COMPUTER VISION
Features

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Why do we need invariant features in CV ?

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The foundations of Computer Vision are based on these tasks, and features play thus a significant role in this field.

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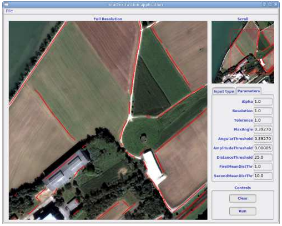
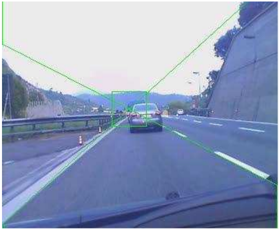
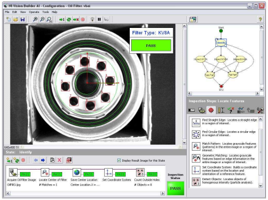
- various applications for specific environments :
  - road / panel / text detection
  - medical and satellite imagery
  - inspection for industrial vision



Aerial imagery



Lane detection



Industrial vision

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  - road / panel / text detection
  - medical and satellite imagery
  - inspection for industrial vision

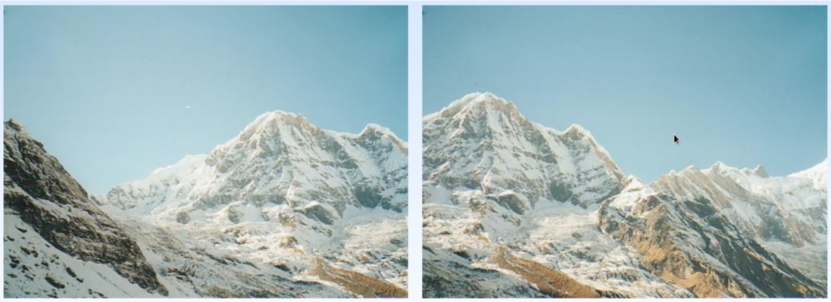
✓ Fast, specialized tasks

✓ Intensity variation invariant

✗ Sensitive to other geometric transforms

✗ Problem for pattern recognition

Simple motivator - panoramic images



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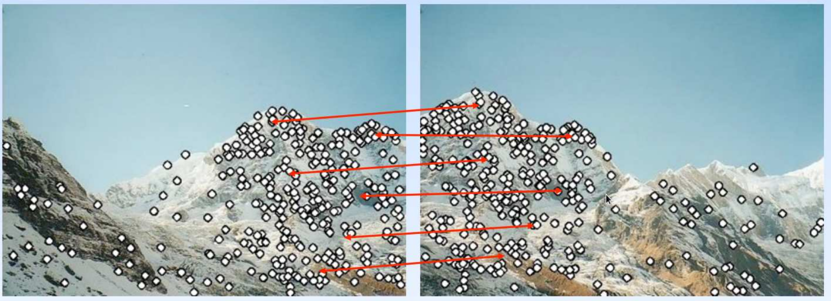
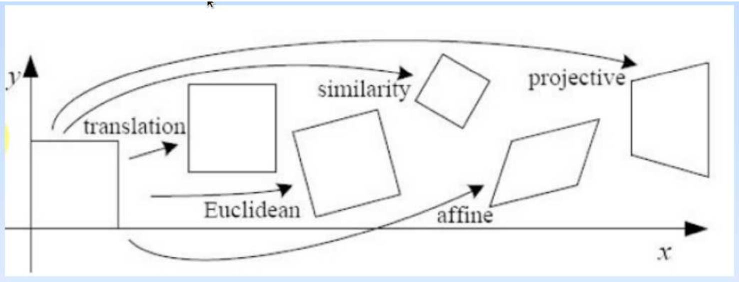


Simple motivator - panoramic images

The core of the problem



- translation
- Euclidean (translation + rotation)
- similarity transform (tr. + rot. + scale)
- affine (rot. + scale + shear + translation)
- projective

