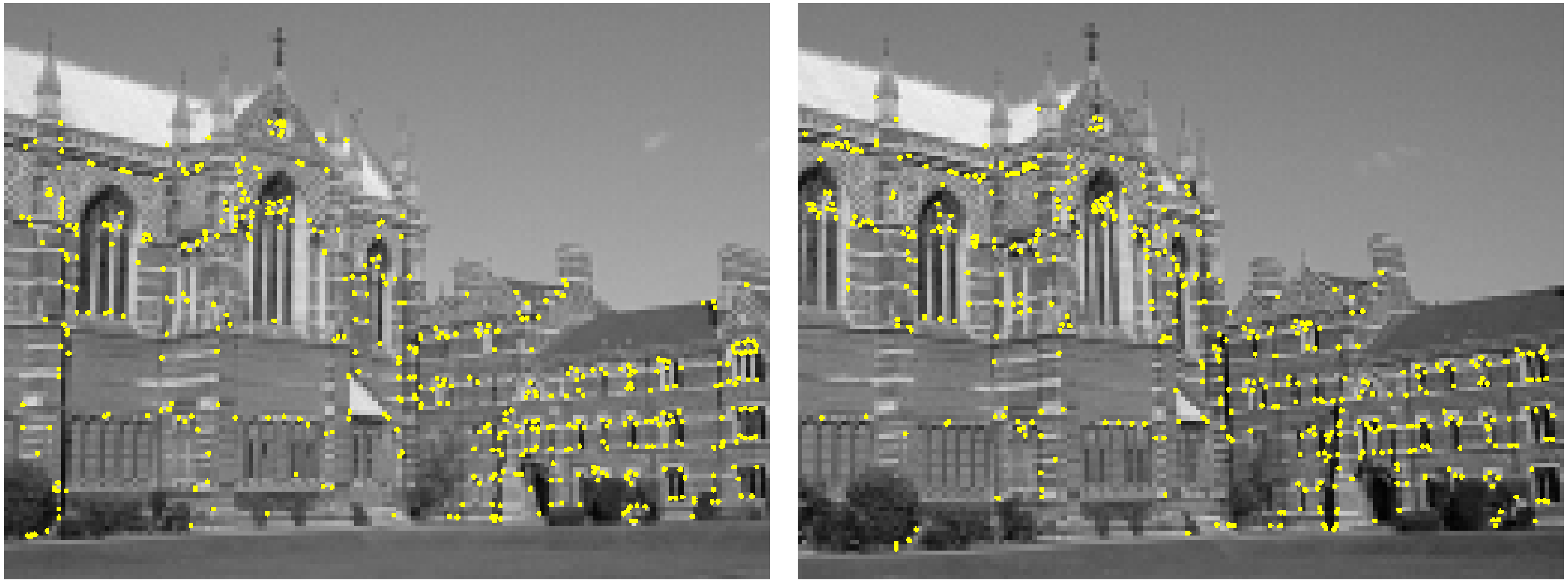


Application: Matching



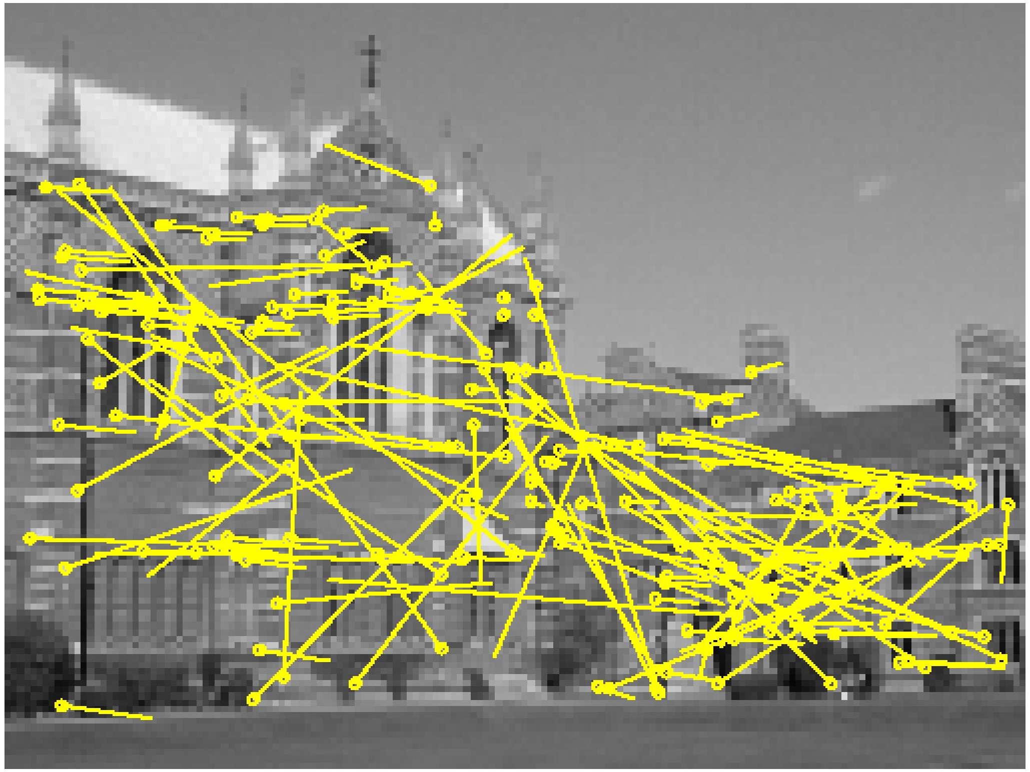
Find corresponding locations in the image

Illustration – Matching



Interest points extracted with Harris detector (~ 500 points)

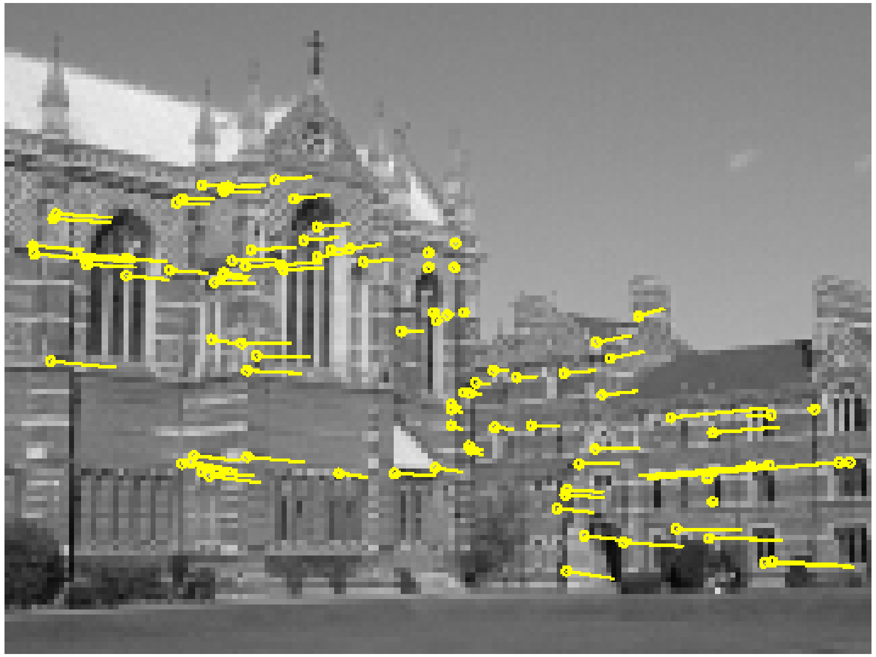
Illustration – Matching



Interest points matched based on cross-correlation (188 pairs)

Illustration – Matching

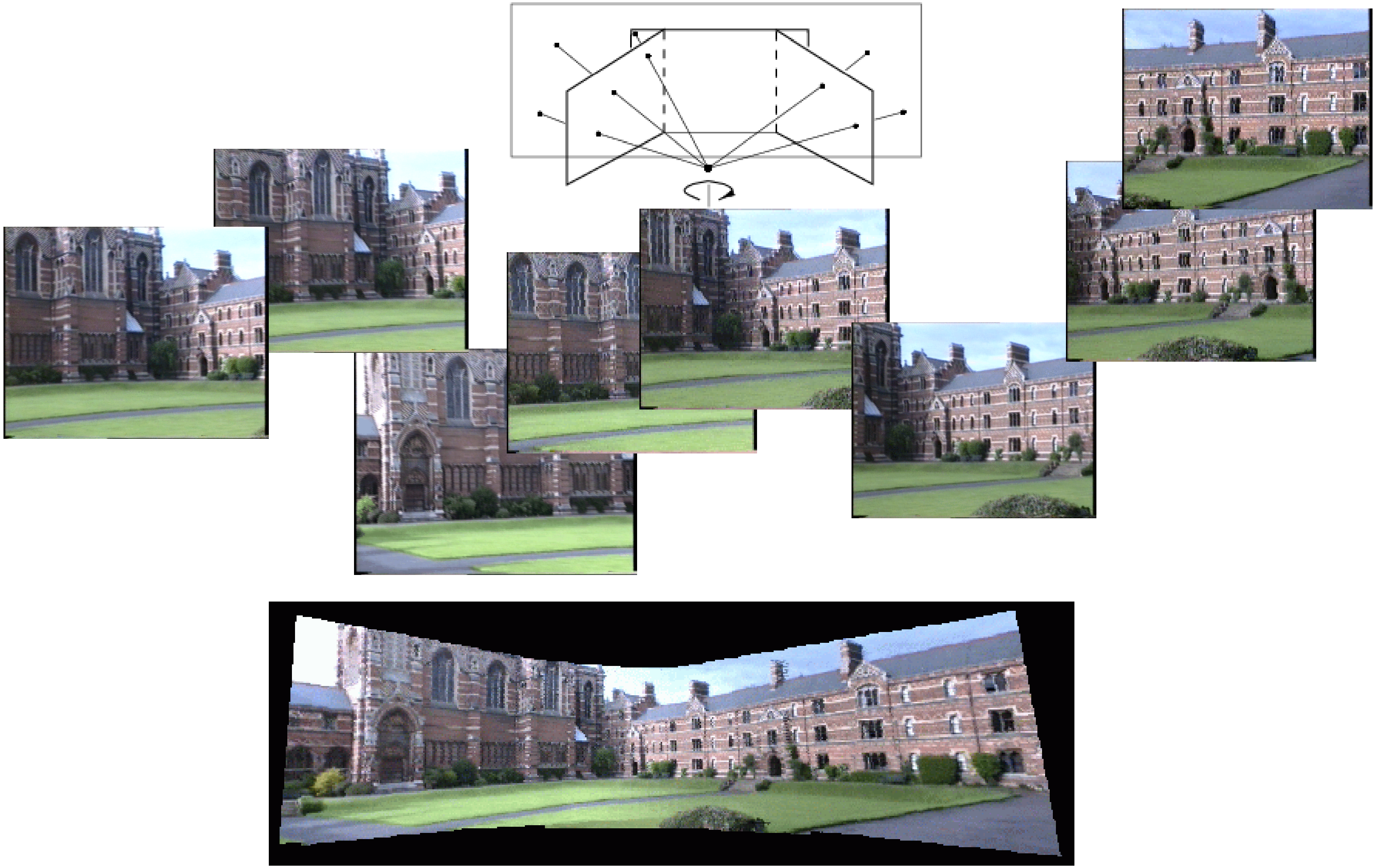
Global constraint - Robust estimation of the fundamental matrix



