Juergen Gall

Image features and descriptors
MA-INF 2201 - Computer Vision
WS24/25

Motivation for feature-based alignment: Image mosaics

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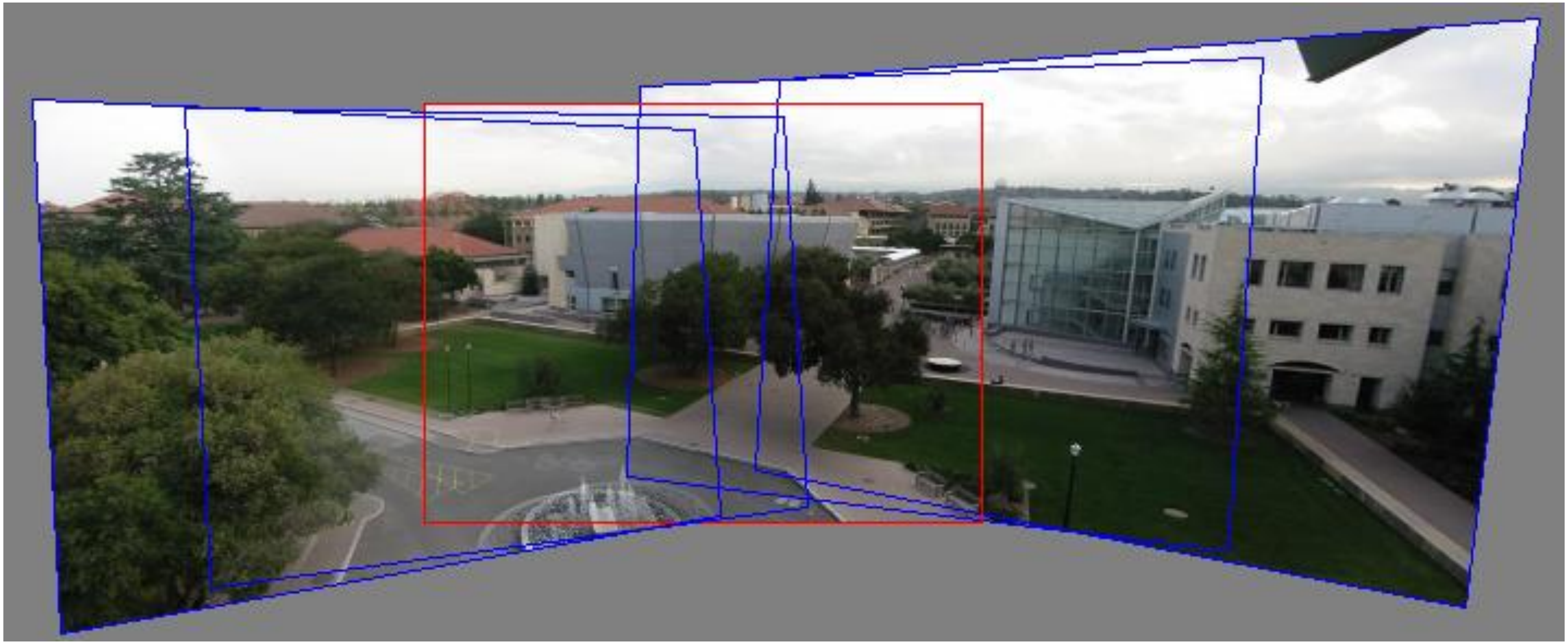
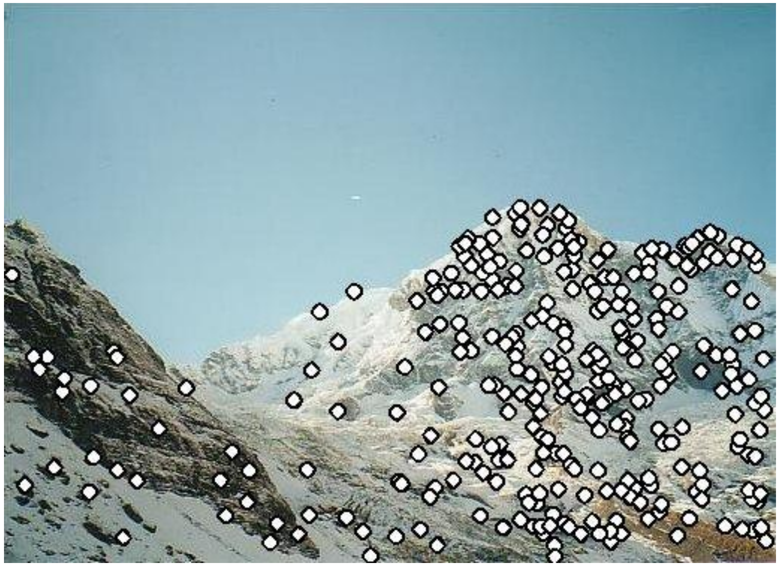


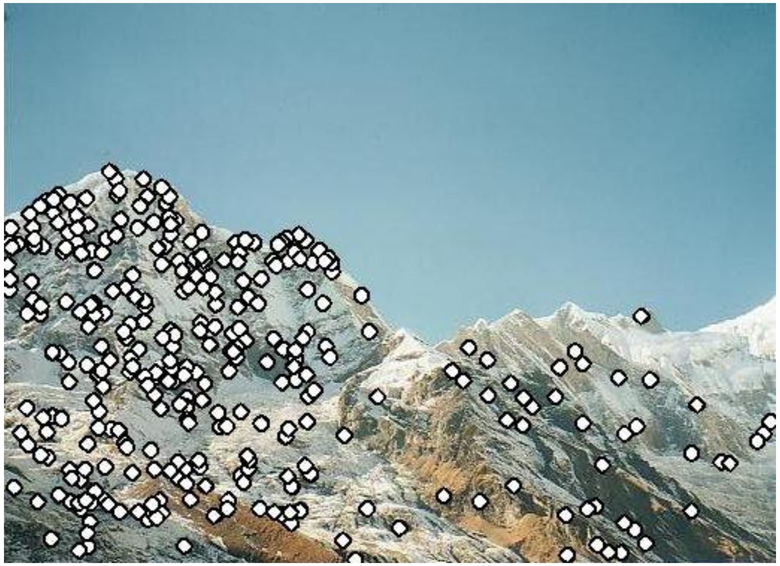
Image from http://graphics.cs.cmu.edu/courses/15-463/2010_fall/

Feature-based alignment

Source: L. Lazebnik

Feature-based alignment





- Extract features

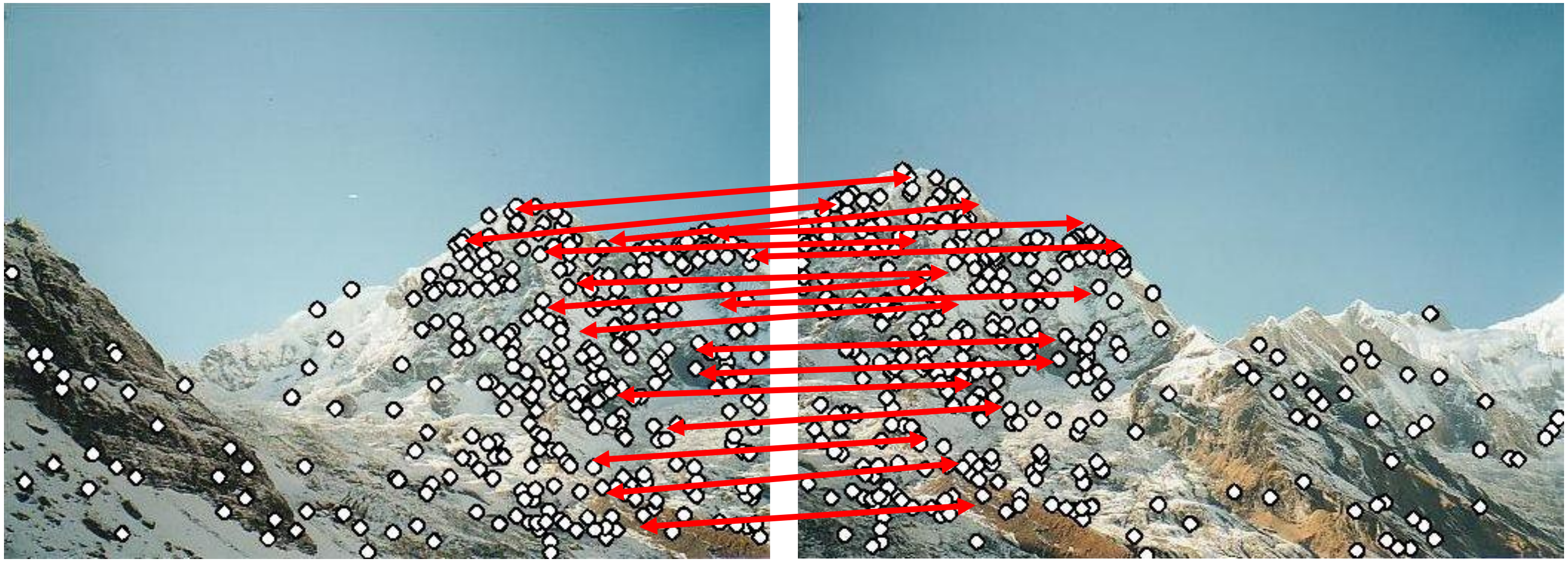
Source: L. Lazebnik

Feature-based alignment

- Extract features
- Compute matches

Source: L. Lazebnik

Feature-based alignment



- Extract features
- Compute matches
- Filter matches

Source: L. Lazebnik

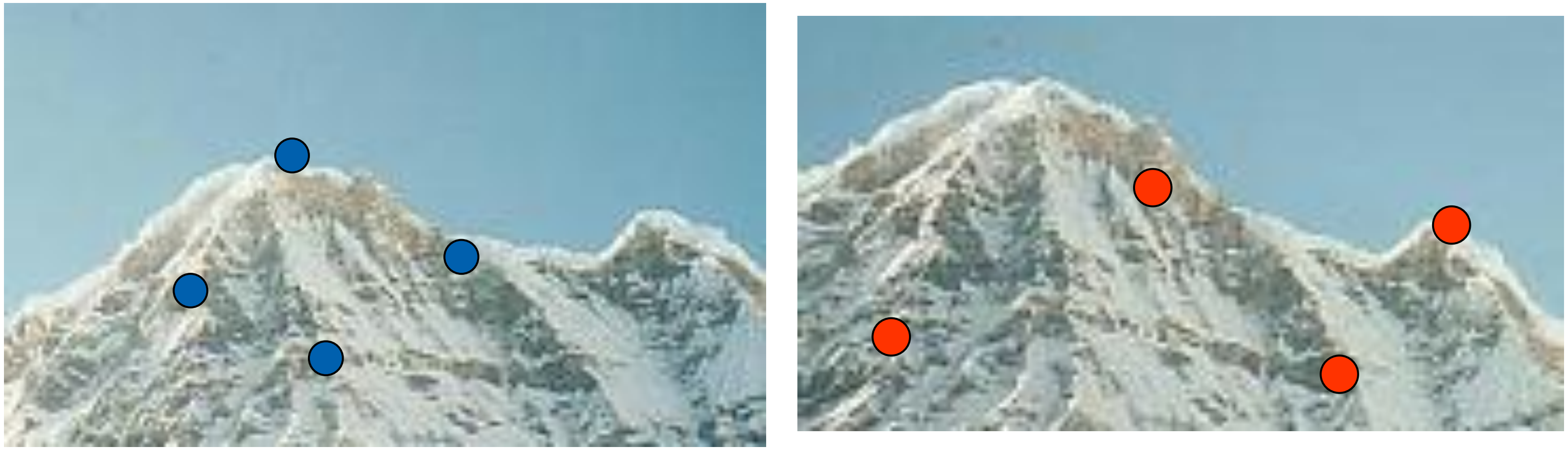
Feature-based alignment

- Extract features
- Compute matches
- Filter matches
- Compute transformation

Source: L. Lazebnik

Local features: desired properties

- Repeatability:
  - The same feature can be found in several images despite geometric and photometric transformations



No chance to find true matches!

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

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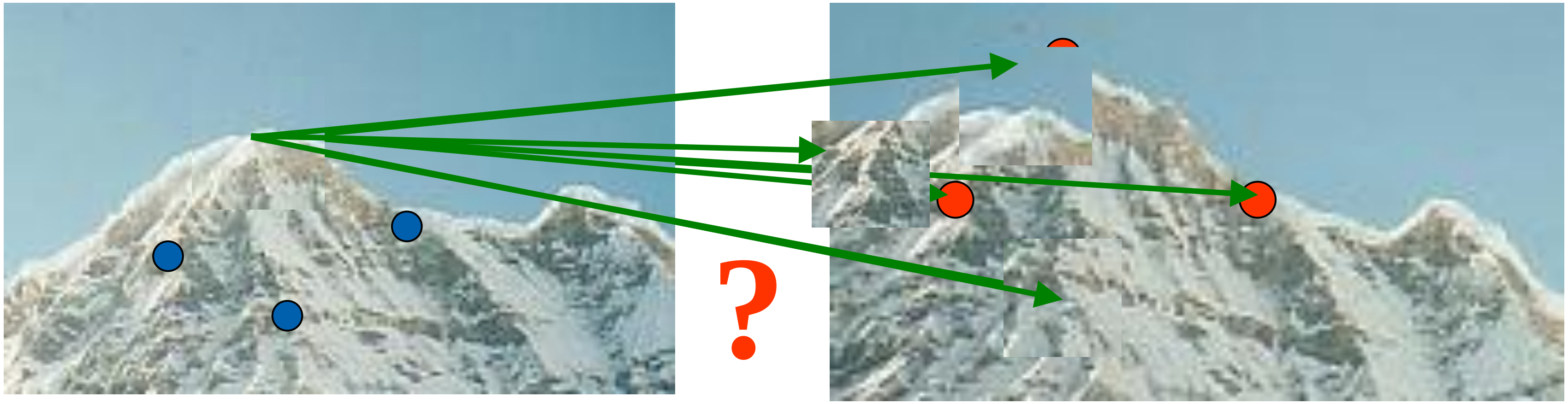
Local features: desired properties

- Repeatability:
  - The same feature can be found in several images despite geometric and photometric transformations
- Saliency:
  - Each feature has a distinctive description



Invariance to geometric and photometric differences between the two views.

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Local features: desired properties

- Repeatability:
  - The same feature can be found in several images despite geometric and photometric transformations
- Saliency:
  - Each feature has a distinctive description
- Locality:
  - A feature occupies a relatively small area of the image; robust to clutter and occlusion
- Sometimes compactness and efficiency:
  - Low dimensionality or binary

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What points would you choose?

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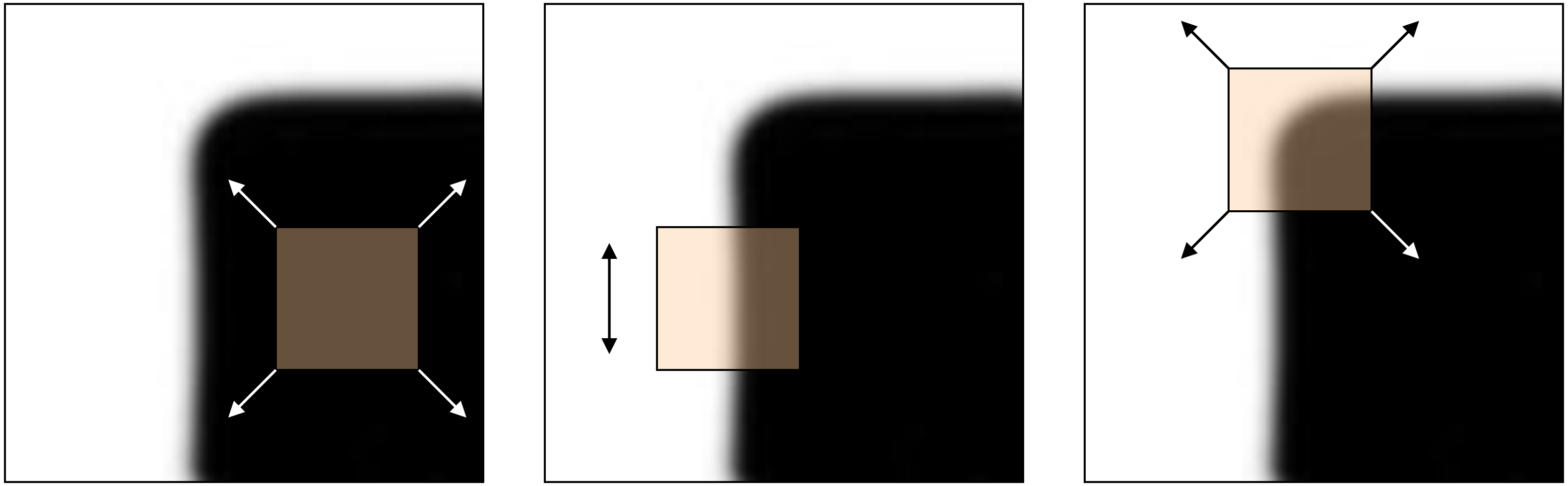
Distinctive interest points

- We should easily recognize the point by looking through a small window
- Shifting a window in *any direction* should give *a large change* in intensity



"flat" region:
no change in all directions

"edge":
no change along the edge direction

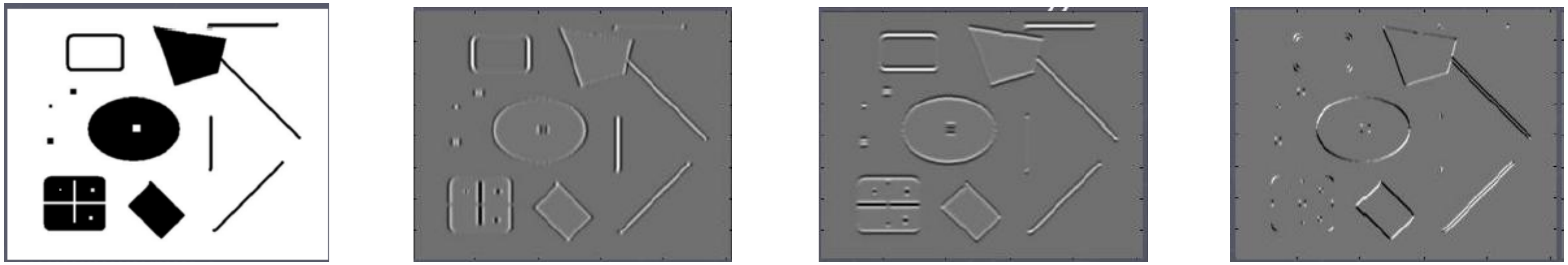
"corner":
significant change in all directions

Slide credit: Alyosha Efros, Darya Frolova, Denis Simakov

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: $I_x \Leftrightarrow \dfrac{\partial I}{\partial x}$ $\quad I_y \Leftrightarrow \dfrac{\partial I}{\partial y}$ $\quad I_x I_y \Leftrightarrow \dfrac{\partial I}{\partial x}\dfrac{\partial I}{\partial y}$

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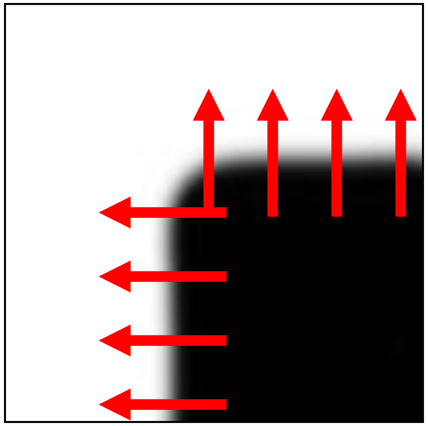
What does this matrix reveal?

