Student presentation: Scale & Affine Invariant Interest Point Detectors

Boris Dalstein Philippe Weinzaepfel

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Outline

1. Introduction
   - Local features
   - Harris detector
   - Multi-scale Harris detector
   - Laplacian of Gaussian
2. Scale invariant detector
3. Affine invariant detector
4. Conclusion

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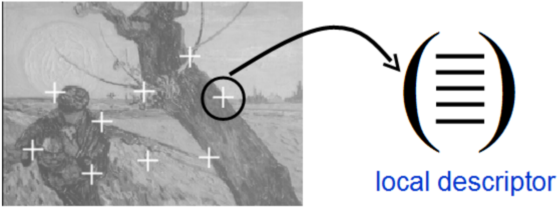
Local features

Why using local features

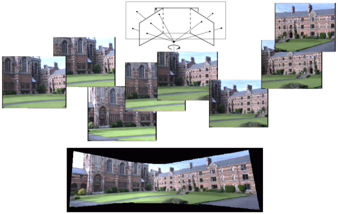
- Robust to occlusion
- Robust to background clutter
- Avoid having to segment the image



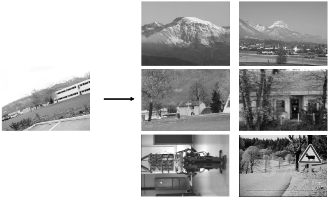
Local features: Applications

- Matching

- Panorama



- Recognition



Local features

Challenge: design a detector invariant to viewing condition

- Illumination changes
- Translation
- Rotation
- Scale change
- Affine transformation

Local features: state-of-the-art

Harris detector

Excellent performance at a given scale

But

Not invariant to scale and affine transformation

Local features: state-of-the-art

Harris detector

Excellent performance at a given scale

But

Not invariant to scale and affine transformation

Laplacian of Gaussian

Good performance to select the characteristic scale

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Harris detector

- Compute Gaussian derivatives with derivation scale σ_D at each pixel $\mathbf{x}$
- Compute the second moment matrix μ in a Gaussian window with integration scale σ_I around each pixel
- Compute the cornerness
- Threshold it
- Find local maxima of cornerness

Harris detector

- Compute Gaussian derivatives with derivation scale σ_D at each pixel $\mathbf{x}$
- Compute the second moment matrix μ in a Gaussian window with integration scale σ_I around each pixel
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Second moment matrix μ

$$\mu(\mathbf{x}, \sigma_I, \sigma_D) = \sigma_D^2 \times g(\sigma_I) \otimes \begin{bmatrix} I_x^2(\mathbf{x}, \sigma_D) & I_x I_y(\mathbf{x}, \sigma_D) \\ I_x I_y(\mathbf{x}, \sigma_D) & I_y^2(\mathbf{x}, \sigma_D) \end{bmatrix}$$

Cornerness

$$cornerness = det(\mu) - \alpha \times trace^2(\mu)$$

with $\alpha \simeq 0.05$

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Multi-scale approach

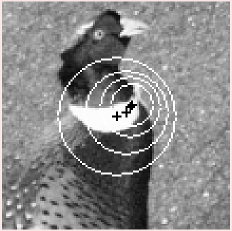
Multi-scale approach

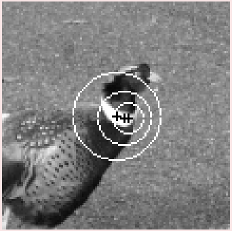
Extract points at different scales

$$\sigma^n = \xi^n \sigma_0$$

$$\xi = 1.4$$

Drawback





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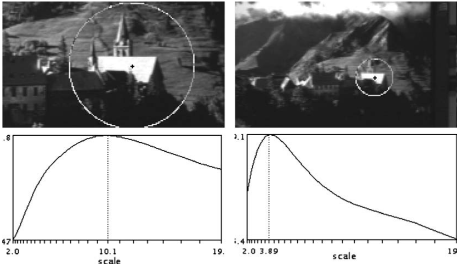
Laplacian of Gaussian

LoG

$$|LoG(\mathbf{x}, \sigma_n)| = \sigma_n^2 |I_{xx}(\mathbf{x}, \sigma_n) + I_{yy}(\mathbf{x}, \sigma_n)|$$



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Harris-Laplace detector

2 steps

- Multi-scale Harris detector
- Iterative algorithm to refine scale with LoG and location with Harris