99 inliers

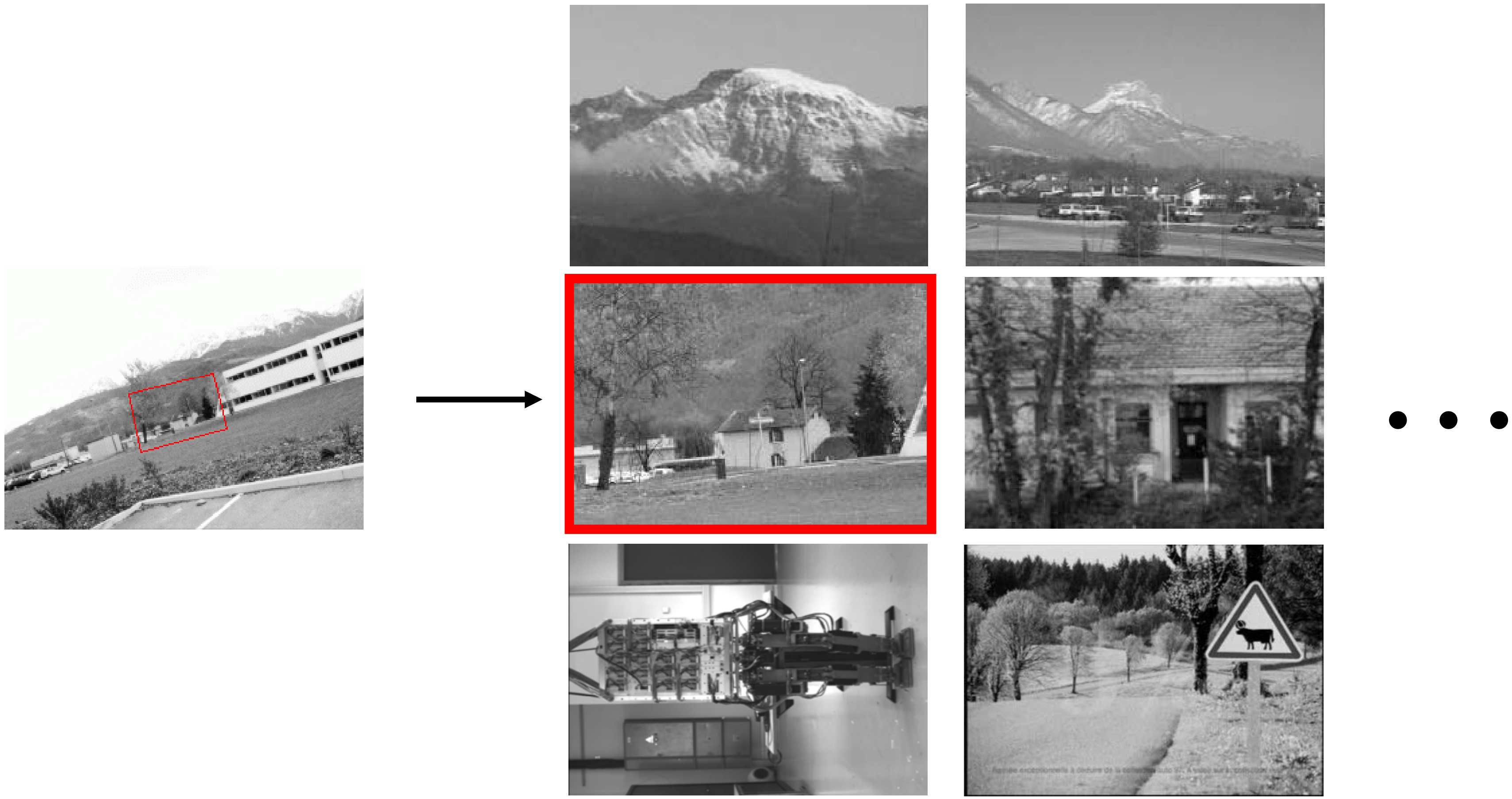
89 outliers

Application: Panorama stitching



Application: Instance-level recognition

Search for particular objects and scenes in large databases

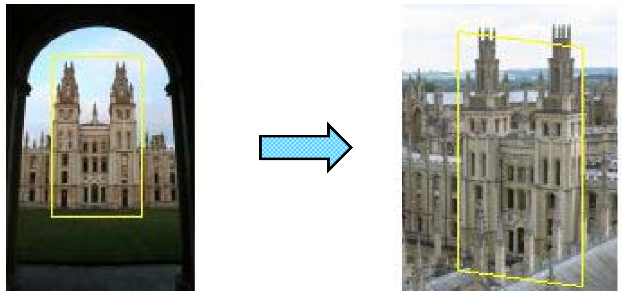


Difficulties

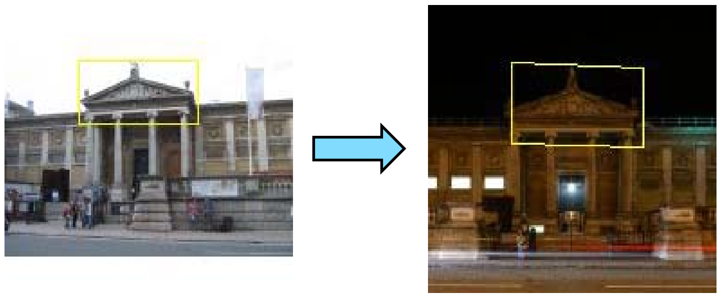
Finding the object despite possibly large changes in scale, viewpoint, lighting and partial occlusion

→ **requires invariant description**

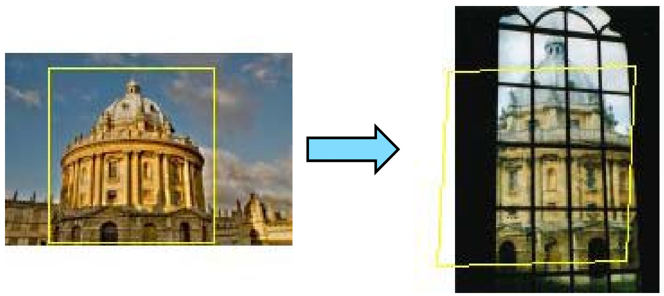
Scale



Viewpoint



Lighting



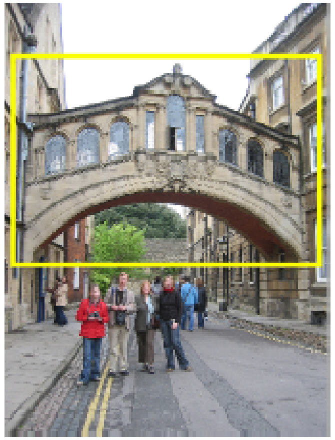
Occlusion

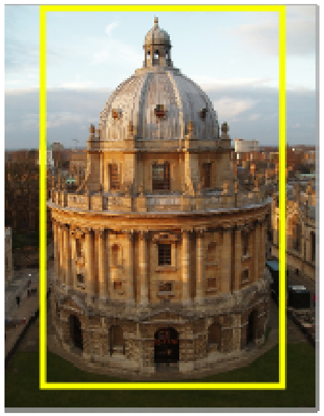
Difficulties

- Very large images collection → need for efficient indexing
  - Flickr has 2 billion photographs, more than 1 million added daily
  - Facebook has 15 billion images (~27 million added daily)
  - Large personal collections
  - Video collections, i.e., YouTube

Applications

Search photos on the web for particular places





Find these landmarks

...in these images and 1M more

Applications

- Take a picture of a product or advertisement
  → find relevant information on the web

[Pixee – Milpix]

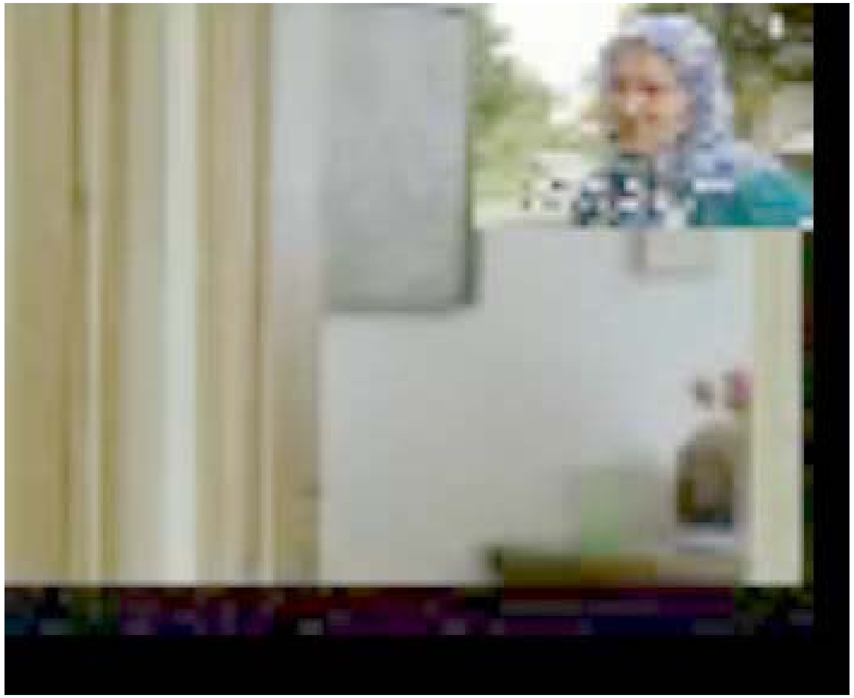
Applications

- Finding stolen/missing objects in a large collection

Applications

- Copy detection for images and videos

Query video



Search in 200h of video

Applications

- Sony Aibo – Robotics
  - Recognize docking station
  - Communicate with visual cards
  - Place recognition
  - Loop closure in SLAM

