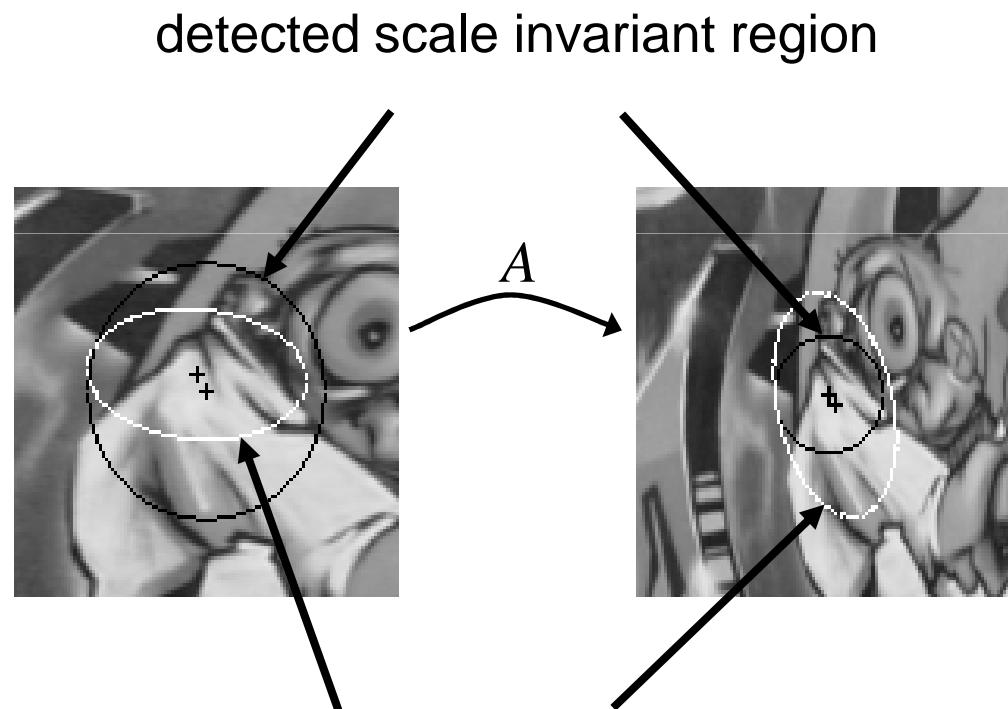


Overview

- 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

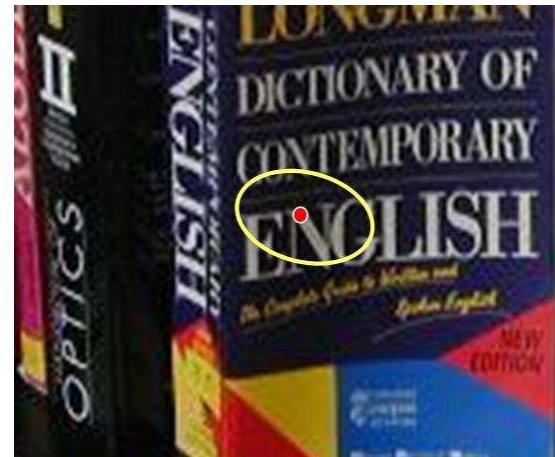
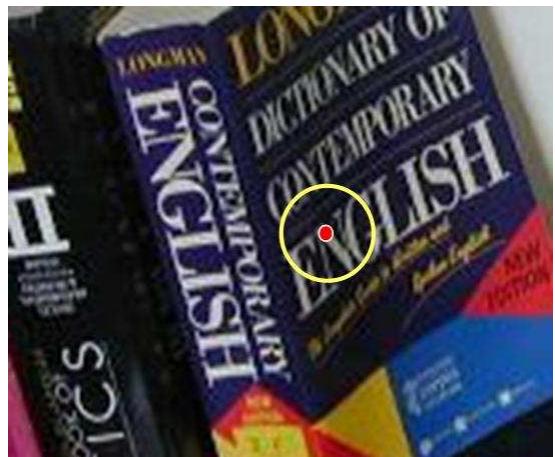
Affine invariant regions - Motivation

- Scale invariance is not sufficient for large baseline changes

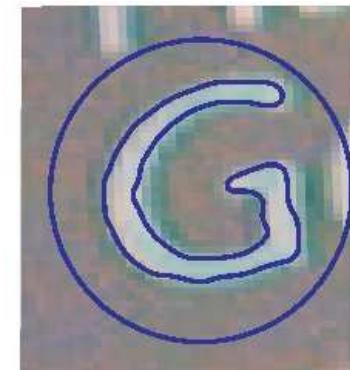


projected regions, viewpoint changes can locally
be approximated by an affine transformation A

Affine invariant regions - Motivation



Affine invariant regions - Example



Harris/Hessian/Laplacian-Affine

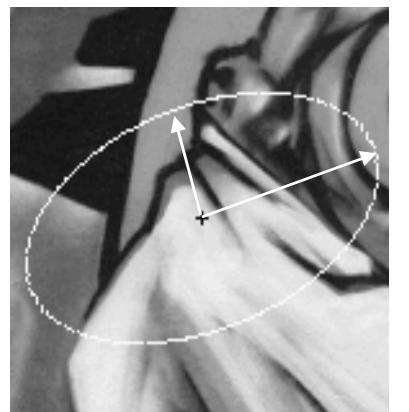
- Initialize with scale-invariant Harris/Hessian/Laplacian points
- Estimation of the affine neighbourhood with the second moment matrix [Lindeberg'94]
- Apply affine neighbourhood estimation to the scale-invariant interest points [Mikolajczyk & Schmid'02, Schaffalitzky & Zisserman'02]
- Excellent results in a comparison [Mikolajczyk et al.'05]

Affine invariant regions

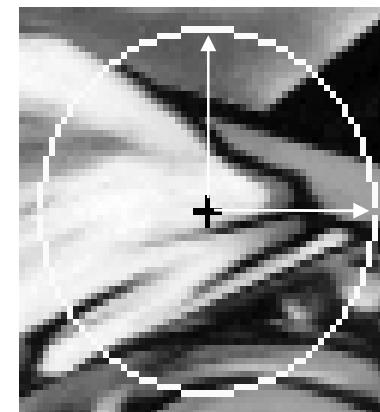
- Based on the second moment matrix (Lindeberg'94)

$$M = \mu(\mathbf{x}, \sigma_I, \sigma_D) = \sigma_D^2 G(\sigma_I) \otimes \begin{bmatrix} L_x^2(\mathbf{x}, \sigma_D) & L_x L_y(\mathbf{x}, \sigma_D) \\ L_x L_y(\mathbf{x}, \sigma_D) & L_y^2(\mathbf{x}, \sigma_D) \end{bmatrix}$$

