T13 - Local features: detection and description

Computer Vision, FCUP, 2012

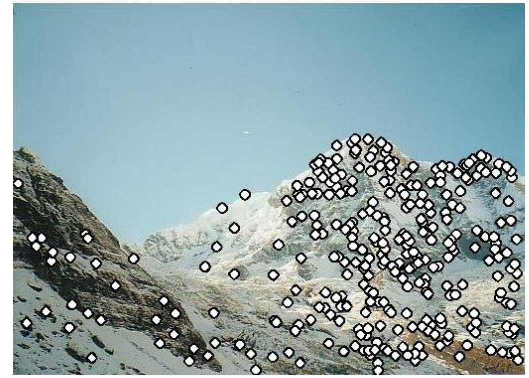
Miguel Coimbra
Slides by Prof. Kristen Grauman

Today

- Local invariant features
  - Detection of interest points
    - (Harris corner detection)
    - Scale invariant blob detection: LoG
  - Description of local patches
    - SIFT : Histograms of oriented gradients

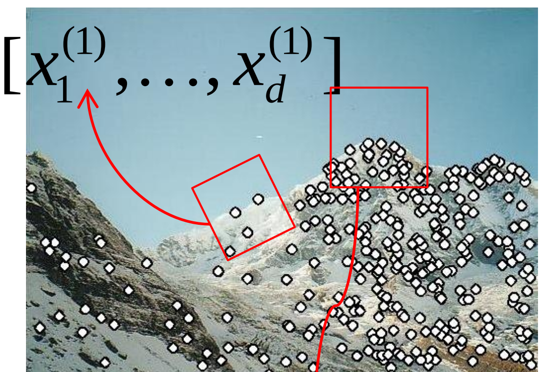
Local features: main components

1) Detection: Identify the interest points



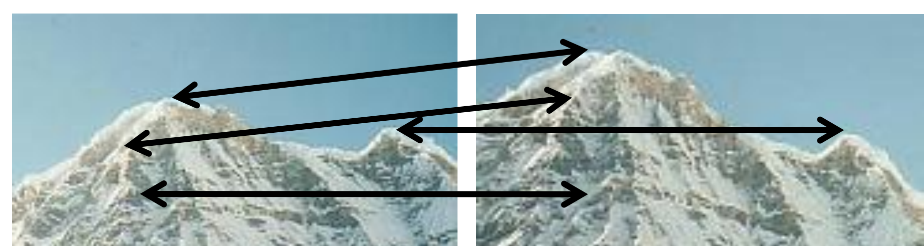
2) Description: Extract vector feature descriptor surrounding each interest point.

$$\mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}]$$



$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

3) Matching: Determine correspondence between descriptors in two views



Kristen Grauman

Goal: interest operator repeatability

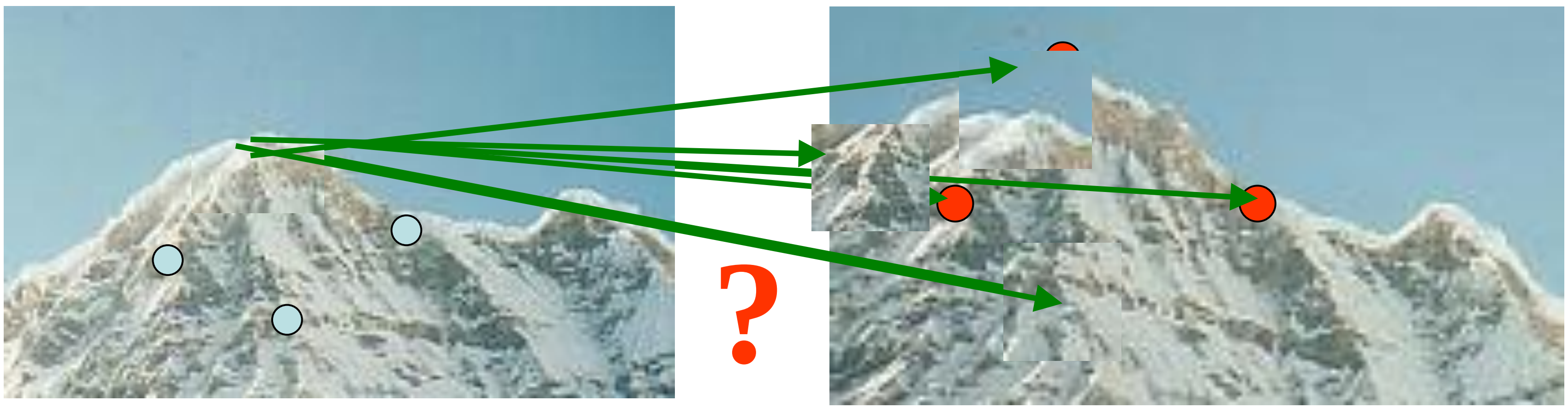
- We want to detect (at least some of) the same points in both images.


No chance to find true matches!

- Yet we have to be able to run the detection procedure *independently* per image.

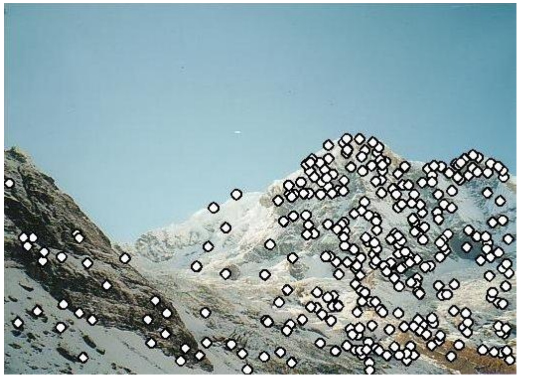
Goal: descriptor distinctiveness

- We want to be able to reliably determine which point goes with which.



- Must provide some invariance to geometric and photometric differences between the two views.

Local features: main components



1) Detection: Identify the interest points

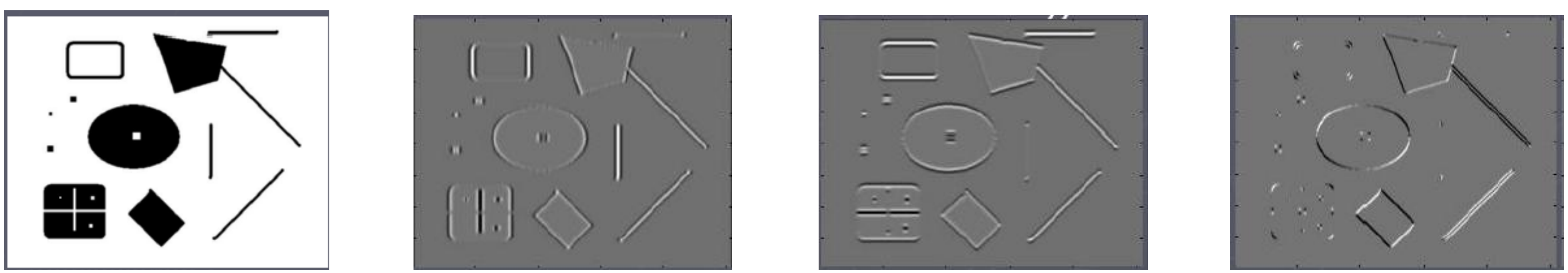
2) Description: Extract vector feature descriptor surrounding each interest point.

3) Matching: Determine correspondence between descriptors in two views

Recall: Corners as distinctive interest points

$$M = \sum w(x,y) \begin{bmatrix} I_x I_x & I_x I_y \\ I_x I_y & I_y I_y \end{bmatrix}$$

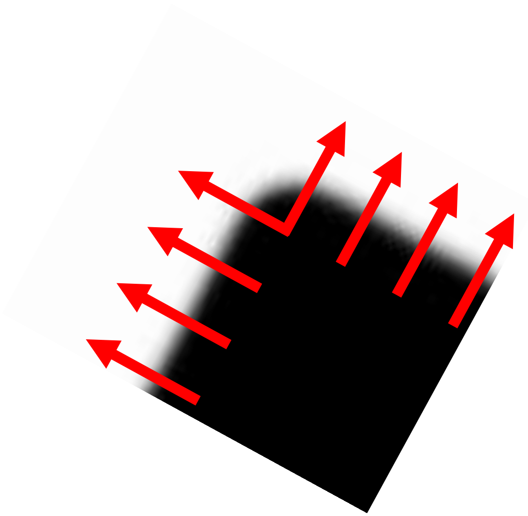
2 x 2 matrix of image derivatives (averaged in neighborhood of a point).



Notation:
$$I_x \Leftrightarrow \frac{\partial I}{\partial x} \qquad I_y \Leftrightarrow \frac{\partial I}{\partial y} \qquad I_x I_y \Leftrightarrow \frac{\partial I}{\partial x}\frac{\partial I}{\partial y}$$

Recall: Corners as distinctive interest points

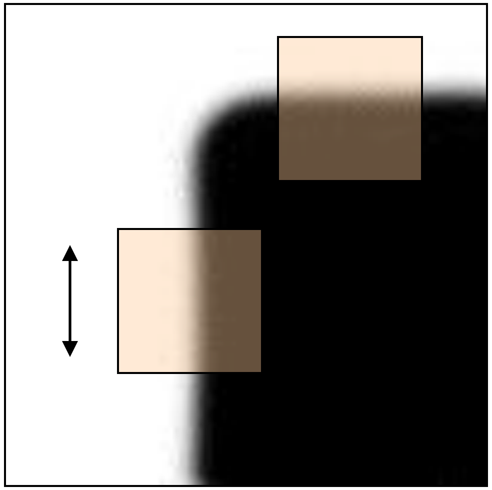
Since *M* is symmetric, we have $M = X \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} X^T$



$$Mx_i = \lambda_i x_i$$

The *eigenvalues* of *M* reveal the amount of intensity change in the two principal orthogonal gradient directions in the window.

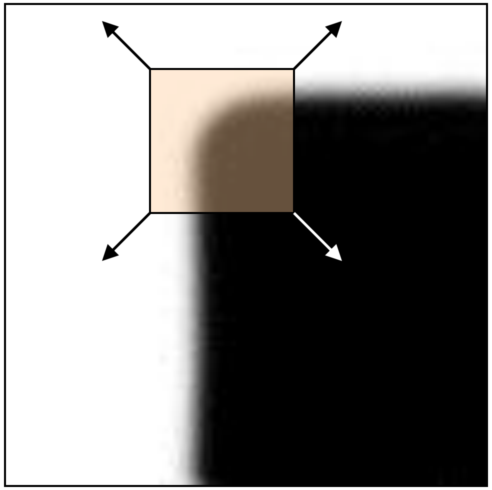
Recall: Corners as distinctive interest points



"edge":

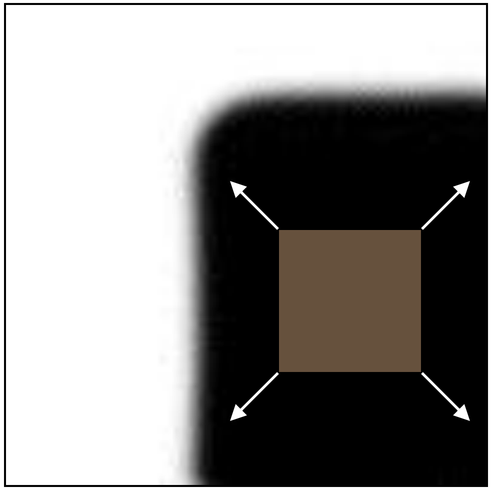
$\lambda_1 >> \lambda_2$

$\lambda_2 >> \lambda_1$



"corner":

λ_1 and λ_2 are large,
$\lambda_1 \sim \lambda_2$;



"flat" region

λ_1 and λ_2 are small;

One way to score the cornerness:

$$f = \frac{\lambda_1 \lambda_2}{\lambda_1 + \lambda_2}$$

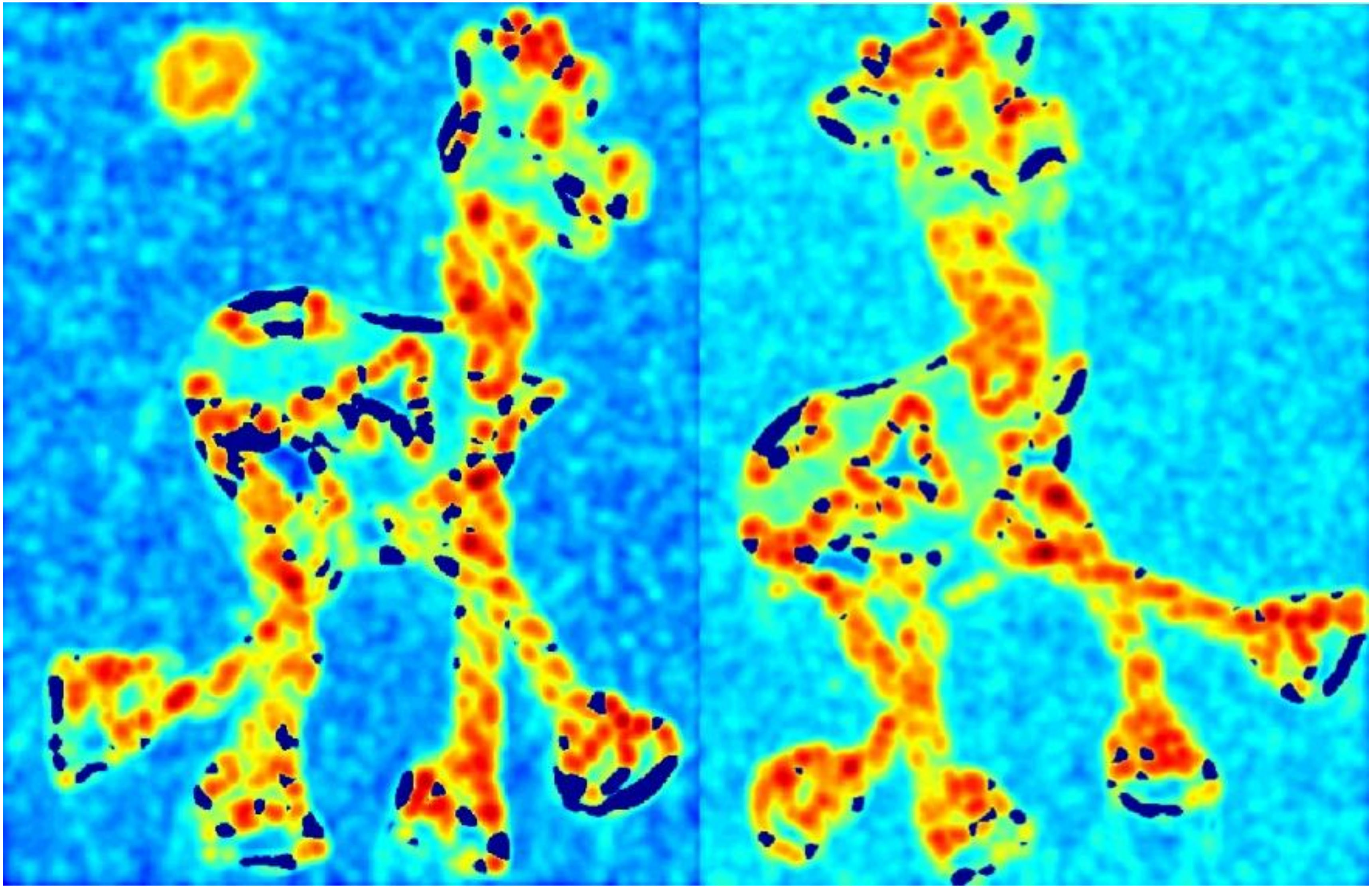
Harris corner detector

1) Compute *M* matrix for image window surrounding each pixel to get its *cornerness* score.
2) Find points with large corner response (f > threshold)
3) Take the points of local maxima, i.e., perform non-maximum suppression