Local features

1) Extraction of local features
- Contours/segments
- Interest points & regions
- Regions by segmentation
- Dense features, points on a regular grid

2) Description of local features
- Dependant on the feature type
- Contours/segments → angles, length ratios
- Interest points → greylevels, gradient histograms
- Regions (segmentation) → texture + color distributions

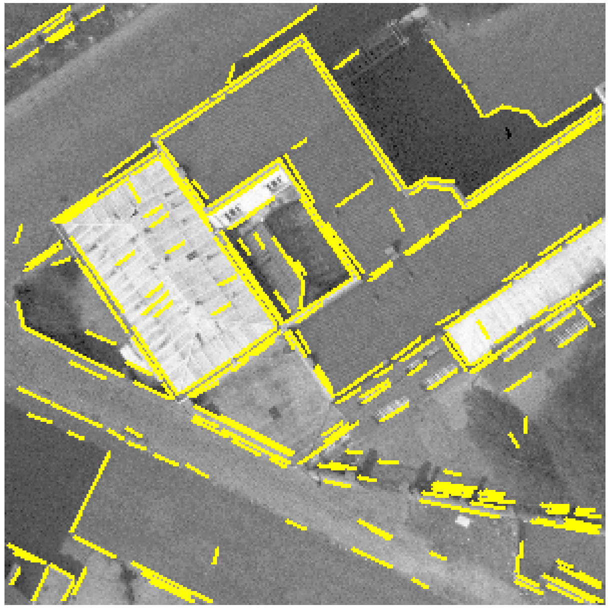
Line matching

- Extraction de contours
  - Zero crossing of Laplacian
  - Local maxima of gradients
- Chain contour points (hysteresis)
- Extraction of line segments
- Description of segments
  - Mi-point, length, orientation, angle between pairs etc.

Experimental results – line segments

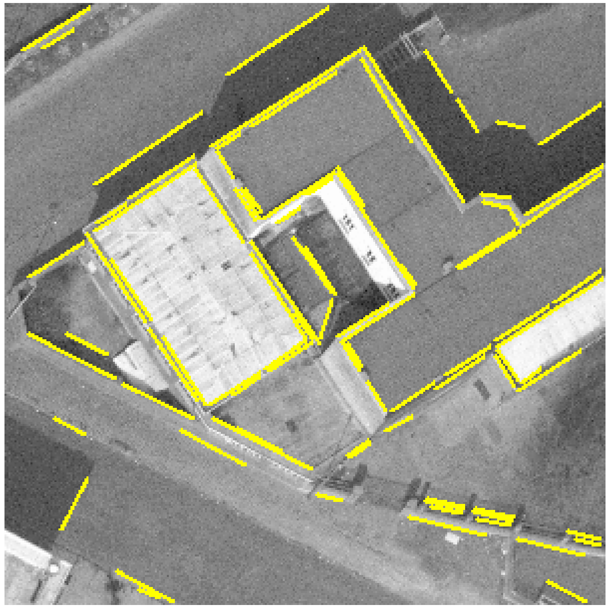
images 600 x 600

Experimental results – line segments



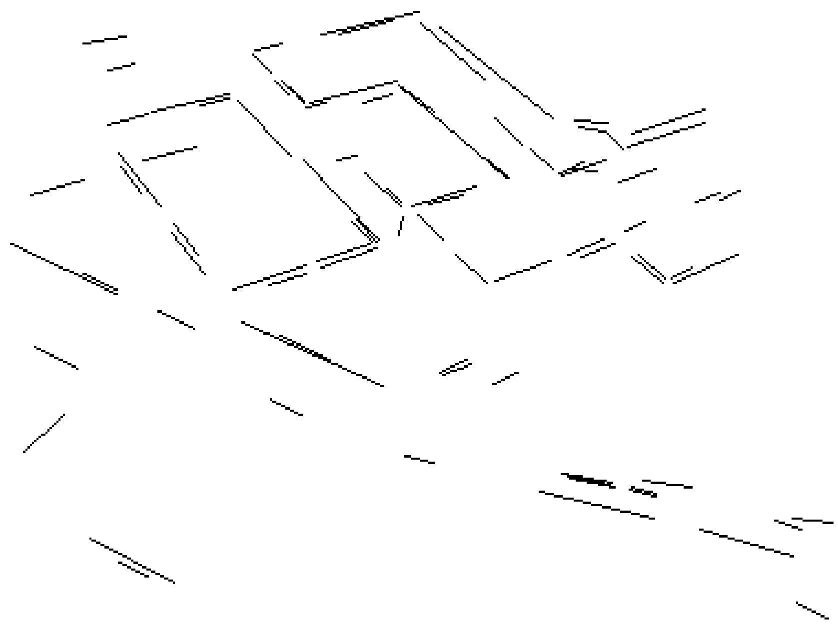
248 / 212 line segments extracted

Experimental results – line segments



89 matched line segments - 100% correct

Experimental results – line segments



3D reconstruction

Problems of line segments

- Often only partial extraction
  - Line segments broken into parts
  - Missing parts

- Information not very discriminative
  - 1D information
  - Similar for many segments

- Potential solutions
  - Pairs and triplets of segments
  - Interest points

Overview

- Introduction to local features
- **Harris interest points + SSD, ZNCC, SIFT**
- Scale & affine invariant interest point detectors
- Evaluation and comparison of different detectors
- Region descriptors and their performance

Harris detector [Harris & Stephens'88]

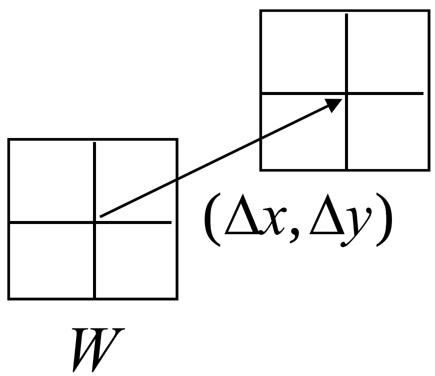
Based on the idea of auto-correlation

Important difference in all directions => interest point

Harris detector

Auto-correlation function for a point (x, y) and a shift $(\Delta x, \Delta y)$

$$A(x, y) = \sum_{(x_k, y_k) \in W(x,y)} (I(x_k, y_k) - I(x_k + \Delta x, y_k + \Delta y))^2$$



Harris detector

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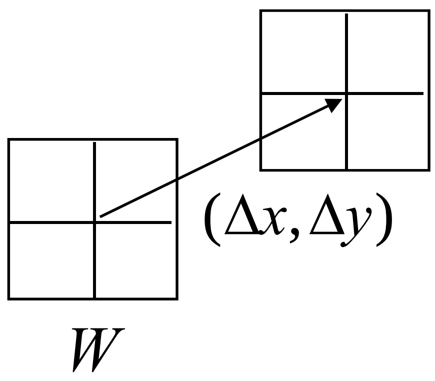
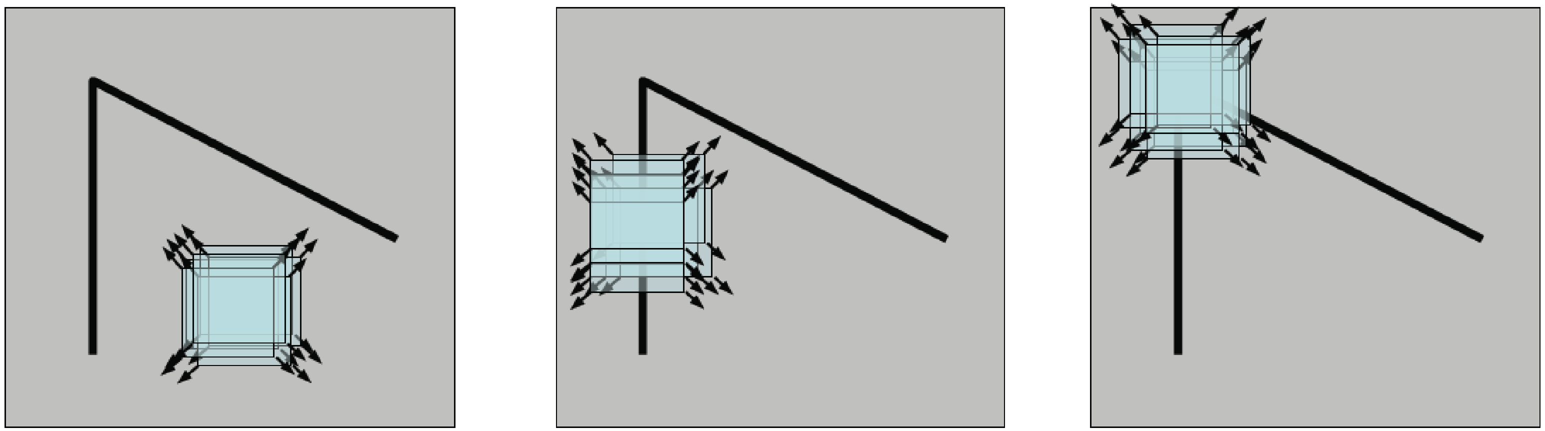
$$A(x,y) = \sum_{(x_k, y_k) \in W(x,y)} \left(I(x_k, y_k) - I(x_k + \Delta x, y_k + \Delta y) \right)^2$$



$A(x,y)$
- small in all directions $\rightarrow$ uniform region
- large in one directions $\rightarrow$ contour
- large in all directions $\rightarrow$ interest point

