COMPUTER VISION
Features

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Why do we need invariant features in CV ?

Multiple views require reliable correspondences

- how do we *usually* get multiple views ?
  - we use multiple cameras simultaneously
  - one camera is moving while acquiring data - and the scene is static

A fundamental step for :

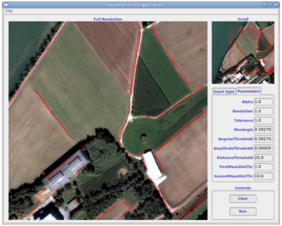
- estimating how cameras are located relatively to each other
- recovering scene depth
- estimating ego-movement (visual odometry)
- matching image content in general

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

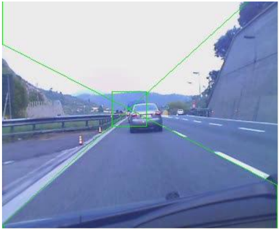
Why do we need invariant features in CV ?

Why not use contours ?

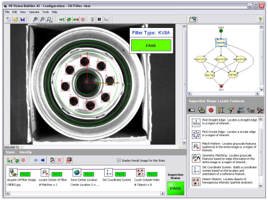
- the processing effort is relatively low
- parametric curves may be extracted relatively easy as well (Hough)
- various applications for specific environments :
  - road / panel / text detection
  - medical and satellite imagery
  - inspection for industrial vision



Aerial imagery



Lane detection

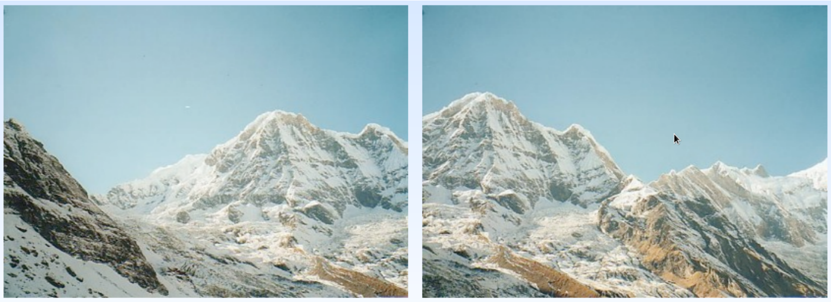


Industrial vision

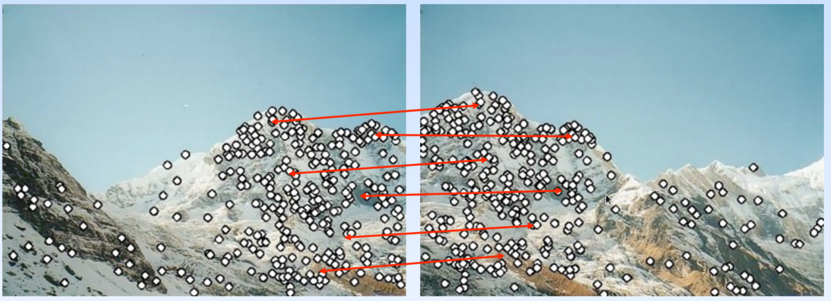
✓ Fast, specialized tasks

✓ Intensity variation invariant

Simple motivator - panoramic images

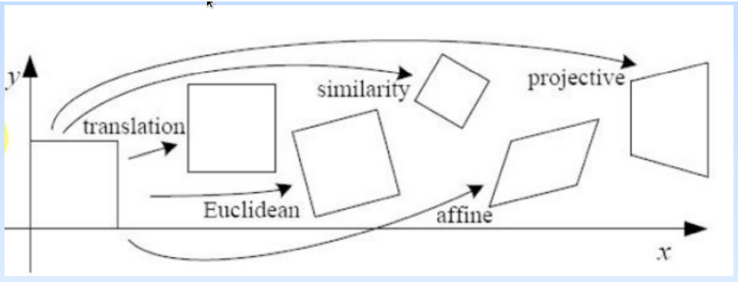


Simple motivator - panoramic images



Simple motivator - panoramic images

The core of the problem

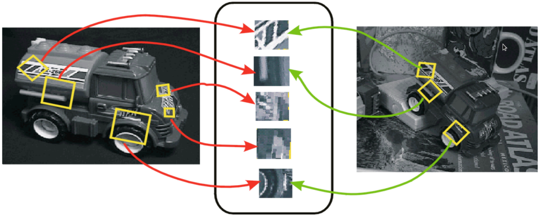


- translation
- Euclidean (translation + rotation)
- similarity transform (tr. + rot. + scale)
- affine (rot. + scale + shear + translation)
- projective

