EECS 442 – Computer vision

Detectors part II
Descriptors

- Blob detectors
- Invariance
- Descriptors

Some slides of this lectures are courtesy of prof F. Li, prof S. Lazebnik, and various other lecturers

Goal:

Identify interesting regions from the images (edges, corners, blobs…)

Descriptors e.g. SIFT

Matching / Indexing / Recognition

- Repeatability
  - The same feature can be found in several images despite geometric and photometric transformations
- Saliency
  - Each feature is found at an “interesting” region of the image
- Locality
  - A feature occupies a “relatively small” area of the image;

Repeatability

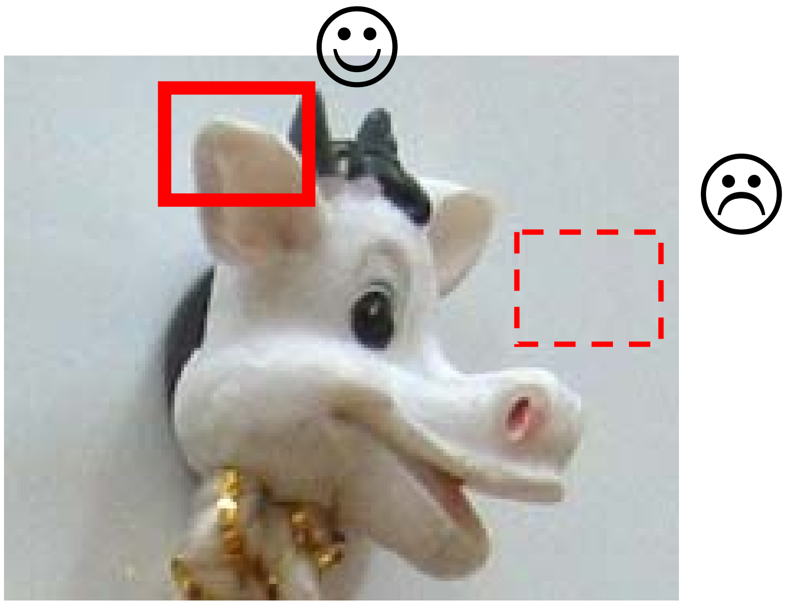
Illumination invariance

Scale invariance

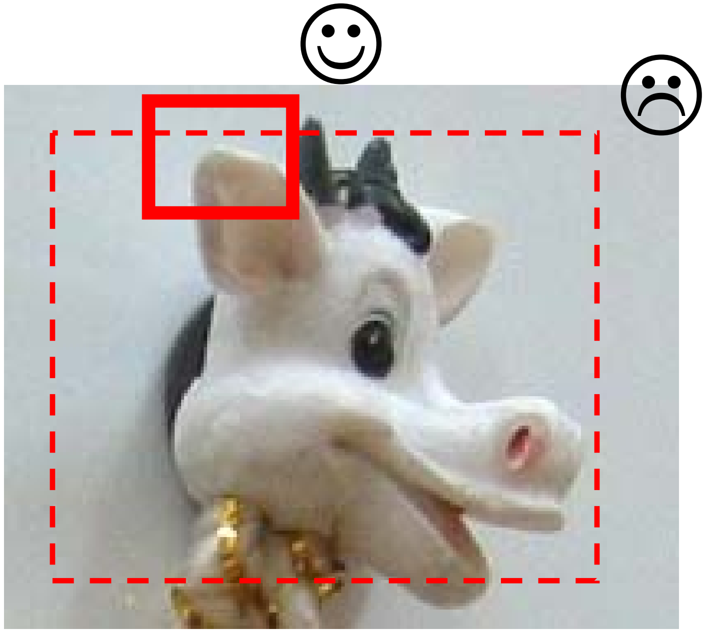
Pose invariance

- Rotation
- Affine

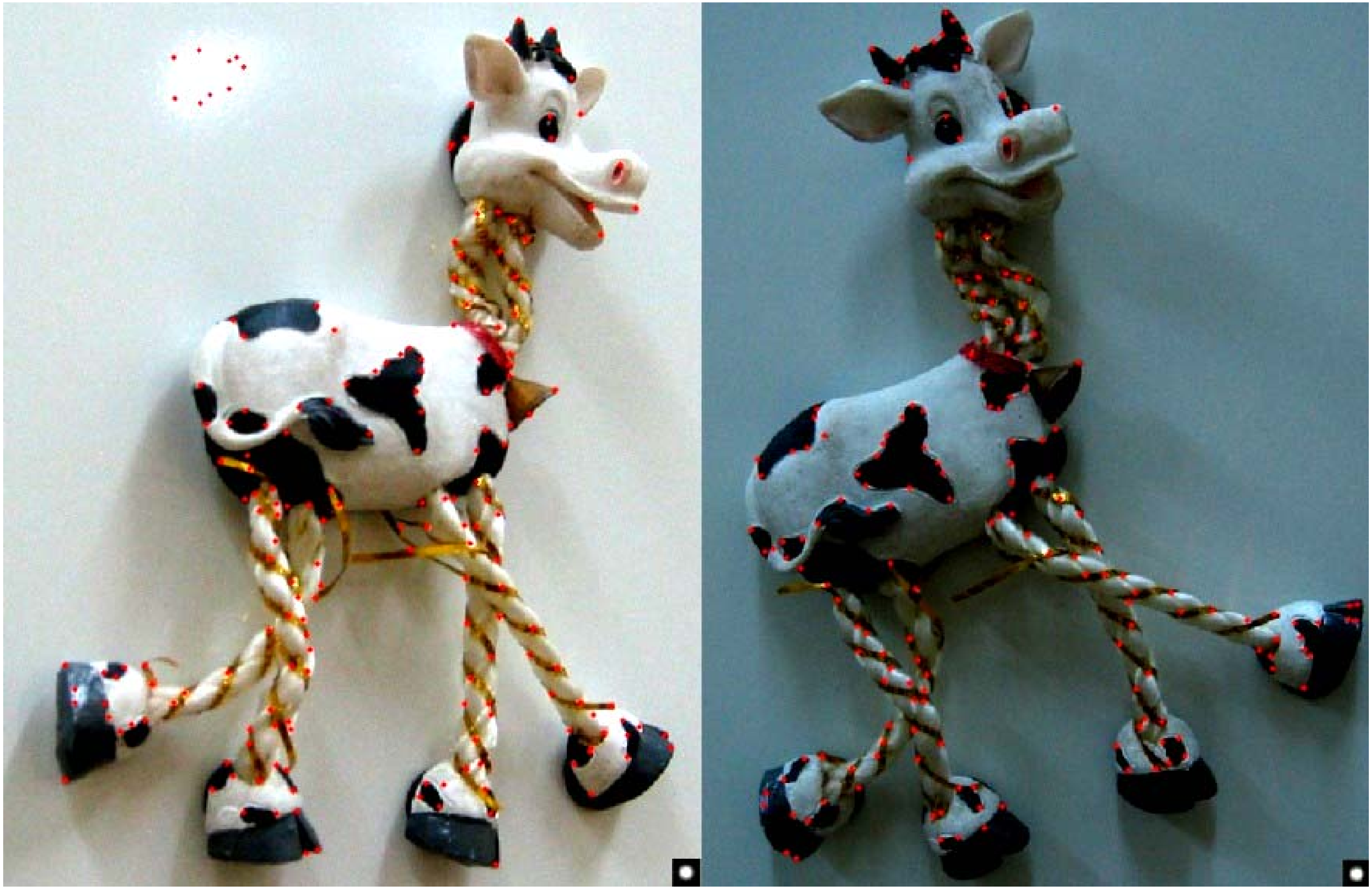
- Saliency



- Locality



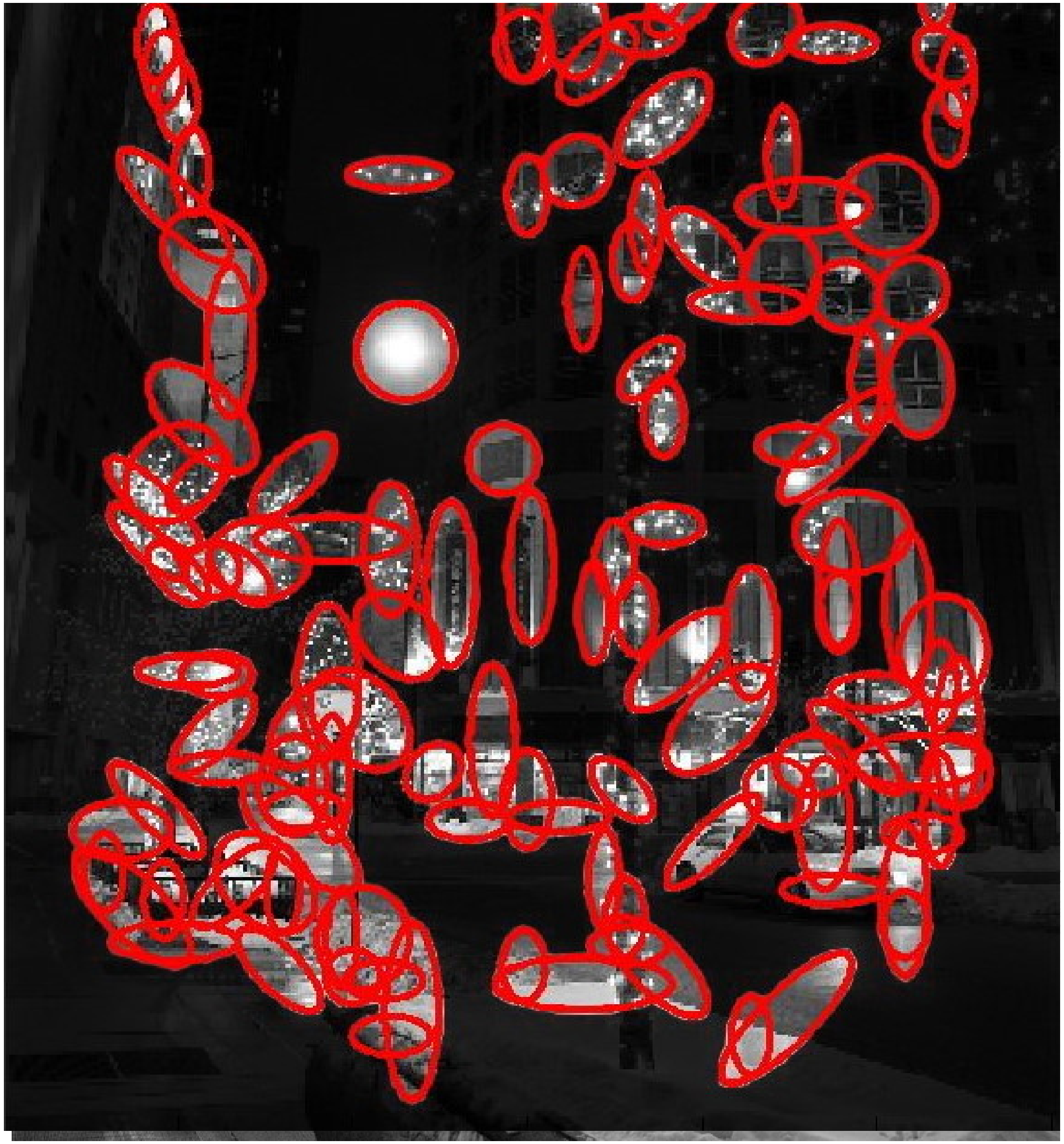
Harris Detector



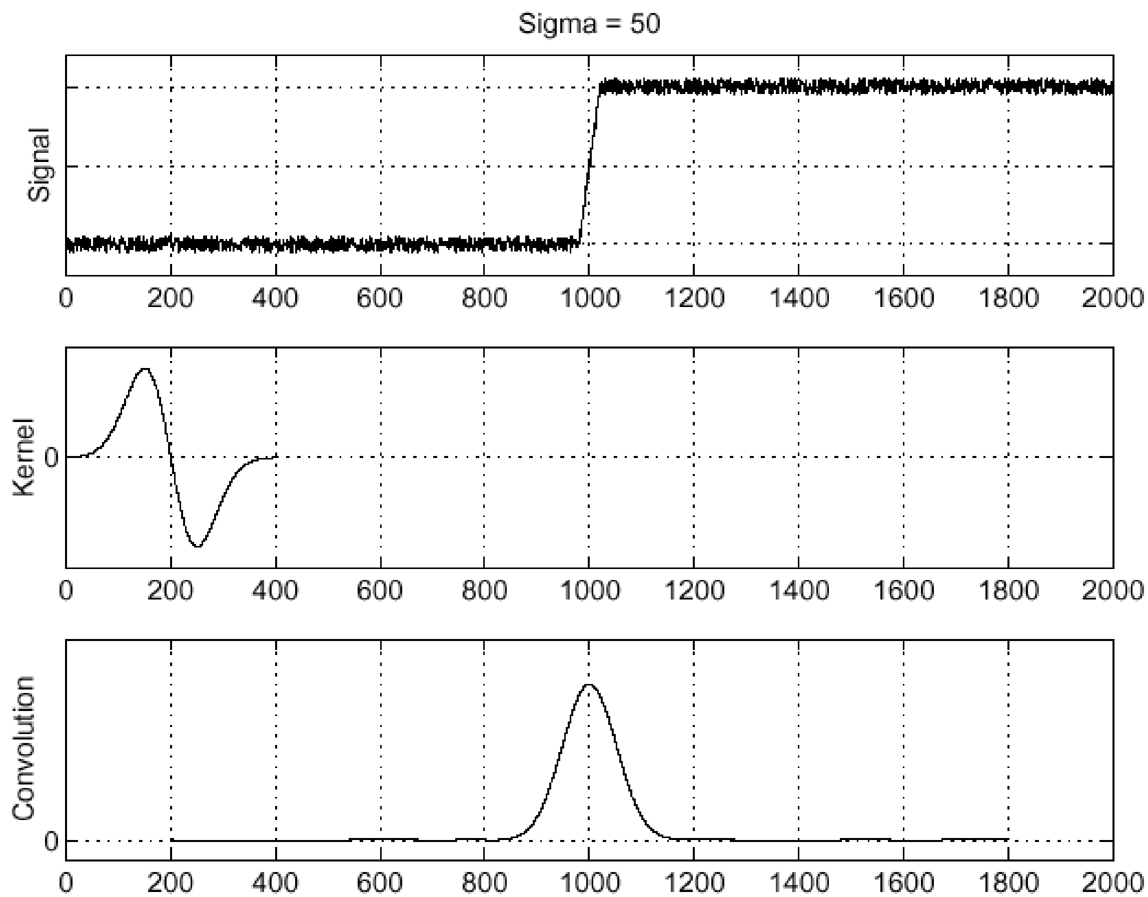
Invariance

Detector	Illumination	Rotation	Scale	View point
Harris corner	partial	Yes	No	No

Extract useful building blocks: blobs



Edge detection



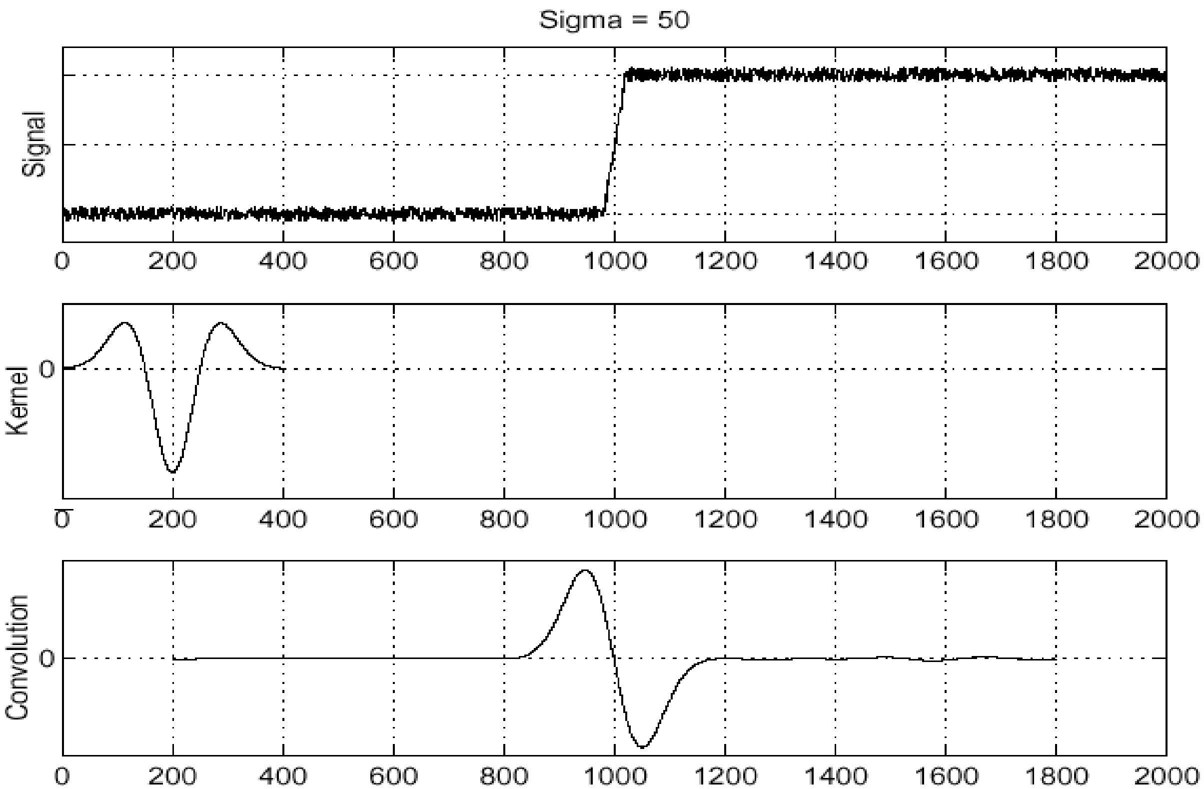
f — Edge

$\frac{d}{dx} g$ — Derivative of Gaussian

$f * \frac{d}{dx} g$ — Edge = maximum of derivative

Source: S. Seitz

Edge detection as zero crossing



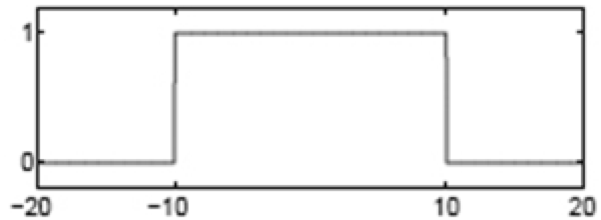
f — Edge

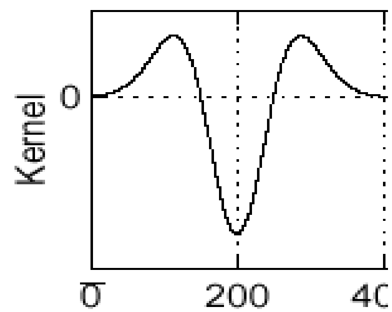
$$\frac{d^2}{dx^2} g$$ — Second derivative of Gaussian (Laplacian)

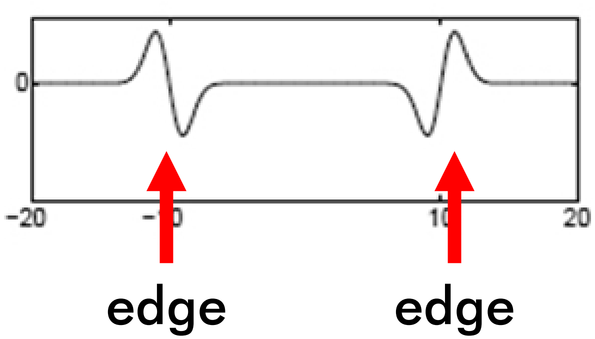
$$f * \frac{d^2}{dx^2} g$$ — Edge = zero crossing of second derivative