Harris detector



"flat" region:
no change in
all directions

"edge":
no change along
the edge direction

"corner":
significant change
in all directions

Harris detector

Discret shifts are avoided based on the auto-correlation matrix

with first order approximation

$$I(x_k + \Delta x, y_k + \Delta y) = I(x_k, y_k) + \begin{pmatrix} I_x(x_k, y_k) & I_y(x_k, y_k) \end{pmatrix} \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix}$$

$$A(x, y) = \sum_{(x_k, y_k) \in W(x,y)} (I(x_k, y_k) - I(x_k + \Delta x, y_k + \Delta y))^2$$

$$= \sum_{(x_k, y_k) \in W} \left(\begin{pmatrix} I_x(x_k, y_k) & I_y(x_k, y_k) \end{pmatrix} \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix} \right)^2$$

Harris detector

$$= \begin{pmatrix} \Delta x & \Delta y \end{pmatrix} \begin{bmatrix} \sum_{(x_k, y_k) \in W} (I_x(x_k, y_k))^2 & \sum_{(x_k, y_k) \in W} I_x(x_k, y_k) I_y(x_k, y_k) \\ \sum_{(x_k, y_k) \in W} I_x(x_k, y_k) I_y(x_k, y_k) & \sum_{(x_k, y_k) \in W} (I_y(x_k, y_k))^2 \end{bmatrix} \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix}$$

Auto-correlation matrix

the sum can be smoothed with a Gaussian

$$= \begin{pmatrix} \Delta x & \Delta y \end{pmatrix} G \otimes \begin{bmatrix} I_x^{\,2} & I_x I_y \\ I_x I_y & I_y^{\,2} \end{bmatrix} \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix}$$

Harris detector

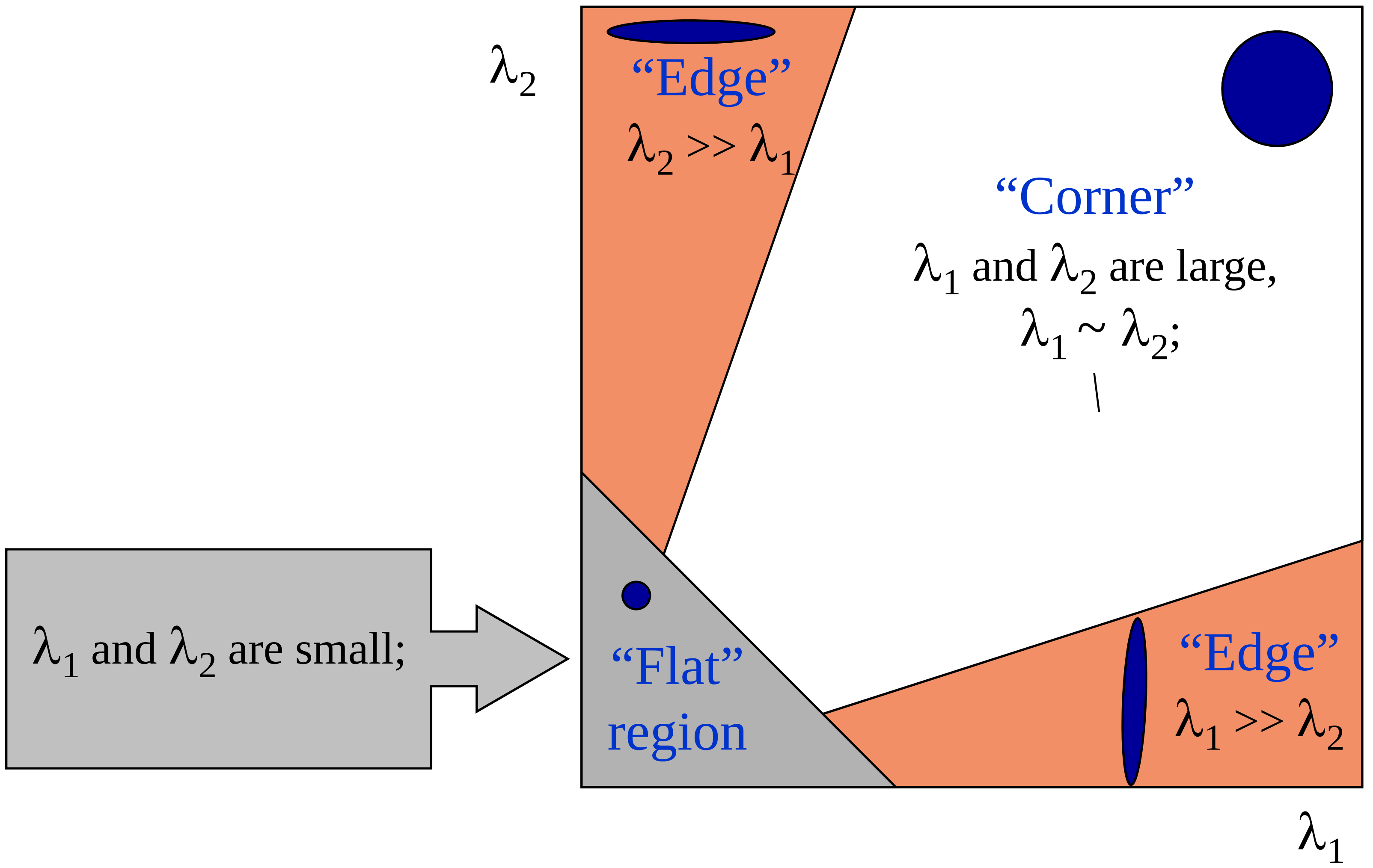
- Auto-correlation matrix

$$A(x,y) = G \otimes \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

  - captures the structure of the local neighborhood
  - measure based on eigenvalues of this matrix
    - 2 strong eigenvalues => interest point
    - 1 strong eigenvalue => contour
    - 0 eigenvalue => uniform region

Interpreting the eigenvalues

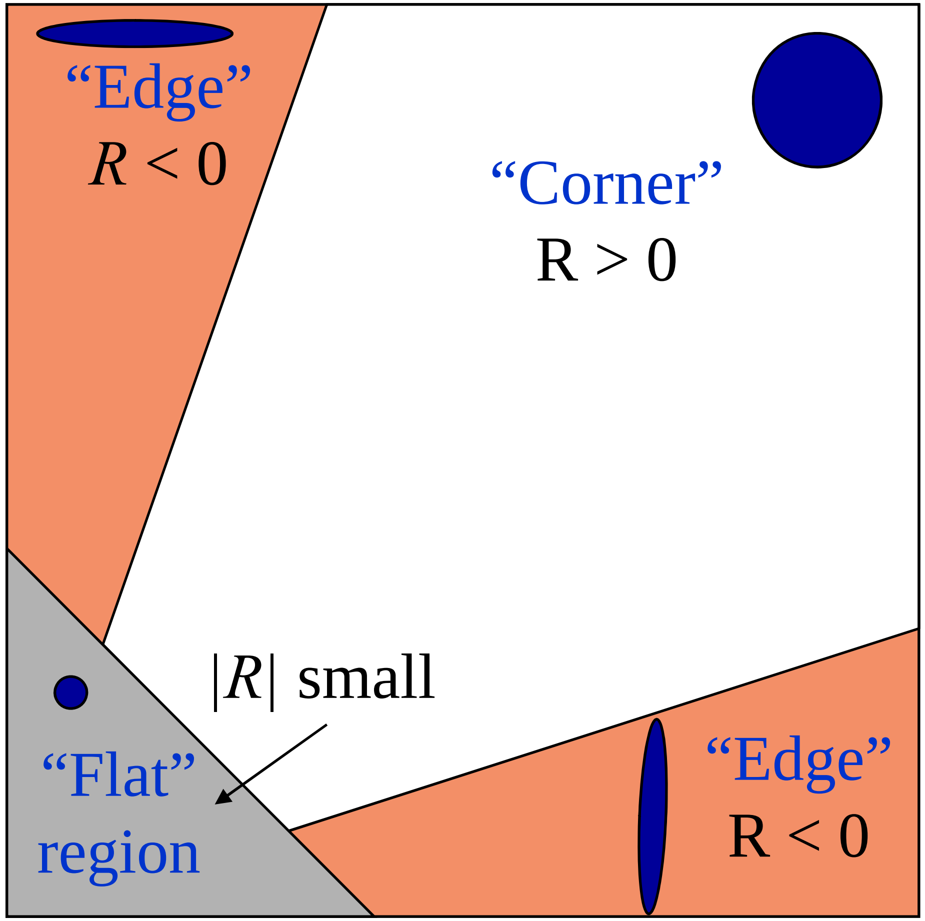
Classification of image points using eigenvalues of autocorrelation matrix:



Corner response function

$$R = \det(A) - \alpha\, \mathrm{trace}(A)^2 = \lambda_1 \lambda_2 - \alpha(\lambda_1 + \lambda_2)^2$$

α: constant (0.04 to 0.06)



Harris detector

- Cornerness function

$$f = \det(A) - k(trace(A))^2 = \lambda_1 \lambda_2 - k(\lambda_1 + \lambda_2)^2$$