Why we need invariance in CV

Objective

- identify structures which are invariant with respect to rotation, rescaling, etc.
- these structures are commonly called interest points or corners



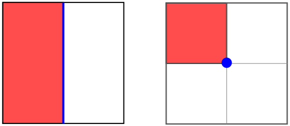
How to :

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

Corner detectors : the basics

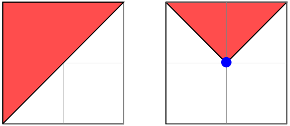
Definition

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



We will still need to compute the local image gradients

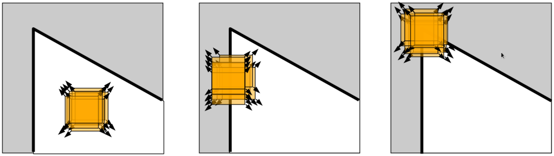
- but it is not enough (to do it only in the image reference system) !



Corner detectors : the basics

Definition

Strategy : the content of a patch centered in the corner should vary across all possible directions



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 $(\Delta x, \Delta y)$

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

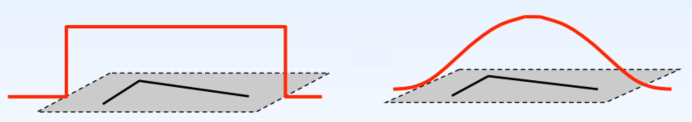


FIGURE – Possible choices for the support function $w(x, y)$

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

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

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

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

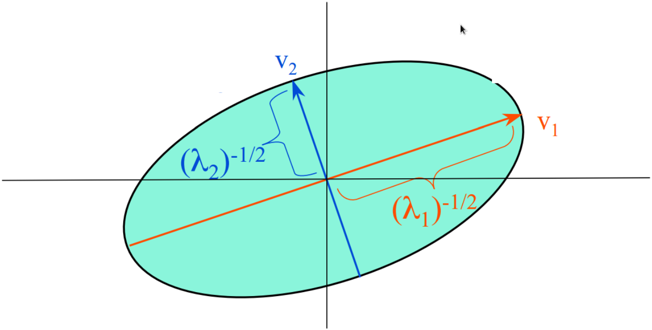
$$\begin{aligned}
\sum \left[I(x+\Delta x, y+\Delta y) - I(x,y)\right]^2 &\approx \sum \left[I(x,y) + \Delta x I_x(x,y) + \Delta y I_y(x,y) - I(x,y)\right]^2 \\
&\approx \sum \Delta x^2 I_x^2 + 2\Delta x \Delta y I_x I_y + \Delta y^2 I_y^2 \\
&\approx \sum [\Delta x \Delta y] \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \\
&\approx [\Delta x \Delta y] \left(\sum \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \right) \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}
\end{aligned}$$

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

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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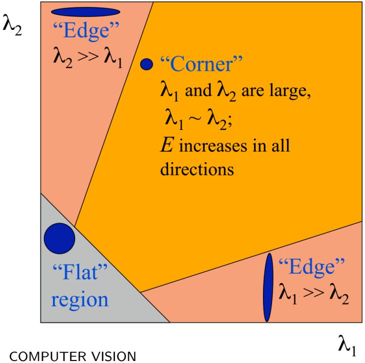

Corner detectors : the structure tensor

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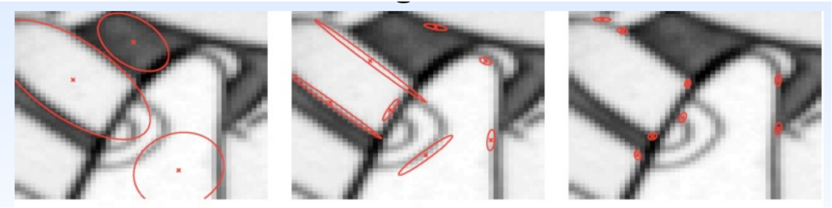


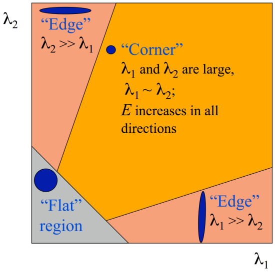
Corner detectors : the structure tensor

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 :

$$M = g(\sigma_I) \star \begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix}$$