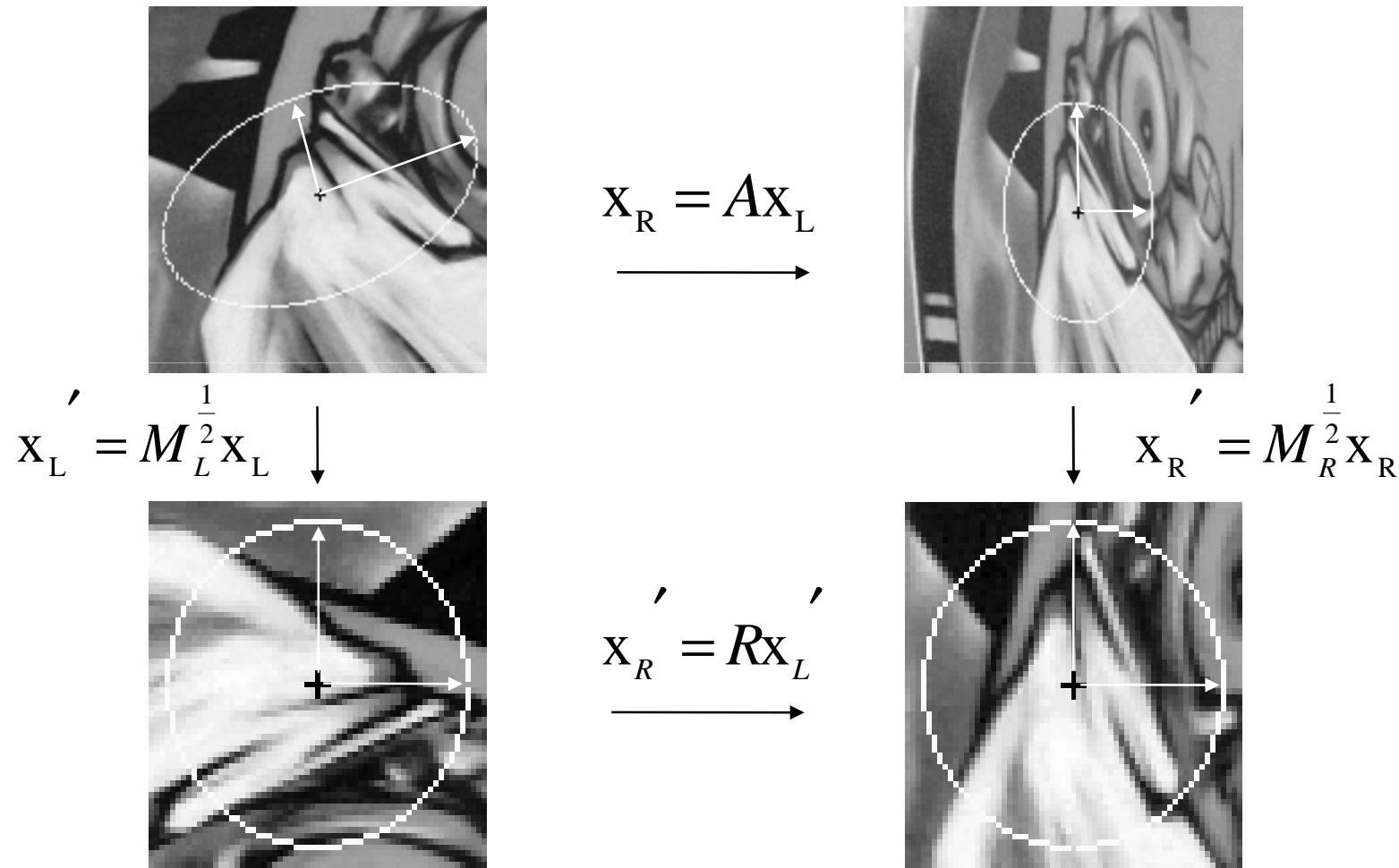
- Normalization with eigenvalues/eigenvectors



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



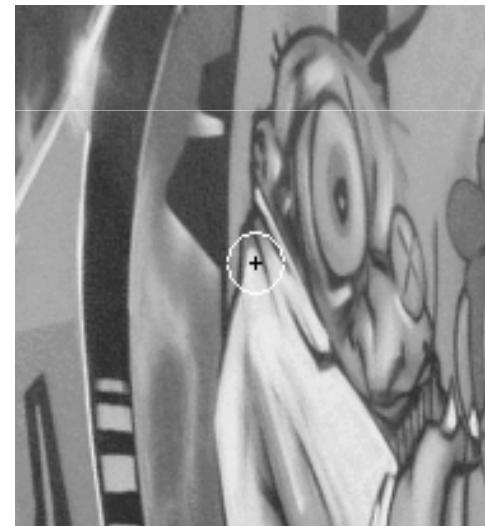
Affine invariant regions



Isotropic neighborhoods related by image rotation

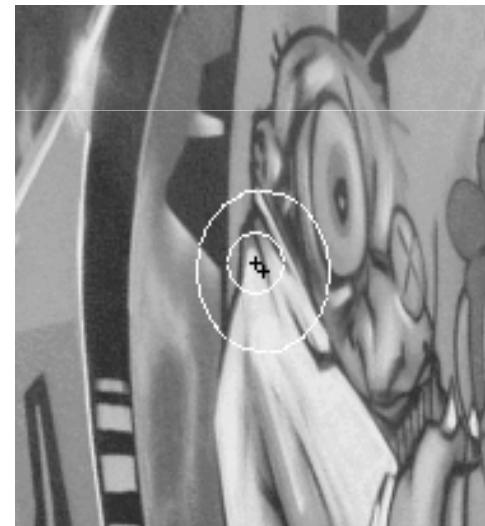
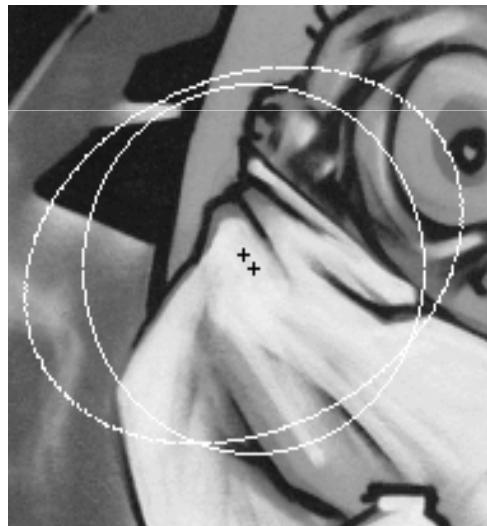
Affine invariant regions - Estimation