Harris Detector: Steps

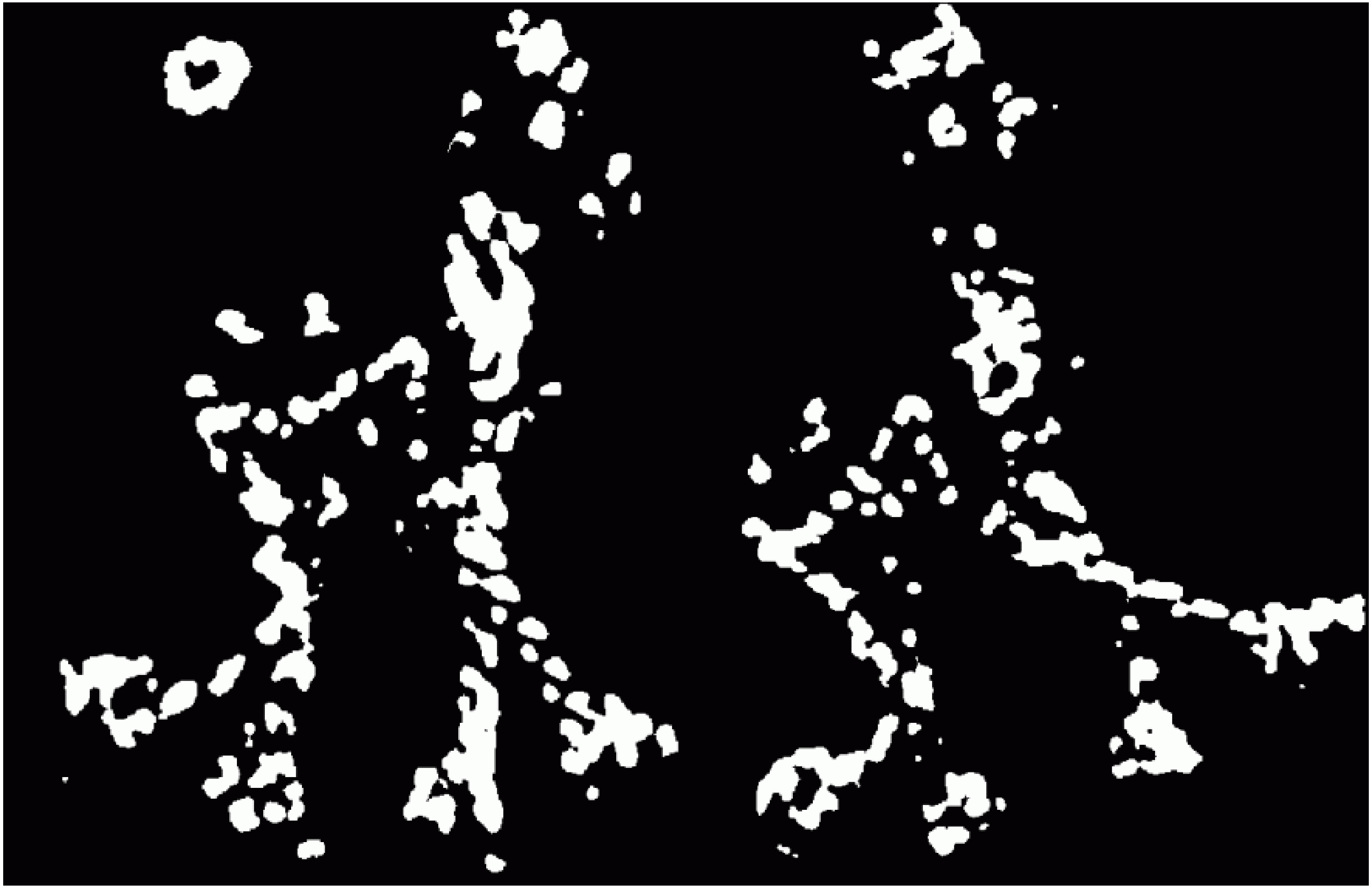
Harris Detector: Steps

Compute corner response f



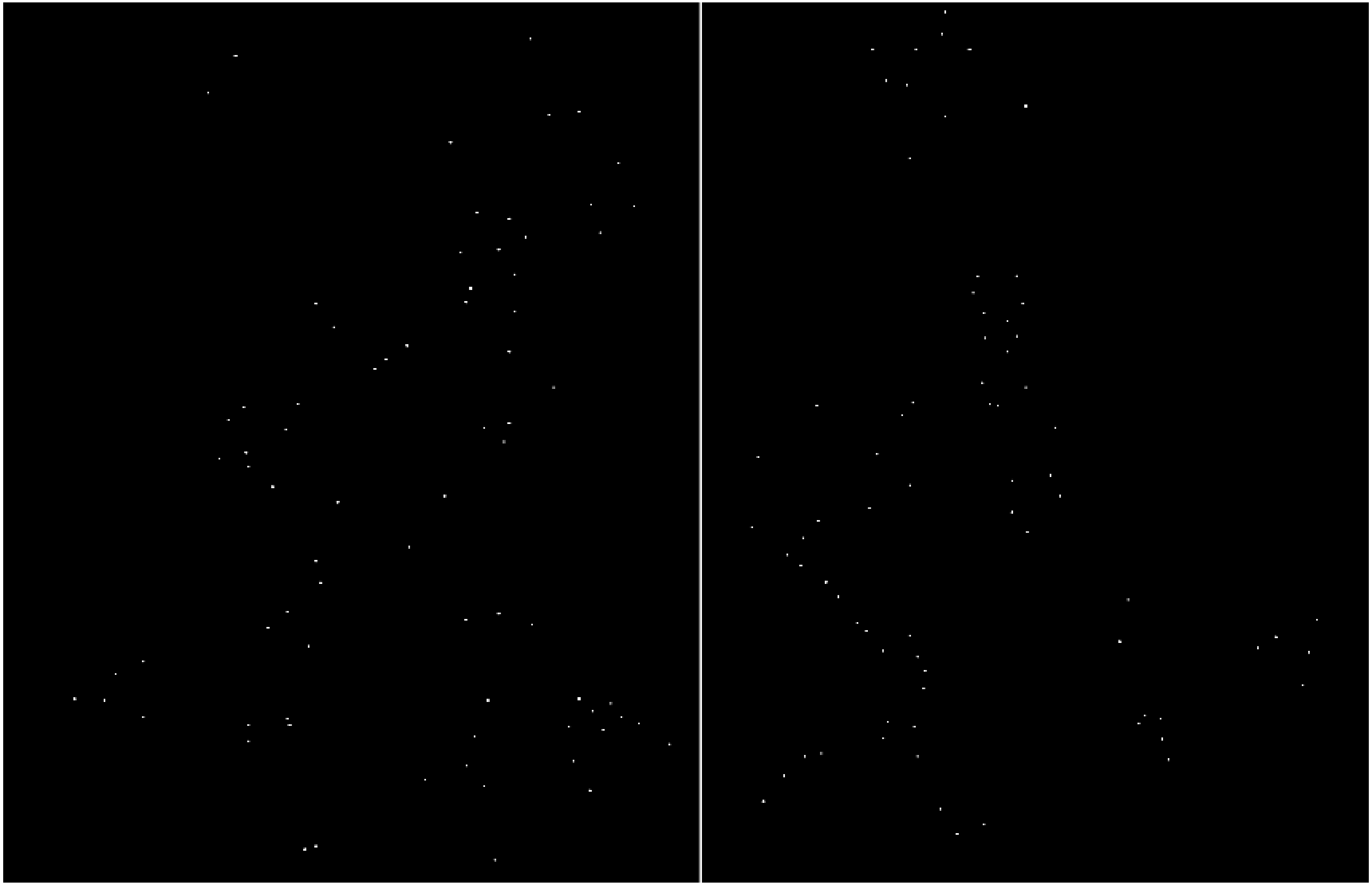
Harris Detector: Steps

Find points with large corner response: $f >$ threshold

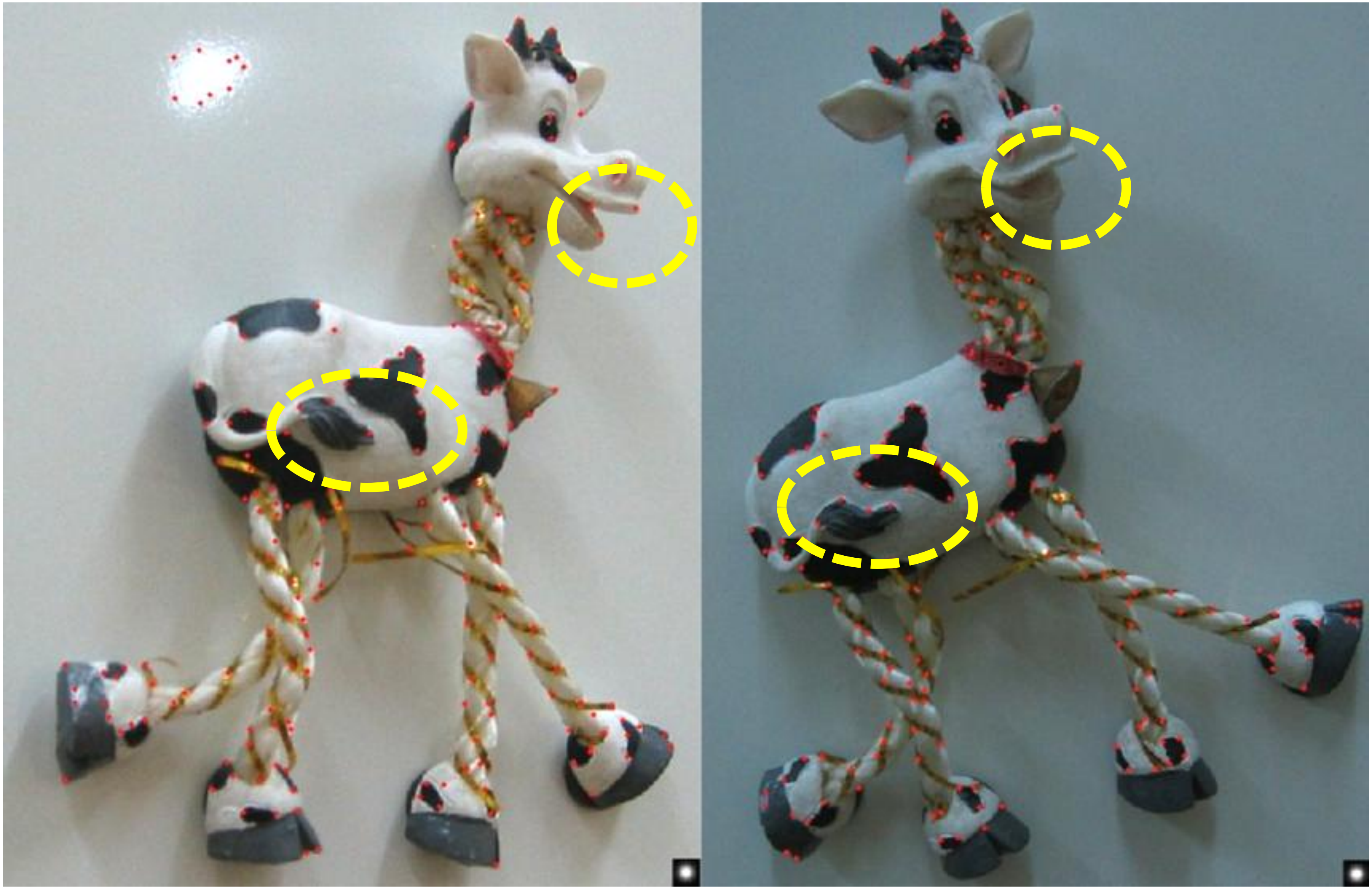


Harris Detector: Steps

Take only the points of local maxima of f



Harris Detector: Steps



Properties of the Harris corner detector

Rotation invariant? Yes

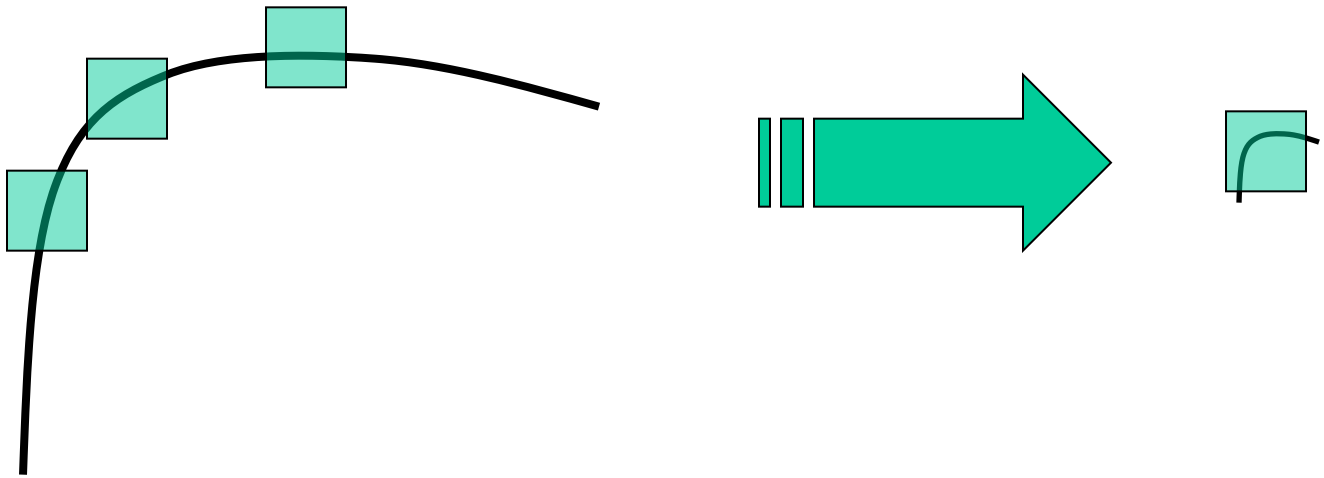
$$M = X \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} X^T$$

Scale invariant?

Properties of the Harris corner detector

Rotation invariant? Yes

Scale invariant? No



All points will be classified as edges

Corner !

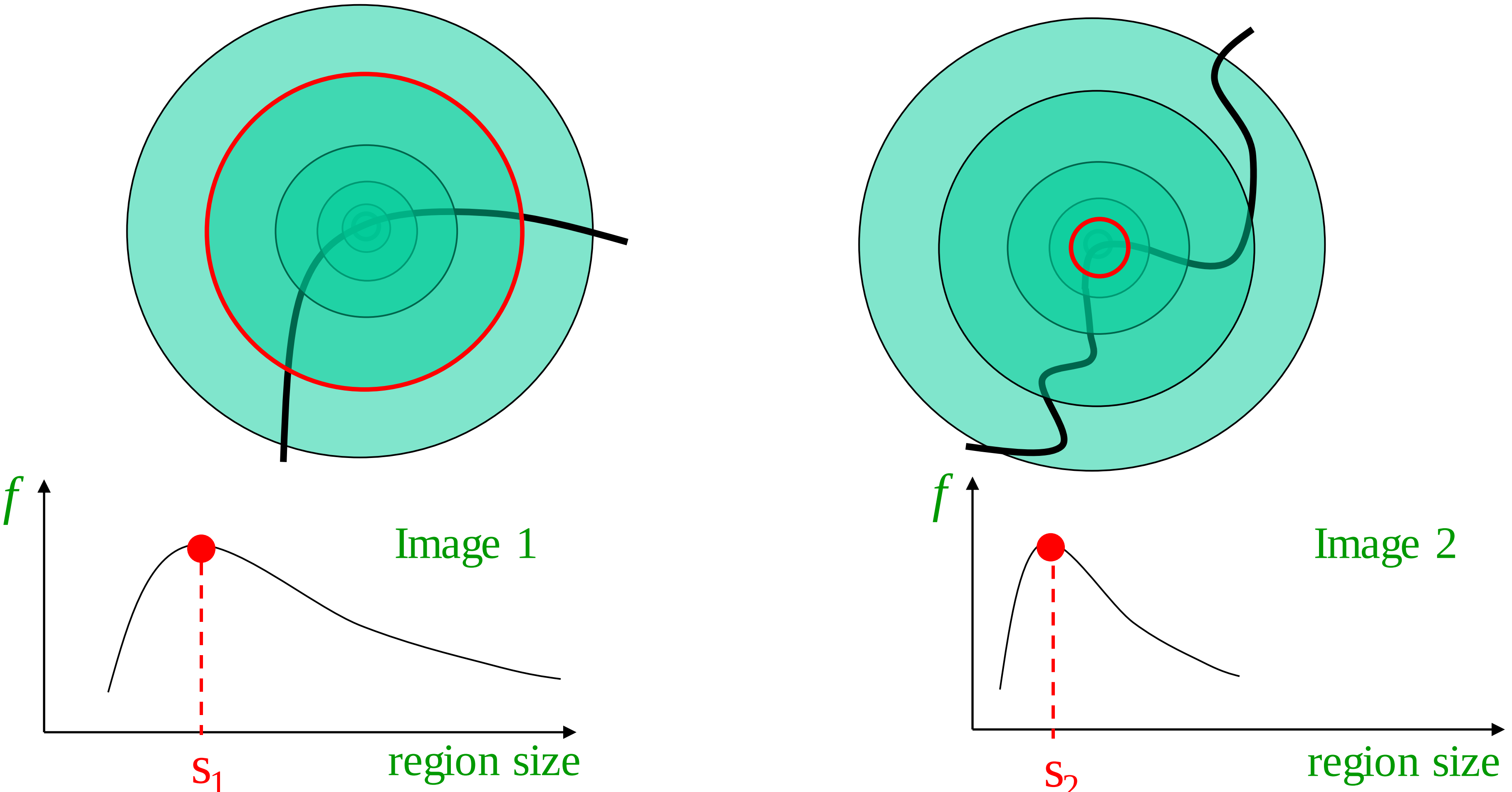
Scale invariant interest points

How can we independently select interest points in each image, such that the detections are repeatable across different scales?

Automatic scale selection

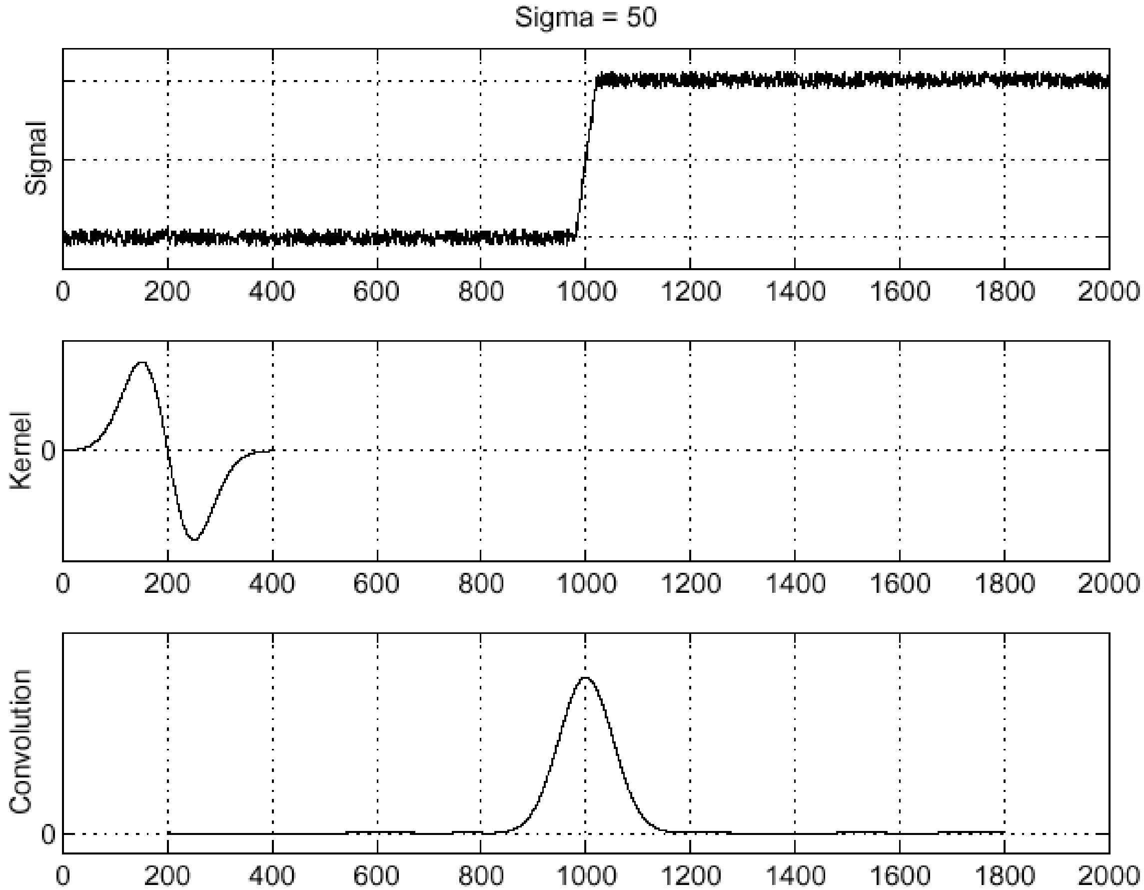
Intuition:

- Find scale that gives local maxima of some function *f* in both position and scale.



