Interest points

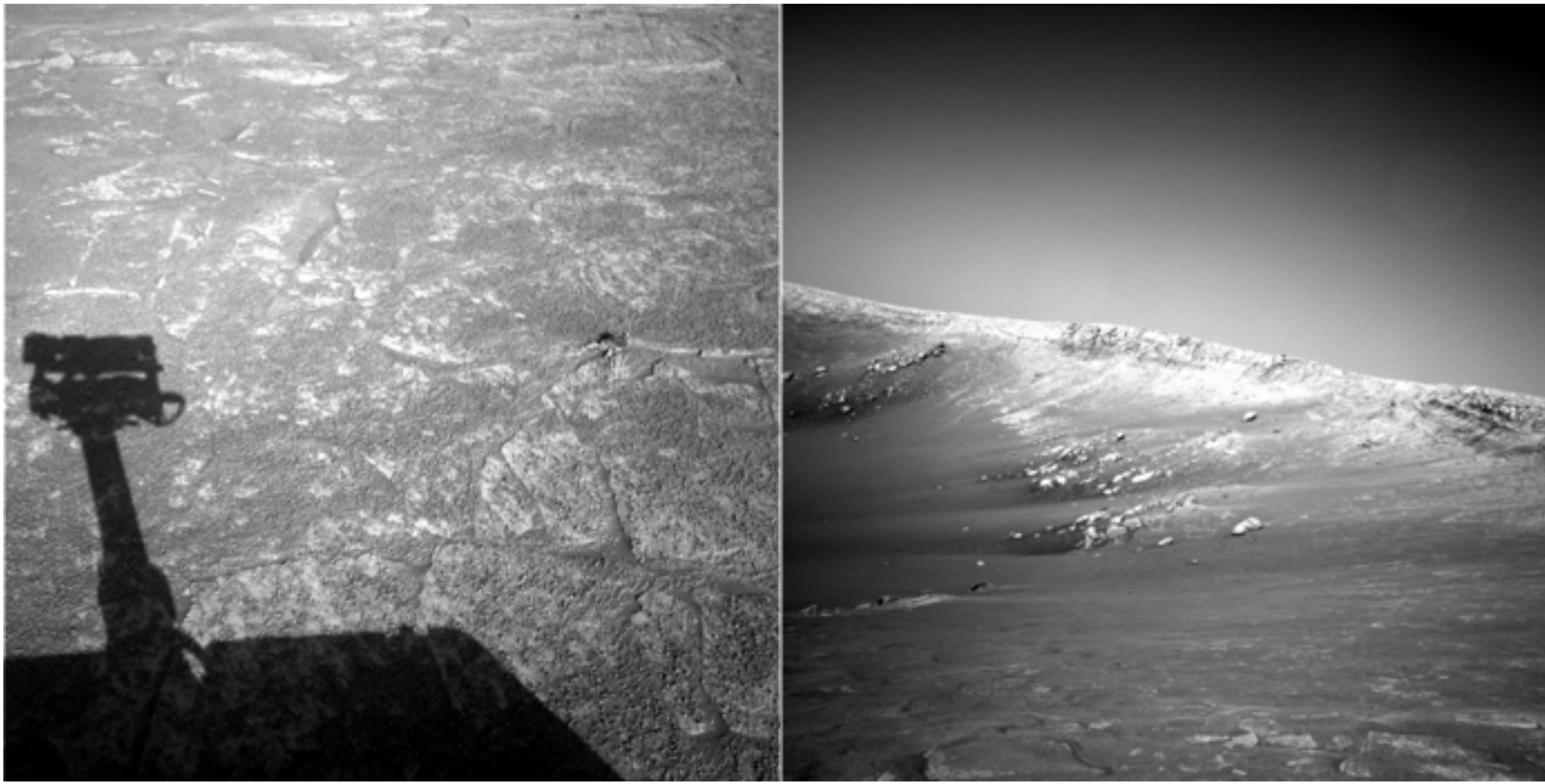
CSE 576

Ali Farhadi

Many slides from Steve Seitz, Larry Zitnick

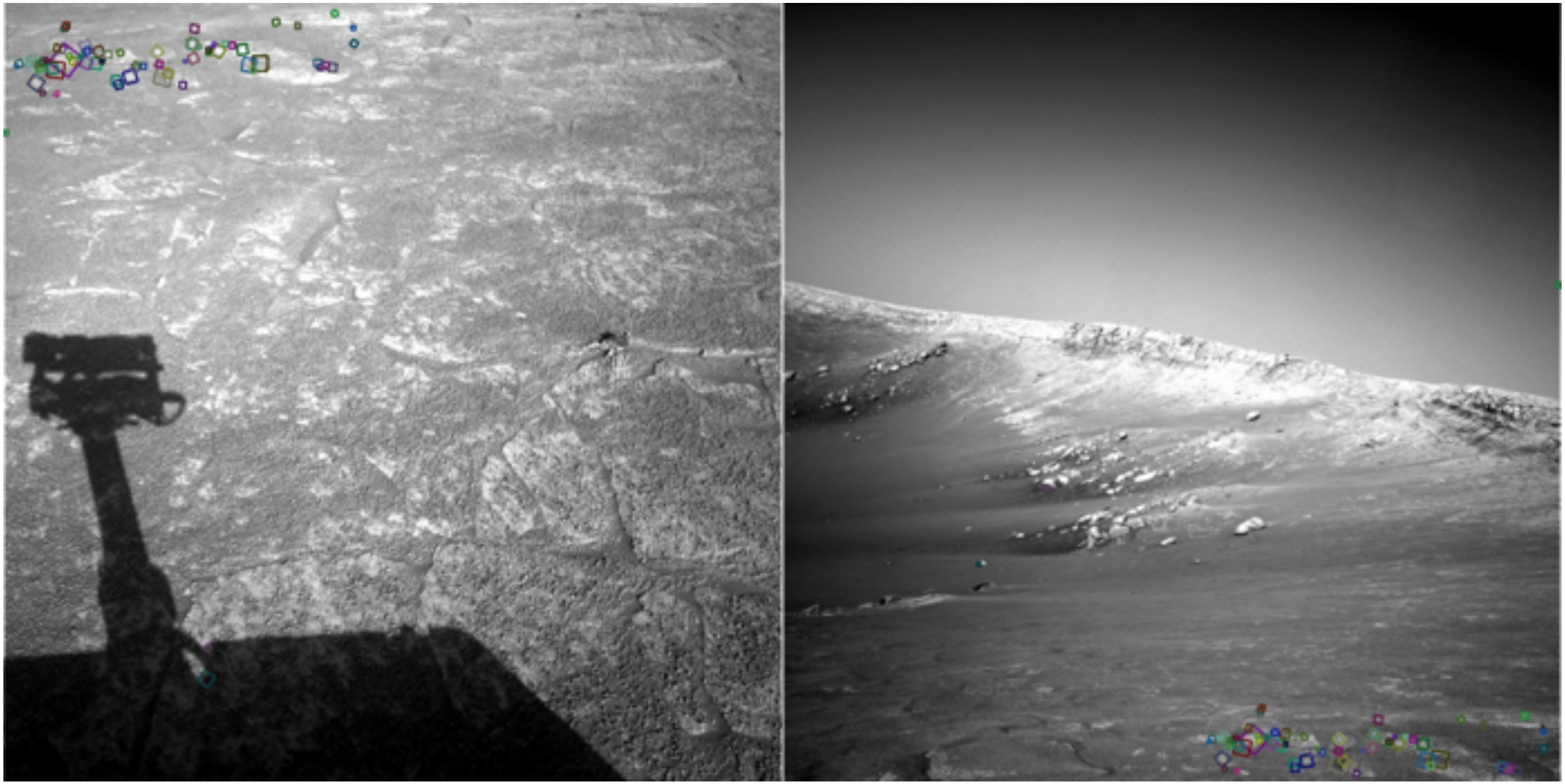
How can we find corresponding points?