- Iterative estimation – initial points



Affine invariant regions - Estimation

- Iterative estimation – iteration #1



Affine invariant regions - Estimation

- Iterative estimation – iteration #2

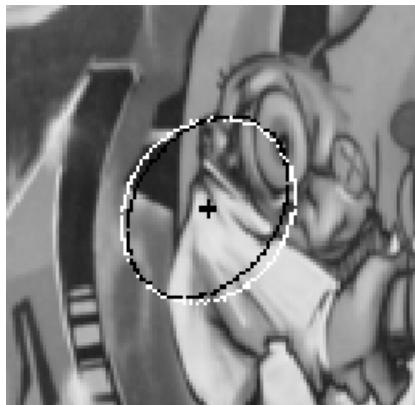
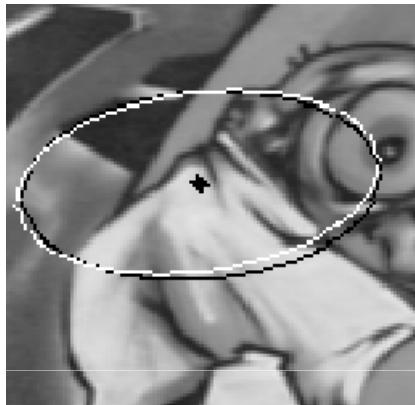


Affine invariant regions - Estimation

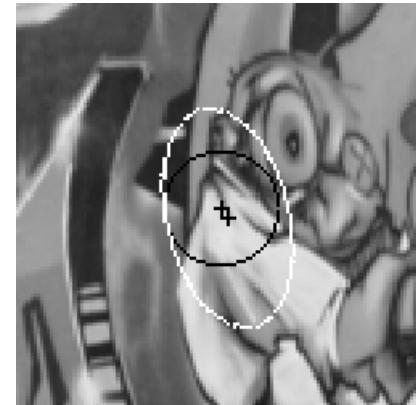
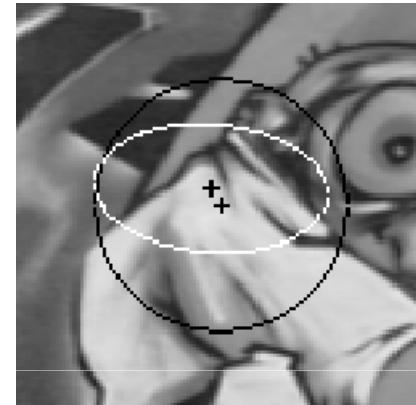
- Iterative estimation – iteration #3, #4



Harris-Affine versus Harris-Laplace

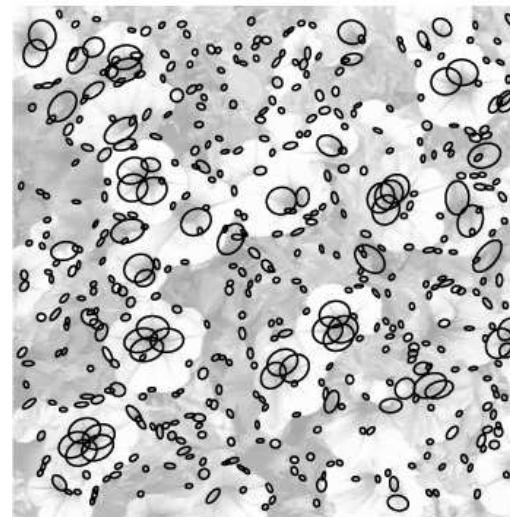
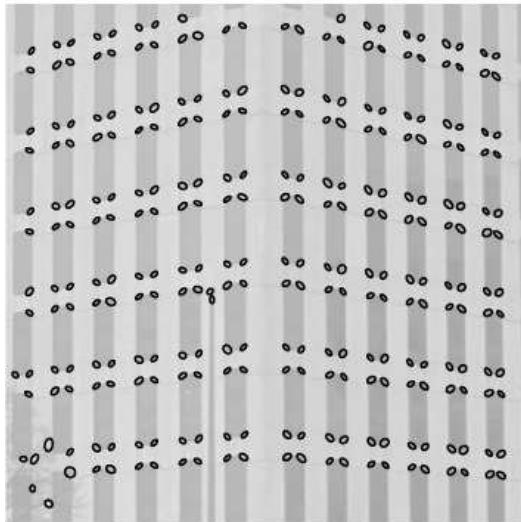


Harris-Affine

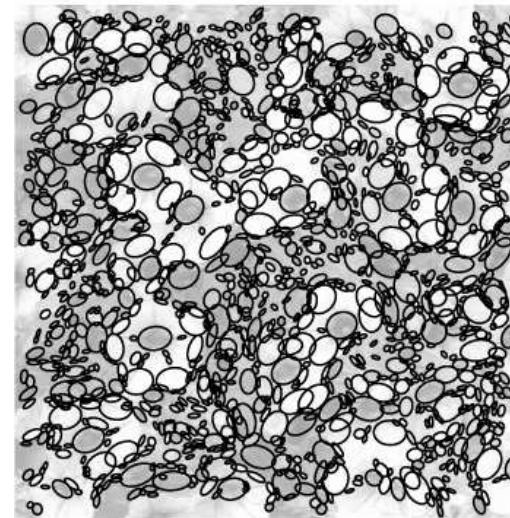
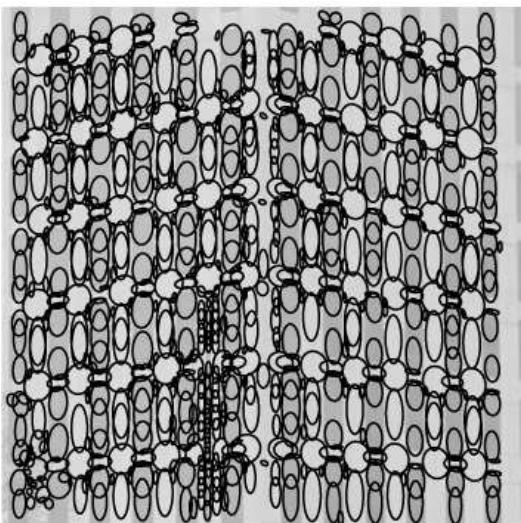


