SIFT keypoint detection

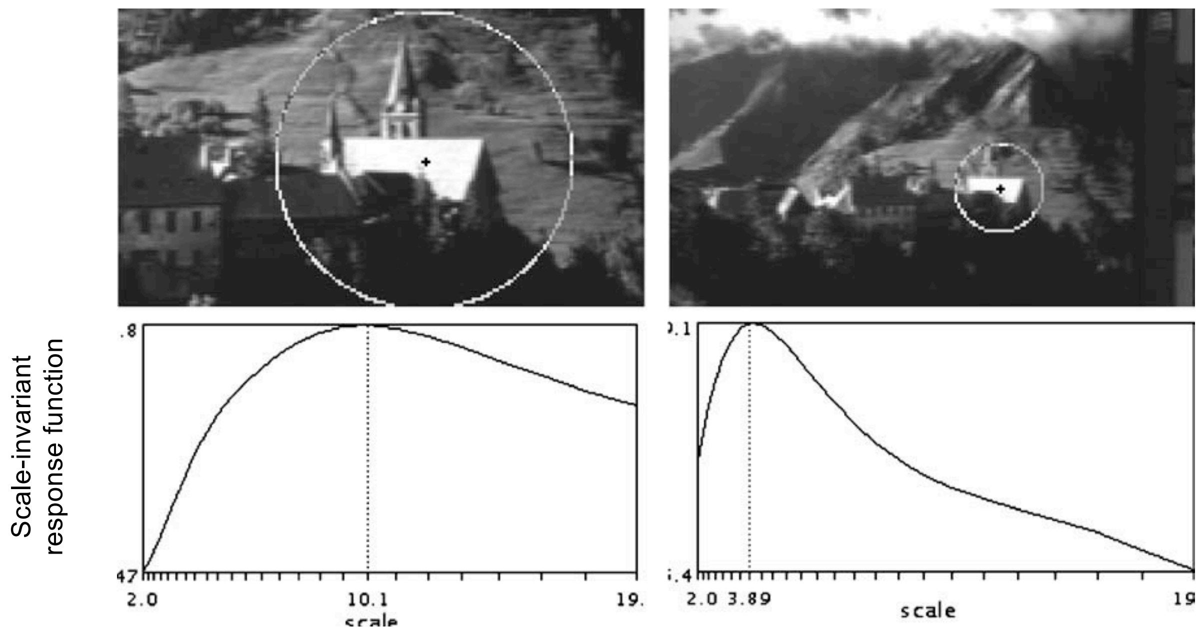
D. Lowe, Distinctive image features from scale-invariant keypoints,
IJCV 60 (2), pp. 91-110, 2004

Overview

- Multiscale blob detection: Key idea
- Laplacian of Gaussian filter
- Multiscale blob detection algorithm
- SIFT detector
- SIFT descriptors

Keypoint detection with scale selection

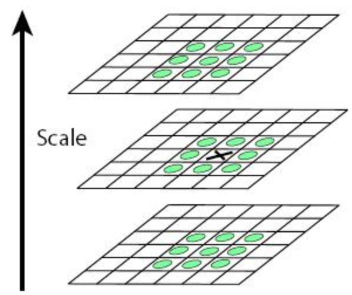
- We want to extract keypoints with *characteristic scales* that are *equivariant* (or *covariant*) w.r.t. to scaling of the image



K. Mikolajczyk and C. Schmid. Indexing based on scale invariant interest points. ICCV 2001
T. Lindeberg, Feature detection with automatic scale selection, *IJCV* 30(2), pp. 77-116, 1998

Keypoint detection with scale selection

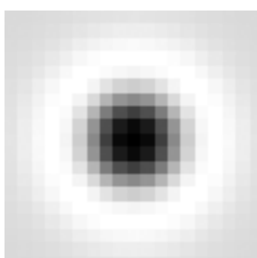
- We want to extract keypoints with *characteristic scales* that are *equivariant* (or *covariant*) w.r.t. to scaling of the image
- Approach: compute a *scale-invariant* response function over neighborhoods centered at each location (x, y) and a range of scales (σ), find *scale-space locations* (x, y, σ) where this function reaches a local maximum



"scale space"

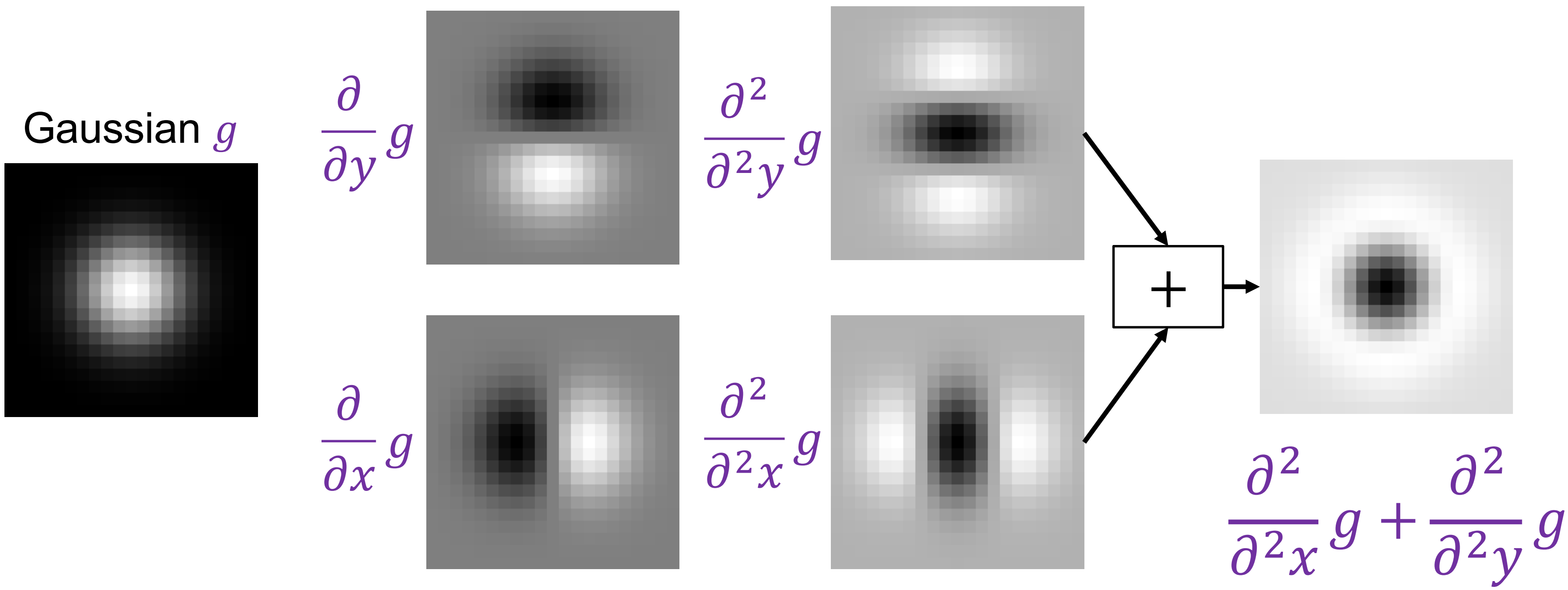
Keypoint detection with scale selection

- We want to extract keypoints with *characteristic scales* that are *equivariant* (or *covariant*) w.r.t. to scaling of the image
- Approach: compute a *scale-invariant* response function over neighborhoods centered at each location (x, y) and a range of scales (σ), find *scale-space locations* (x, y, σ) where this function reaches a local maximum
- A particularly convenient response function is given by the *scale-normalized Laplacian of Gaussian (LoG) filter*:



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

Laplacian of Gaussian

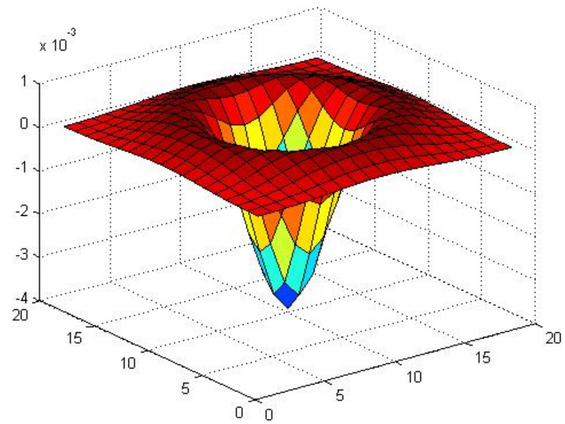


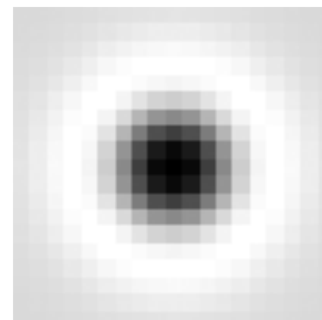
Is this filter separable?

Source: [J. Johnson and D. Fouhey]

Scale-normalized Laplacian

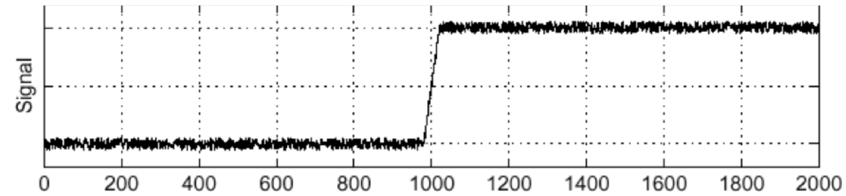
- You need to multiply the LoG by σ^2 to make responses comparable across scales





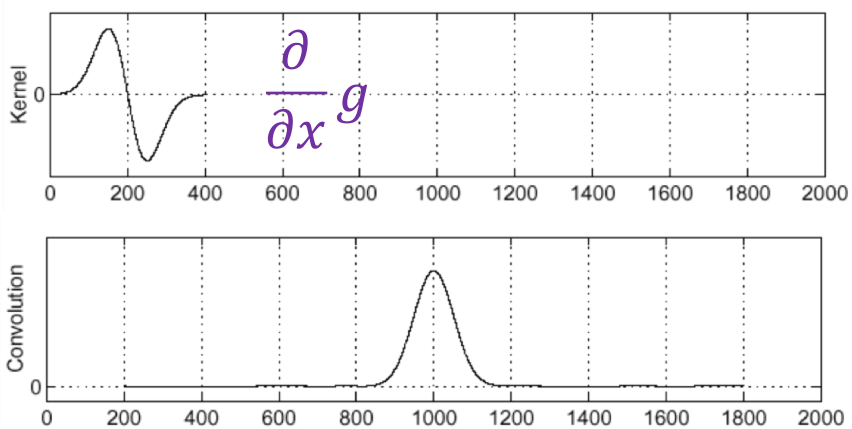
$$\nabla^2_{\text{norm}} = \sigma^2 \left(\frac{\partial^2}{\partial x^2} g + \frac{\partial^2}{\partial^2 y} g \right)$$

Edge detection with LoG



Edge

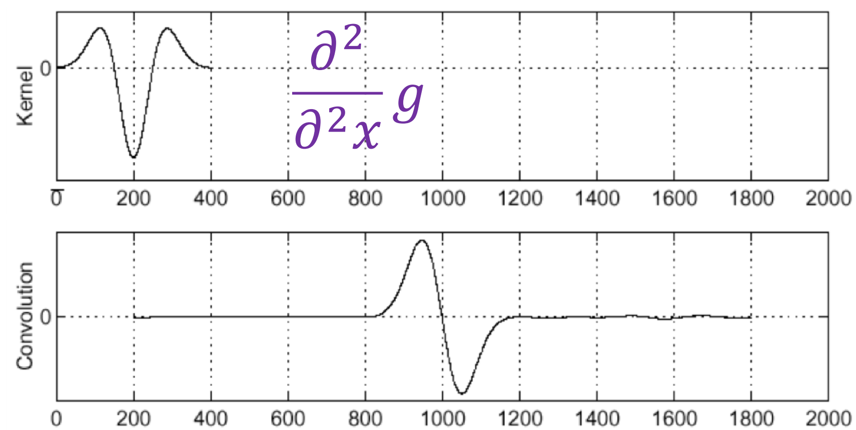
Derivative of Gaussian



$$\frac{\partial}{\partial x} g$$

Edge = *local maximum* of derivative

Laplacian of Gaussian



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

Edge = *zero-crossing* of Laplacian

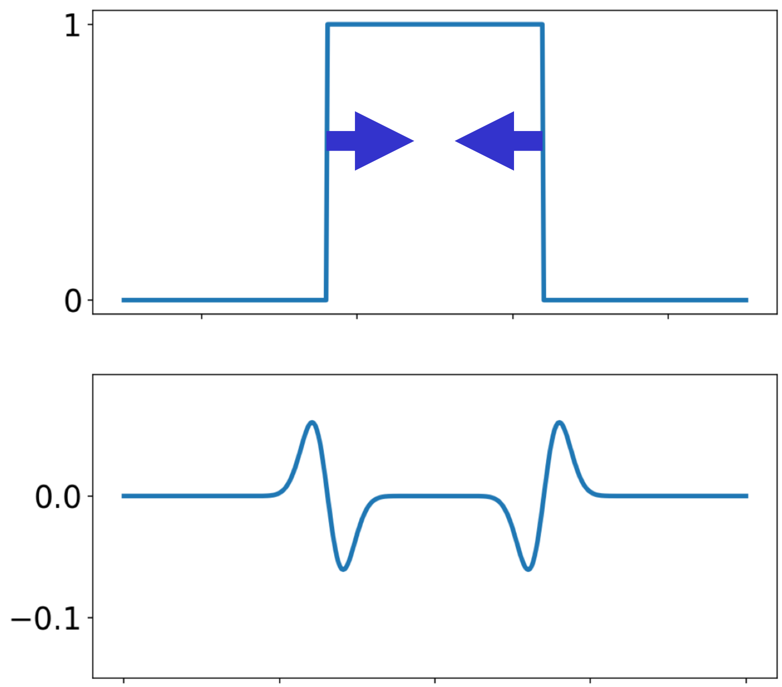
D. Marr and E. Hildreth, Theory of Edge Detection, Proc. of the Royal Society of London. Series B, Biological Sciences, 207 (1167): 187–217, 1980