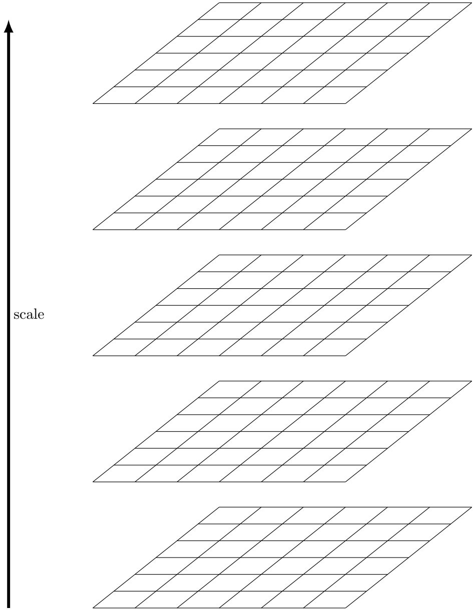
Harris-Laplace detector

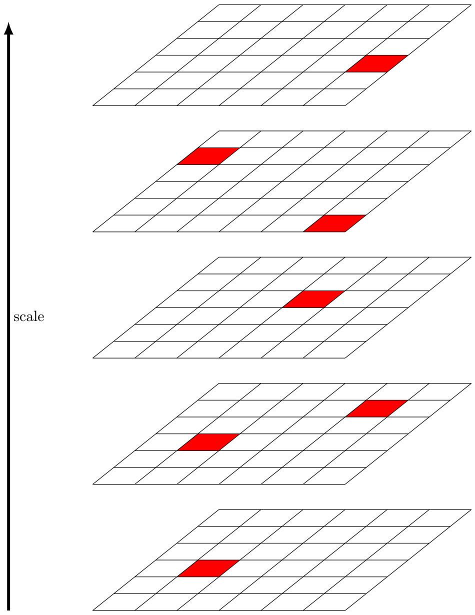
2 steps

- Multi-scale Harris detector
- Iterative algorithm to refine scale with LoG and location with Harris

Iterative algorithm

- Find the best scale between the finer and the coarser level according to LoG
- Find the best location at this scale according to Harris measure
- Restart if something has changed