Why we need invariance in CV

Objective

- identify structures which are invariant with respect to rotation, rescaling, etc.
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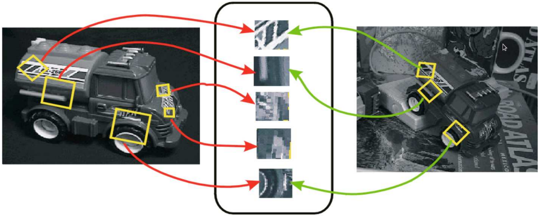

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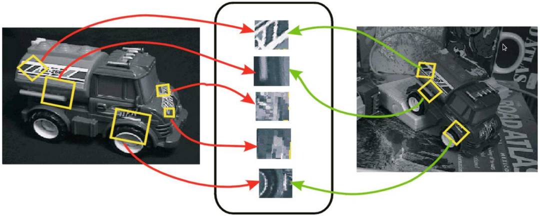


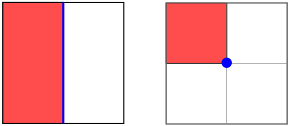
How to :

- identify them in a non supervised manner ?
- associate them robustly ?

Corner detectors : the basics

Definition

Corner : a location in the image which is characterized by strong intensity variation along two different directions.



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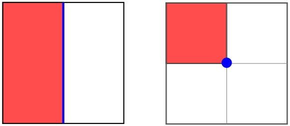

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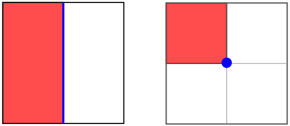

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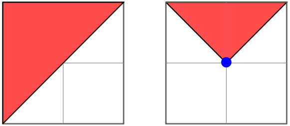
- but it is not enough (to do it only in the image reference system) !



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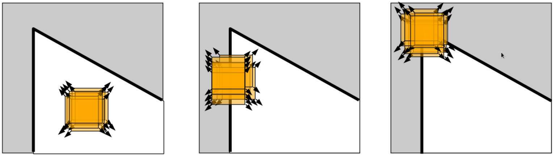

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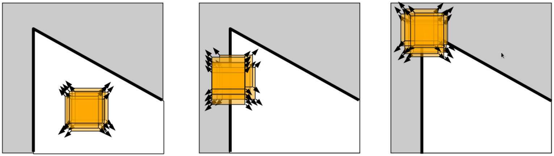

Typical behavior :

- homogeneous regions : no change in patch content
- contours : no change along the contour
- corners : important change across all directions
- corner quality : defined by the smallest possible change
- proposed by Moravec in 1980

Corner detectors : the basics

Intensity change by shift of $(\Delta x, \Delta y)$

$$E(x, y, \Delta x, \Delta y) = \sum_x \sum_y w(x, y) \big[I(x, y) - I(x + \Delta x, y + \Delta y) \big]^2$$

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Corner detectors : the basics

Intensity change by shift of $(\Delta x, \Delta y)$

$$E(x, y, \Delta x, \Delta y) = \sum_x \sum_y \underbrace{w(x, y)}_{\text{support}} \big[\underbrace{I(x, y)}_{\text{intensity}} - \underbrace{I(x + \Delta x, y + \Delta y)}_{\text{shifted intensity}} \big]^2$$

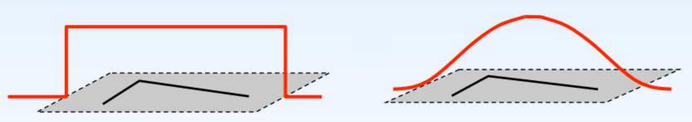

FIGURE – Possible choices for the support function $w(x, y)$

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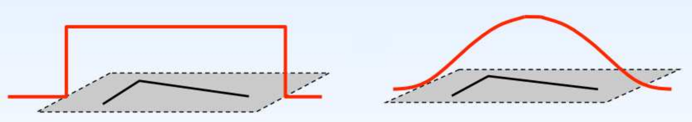

FIGURE – Possible choices for the support function $w(x,y)$

$E(x,y)$ large highlights a potential corner.

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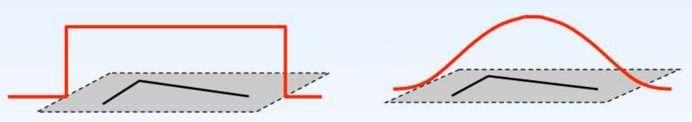

FIGURE – Possible choices for the support function $w(x,y)$

Costly if we do not use any tricks

- what is approximately the computational cost for an image of side N if we implement this method naively using a patch of side K ?