Blob detection with LoG

- Let’s convolve a 1D “blob” with the Laplacian:

f

$f * \frac{\partial^2}{\partial^2 x} g$



Source: [J. Johnson and D. Fouhey]()

Blob detection with LoG

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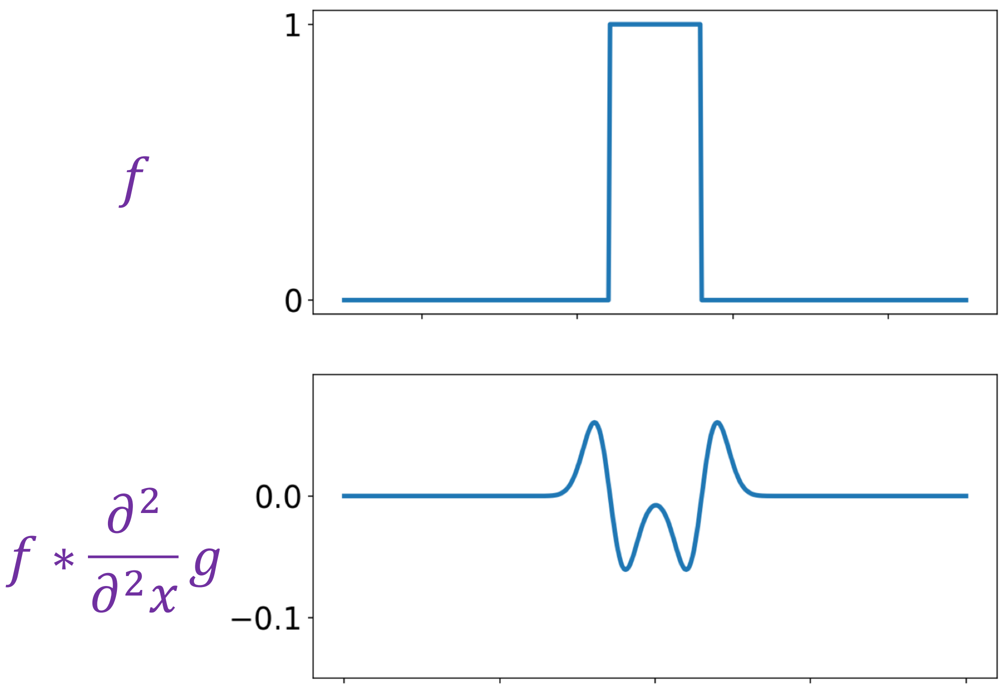

Source: [J. Johnson and D. Fouhey]

Blob detection with LoG

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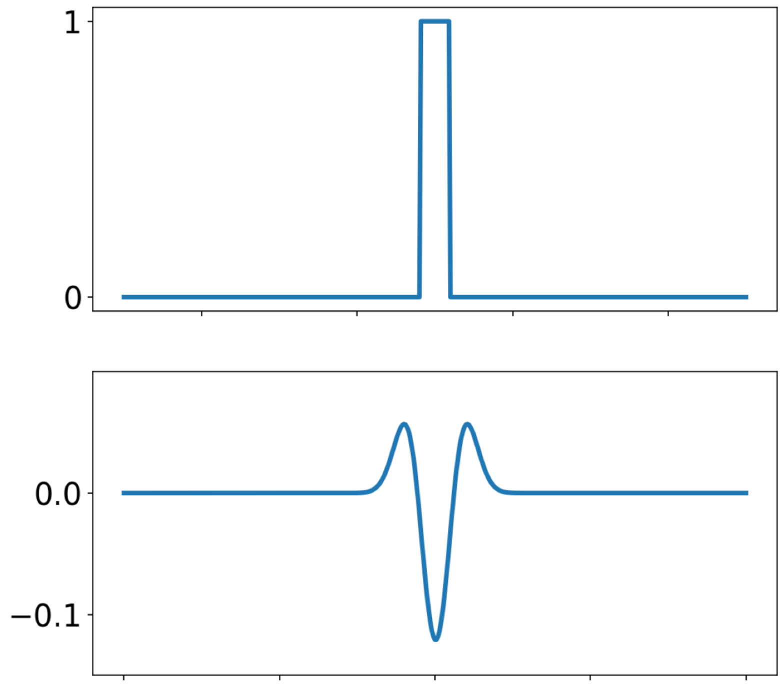
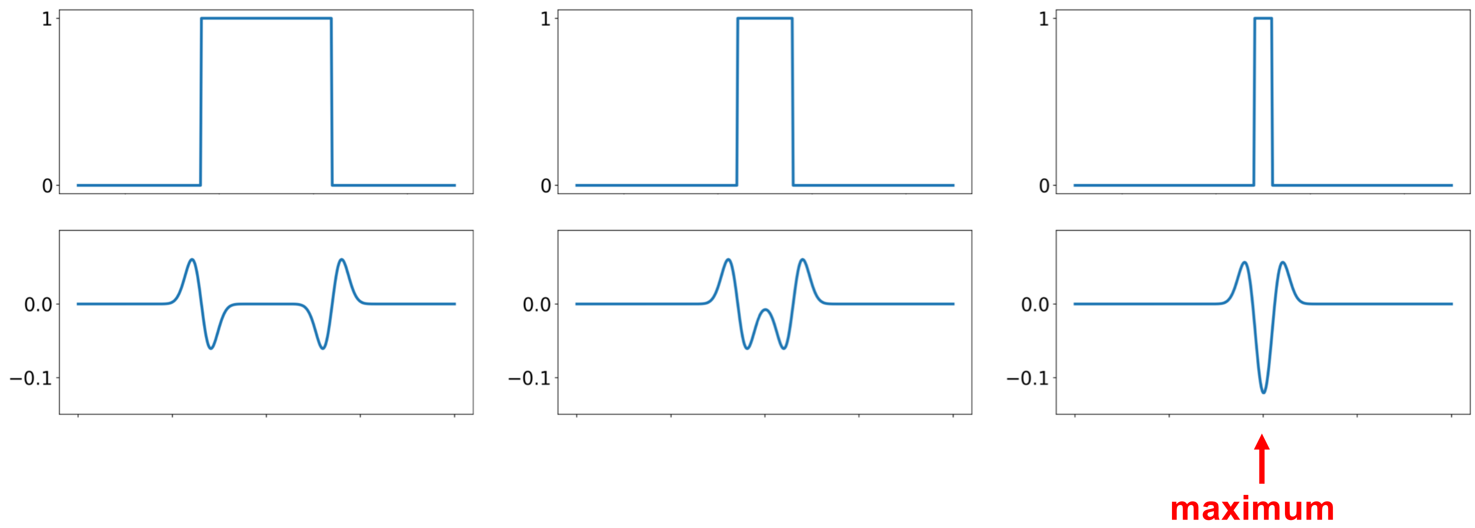