Harris-Laplace

Harris/Hessian-Affine



Harris-Affine



Hessian-Affine

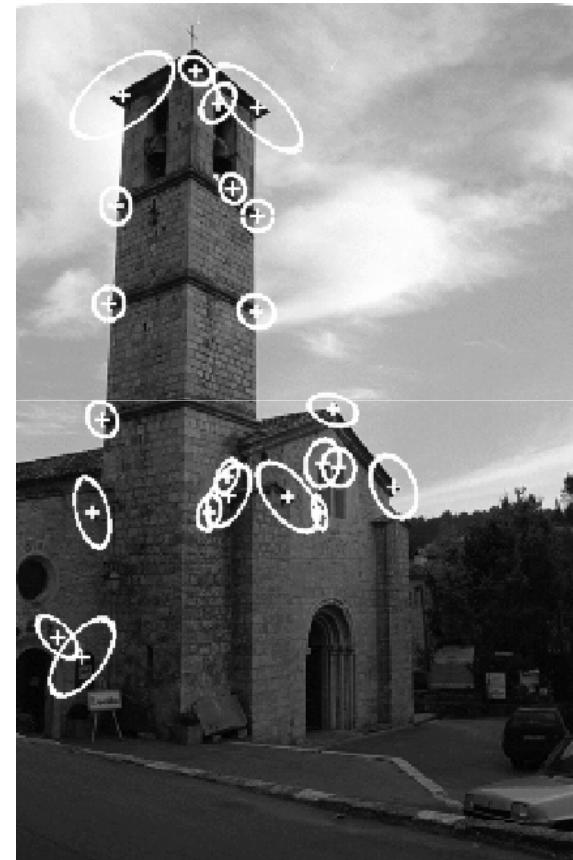
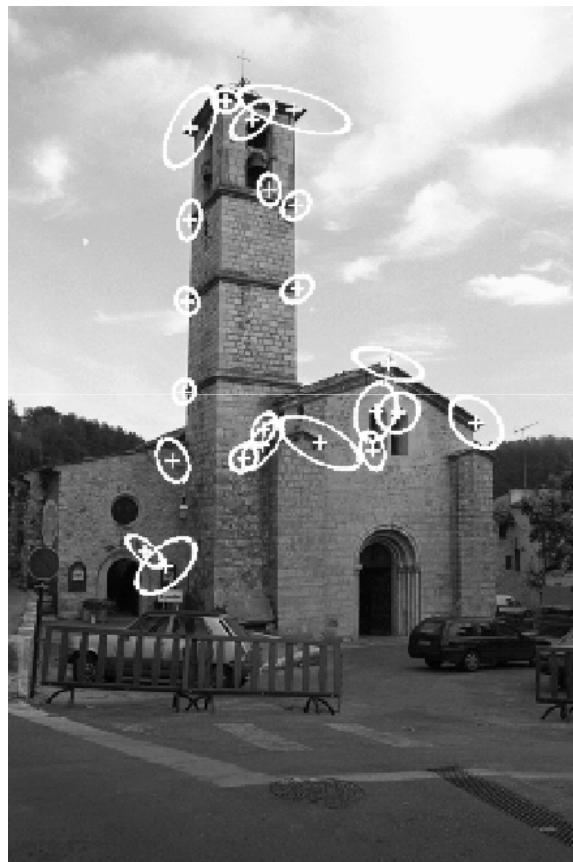
Harris-Affine



Hessian-Affine



Matches



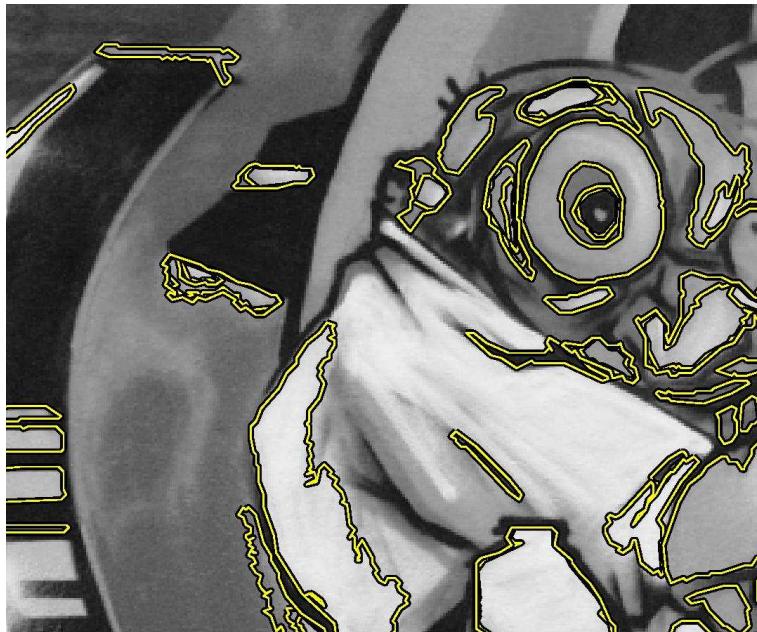
22 correct matches

Matches



33 correct matches

Maximally stable extremal regions (MSER) [Matas'02]



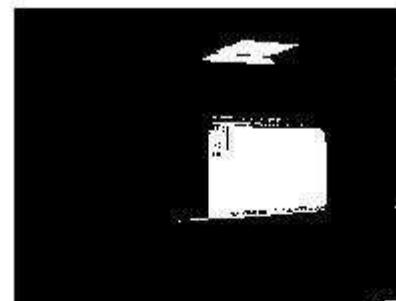
- Based on the idea of region segmentation
- State of the art results

Maximally stable extremal regions (MSER) [Matas'02]

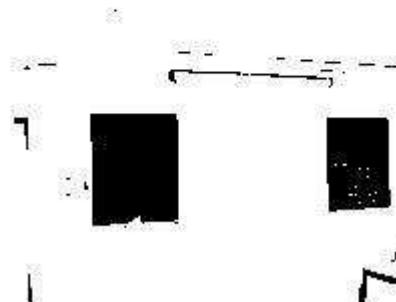
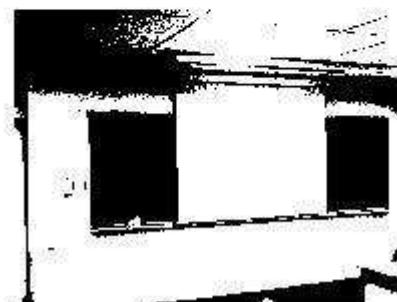
- Extremal regions: connected components in a thresholded image (all pixels above/below a threshold)
- Maximally stable: minimal change of the component (area) for a change of the threshold, i.e. region remains stable for a change of threshold

Maximally stable extremal regions (MSER)