What can be the “signature” function?

Recall: Edge detection



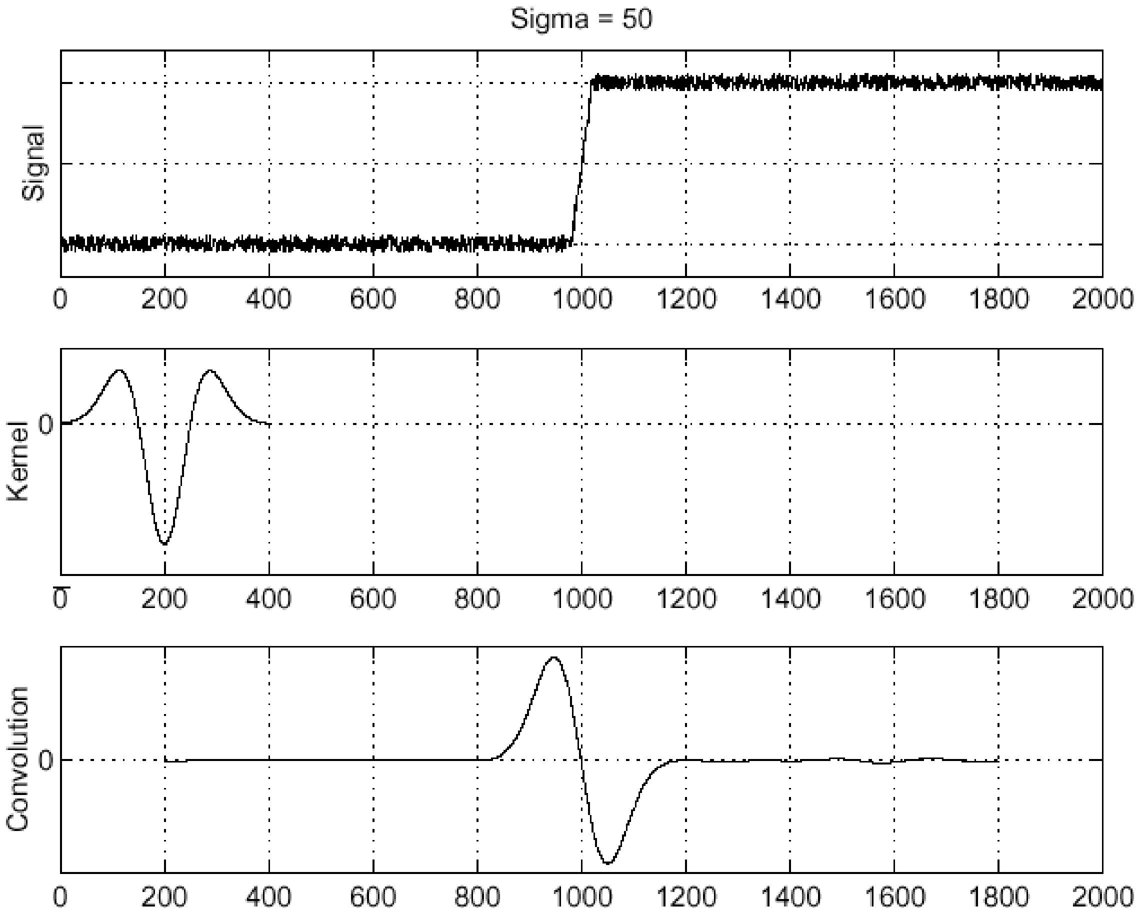
f — Edge

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

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

Source: S. Seitz

Recall: Edge detection



f — Edge

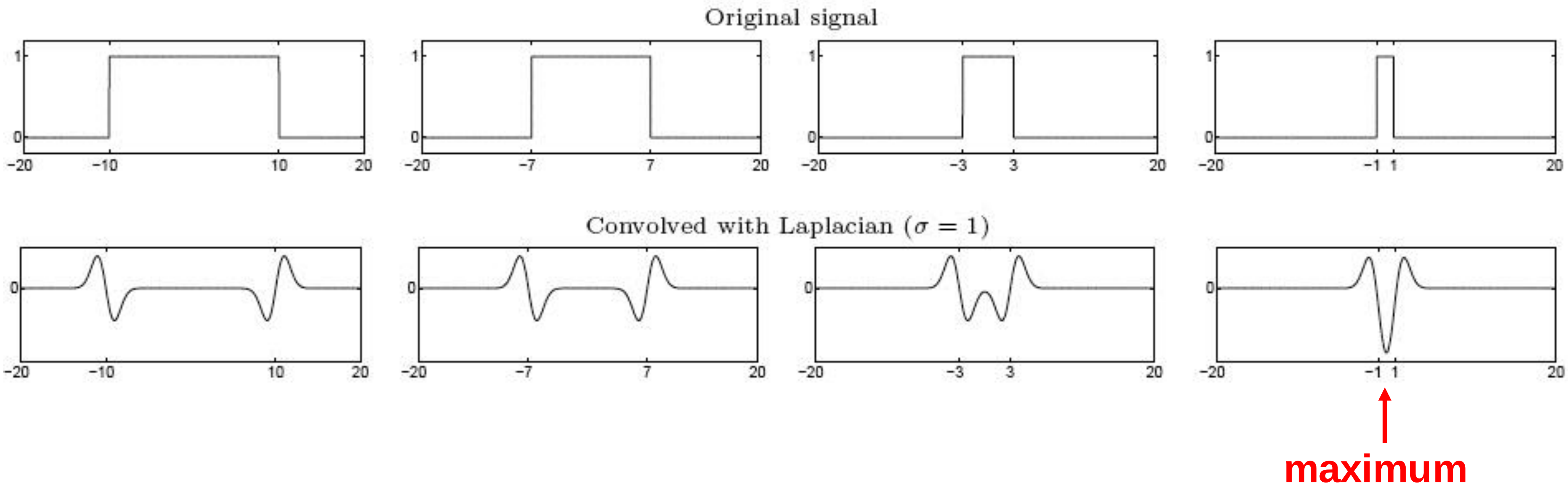
$\frac{d^2}{dx^2} g$ — Second derivative of Gaussian (Laplacian)

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

Source: S. Seitz

From edges to blobs

- Edge = ripple
- Blob = superposition of two ripples

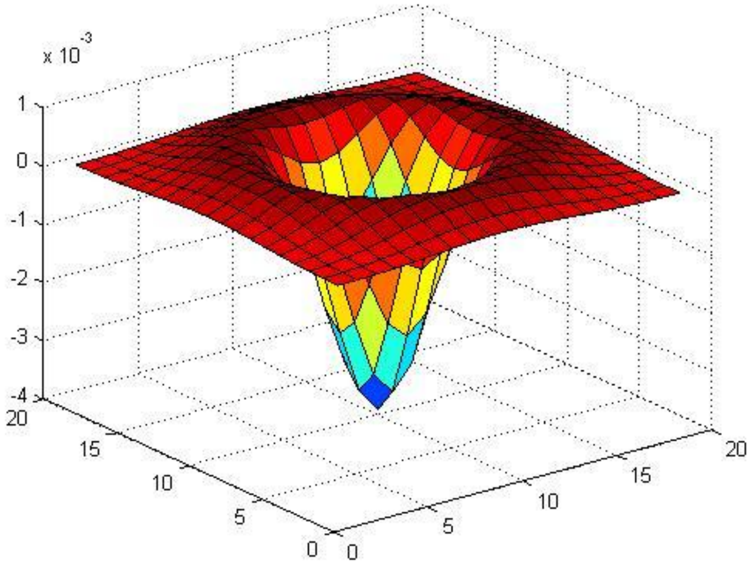


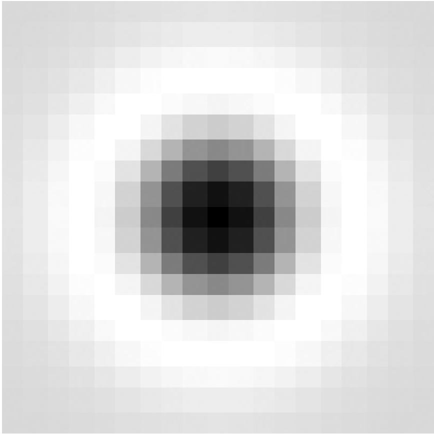
Spatial selection: the **magnitude** of the Laplacian response will achieve a maximum at the center of the blob, provided the scale of the Laplacian is "matched" to the scale of the blob

Slide credit: Lana Lazebnik

Blob detection in 2D

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

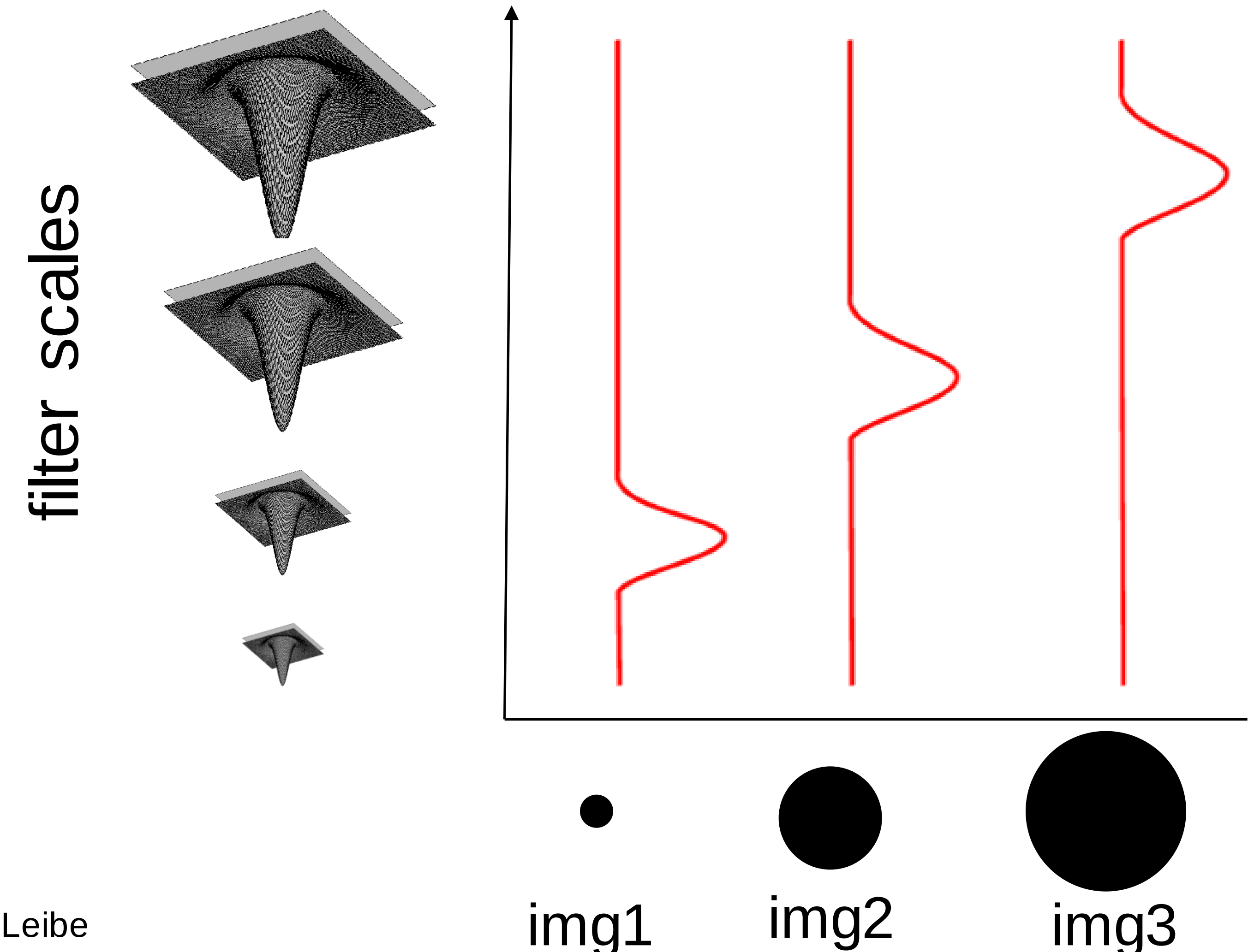




$$\nabla^2 g = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2}$$

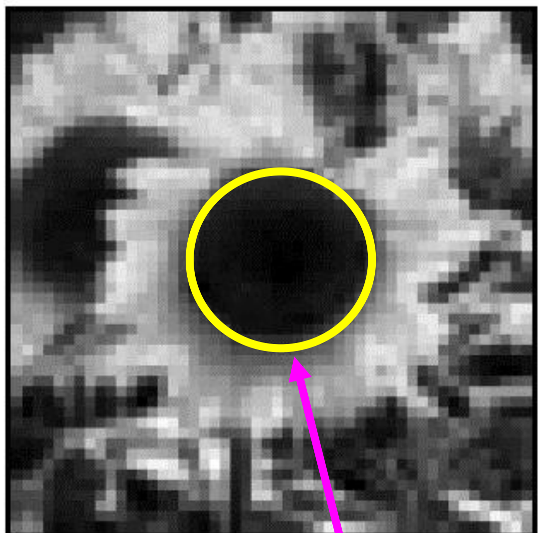
Blob detection in 2D: scale selection

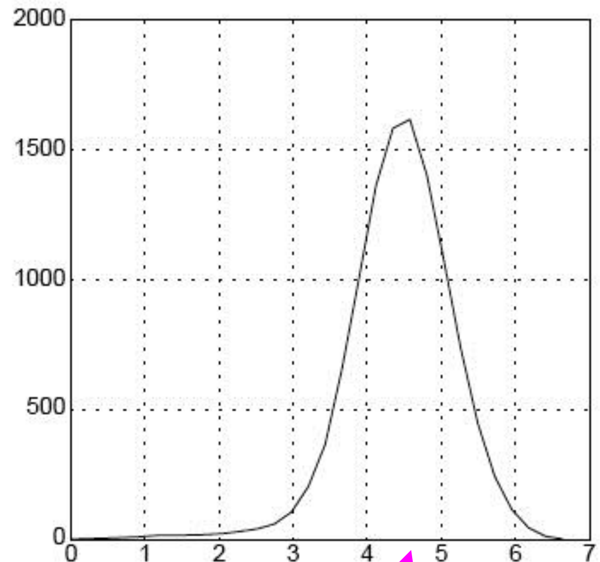
Laplacian-of-Gaussian = "blob" detector $\nabla^2 g = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2}$