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

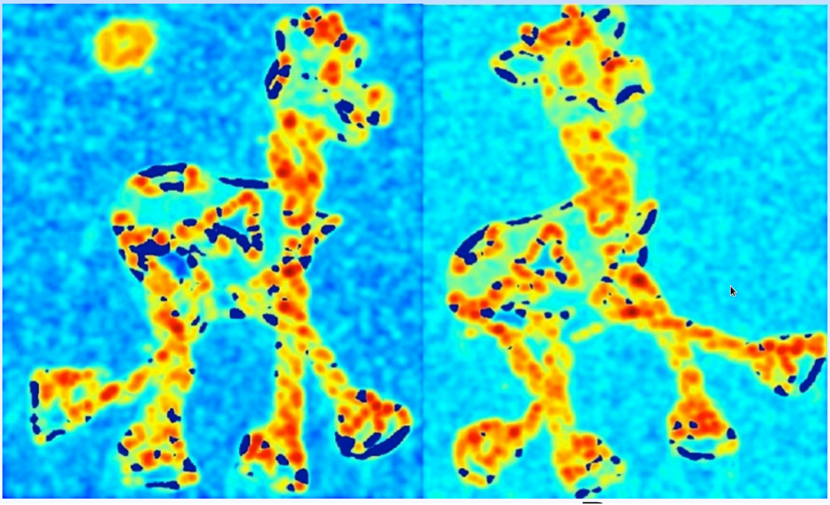


FIGURE – response function R

Corner detectors : example

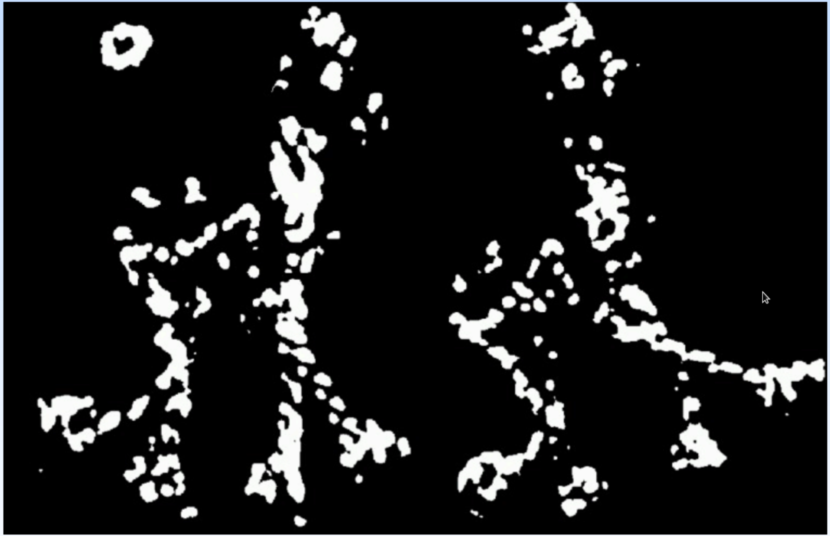


FIGURE – Thresholding R

Corner detectors : example

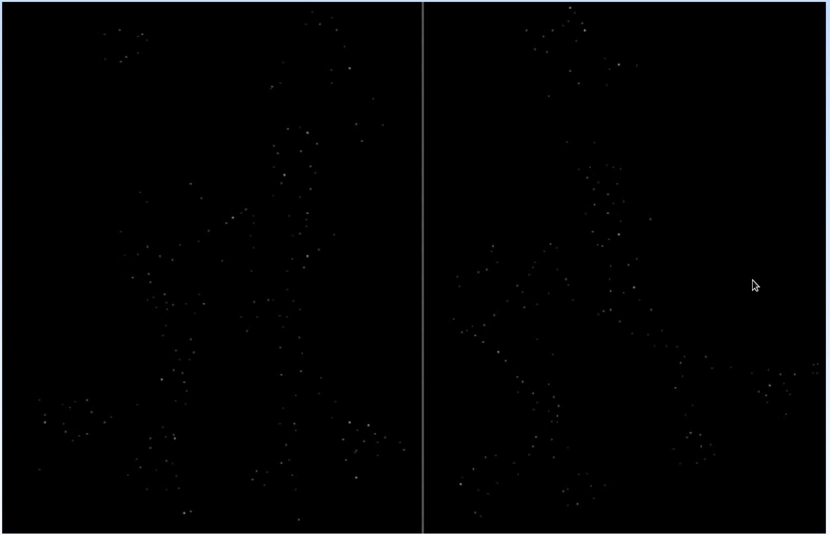


FIGURE – Non maximal suppression on R

Corner detectors : example

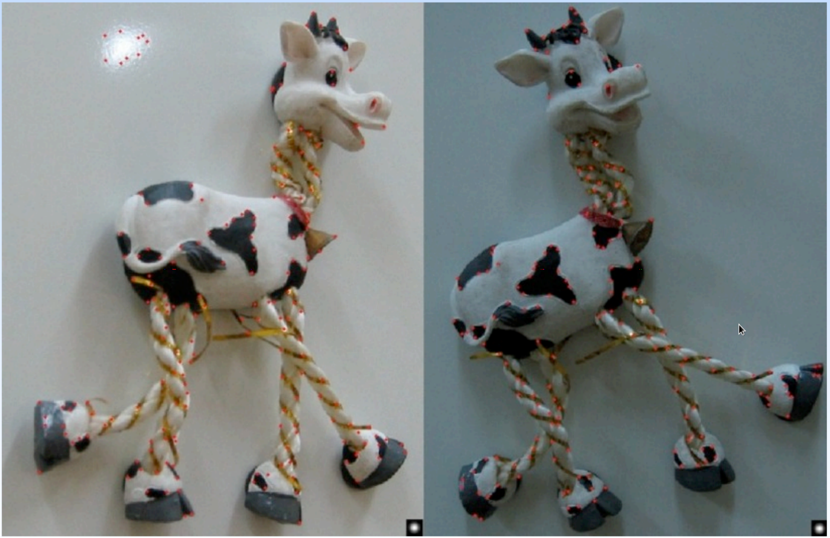
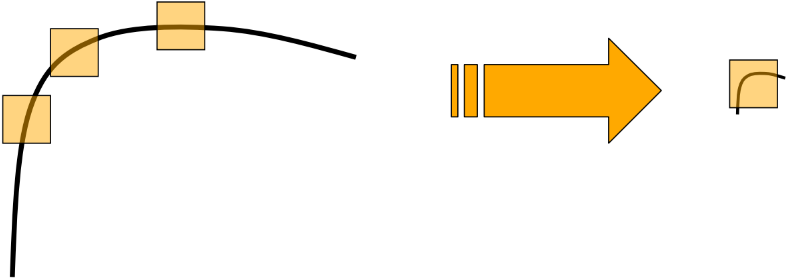