Reduces the effect of a strong contour

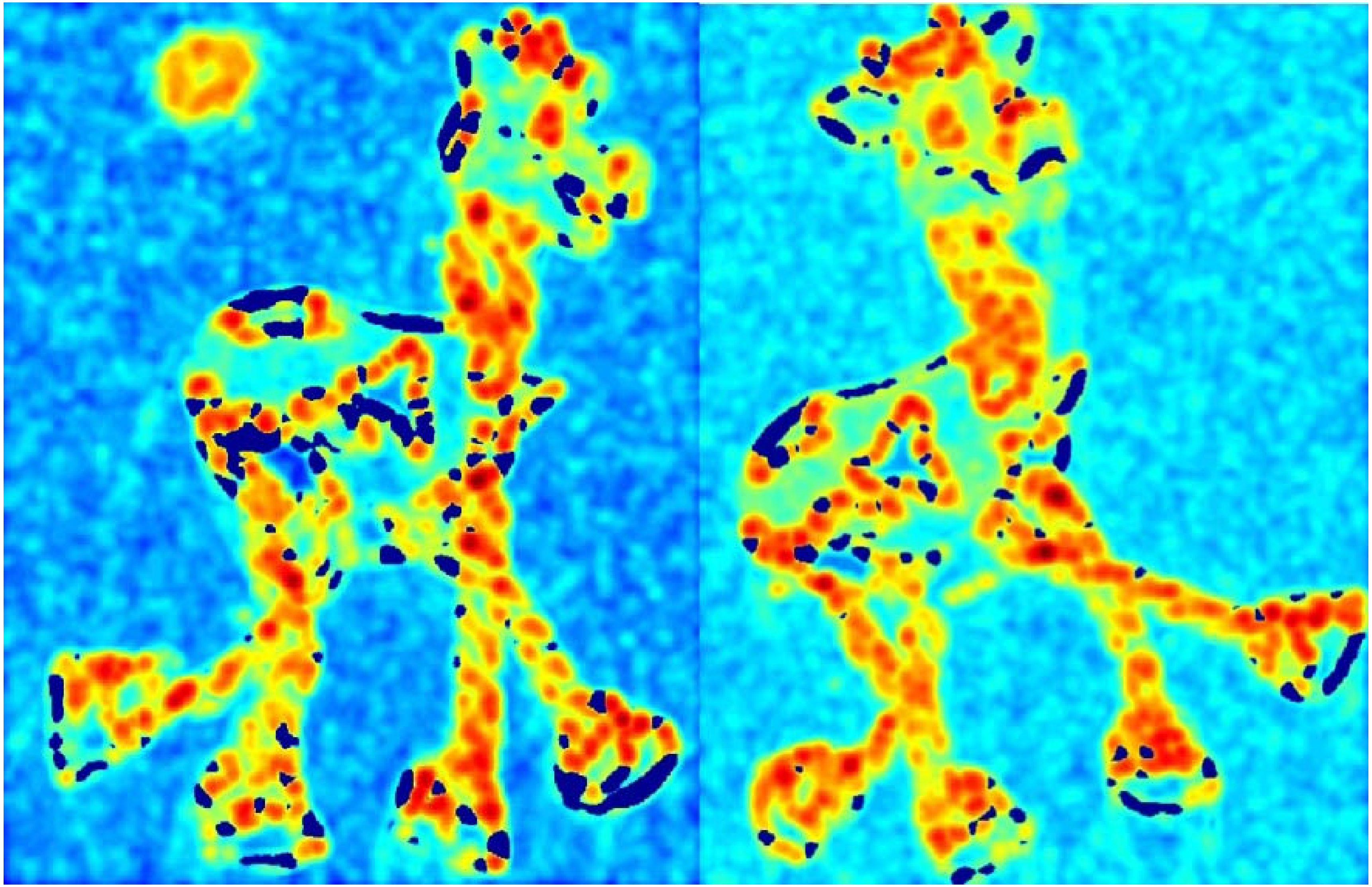
- Interest point detection
  - Treshold (absolut, relatif, number of corners)
  - Local maxima

$$f > thresh \;\wedge\; \forall x, y \in 8-neighbourhood \;\; f(x,y) \geq f(x',y')$$