Blob detection in 2D

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





characteristic scale

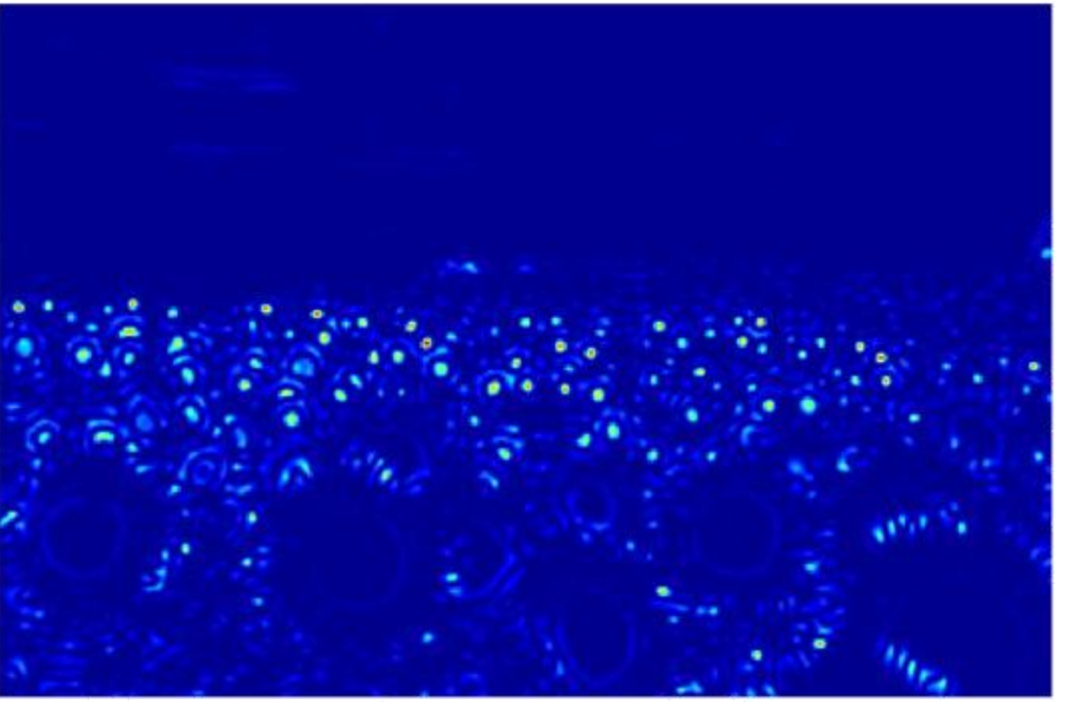
Slide credit: Lana Lazebnik

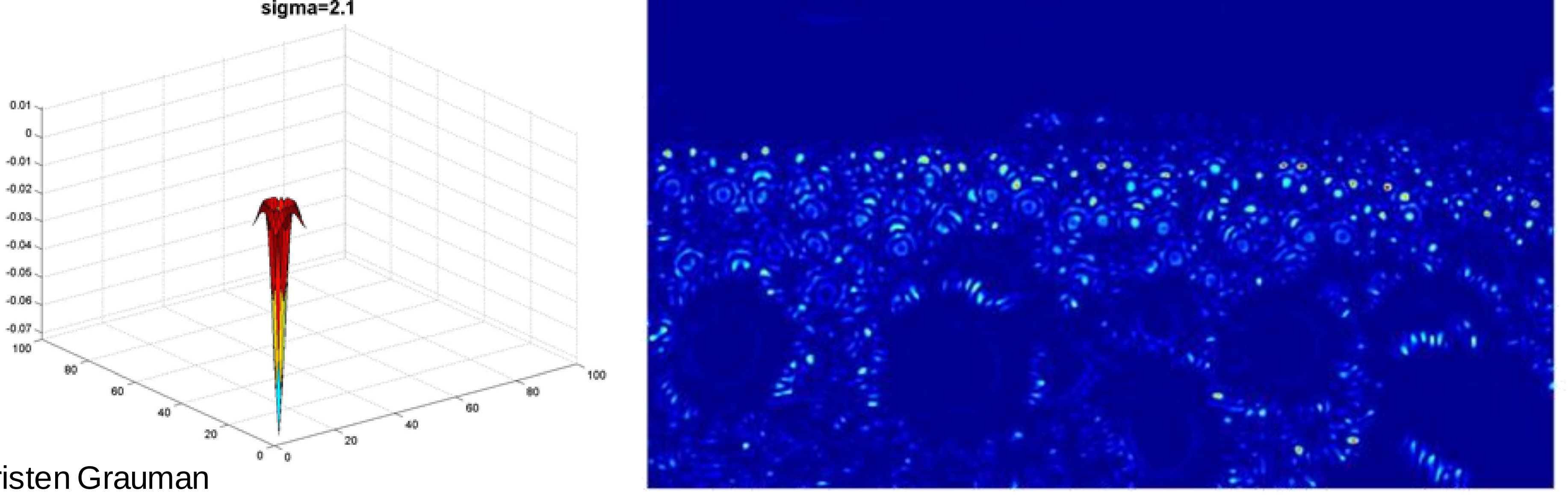
Example

Original image
at ¾ the size

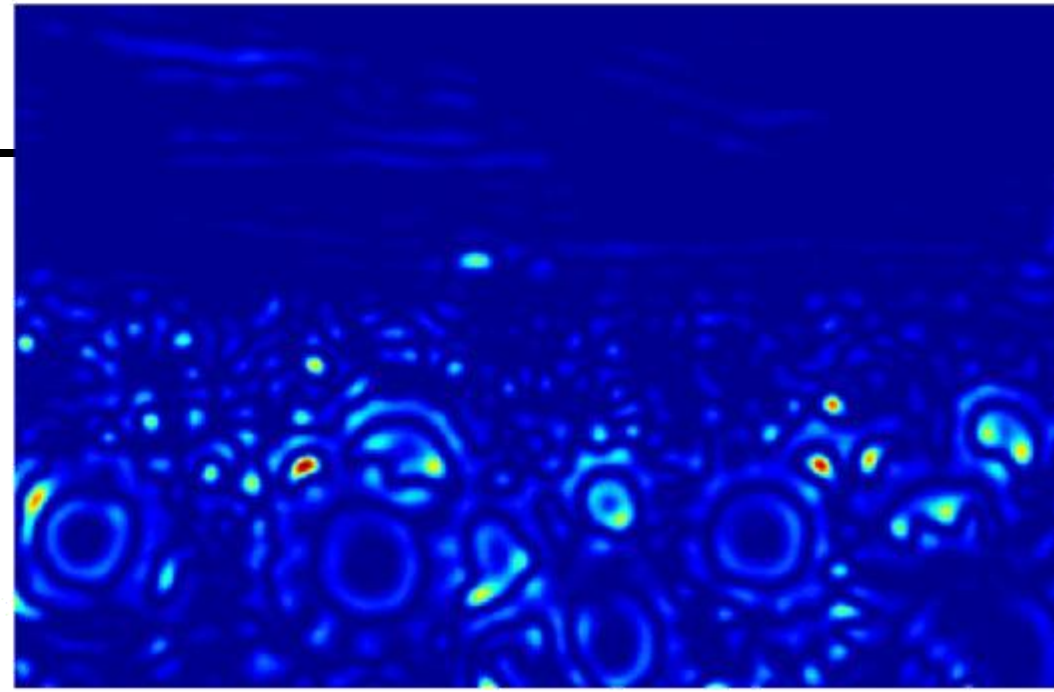
Kristen Grauman

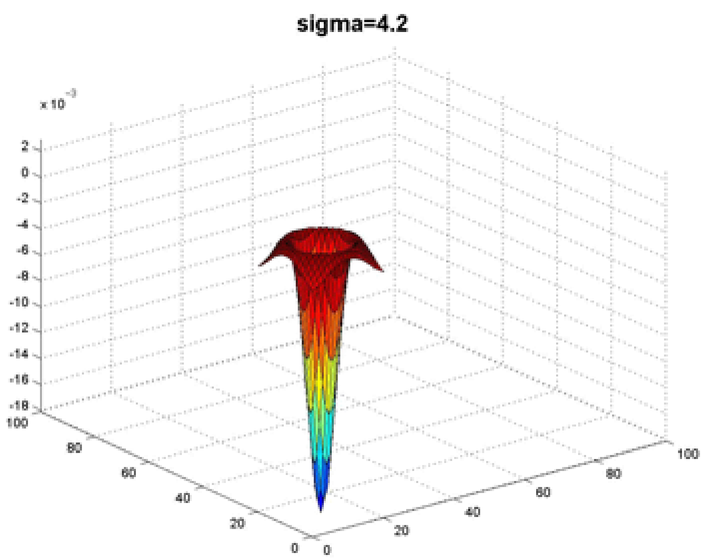
Original image
at ¾ the size

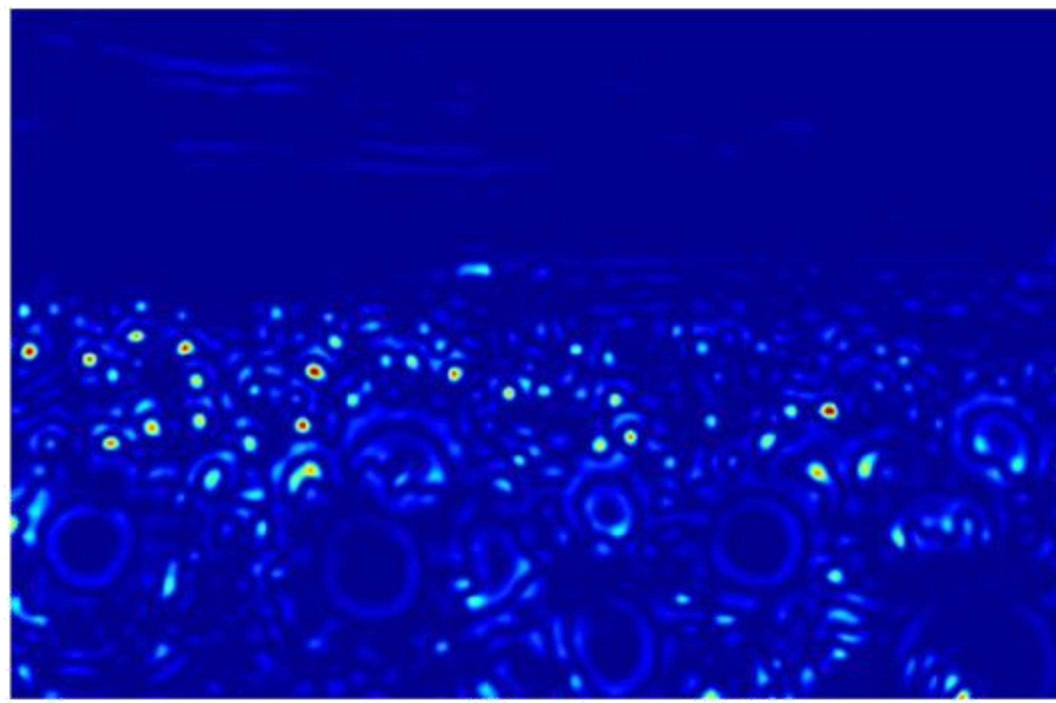




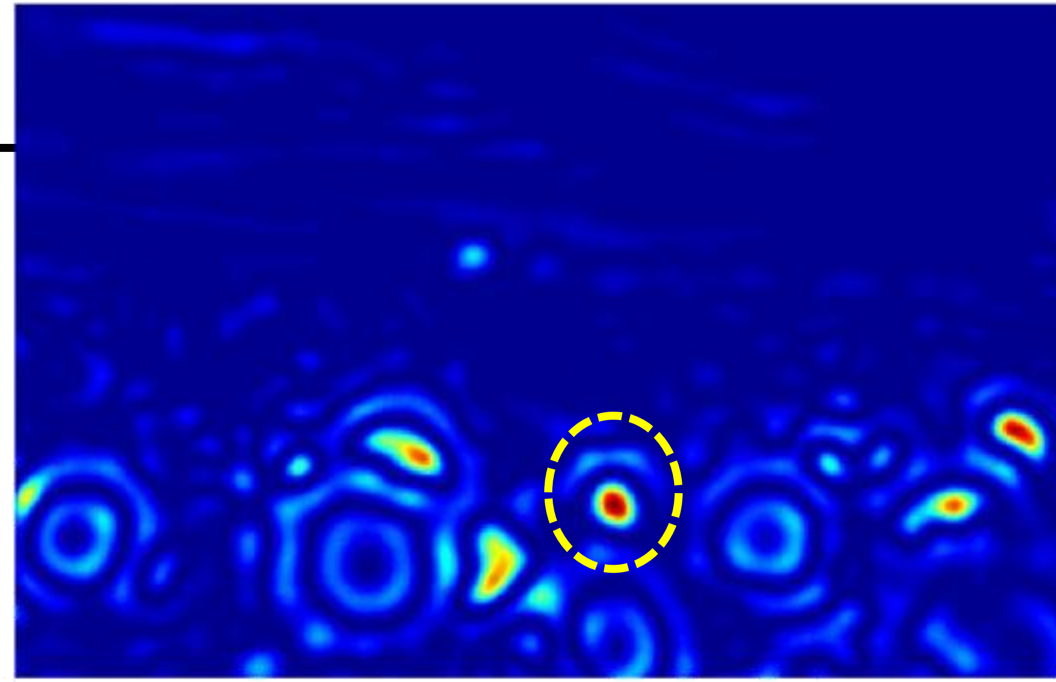
Kristen Grauman

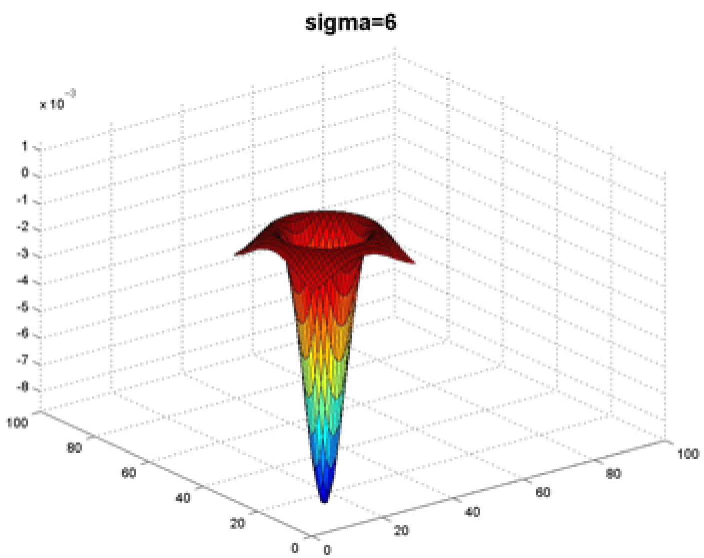


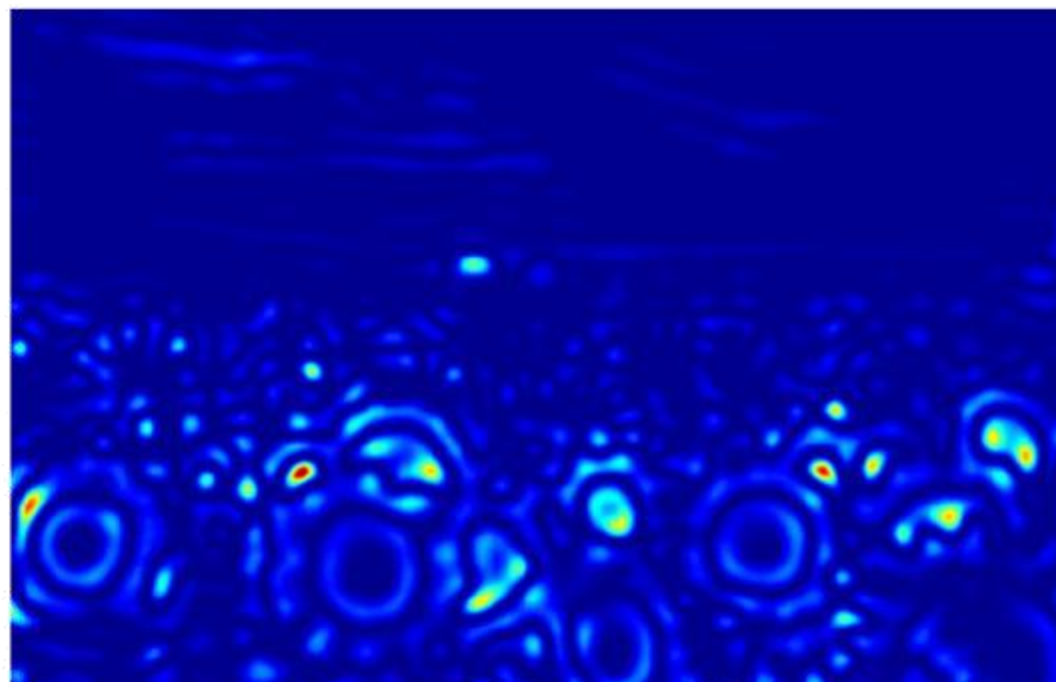




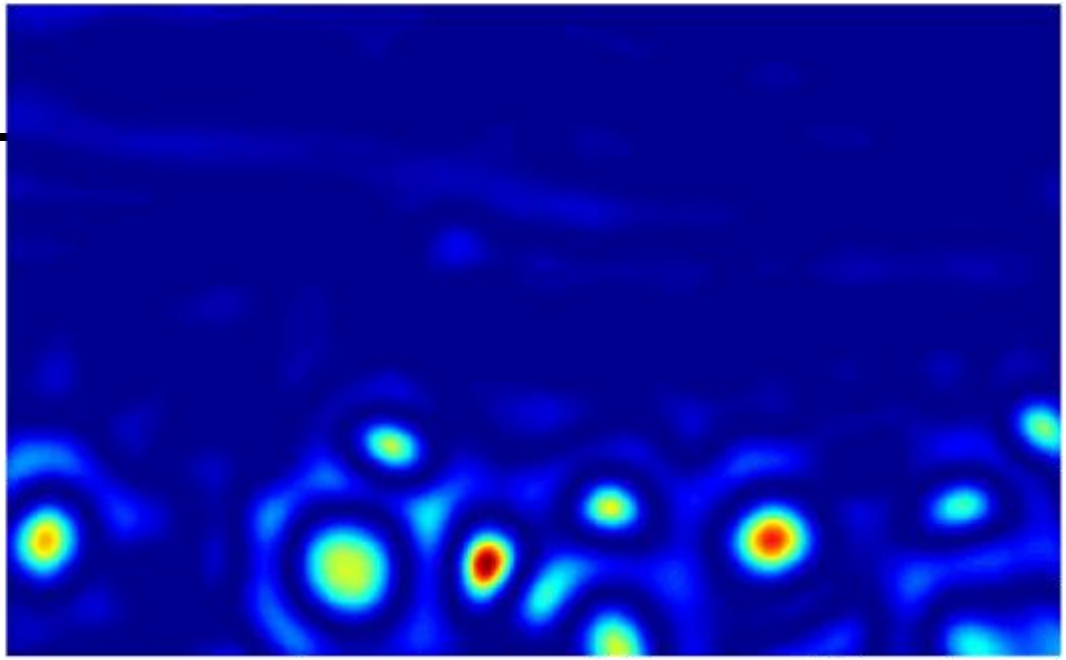