FIGURE – Detector results

Conclusion : Harris detector

Conclusions

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



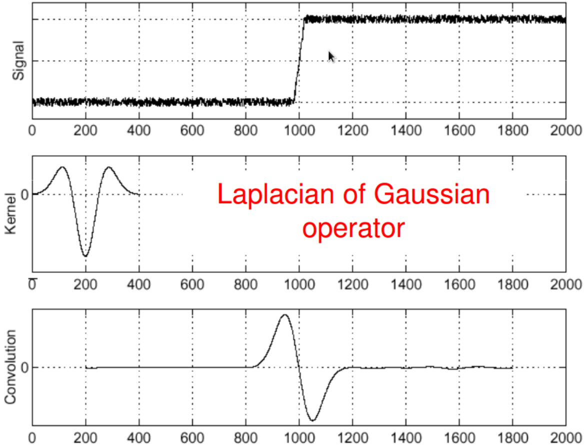
The characteristic scale

Short intro to Laplacian filtering :

$$f$$

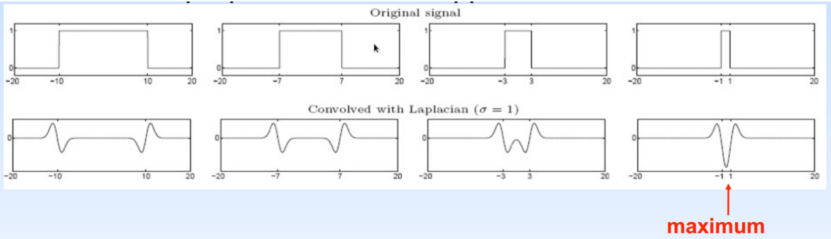
$$\frac{\partial^2}{\partial x^2}h$$

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



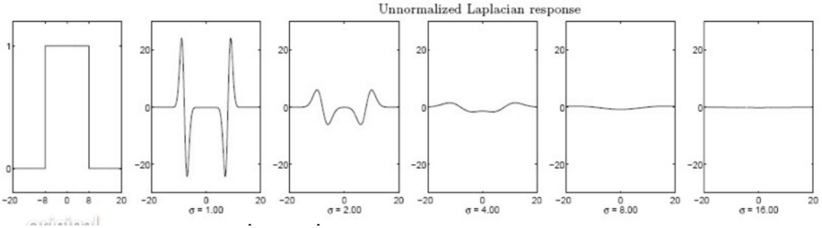
Gaussian filter + Laplace (LoG) - zero crossing