First, consider an axis-aligned corner:



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What does this matrix reveal?

First, consider an axis-aligned corner:

$$M = \sum \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

This means dominant gradient directions align with x or y axis

Look for locations where **both** λ's are large.

If either λ is close to 0, then this is **not** corner-like.

What if we have a corner that is not aligned with the image axes?

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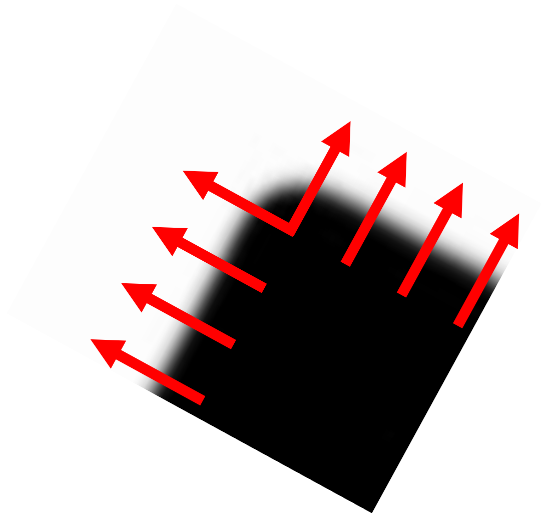
What does this matrix reveal?

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.

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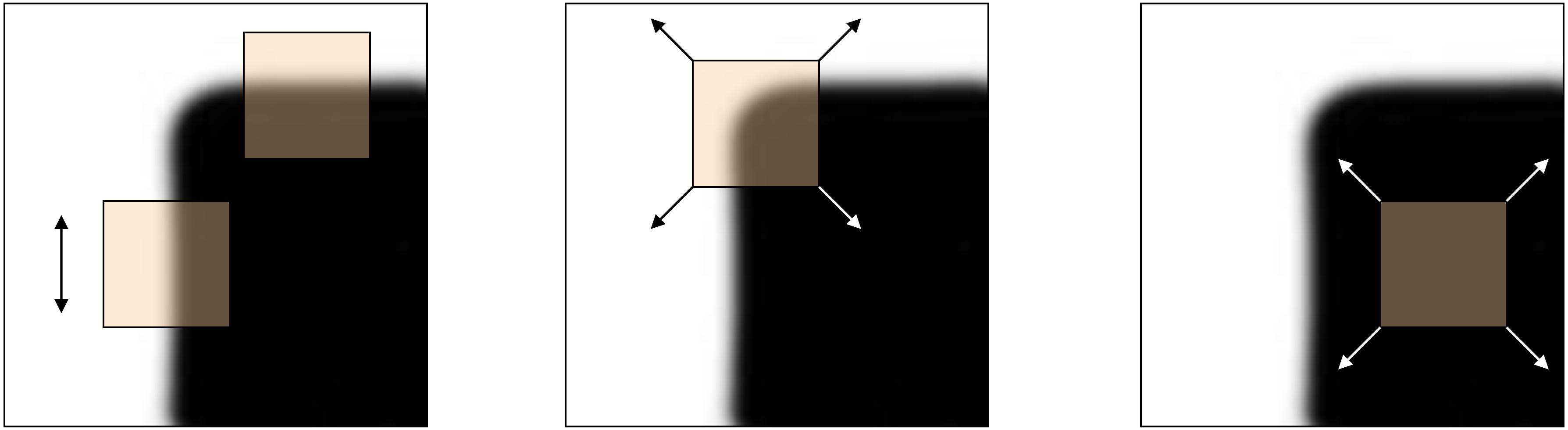
Corner response function



"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;

$$f = |M| - k\,(\mathrm{Tr}(M))^2 = \lambda_1\lambda_2 - k\,(\lambda_1 + \lambda_2)^2$$

$$k \approx 0.04$$

Harris corner detector

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

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Harris Detector

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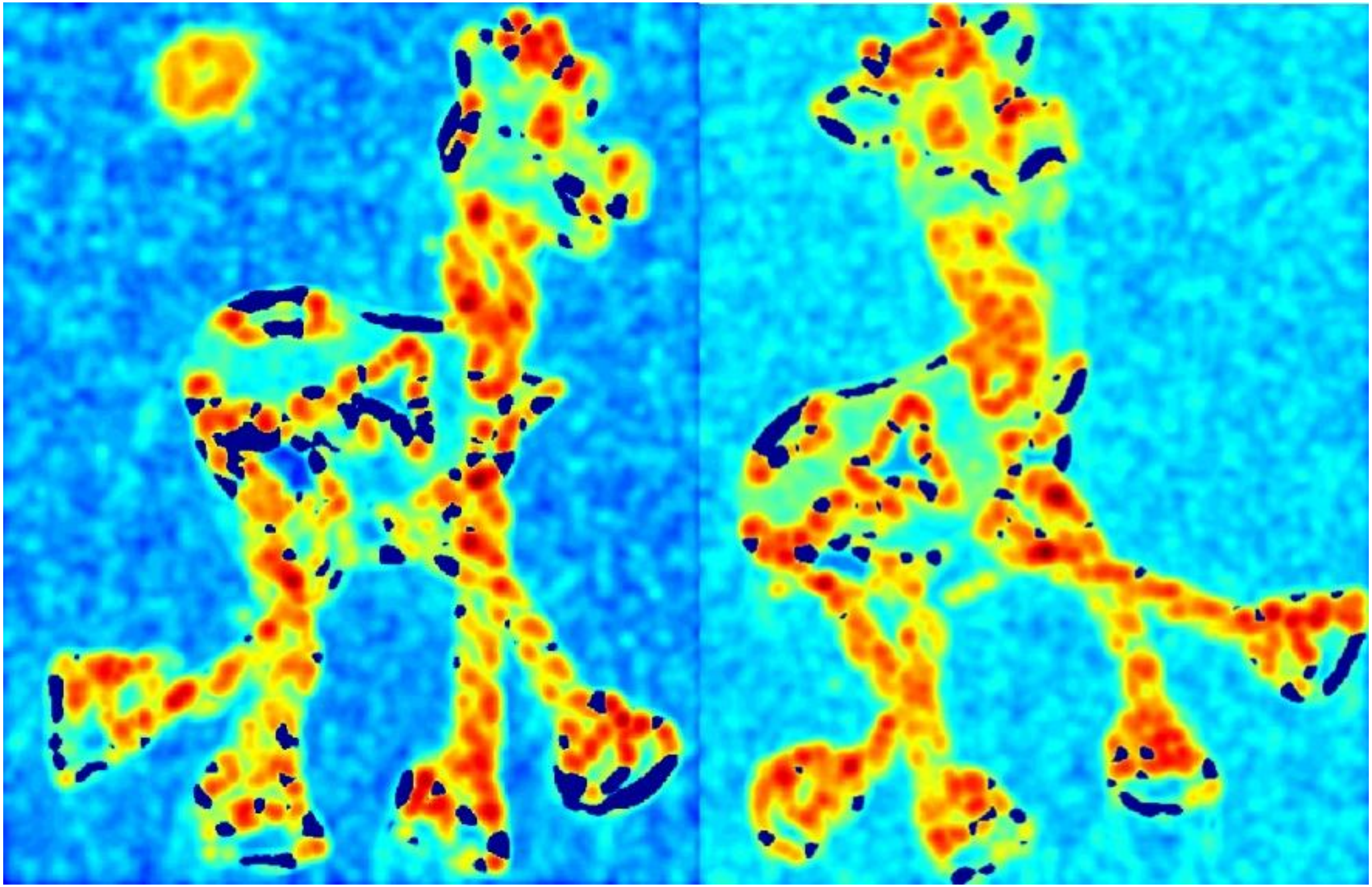
Harris Detector

Compute corner response f



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Harris Detector

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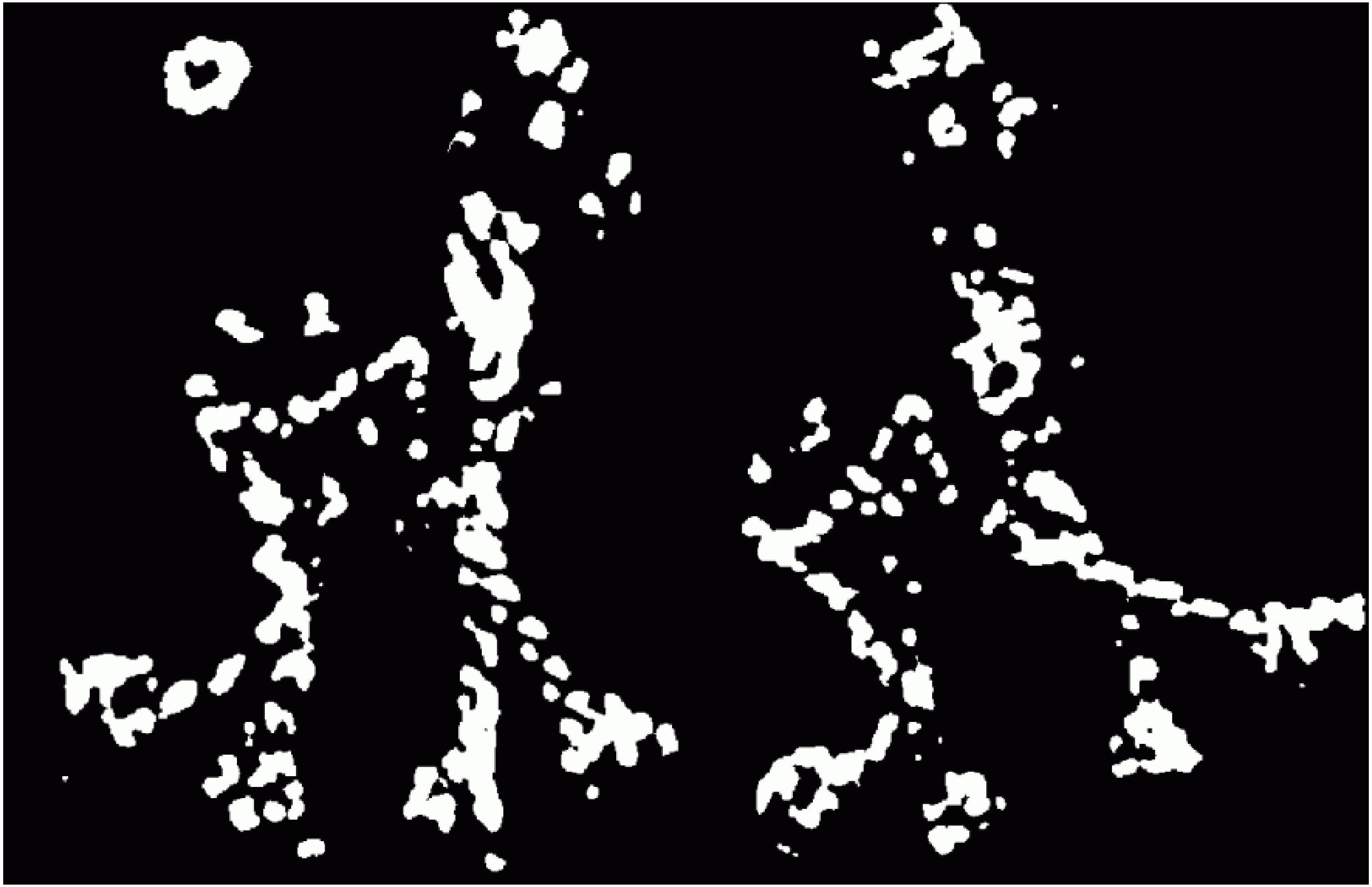
Find points with large corner response: f > threshold



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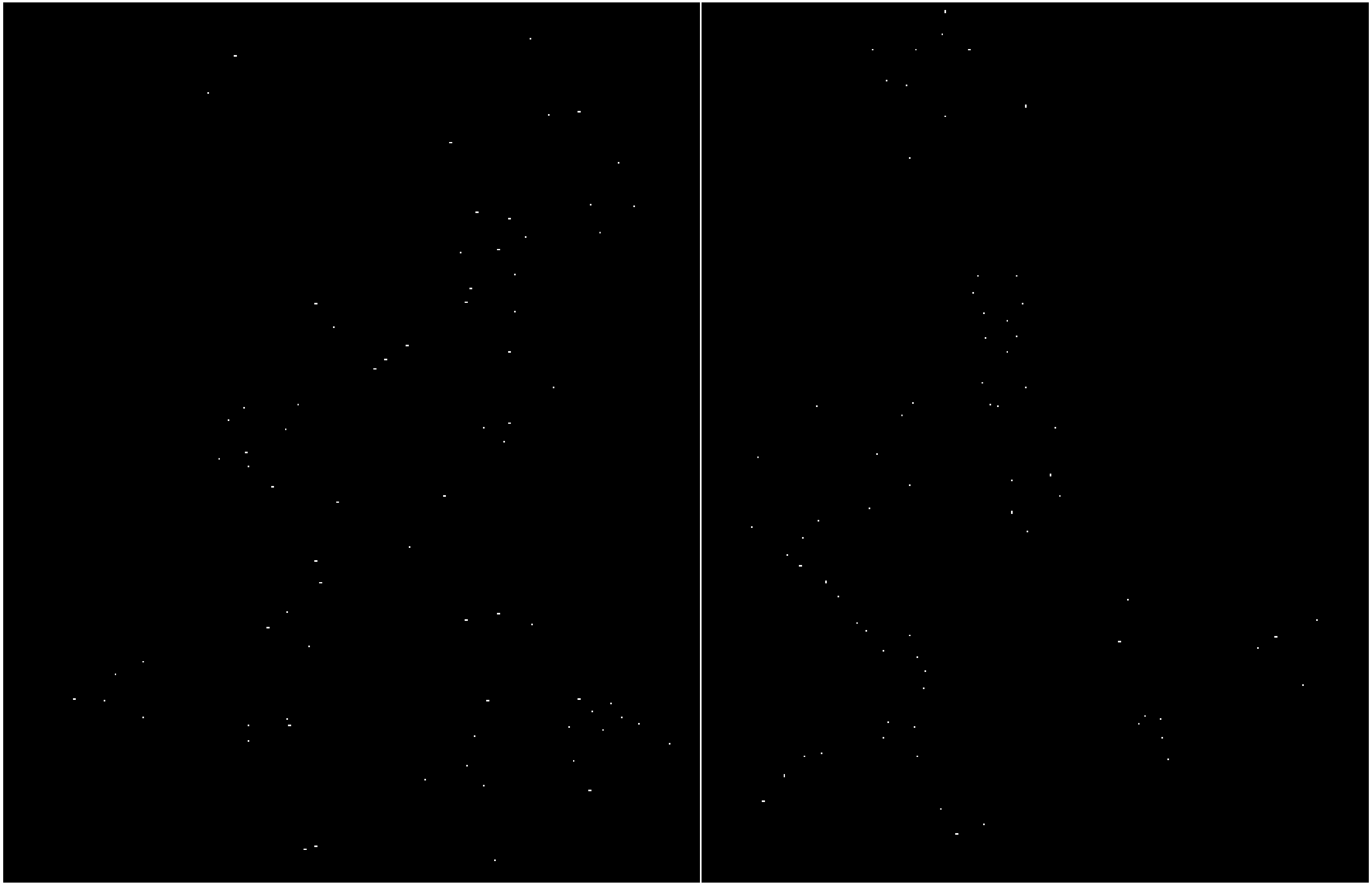
Harris Detector

Take only the points of local maxima of *f*



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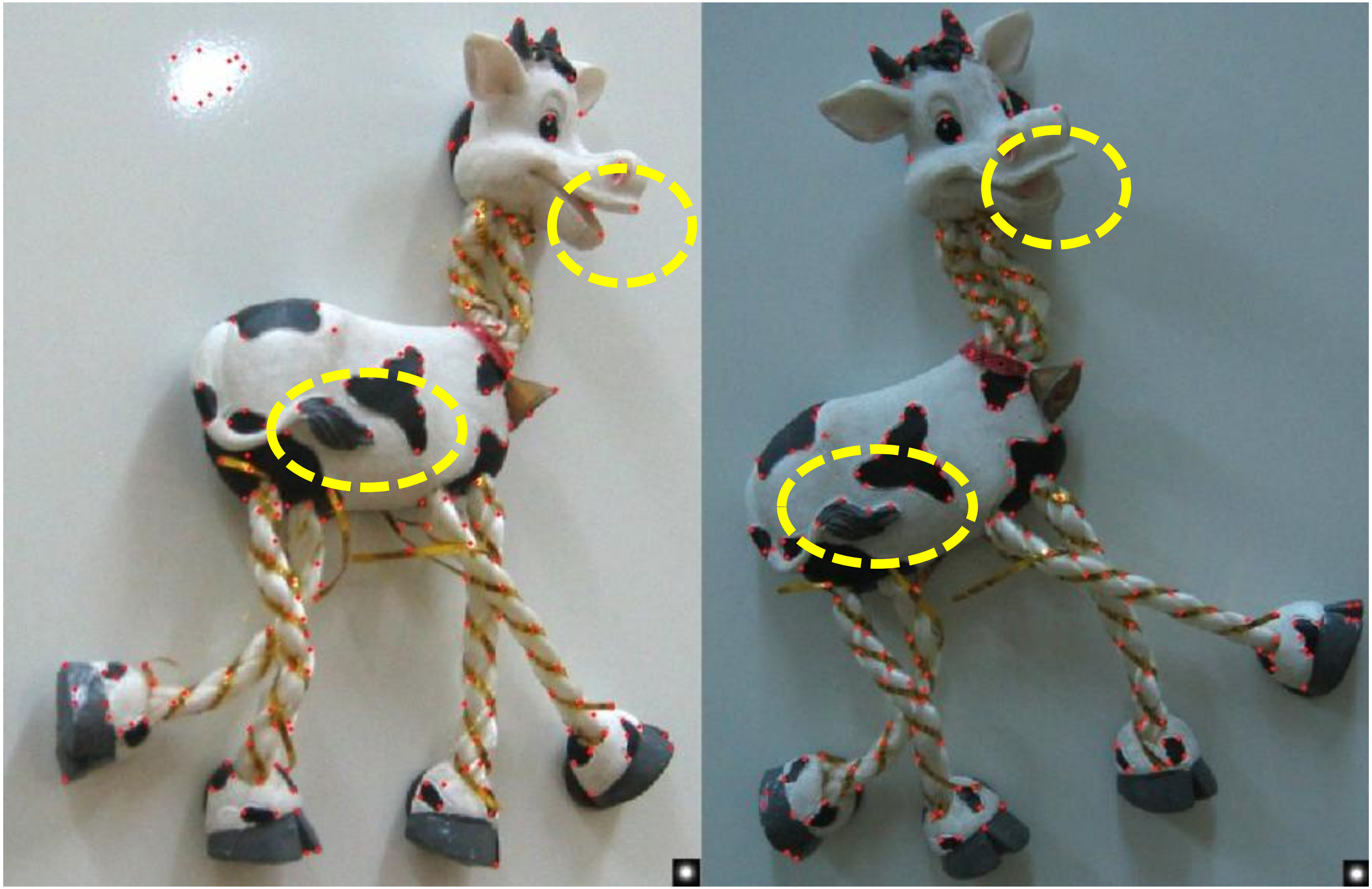
Harris Detector