Not always easy



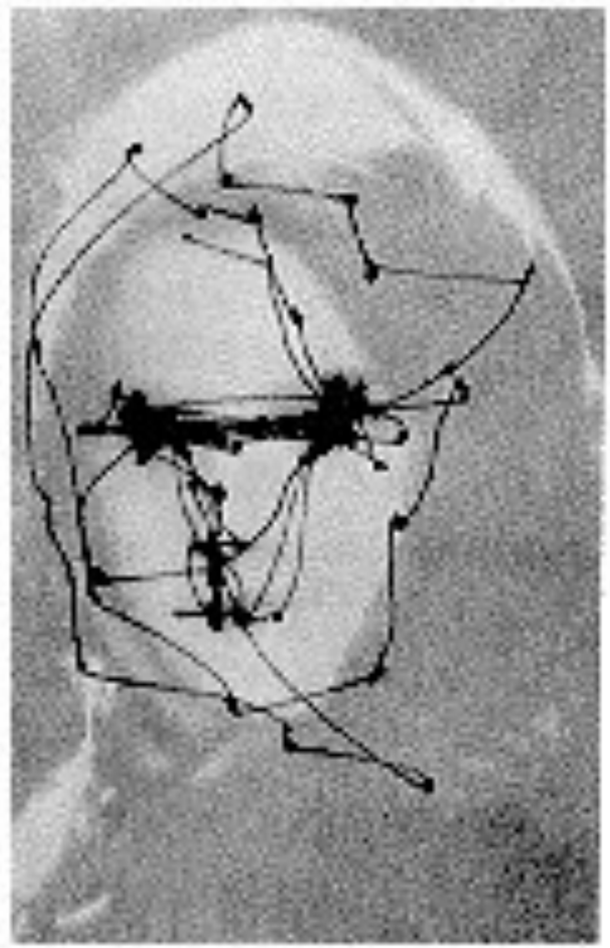
NASA Mars Rover images

Answer below (look for tiny colored squares…)



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

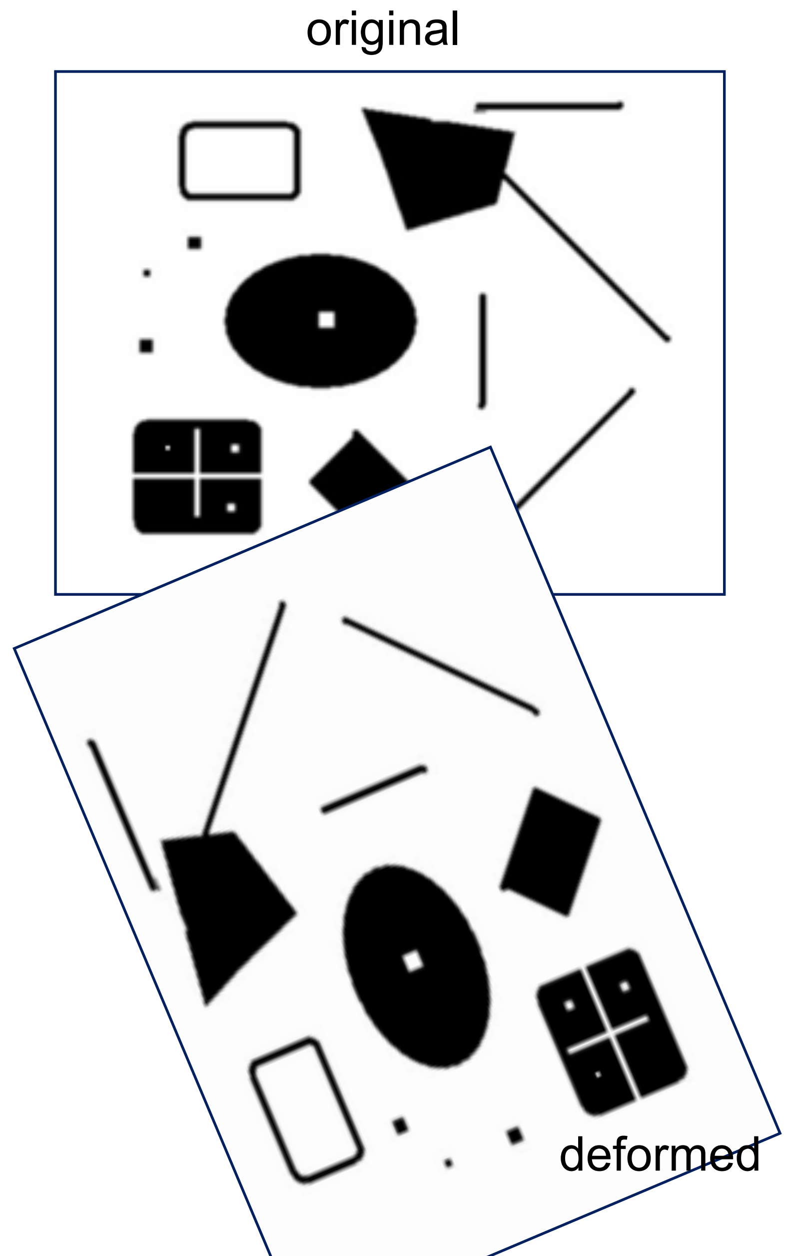
Human eye movements



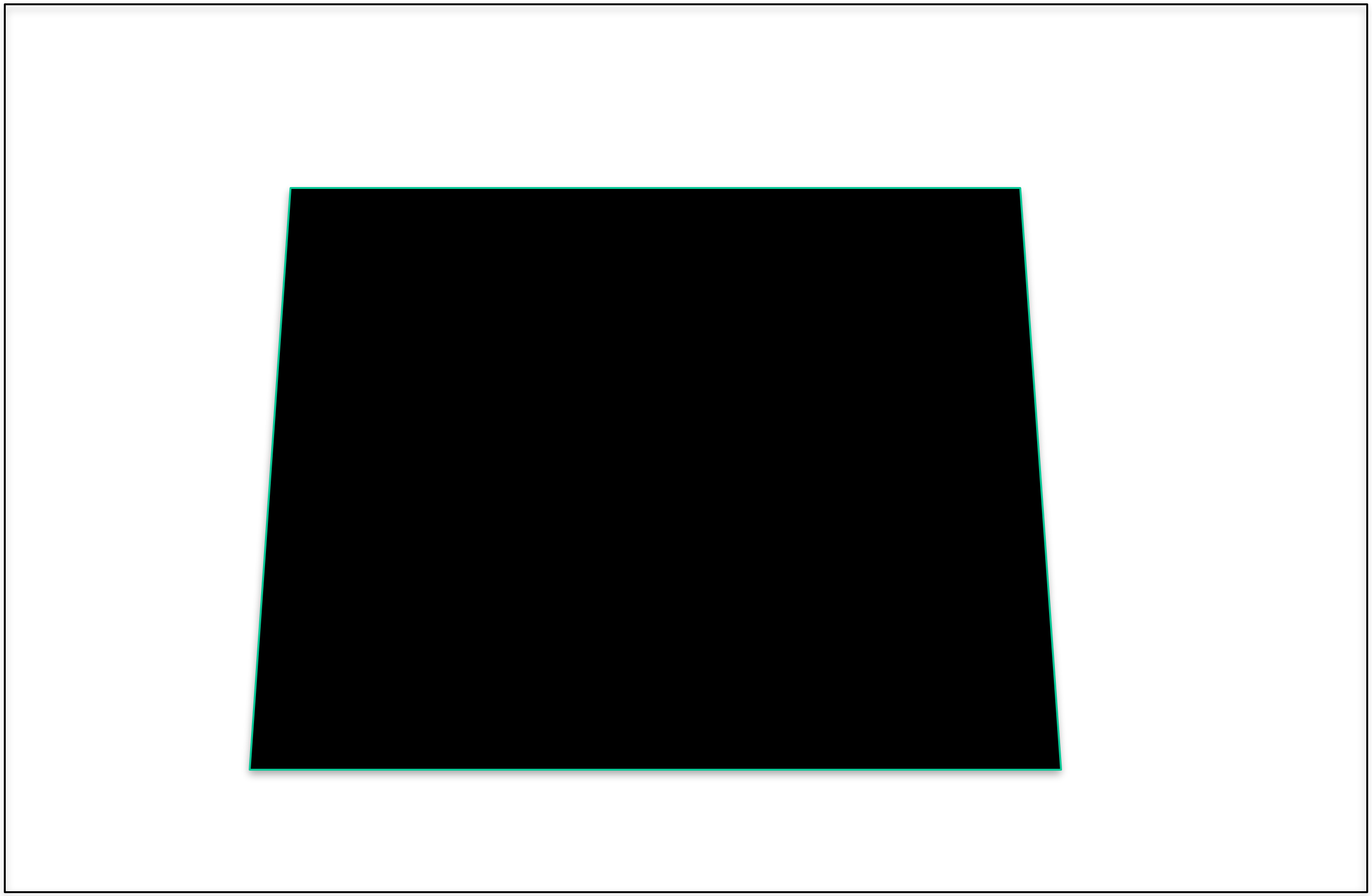
Yarbus eye tracking

Interest points

- Suppose you have to click on some point, go away and come back after I deform the image, and click on the same points again.
  - Which points would you choose?