scale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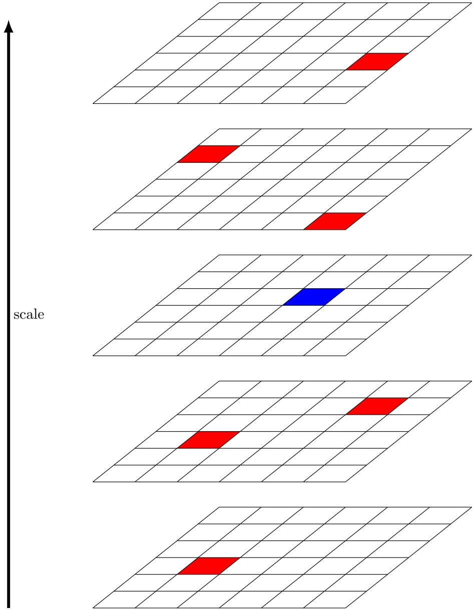
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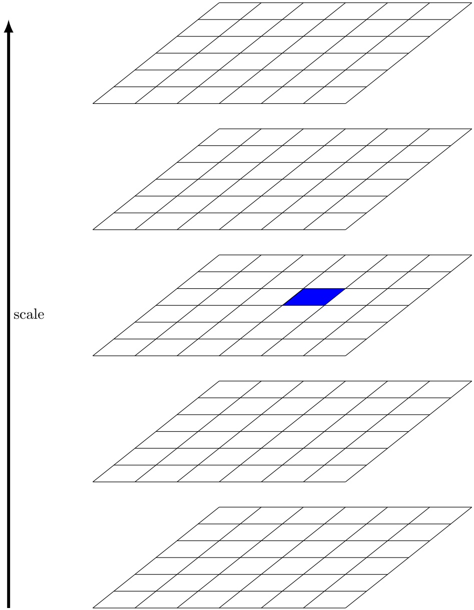
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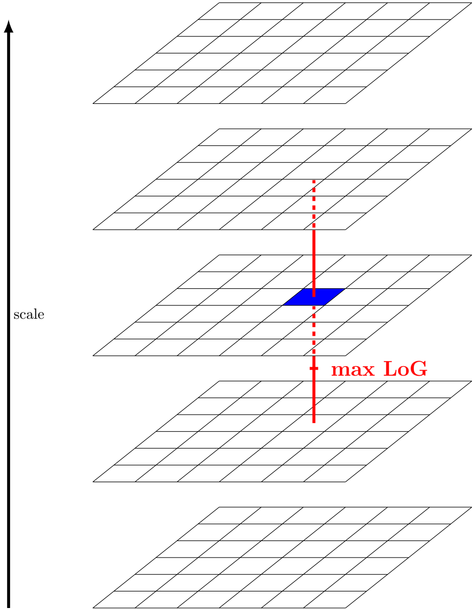
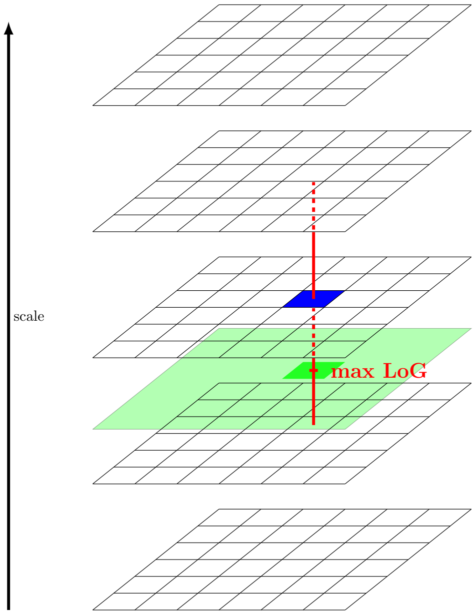
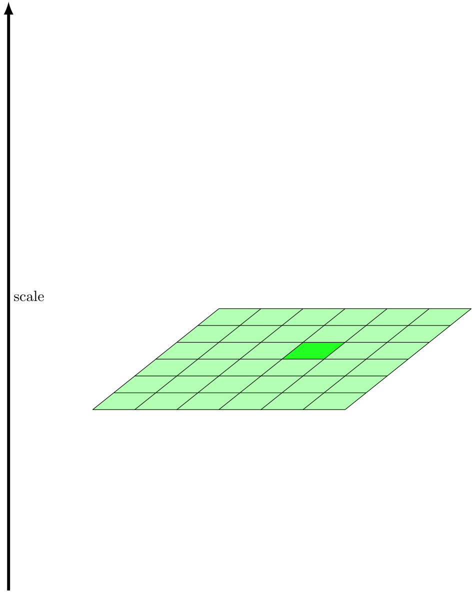
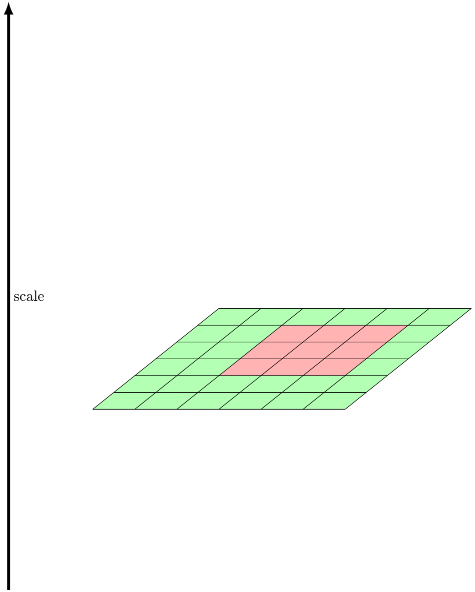
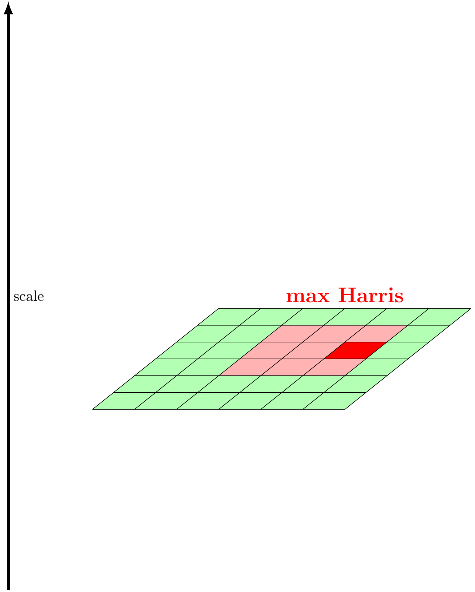
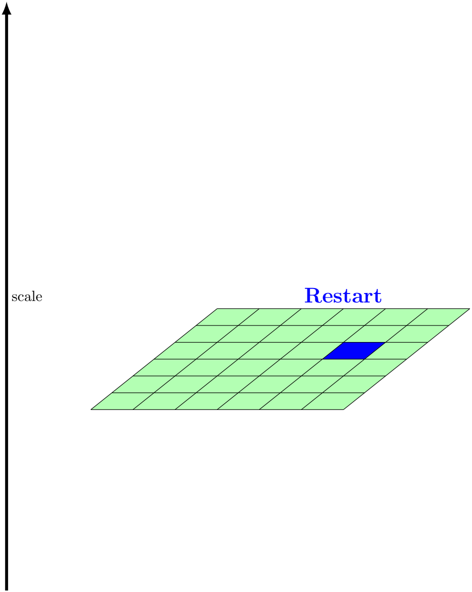