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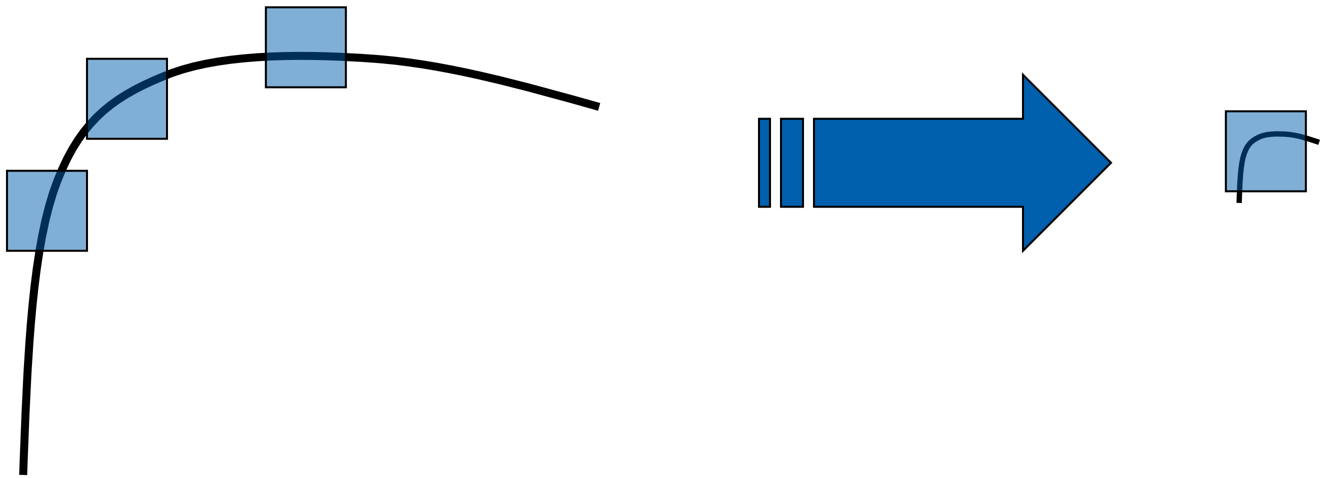
Properties of the Harris corner detector

- Rotation invariant? Yes

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

- Scale invariant? No



All points will be classified as edges

Corner !

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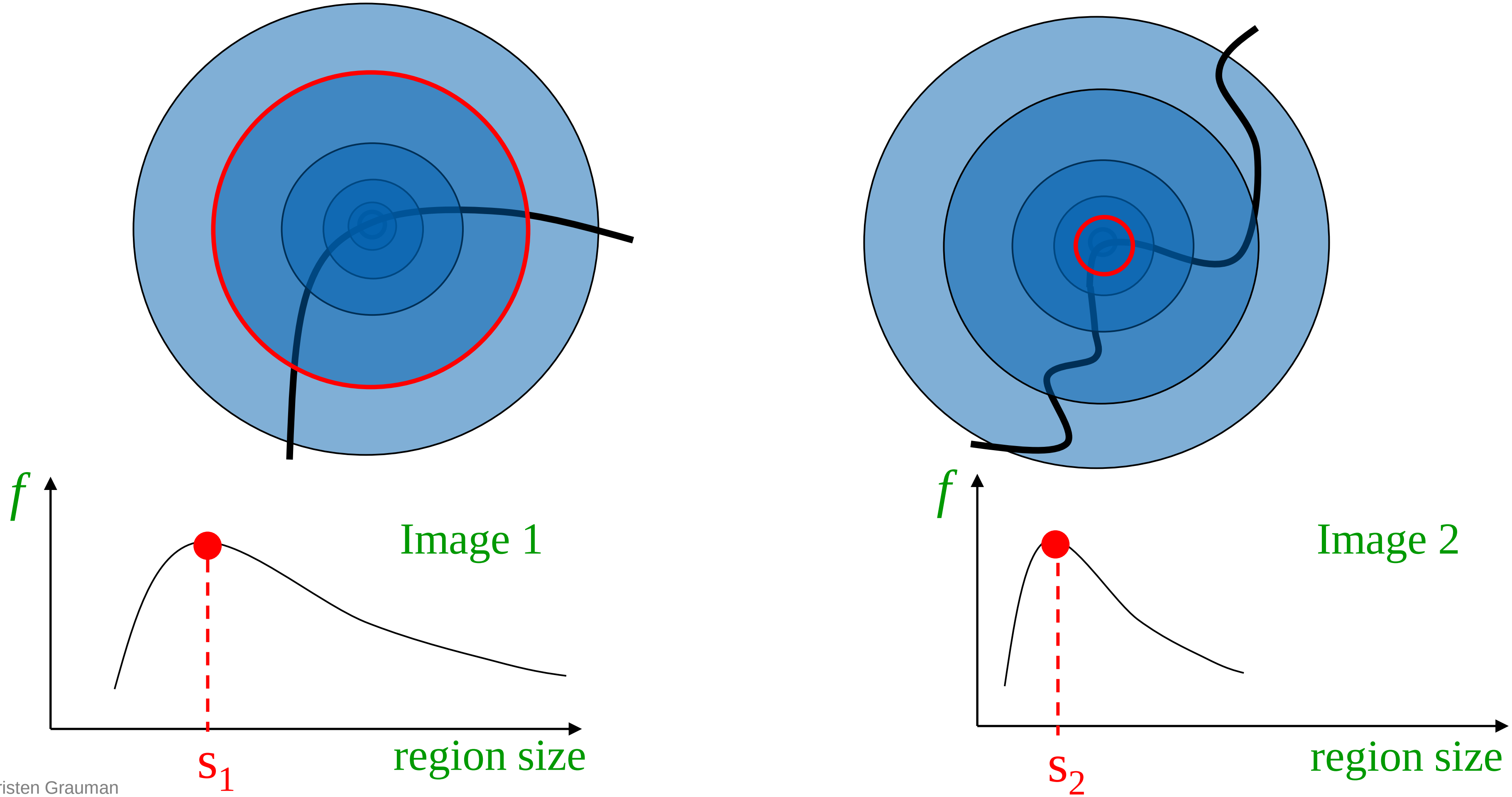
Automatic scale selection

Intuition:

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



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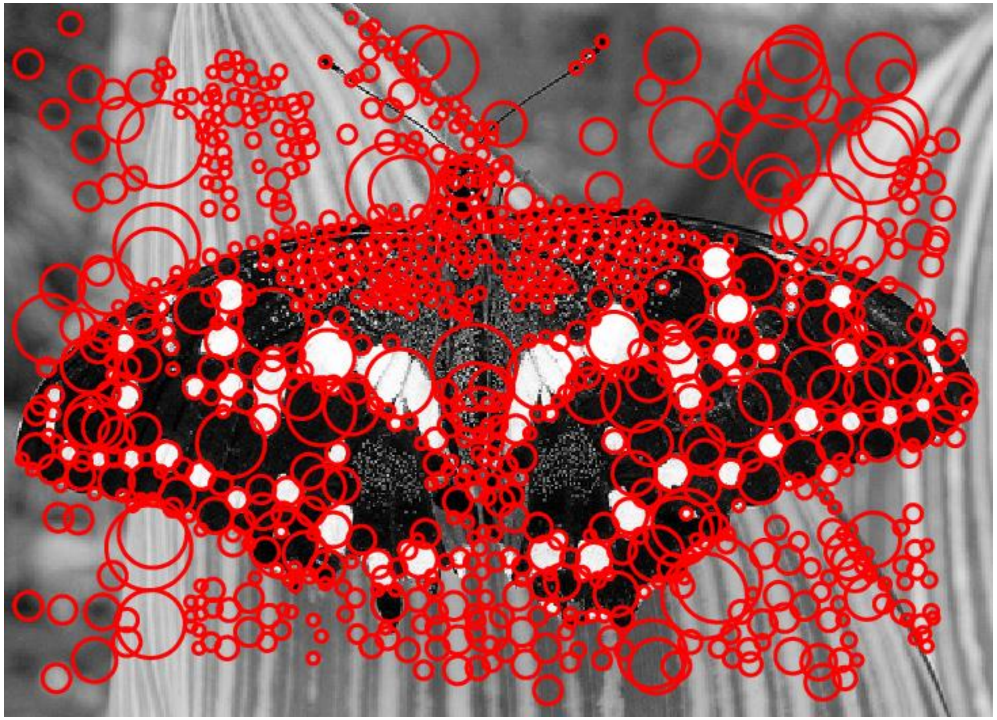
Scale invariant blob detection



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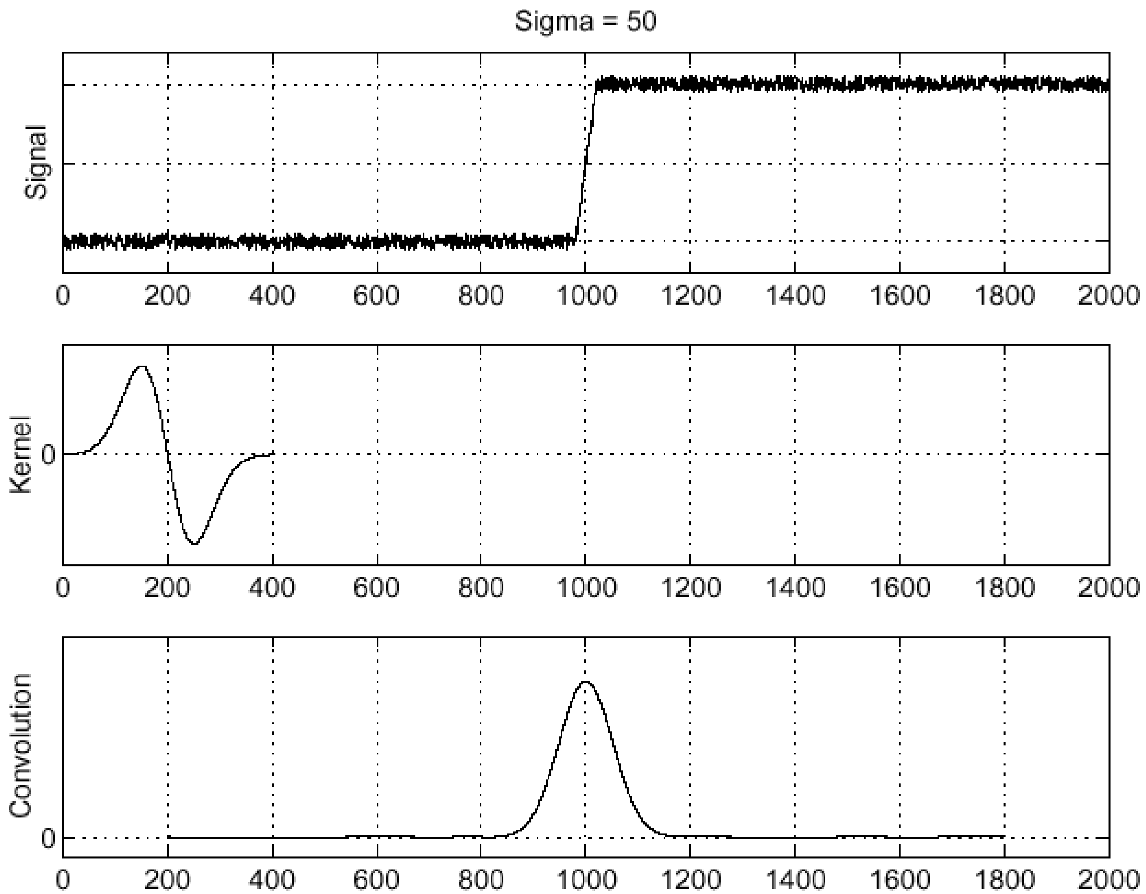
Recall: Edge detection



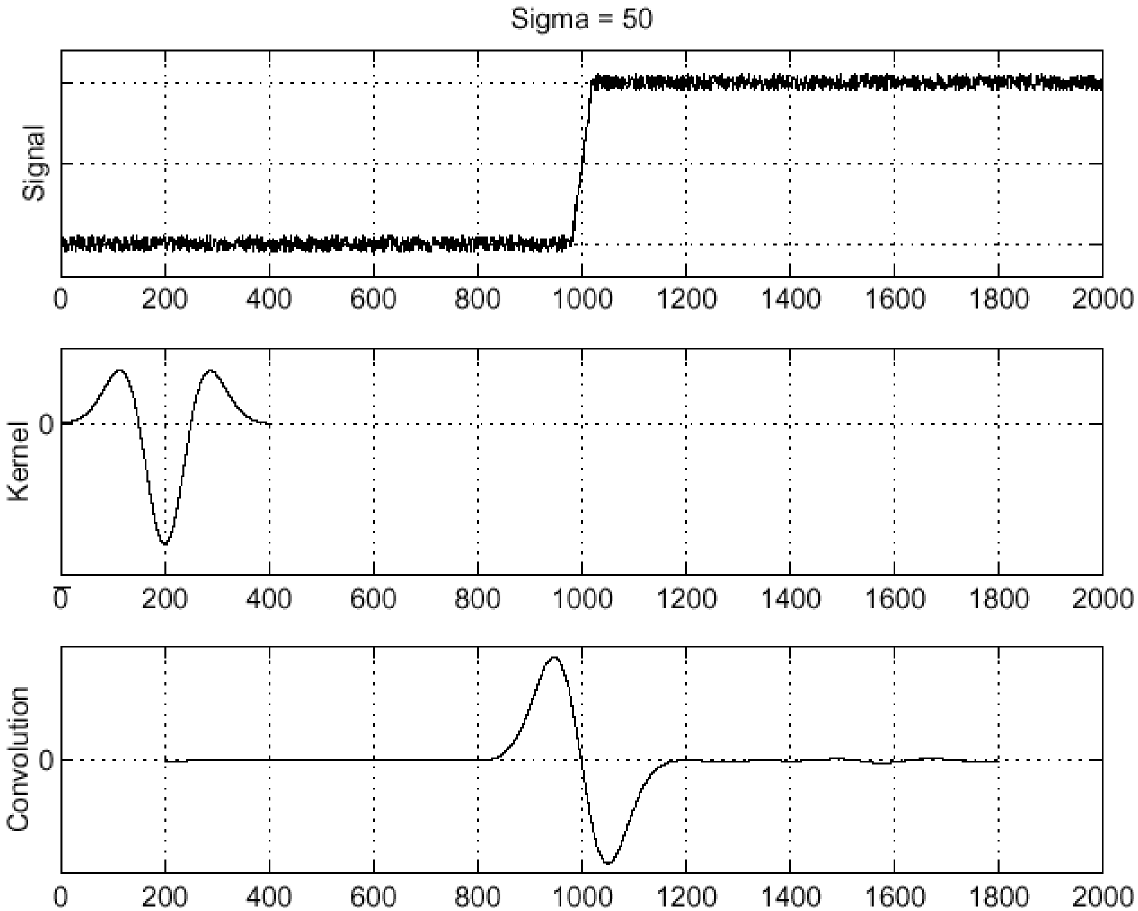
f Edge

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

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

Source: S. Seitz

Recall: Edge detection



f — Edge

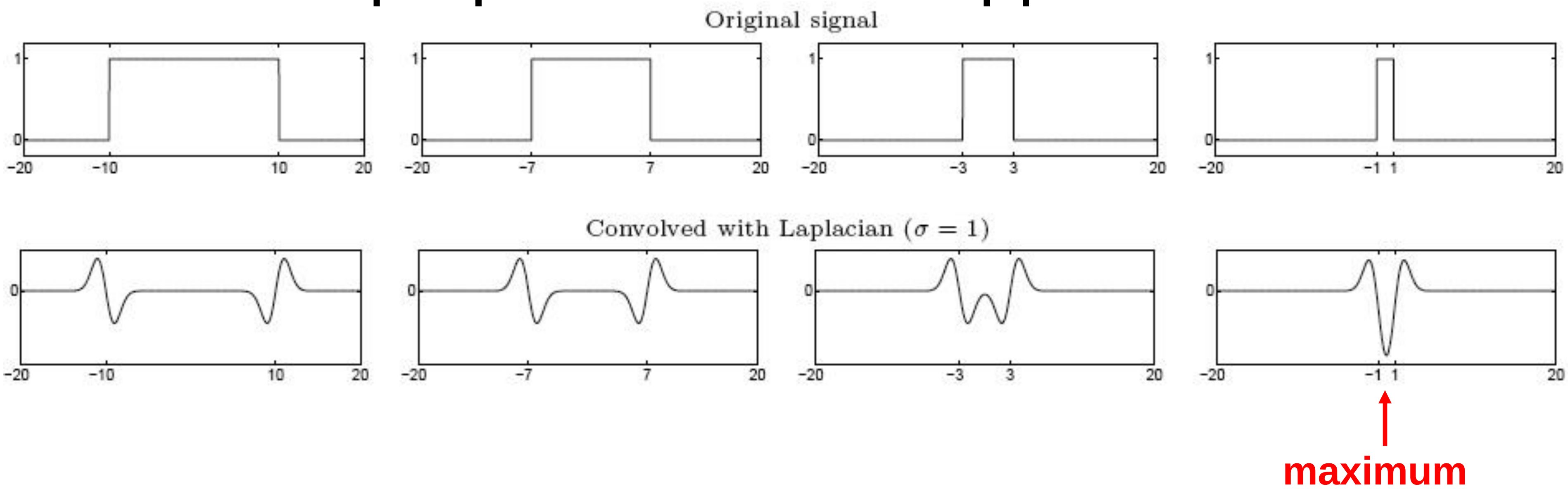
$\frac{d^2}{dx^2} g$ — Second derivative of Gaussian (Laplacian)