Kristen Grauman

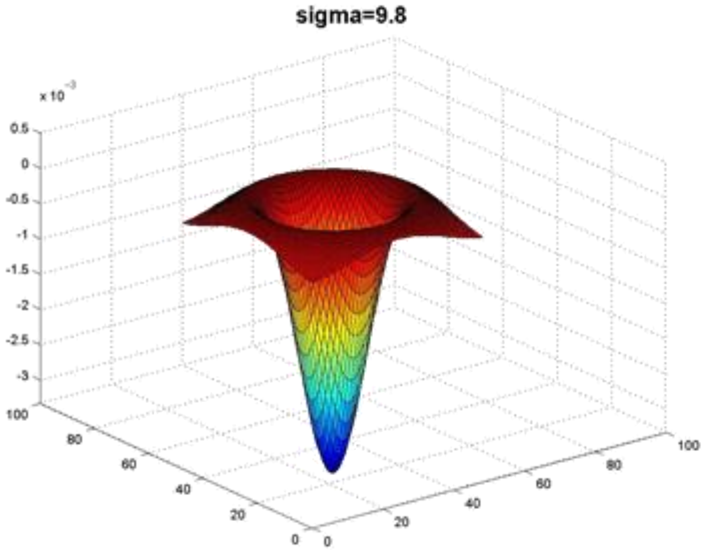


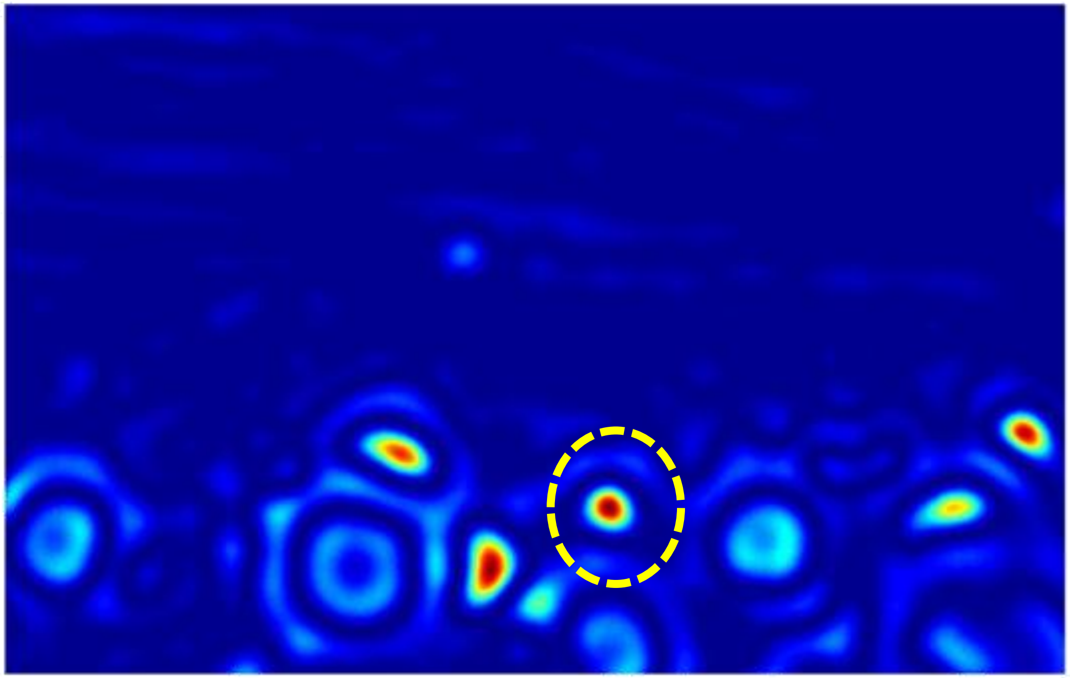




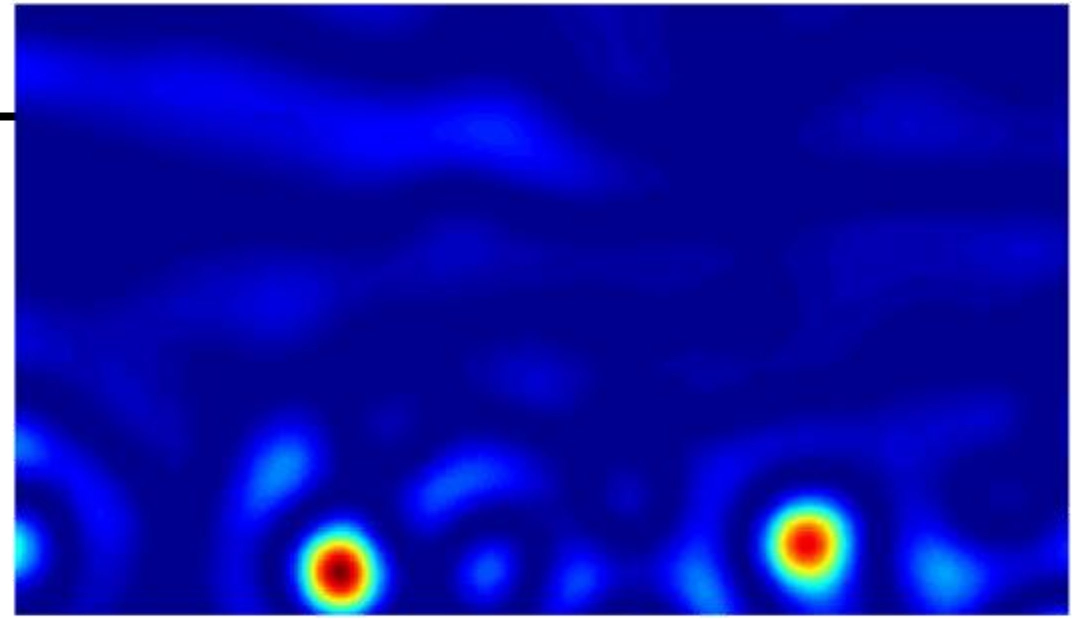
Kristen Grauman

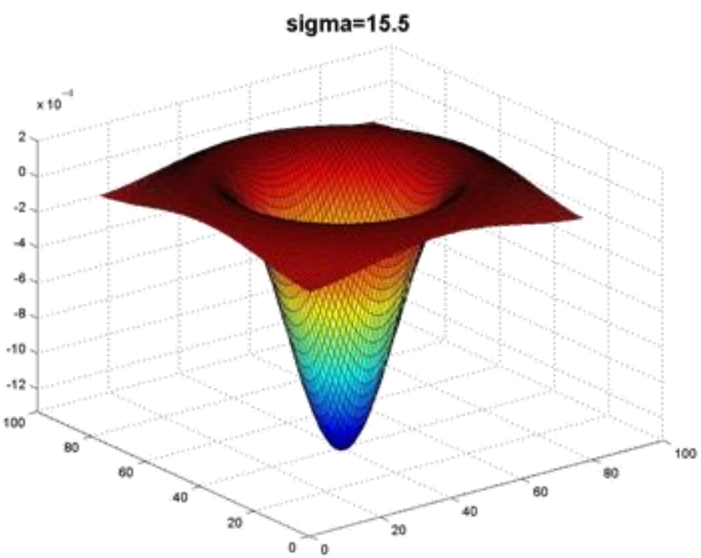


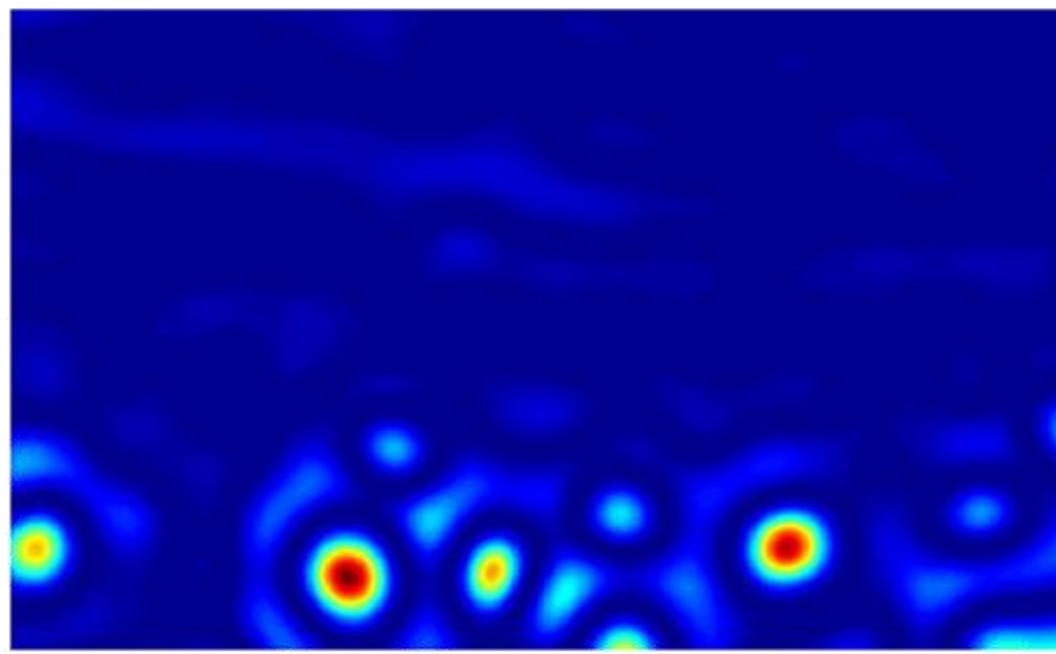




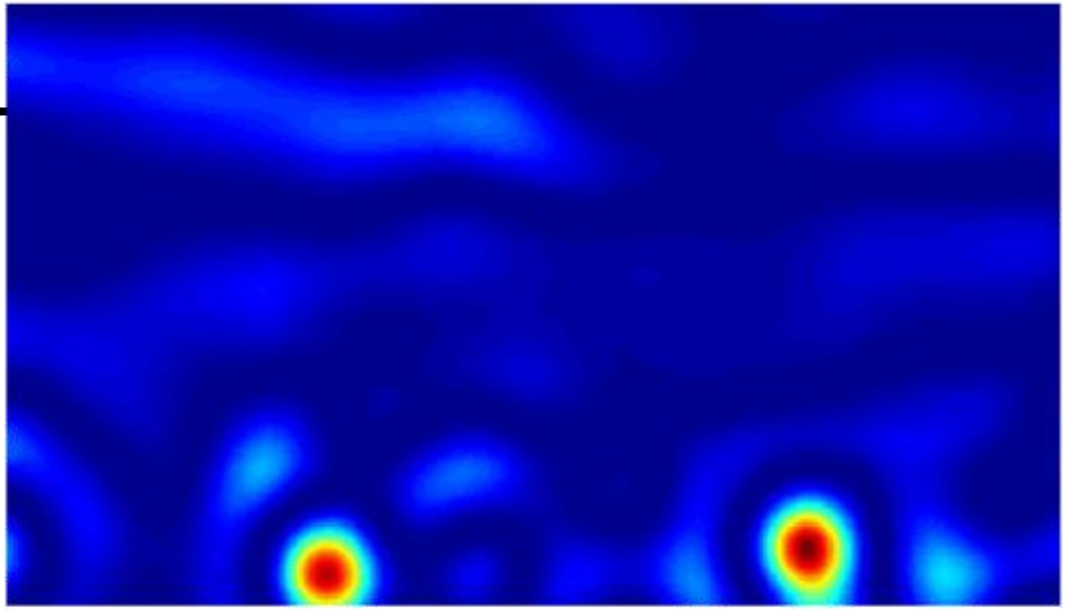
Kristen Grauman

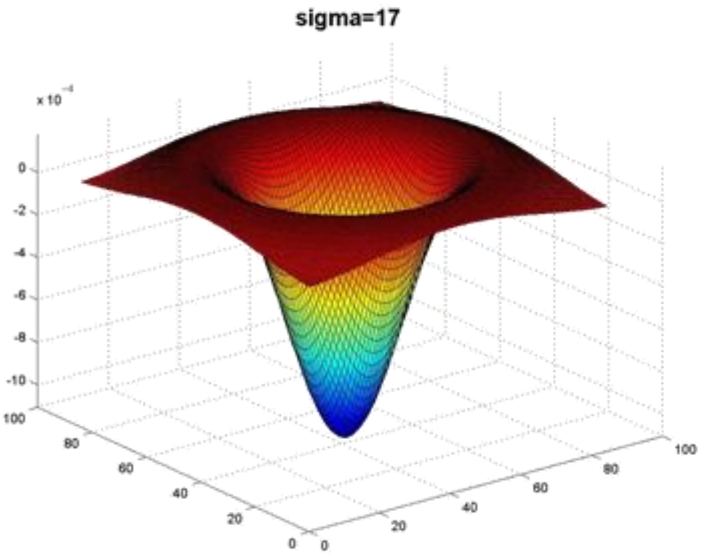


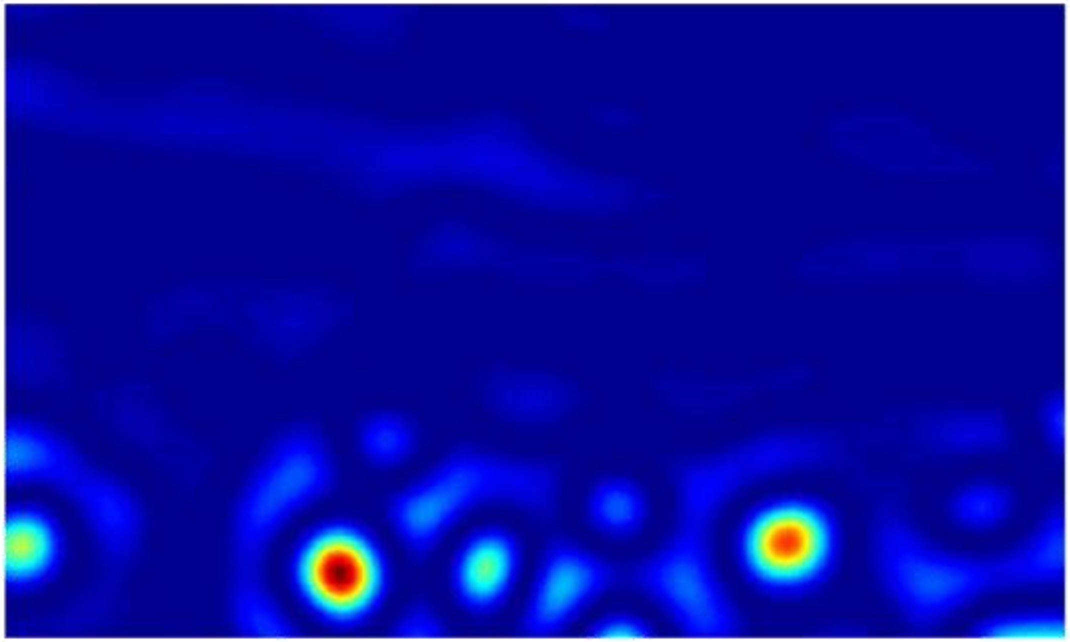




Kristen Grauman



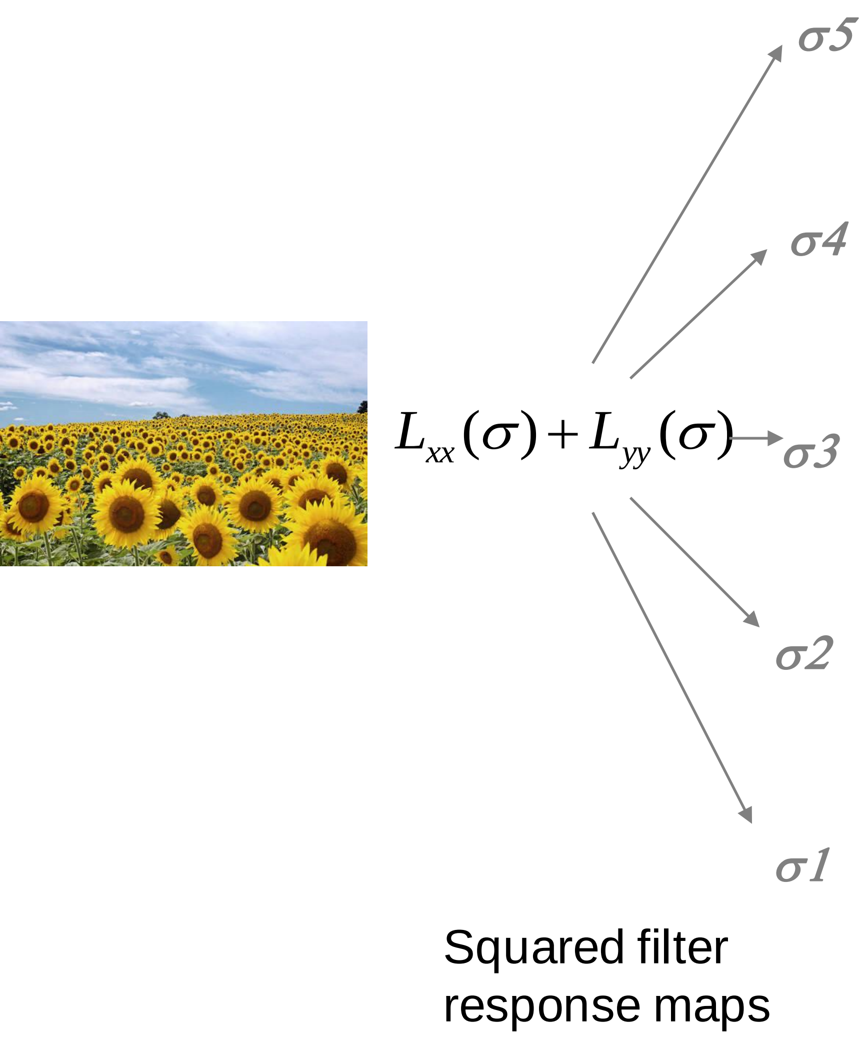


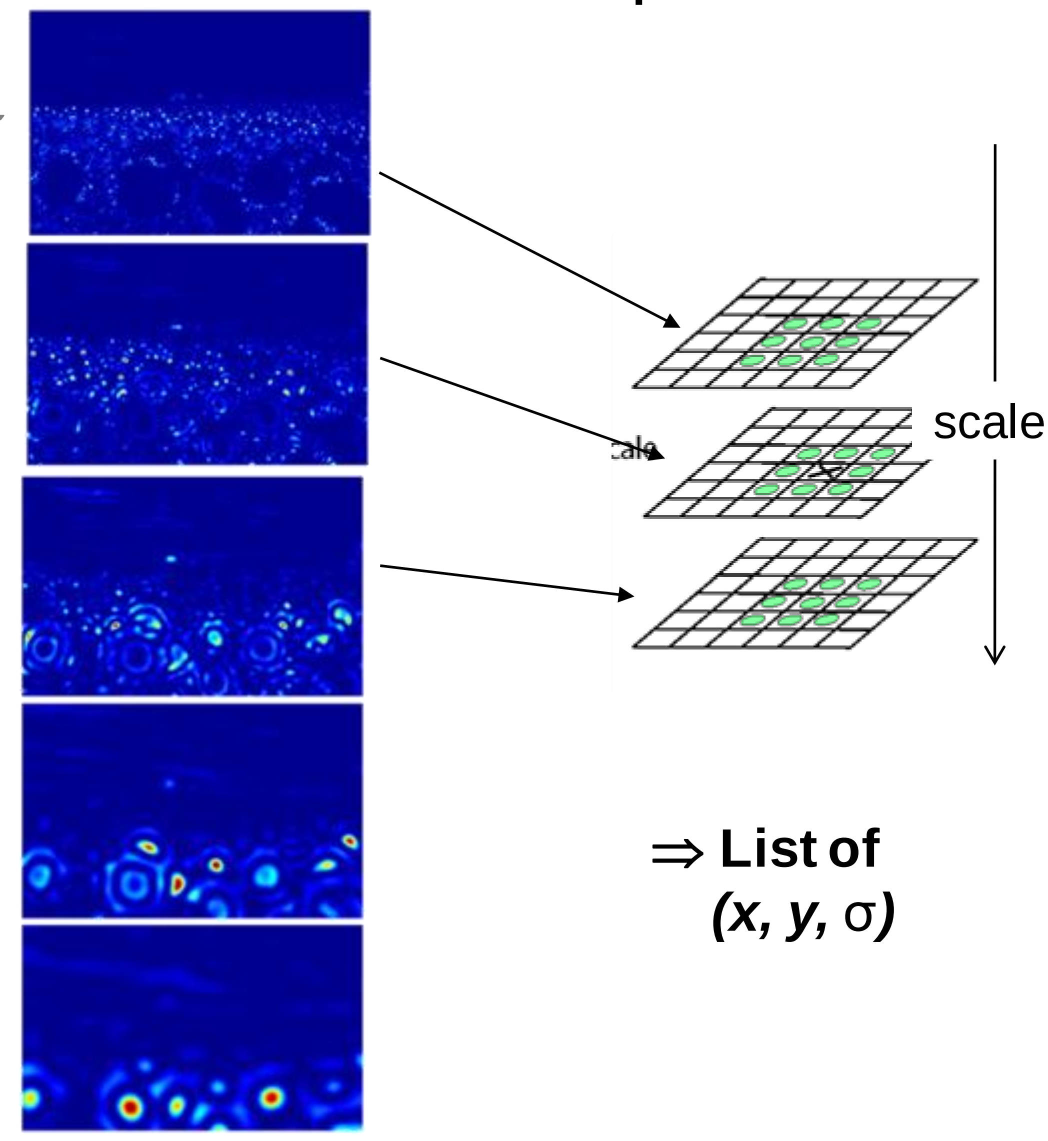


Kristen Grauman

Scale invariant interest points

Interest points are local maxima in both position and scale.