Examples of thresholded images

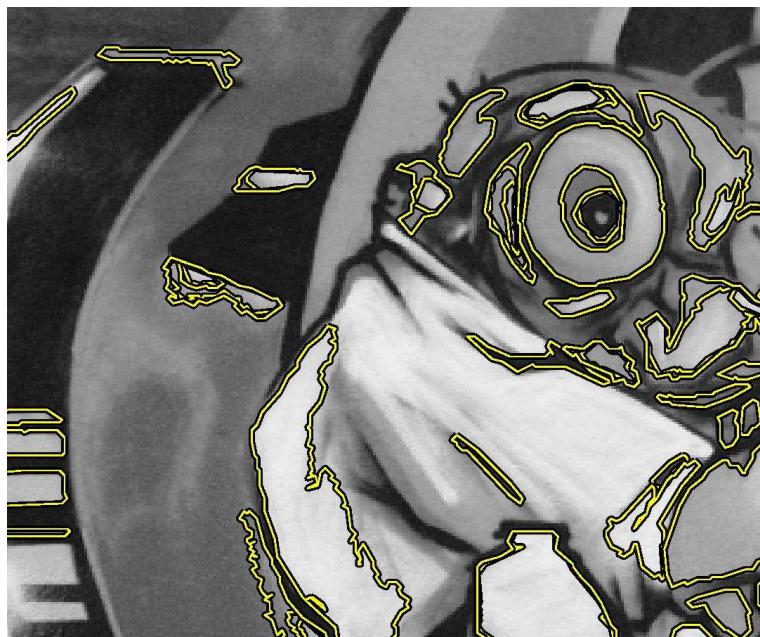


high threshold



low threshold

MSER



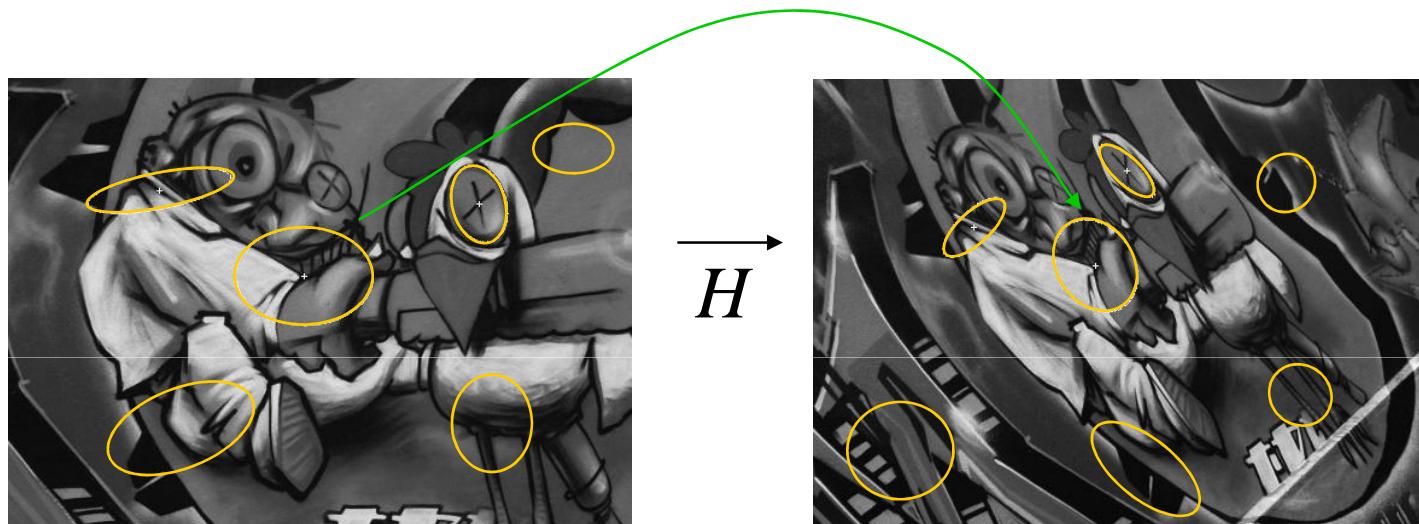
Overview

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- **Evaluation and comparison of different detectors**
- Region descriptors and their performance

Evaluation of interest points

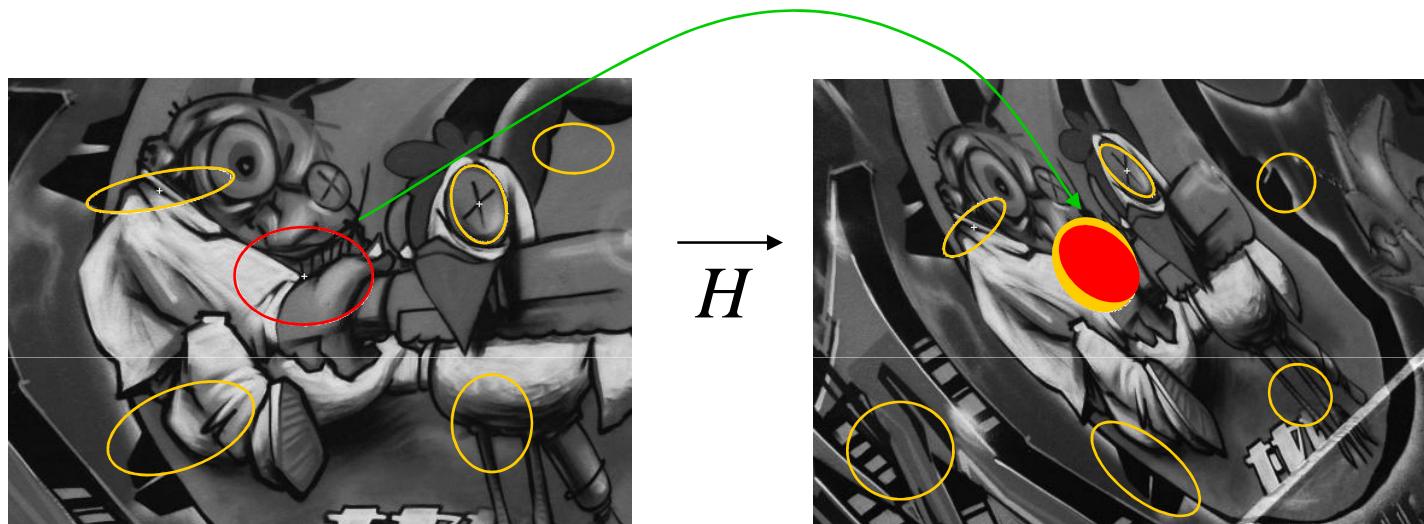
- Quantitative evaluation of interest point/region detectors
 - points / regions at the same relative location and area
- Repeatability rate : percentage of corresponding points
- Two points/regions are corresponding if
 - location error small
 - area intersection large
- [K. Mikolajczyk, T. Tuytelaars, C. Schmid, A. Zisserman, J. Matas, F. Schaffalitzky, T. Kadir & L. Van Gool '05]