Source: [J. Johnson and D. Fouhey]

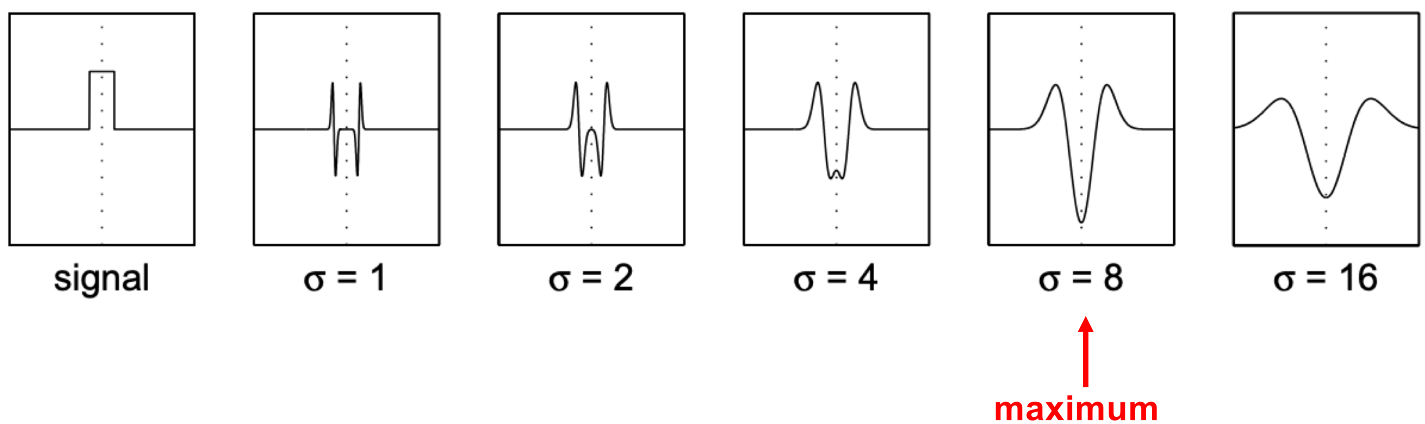
Spatial selection

- The 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 can find the *characteristic scale* of the blob by convolving it with *scale-normalized* Laplacians at several scales (σ) and looking for the maximum response

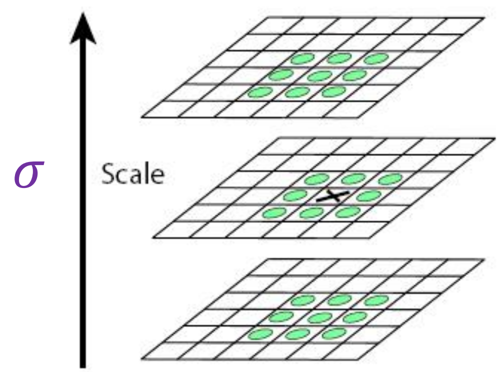


Overview

- Multiscale blob detection: Key idea
- Laplacian of Gaussian filter
- Multiscale blob detection algorithm

2D multiscale blob detection

1. Convolve image with *scale-normalized* Laplacian at several scales (values of σ)
2. Find maxima of squared Laplacian response in space *and* across scales



"Scale space"

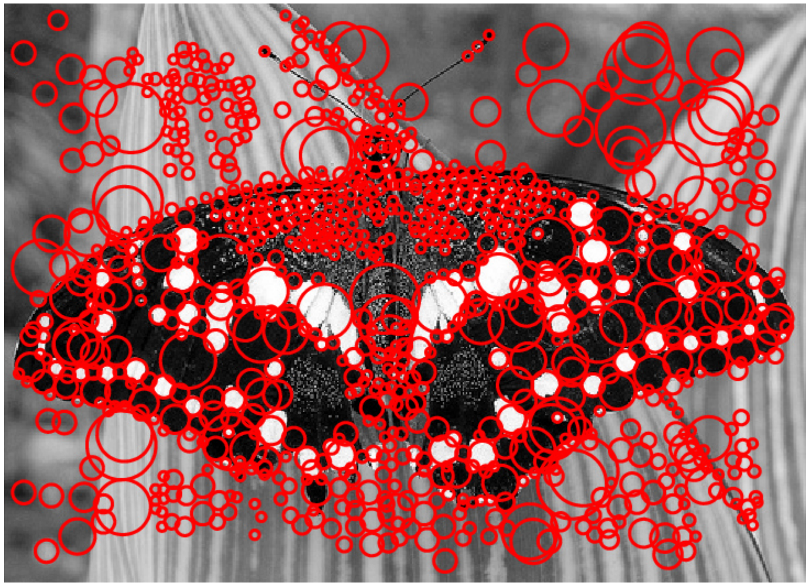
2D multiscale blob detection: Example

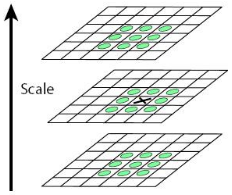
2D multiscale blob detection: Example

sigma = 11.9912

2D multiscale blob detection: Example

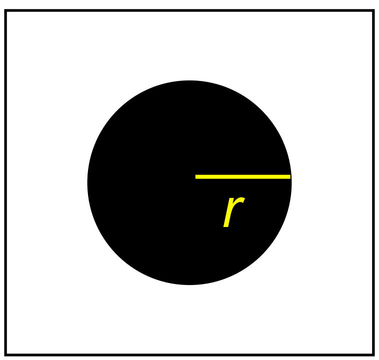
After scale-space NMS



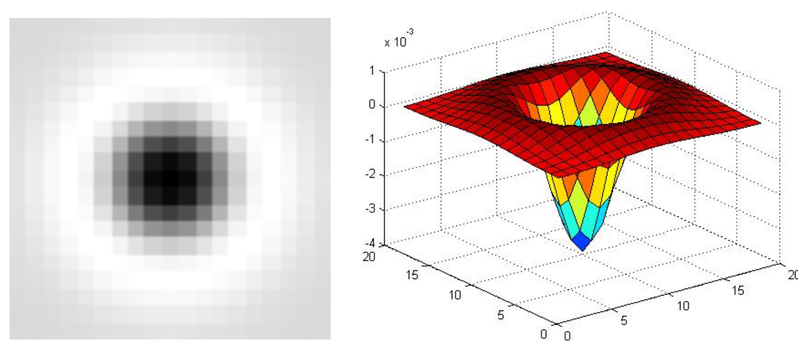


Technical detail 1: Drawing circles

- At what scale does the Laplacian achieve a maximum response to a binary circle of radius r?