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

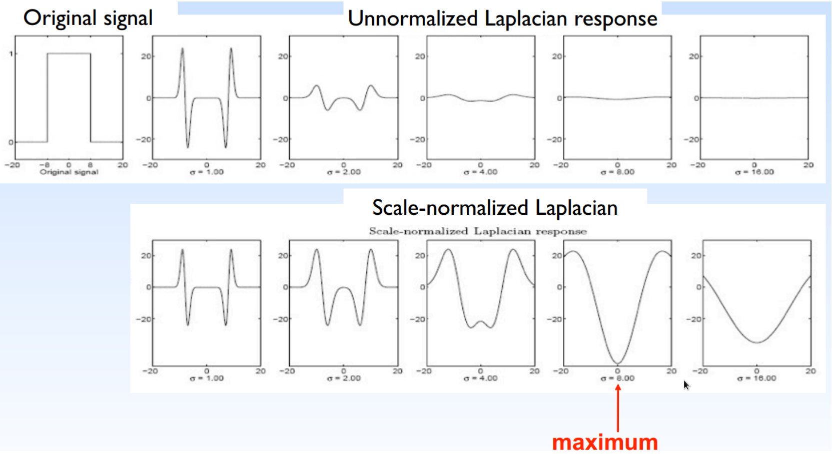
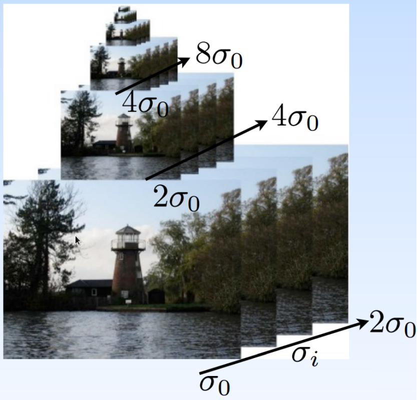


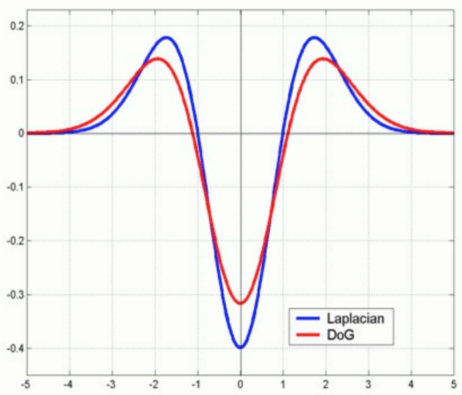
FIGURE – Multi scale normalized Laplacian response

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 SIFT detector

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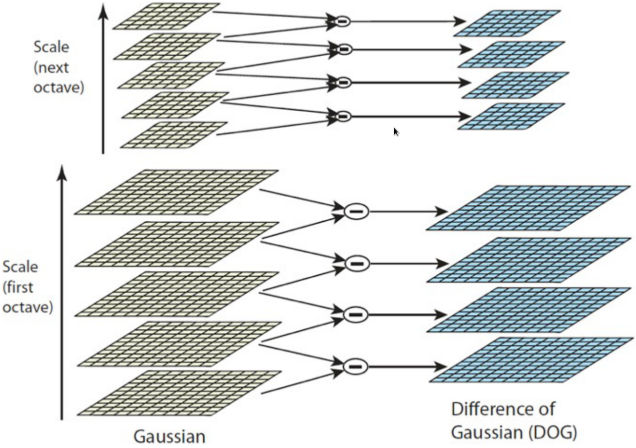
Computing the DoGs