⇒ **List of (x, y, σ)**

Scale-space blob detector: Example

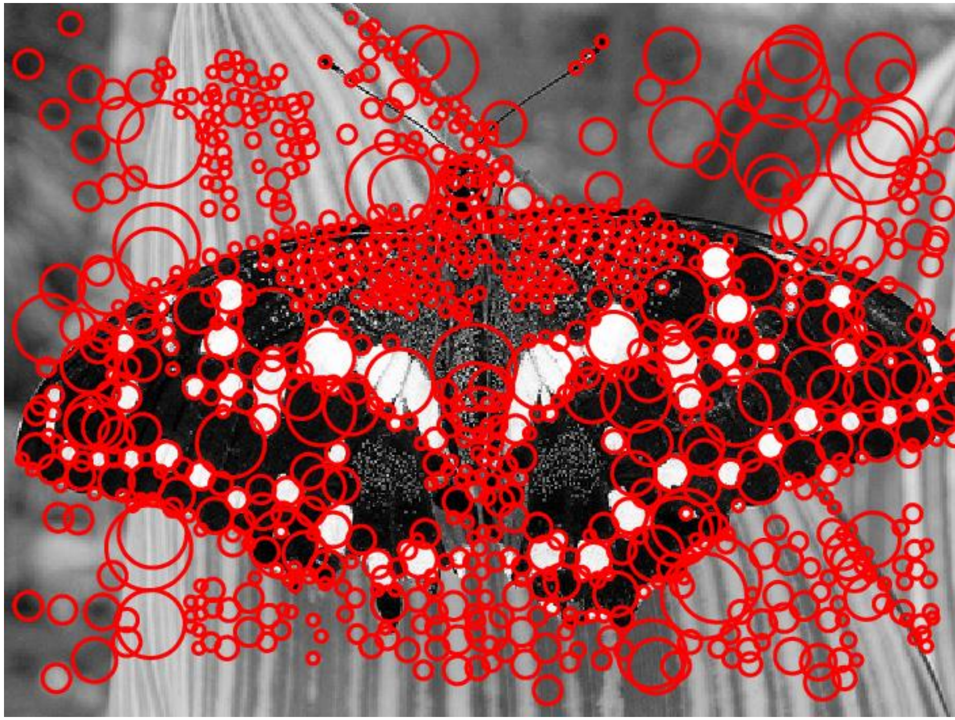



Image credit: Lana Lazebnik

Technical detail

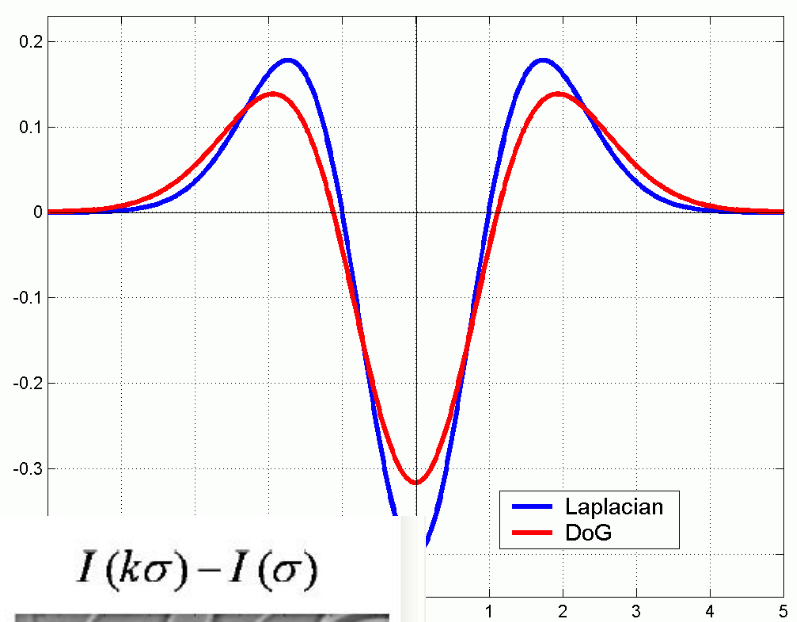
We can approximate the Laplacian with a difference of Gaussians; more efficient to implement.

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

(Laplacian)

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

(Difference of Gaussians)



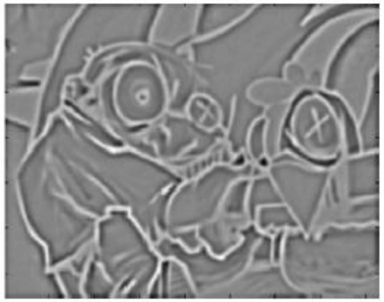
$I(k\sigma)$

-

$I(\sigma)$

=

$I(k\sigma) - I(\sigma)$

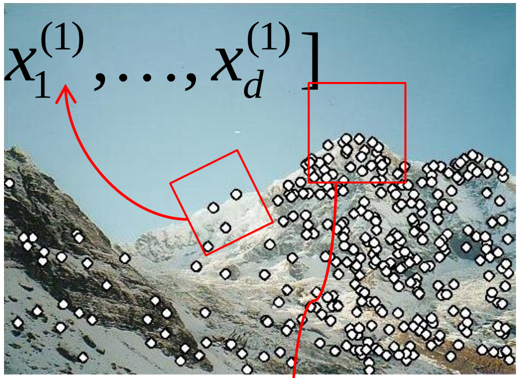


Local features: main components

1) Detection: Identify the interest points

2) Description: Extract vector feature descriptor surrounding each interest point.

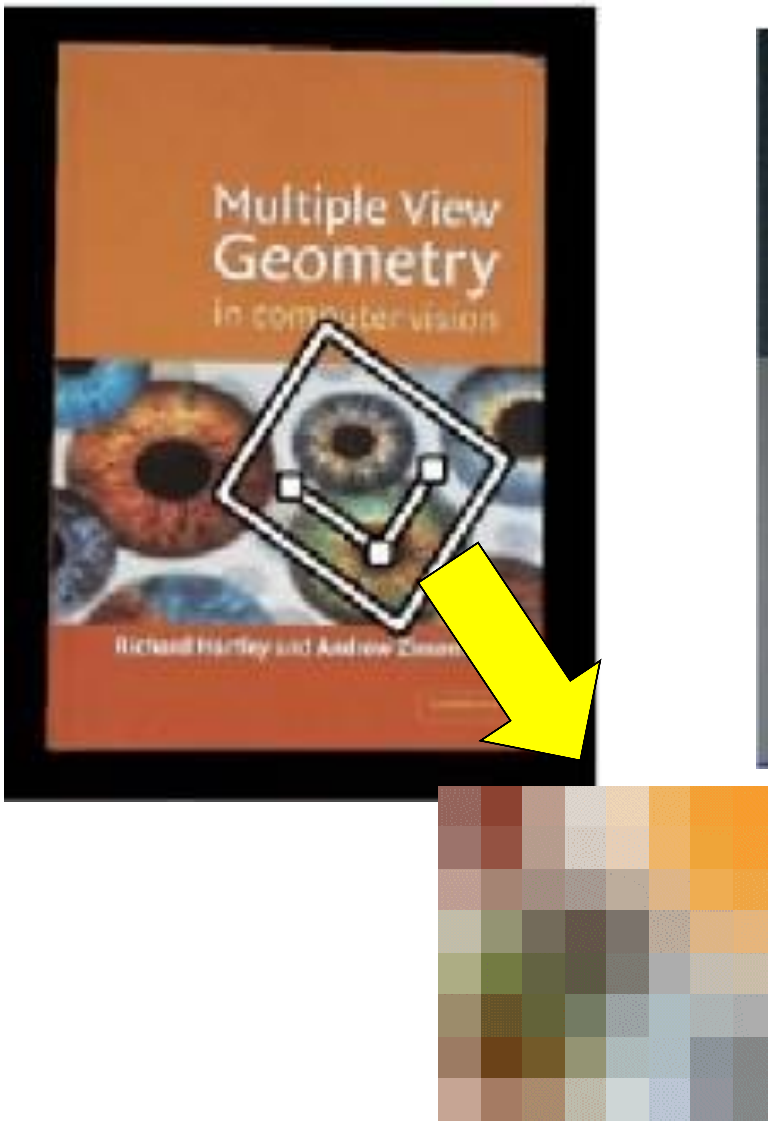
$$\mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}]$$

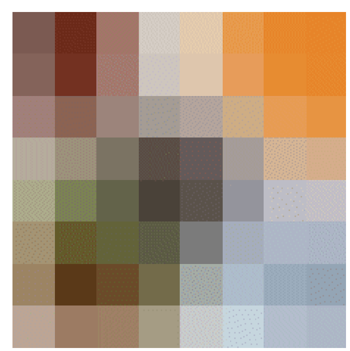


$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

3) Matching: Determine correspondence between descriptors in two views

Geometric transformations



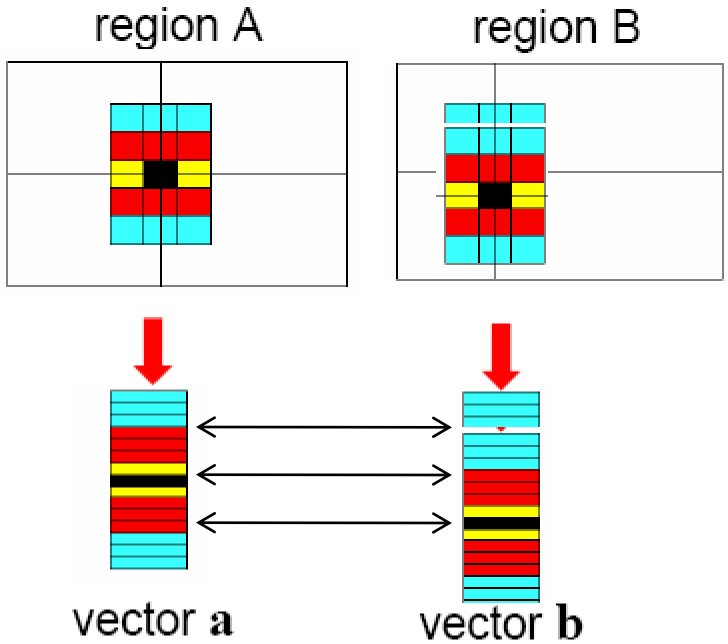


e.g. scale,
translation,
rotation

Photometric transformations

Figure from T. Tuytelaars ECCV 2006 tutorial

Raw patches as local descriptors

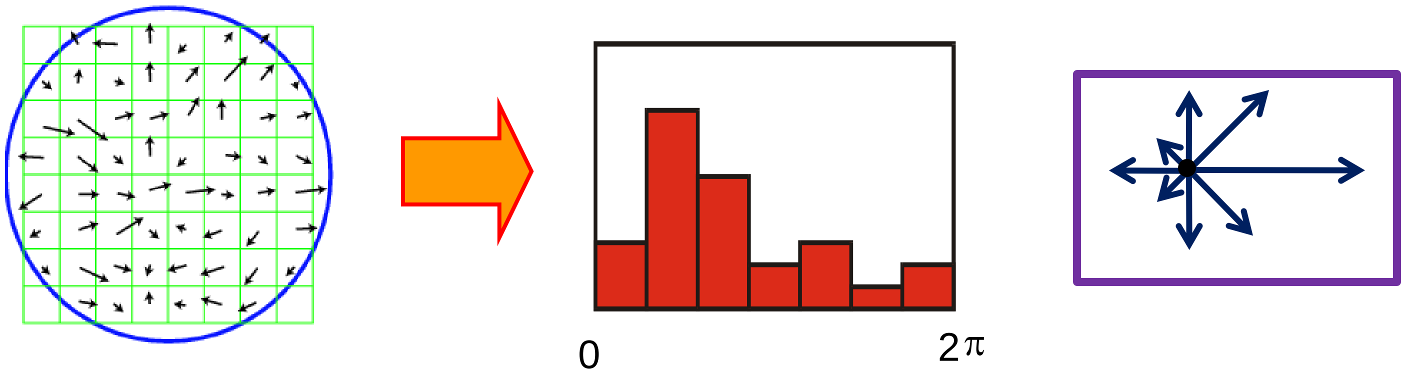


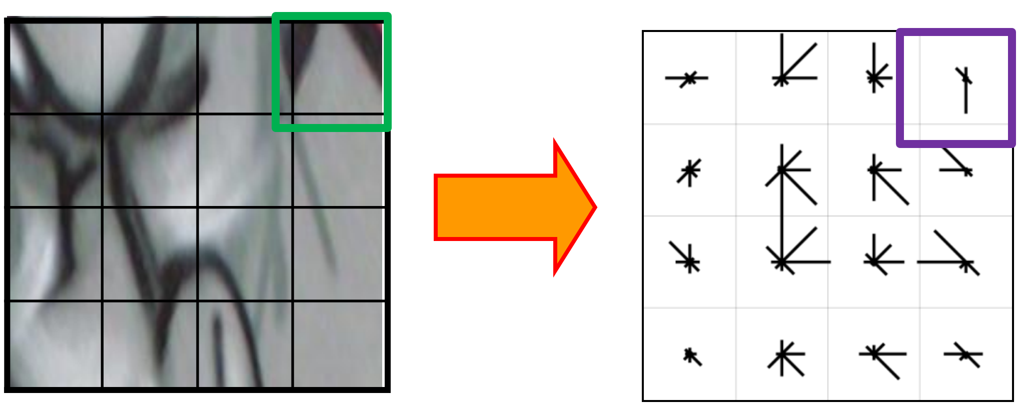
The simplest way to describe the neighborhood around an interest point is to write down the list of intensities to form a feature vector.

But this is very sensitive to even small shifts, rotations.

SIFT descriptor [Lowe 2004]

- Use histograms to bin pixels within sub-patches according to their orientation.

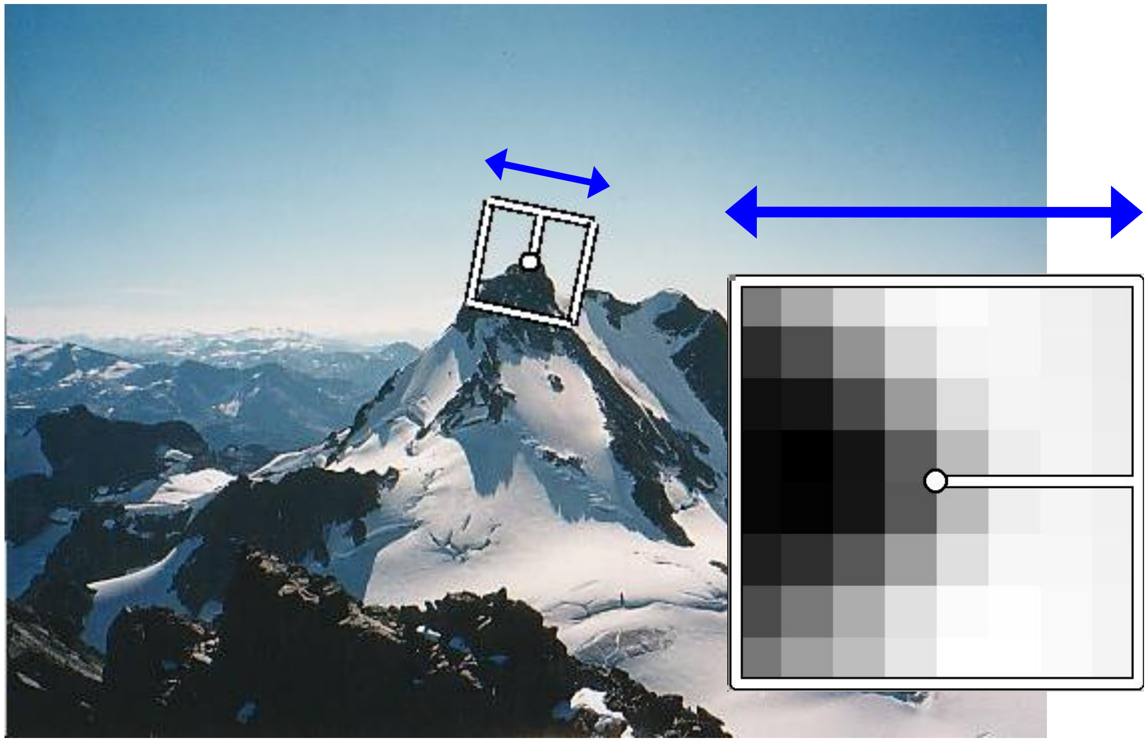




Why subpatches?