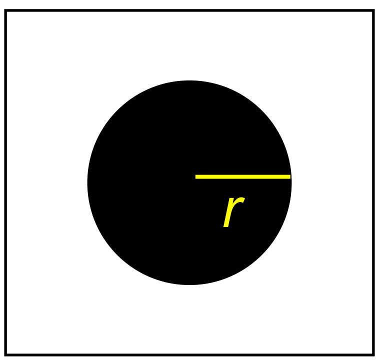
image



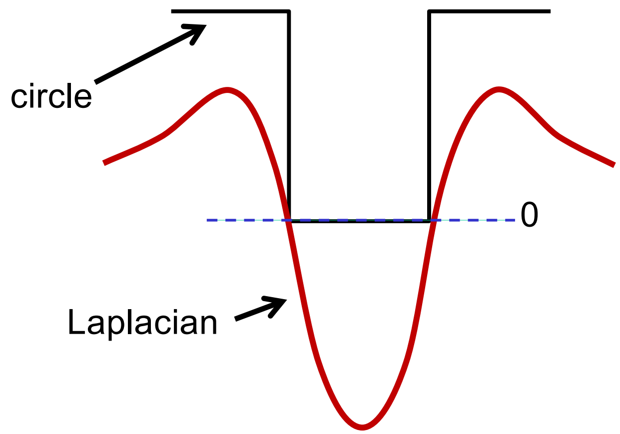
Laplacian

Technical detail 1: Drawing circles

- At what scale does the Laplacian achieve a maximum response to a binary circle of radius r?
  - To get maximum response, the zeros of the Laplacian have to be aligned with the circle
  - Up to scale, the Laplacian is given by $(x^2 + y^2 - 2\sigma^2)e^{-(x^2+y^2)/2\sigma^2}$, so the maximum response occurs at $\sigma = r/\sqrt{2}$
- Therefore, for display purposes, you should multiply the characteristic scales of detected keypoints by $\sqrt{2}$

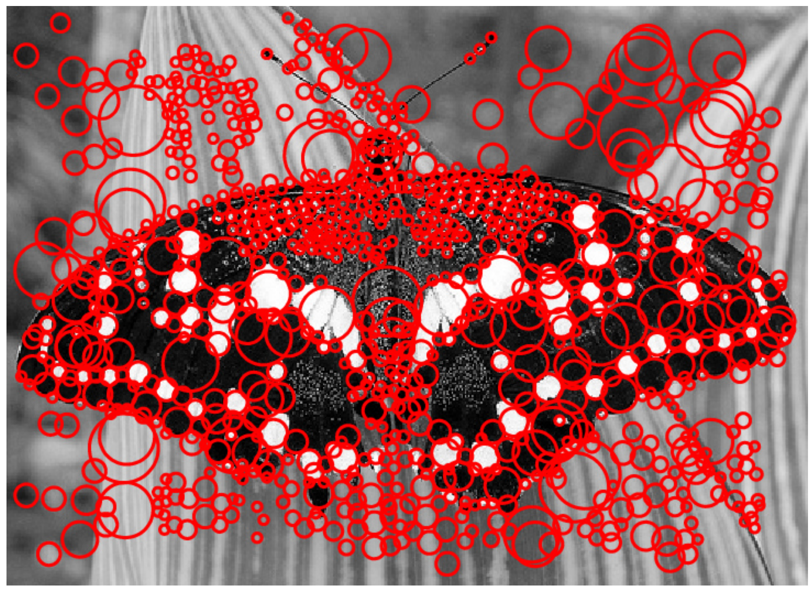


image



Technical detail 2: Eliminating edge responses

- Laplacian has strong response along edges



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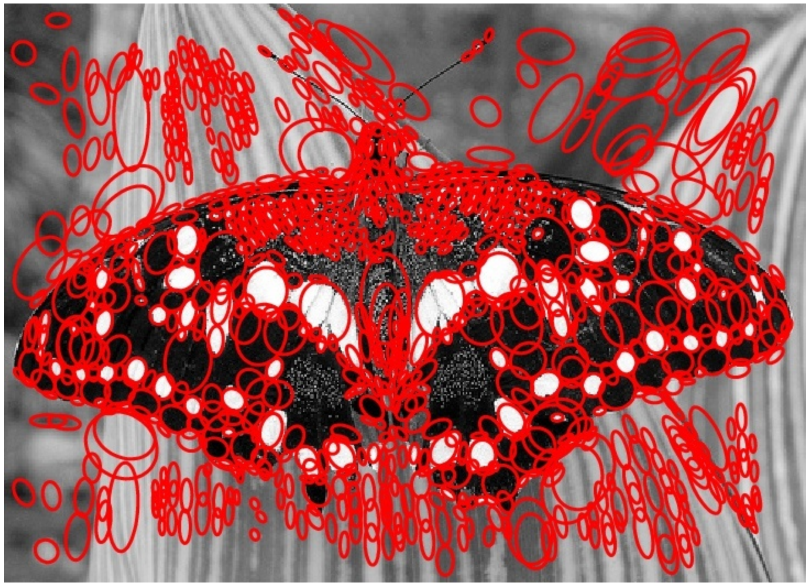


- Solution: filter based on Harris response function over neighborhoods containing the “blobs”

Overview

- Multiscale blob detection: Key idea
- Laplacian of Gaussian filter
- Multiscale blob detection algorithm
- SIFT detector
- SIFT descriptors

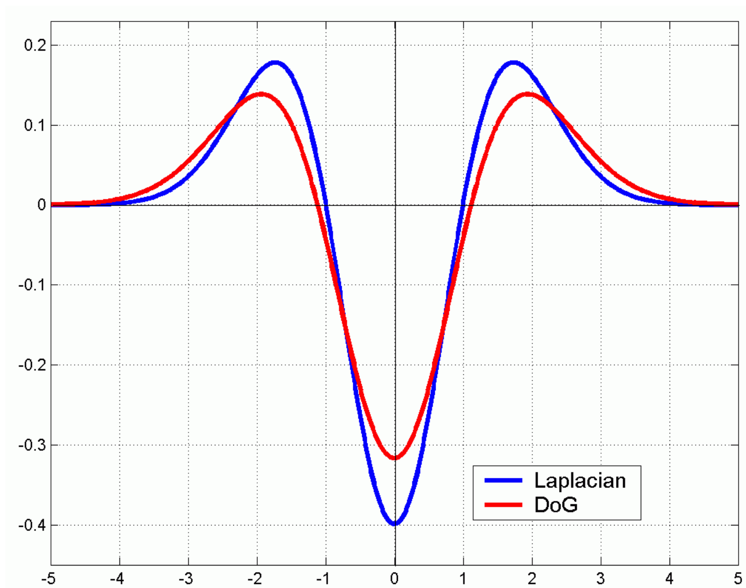
SIFT: Scale-invariant feature transform

D. Lowe. Object recognition from local scale-invariant features. ICCV 1999

D. Lowe. Distinctive image features from scale-invariant keypoints. *IJCV* 60 (2), pp. 91-110, 2004

SIFT detector: Efficient implementation

- Approximate LoG with a *difference of Gaussians* (DoG)
  - Laplacian: $\sigma^2\big(G_{xx}(x,y,\sigma) + G_{yy}(x,y,\sigma)\big)$
  - DoG: $G(x,y,k\sigma) - G(x,y,\sigma)$