Source: S. Seitz

Edge detection as zero crossing

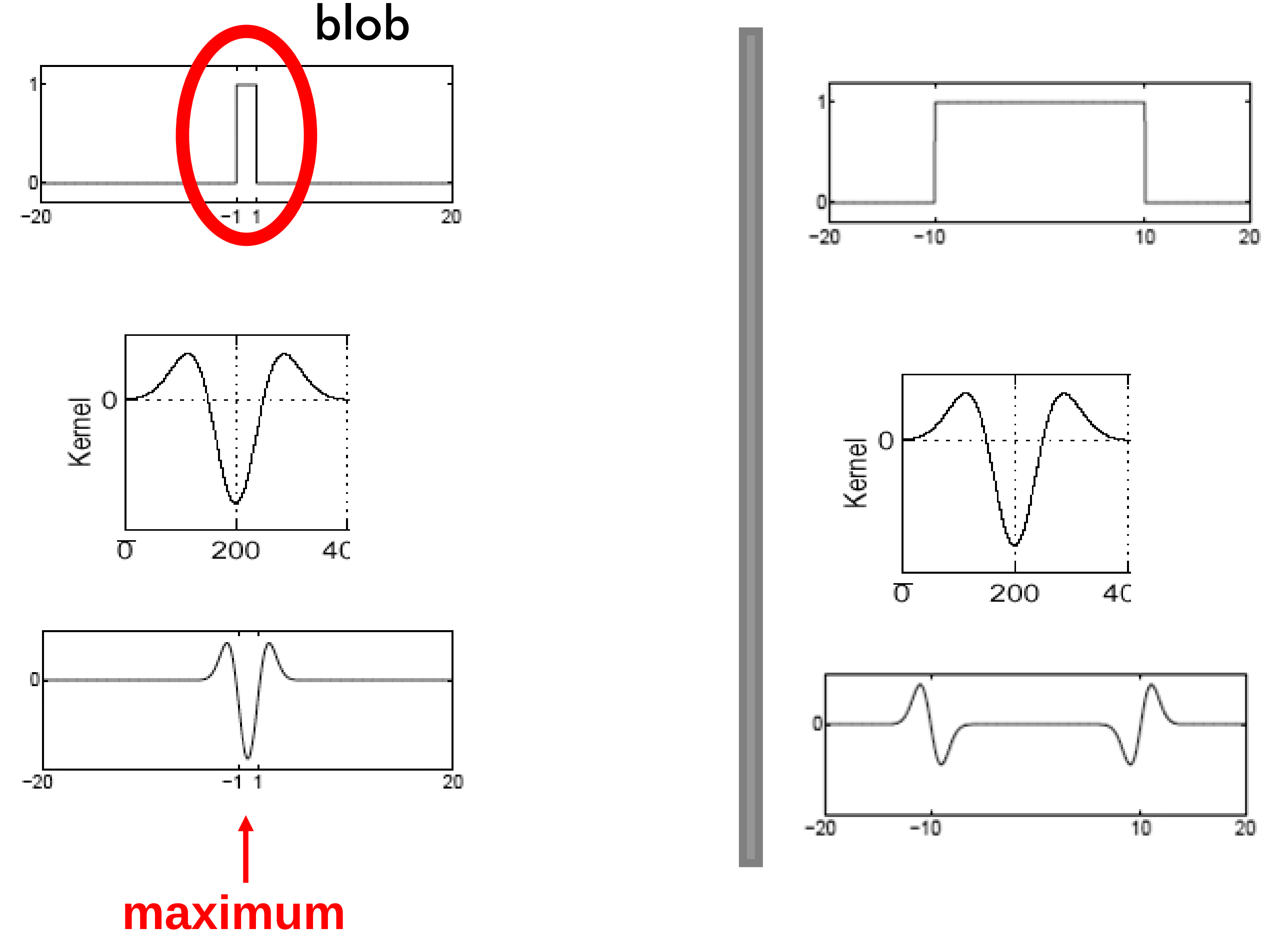






From edges to blobs

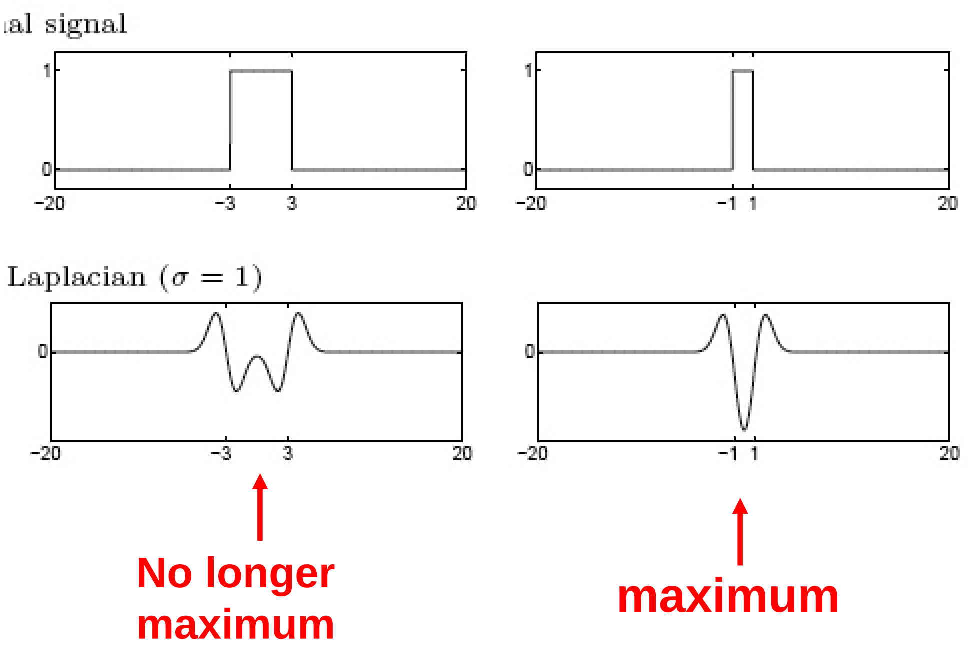
- Blob = superposition of nearby edges



Ok, great, but what if the blob is slightly thicker or slimmer?

From edges to blobs

- Blob = superposition of nearby edges

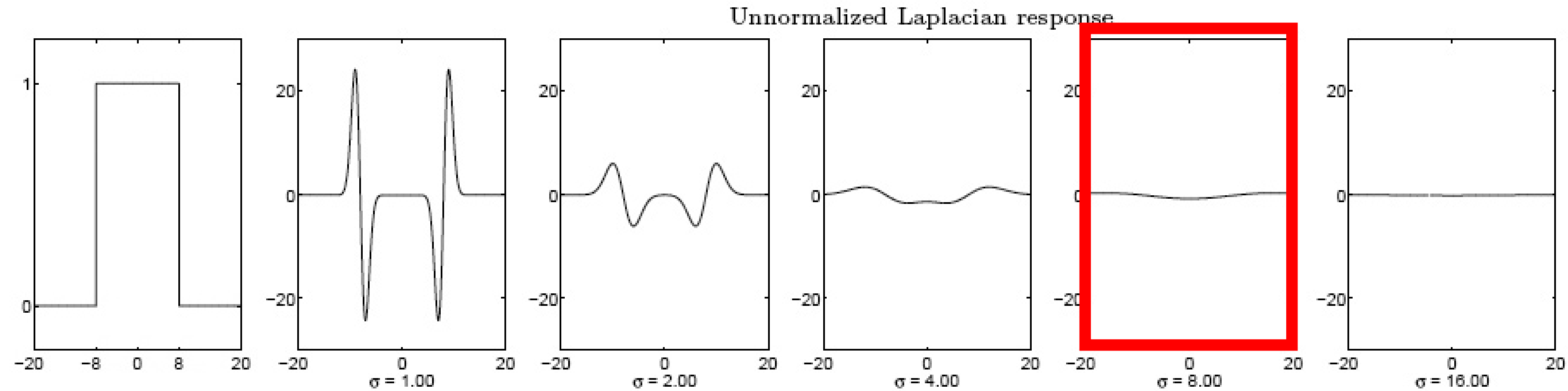


Spatial selection: magnitude of the Laplacian response will achieve a maximum at the center of the blob, provided the scale of the Laplacian is "matched" to the scale of the blob

Scale selection

- We want to find the characteristic scale of the blob by convolving it with Laplacians at several scales and looking for the maximum response

- However, Laplacian response decays as scale increases:



original signal (radius=8)

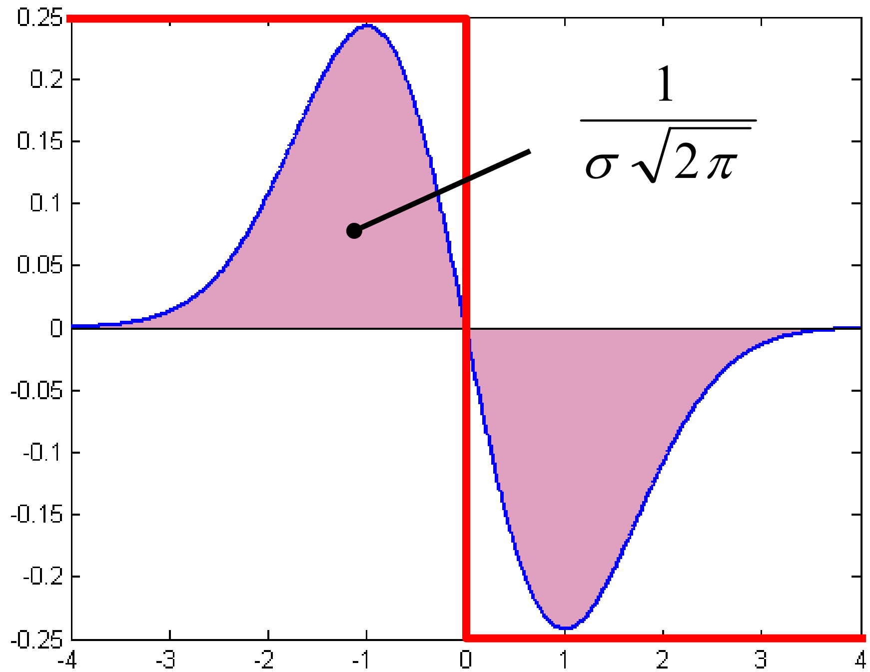
increasing σ →

This should give the max response ☹

Why does this happen?

Scale normalization

- The response of a derivative of Gaussian filter to a perfect step edge decreases as σ increases

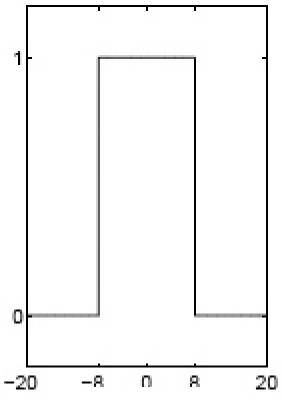


Scale normalization

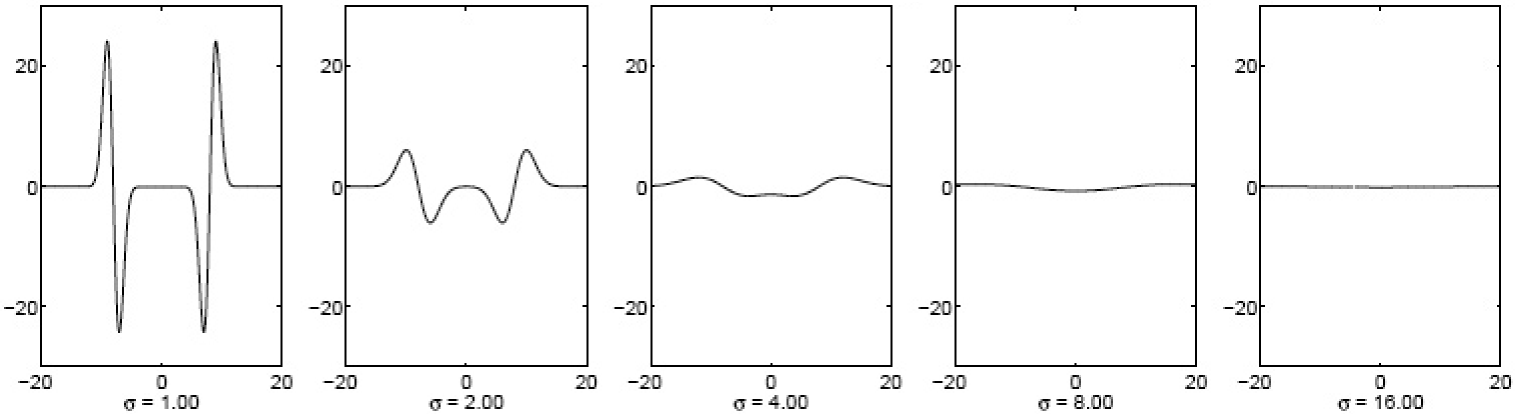
- To keep response the same (scale-invariant), must multiply Gaussian derivative by σ
- Laplacian is the second Gaussian derivative, so it must be multiplied by σ^2

Effect of scale normalization

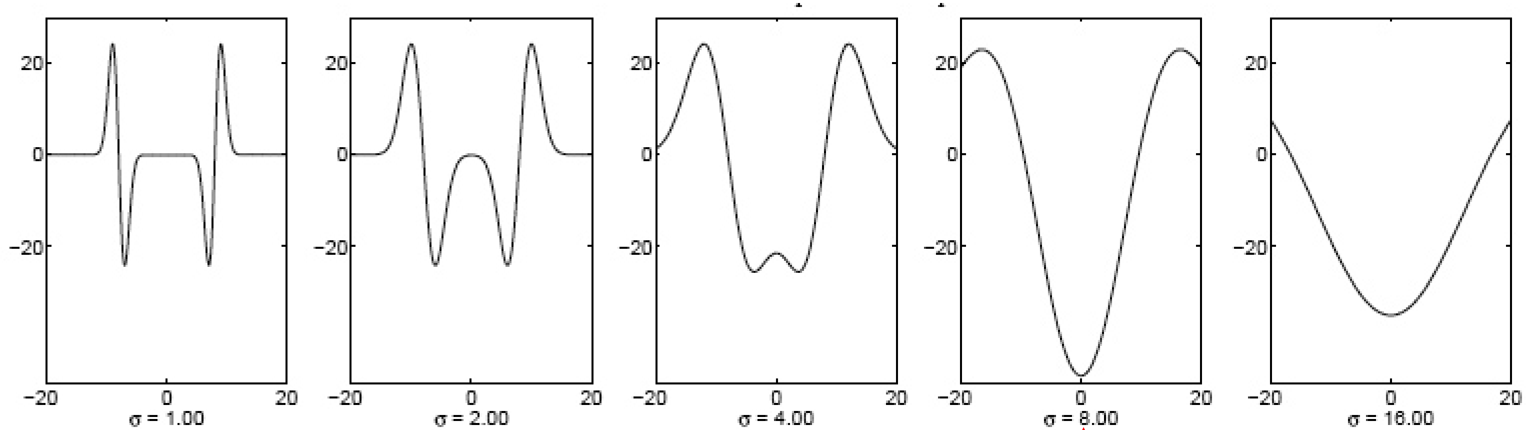
Original signal



Unnormalized Laplacian response



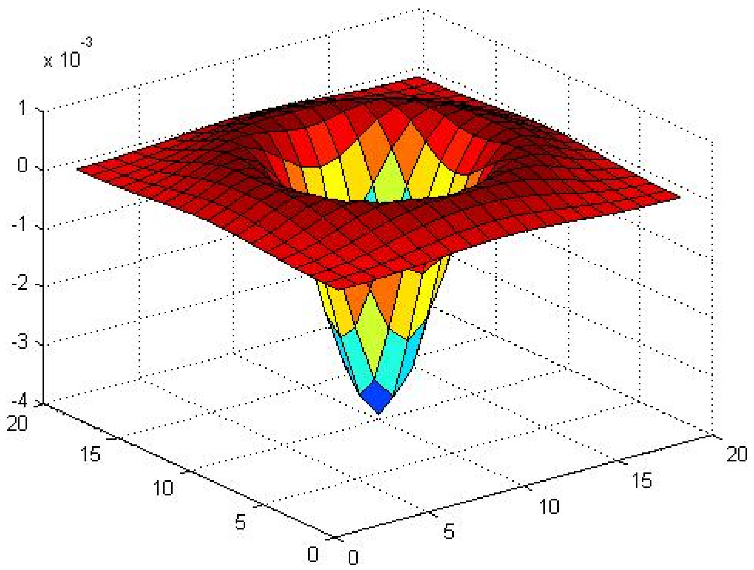
Scale-normalized Laplacian response

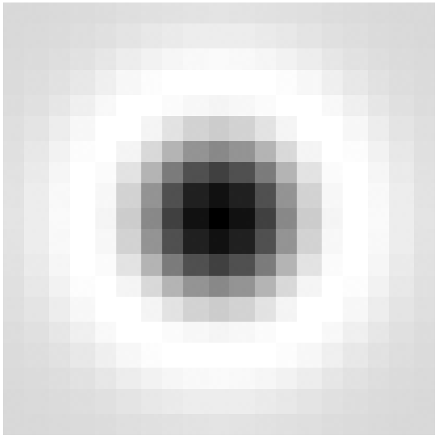


Maximum ☺

Blob detection in 2D

- Laplacian of Gaussian: Circularly symmetric operator for blob detection in 2D

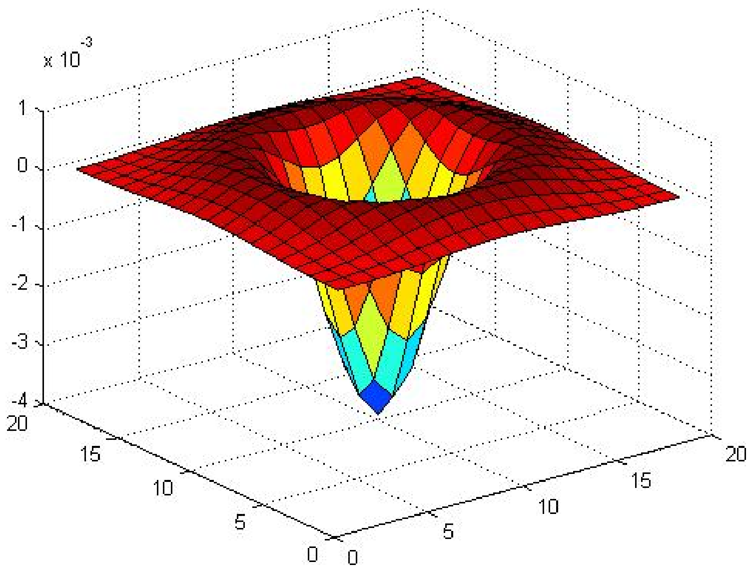


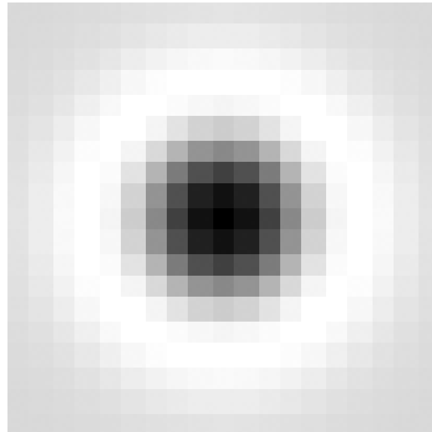


$$\nabla^2 g = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2}$$

Blob detection in 2D

- Laplacian of Gaussian: Circularly symmetric operator for blob detection in 2D

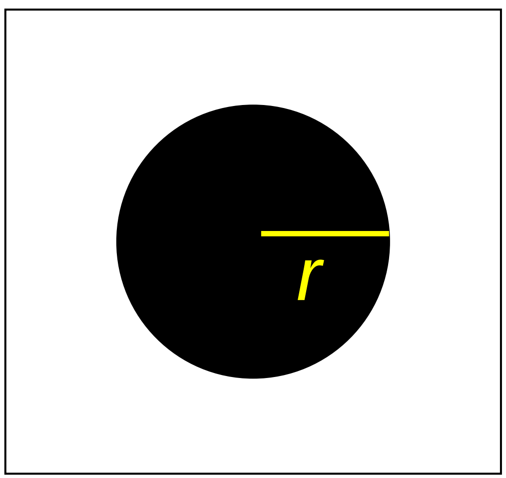




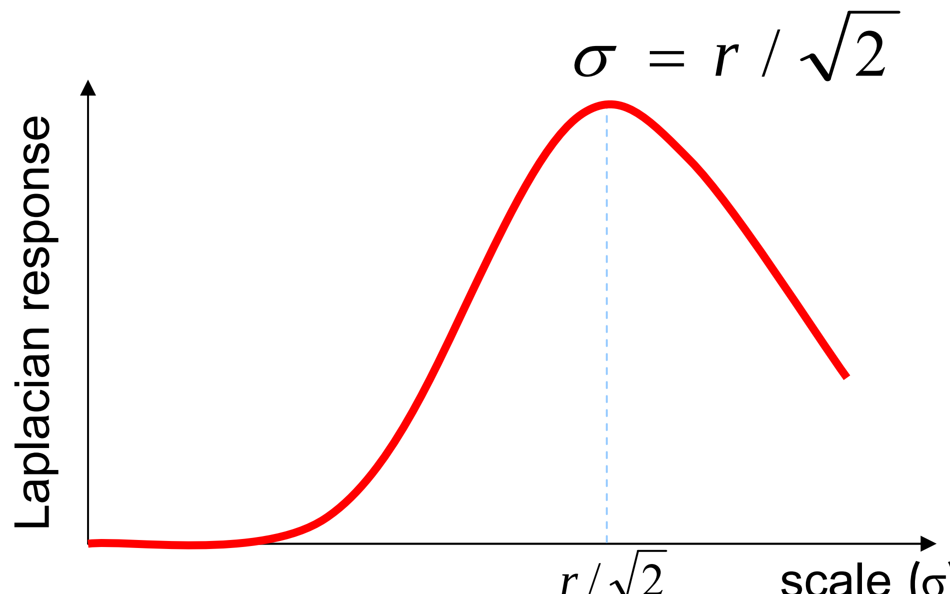
Scale-normalized: $$\nabla^2_{\text{norm}} g = \sigma^2 \left(\frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2} \right)$$