Evaluation criterion



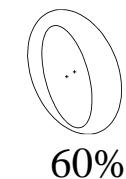
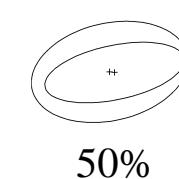
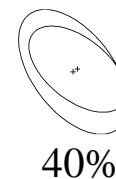
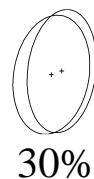
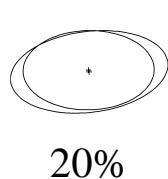
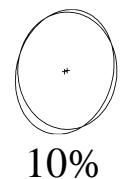
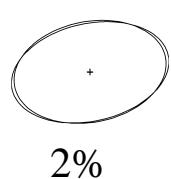
$$repeatability = \frac{\# \text{corresponding regions}}{\# \text{detected regions}} \cdot 100\%$$

Evaluation criterion



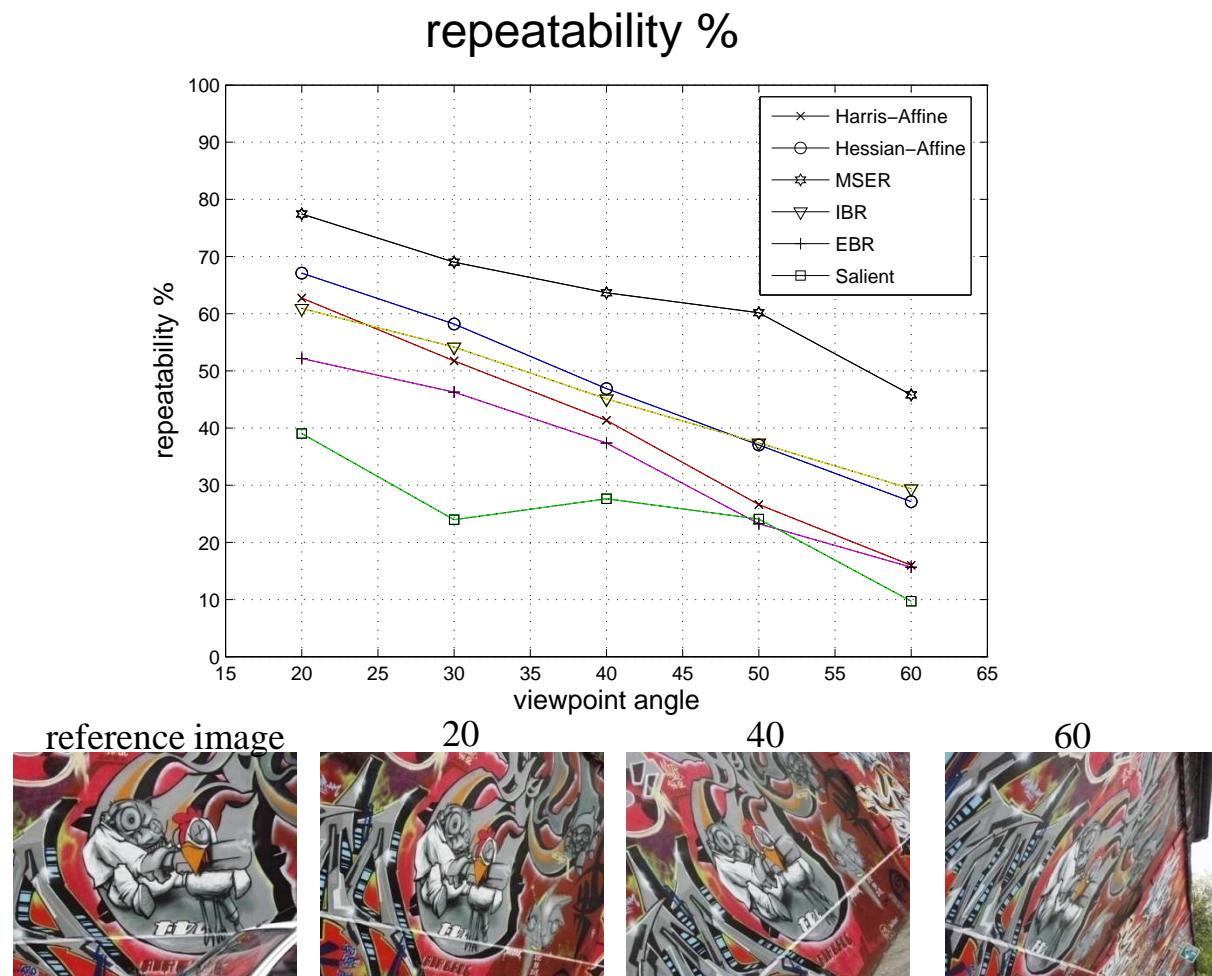
$$repeatability = \frac{\# \text{corresponding regions}}{\# \text{detected regions}} \cdot 100\%$$

$$overlap error = (1 - \frac{\text{intersection}}{\text{union}}) \cdot 100\%$$



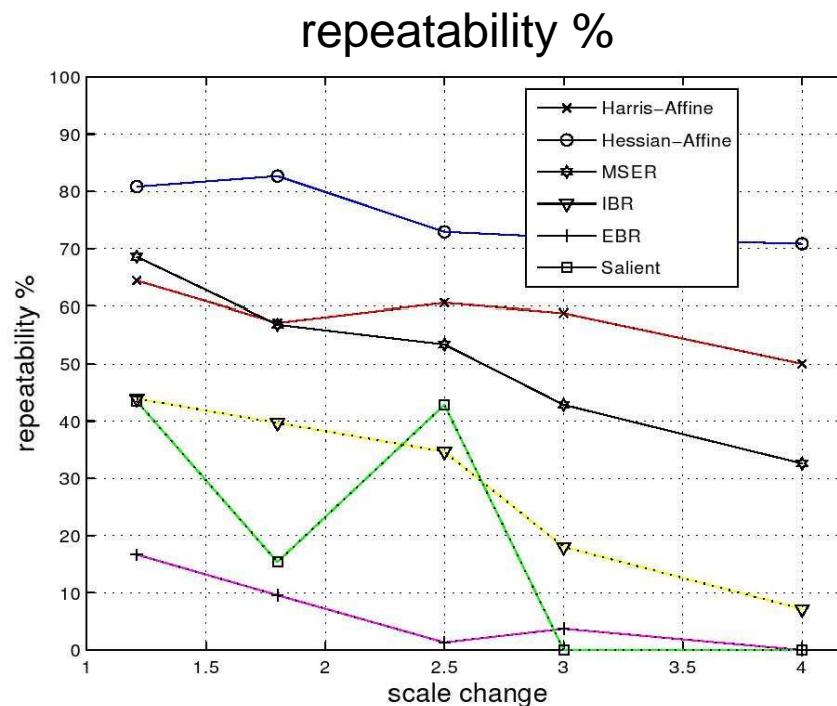
Comparison of affine invariant detectors