Corner detectors : the basics

First order approximation by Taylor series development

$$f(x+\Delta x, y+\Delta y) = f(x,y) + f_x(x,y)\Delta x + f_y(x,y)\Delta y$$

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We use this approximation to rewrite the intensity variation due to shift :

$$\begin{aligned}
\sum \left[I(x+\Delta x, y+\Delta y) - I(x,y)\right]^2 &\approx \sum \left[I(x,y) + \Delta x I_x(x,y) + \Delta y I_y(x,y) - I(x,y)\right]^2 \\
&\approx \sum \Delta x^2 I_x^2 + 2\Delta x \Delta y I_x I_y + \Delta y^2 I_y^2 \\
&\approx \sum [\Delta x \Delta y] \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \\
&\approx [\Delta x \Delta y] \left(\sum \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \right) \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}
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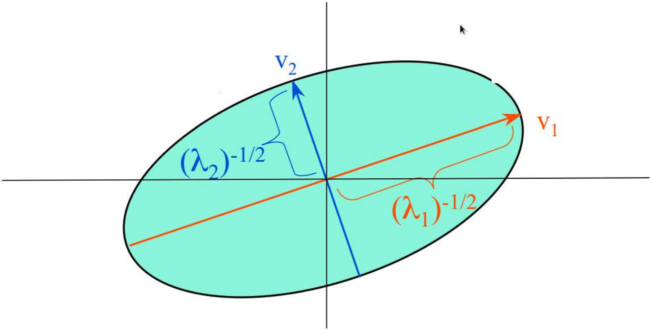
E(x,y,\Delta x,\Delta y) &\approx [\Delta x \Delta y] \left(\sum g(\sigma_I) \star \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \right) \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \\
&\approx [\Delta x \Delta y] \underbrace{\begin{bmatrix} \langle I_x^2 \rangle & \langle I_x I_y \rangle \\ \langle I_x I_y \rangle & \langle I_y^2 \rangle \end{bmatrix}}_{\text{structure tensor}} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}
\end{aligned}$$

Corner detectors : the structure tensor

Properties

- the eigenvectors highlight the main directions of gradient variation around the location we consider (see the ellipse of constant change)
- ex. : if $\lambda_2 > \lambda_1$, strong variation along v_2 and smaller variation in the direction of v_1
- if corner, λ_1, λ_2 are large



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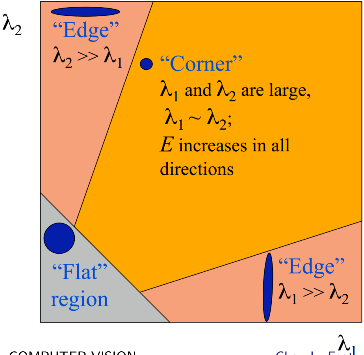

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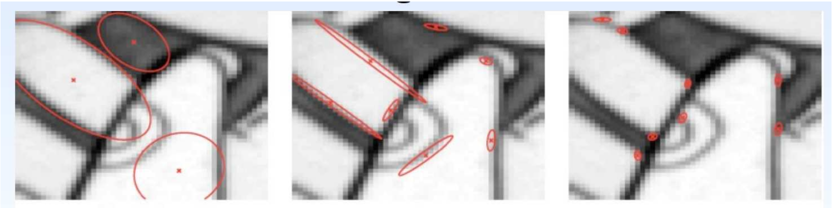


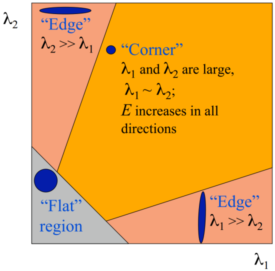
Corner detectors : the structure tensor

Decision based on the tensor eigenvalues

- one may compute λ_1, λ_2 explicitly, but too costly
- prefered method :

$$R = det(M) - \alpha trace^2(M) = \lambda_1 \lambda_2 - \alpha(\lambda_1 + \lambda_2)^2$$