Scale selection

- For a binary circle of radius r, the Laplacian achieves a maximum at

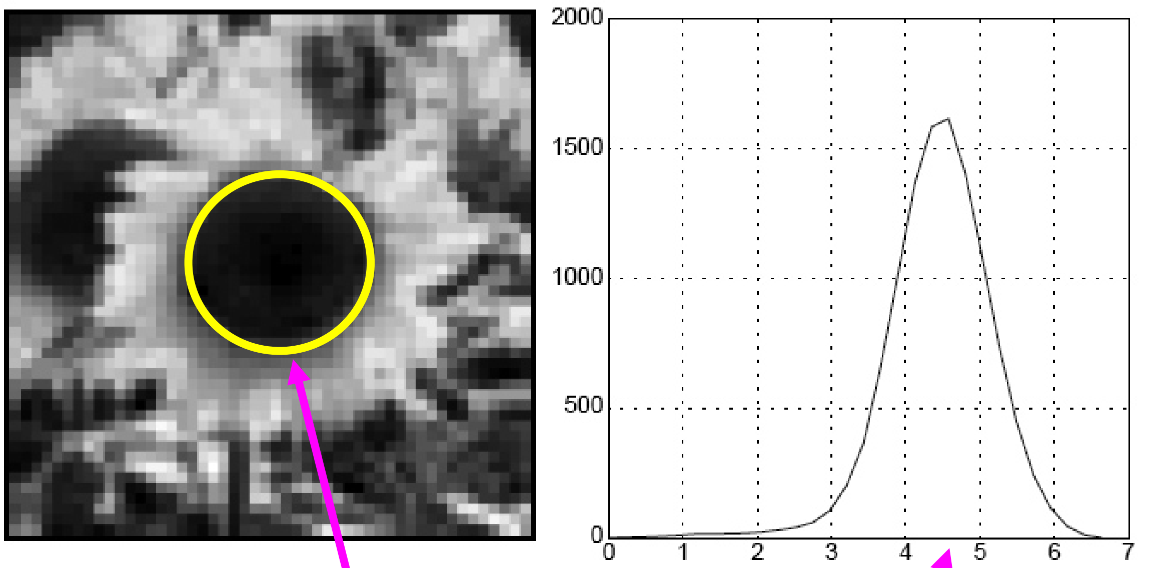


image



Characteristic scale

- We define the characteristic scale as the scale that produces peak of Laplacian response

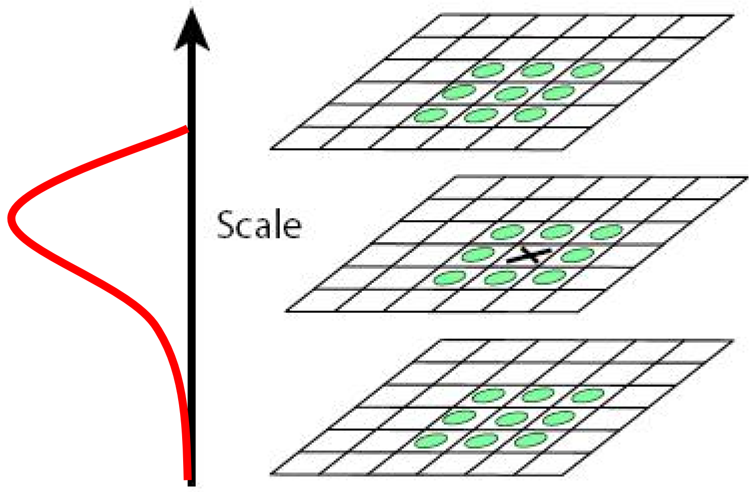


characteristic scale

T. Lindeberg (1998). "Feature detection with automatic scale selection." *International Journal of Computer Vision* **30** (2): pp 77--116.

Scale-space blob detector

1. Convolve image with scale-normalized Laplacian at several scales
2. Find maxima of squared Laplacian response in scale-space

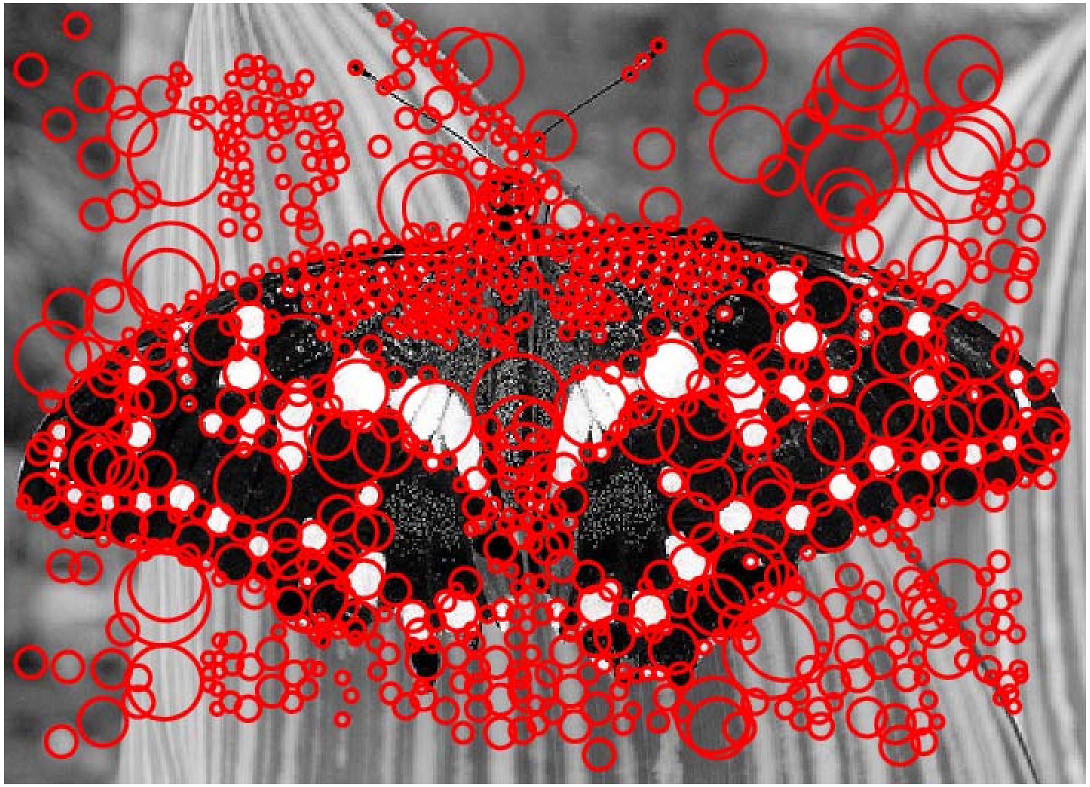


Scale-space blob detector: Example

Scale-space blob detector: Example

sigma = 11.9912

Scale-space blob detector: Example



DOG

David G. Lowe. "Distinctive image features from scale-invariant keypoints." *IJCV* 60 (2), 04

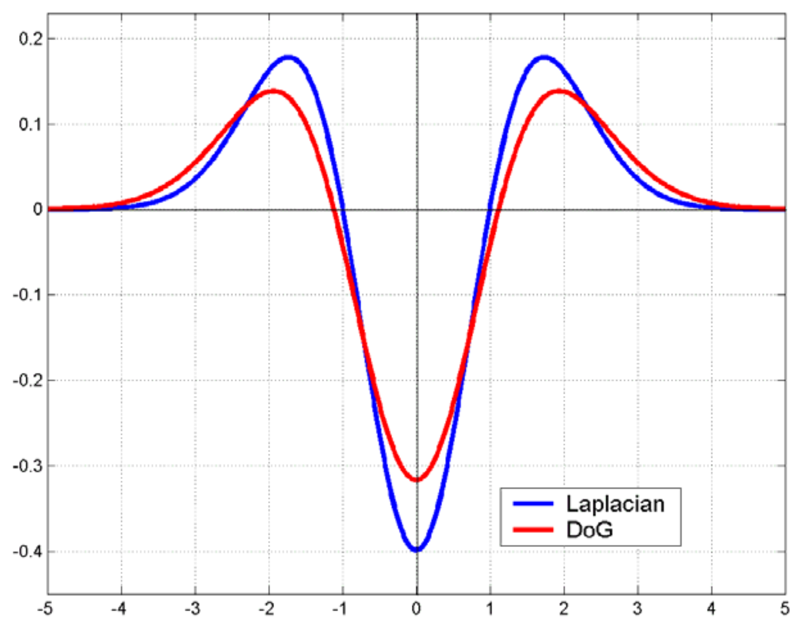
- Approximating the Laplacian with a difference of Gaussians:

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

(Laplacian)

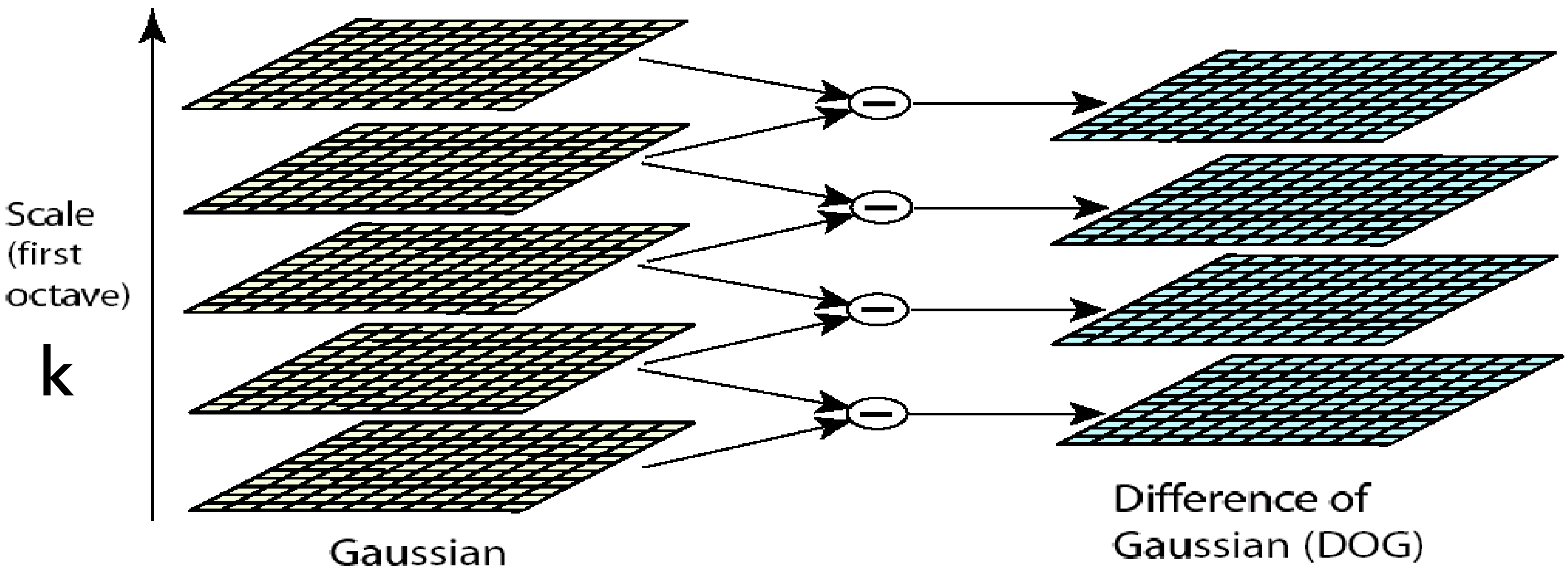
$$DoG = G(x, y, k\sigma) - G(x, y, \sigma)$$

(Difference of Gaussians)



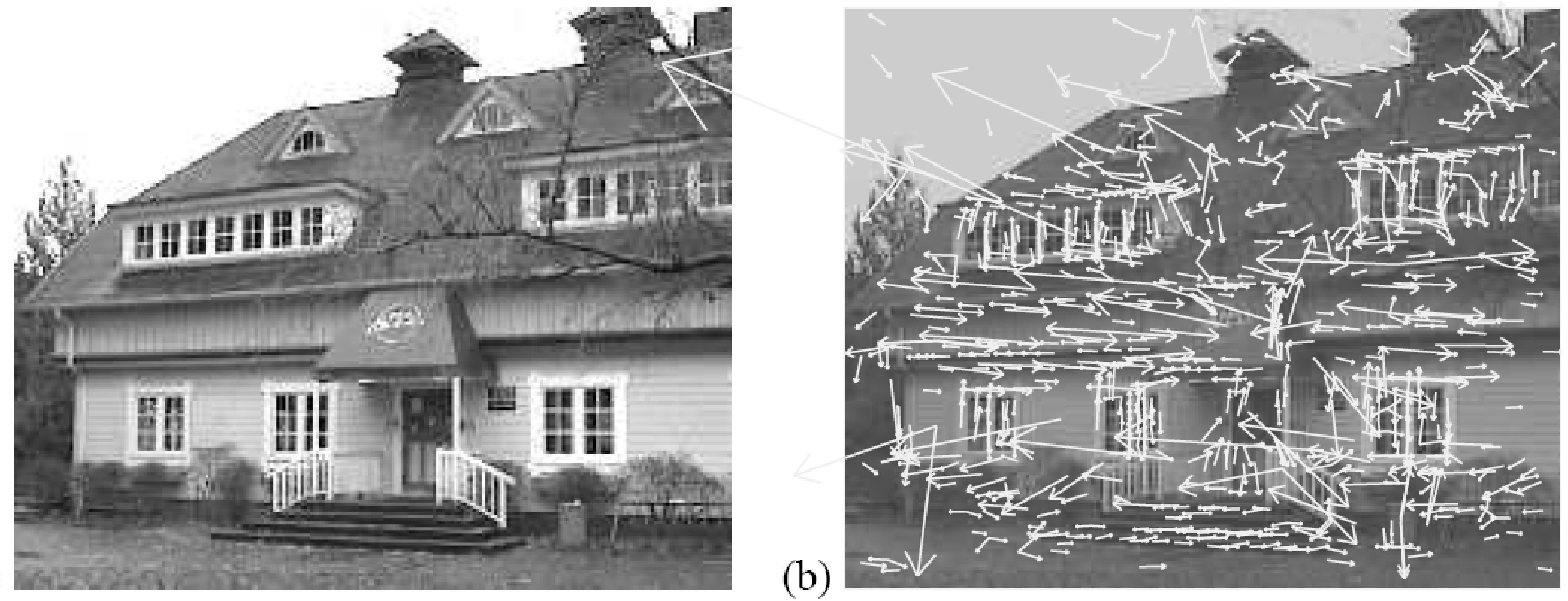
$$G(x, y, k\sigma) - G(x, y, \sigma) \approx (k-1)\sigma^2 \boldsymbol{L}$$

DOG



Output: location, scale, orientation (more later)

Example of keypoint detection



(b)

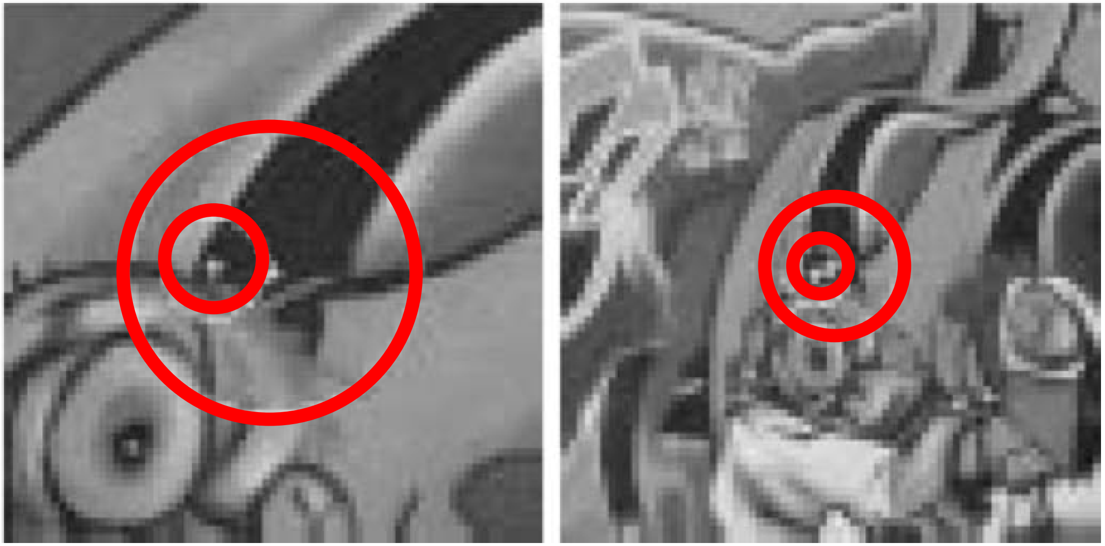
Invariance

Detector	Illumination	Rotation	Scale	View point
Harris corner	Yes	Yes	No	No
Lowe ’99 (DoG)	Yes	Yes	Yes	No

Harris-Laplace

[Mikolajczyk & Schmid '01]

- Collect locations (x,y) of detected Harris features for $\sigma = \sigma_1 \ldots \sigma_2$ (the sigma is here comes from $g_{x,}$ g_y)
- For each detected location (x,y) and for each σ, reject detection if Laplacian(x,y, σ) is not a local maximum



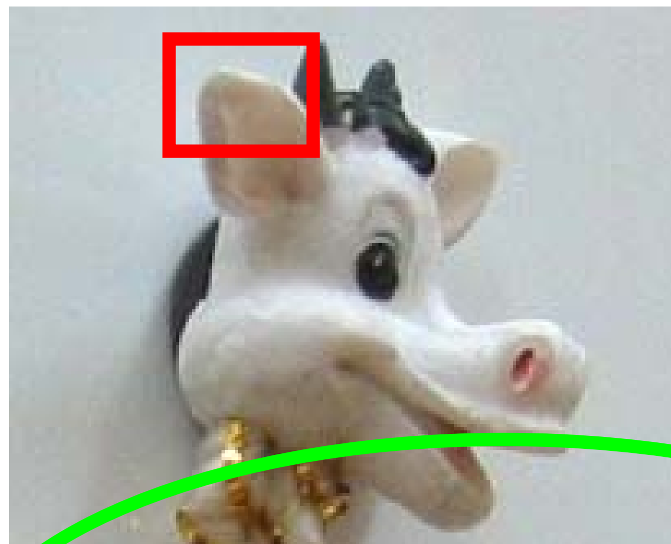
Output: location, scale

Invariance

Detector	Illumination	Rotation	Scale	View point
Harris corner	Yes	Yes	No	No
Lowe '99 (DoG)	Yes	Yes	Yes	No
Mikolajczyk & Schmid '01	Yes	Yes	Yes	No

Repeatability

Illumination invariance



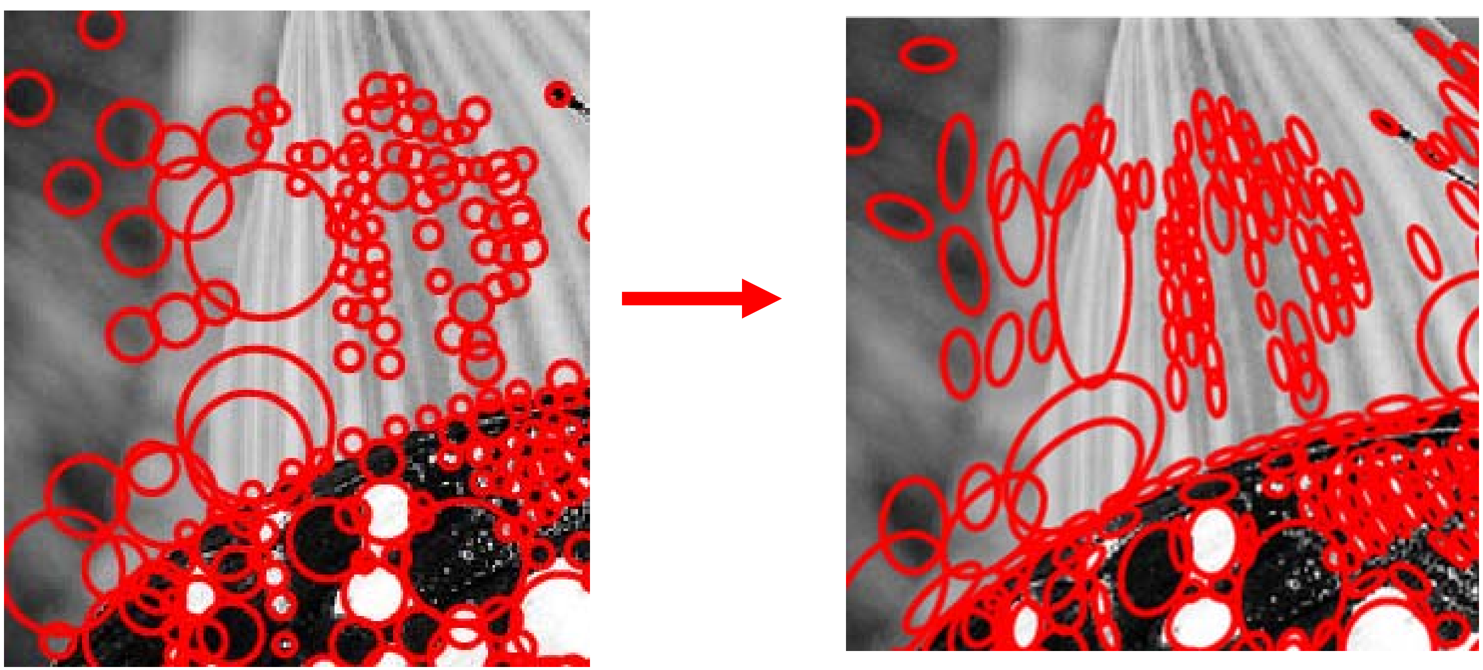
Scale invariance

Pose invariance
- Rotation
- Affine

Affine invariance

K. Mikolajczyk and C. Schmid, Scale and Affine invariant interest point detectors, IJCV 60(1):63-86, 2004.

Similarly to characteristic scale selection, detect the characteristic shape of the local feature