Viewpoint change - structured scene



Comparison of affine invariant detectors

Scale change – textured scene



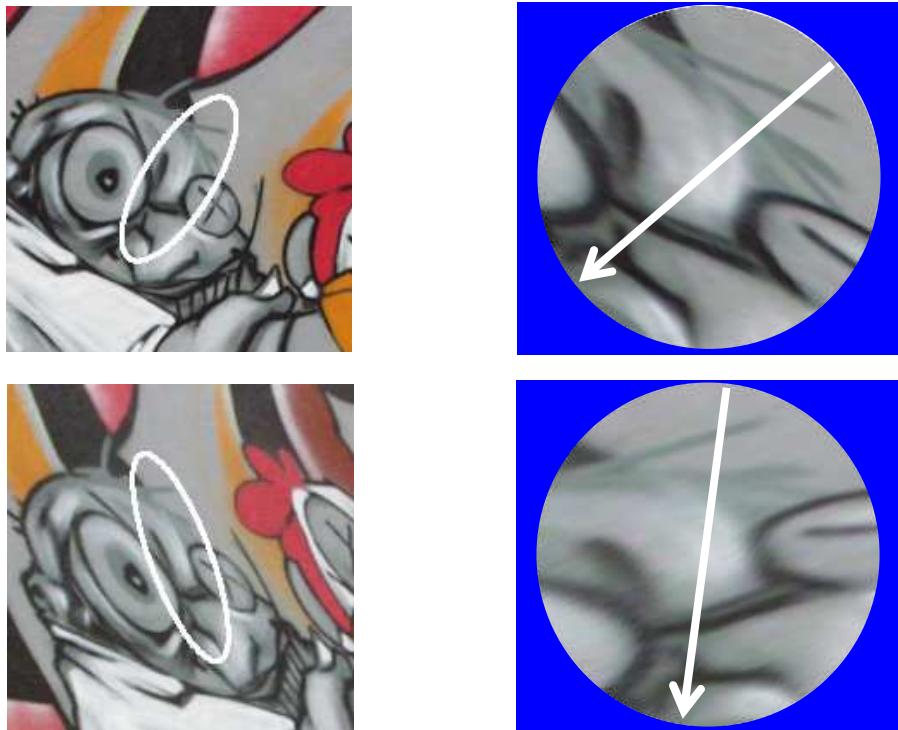
Conclusion - detectors

- Good performance for large viewpoint and scale changes
- Results depend on transformation and scene type, no one best detector
- Detectors are complementary
 - MSER adapted to structured scenes
 - Harris and Hessian adapted to textured scenes
- Performance of the different scale invariant detectors is very similar (Harris-Laplace, Hessian, LoG and DOG)
- Scale-invariant detector sufficient up to 40 degrees of viewpoint change

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Region descriptors

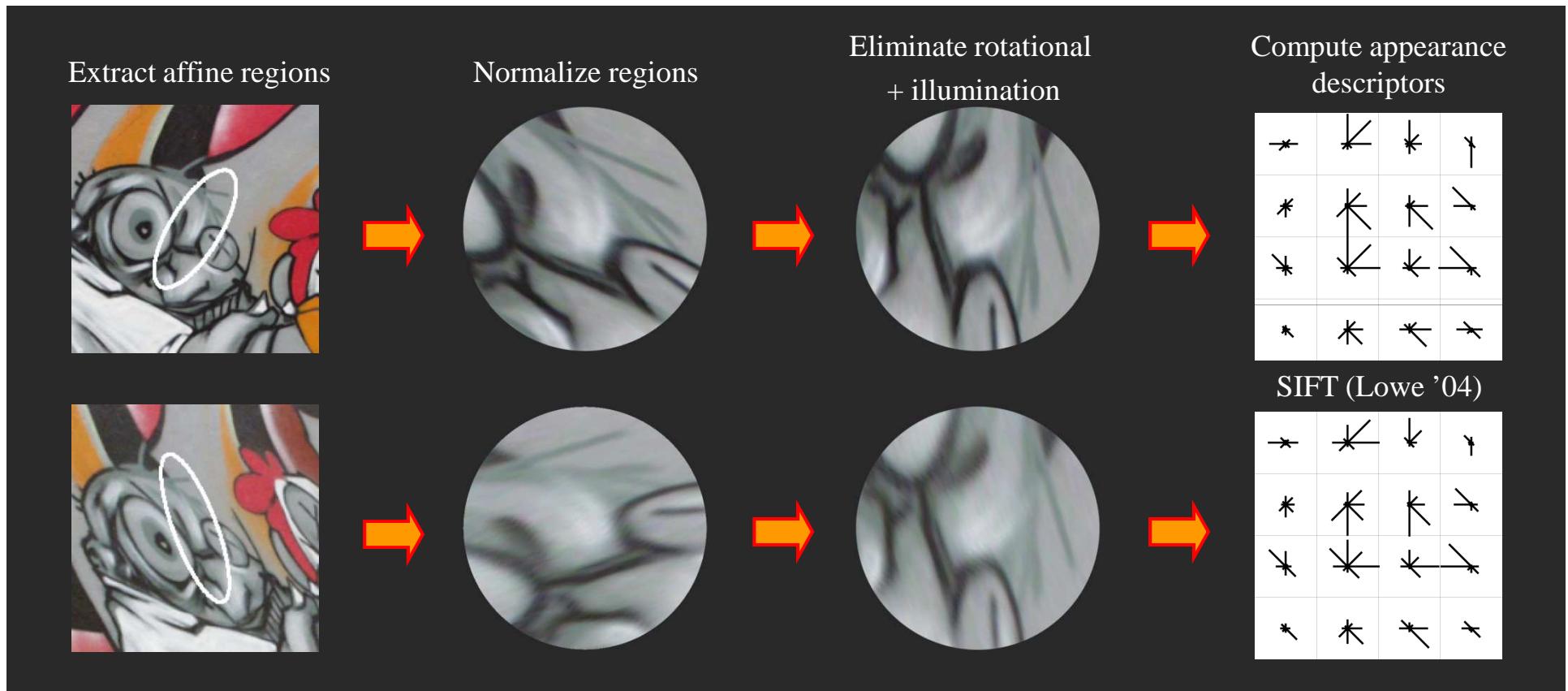


- Normalized regions are
 - invariant to geometric transformations except rotation
 - not invariant to photometric transformations

Descriptors

- Regions invariant to geometric transformations except rotation
 - rotation invariant descriptors
 - **normalization with dominant gradient direction**
- Regions not invariant to photometric transformations
 - invariance to affine photometric transformations
 - **normalization with mean and standard deviation of the image patch**