- the value of parameter α is usually 0.04 - 0.06
- interesting eigenvalues = local maxima of R



Corner detectors : Harris detector

Main algorithm steps

1. compute gradients $I_x = \frac{\partial}{\partial x} g(\sigma_D) \star I$, $I_y = \frac{\partial}{\partial y} g(\sigma_D) \star I$
2. compute the structure tensor :

$$M = g(\sigma_I) \star \left[\begin{array}{cc} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{array} \right]$$

3. compute the response function R :

$$R = det(M) - \alpha trace^2(M)$$

4. apply thresholding to R
5. non maximal suppression on the values of R

Corner detectors : example

FIGURE – Initial pair

Corner detectors : example

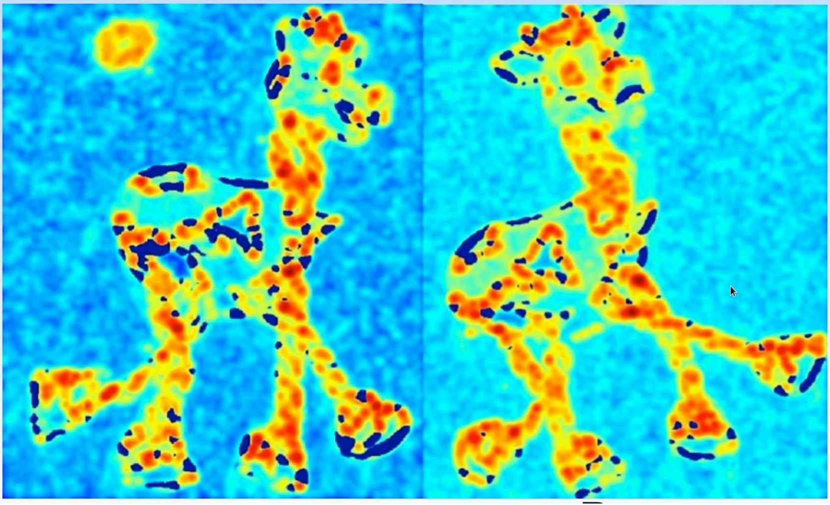


FIGURE – response function R

Corner detectors : example