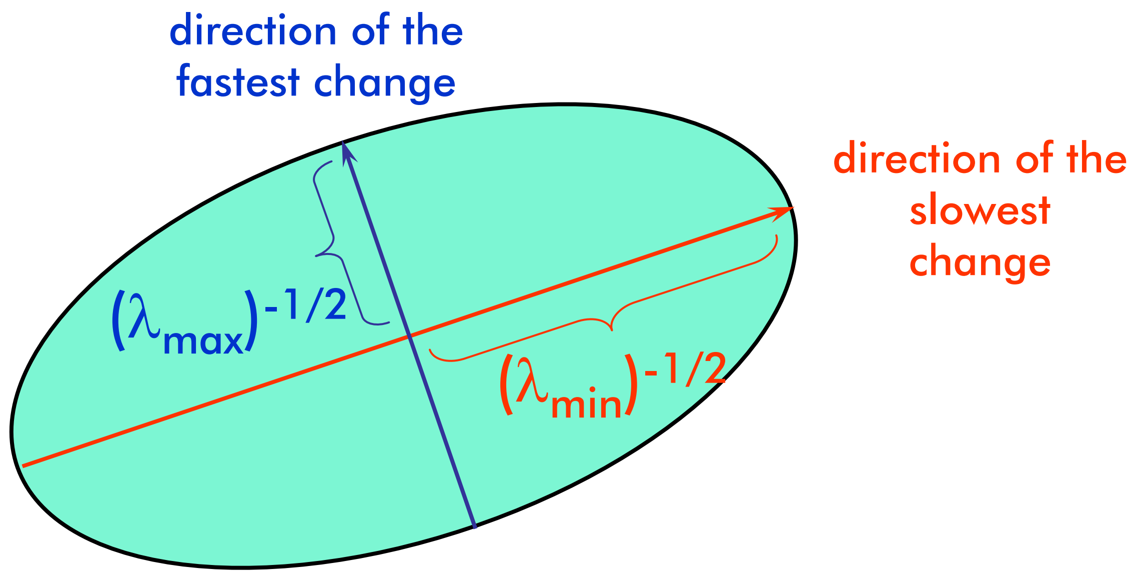
Affine adaptation

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} = R^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$$

We can visualize *M* as an ellipse with axis lengths determined by the eigenvalues and orientation determined by *R*

Ellipse equation:

$$[u \;\; v] \;\; M \begin{bmatrix} u \\ v \end{bmatrix} = \text{const}$$

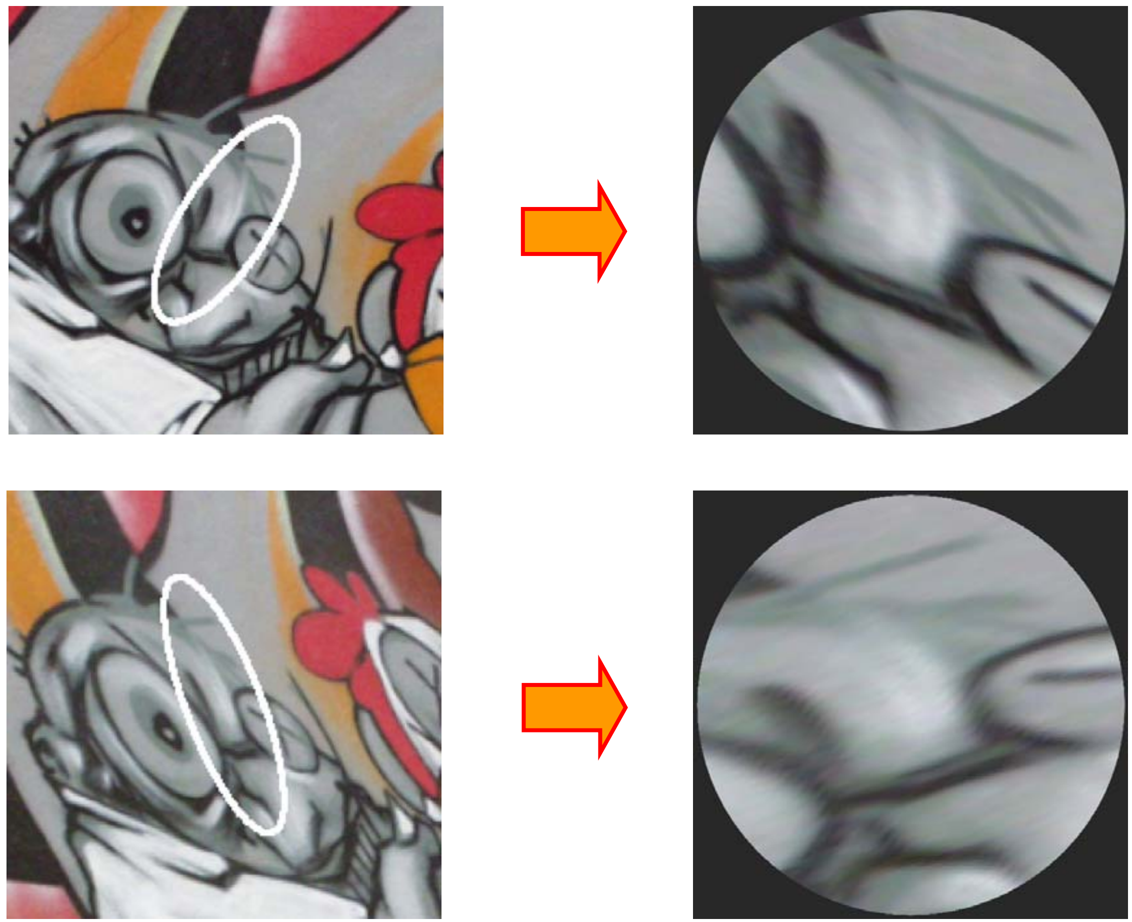


The second moment ellipse can be viewed as the "characteristic shape" of a region

Affine adaptation

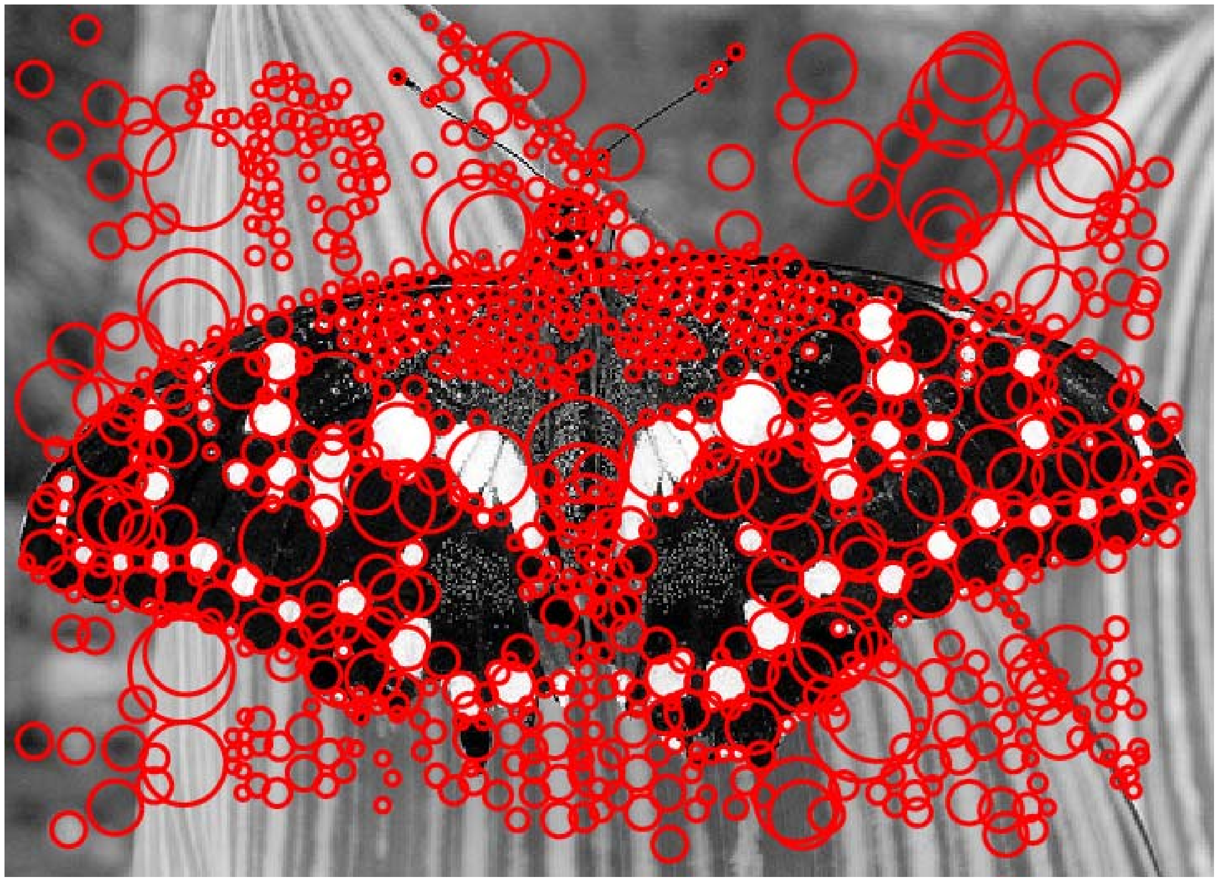
1. Detect initial region with Harris Laplace
2. Estimate affine shape with M
3. Normalize the affine region to a circular one
4. Re-detect the new location and scale in the normalized image
5. Go to step 2 if the eigenvalues of the M for the new point are not equal [detector not yet adapted to the characteristic shape]

Affine adaptation



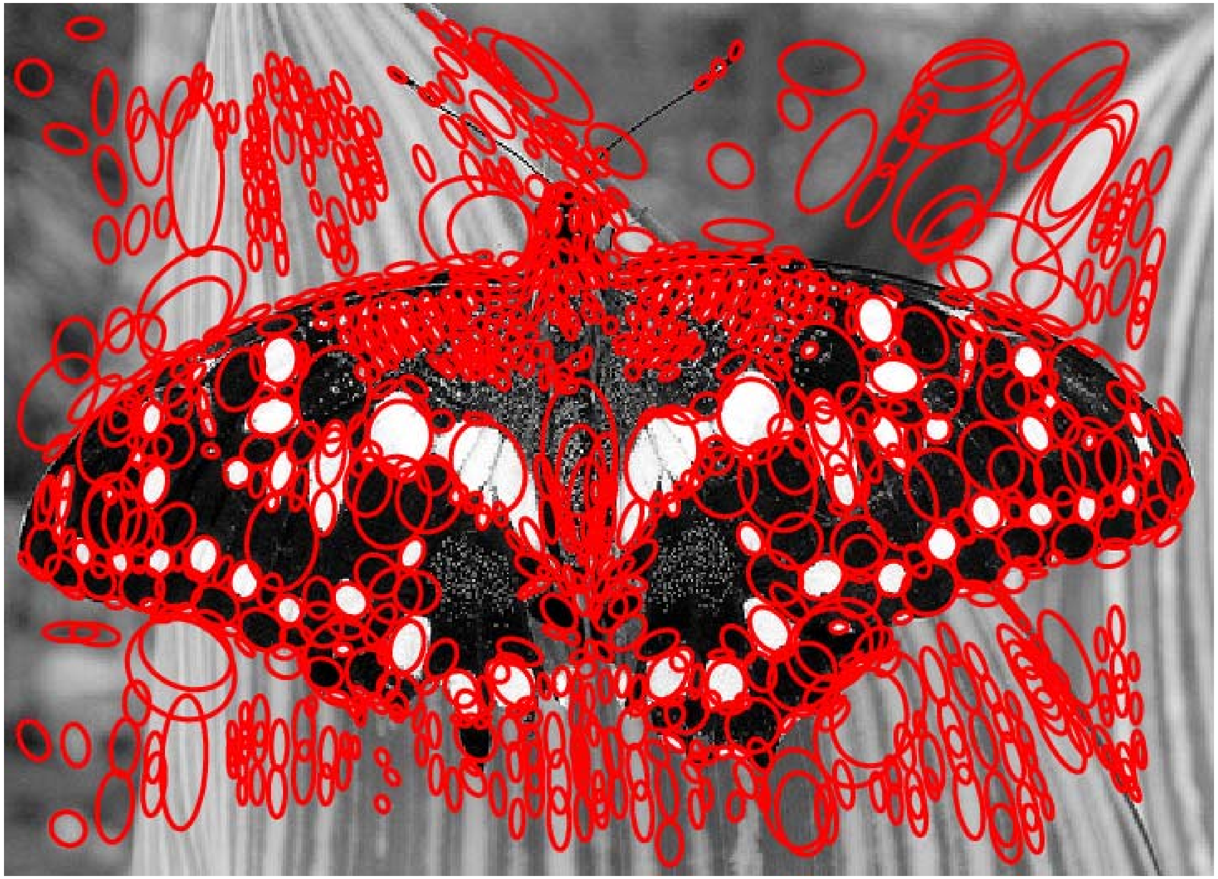
Output: location, scale, affine shape, rotation (more later)

Affine adaptation example



Scale-invariant regions (blobs)

Affine adaptation example



Affine-adapted blobs

Invariance

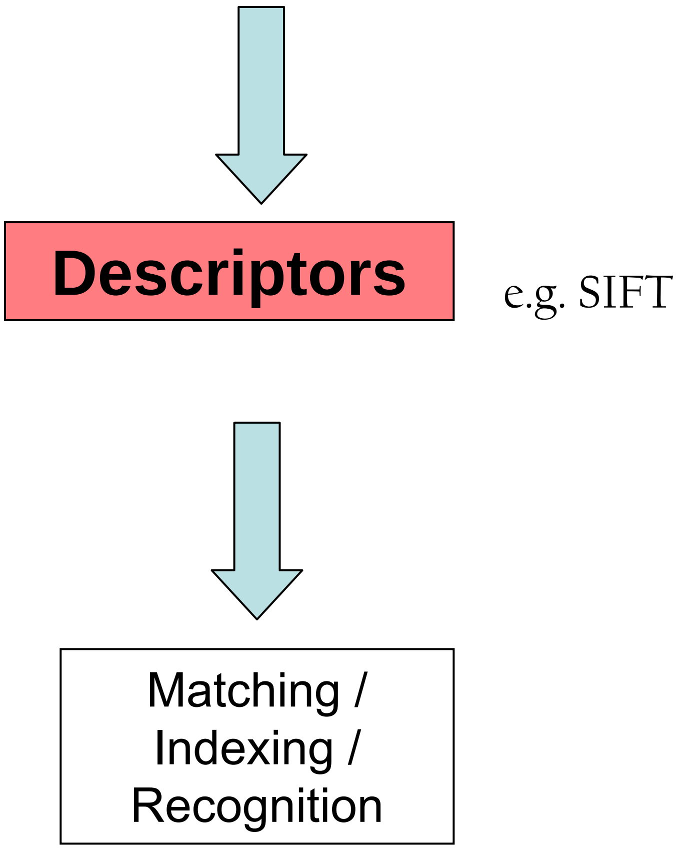
Detector	Illumination	Rotation	Scale	View point
Harris corner	Yes	Yes	No	No
Lowe '99 (DoG)	Yes	Yes	Yes	No
Mikolajczyk & Schmid '01	Yes	Yes	Yes	No
Mikolajczyk & Schmid '02	Yes	Yes	Yes	Yes

Detector	Illumination	Rotation	Scale	View point
Harris corner	Yes	Yes	No	No
Lowe '99 (DoG)	Yes	Yes	Yes	Yes
Mikolajczyk & Schmid '01, '02	Yes	Yes	Yes	Yes
Tuytelaars, '00	Yes	Yes	No (Yes '04)	Yes
Kadir & Brady, 01	Yes	Yes	Yes	no
Matas, '02	Yes	Yes	Yes	no

- Blob detectors
- Invariance
- Descriptors

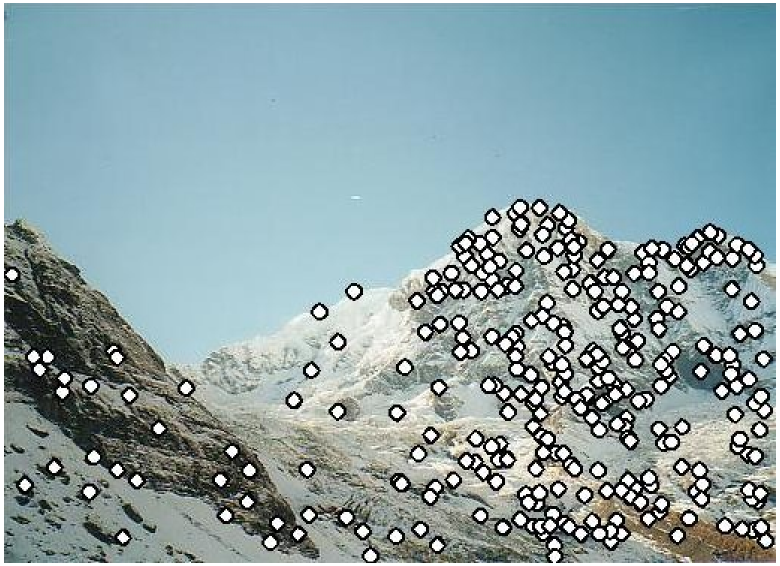
Goal:

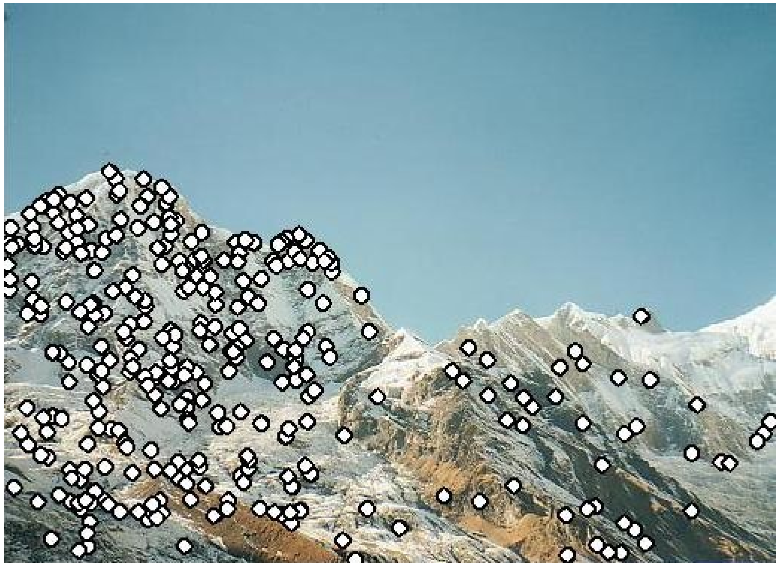
Identify interesting regions from the images (edges, corners, blobs…)



Matching Features
(stitching images)