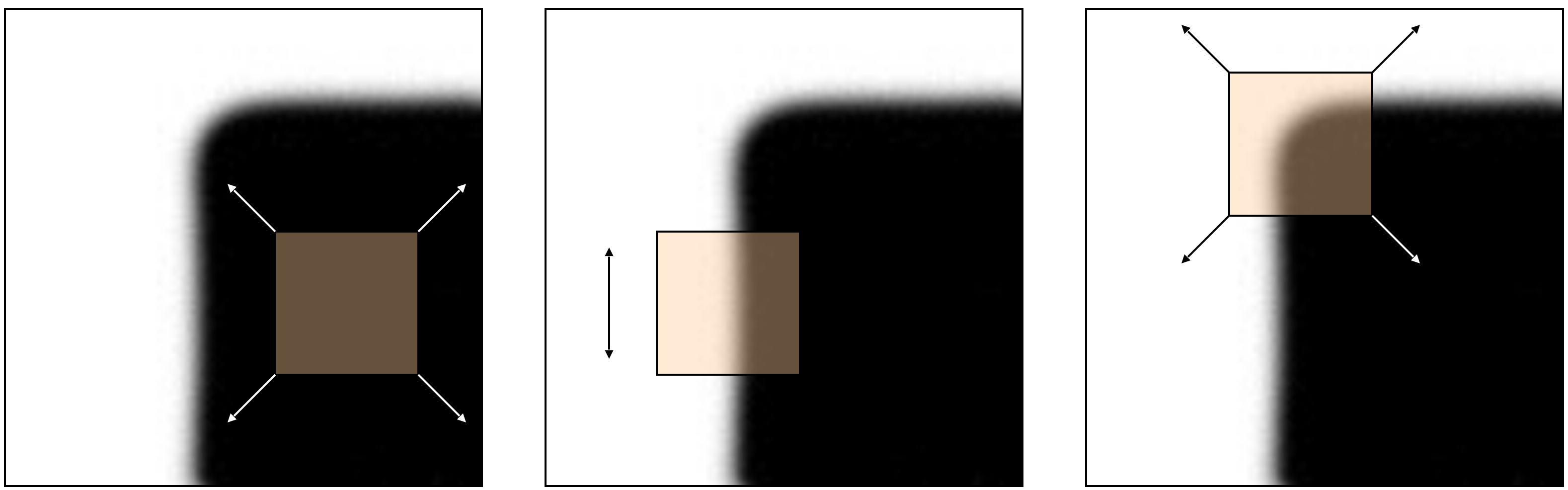


Intuition



Corners

- 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



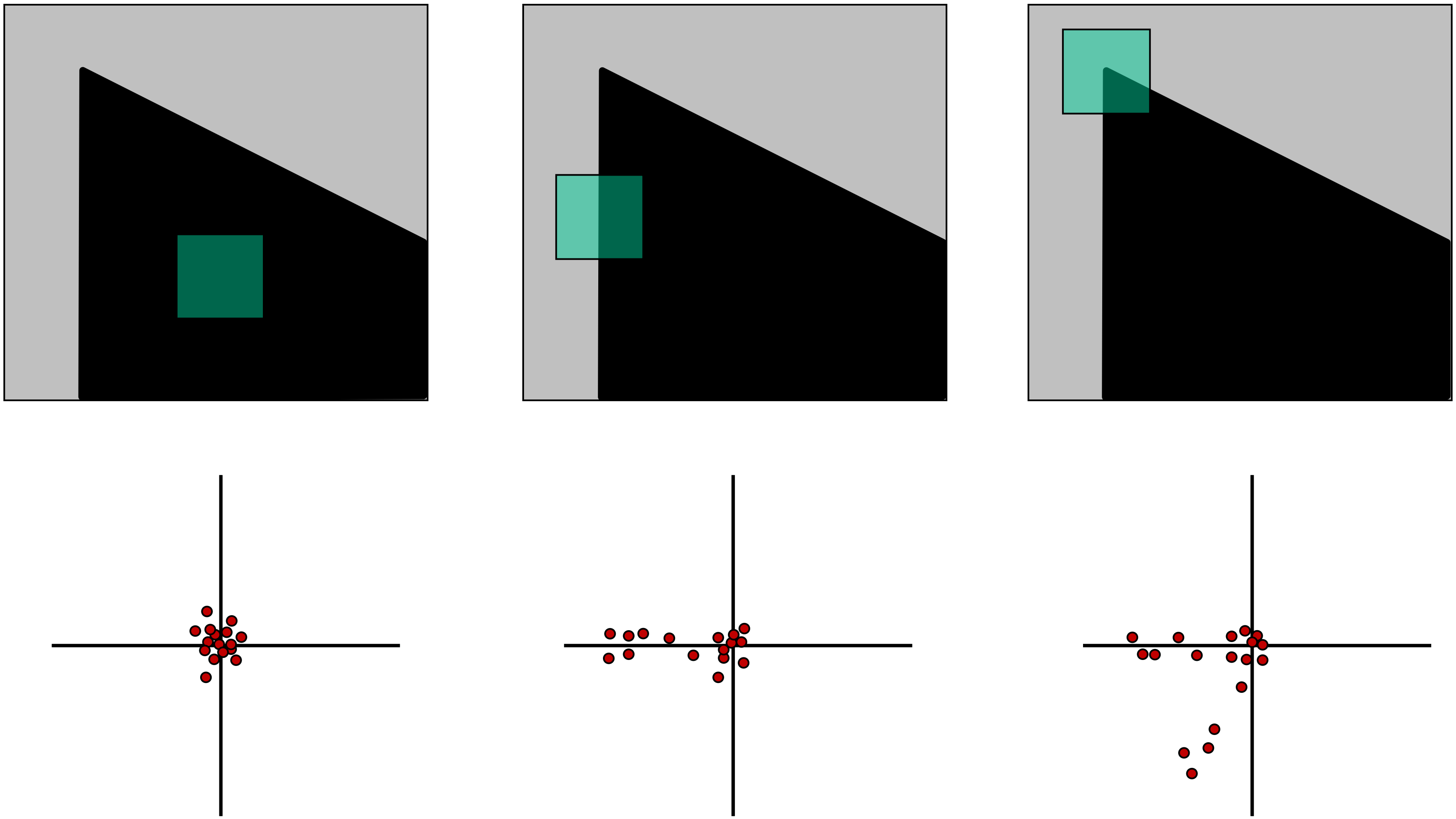
"flat" region: no change in all directions