Why does SIFT have some illumination invariance?

Making descriptor rotation invariant

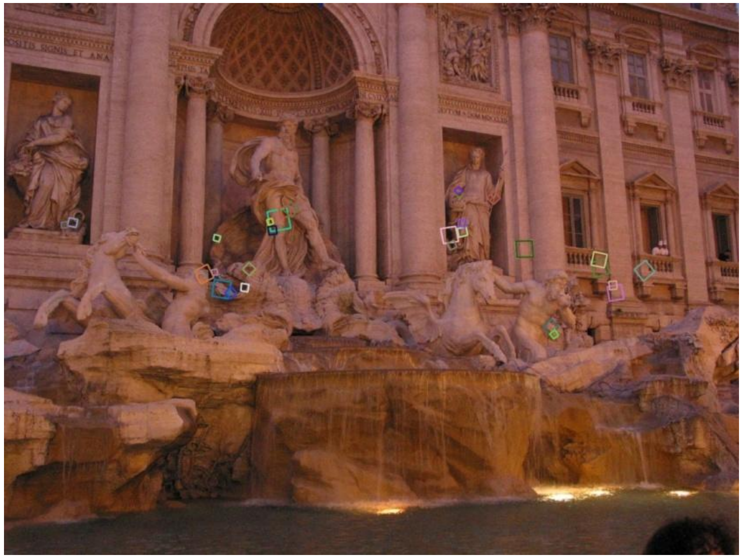


- Rotate patch according to its dominant gradient orientation
- This puts the patches into a canonical orientation.

Image from Matthew Brown

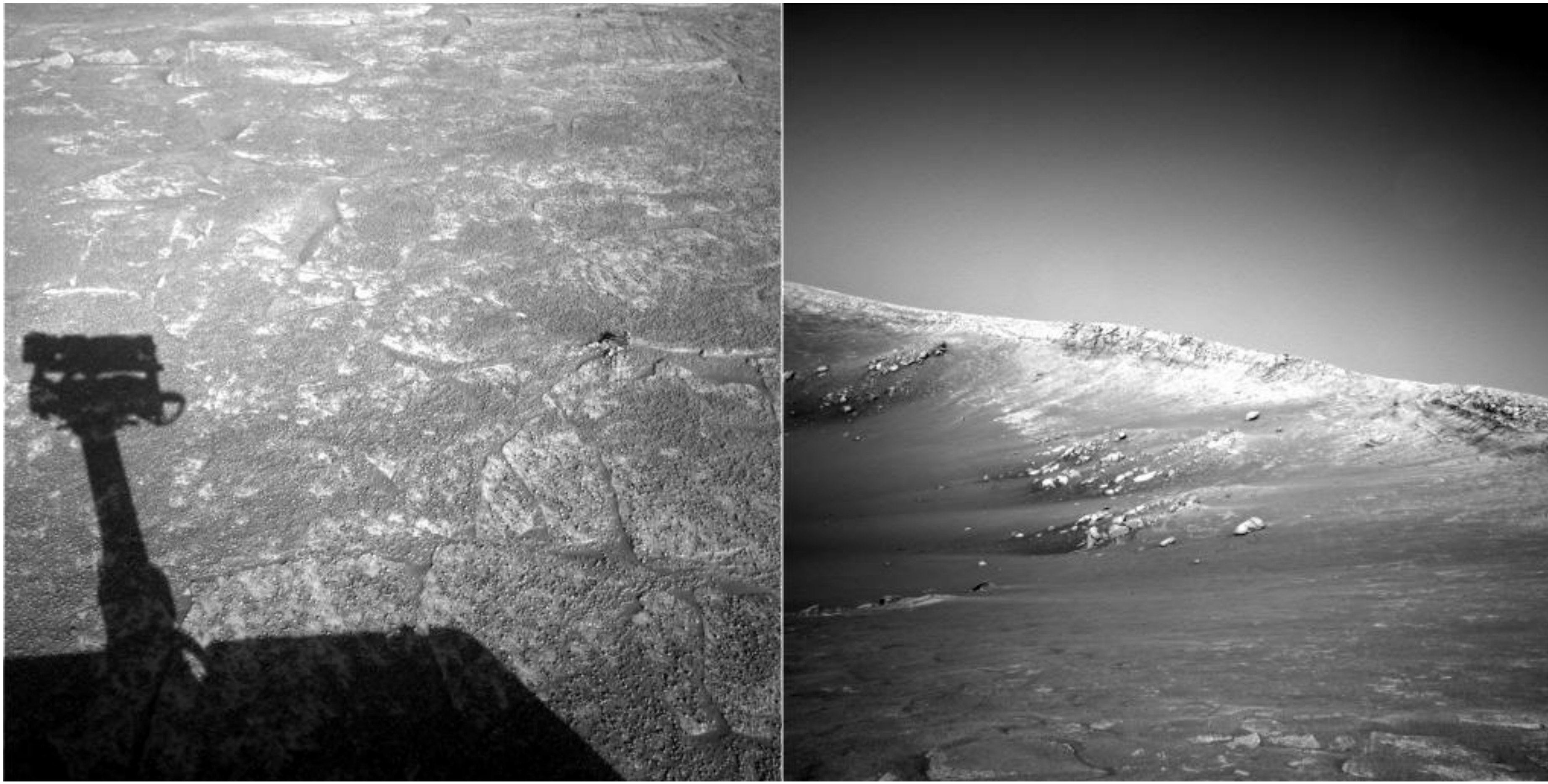
SIFT descriptor [Lowe 2004]

- Extraordinarily robust matching 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 (below)
  - Fast and efficient—can run in real time
  - Lots of code available
    - http://people.csail.mit.edu/albert/ladypack/wiki/index.php/Known_implementations_of_SIFT



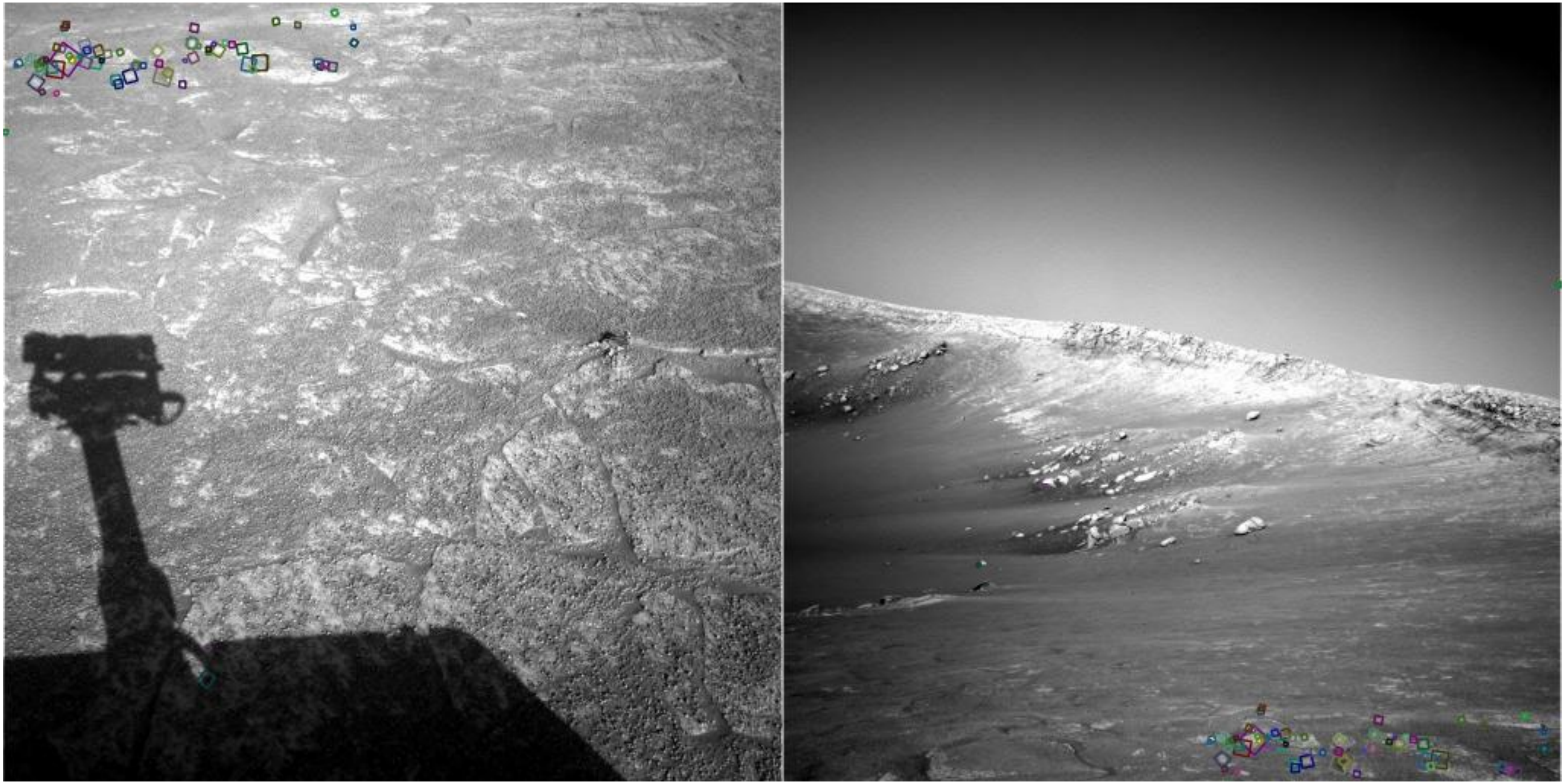
Steve Seitz

Example



NASA Mars Rover images

Example



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

SIFT properties

- Invariant to
  - Scale
  - Rotation

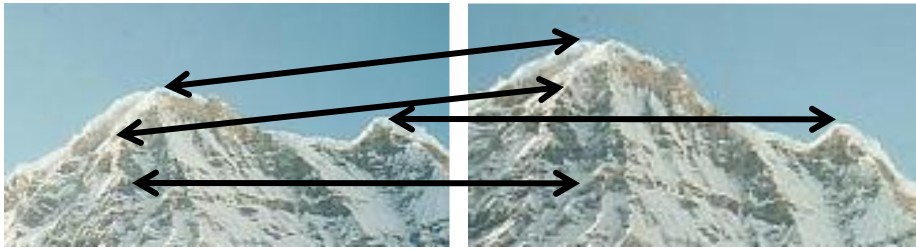
- Partially invariant to
  - Illumination changes
  - Camera viewpoint
  - Occlusion, clutter

Local features: main components

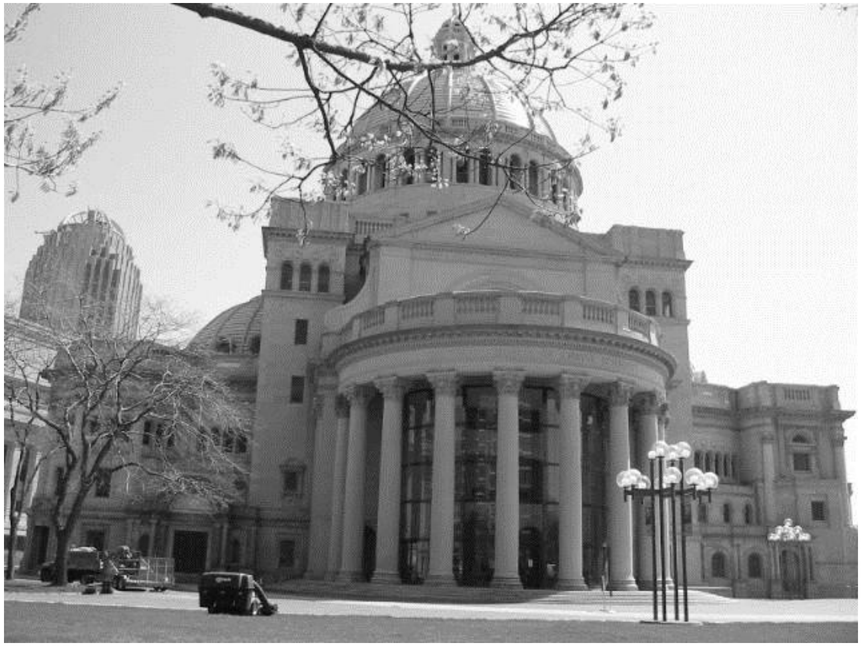
1) Detection: Identify the interest points

2) Description: Extract vector feature descriptor surrounding each interest point.

3) Matching: Determine correspondence between descriptors in two views

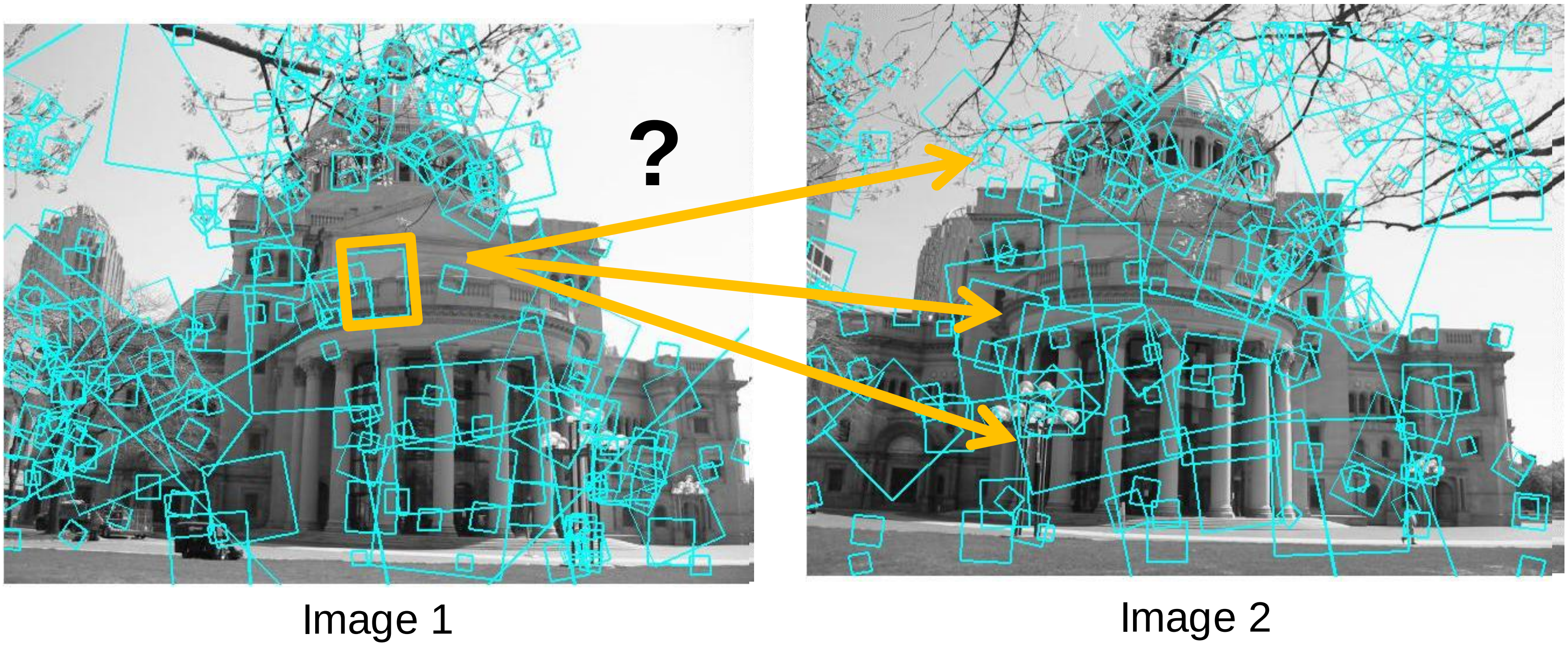


Matching local features



Kristen Grauman

Matching local features



To generate **candidate matches**, find patches that have the most similar appearance (e.g., lowest SSD)

Simplest approach: compare them all, take the closest (or closest k, or within a thresholded distance)

Kristen Grauman

Ambiguous matches

Image 1

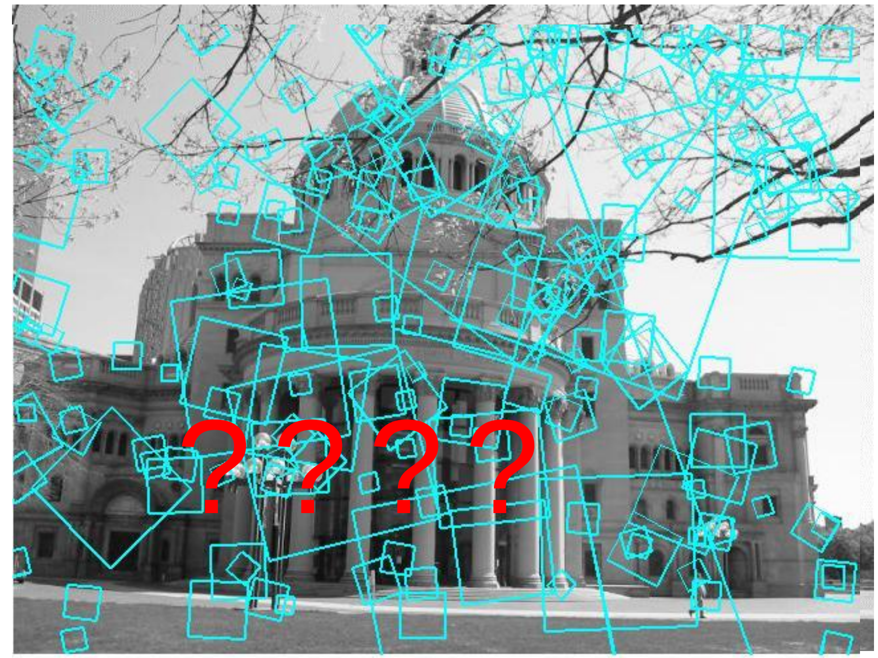


Image 2

At what SSD value do we have a good match?