scale
max LoG


scale
max LoG


scale


scale


scale
max Harris


scale
Restart

Iterative algorithm

Initialization

A point **x** with scale σ_I computed with a multi-scale Harris detector of step 1.4

Iteration k

Iterative algorithm

Initialization

A point $\mathbf{x}$ with scale σ_I computed with a multi-scale Harris detector of step 1.4

Iteration k

- Among the range $t\sigma_I^{(k)}$, $t \in [0.7, ..., 1.4]$, set $\sigma_I^{(k+1)}$ to the local extremum of the LoG over the scale. If it doesn't exist, reject the point.

Iterative algorithm

Initialization

A point $\mathbf{x}$ with scale σ_I computed with a multi-scale Harris detector of step 1.4

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- Among the range $t\sigma_I^{(k)}$, $t \in [0.7, ..., 1.4]$, set $\sigma_I^{(k+1)}$ to the local extremum of the LoG over the scale. If it doesn't exist, reject the point.
- For the scale $\sigma_I^{(k+1)}$, set $\mathbf{x}^{(k+1)}$ to the location of the maximum of the Harris measure in the neighborhood of $\mathbf{x}^{(k)}$.

Iterative algorithm

Initialization

A point **x** with scale σ_I computed with a multi-scale Harris detector of step 1.4

Iteration k

- Among the range $t\sigma_I^{(k)}$, $t \in [0.7, ..., 1.4]$, set $\sigma_I^{(k+1)}$ to the local extremum of the LoG over the scale. If it doesn't exist, reject the point.
- For the scale $\sigma_I^{(k+1)}$, set $\mathbf{x}^{(k+1)}$ to the location of the maximum of the Harris measure in the neighborhood of $\mathbf{x}^{(k)}$.
- Restart if $\sigma_I^{(k+1)} \neq \sigma_I^{(k)}$ or $\mathbf{x}^{(k+1)} \neq \mathbf{x}^{(k)}$.

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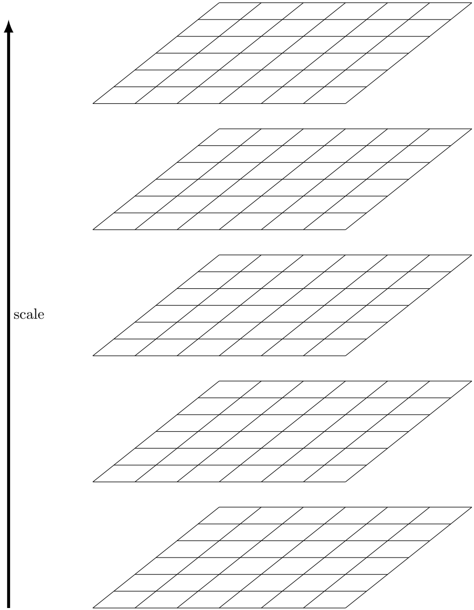
Simplified Harris-Laplace detector