Harris Detector: Steps

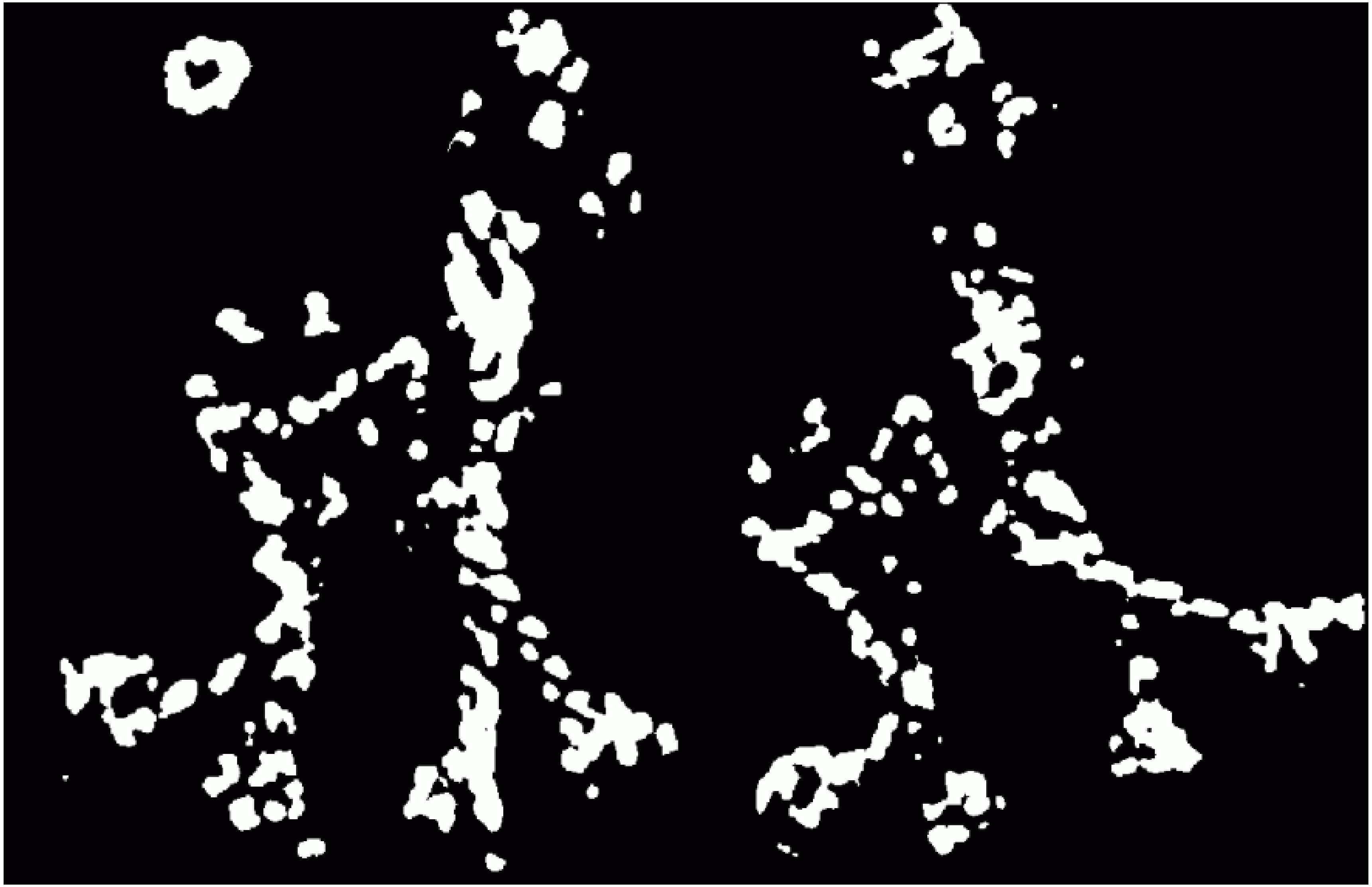
Harris Detector: Steps

Compute corner response R



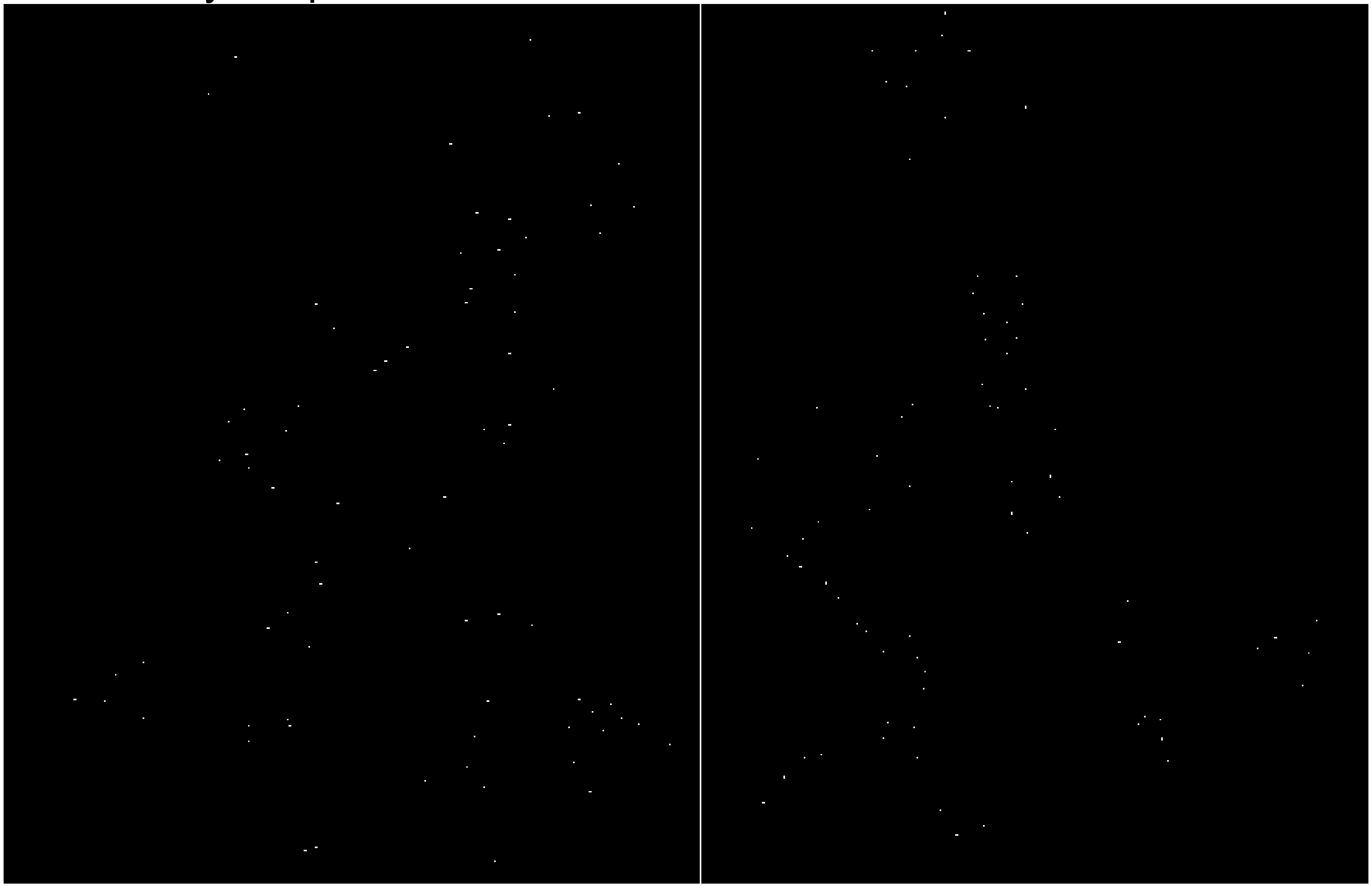
Harris Detector: Steps

Find points with large corner response: R>threshold



Harris Detector: Steps

Take only the points of local maxima of *R*



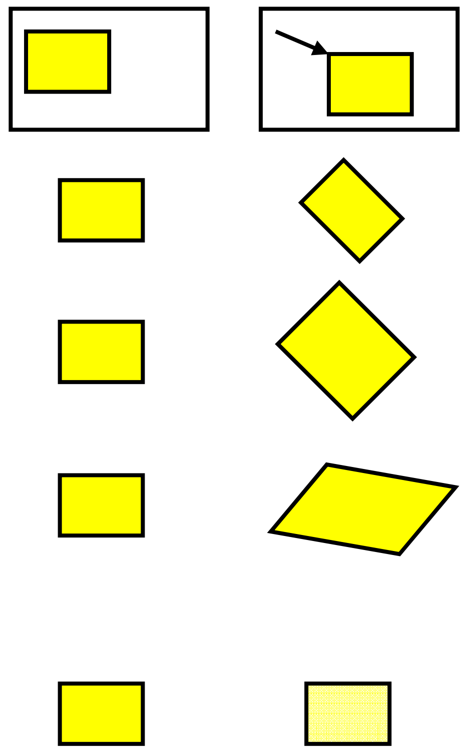
Harris Detector: Steps

Harris detector: Summary of steps

1. Compute Gaussian derivatives at each pixel
2. Compute second moment matrix *A* in a Gaussian window around each pixel
3. Compute corner response function *R*
4. Threshold *R*
5. Find local maxima of response function (non-maximum suppression)

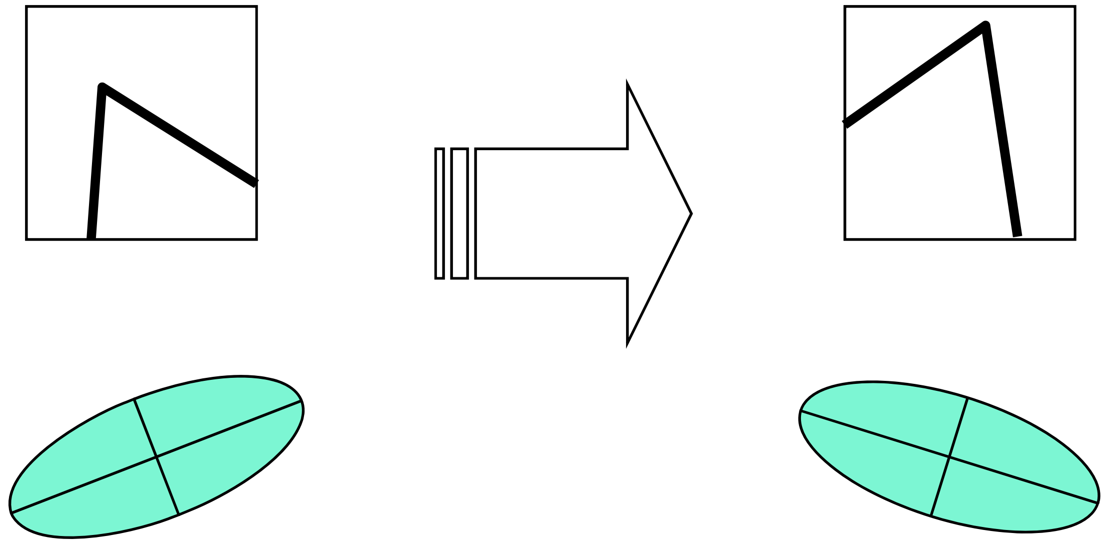
Harris - invariance to transformations

- Geometric transformations
  - translation
  - rotation
  - similitude (rotation + scale change)
  - affine (valide for local planar objects)
- Photometric transformations
  - Affine intensity changes ($I \rightarrow a\,I + b$)



Harris Detector: Invariance Properties

- Rotation



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

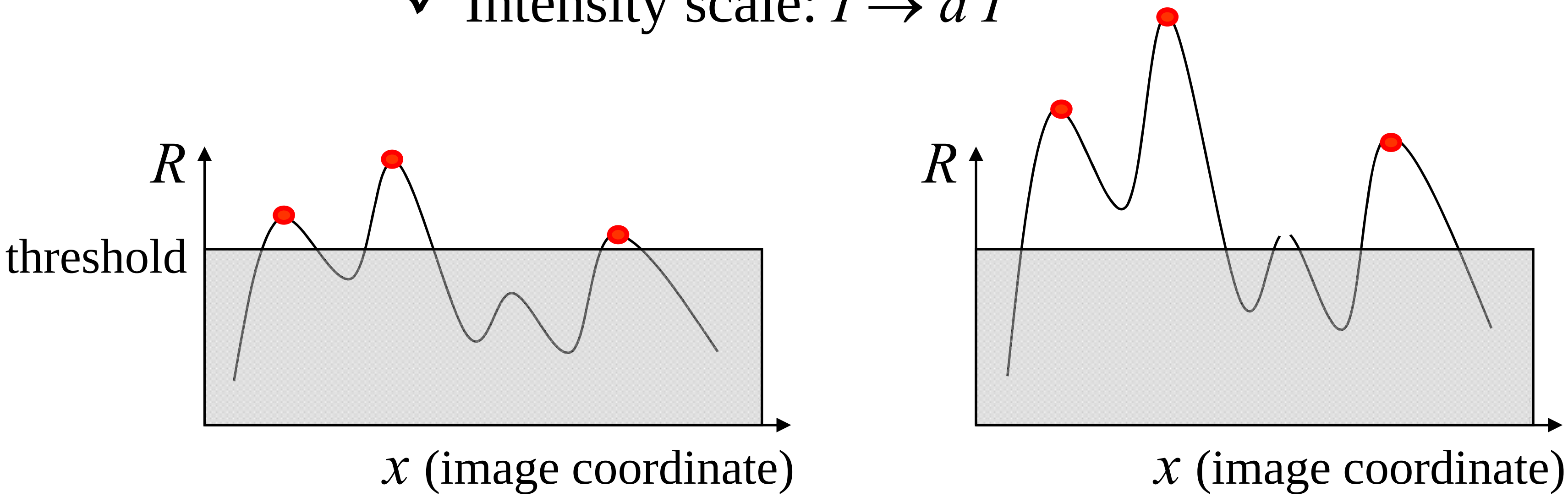
Corner response R is invariant to image rotation

Harris Detector: Invariance Properties

- Affine intensity change

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

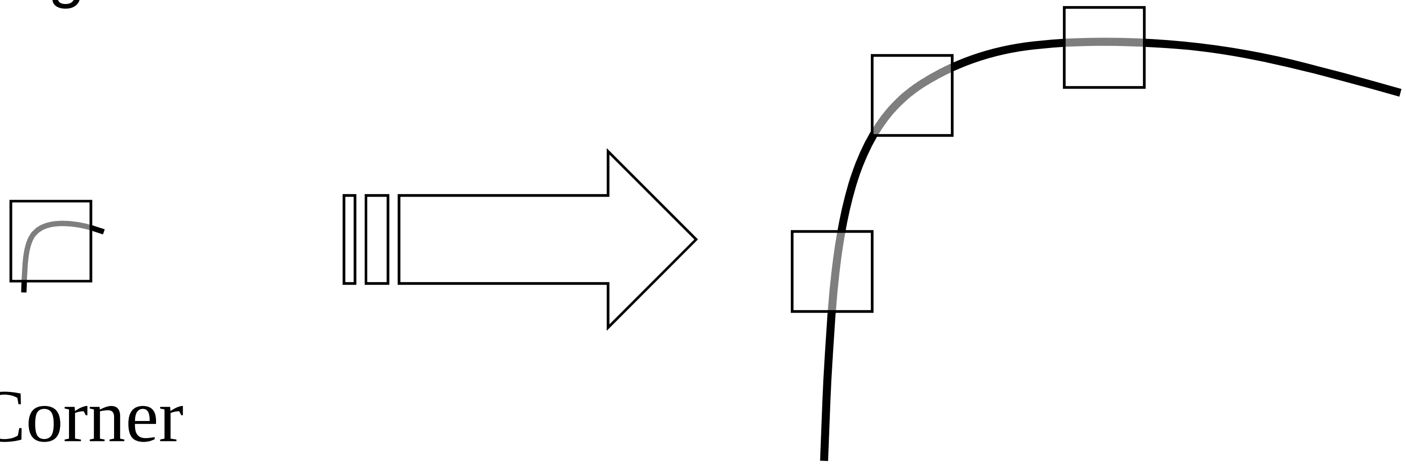
✓ Intensity scale: $I \rightarrow a\, I$



Partially invariant to affine intensity change, dependent on type of threshold

Harris Detector: Invariance Properties

- Scaling



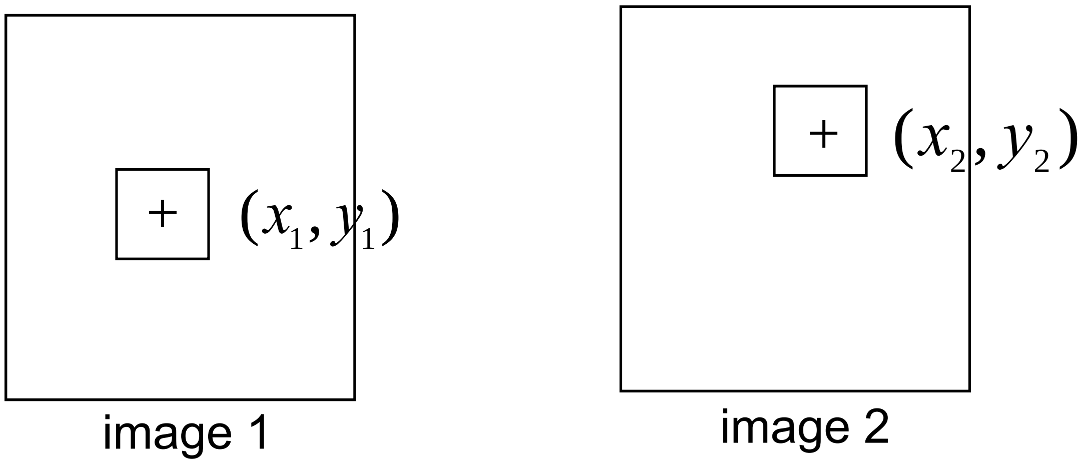
Corner

All points will be classified as edges

Not invariant to scaling

Comparison of patches - SSD

Comparison of the intensities in the neighborhood of two interest points



SSD : sum of square difference

$$\frac{1}{(2N+1)^2}\sum_{i=-N}^{N}\sum_{j=-N}^{N}(I_1(x_1+i, y_1+j) - I_2(x_2+i, y_2+j))^2$$

Small difference values → similar patches

Comparison of patches

SSD :
$$\frac{1}{(2N+1)^2}\sum_{i=-N}^{N}\sum_{j=-N}^{N}(I_1(x_1+i,y_1+j)-I_2(x_2+i,y_2+j))^2$$

Invariance to photometric transformations?