SIFT detector: Efficient implementation

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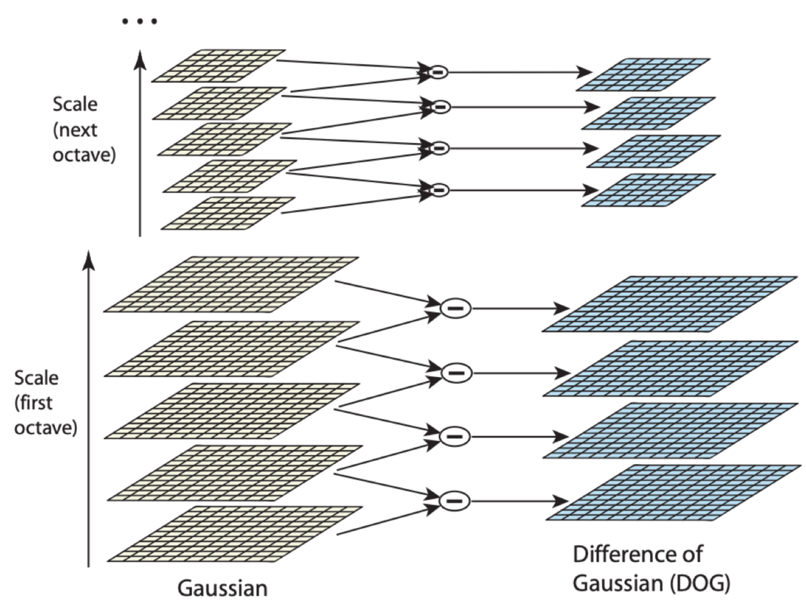
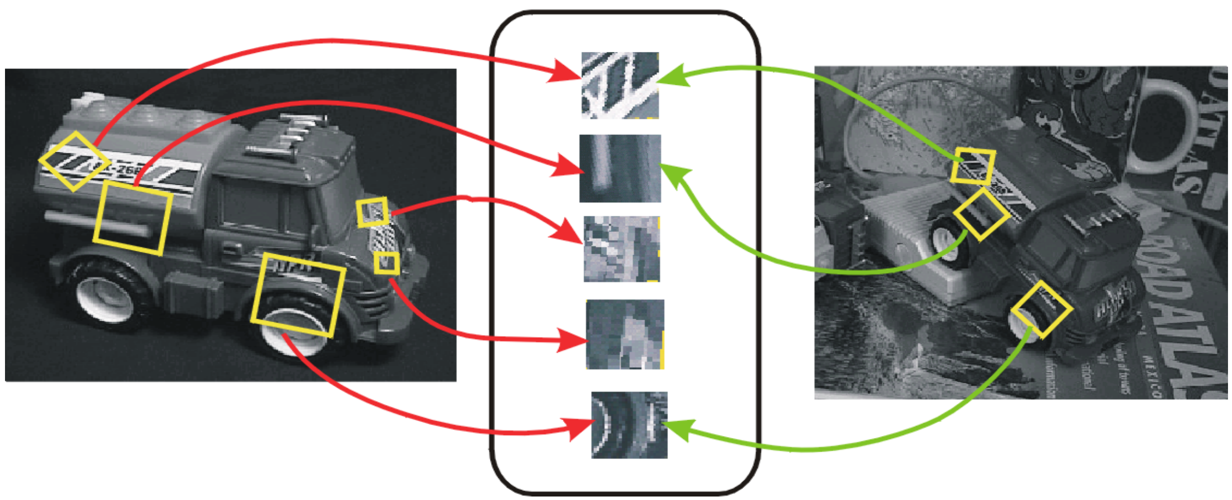
  - Laplacian: $\sigma^2\left(G_{xx}(x,y,\sigma)+G_{yy}(x,y,\sigma)\right)$
  - DoG: $G(x,y,k\sigma)-G(x,y,\sigma)$
- Compute DoG via an *image pyramid*:



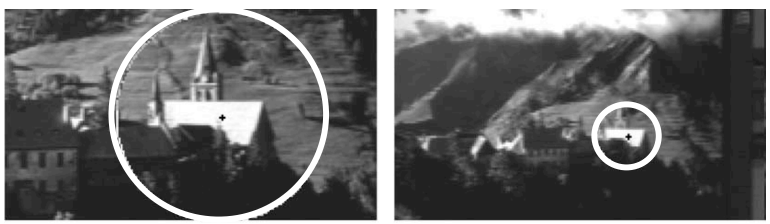
SIFT for matching

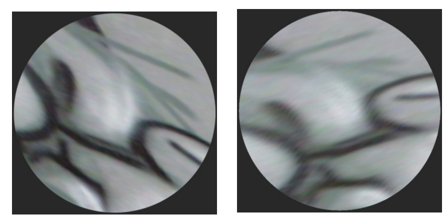
- The main goal of SIFT is to enable image matching in the presence of significant transformations
  - To recognize the same keypoint in multiple images, we need to match appearance descriptors or “signatures” in their neighborhoods
  - Descriptors that are *locally* invariant w.r.t. scale and rotation can handle a wide range of *global* transformations



SIFT for matching

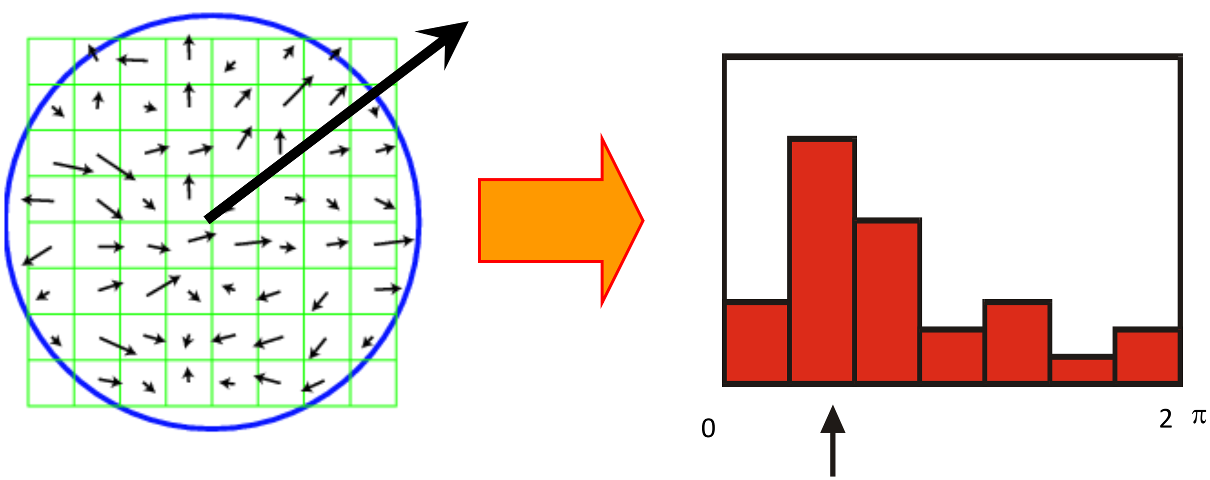
- SIFT detector returns a characteristic scale that can be normalized out, but no characteristic orientation