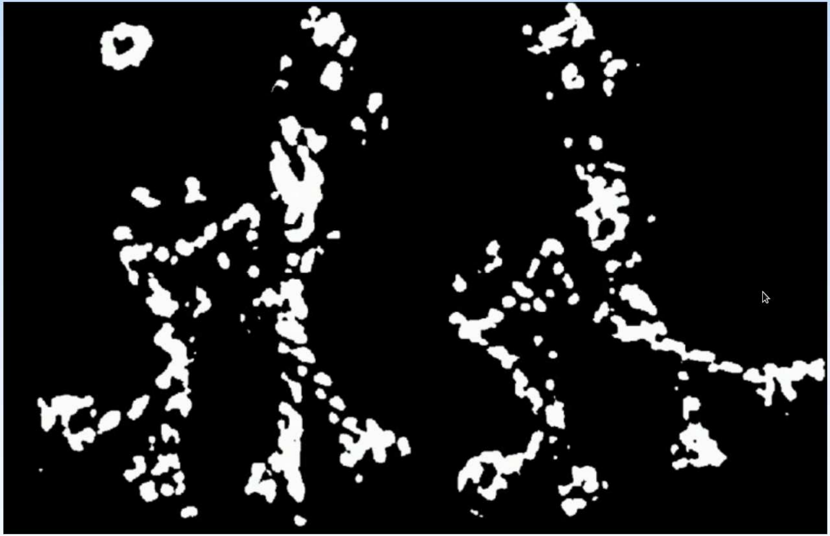


FIGURE – Thresholding R

Corner detectors : example

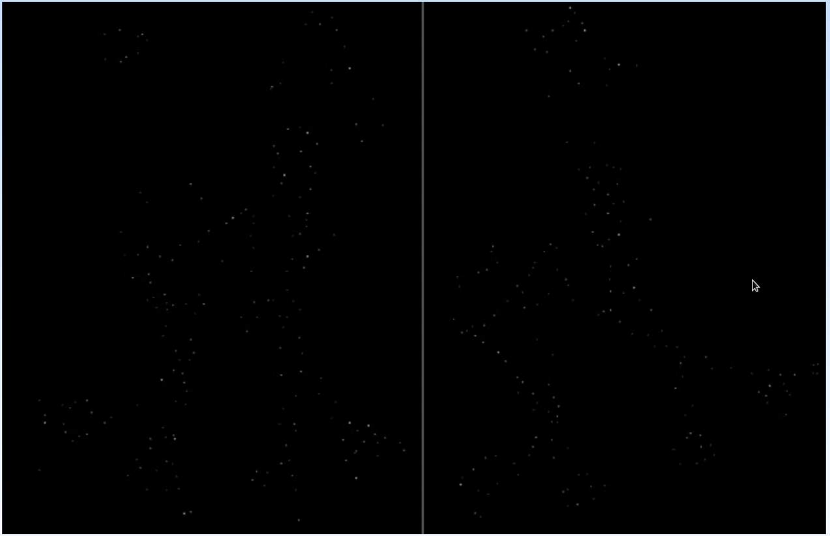


FIGURE – Non maximal suppression on R

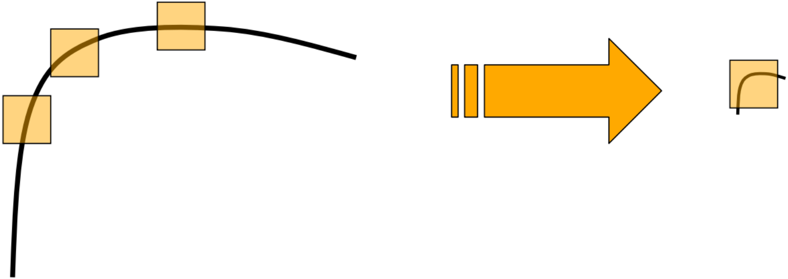
Corner detectors : example

FIGURE – Detector results

Conclusion : Harris detector

Conclusions

- ✓ rotation invariant detector
- ✓ intensity change invariant
- ✗ not robust to scale change
- ✗ no descriptor provided for matching



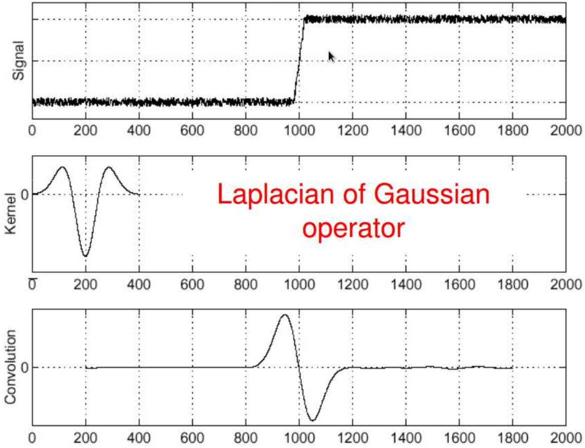
The characteristic scale

Short intro to Laplacian filtering :

$$f$$

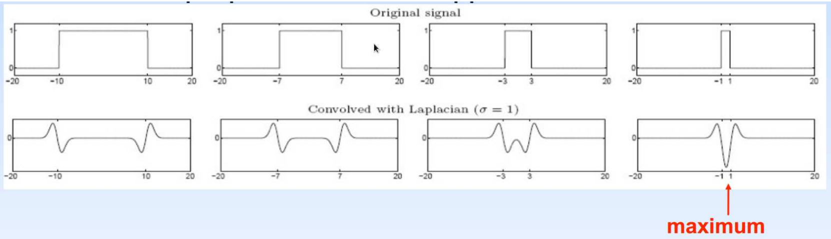
$$\frac{\partial^2}{\partial x^2}h$$

$$\left(\frac{\partial^2}{\partial x^2}h\right) \star f$$



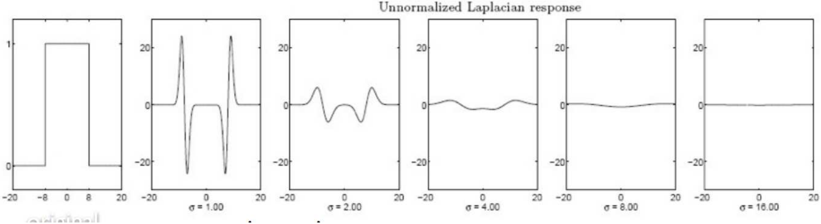
Gaussian filter + Laplace (LoG) - zero crossing