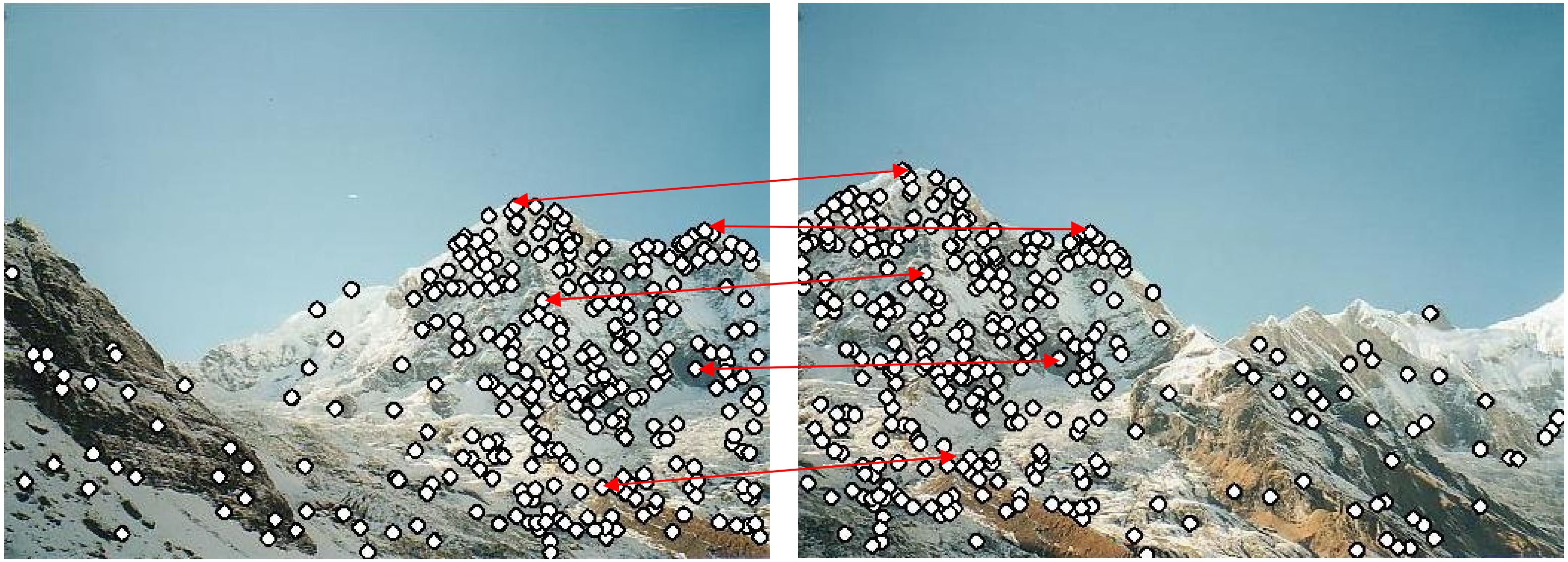
- Detect feature points in both images





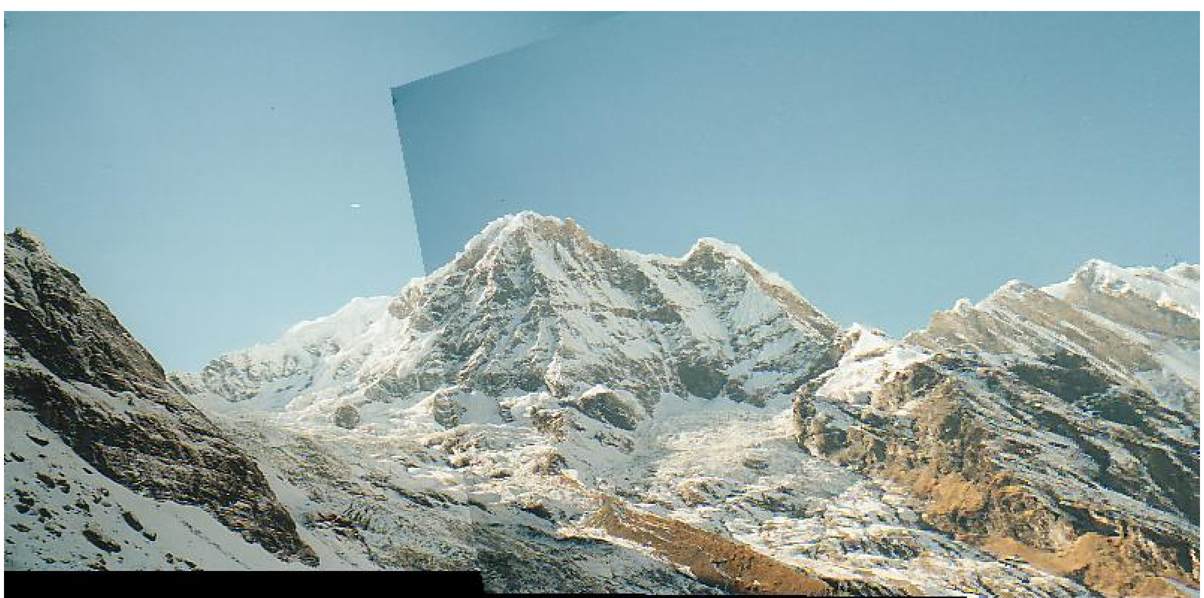
Matching Features
(stitching images)

- Detect feature points in both images
- Find corresponding pairs



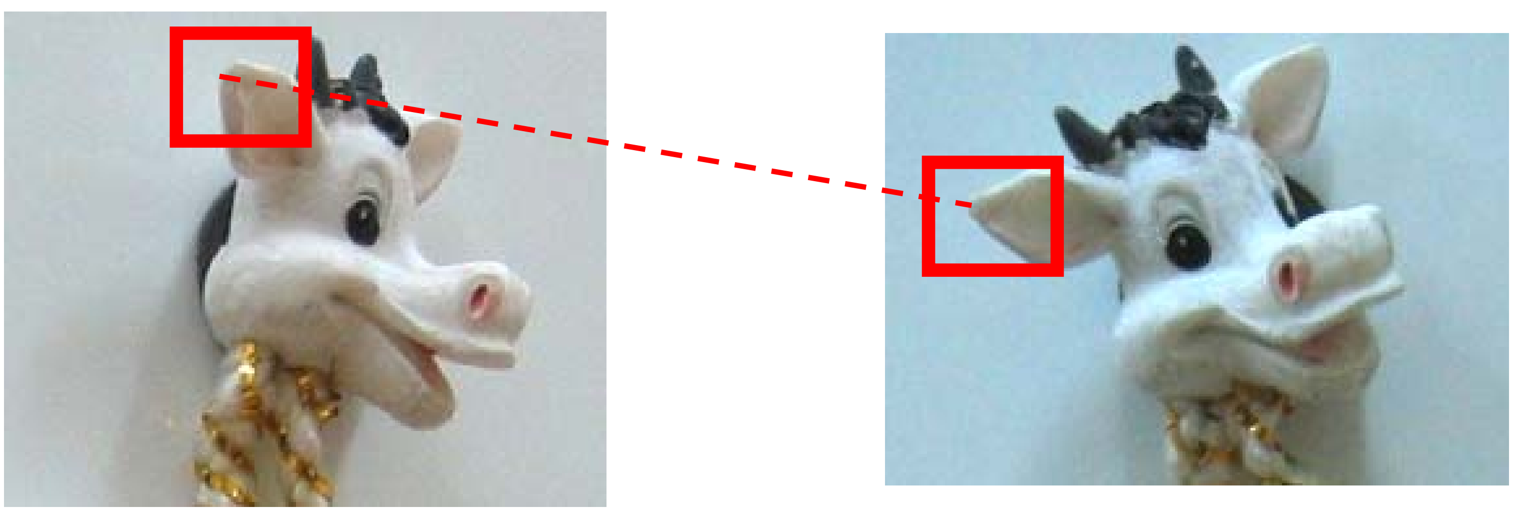
Matching Features
(stitching images)

- Detect feature points in both images
- Find corresponding pairs
- Use these pairs to align images



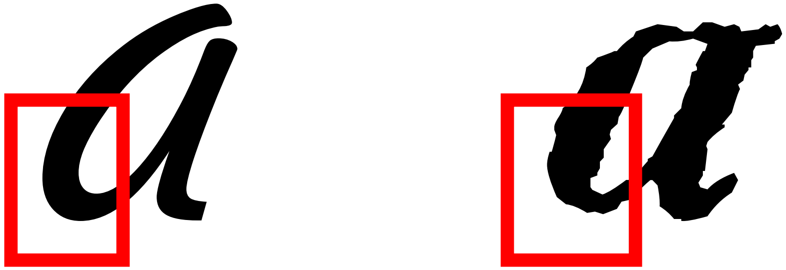
Matching Features
(estimating F)

- Detect feature points in both images
- Find corresponding pairs
- Use these pairs to estimate F



Matching Features
(recognizing objects)

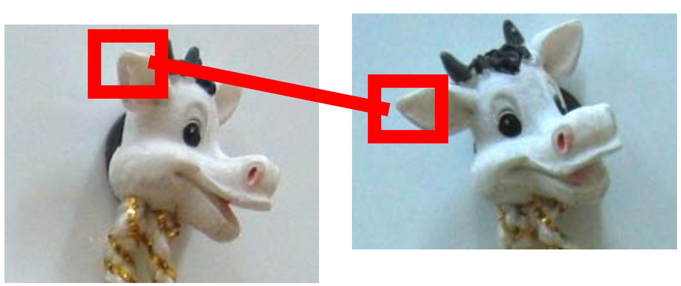
- Detect feature points in both images
- Find corresponding pairs
- Use these pairs to match different object instances

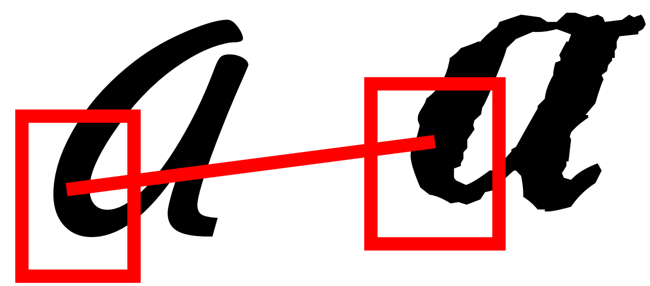


Challenges

Depending on the application a descriptor must incorporate information that is:

- Invariant w.r.t:
  - Illumination
  - Pose
  - Scale
  - Intraclass variability



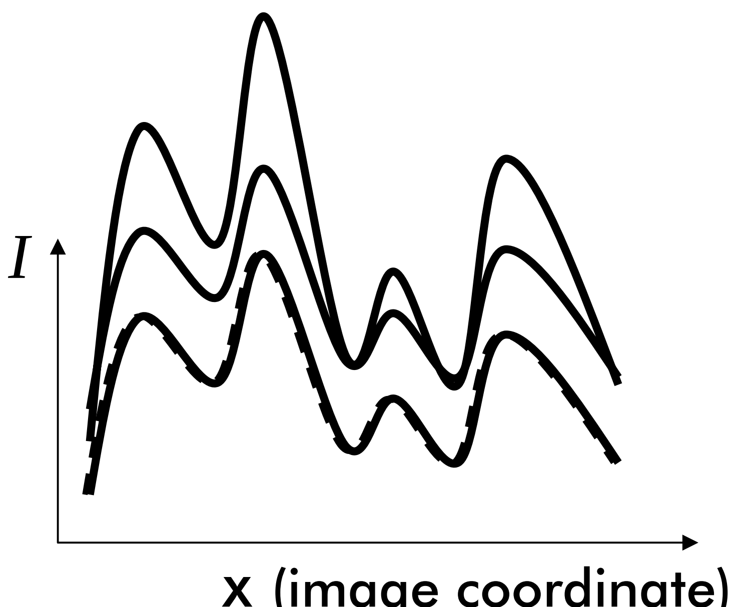


- **Highly distinctive** (allows a single feature to find its correct match with good probability in a large database of features)

Illumination normalization

- *Affine intensity* change:

$$\mathrm{I} \rightarrow \mathrm{I} + \mathrm{b}$$
$$\rightarrow \mathrm{a}\,\mathrm{I} + \mathrm{b}$$



- Make each patch zero mean:

$$\mu = \frac{1}{N}\sum_{x,y} I(x,y)$$

$$Z(x,y) = I(x,y) - \mu$$

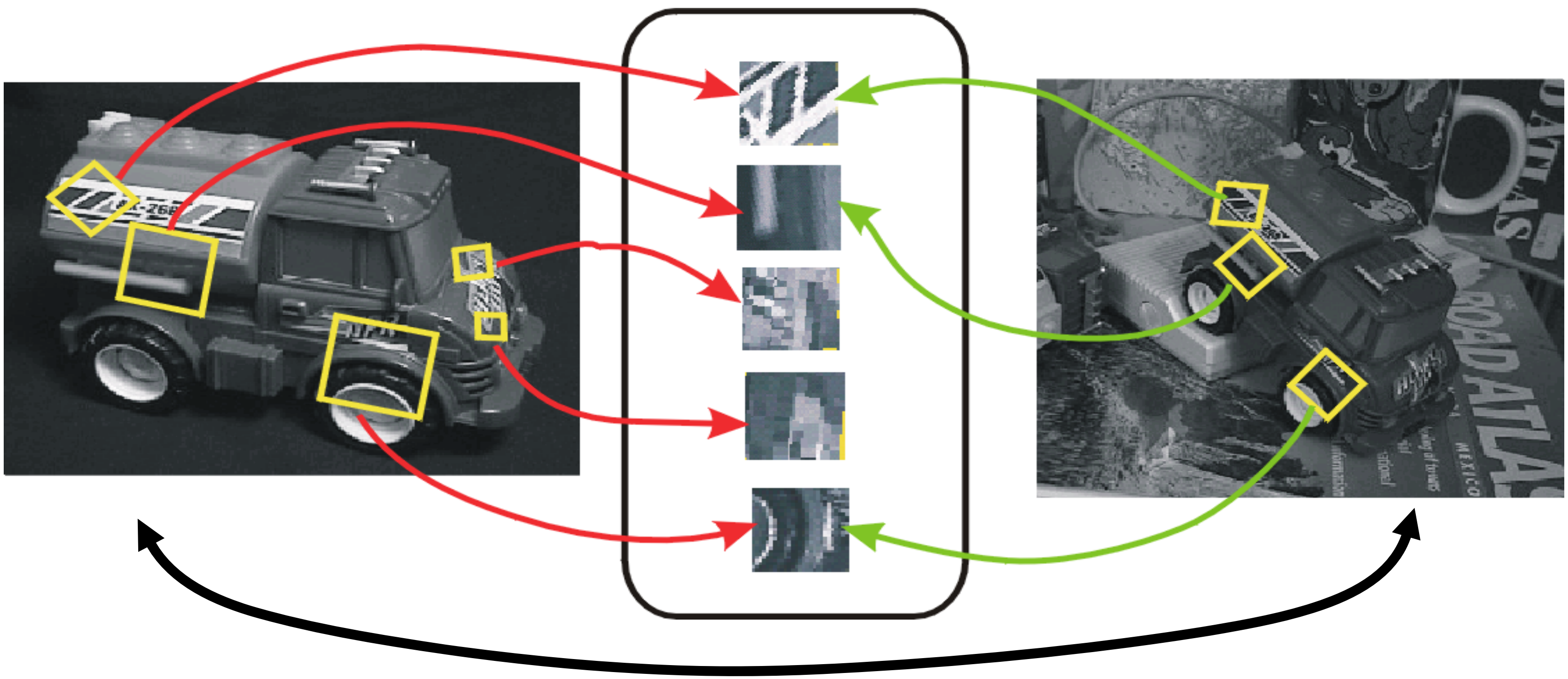
- Then make unit variance:

$$\sigma^2 = \frac{1}{N}\sum_{x,y} Z(x,y)^2$$

$$ZN(x,y) = \frac{Z(x,y)}{\sigma}$$

Pose normalization

- Keypoints are transformed in order to be invariant to translation, rotation, scale, and other geometrical parameters

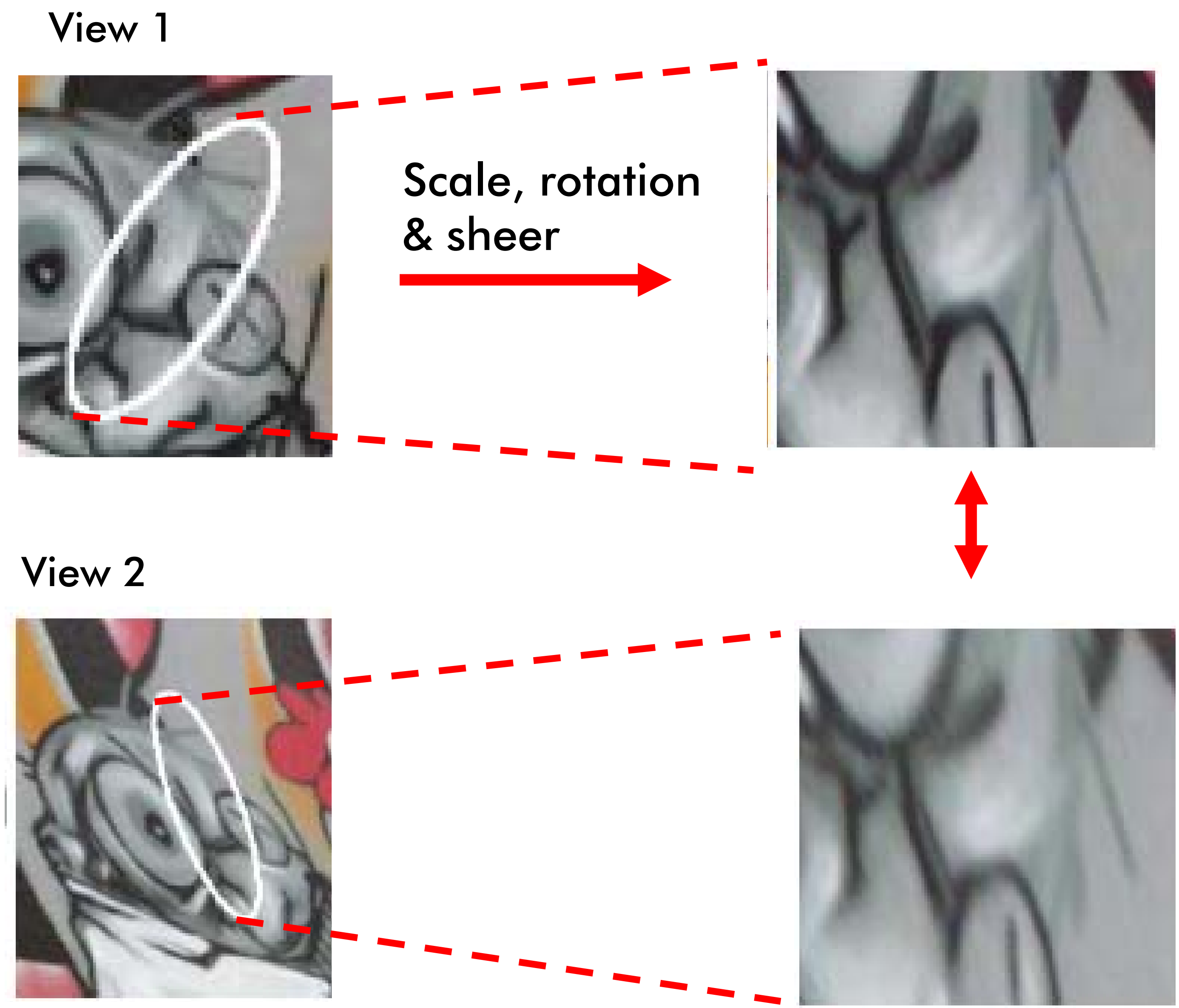


Courtesy of D. Lowe

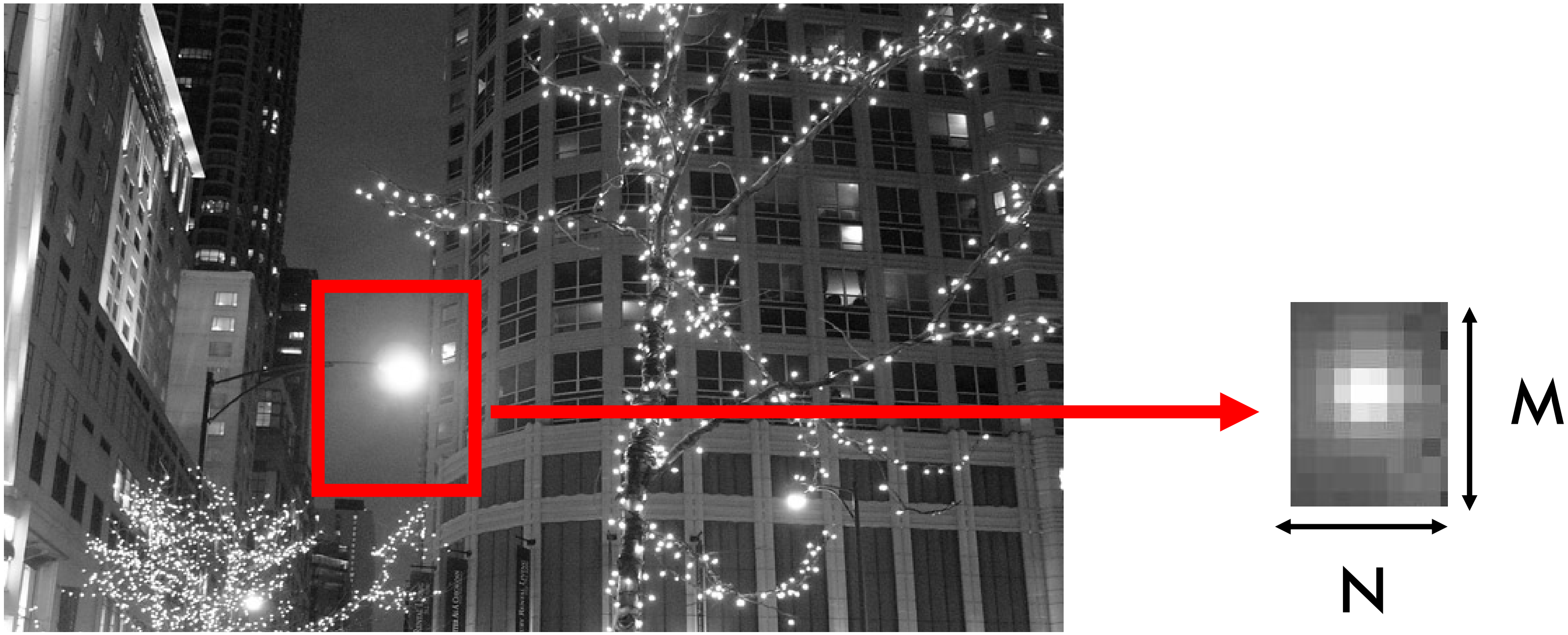
Change of scale, pose, illumination…

Pose normalization

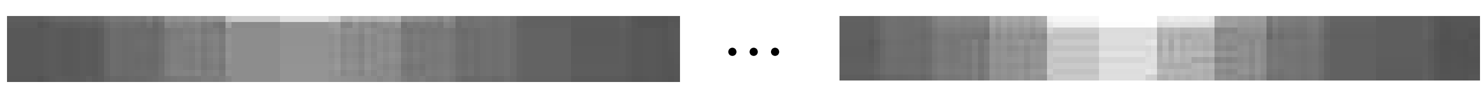
NOTE: location, scale, rotation & affine pose are given by the detector or calculated within the detected regions



The simplest descriptor



1 x NM vector of pixel intensities

w= []

$$w_n = \frac{(w - \overline{w})}{\left\| (w - \overline{w}) \right\|}$$

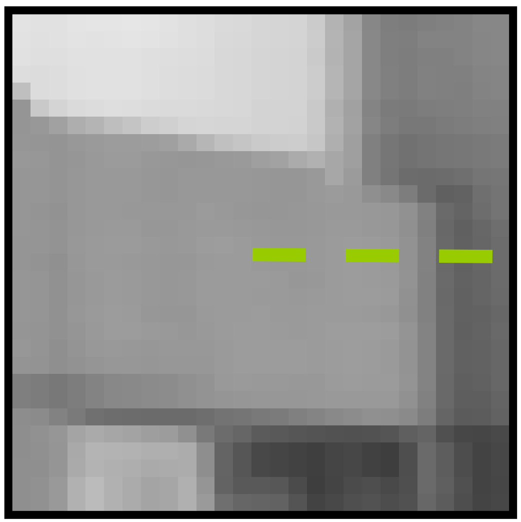
Makes the descriptor invariant with respect to affine transformation of the illumination condition

Why can’t we just use this?