SIFT for matching

- SIFT detector returns a characteristic scale that can be normalized out, but no characteristic orientation
- Hack for finding a reference orientation:
  - Create histogram of local gradient directions in the patch
  - Assign reference orientation at peak of smoothed histogram

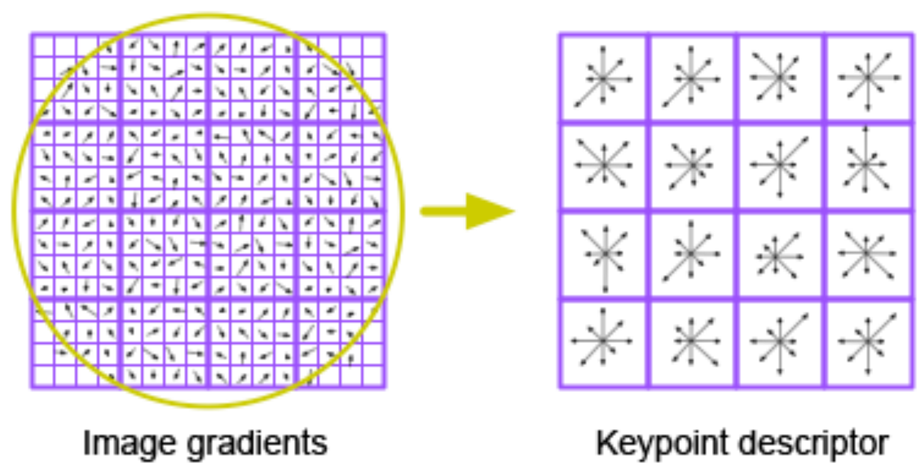


SIFT detector: Example outputs

- Detected keypoints with characteristic scales and orientations:

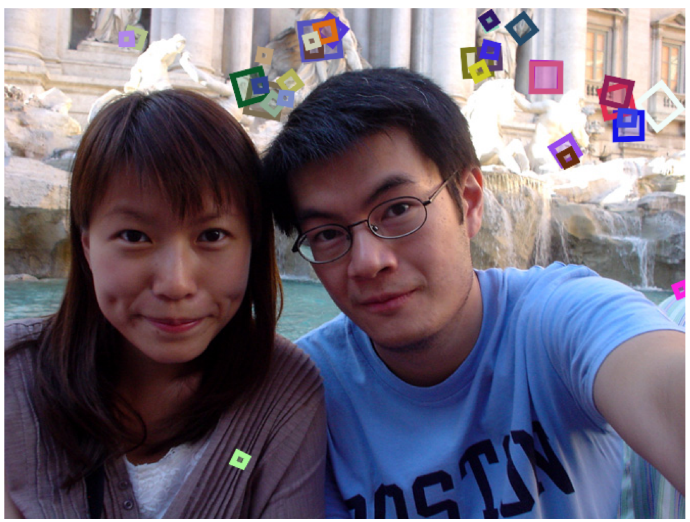
SIFT descriptors

- Inspiration: complex neurons in the primary visual cortex

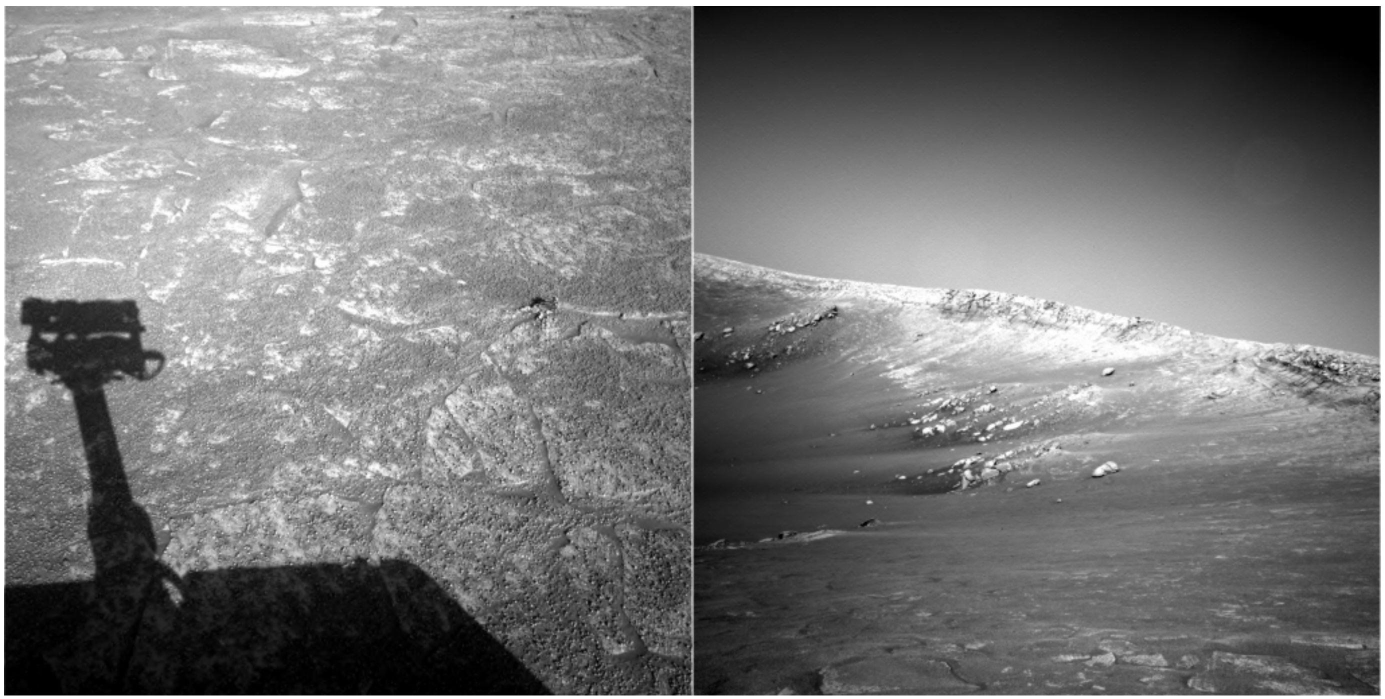


SIFT for matching

- Extraordinarily robust detection and description technique
  - Can handle changes in viewpoint
    - Up to about 60 degree out-of-plane rotation
  - Can handle significant changes in illumination
    - Sometimes even day vs. night
  - Fast and efficient—can run in real time
  - Lots of code available