"edge": no change along the edge direction

"corner": significant change in all directions

Source: A. Efros

Let's look at the gradient distributions



Principle Component Analysis

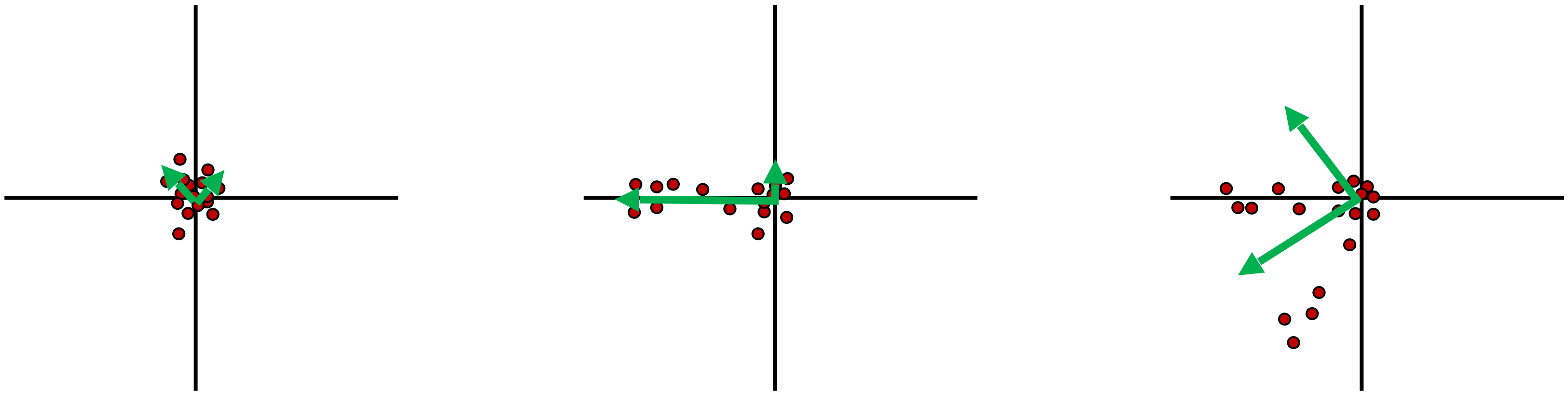
Principal component is the direction of highest variance.

Next, highest component is the direction with highest variance *orthogonal* to the previous components.

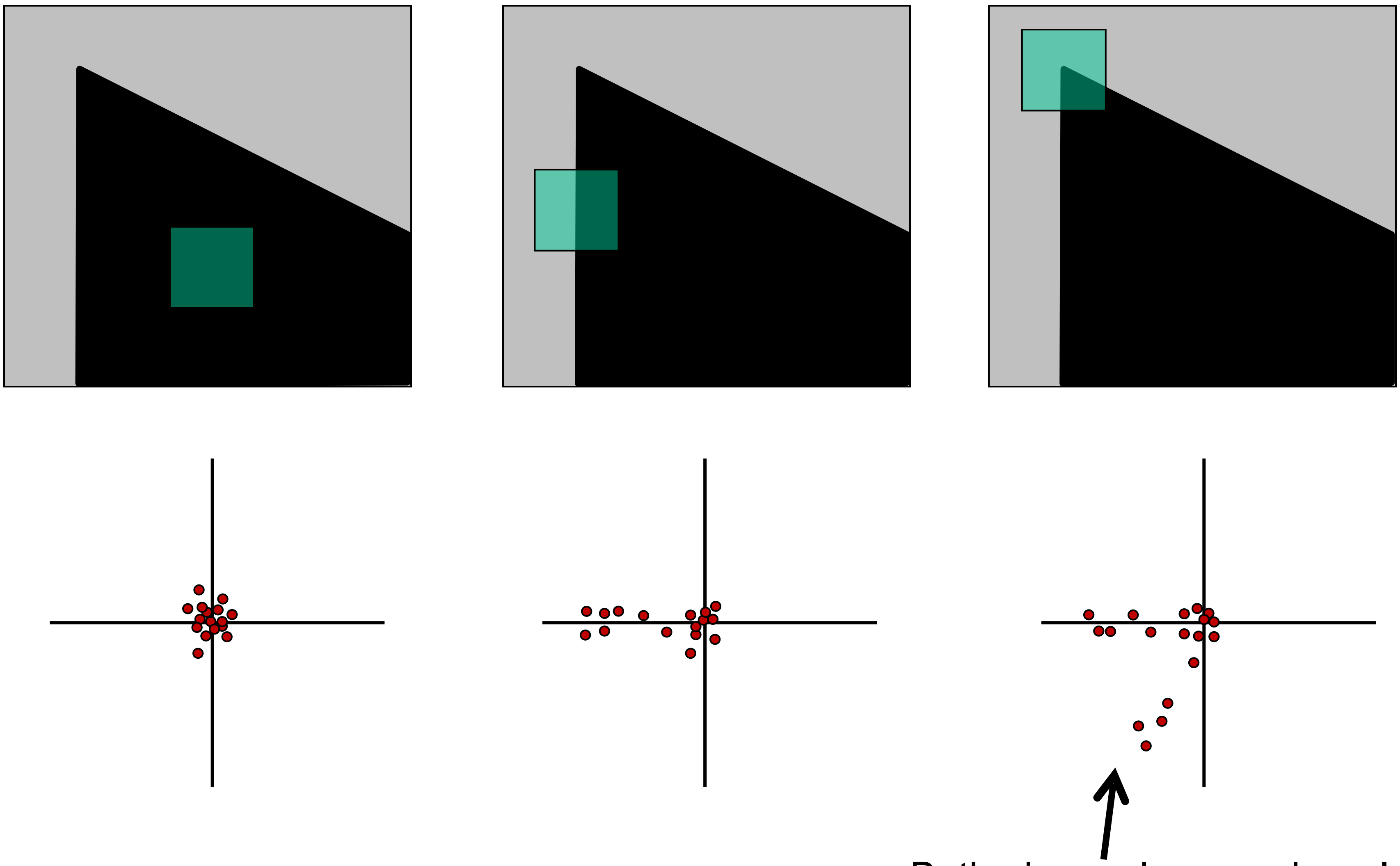
How to compute PCA components:

1. Subtract off the mean for each data point.
2. Compute the covariance matrix.
3. Compute eigenvectors and eigenvalues.
4. The components are the eigenvectors ranked by the eigenvalues.

$$Hx = \lambda x$$



Corners have …

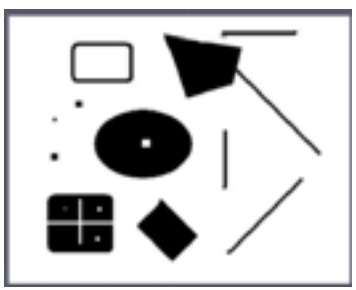


Both eigenvalues are large!

Second Moment Matrix

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

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




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

The math

To compute the eigenvalues:

1. Compute the covariance matrix.

$$H = \sum_{(u,v)} w(u,v) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \qquad I_x = \frac{\partial f}{\partial x}, I_y = \frac{\partial f}{\partial y}$$

Typically Gaussian weights

2. Compute eigenvalues.

$$H = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \quad \lambda_{\pm} = \frac{1}{2}\left((a+d) \pm \sqrt{4bc + (a-d)^2}\right)$$

Corner Response Function

- Computing eigenvalues are expensive
- Harris corner detector uses the following alternative

$$R = det(M) - \alpha \cdot trace(M)^2$$

Reminder:

$$det\left(\begin{bmatrix} a & b \\ c & d \end{bmatrix}\right) = ad - bc \qquad trace\left(\begin{bmatrix} a & b \\ c & d \end{bmatrix}\right) = a + d$$