The characteristic scale



The Laplacian response - maximal if the Laplacian scale corresponds to the scale of the variation in the image space

The characteristic scale



If one varies σ, the Laplacien response varies as well ; the operation has to be normalized by a multiplication by σ^2

The characteristic scale

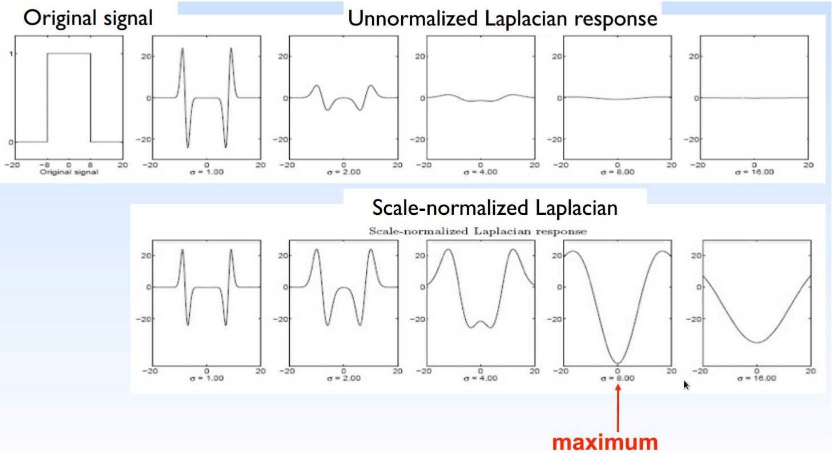
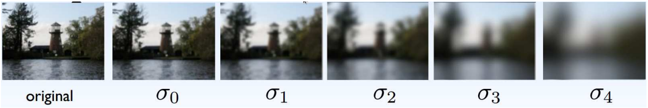
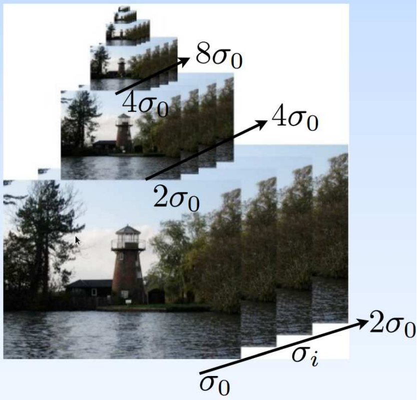


FIGURE – Multi scale normalized Laplacian response

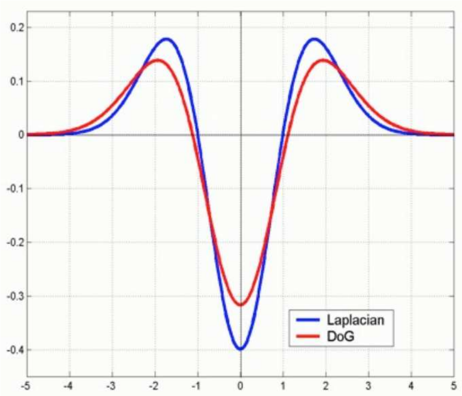
The pyramid representation





$$\sigma_i = 2^{\frac{i}{s-1}} \sigma_0$$

Approximating the Laplacian



Laplacian :

$$L = \sigma^2 (G_{xx}(x, y, \sigma) + G_{yy}(x, y, \sigma))$$

Difference of Gaussians :