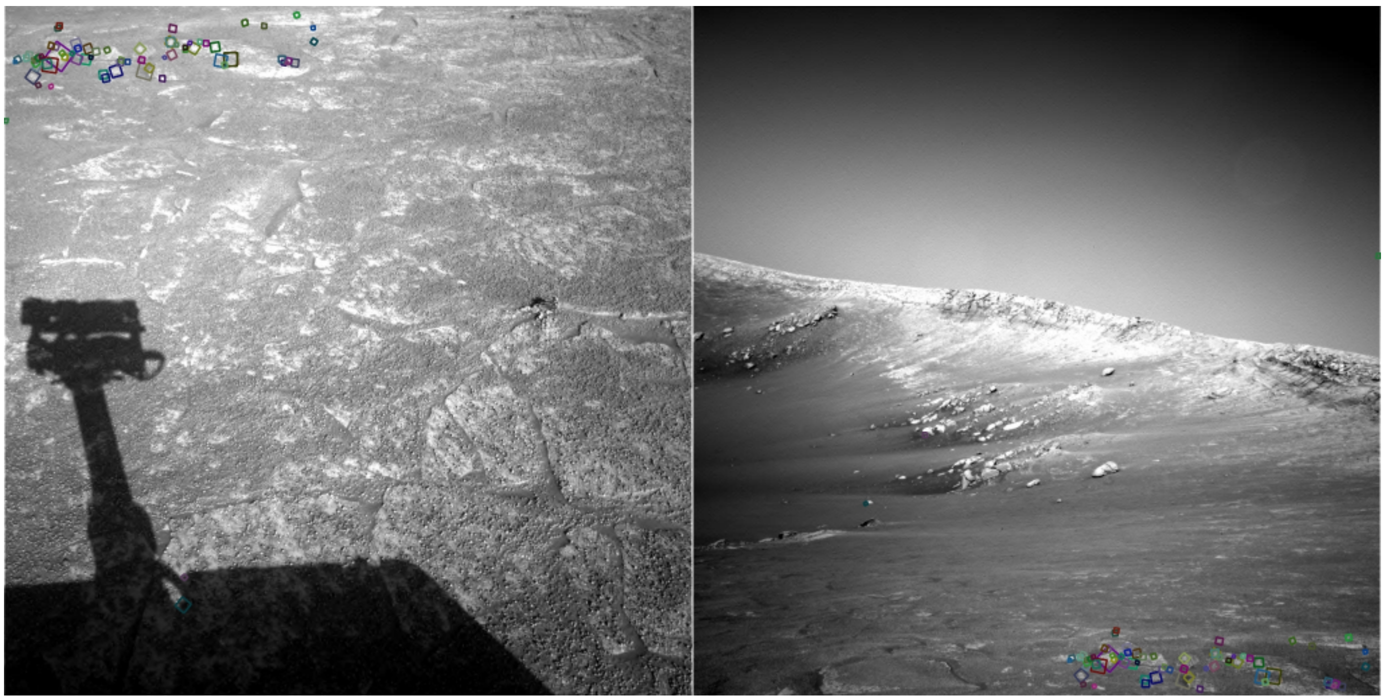


A hard matching problem



NASA Mars Rover images

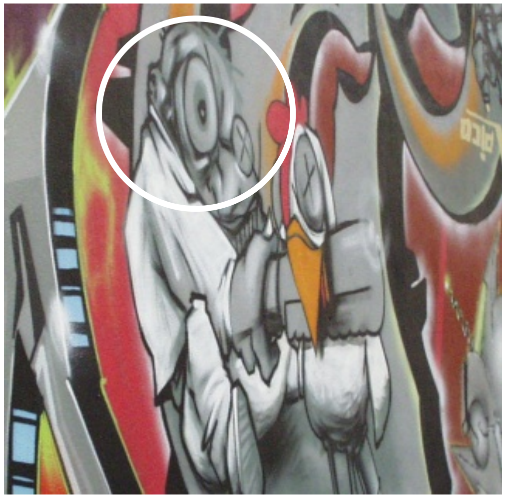
Answer below (look for tiny colored squares…)



NASA Mars Rover images
with SIFT feature matches
Figure by Noah Snavely

Local invariance beyond SIFT

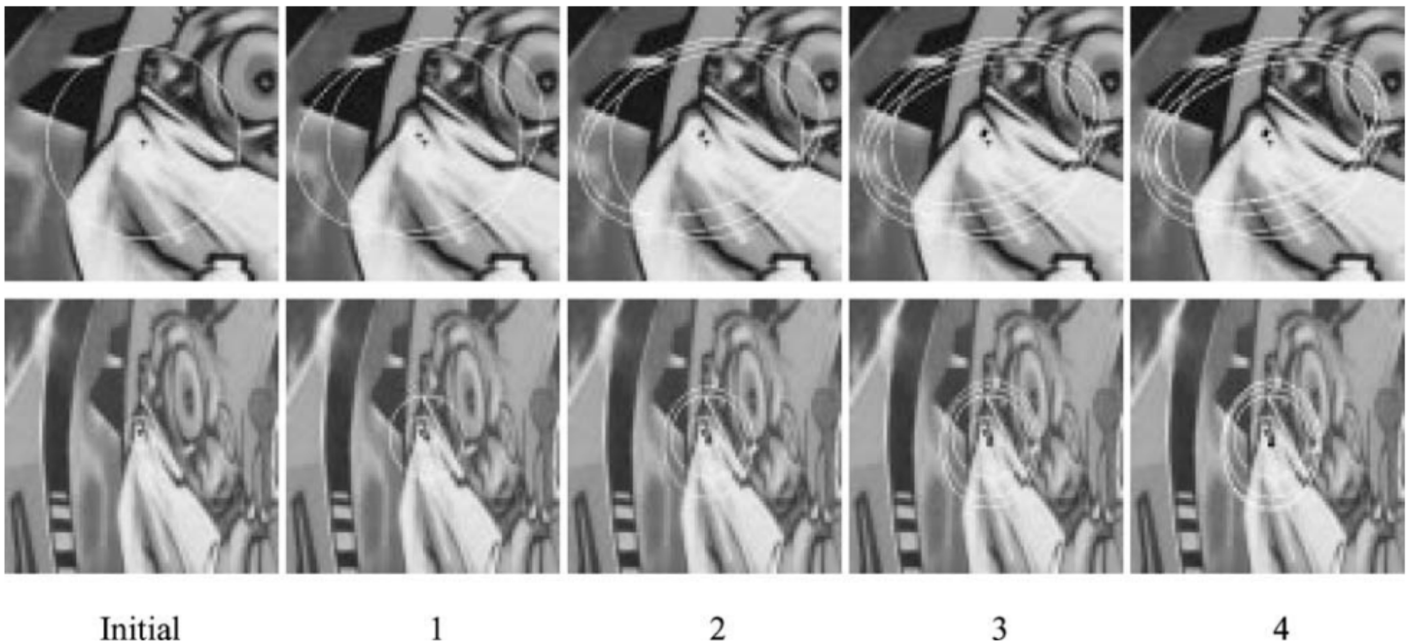
- Can we make local descriptors invariant w.r.t. viewpoint changes?



Local invariance beyond SIFT

- Can we make local descriptors invariant w.r.t. viewpoint changes?
- *Affine transformations* approximate viewpoint changes for roughly planar objects and roughly orthographic cameras

Affine adaptation



- More cumbersome in practice and not as successful as SIFT

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