Two steps

- Multi-scale Harris detector
- Keep those LoG is above a threshold, and above the LoG at finer and coarser level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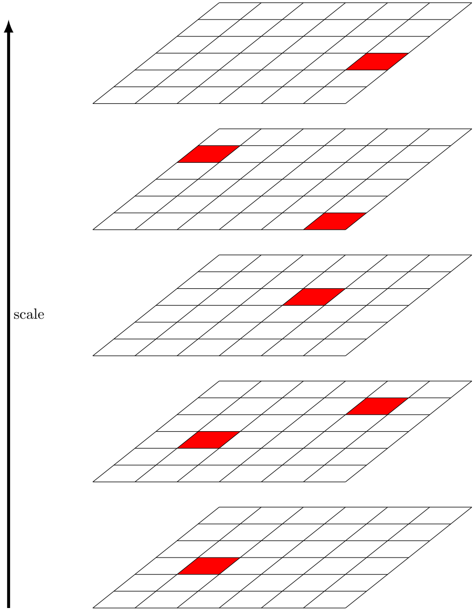
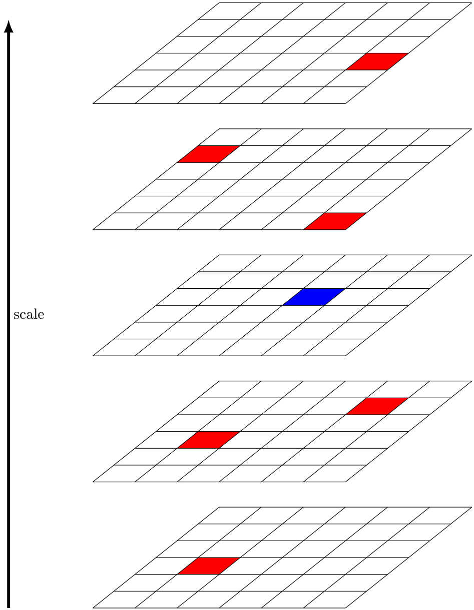

scale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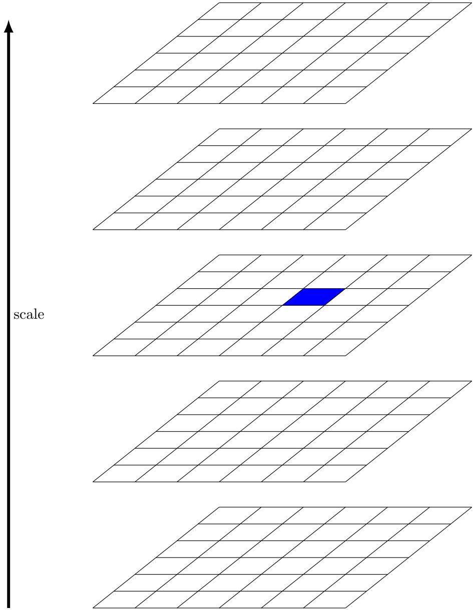
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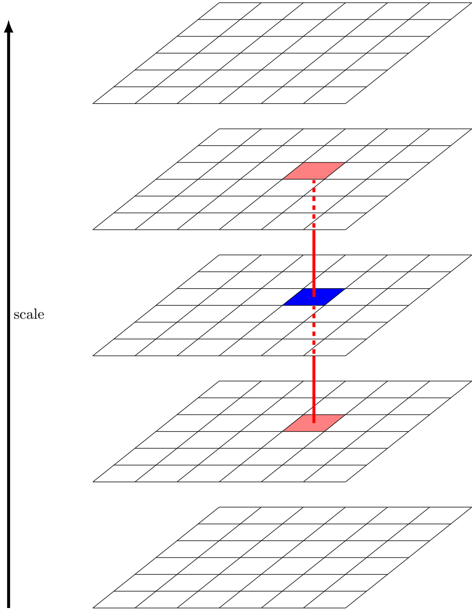
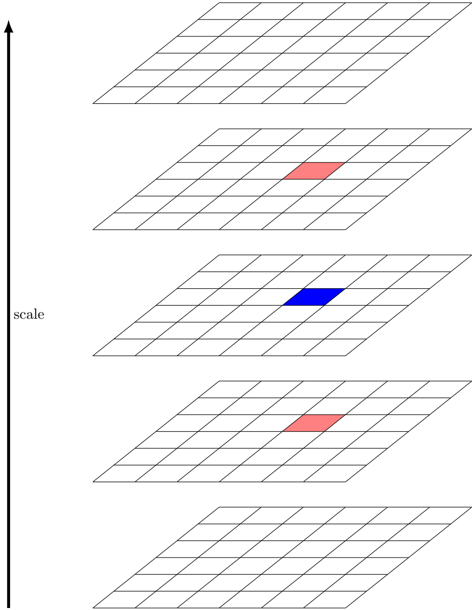