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

Source: S. Seitz

From edges to blobs

- Edge = ripple
- Blob = superposition of two ripples

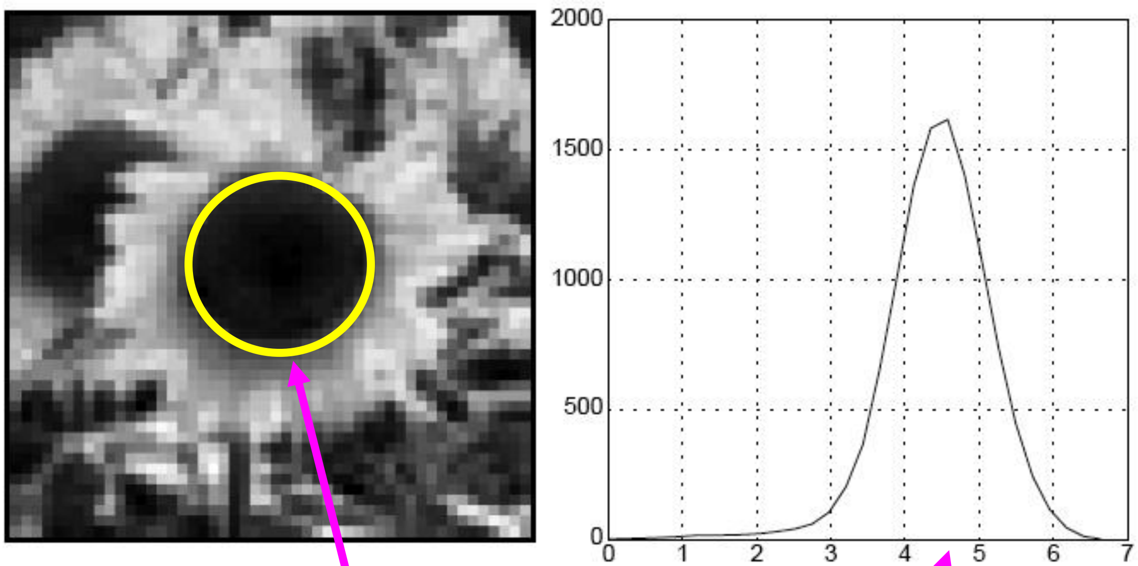


Spatial selection: the **magnitude** of the Laplacian response will achieve a maximum at the center of the blob, provided the scale of the Laplacian is "matched" to the scale of the blob

Lana Lazebnik

Blob detection in 2D

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



characteristic scale

Lana Lazebnik

Example

Original image
at ¾ the size

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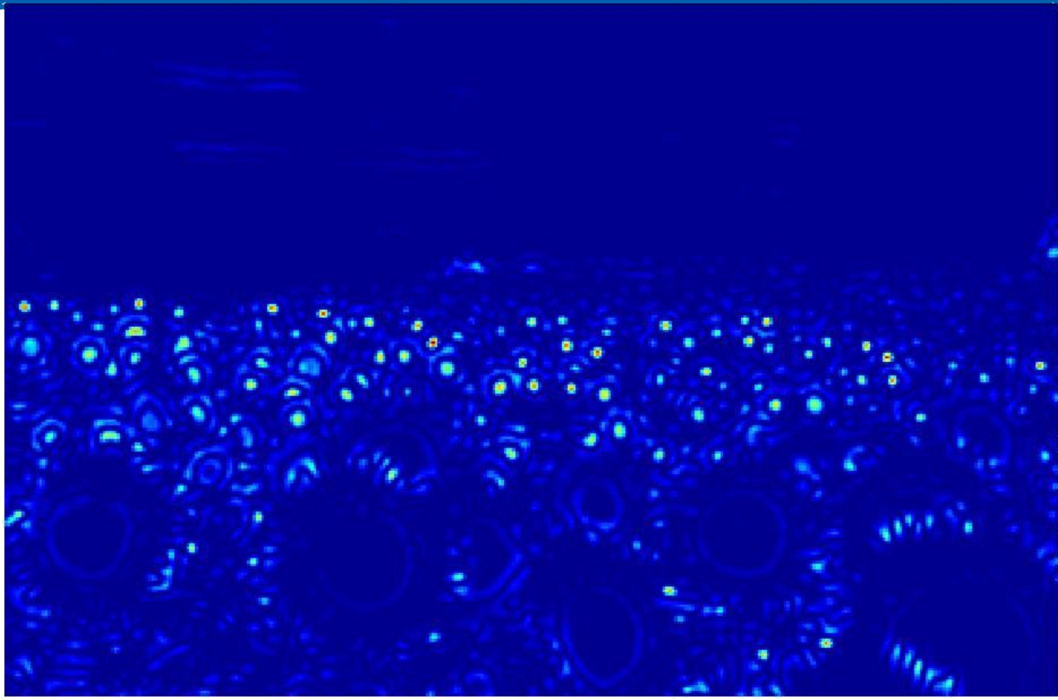
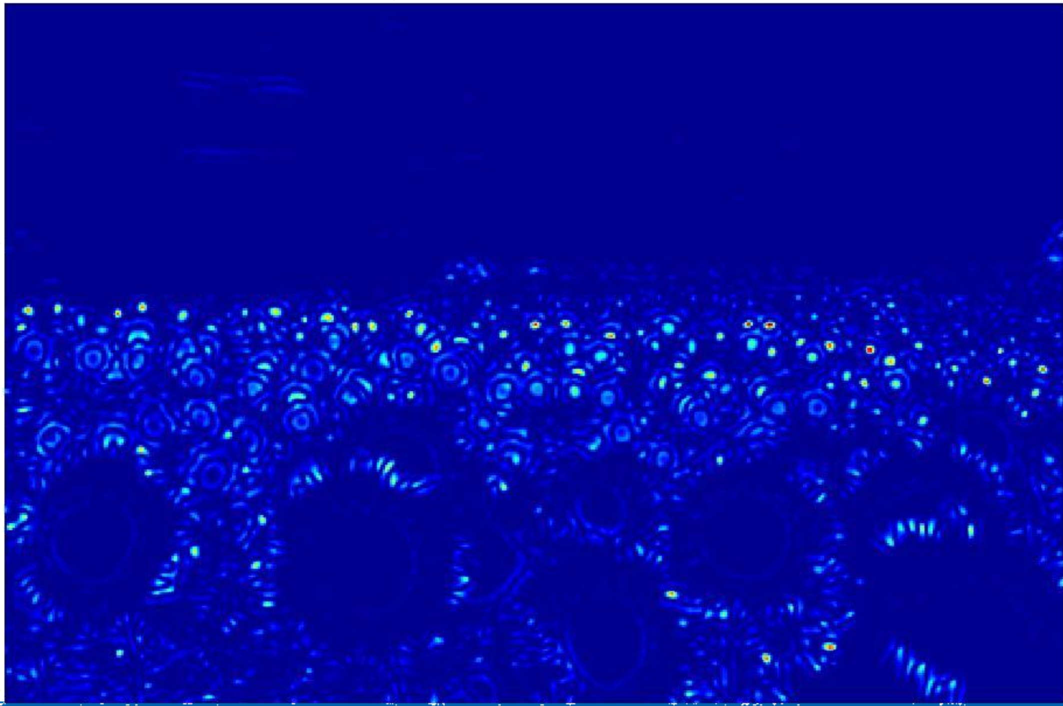
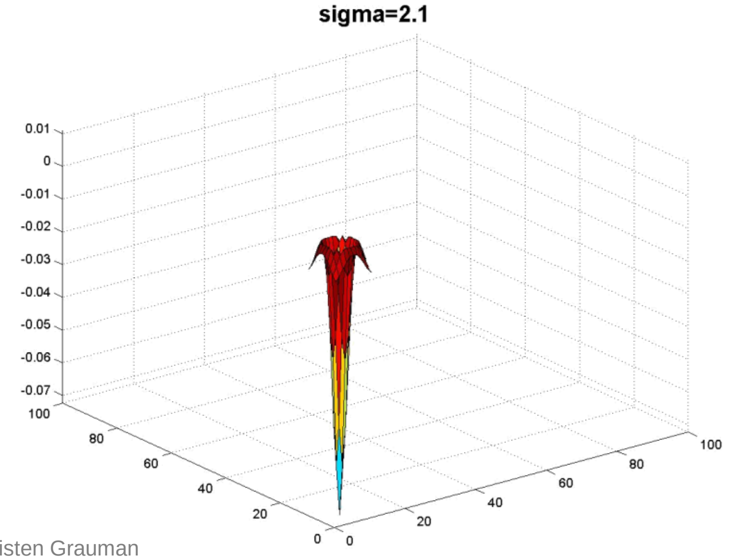
Original image
at ¾ the size







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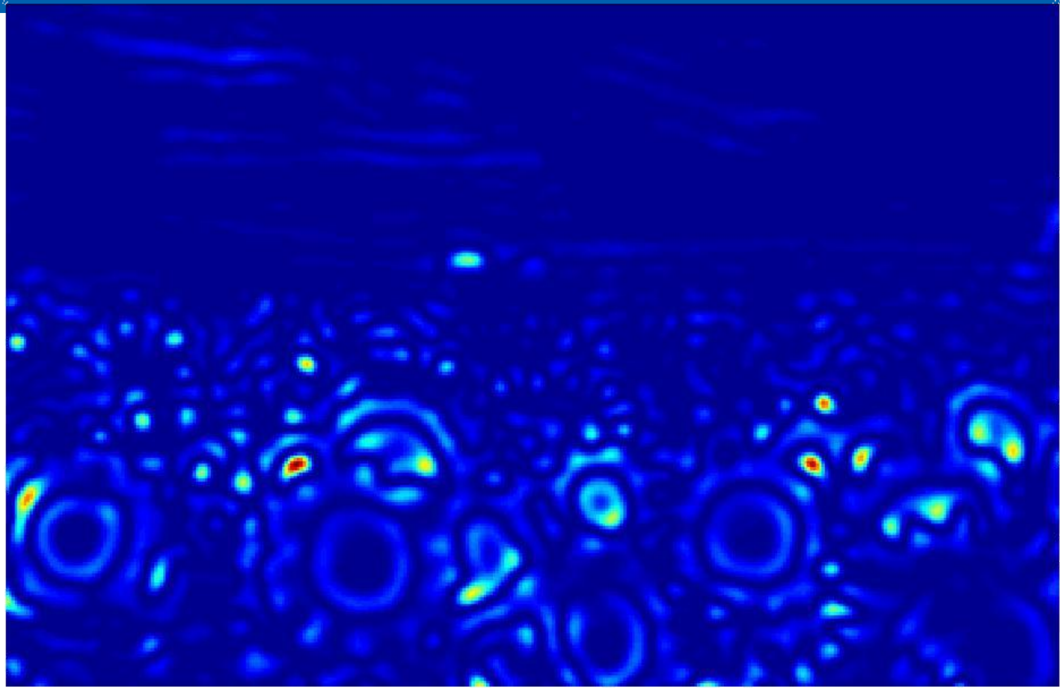

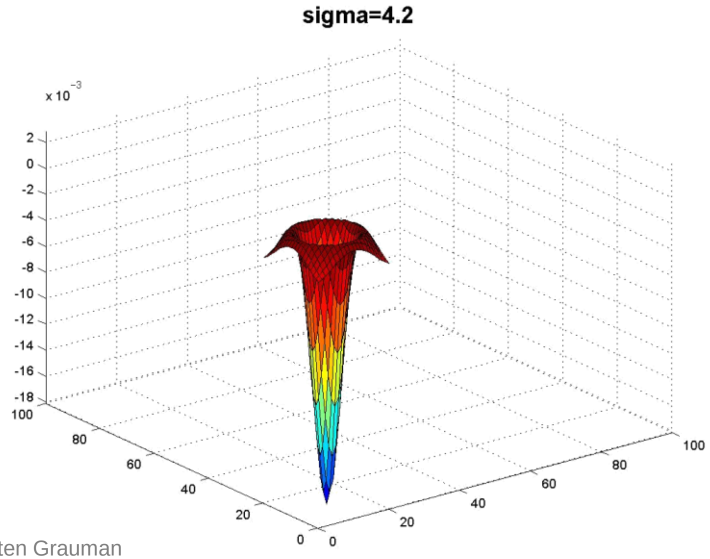

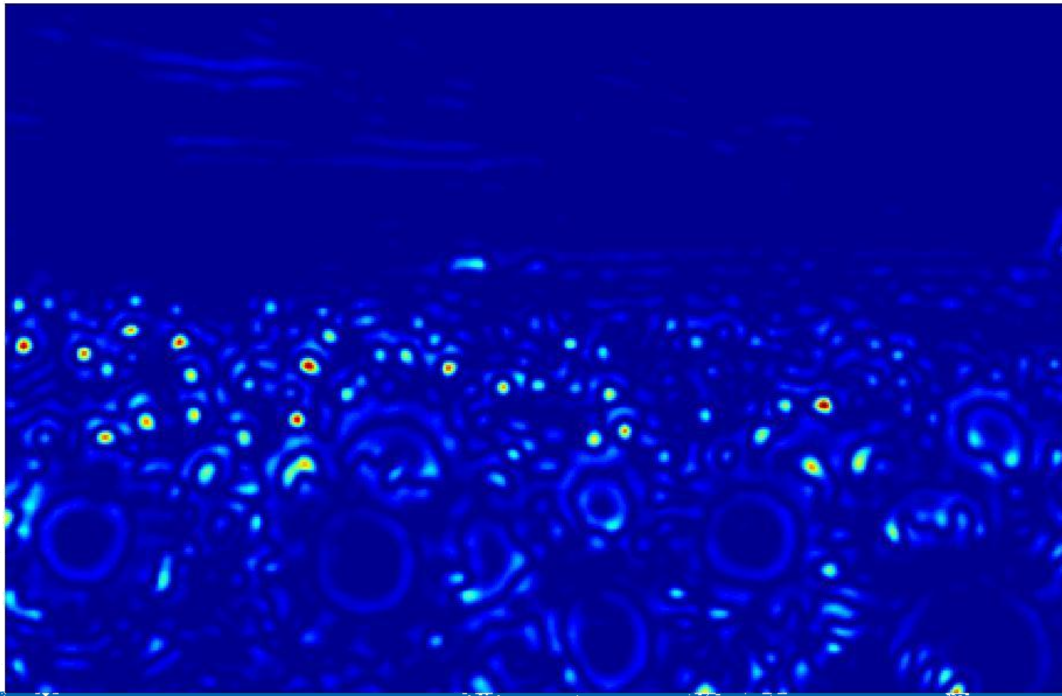

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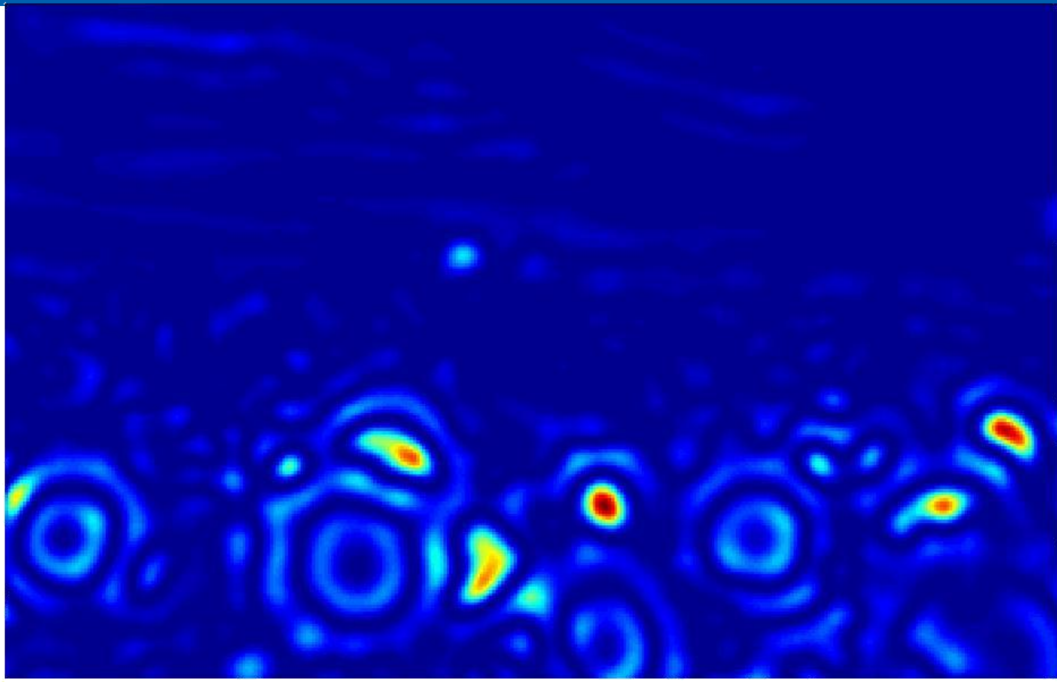