$$DoG = G(x, y, k\sigma) - G(x, y, \sigma)$$

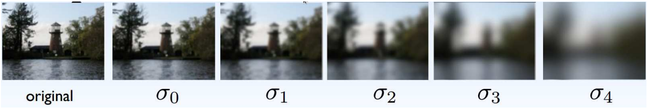
The SIFT detector

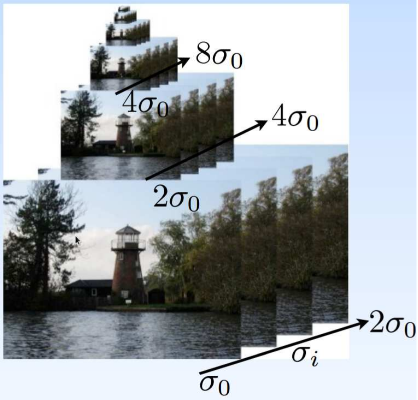
Scale Invariant Feature Transform

- high performance
- very costly
- the descriptor is integrated (it is also provided by the algorithm)

1. Construction of the scale space
2. Computing the DoGs
3. Computing the characteristic scale
4. Sub-pixel localization
5. Eliminating contour responses
6. Computing the orientation
7. Computing the descriptor

The pyramid representation





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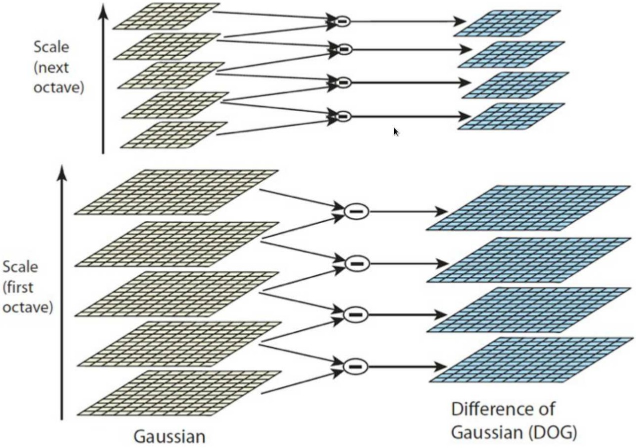
Computing the DoGs



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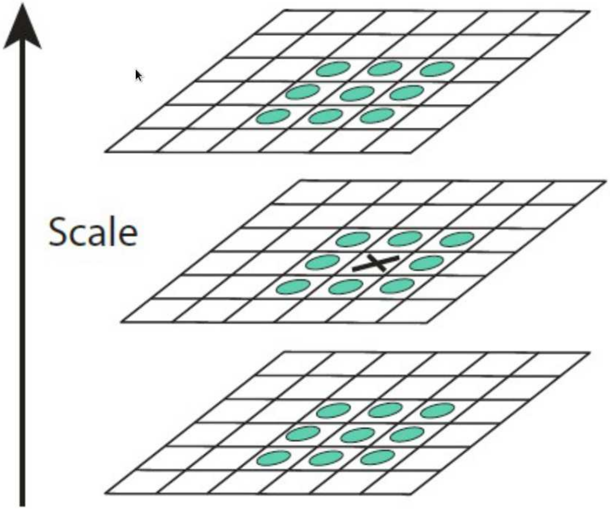
Identifying the extrema



The SIFT detector

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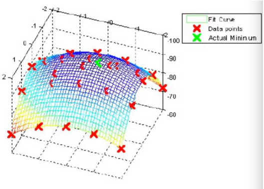
Sub-pixel localization



Interpolation of discrete values of $D(x, y, \sigma)$. Use of the Taylor series second order development :

$$D(\mathbf{x}) = D + \frac{\partial D}{\partial \mathbf{x}}^T \mathbf{x} + \frac{1}{2}\mathbf{x}^T \frac{\partial^2 D}{\partial \mathbf{x}^2}\mathbf{x}$$

Solution :

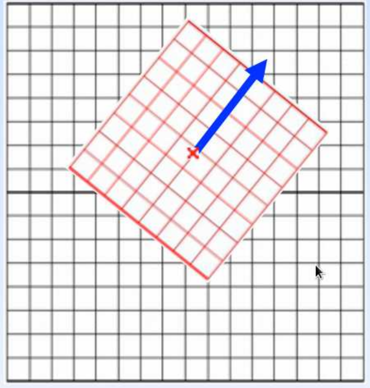
$$\hat{\mathbf{x}} = -\frac{\partial^2 D}{\partial \mathbf{x}^2}^{-1} \frac{\partial D}{\partial \mathbf{x}}$$