scale


scale

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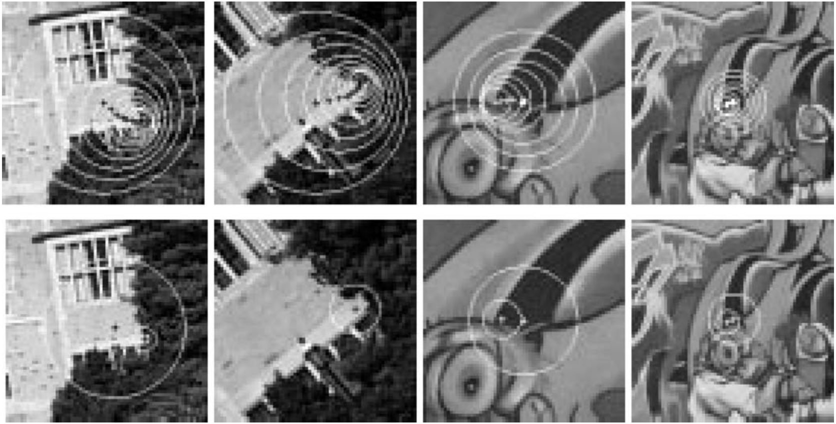
Example



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Evaluation criterion

Repeatability

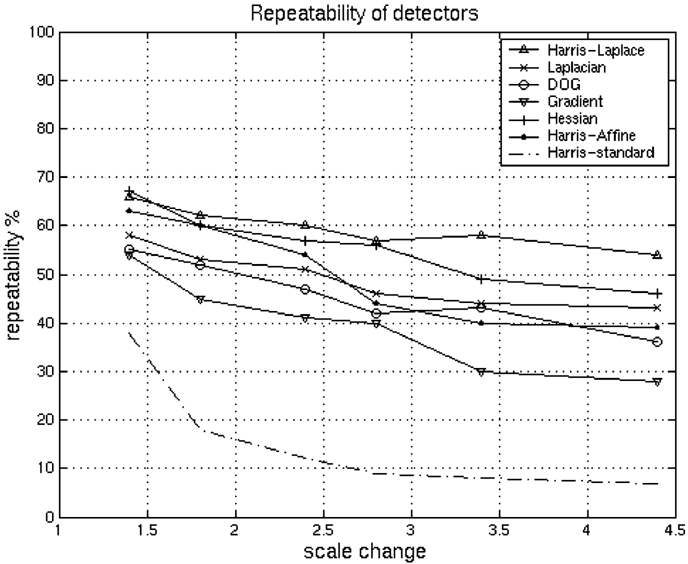
$$repeatability = \frac{\sharp corresponding\ \ regions}{\sharp detecting\ \ regions}$$

for two images with known homographic transformation H

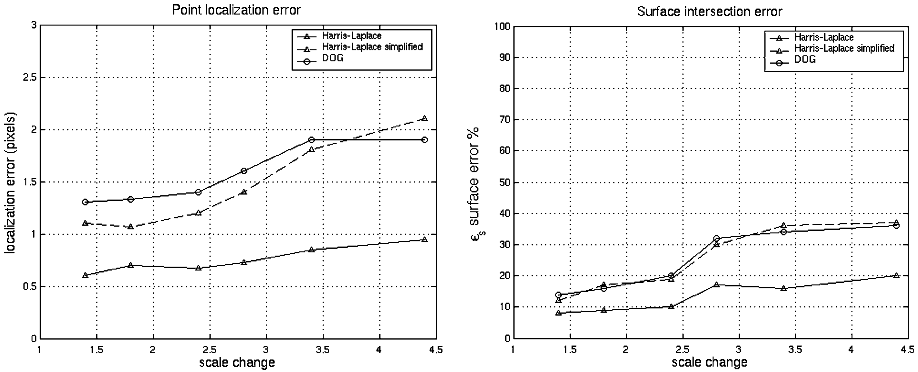
Corresponding regions

- $\|\mathbf{x}_a - H\mathbf{x}_b\| < 1.5\ pixels$
- surface error $\epsilon_s < 0.4$

Comparison with others detectors



Comparison with others detectors



(a) (b)