Intensity changes ($I \rightarrow I + b$)

=> Normalizing with the mean of each patch

$$\frac{1}{(2N+1)^2}\sum_{i=-N}^{N}\sum_{j=-N}^{N}((I_1(x_1+i,y_1+j)-m_1)-(I_2(x_2+i,y_2+j)-m_2))^2$$

Intensity changes ($I \rightarrow aI + b$)

=> Normalizing with the mean and standard deviation of each patch

$$\frac{1}{(2N+1)^2}\sum_{i=-N}^{N}\sum_{j=-N}^{N}\left(\frac{I_1(x_1+i,y_1+j)-m_1}{\sigma_1}-\frac{I_2(x_2+i,y_2+j)-m_2}{\sigma_2}\right)^2$$

Cross-correlation ZNCC

zero normalized SSD

$$\frac{1}{(2N+1)^2}\sum_{i=-N}^{N}\sum_{j=-N}^{N}\left(\frac{I_1(x_1+i,y_1+j)-m_1}{\sigma_1}-\frac{I_2(x_2+i,y_2+j)-m_2}{\sigma_2}\right)^2$$

⬇

ZNCC: zero normalized cross correlation

$$\frac{1}{(2N+1)^2}\sum_{i=-N}^{N}\sum_{j=-N}^{N}\left(\frac{I_1(x_1+i,y_1+j)-m_1}{\sigma_1}\right)\cdot\left(\frac{I_2(x_2+i,y_2+j)-m_2}{\sigma_2}\right)$$

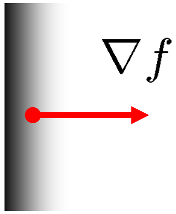
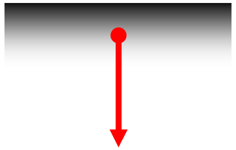
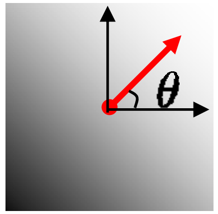
ZNCC values between -1 and 1, 1 when identical patches
in practice threshold around 0.5

Introduction to local descriptors

- Greyvalue derivatives
- Differential invariants [Koenderink'87]
- SIFT descriptor [Lowe'99]

Greyvalue derivatives: Image gradient

- The gradient of an image: $$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

- 
  $\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$
  
  $\nabla f = \left[0, \frac{\partial f}{\partial y}\right]$
  

  $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$

- The gradient points in the direction of most rapid increase in intensity

- The gradient direction is given by $$\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$$
  – how does this relate to the direction of the edge?

- The *edge strength* is given by the gradient magnitude

$$||\nabla f|| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

Differentiation and convolution

- Recall, for 2D function, f(x,y): $$\frac{\partial f}{\partial x} = \lim_{\varepsilon \to 0}\left(\frac{f(x+\varepsilon, y)}{\varepsilon} - \frac{f(x,y)}{\varepsilon}\right)$$

- We could approximate this as $$\frac{\partial f}{\partial x} \approx \frac{f(x_{n+1}, y) - f(x_n, y)}{\Delta x}$$

- Convolution with the filter

-1	**1**

Finite difference filters

- Other approximations of derivative filters exist:

Prewitt: $M_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$; $M_y = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$

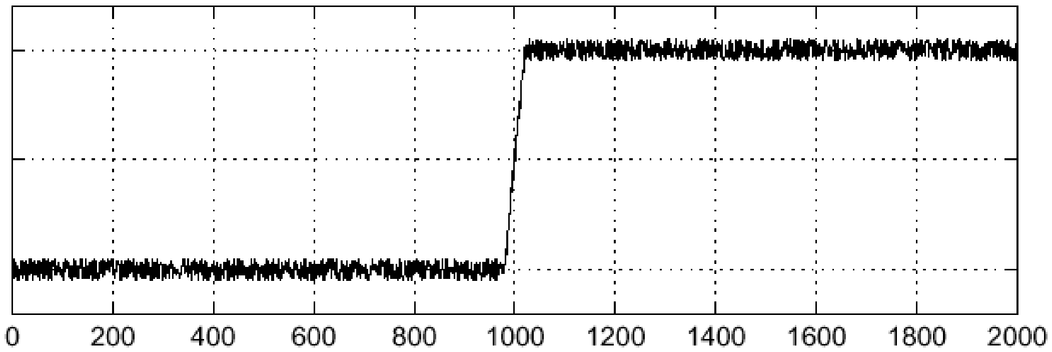
Sobel: $M_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$; $M_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$

Roberts: $M_x = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$; $M_y = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$

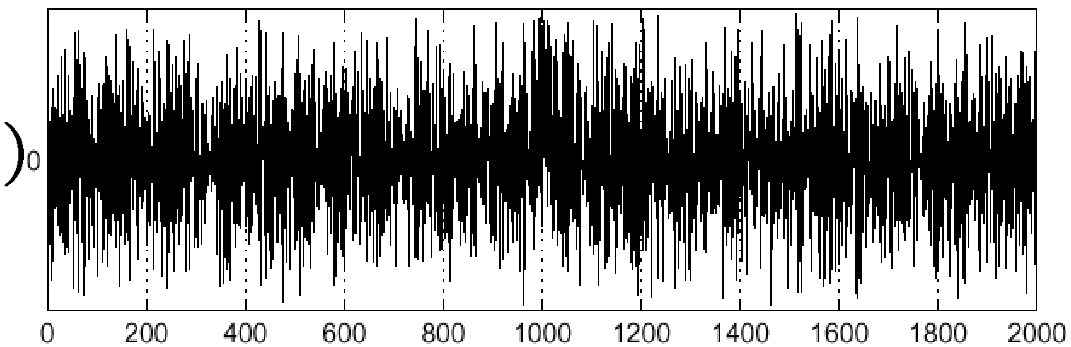
Effects of noise

- Consider a single row or column of the image
  - Plotting intensity as a function of position gives a signal

$f(x)$

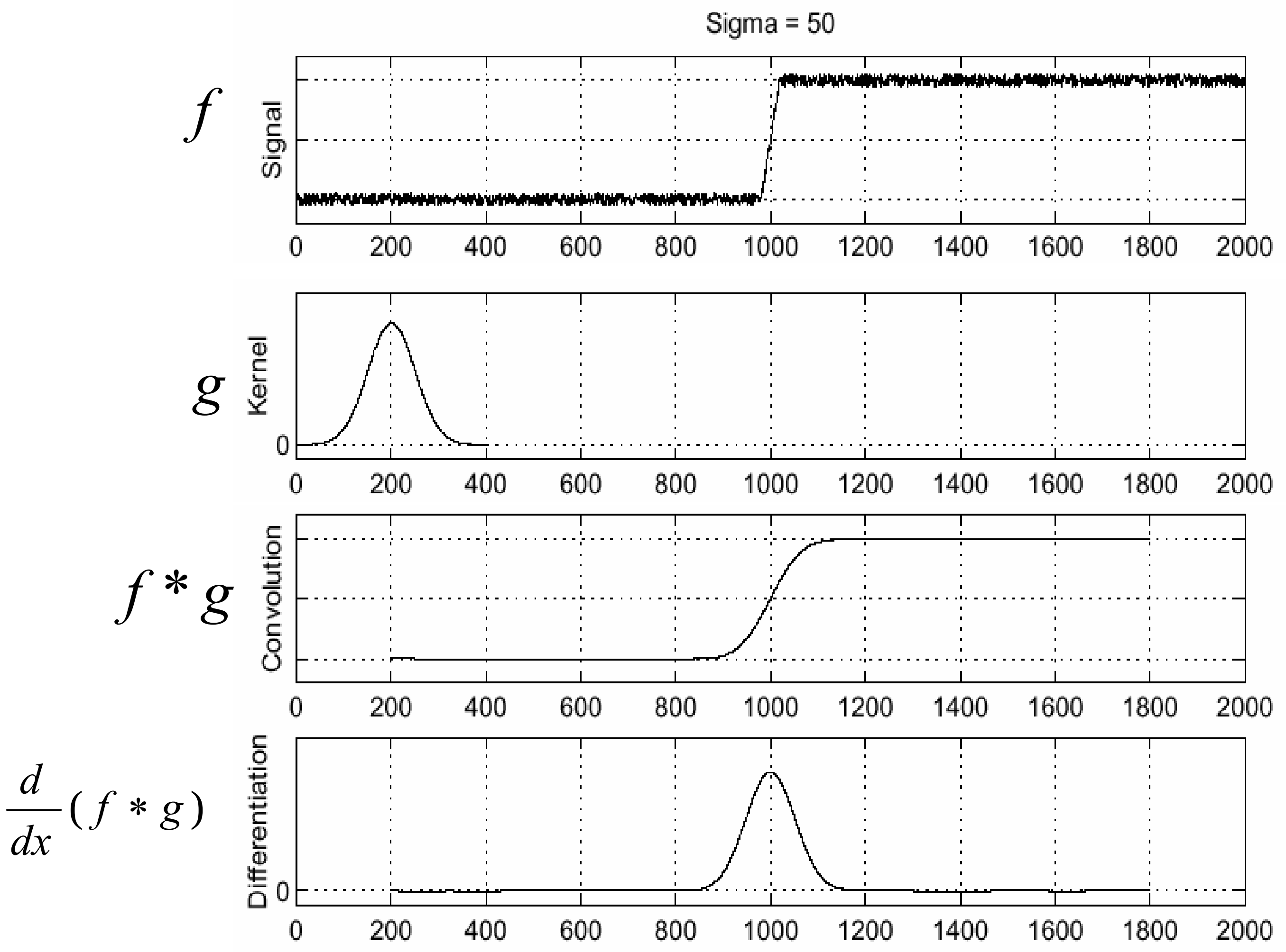


$\frac{d}{dx}f(x)$



- Where is the edge?