Descriptors

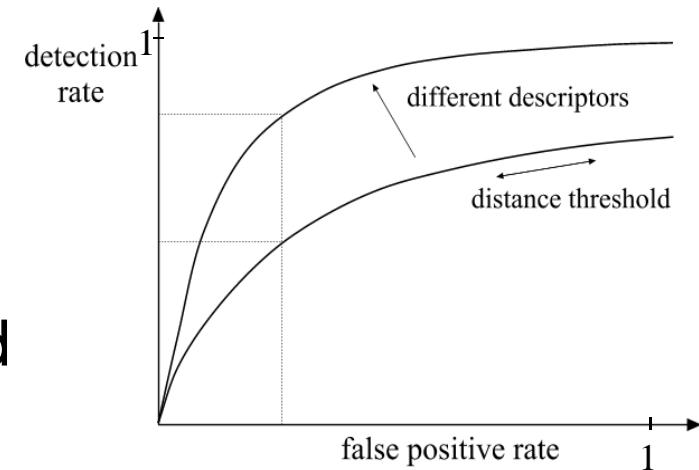


Descriptors

- Gaussian derivative-based descriptors
 - Differential invariants (*Koenderink and van Doorn'87*)
 - Steerable filters (*Freeman and Adelson'91*)
- SIFT (*Lowe'99*)
- Moment invariants [Van Gool et al.'96]
- Shape context [Belongie et al.'02]
- SIFT with PCA dimensionality reduction
- Gradient PCA [Ke and Sukthankar'04]
- SURF descriptor [Bay et al.'08]
- DAISY descriptor [Tola et al.'08, Windler et al'09]

Comparison criterion

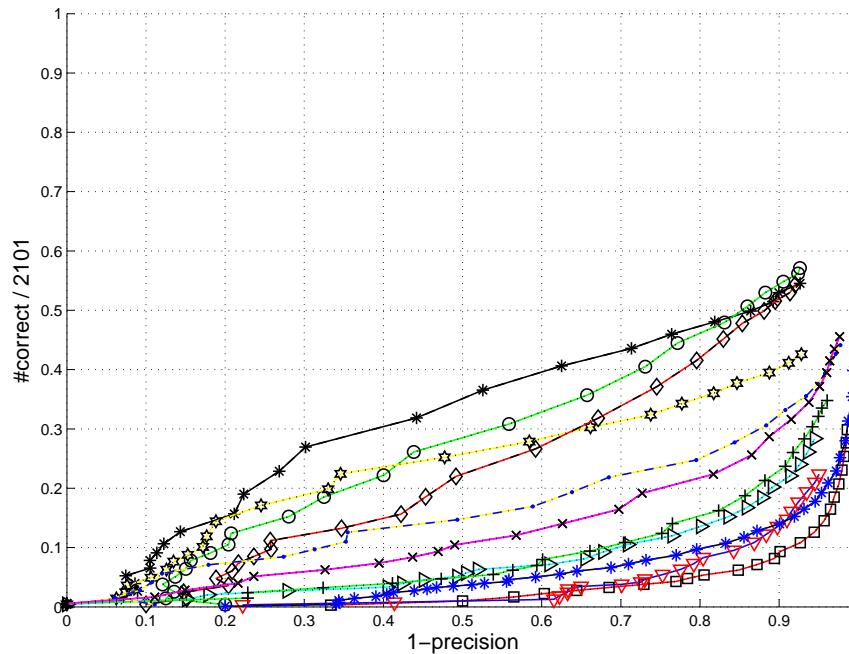
- Descriptors should be
 - Distinctive
 - Robust to changes on viewing conditions as well as to errors of the detector
- Detection rate (recall)
 - $\# \text{correct matches} / \# \text{correspondences}$
- False positive rate
 - $\# \text{false matches} / \# \text{all matches}$
- Variation of the distance threshold
 - $\text{distance } (d_1, d_2) < \text{threshold}$



[K. Mikolajczyk & C. Schmid, PAMI'05]

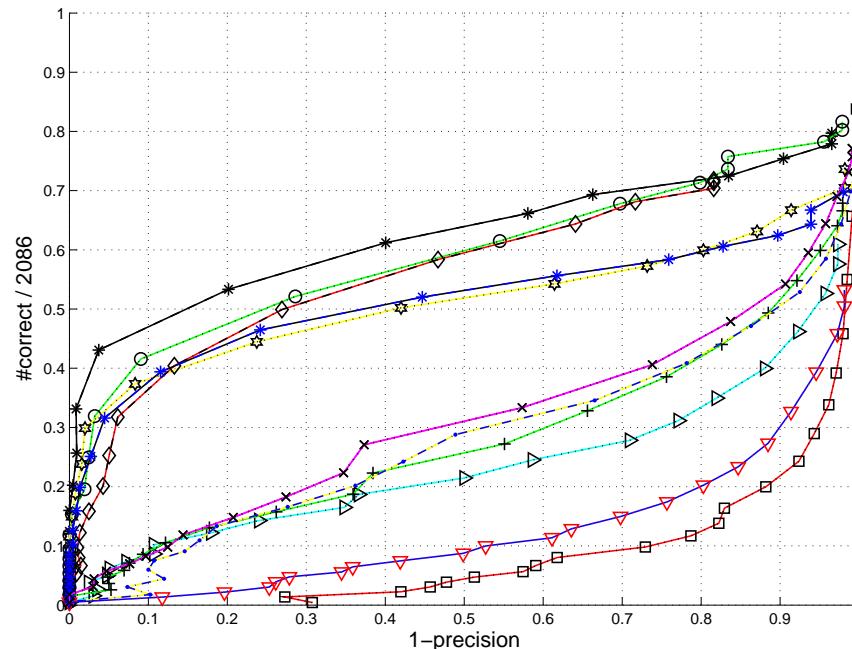
Viewpoint change (60 degrees)

○ - - ○ sift	◊ - - ◊ shape context	+ - - + steerable filters
* - - * esift	x - - x cross correlation	- - - gradient moments
☆ - - ☆ gradient pca	* - - * har-aff esift	□ - - □ complex filters



Scale change (factor 2.8)

○	sift
*	esift
☆	gradient pca
◊	shape context
×	cross correlation
*	har-aff esift
+	steerable filters
—	gradient moments
□	complex filters



Conclusion - descriptors

- SIFT based descriptors perform best
- Significant difference between SIFT and low dimension descriptors as well as cross-correlation
- Robust region descriptors better than point-wise descriptors
- Performance of the descriptor is relatively independent of the detector

Available on the internet

- Binaries for detectors and descriptors
 - *Building blocks for recognition systems*
- Carefully designed test setup
 - Dataset with transformations
 - Evaluation code in matlab
 - *Benchmark for new detectors and descriptors*

<http://lear.inrialpes.fr/software>