The SIFT detector

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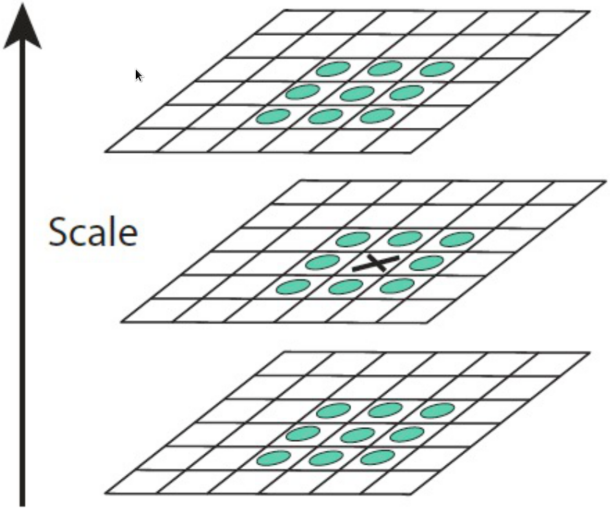
Identifying the extrema



The SIFT detector

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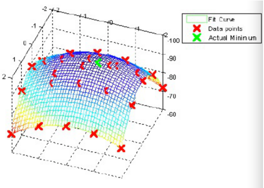
Sub-pixel localization



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

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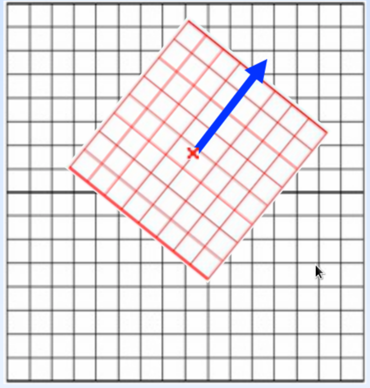
Computing the orientation

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



The SIFT detector

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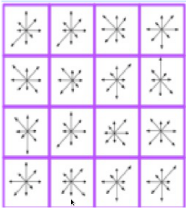
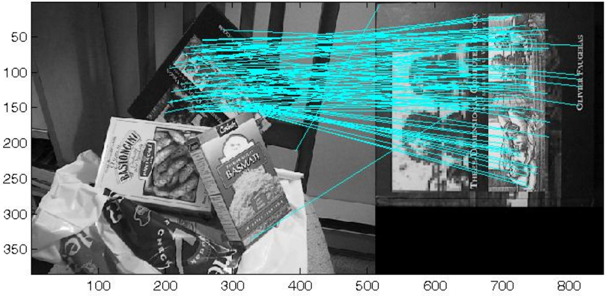
Computing the descriptor

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

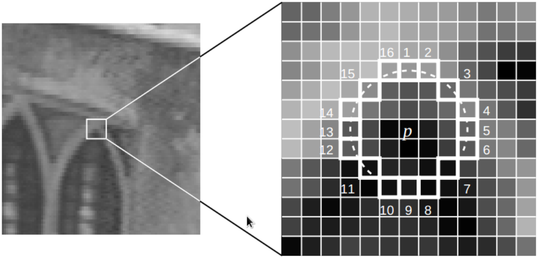
- Scale invariant
- Rotation invariant
- Illumination invariant
- Perspective invariant
- Costly



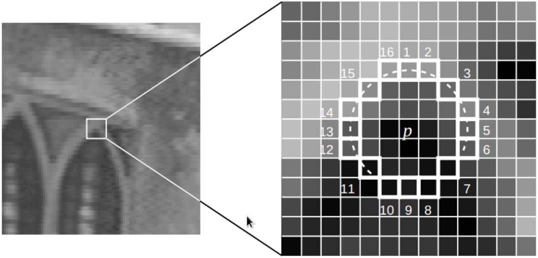
The FAST detector

Features from Accelerated Segment Test

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



The FAST detector - strategy



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

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.

Corner association (matching)

How to do it ?

- matching needs to be fast and reliable
- if the detector provides a descriptor (i.e. SIFT), use it for matching
- otherwise, a simple solution is patch matching : a patch is extracted around the corner, and matched against a candidate in the destination image using a correlation, SSD or SAD function
- other solutions exist (BRIEF, FREAK etc.)

Tricks used commonly in order to improve matching quality

- these tricks usually increase the computation time but remove false matches (and also some good matches sometimes)
- married matching : the best candidate has to pick up the initial corner as best candidate as well
- ranking : the second match must have a significantly larger distance/lower similarity than the best match, in order to avoid confusion between similarly looking corners

Detectors - conclusion

Overview

- FAST : not so robust, no descriptor provided - but runs in 1ms on a regular image ;
- Harris : slightly more robust, no descriptor provided - runs in 25-40ms on a regular image
- SIFT : very robust, descriptor provided - runs in 2-5 seconds on a regular image
- plenty other detectors which provide some advantage in terms of either computational time or some invariance : SURF, AGAST, ORB, HOOFR etc.

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