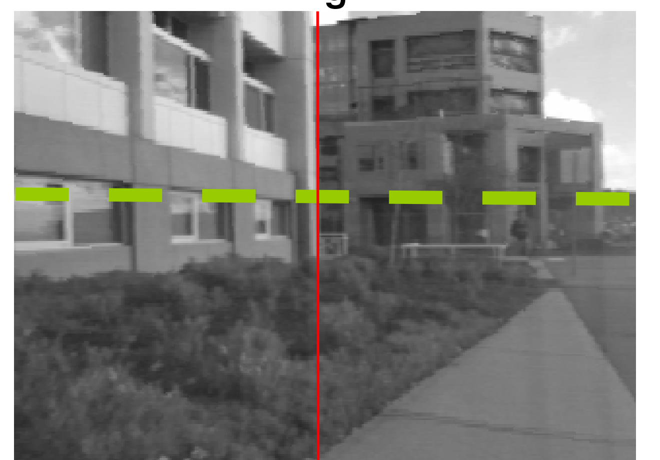
- Sensitive to small variation of:
  - location
  - Pose
  - Scale
  - intra-class variability

- Poorly distinctive

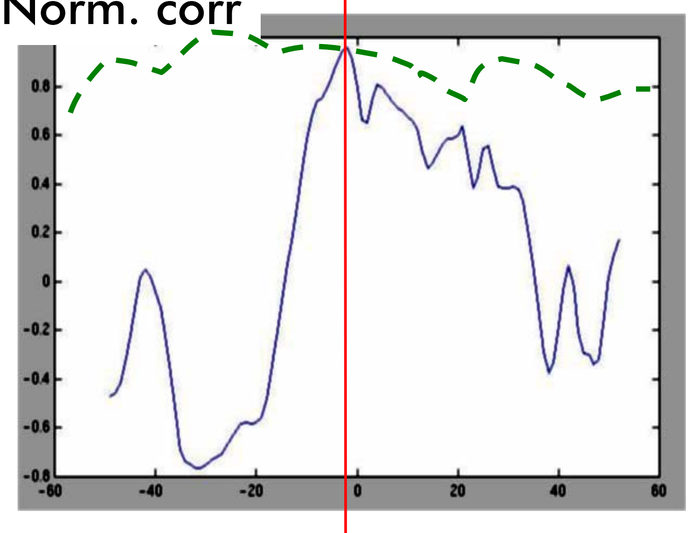
Stereo systems



Right



Norm. corr

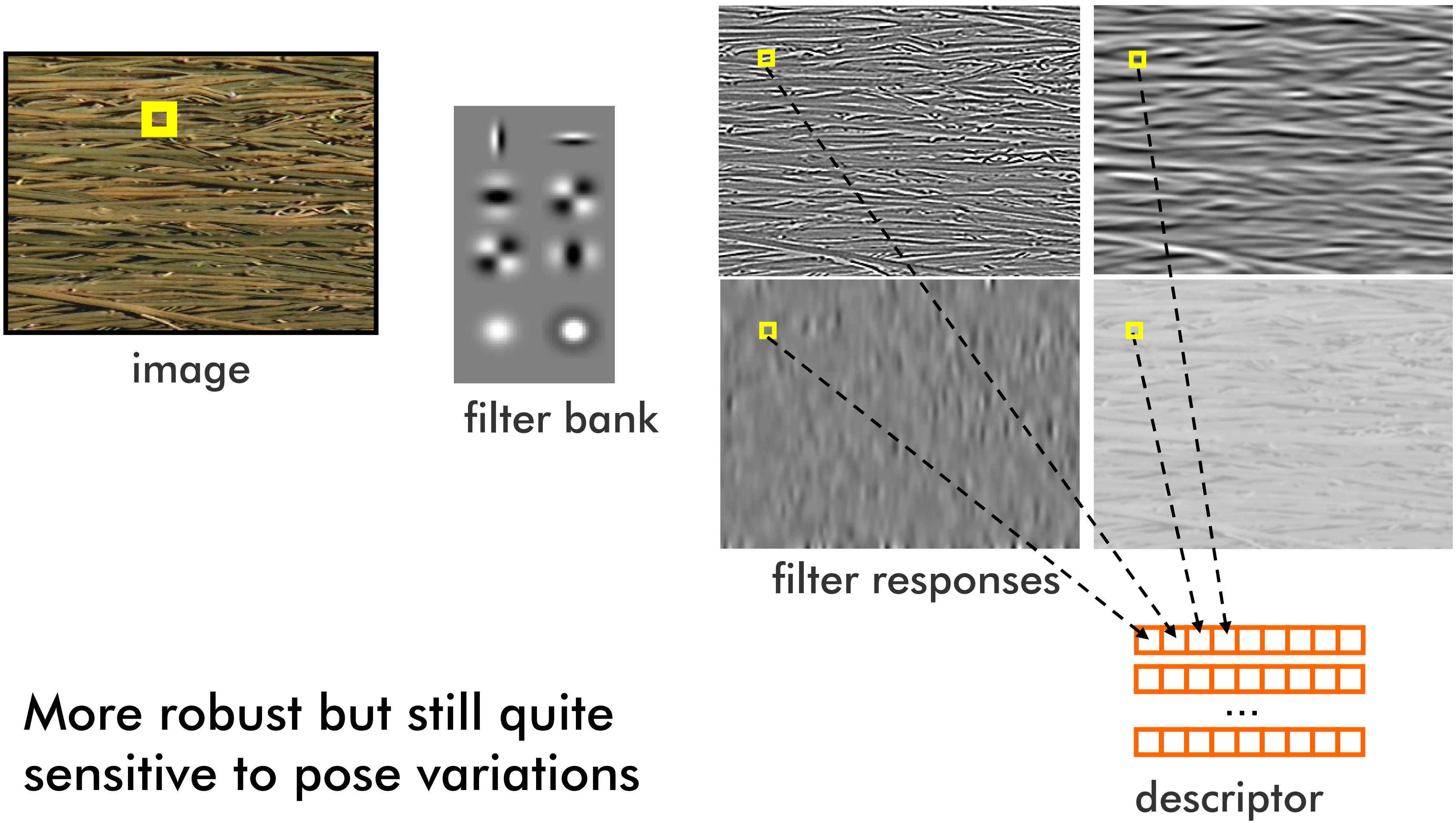


Normalized Correlation:

$$w_n \cdot w'_n = \frac{(w - \overline{w})(w' - \overline{w}')}{\left\|(w - \overline{w})(w' - \overline{w}')\right\|}$$

Detector	Illumination	Pose	Intra-class variab.
PATCH	***	*	*

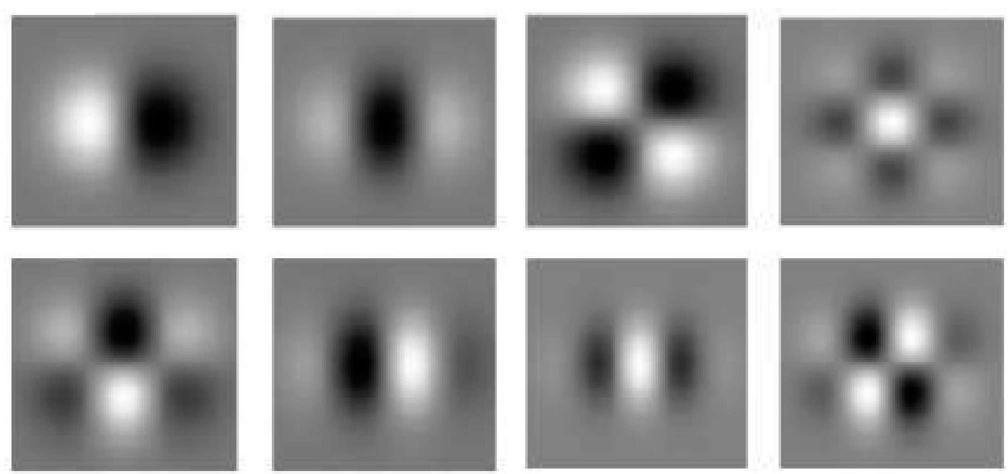
Bank of filters



More robust but still quite sensitive to pose variations

Bank of filters - Steerable filters

Gaussian derivatives up to 4^{th} order. The remaining derivatives can be computed by rotation of 90 degrees.

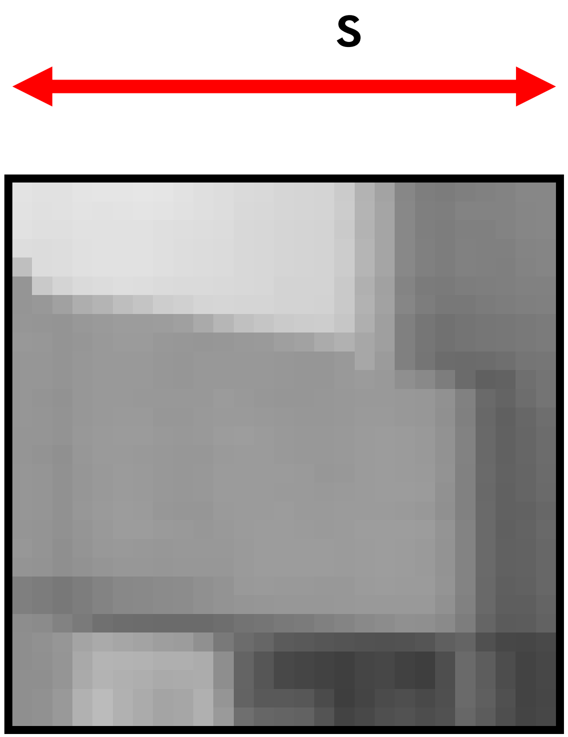


Detector	Illumination	Pose	Intra-class variab.
PATCH	***	*	*
FILTERS	***	**	**

SIFT descriptor

David G. Lowe. "Distinctive image features from scale-invariant keypoints." *IJCV* 60 (2), 04

- Alternative representation for image patches
- Location and characteristic scale s given by DoG detector

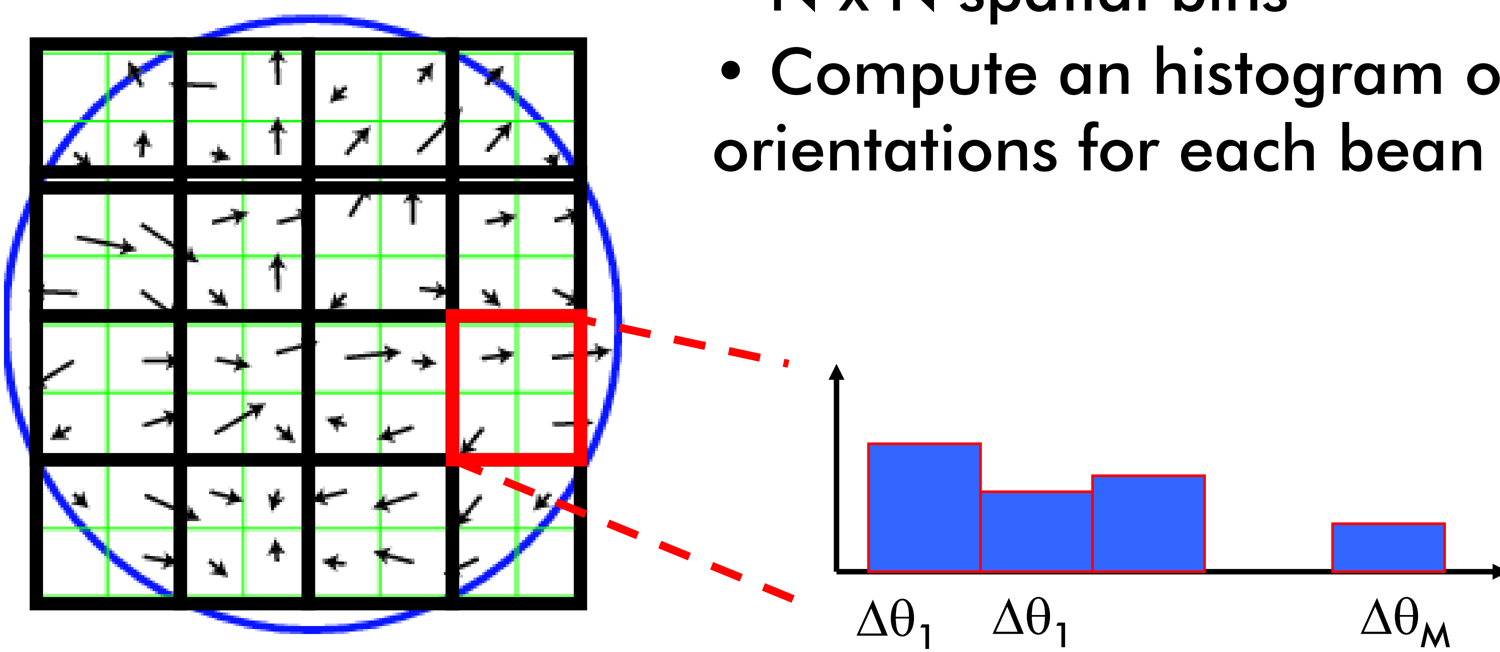


SIFT descriptor

David G. Lowe. "Distinctive image features from scale-invariant keypoints." *IJCV* 60 (2), 04

- Alternative representation for image patches
- Location and characteristic scale s given by DoG detector

- Compute gradient at each pixel
- N x N spatial bins
- Compute an histogram of M orientations for each bean

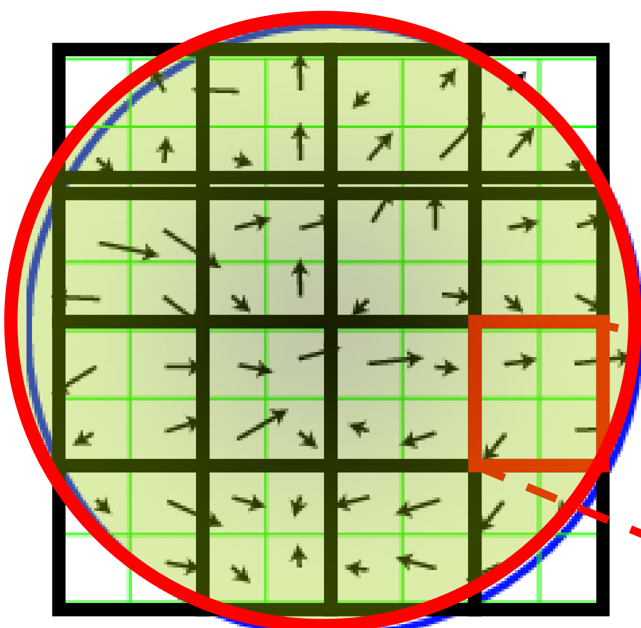


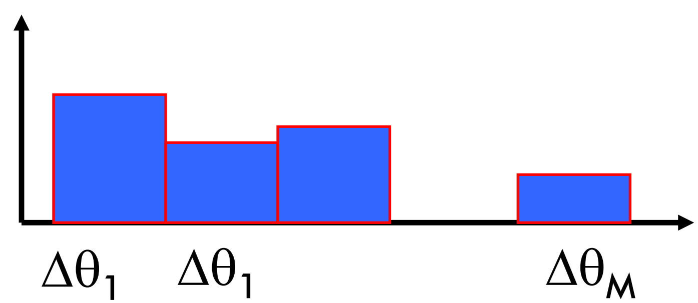
SIFT descriptor

David G. Lowe. "Distinctive image features from scale-invariant keypoints." *IJCV* 60 (2), 04

- Alternative representation for image patches
- Location and characteristic scale s given by DoG detector

- Compute gradient at each pixel
- N x N spatial bins
- Compute an histogram of M orientations for each bean
  - Gaussian center-weighting





SIFT descriptor

David G. Lowe. "Distinctive image features from scale-invariant keypoints." *IJCV* 60 (2), 04

- Alternative representation for image patches
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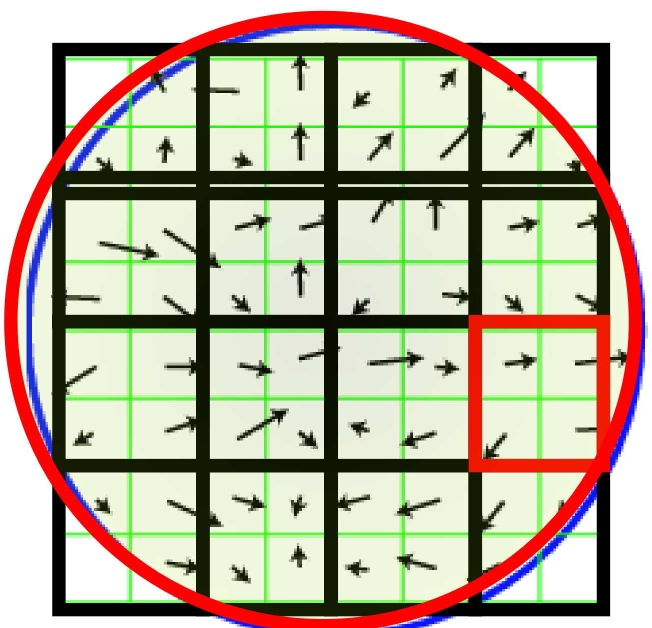


- Compute gradient at each pixel
- N x N spatial bins
- Compute an histogram of M orientations for each bean
  - Gaussian center-weighting
  - Normalized unit norm

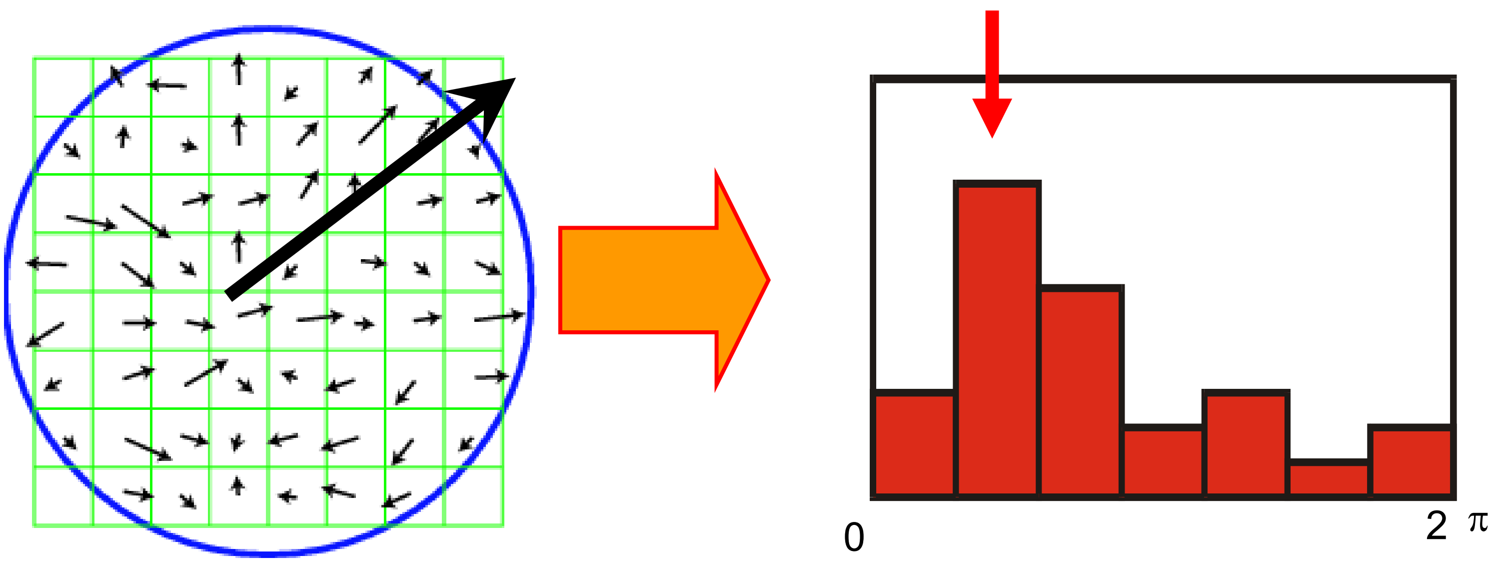
Typically M = 8; N= 4
1 x 128 descriptor