To add robustness to matching, can consider **ratio** : distance to best match / distance to second best match

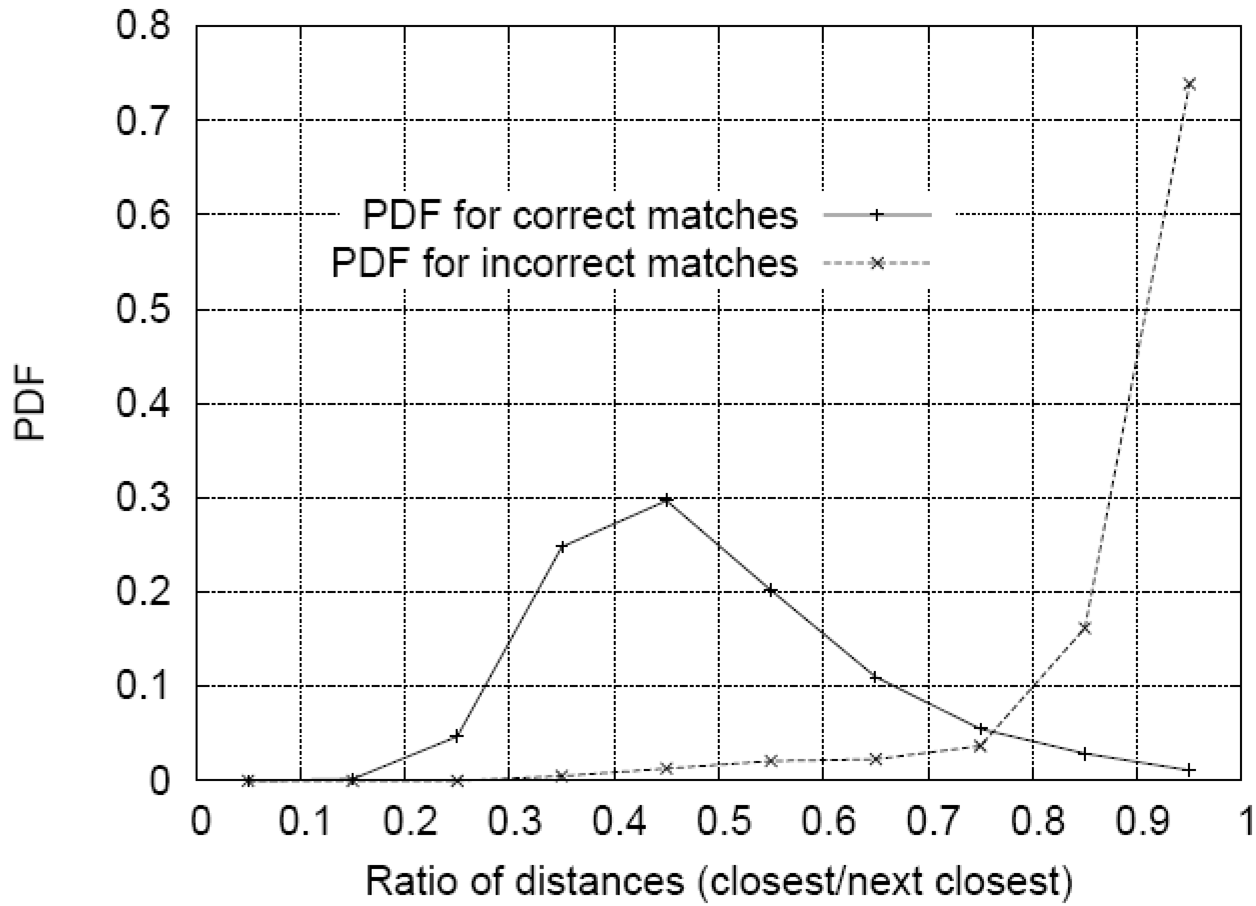
If low, first match looks good.

If high, could be ambiguous match.

Kristen Grauman

Matching SIFT Descriptors

- Nearest neighbor (Euclidean distance)
- Threshold ratio of nearest to 2nd nearest descriptor

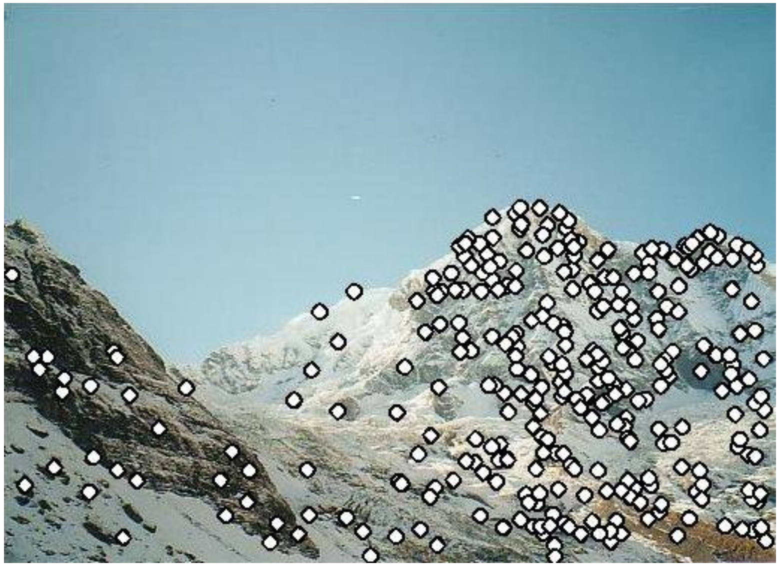


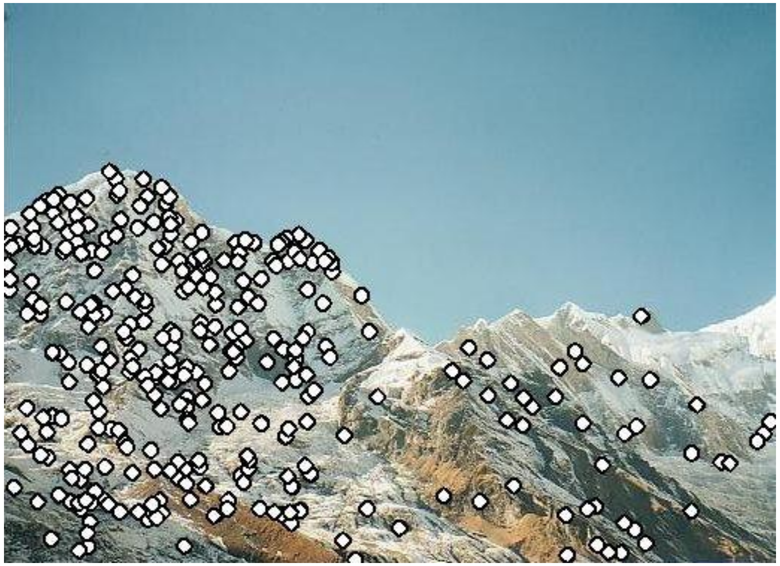
Lowe IJCV 2004

Recap: robust feature-based alignment

Source: L. Lazebnik

Recap: robust feature-based alignment





- Extract features

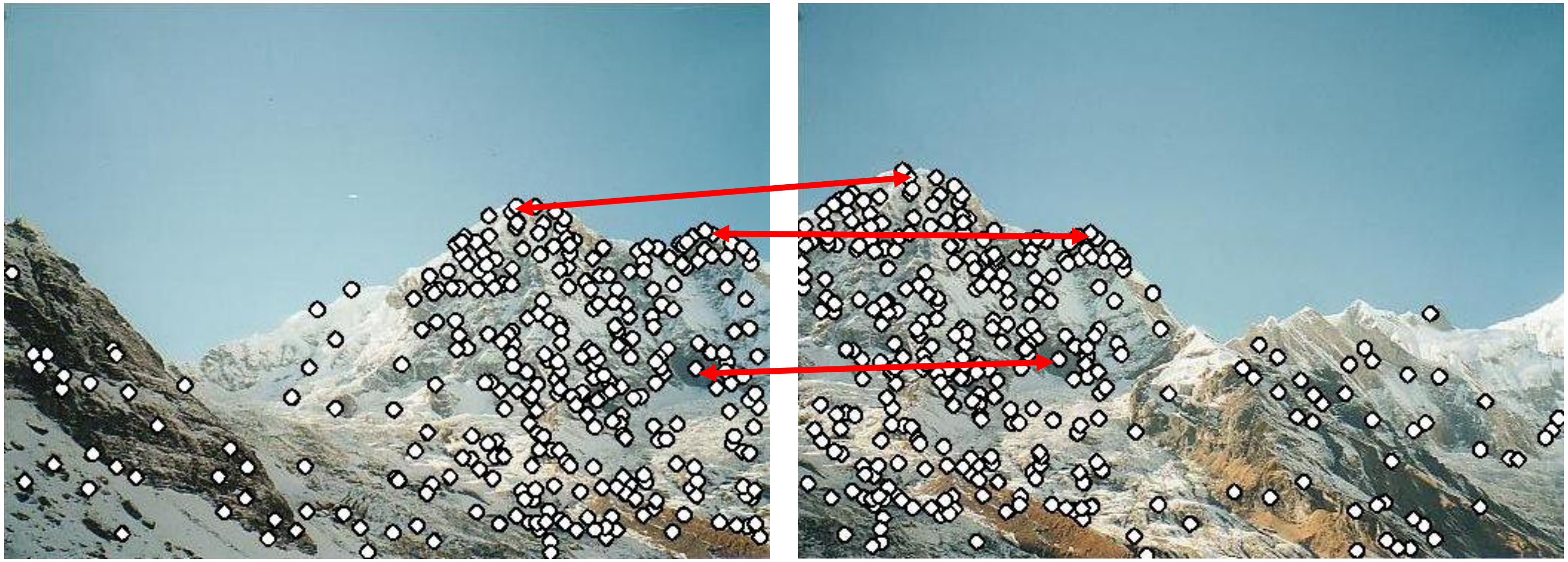
Source: L. Lazebnik

Recap: robust feature-based alignment

- Extract features
- Compute *putative matches*

Source: L. Lazebnik

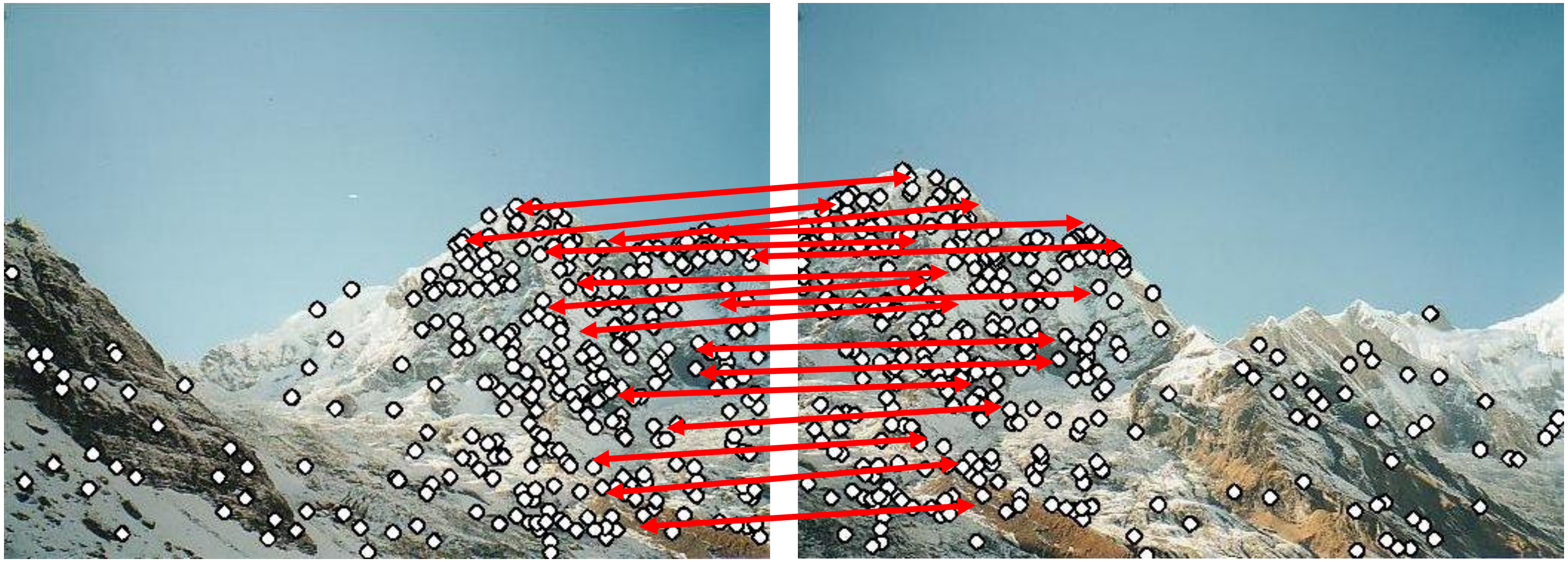
Recap: robust feature-based alignment



- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation T (small group of putative matches that are related by T)

Source: L. Lazebnik

Recap: robust feature-based alignment



- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation T (small group of putative matches that are related by T)
  - *Verify* transformation (search for other matches consistent with T)

Source: L. Lazebnik

Recap: robust feature-based alignment

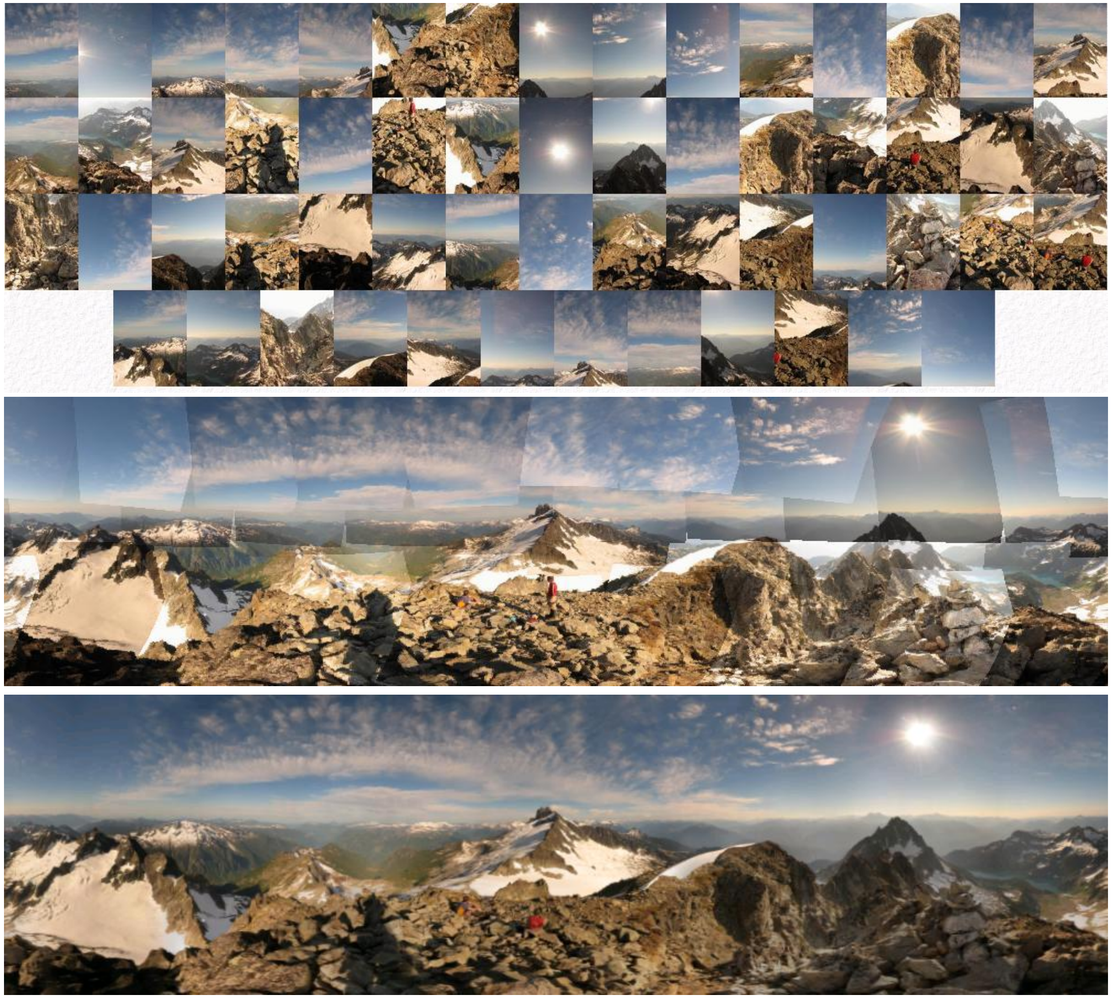
- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation T (small group of putative matches that are related by T)
  - *Verify* transformation (search for other matches consistent with T)

Source: L. Lazebnik

Applications of local invariant features

- Wide baseline stereo
- Motion tracking
- Panoramas
- Mobile robot navigation
- 3D reconstruction
- Recognition
- …

Automatic mosaicing



http://www.cs.ubc.ca/~mbrown/autostitch/autostitch.html

Wide baseline stereo

[Image from T. Tuytelaars ECCV 2006 tutorial]

Recognition of specific objects, scenes

Schmid and Mohr 1997

Sivic and Zisserman, 2003

Rothganger et al. 2003

Lowe 2002

Kristen Grauman

Summary

- Interest point detection
  - Harris corner detector
  - Laplacian of Gaussian, automatic scale selection
- Invariant descriptors
  - Rotation according to dominant gradient direction
  - Histograms for robustness to small shifts and translations (SIFT descriptor)