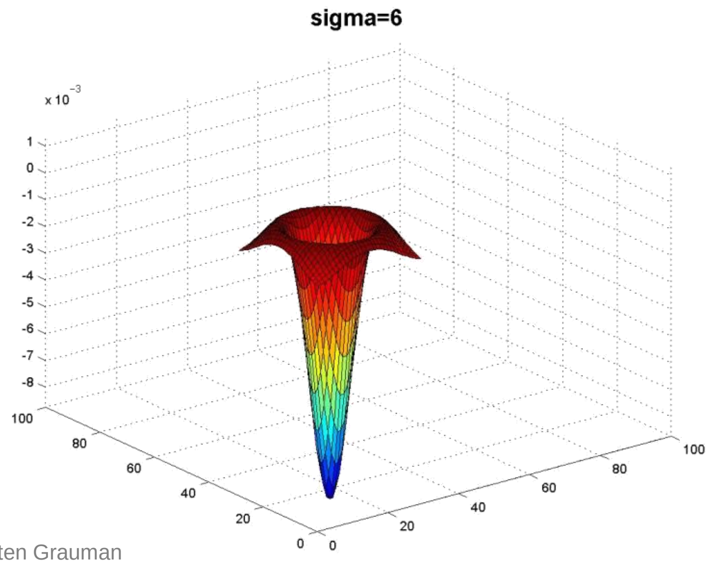

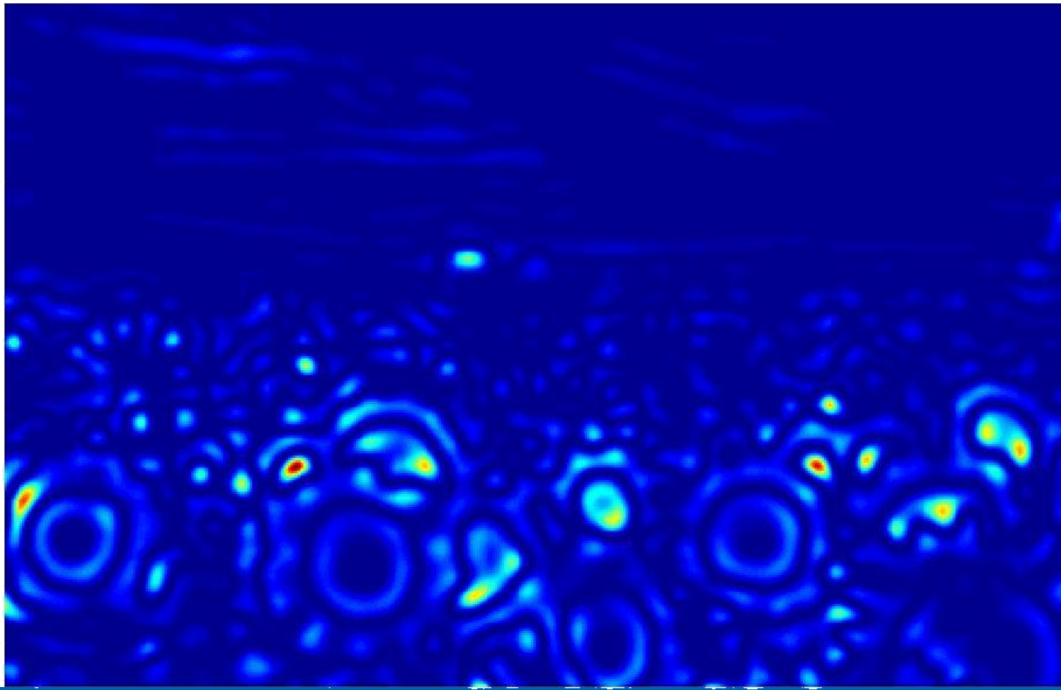

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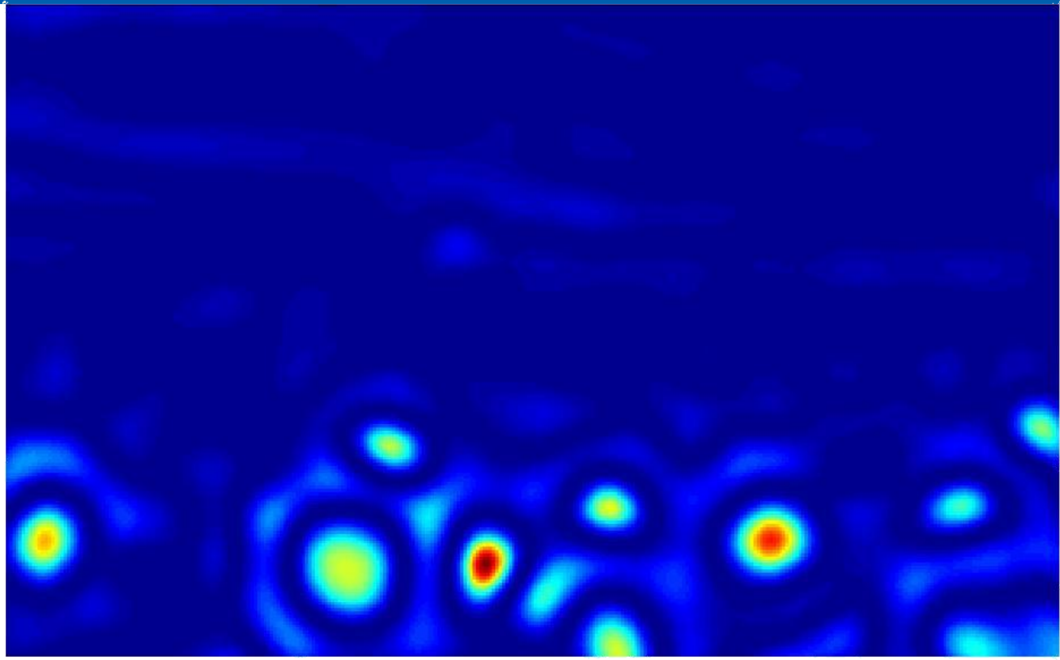

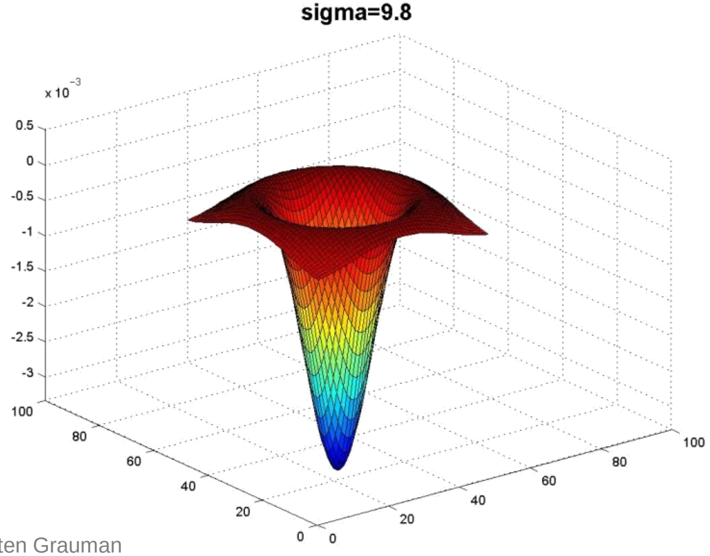

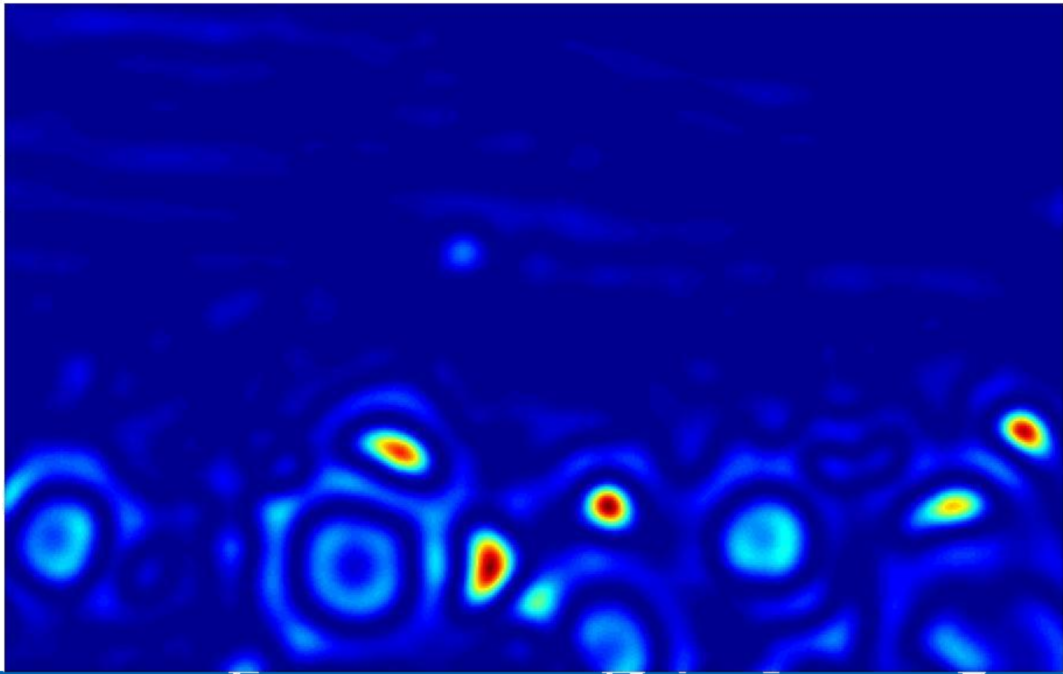

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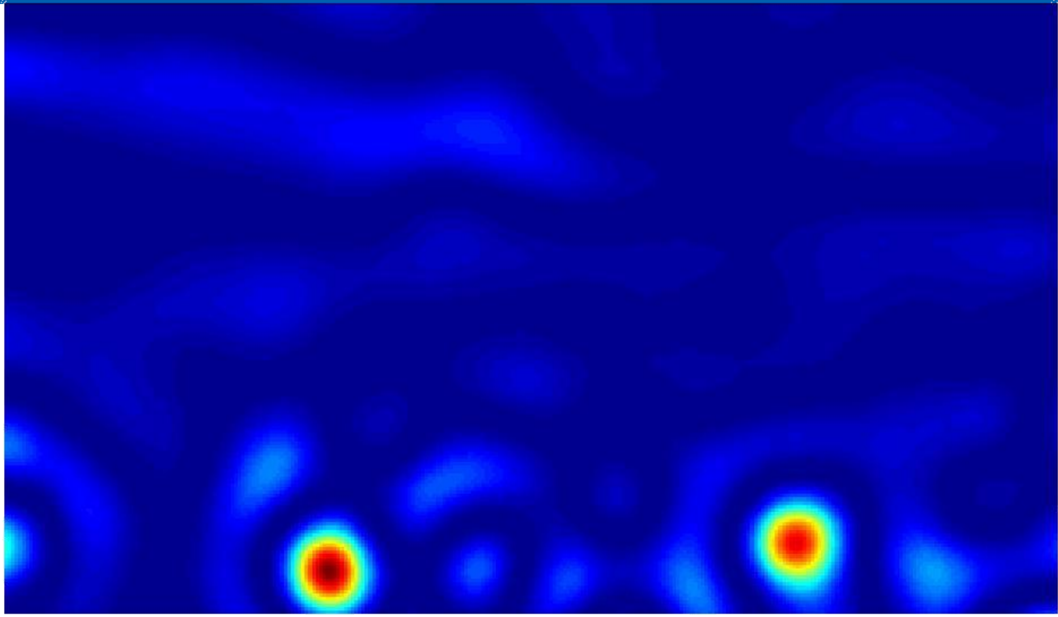

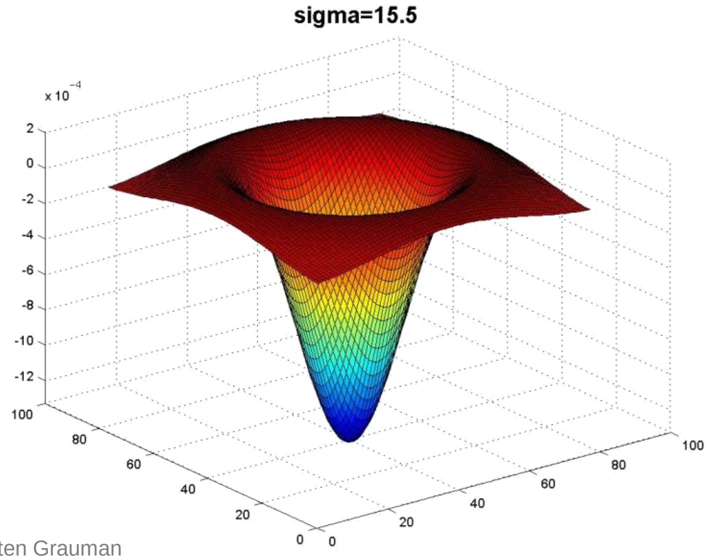

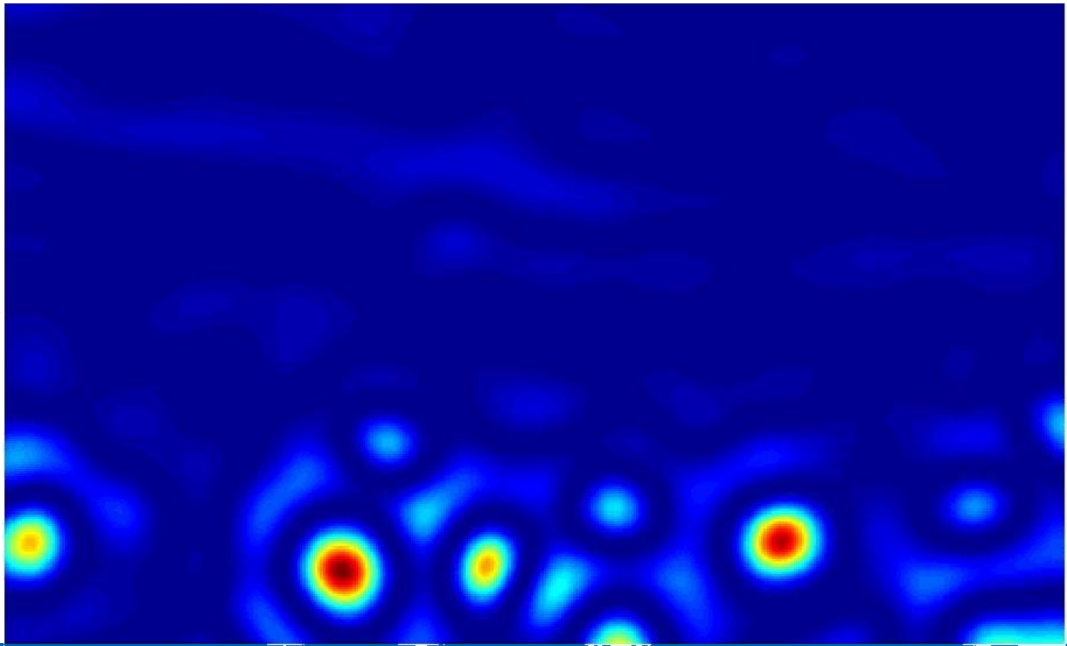

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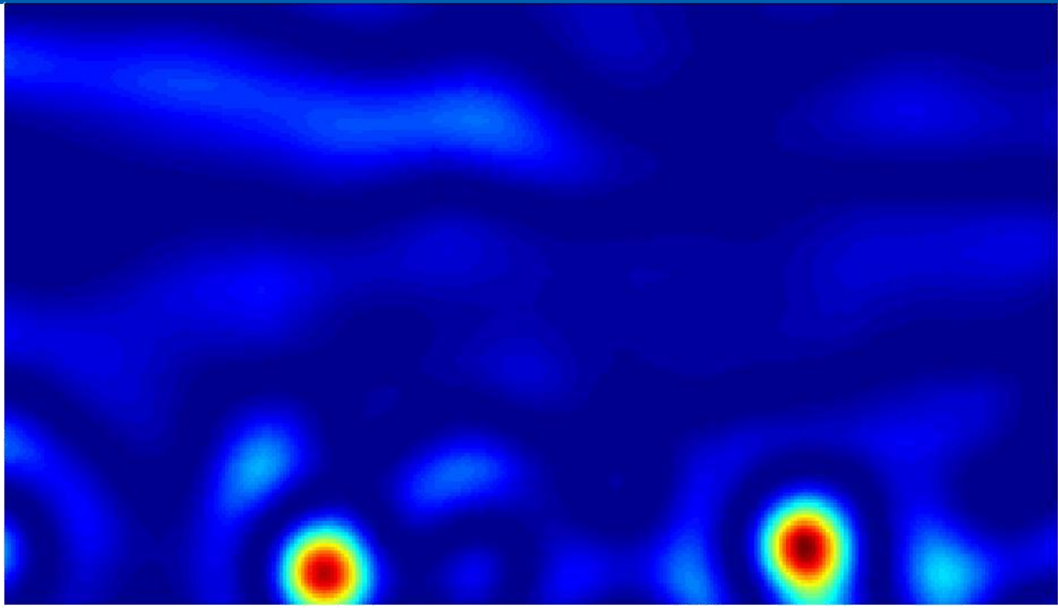