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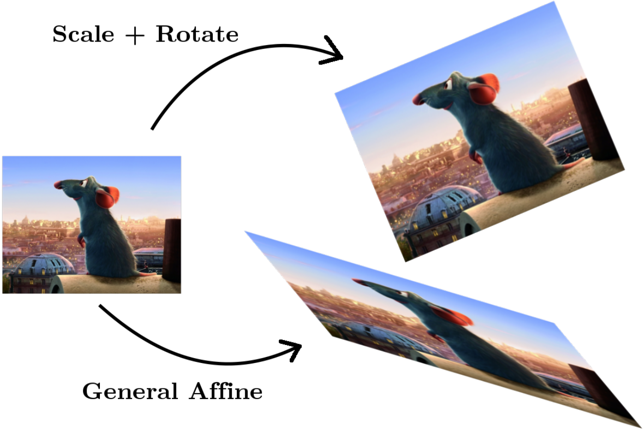
Motivation

Problem

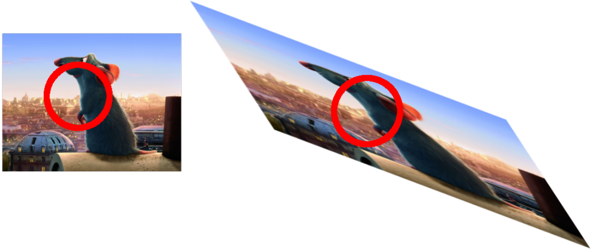
Large affine deformations ⇒ Harris-Laplace fails



Motivation

Reason

The Harris detector does not take into account the same region!



Consequence

Different pixels considered

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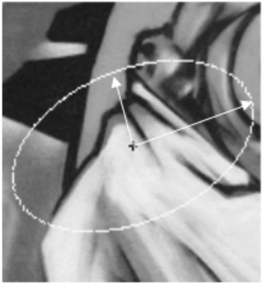
Approach

Idea

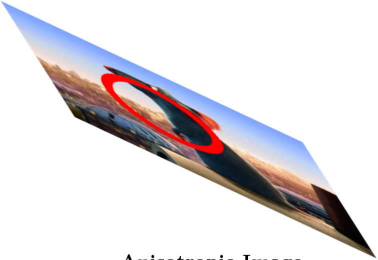
- Select the characteristic **scale**, but also the characteristic **elliptic shape**
- The elliptic shape is estimated by the second moment matrix



Affine Gaussian kernel

Affine

Anisotropy of the image $\Rightarrow$ use an affine Gaussian kernel



Isotropic Image
$+$
Circular Gaussian Kernel

$\Leftrightarrow$

Anisotropic Image
$+$
Affine Gaussian Kernel

Affine Gaussian kernel

Affine second moment matrix

$$\mu(\mathbf{x}, \Sigma_I, \Sigma_D) = det(\Sigma_D) \times g(\Sigma_I) \otimes \left((\nabla I)(\mathbf{x}, \Sigma_D)(\nabla I)(\mathbf{x}, \Sigma_D)^T\right)$$

Explanations

- Computed over the elliptic region instead of the circle
- Σ_I and Σ_D : covariance matrices to define the Gaussian kernel

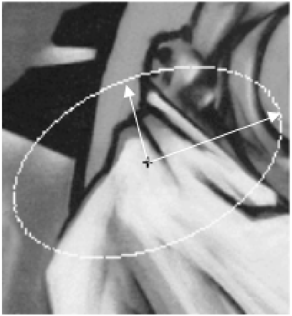
Problem

Computing this involves a 2D convolution: too long!

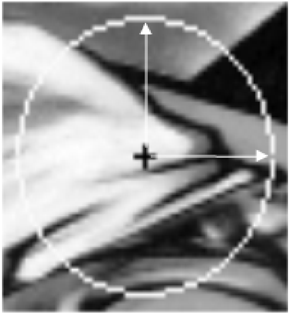
U-transformed image

Solution

- $U = \mu^{-\frac{1}{2}}$: Affine transform from the ellipse to the circle
- Use a circular gaussian kernel (decomposed into two 1D convolutions)