Harris detector: Steps

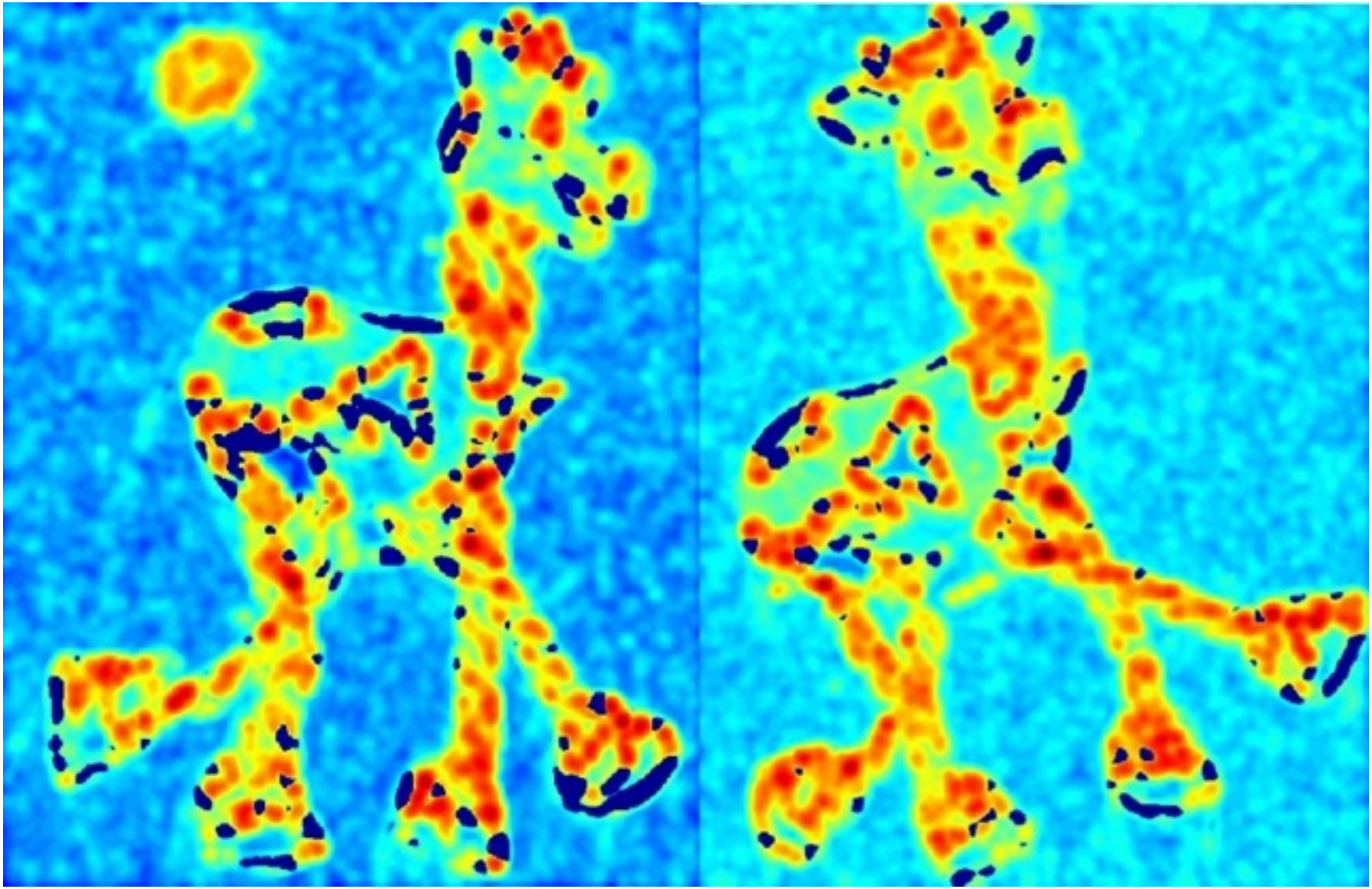
1. Compute Gaussian derivatives at each pixel
2. Compute second moment matrix *M* in a Gaussian window around each pixel
3. Compute corner response function *R*
4. Threshold *R*
5. Find local maxima of response function (nonmaximum suppression)

C.Harris and M.Stephens. "A Combined Corner and Edge Detector." *Proceedings of the 4th Alvey Vision Conference*: pages 147—151, 1988.