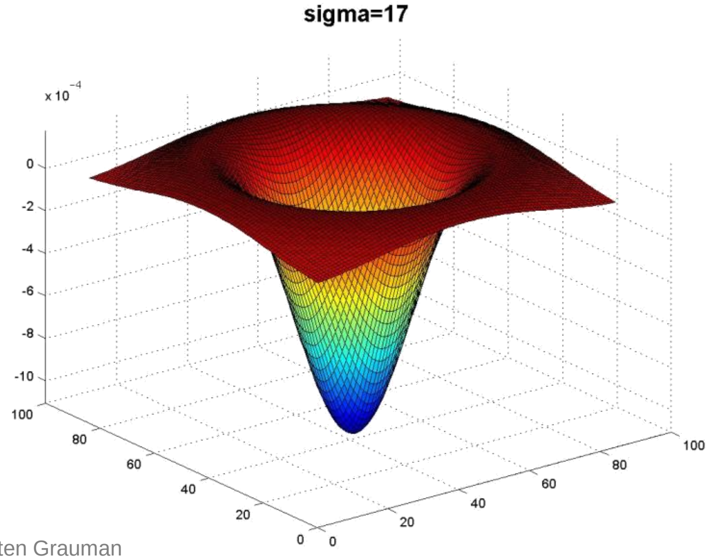

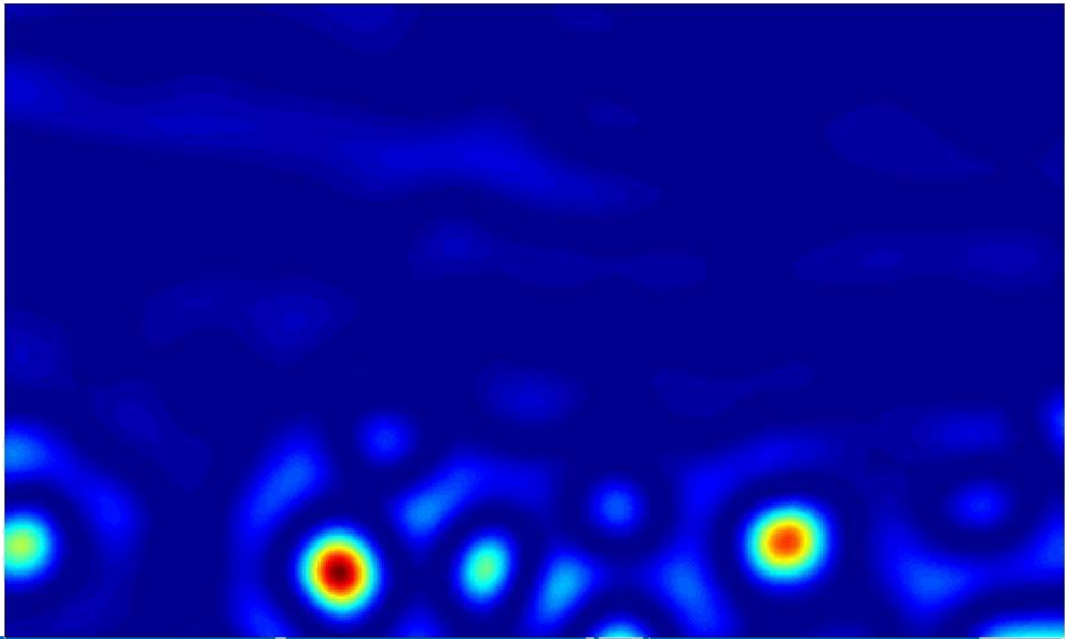

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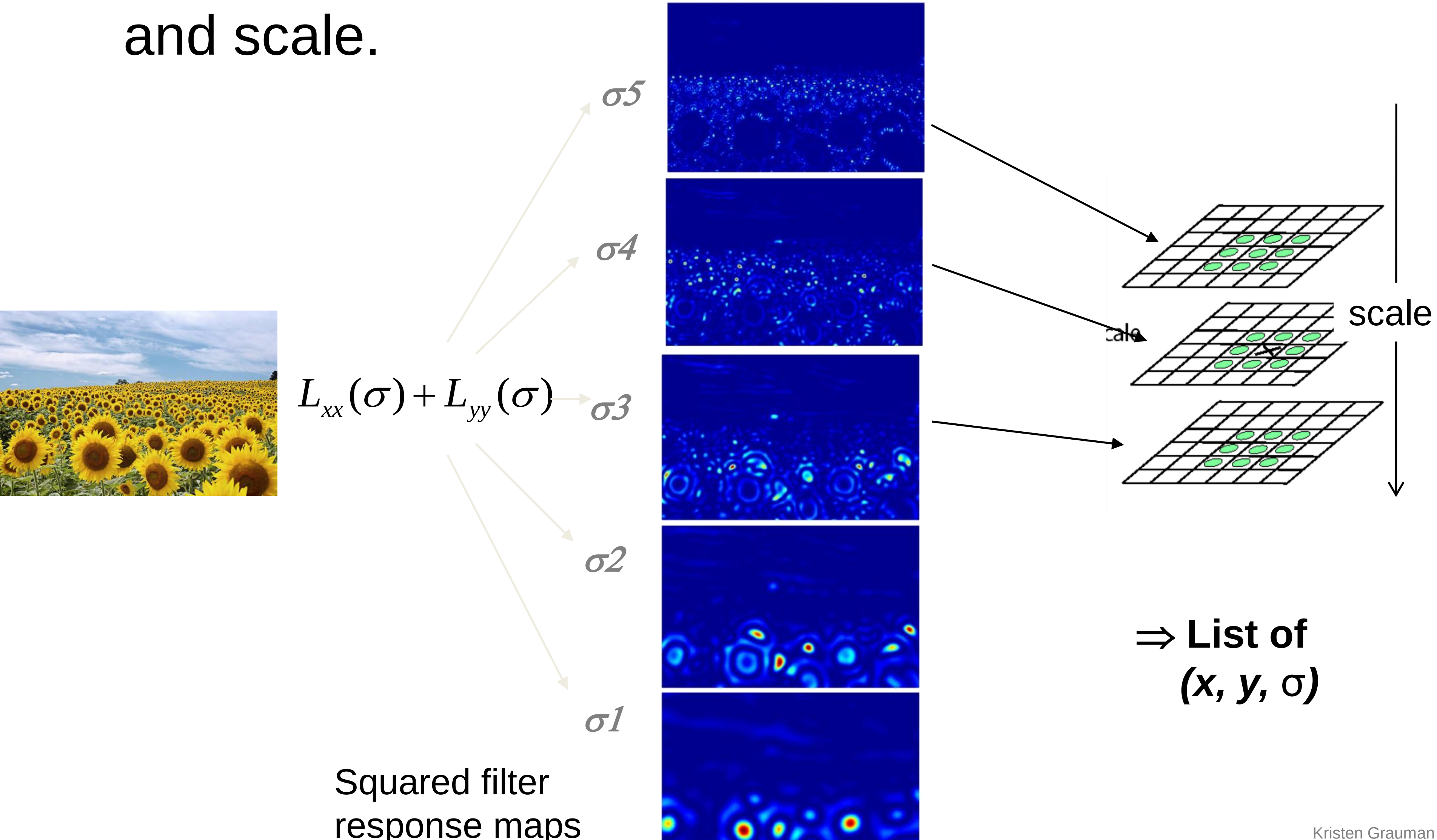
Scale invariant interest points

Interest points are local maxima in both position and scale.



Squared filter response maps

⇒ **List of (*x*, *y*, σ)**

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Scale-space blob detector

Lana Lazebnik

Technical detail

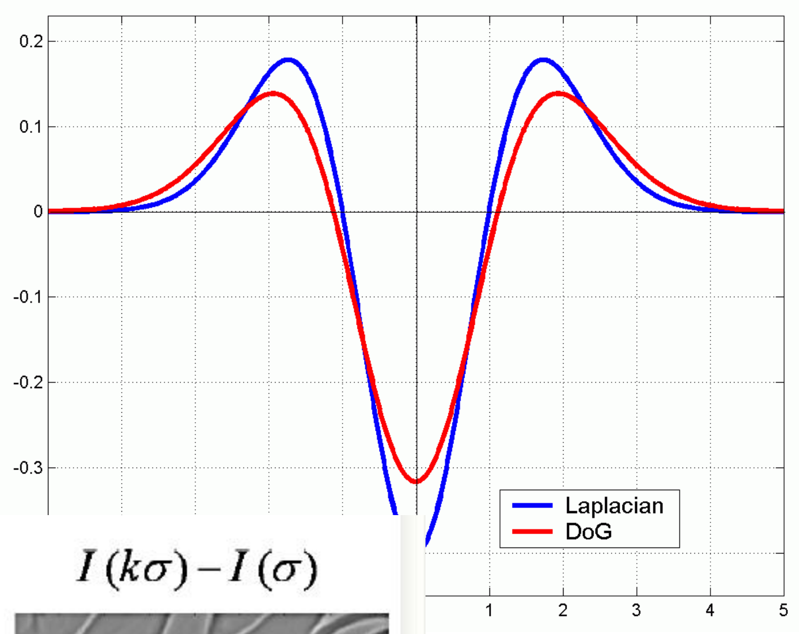
We can approximate the Laplacian with a difference of Gaussians; more efficient to implement.

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

(Laplacian)

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

(Difference of Gaussians)



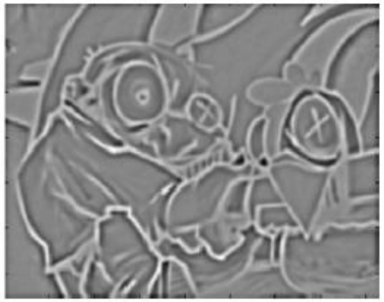
$I(k\sigma)$

-

$I(\sigma)$

=

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



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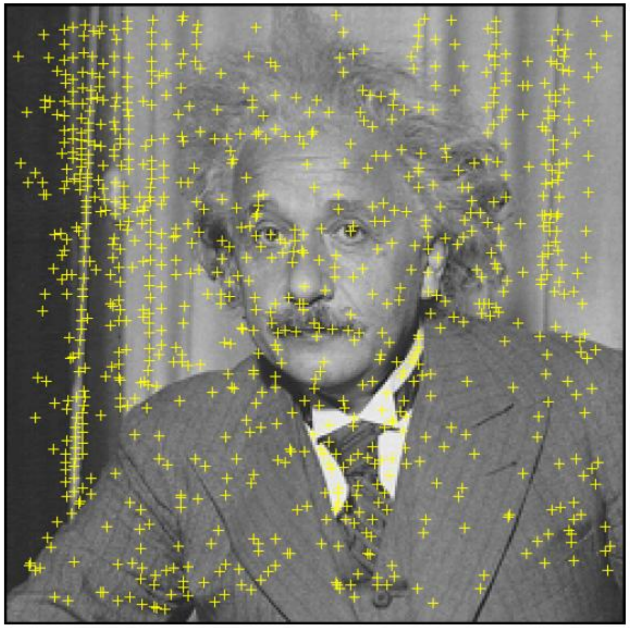
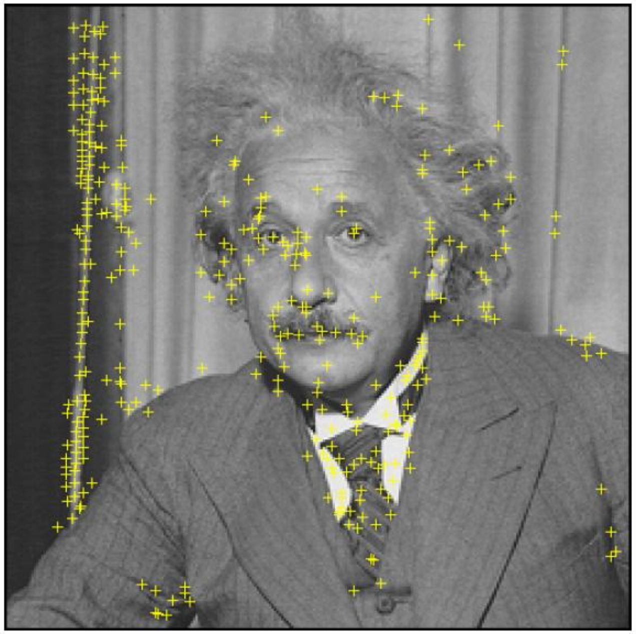
Technical detail

- Reject points with low contrast
- Reject edge points using Hessian H (like corner detector)

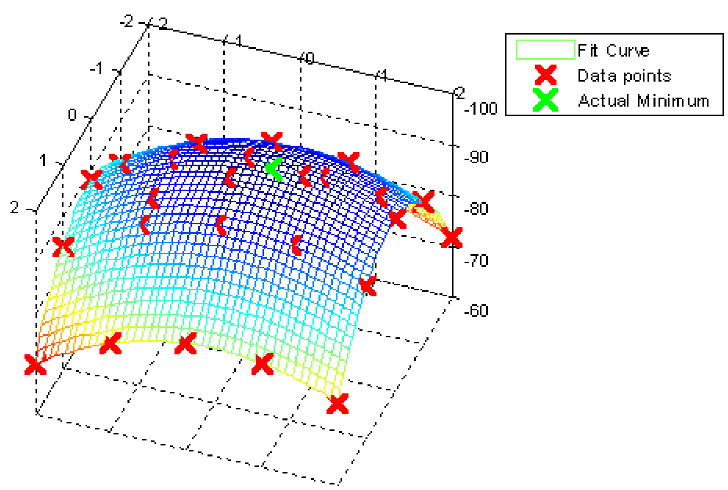
$$\frac{Tr(H)^2}{Det(H)} < \frac{(r+1)^2}{r}$$

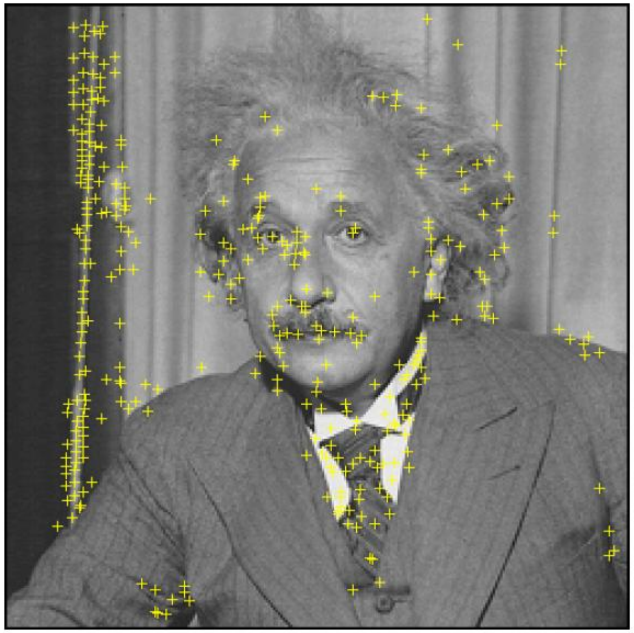




Technical detail

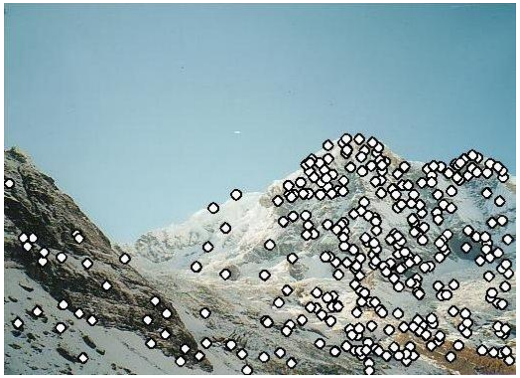
Accurate keypoint localization by fitting quadratic function for interpolation





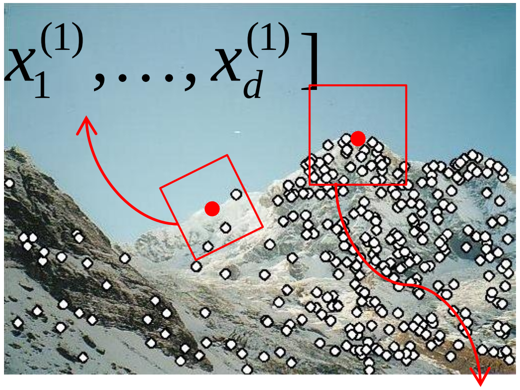
Local features and matching

1) Detection: Identify the interest points



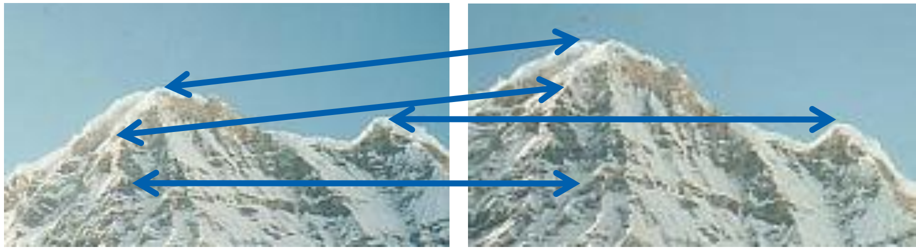
2) Description: Extract vector feature descriptor surrounding each interest point.

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



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

3) Matching: Determine correspondence between descriptors in two views



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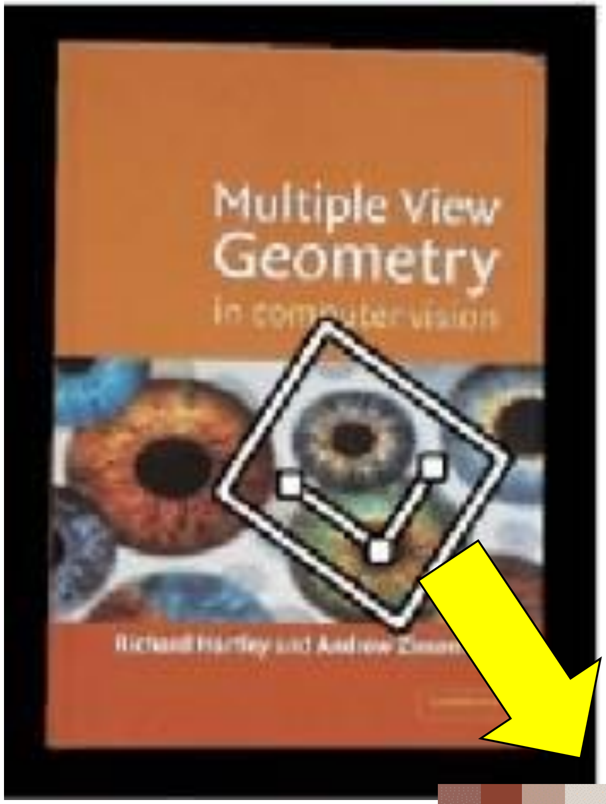
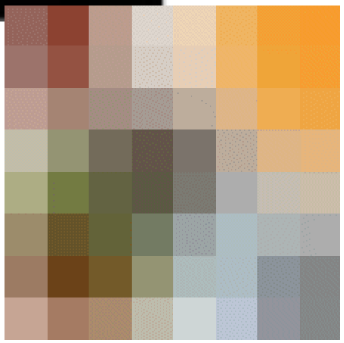
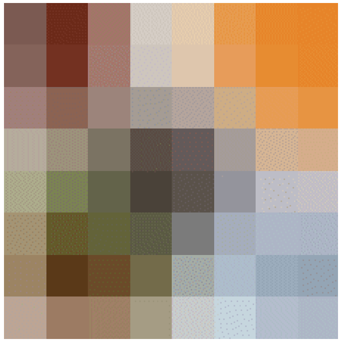
Geometric transformations







e.g. scale,
translation,
rotation

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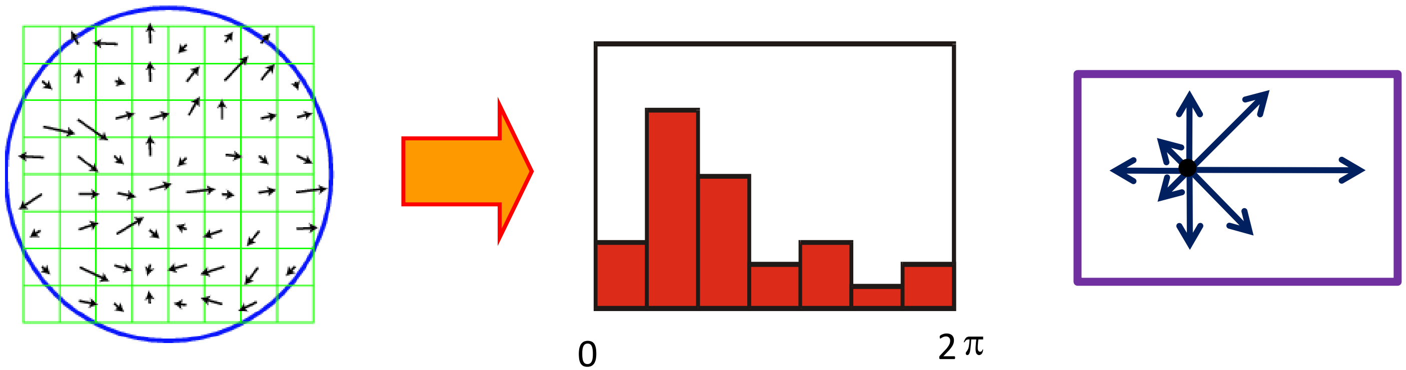
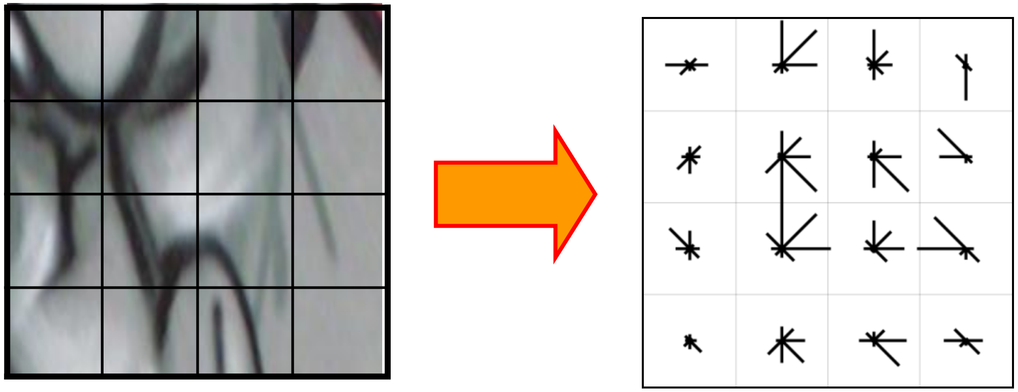
Photometric transformations