SIFT descriptor

- Robust w.r.t. small variation in:
  - Illumination (thanks to gradient & normalization)
  - Pose (small affine variation thanks to orientation histogram)
  - Scale (scale is fixed by DOG)
  - Intra-class variability (small variations thanks to histograms)

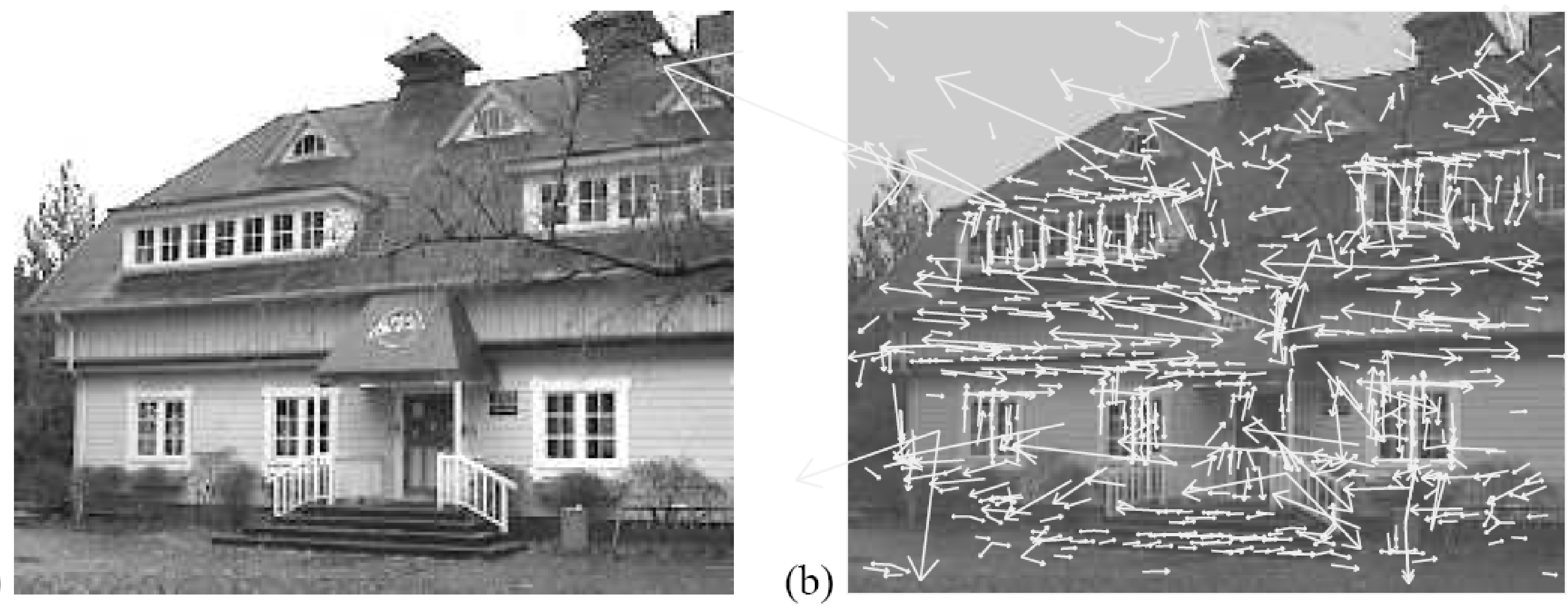
Rotational invariance

- Find dominant orientation by building smoothed orientation histogram
- Rotate all orientations by the dominant orientation

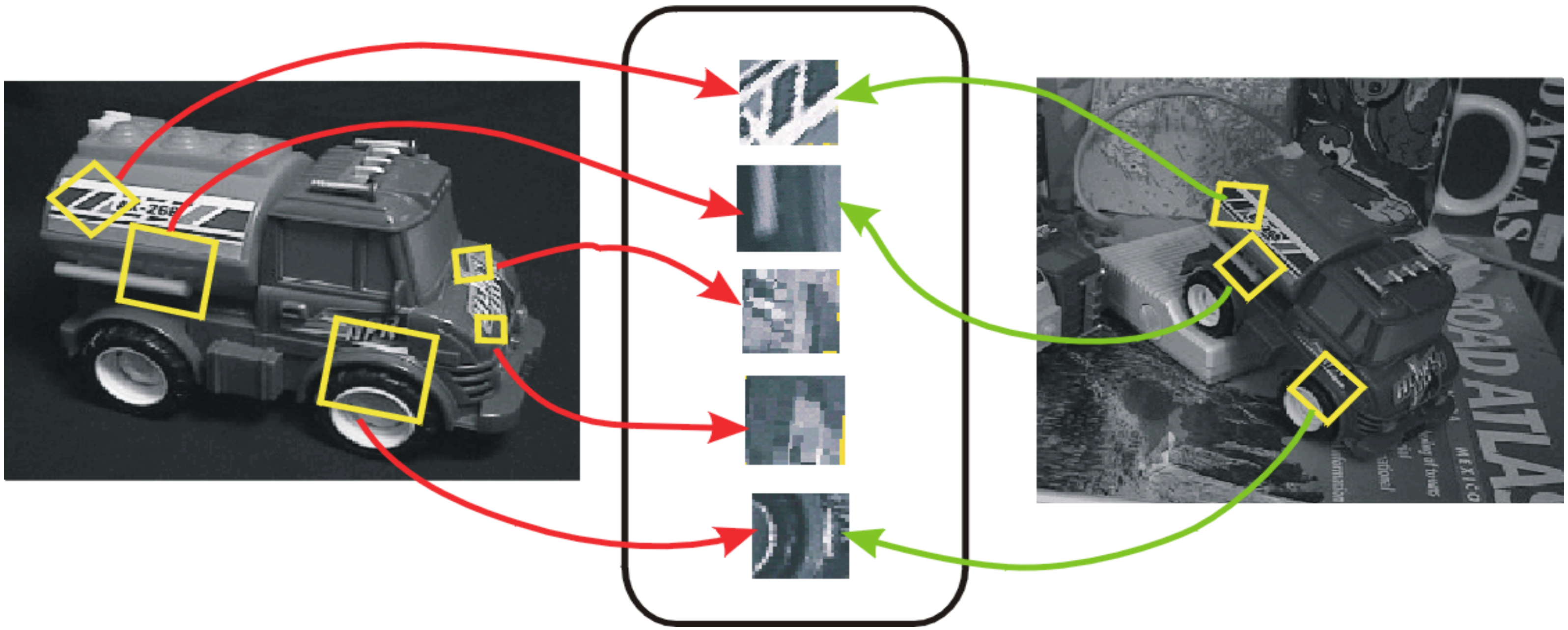


This makes the SIFT descriptor rotational invariant

Rotational invariance



Rotational invariance

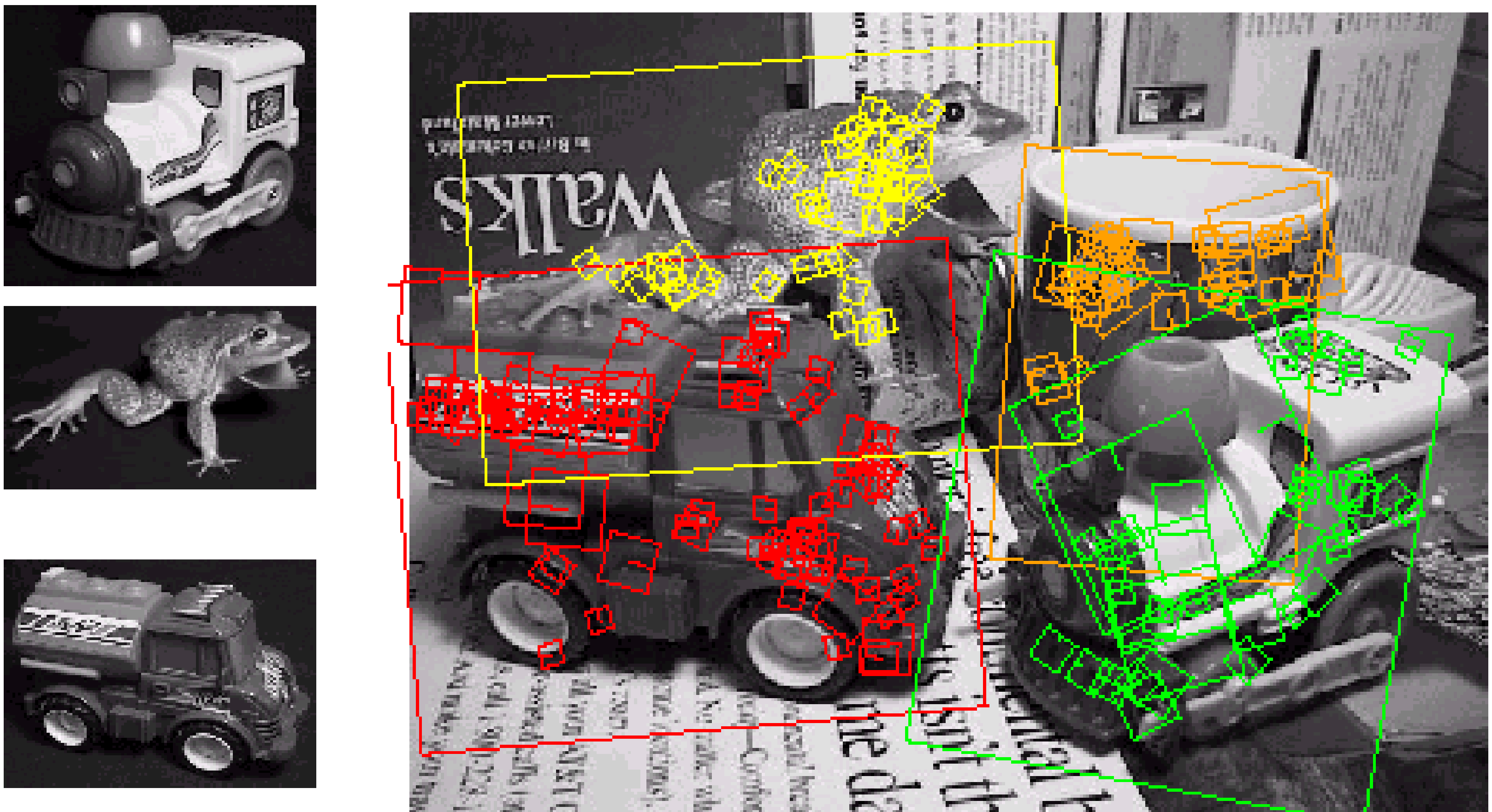


Matching using SIFT

David G. Lowe. "Distinctive image features from scale-invariant keypoints." *IJCV* 60 (2), 04

Matching using SIFT

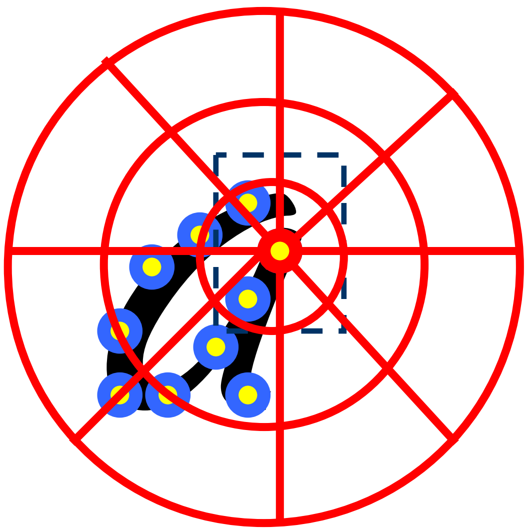
David G. Lowe. "Distinctive image features from scale-invariant keypoints." *IJCV* 60 (2), 04

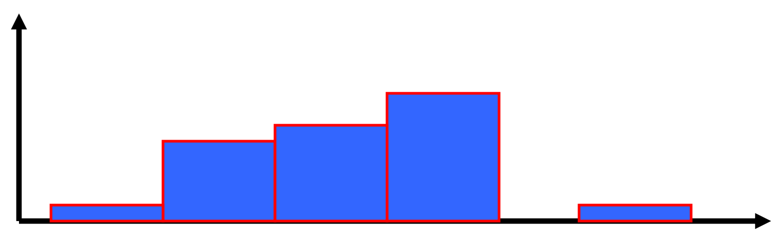


Detector	Illumination	Pose	Intra-class variab.
PATCH	***	*	*
FILTERS	***	**	**
SIFT	***	***	***

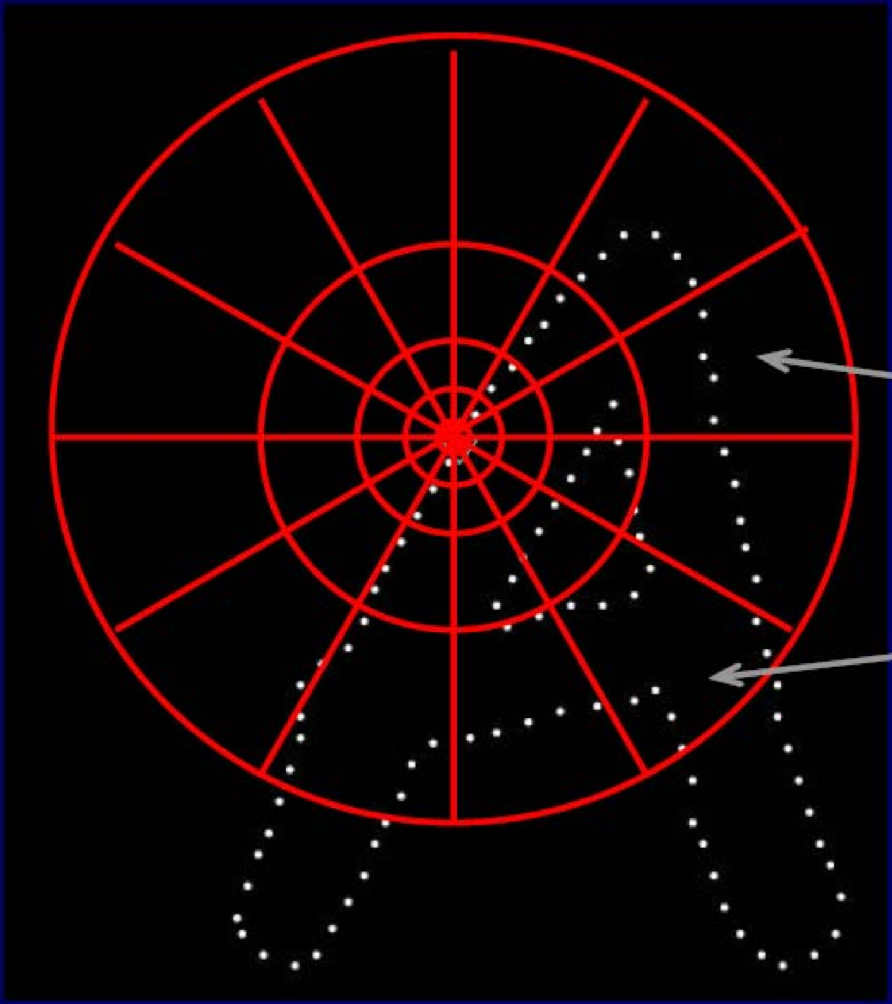
Shape context

Belongie et al. 2002





Shape Context



Count the number of points inside each bin, e.g.:

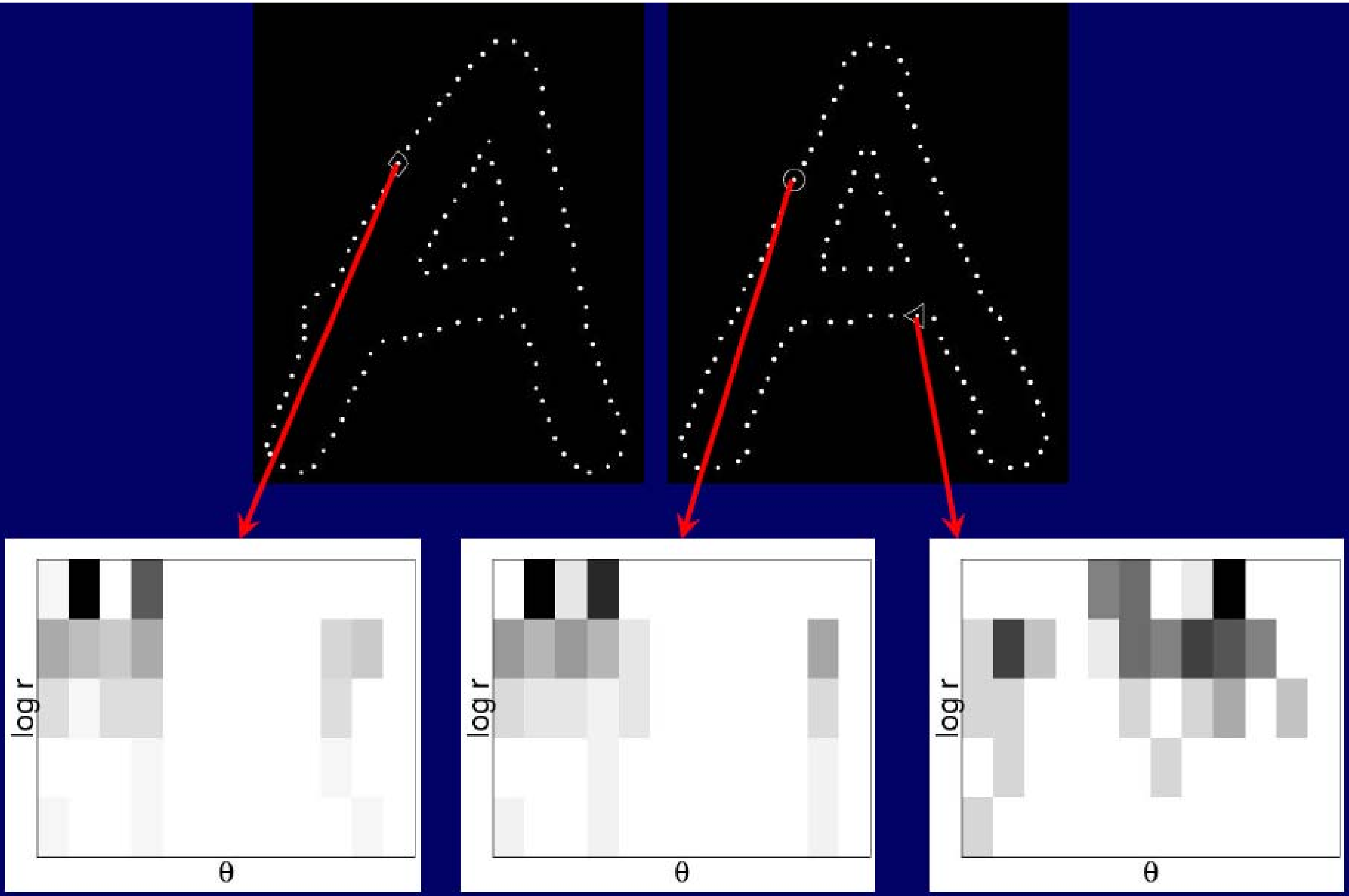
Count = 4

⋮

Count = 10

☞ Compact representation of distribution of points relative to each point

Matching different instances

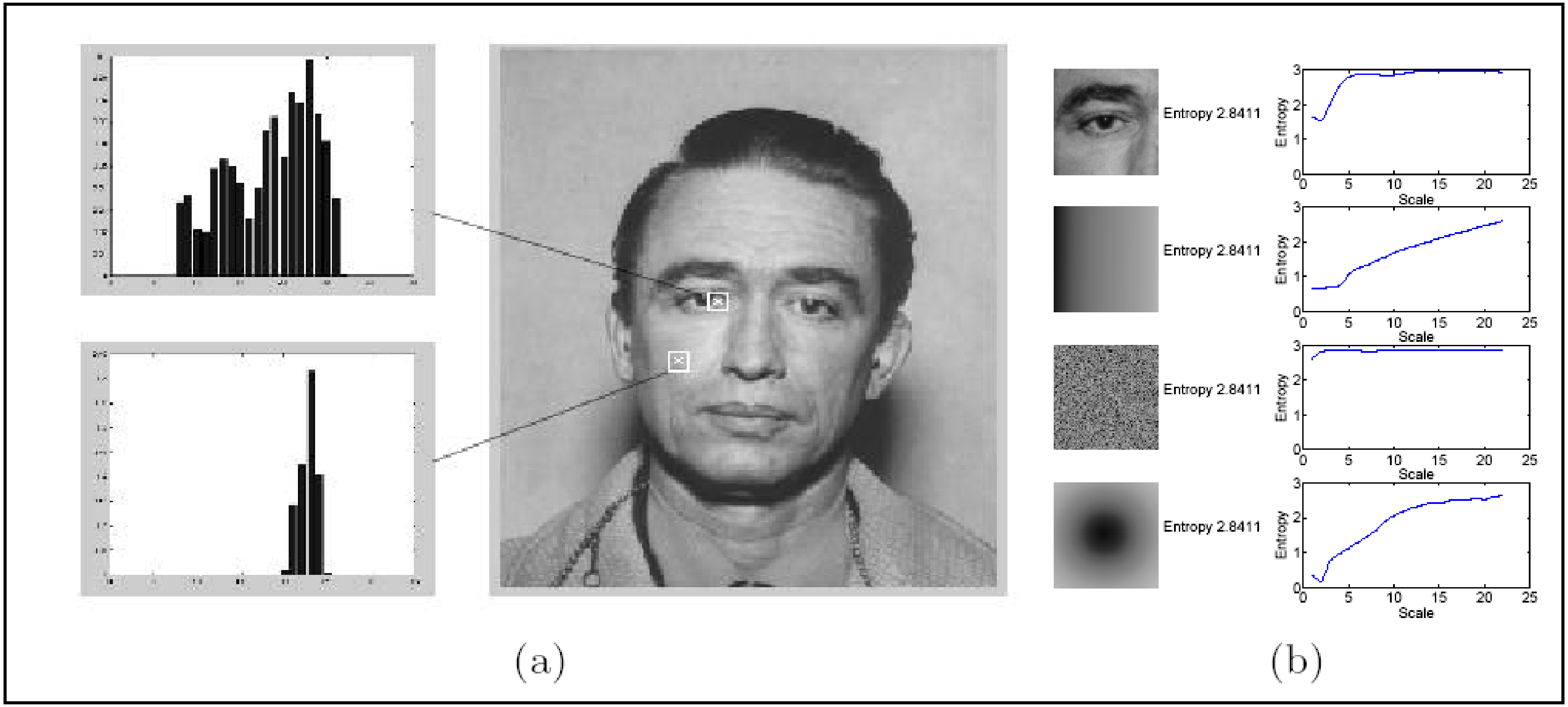


EECS 442 – Computer vision

Next lecture:
Mid level representations

Other interest point detectors

Scale Saliency [*Kadir & Brady* '01, '03]