Harris Detector: Steps

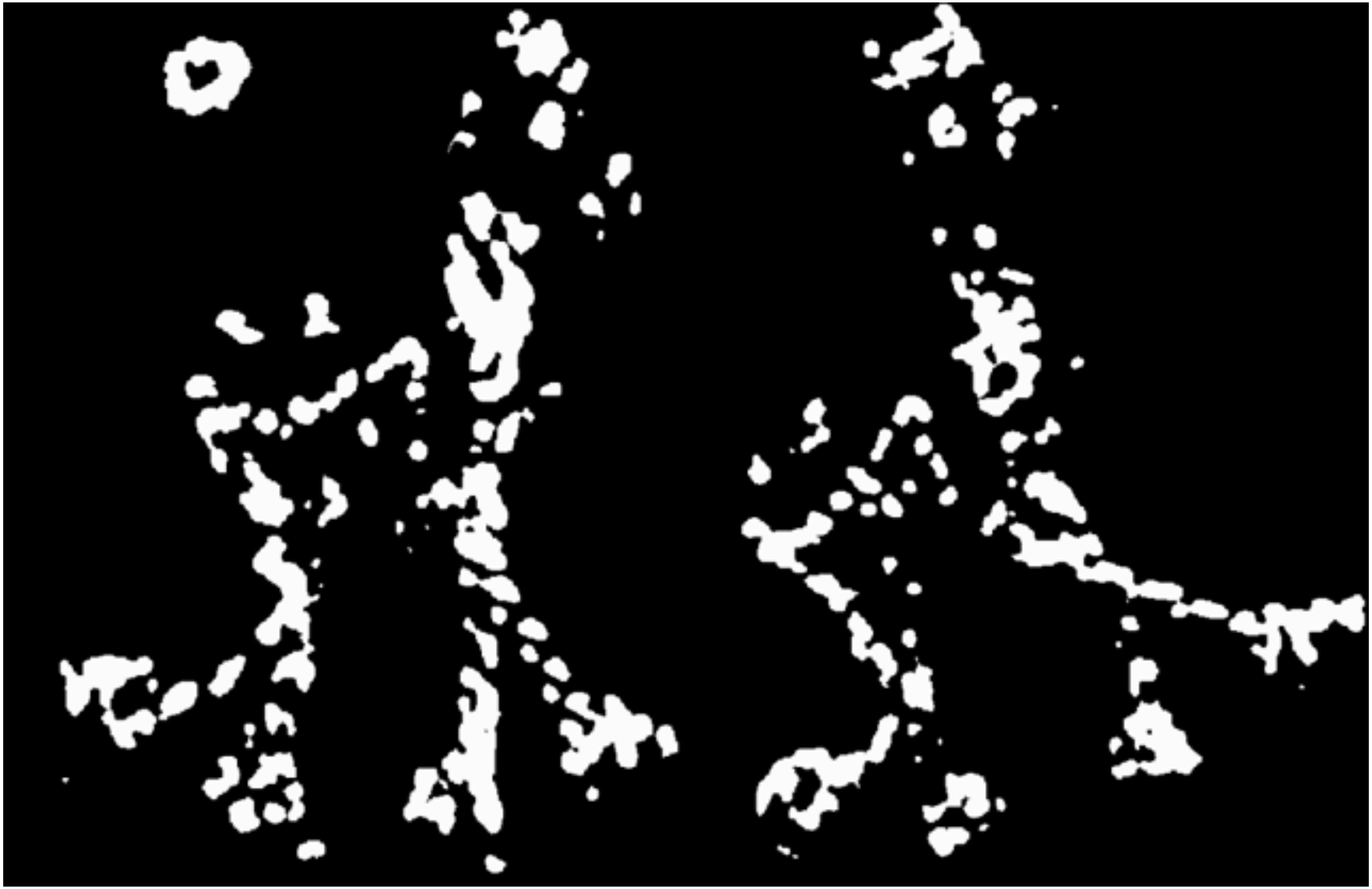
Harris Detector: Steps

Compute corner response R



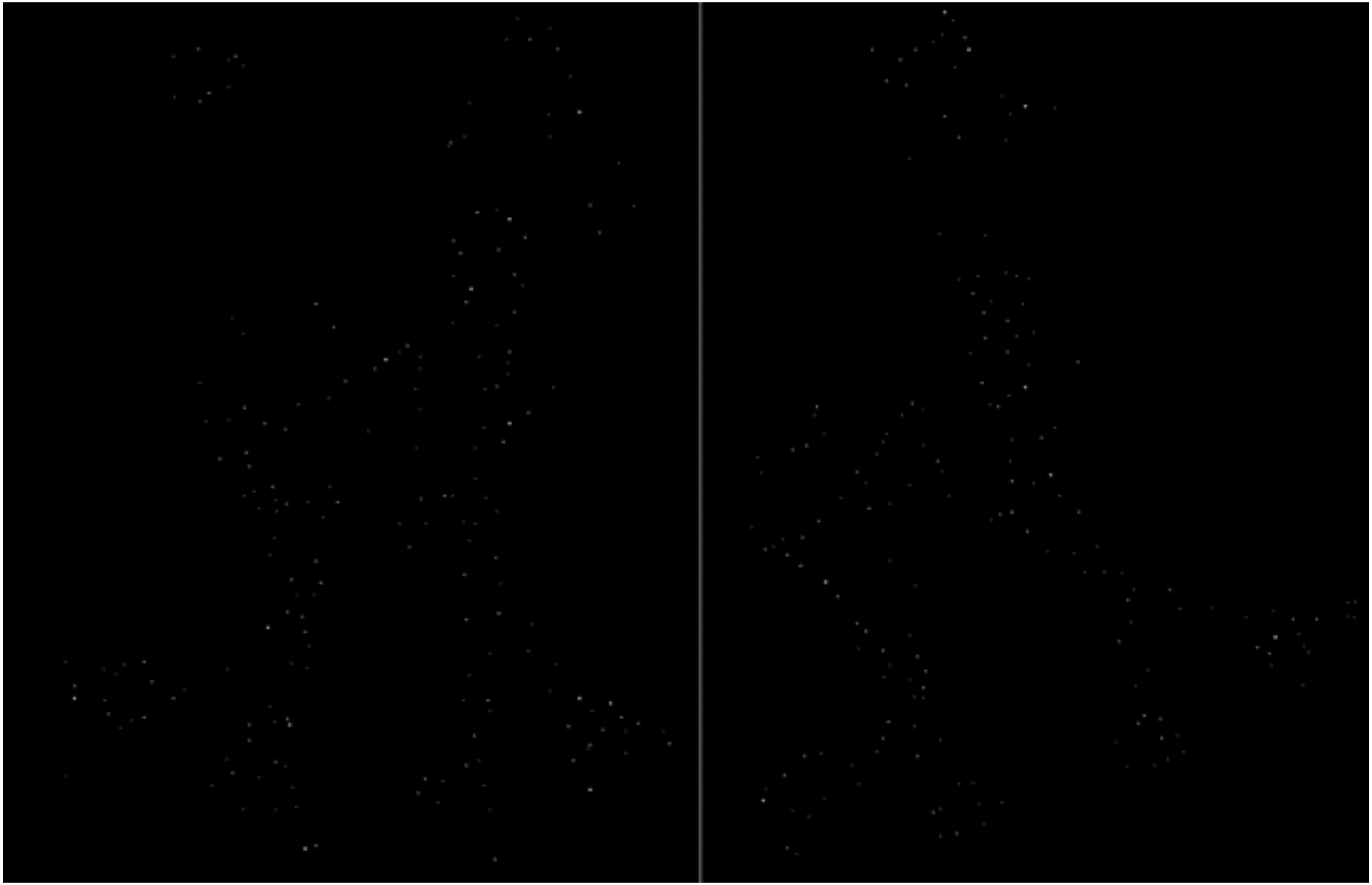
Harris Detector: Steps

Find points with large corner response: R>threshold



Harris Detector: Steps

Take only the points of local maxima of R



Harris Detector: Steps

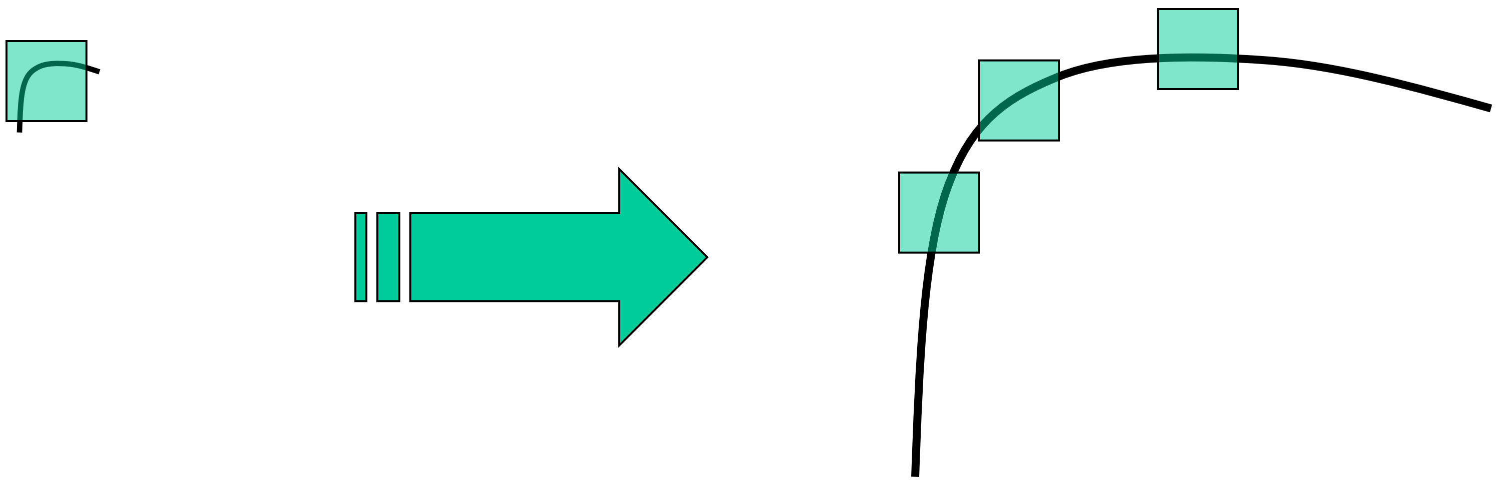
Simpler Response Function

$$R = det(M) - \alpha \cdot trace(M)^2$$

$$f = \frac{1}{\frac{1}{\lambda_1} + \frac{1}{\lambda_2}} = \frac{Det(H)}{Tr(H)}$$

Properties of the Harris corner detector

- Translation invariant? Yes
- Rotation invariant? Yes
- Scale invariant? No

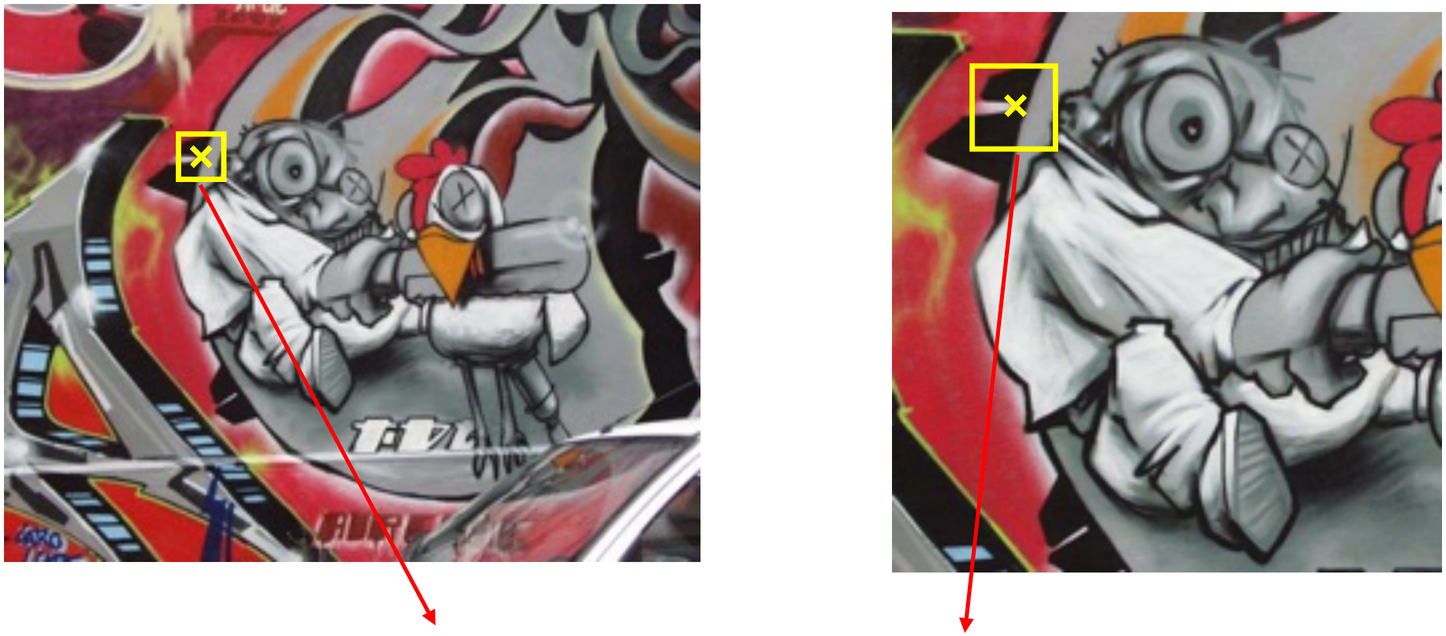


Scale

Let's look at scale first:

What is the "best" scale?