$$\mathbf{x}' = \mu^{-\frac{1}{2}}\mathbf{x}$$

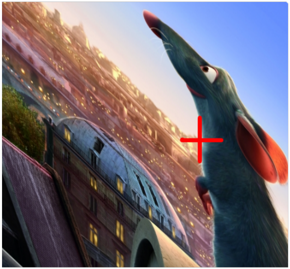


Algorithm

Algorithm

Initial Image

Algorithm



Interest point

Algorithm

Compute μ

Algorithm

$\Longrightarrow$

U-transform a window around the point

Algorithm

Perform Harris and LoG in this transformed image

Algorithm

Get new Interest points

Algorithm

Restart

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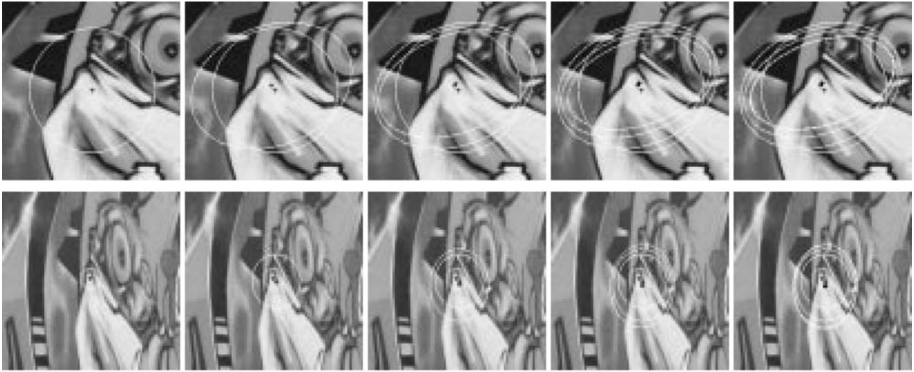
Example



Initial 1 2 3 4

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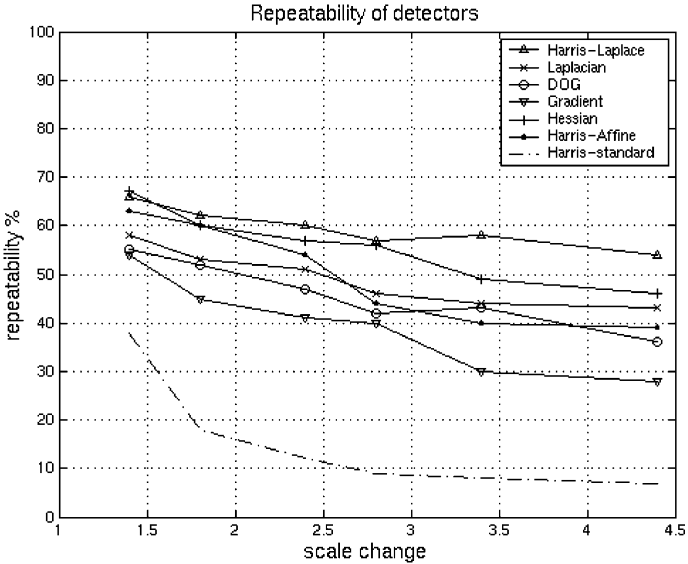
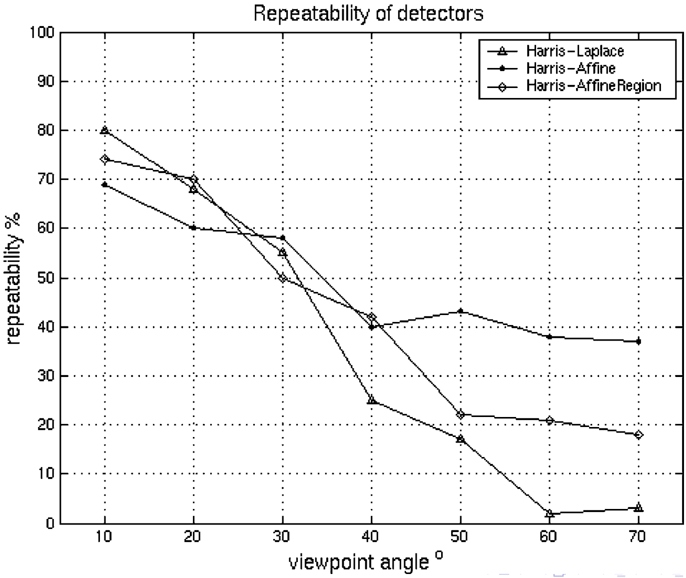
Scale invariance



Viewpoint invariance



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Conclusion

Scale invariant detectors

- Harris-Laplace performs better than Harris-Affine (especially for big scale change)
- Simplified algorithm less accurate but 5 times faster

Affine invariant detectors

- Low performance of Harris-Laplace
- High performance of Harris-Affine

Adaptation to other detectors

- Harris-Affine
- Hessian-Affine
- Laplacian-Affine