Solution: smooth first



- To find edges, look for peaks in $\frac{d}{dx}(f * g)$

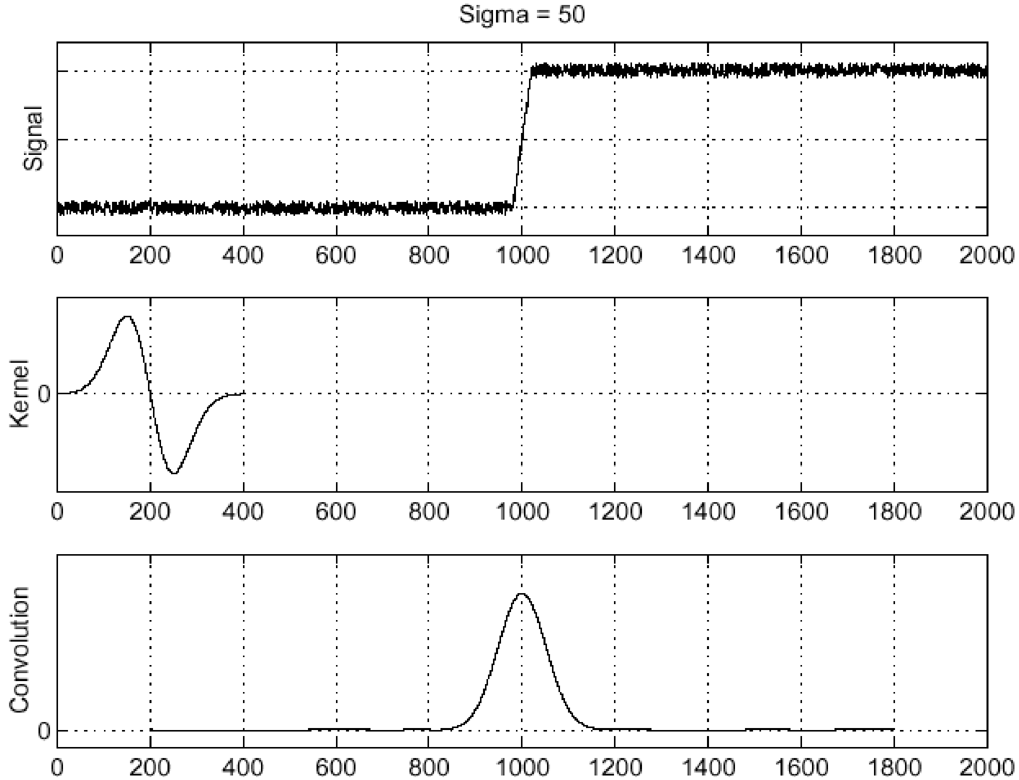
Derivative theorem of convolution

- Differentiation is convolution, and convolution is associative: $\frac{d}{dx}(f * g) = f * \frac{d}{dx} g$
- This saves us one operation:

f

$\frac{d}{dx} g$

$f * \frac{d}{dx} g$



Local descriptors

- Greyvalue derivatives
  - Convolution with Gaussian derivatives

$$\mathbf{v}(x,y) = \begin{pmatrix} I(x,y) * G(\sigma) \\ I(x,y) * G_x(\sigma) \\ I(x,y) * G_y(\sigma) \\ I(x,y) * G_{xx}(\sigma) \\ I(x,y) * G_{xy}(\sigma) \\ I(x,y) * G_{yy}(\sigma) \\ \vdots \end{pmatrix}$$

$$I(x,y) * G(\sigma) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} G(x',y',\sigma) I(x-x',y-y') dx'dy'$$

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

Local descriptors

Notation for greyvalue derivatives [Koenderink'87]

$$\mathbf{v}(x,y)=\begin{pmatrix} I(x,y)*G(\sigma) \\ I(x,y)*G_x(\sigma) \\ I(x,y)*G_y(\sigma) \\ I(x,y)*G_{xx}(\sigma) \\ I(x,y)*G_{xy}(\sigma) \\ I(x,y)*G_{yy}(\sigma) \\ \vdots \end{pmatrix}=\begin{pmatrix} L(x,y) \\ L_x(x,y) \\ L_y(x,y) \\ L_{xx}(x,y) \\ L_{xy}(x,y) \\ L_{yy}(x,y) \\ \vdots \end{pmatrix}$$

Invariance?

Local descriptors – rotation invariance

Invariance to image rotation : differential invariants [Koen87]

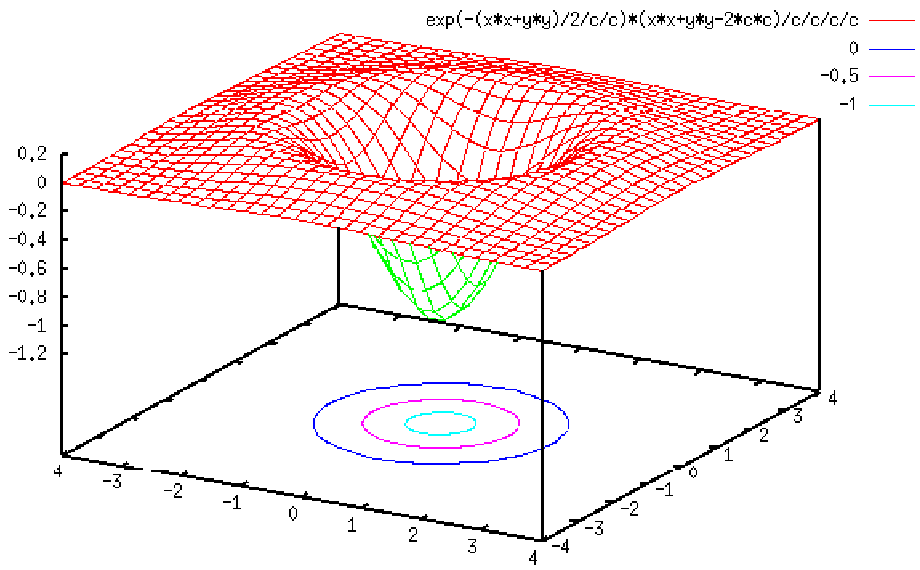
gradient magnitude → $L_x L_x + L_y L_y$

Laplacian → $L_{xx} + L_{yy}$

$$\begin{bmatrix} L \\ L_x L_x + L_y L_y \\ L_{xx} L_x L_x + 2L_{xy} L_x L_y + L_{yy} L_{yy} \\ L_{xx} + L_{yy} \\ L_{xx} L_{xx} + 2L_{xy} L_{xy} + L_{yy} L_{yy} \\ \cdots \\ \cdots \\ \cdots \\ \cdots \end{bmatrix}$$

Laplacian of Gaussian (LOG)

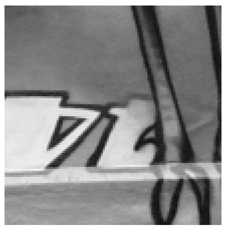
$$LOG = G_{xx}(\sigma) + G_{yy}(\sigma)$$



SIFT descriptor [Lowe'99]

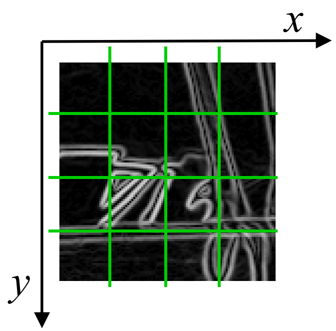
- Approach
  - 8 orientations of the gradient
  - 4x4 spatial grid
  - Dimension 128
  - soft-assignment to spatial bins
  - normalization of the descriptor to norm one
  - comparison with Euclidean distance

image patch



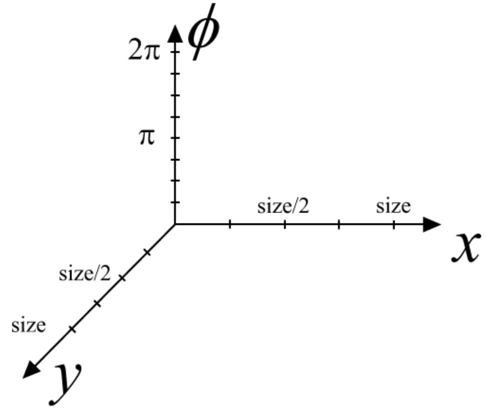
→

gradient



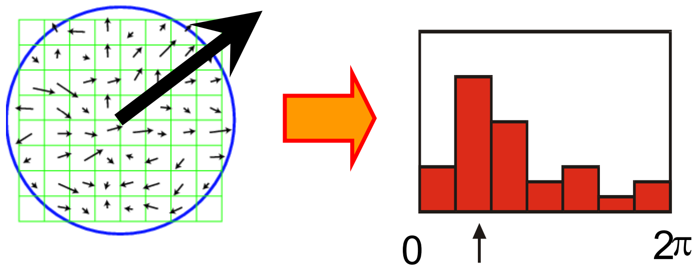
→

3D histogram

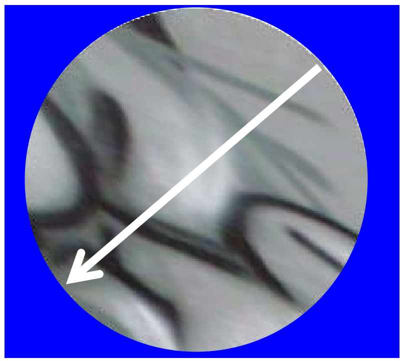


Local descriptors - rotation invariance

- Estimation of the dominant orientation
  - extract gradient orientation
  - histogram over gradient orientation
  - peak in this histogram



- Rotate patch in dominant direction



Local descriptors – illumination change

- Robustness to illumination changes

  in case of an affine transformation $I_1(\mathbf{x}) = aI_2(\mathbf{x}) + b$

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- Normalization of the image patch with mean and variance

Invariance to scale changes

- Scale change between two images
- Scale factor s can be eliminated
- Support region for calculation!!
  - In case of a convolution with Gaussian derivatives defined by σ

$$I(x,y) * G(\sigma) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} G(x',y',\sigma) I(x-x',y-y') dx' dy'$$

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