Scale Invariance

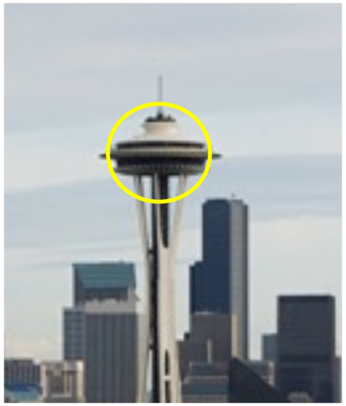


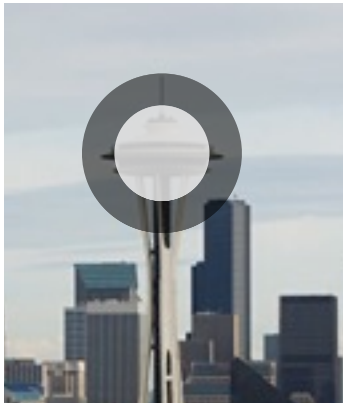
$$f(I_{i_1 \ldots i_m}(x,\sigma)) = f(I_{i_1 \ldots i_m}(x',\sigma'))$$

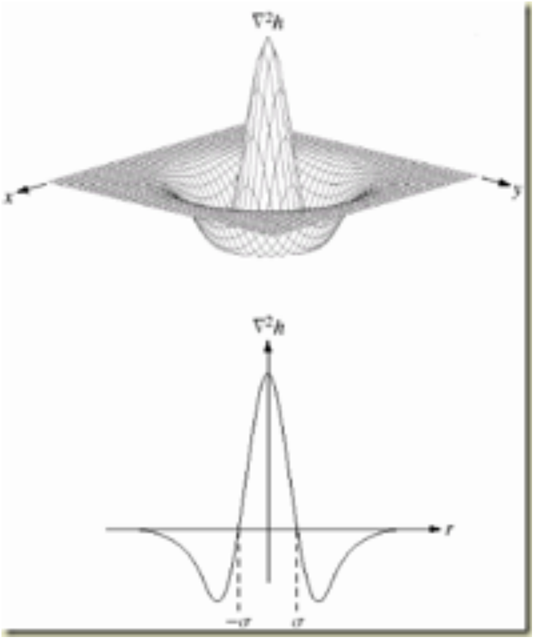
How can we independently select interest points in each image, such that the detections are repeatable across different scales?

K. Grauman, B. Leibe

Differences between Inside and Outside





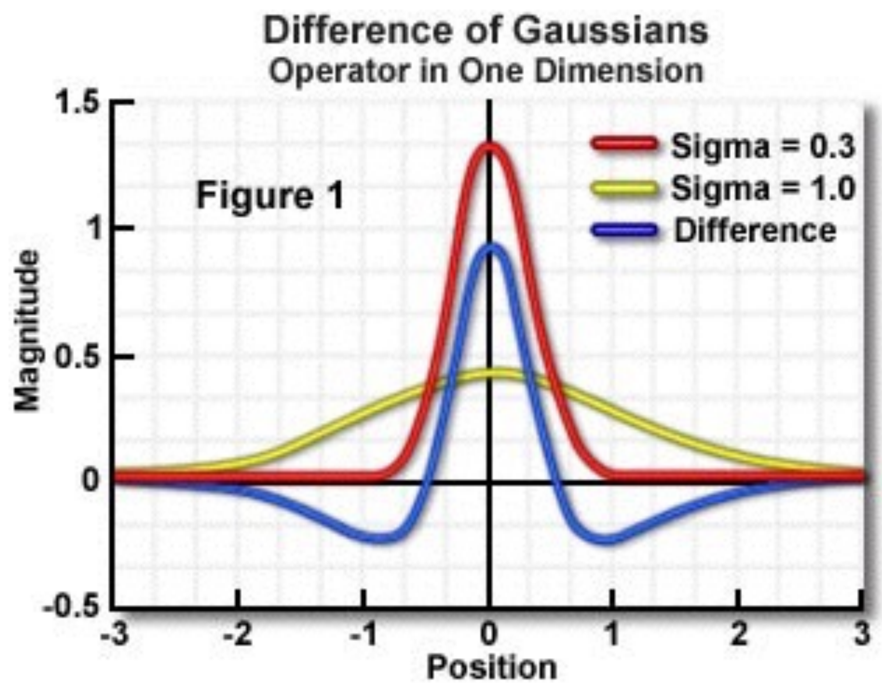


Scale

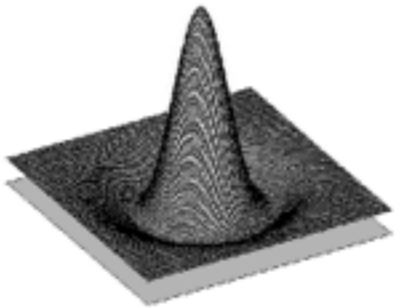
Why Gaussian?

It is invariant to scale change, i.e., $f * \mathcal{G}_\sigma * \mathcal{G}_{\sigma'} = f * \mathcal{G}_{\sigma''}$ and has several other nice properties. Lindeberg, 1994

In practice, the Laplacian is approximated using a Difference of Gaussian (DoG).

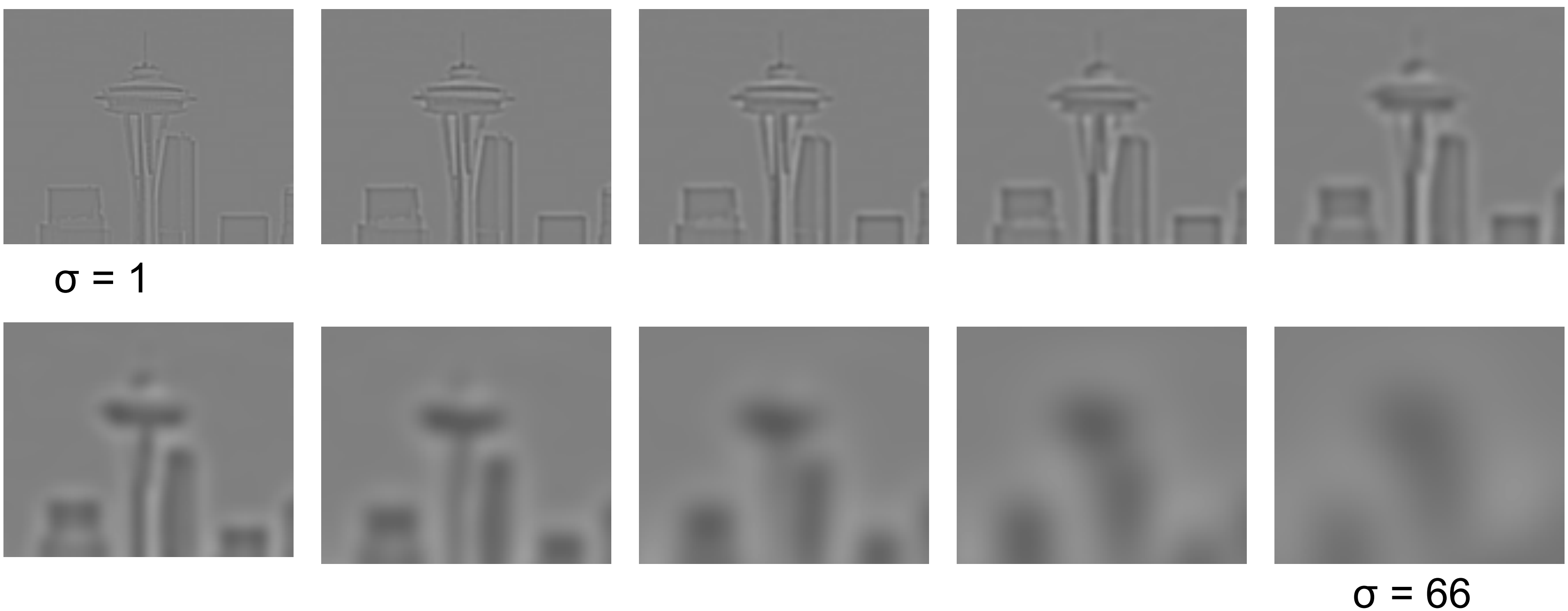


Difference-of-Gaussian (DoG)