Other interest point detectors
Scale Saliency [*Kadir & Brady* '01, '03]

- Uses entropy measure of local pdf of intensities:

$$H_D(s,\mathbf{x}) = -\int_{d \in D} p(d,s,\mathbf{x}) \log_2 p(d,s,\mathbf{x}).\mathrm{d}d$$

- Takes local maxima in scale
- Weights with 'change' of distribution with scale:

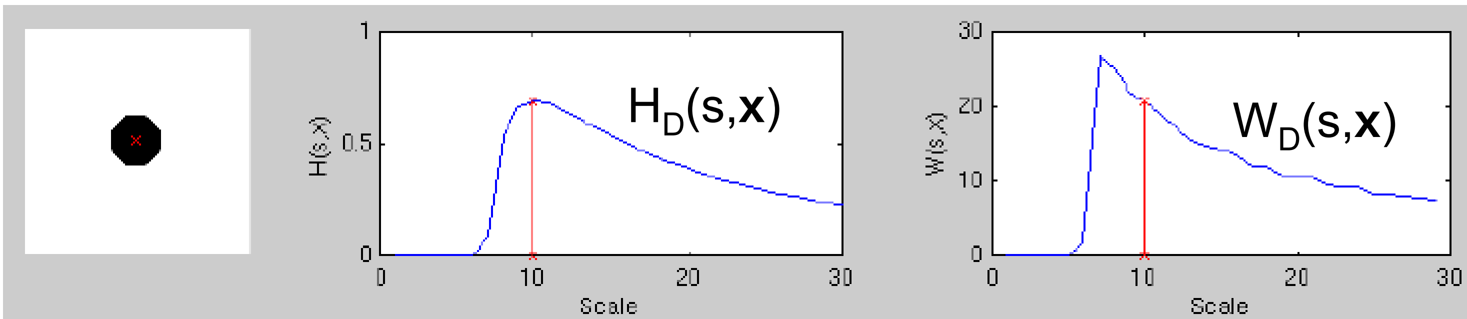
$$W_D(s,\mathbf{x}) = s \int_{d \in D} \left| \frac{\partial}{\partial s} p(d,s,\mathbf{x}) \right| .\mathrm{d}d$$

- To get saliency measure:

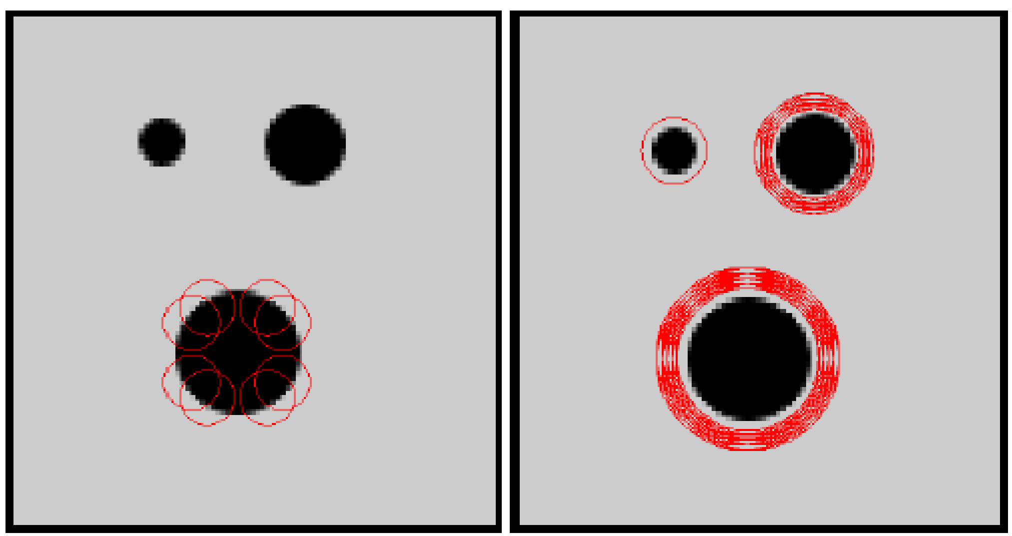
$$Y_D(s,\mathbf{x}) = H_D(s,\mathbf{x}) \times W_D(s,\mathbf{x})$$

Other interest point detectors

Scale Saliency [*Kadir & Brady* '01, '03]



Just using $H_D(s,\mathbf{x})$



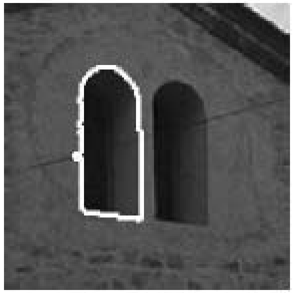
Using $Y_D(s,\mathbf{x}) = H_D W_D$

Most salient parts detected

Other interest point detectors

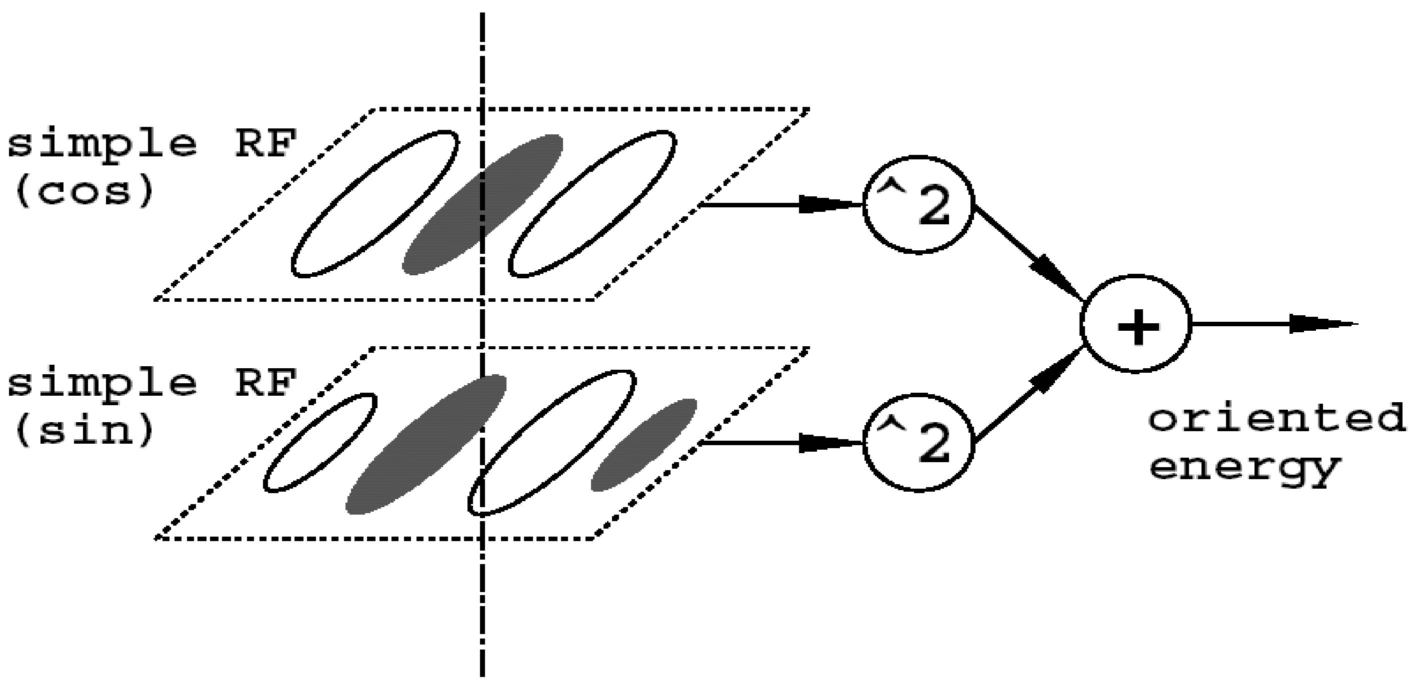
maximum stable extremal regions [matas et al. 02]

- Sweep threshold of intensity from black to white
- Locate regions based on stability of region with respect to change of threshold



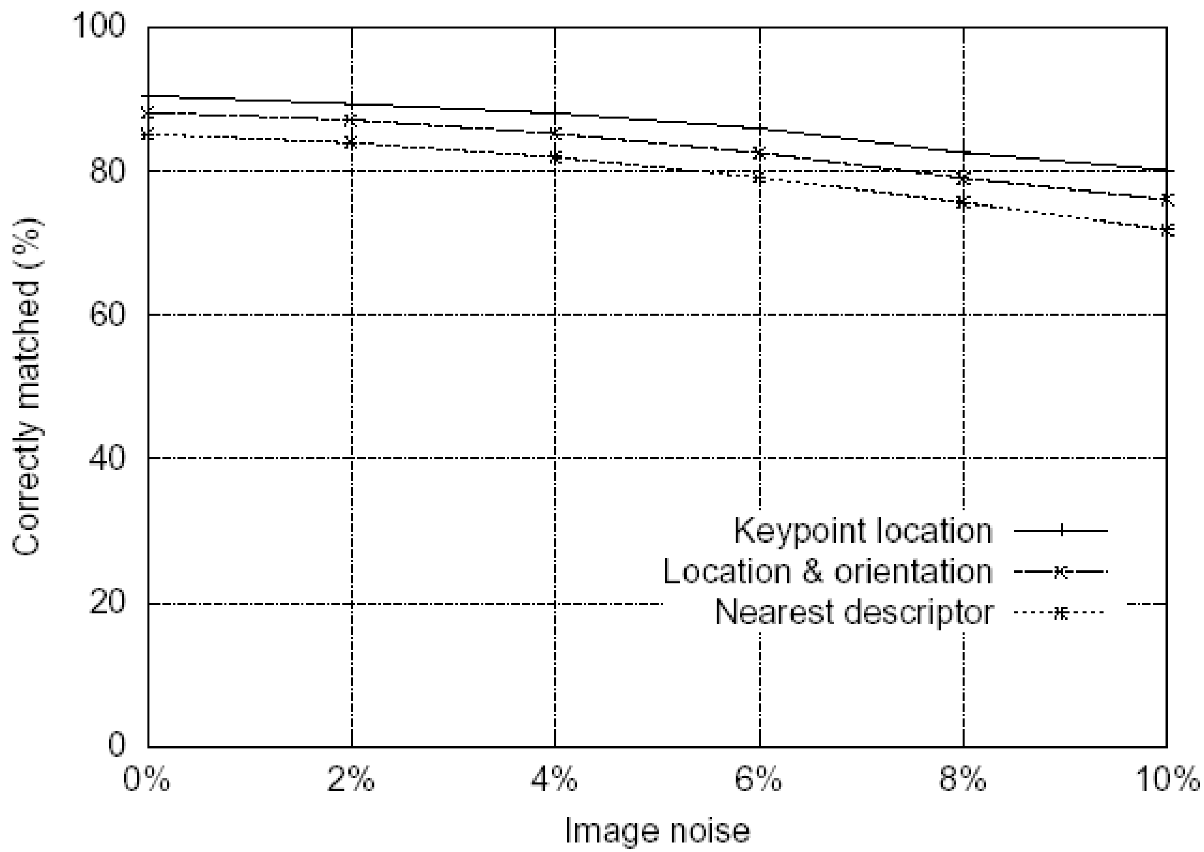
Creating features stable to viewpoint change

- Edelman, Intrator & Poggio (97) showed that complex cell outputs are better for 3D recognition than simple correlation



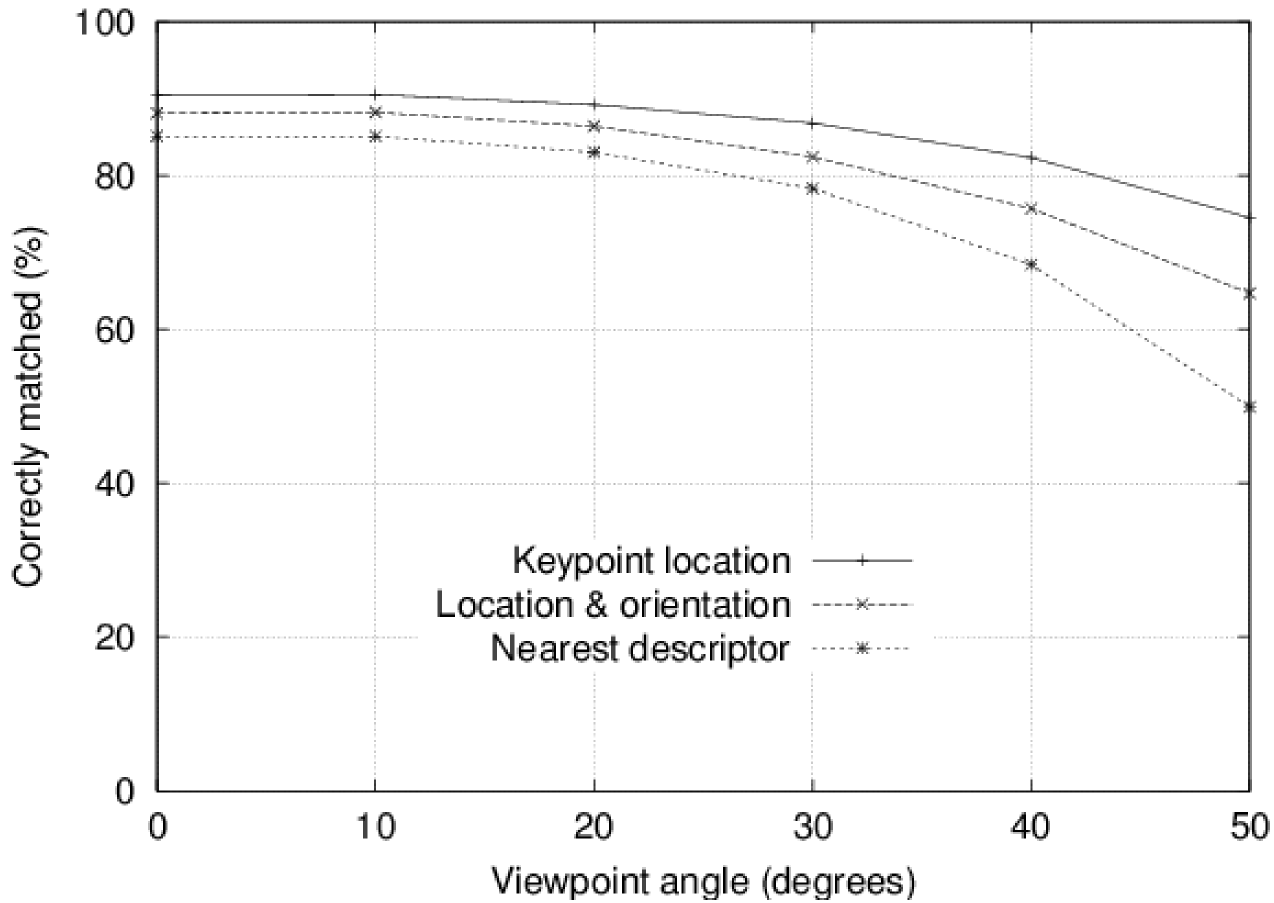
Feature stability to noise

- Match features after random change in image scale & orientation, with differing levels of image noise
- Find nearest neighbor in database of 30,000 features

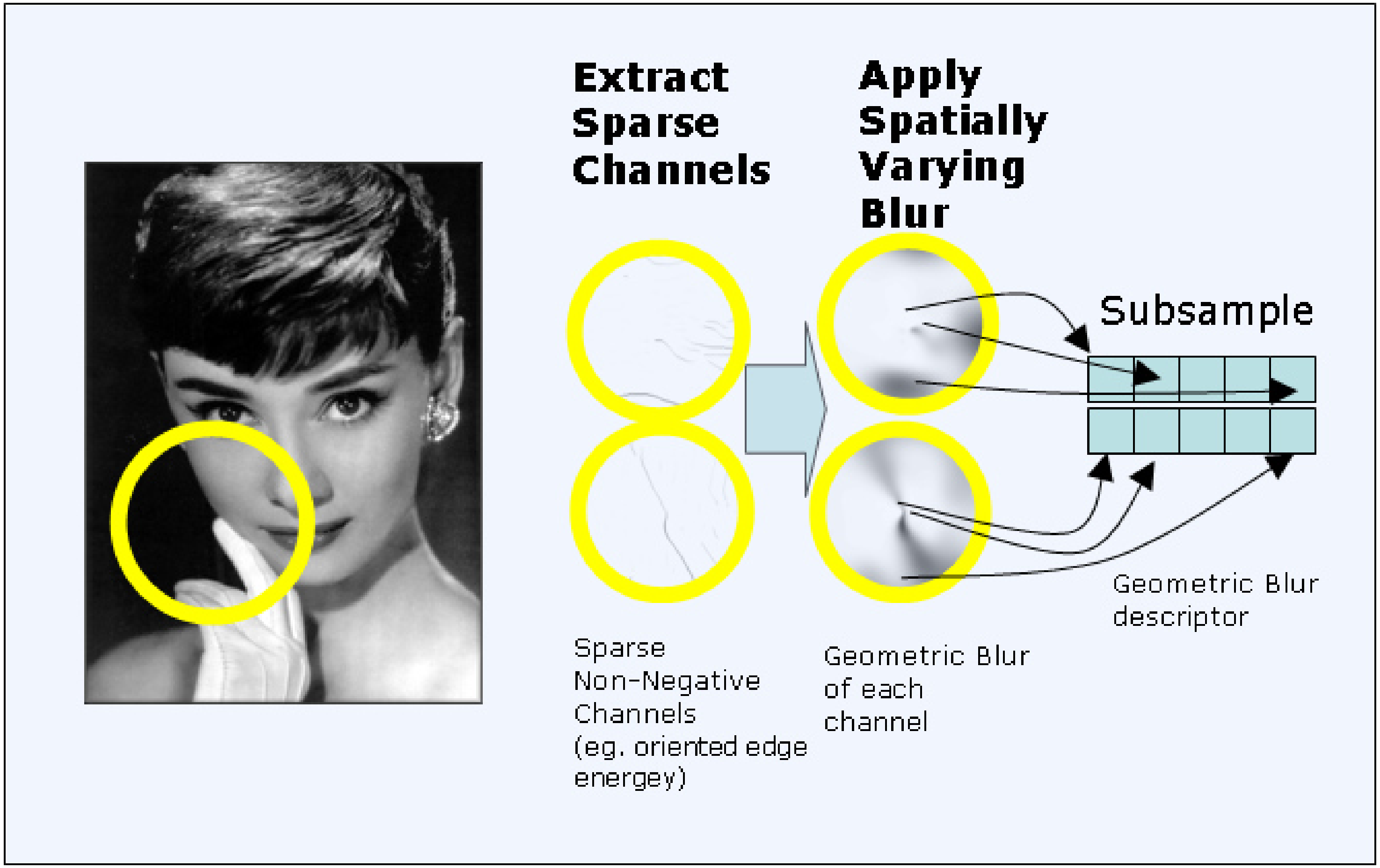


Feature stability to affine change

- Match features after random change in image scale & orientation, with 2% image noise, and affine distortion
- Find nearest neighbor in database of 30,000 features



Geometric blur



Berg et al. 2001

Geometric blur