The SIFT detector

1. Construction of the scale space
2. Computing the DoGs
3. Computing the characteristic scale
4. Sub-pixel localization
5. Eliminating contour responses
6. Computing the orientation
7. Computing the descriptor

Computing the orientation

1. Compute local gradients at the characteristic scale
2. Compute local gradient histogram
3. The canonic orientation is the maximal direction
4. Each corner is characterized by : location, scale, orientation
5. Local coordinate system for building up the descriptor



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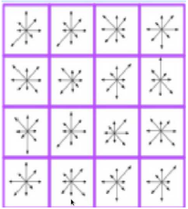
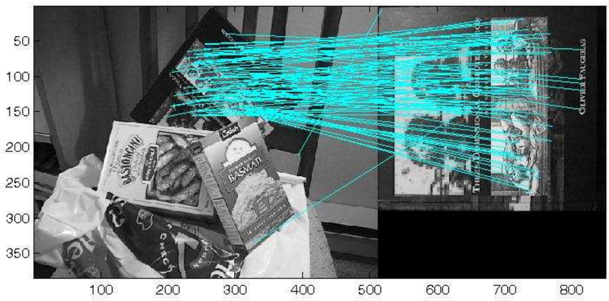
Computing the descriptor

1. Local gradient orientations in 16 neghboring regions
2. Coordinate system defined by the corner
3. 4*4*8 orientations = 128 (descriptor dimension)



Conclusions about SIFT

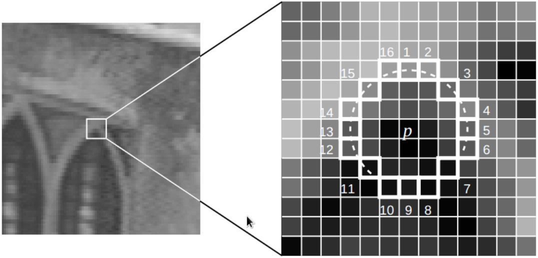
- Scale invariant
- Rotation invariant
- Illumination invariant
- Perspective invariant
- Costly



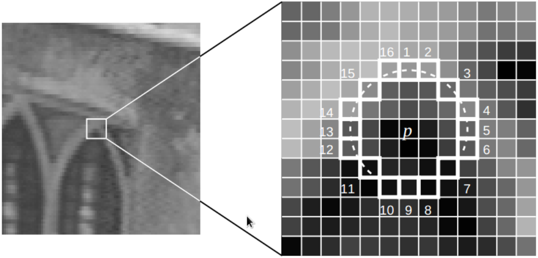
The FAST detector

Features from Accelerated Segment Test

- extremely fast
- no complex operations (convolution, gradient computation etc.)
- not too robust
- no descriptor



The FAST detector - strategy



$$S_{p\to x} = \begin{cases} d, & I_{p\to x} \leq I_p - t \\ s, & I_p - t < I_{p\to x} < I_p + t \\ b, & I_p + t \leq I_{p\to x} \end{cases}$$

The FAST detector

Question 1

Sketch a naive implementation in order to test whether a pixel is a FAST corner or not.

The FAST detector

Question 2

How many possible configurations are in total ?
How many coin configurations $c \in Q$ are there ?
What does the following function :

$$H(Q) = (c + \bar{c}) \log(c + \bar{c}) - c \log c - \bar{c} \log \bar{c}$$

represent ?

The FAST detector

Question 3

Given that the entropy gain is :

$$H_g = H(Q) - H(A) - H(B)$$

where $Q = A \cup B$, think of a trick in order to improve the test that you proposed for Question 1.

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- ranking : the second match must have a significantly larger distance/lower similarity than the best match, in order to avoid confusion between similarly looking corner

Detectors - conclusion

Overview

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Which detector to choose ?

- the choice is application dependent
- FAST : great for real time robotic navigation
- SIFT : useful when quality is important
- most other descriptors provide a compromise between robustness and cost