T. Tuytelaars

SIFT descriptor [Lowe 2004]

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





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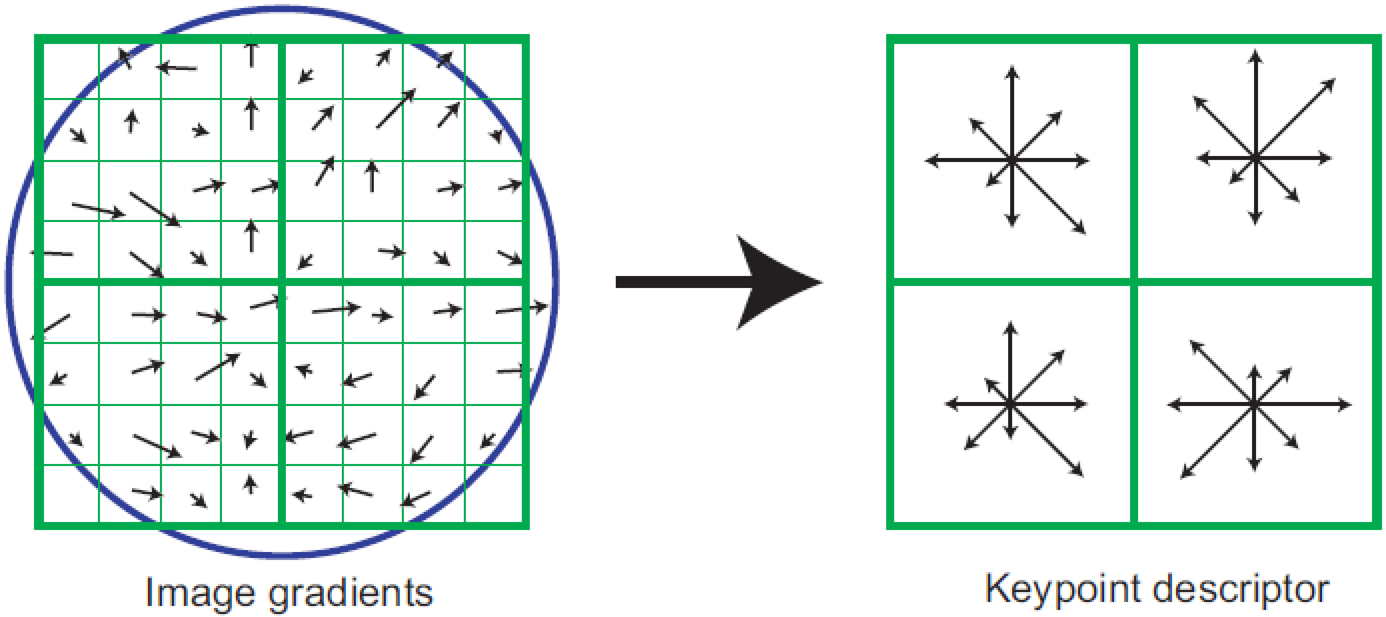
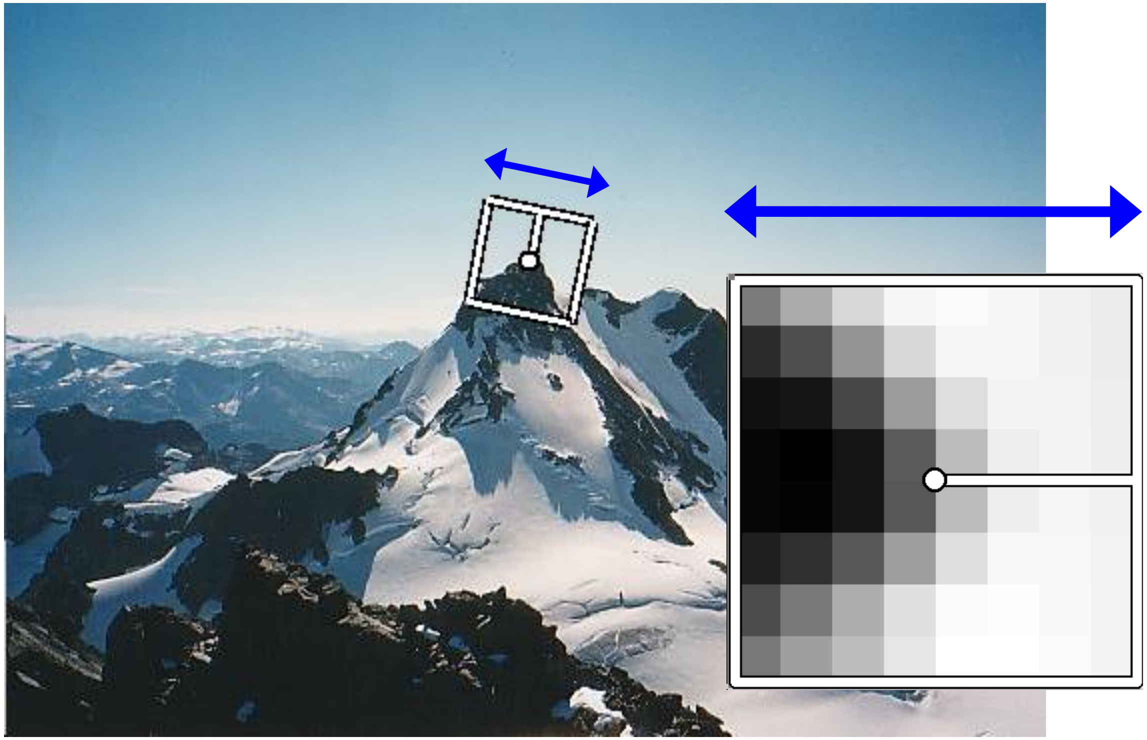
SIFT descriptor [Lowe 2004]

- 128 D vector (4x4x8)



- Normalize to 1 (robust to illumination changes)
- Entries above 0.2 are set to 0.2 (reduce impact of very strong gradients e.g. shadow)
- Normalize to 1

Making descriptor rotation invariant

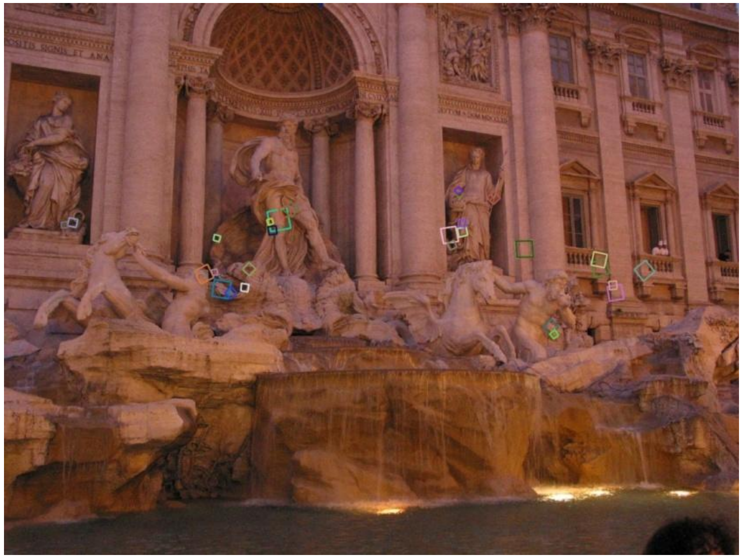


- Rotate patch according to its dominant gradient orientation
- This puts the patches into a canonical orientation.

Matthew Brown

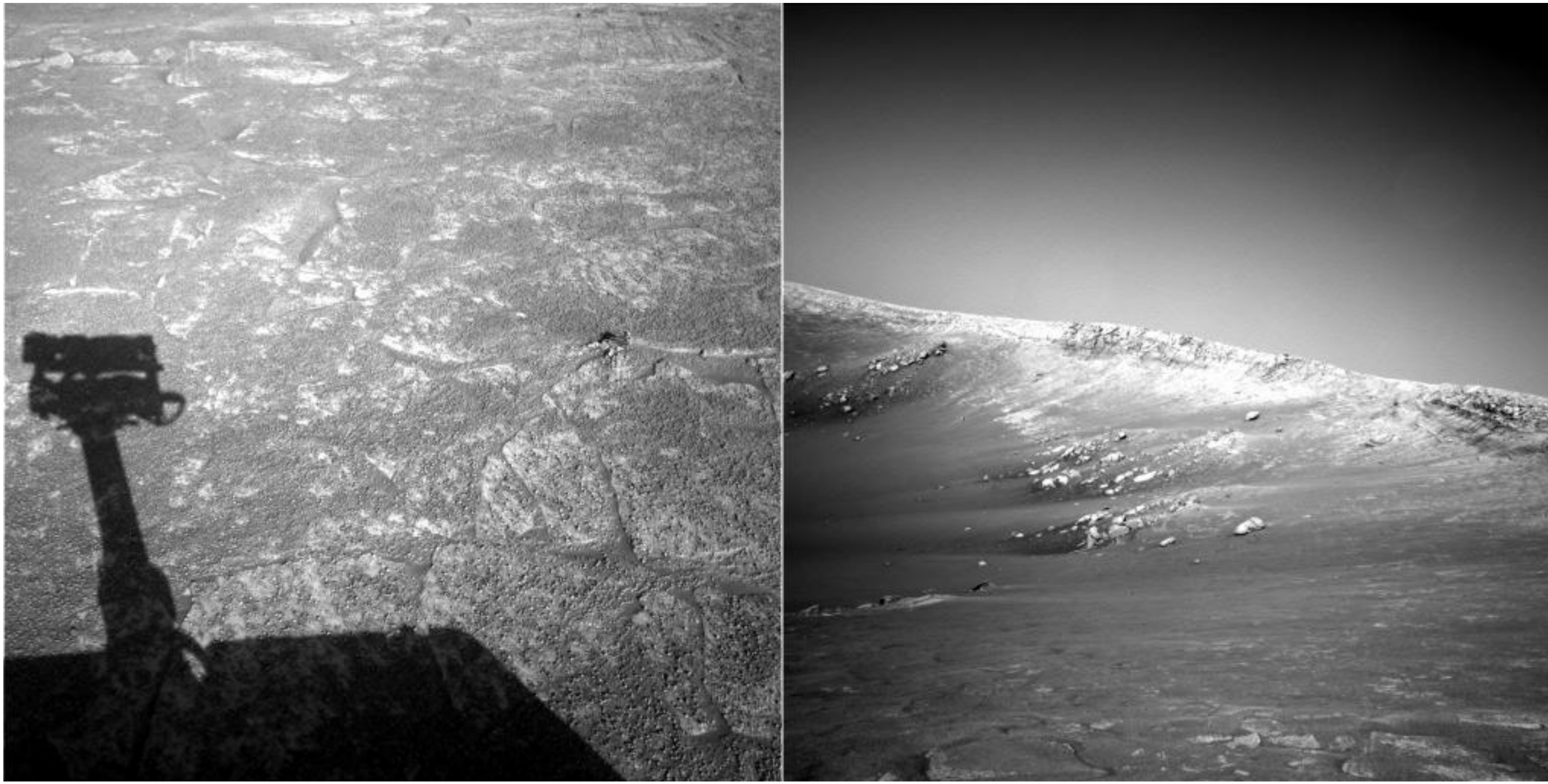
SIFT descriptor [Lowe 2004]

- 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



Steve Seitz

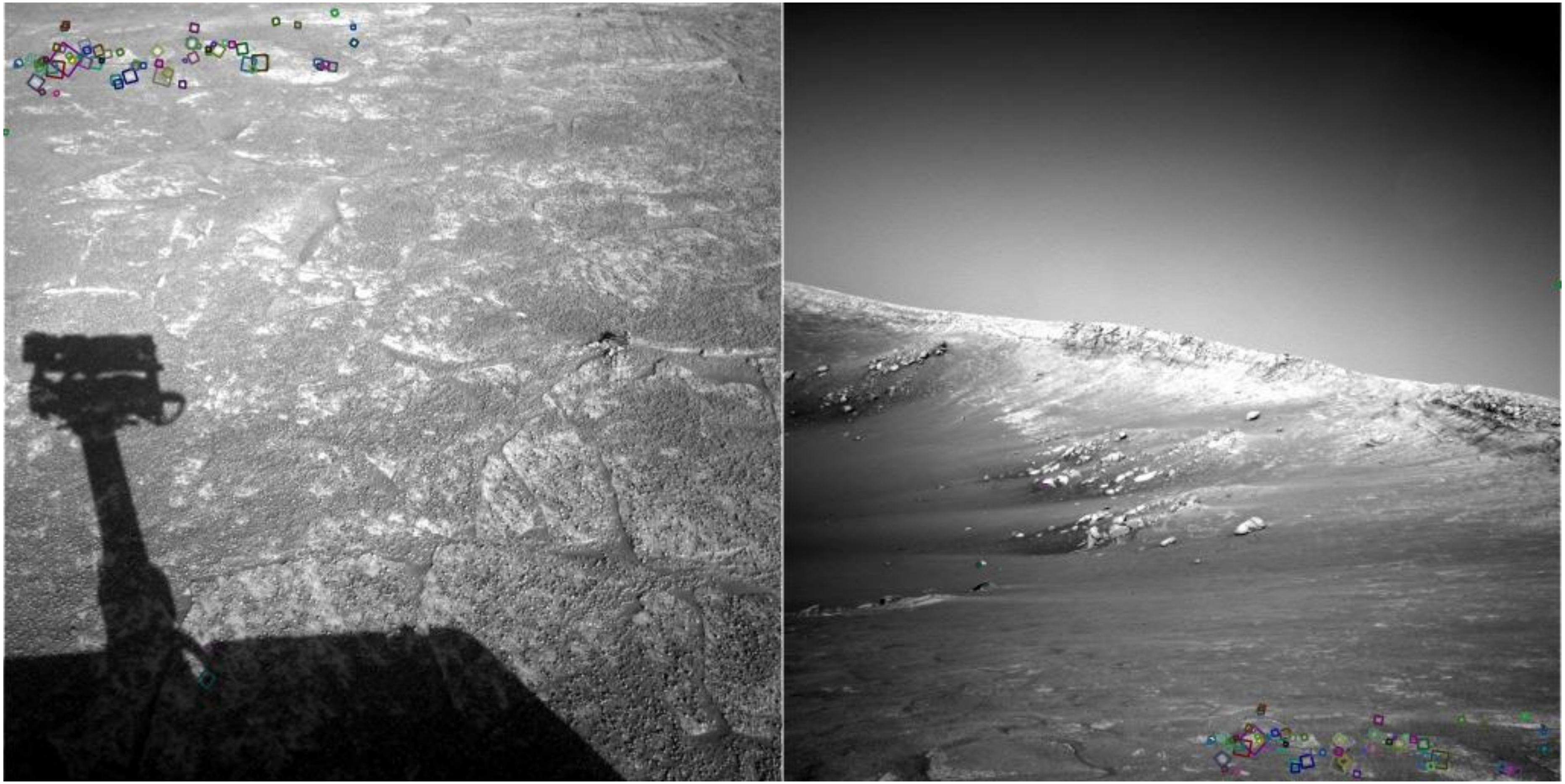
Example



NASA Mars Rover images

Kristen Grauman

Example



NASA Mars Rover images
with SIFT feature matches

Noah Snavely

SIFT properties

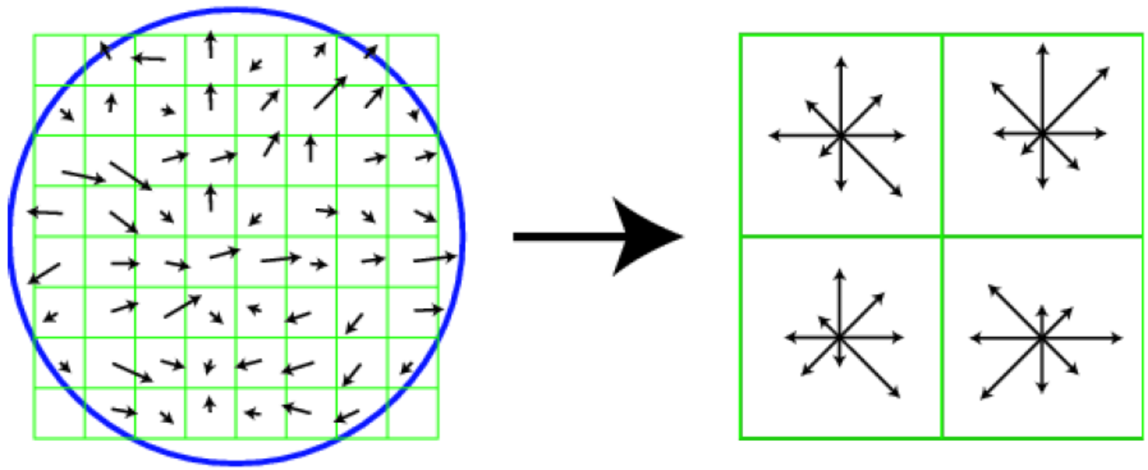
- Invariant to
  - Scale
  - Rotation

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

Kristen Grauman

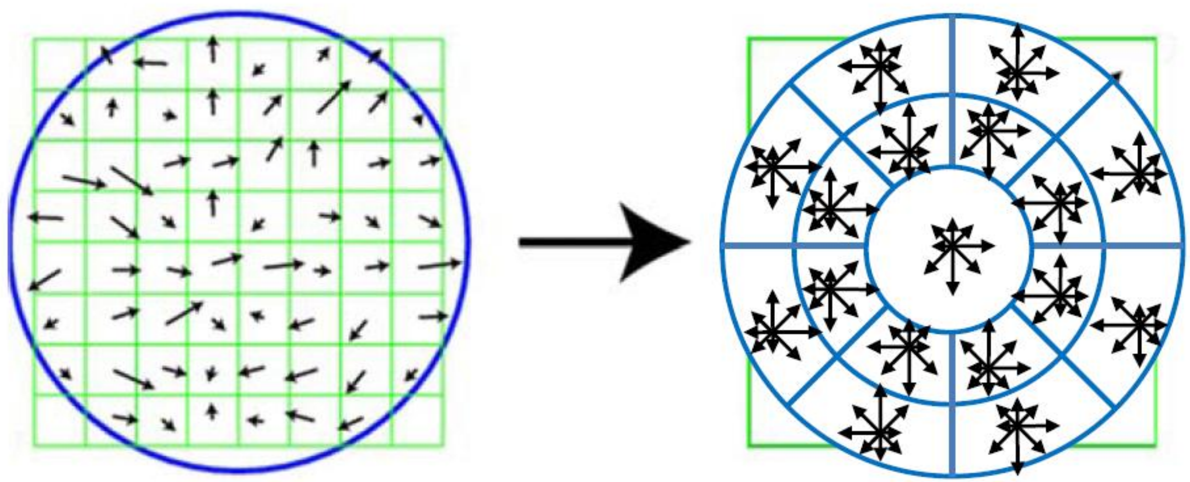
Other feature descriptors

SIFT:



(a) image gradients (b) keypoint descriptor

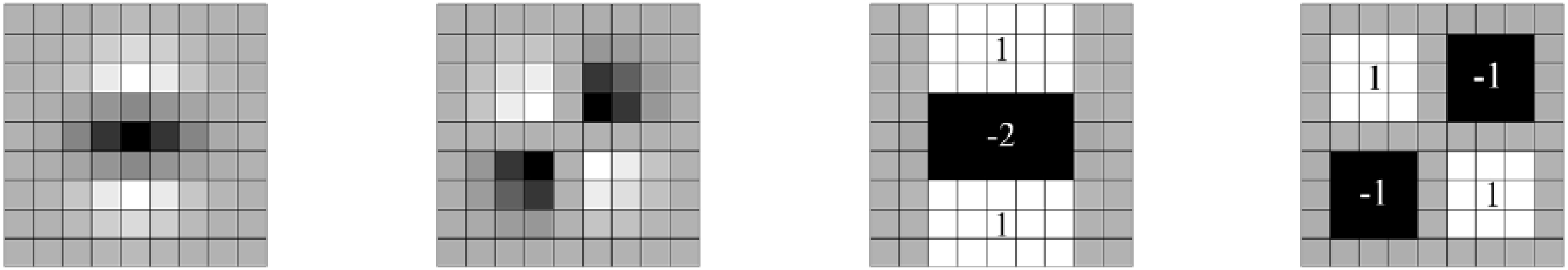
GLOH:



(a) image gradients (b) keypoint descriptor

Other feature descriptors

SURF: Approximate second order derivatives of Gaussian



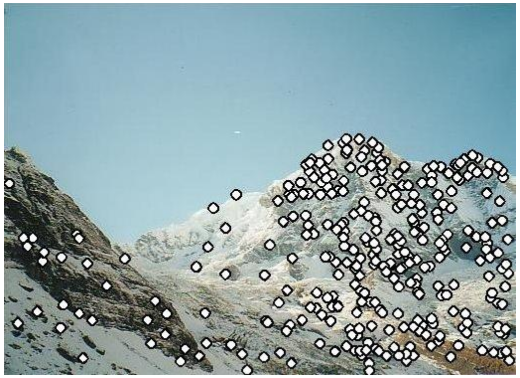
Fast to compute with integral images

Feature descriptors

- Countless number of SIFT variations
- SIFT sometimes too slow, many approximations for real-time applications
- Color versions exist
- Most popular SIFT, SURF

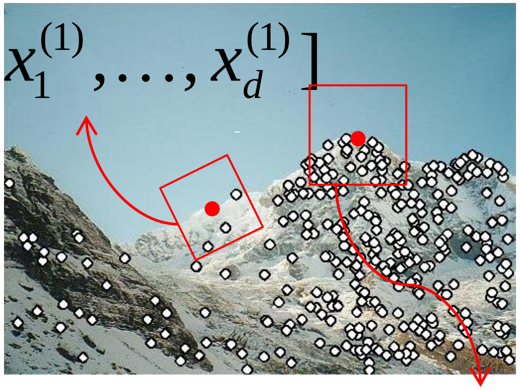
Local features and matching

1) Detection: Identify the interest points



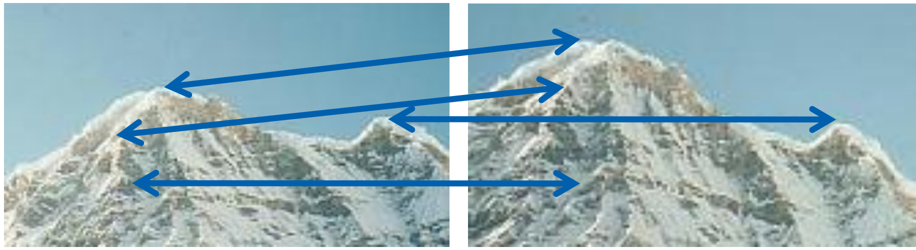
2) Description: Extract vector feature descriptor surrounding each interest point.

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



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

3) Matching: Determine correspondence between descriptors in two views



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Matching local features

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Matching local features

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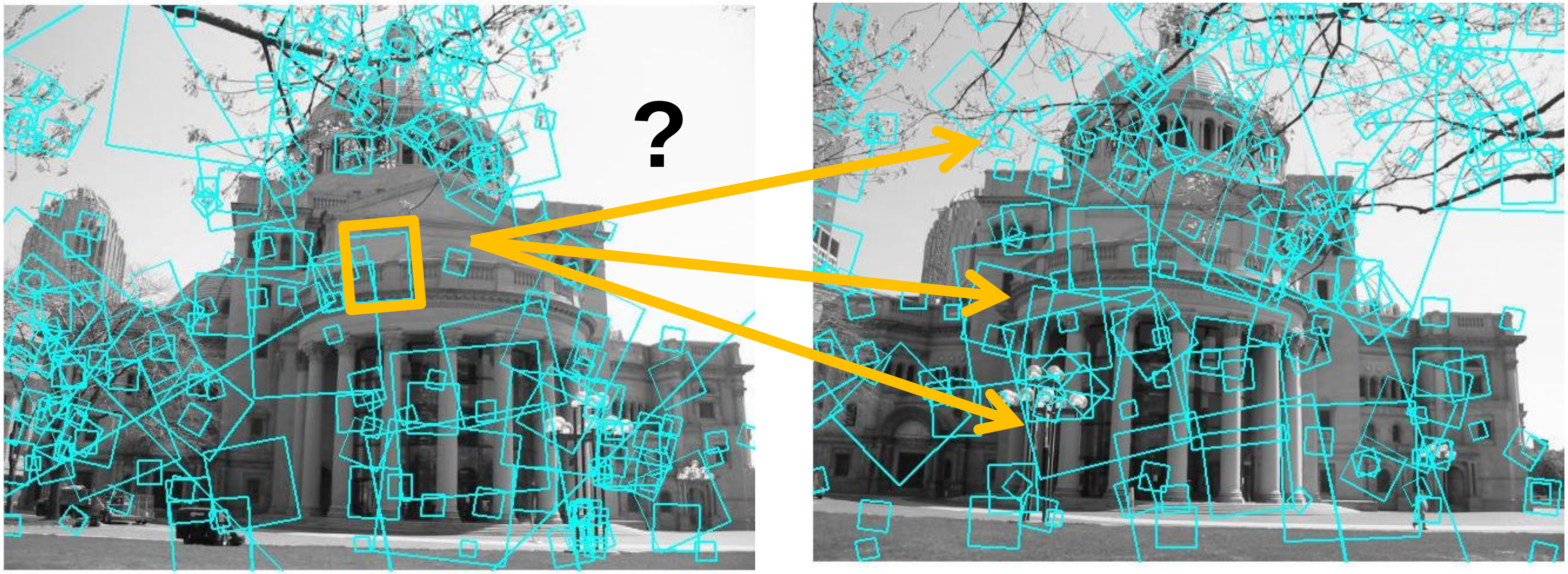

Image 1

Image 2

To generate **candidate matches**, find patches that have the most similar descriptor (e.g., Euclidean distance)

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

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Matching local features

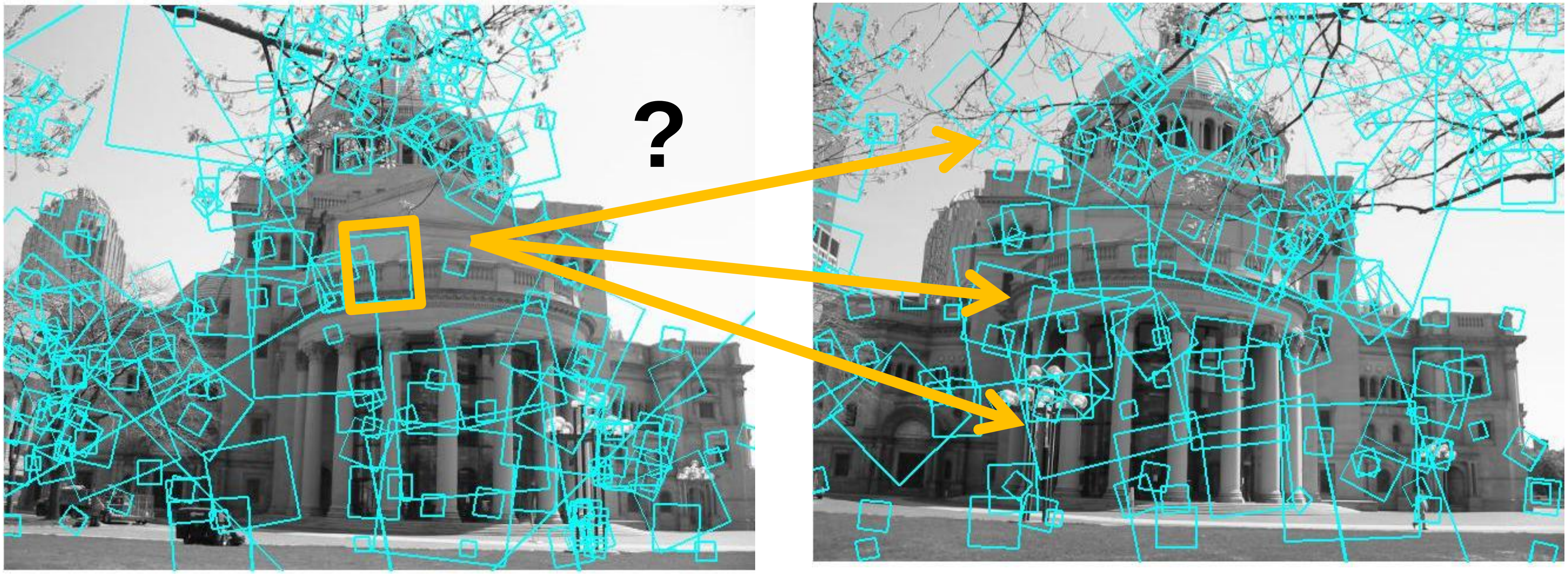

Image 1 Image 2

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 and close to one, could be ambiguous match.

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Matching SIFT Descriptors

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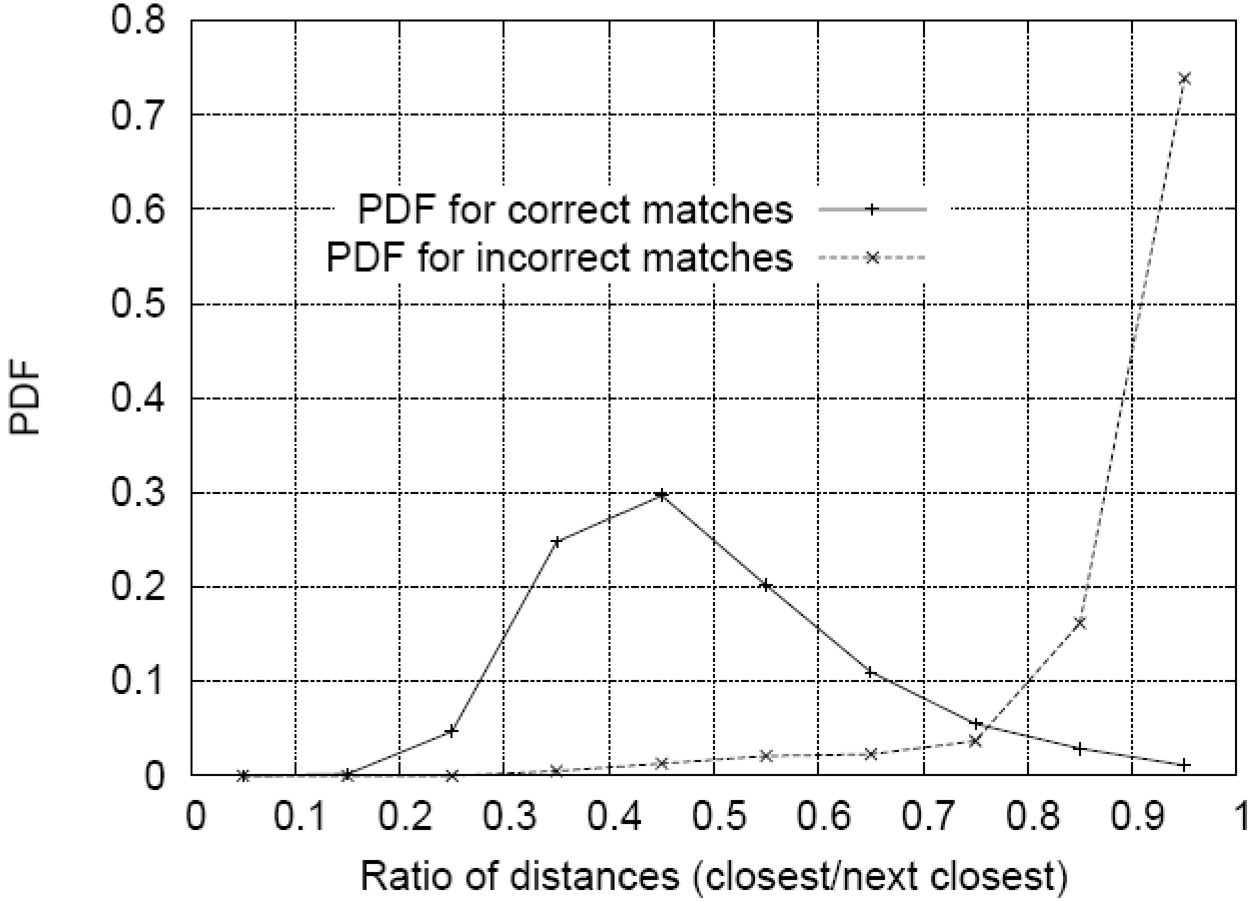
- Nearest neighbor (Euclidean distance)
- Threshold ratio of nearest to 2nd nearest descriptor



Lowe IJCV 2004

Applications of local invariant features

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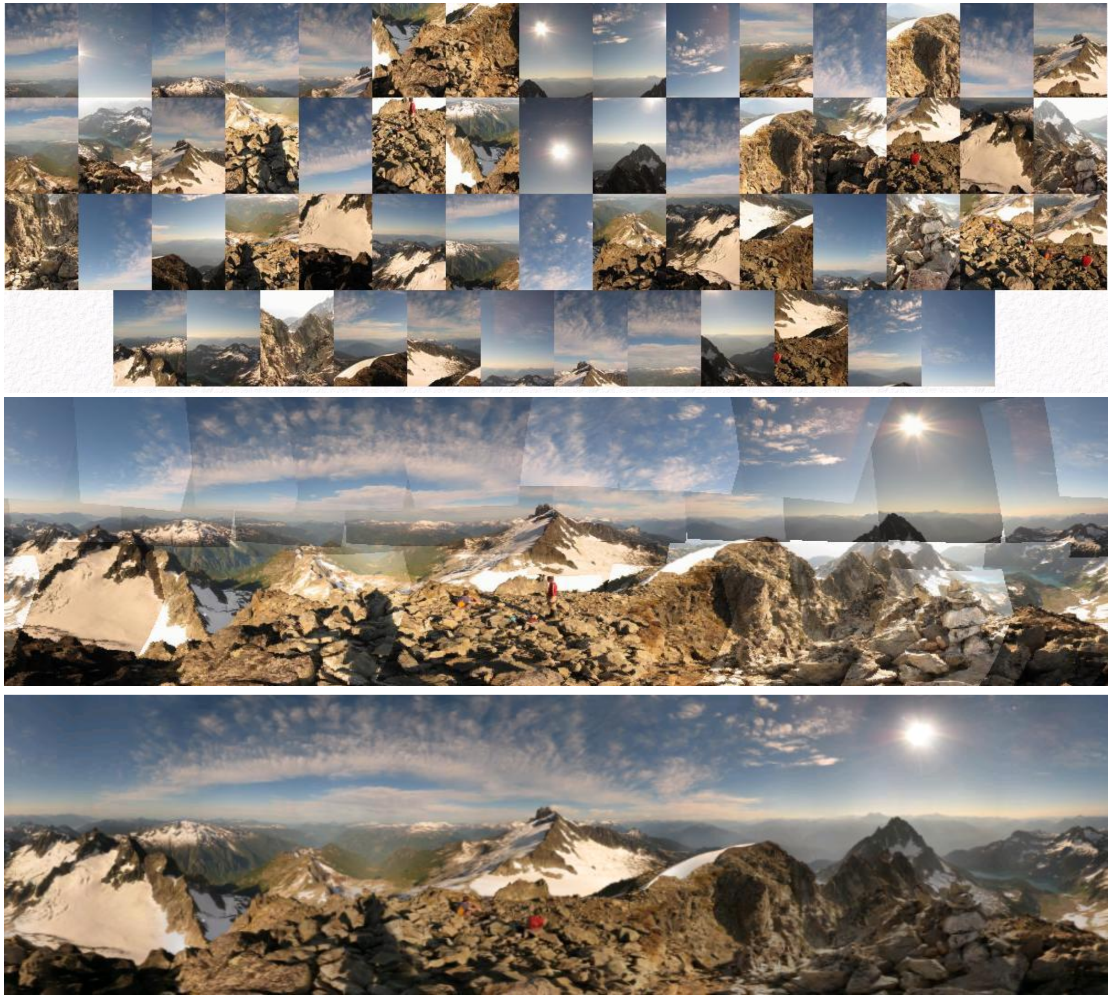
- Wide baseline stereo
- Motion tracking
- Panoramas
- Mobile robot navigation
- 3D reconstruction
- Recognition
- …

Automatic mosaicing



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

Wide baseline stereo

T. Tuytelaars