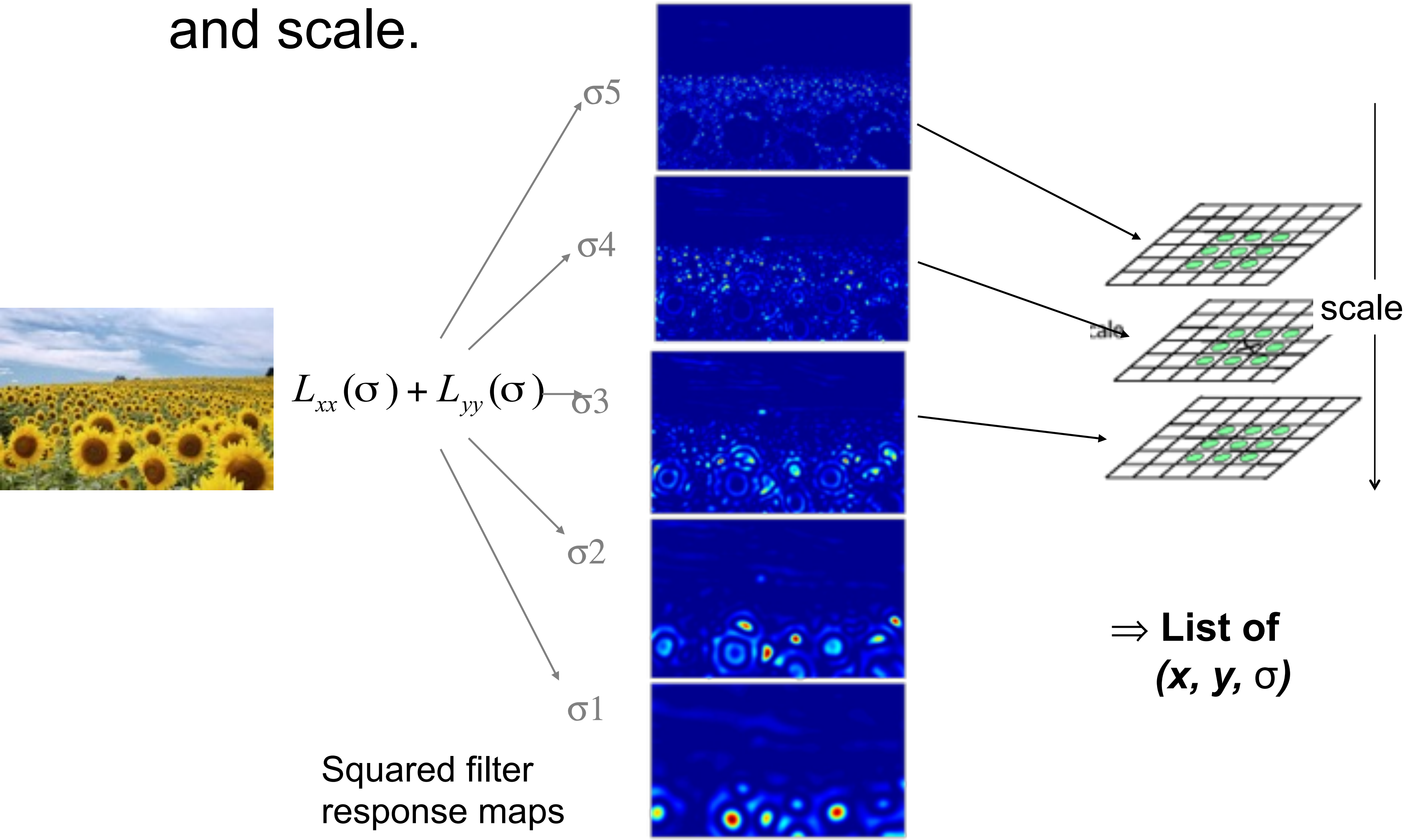
K. Grauman, B. Leibe

DoG example



Scale invariant interest points

Interest points are local maxima in both position and scale.

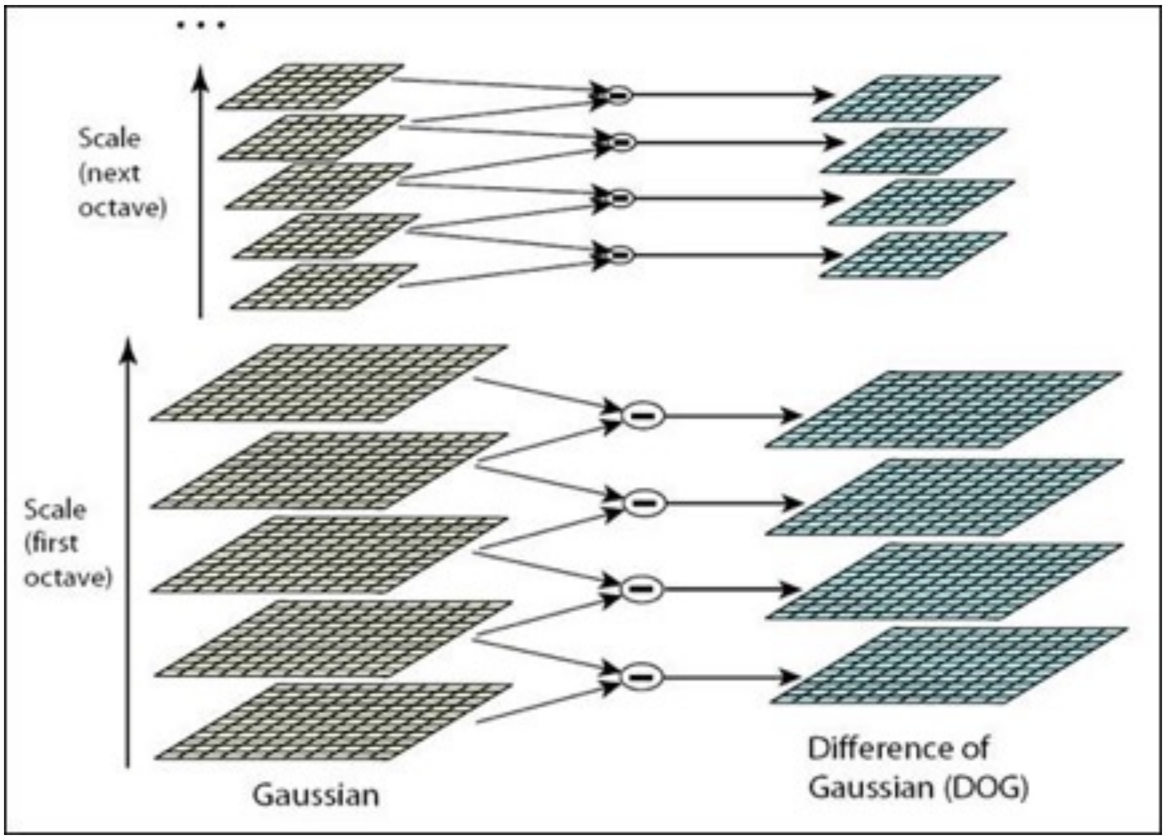


Squared filter response maps

⇒ **List of *(x, y,* σ*)***

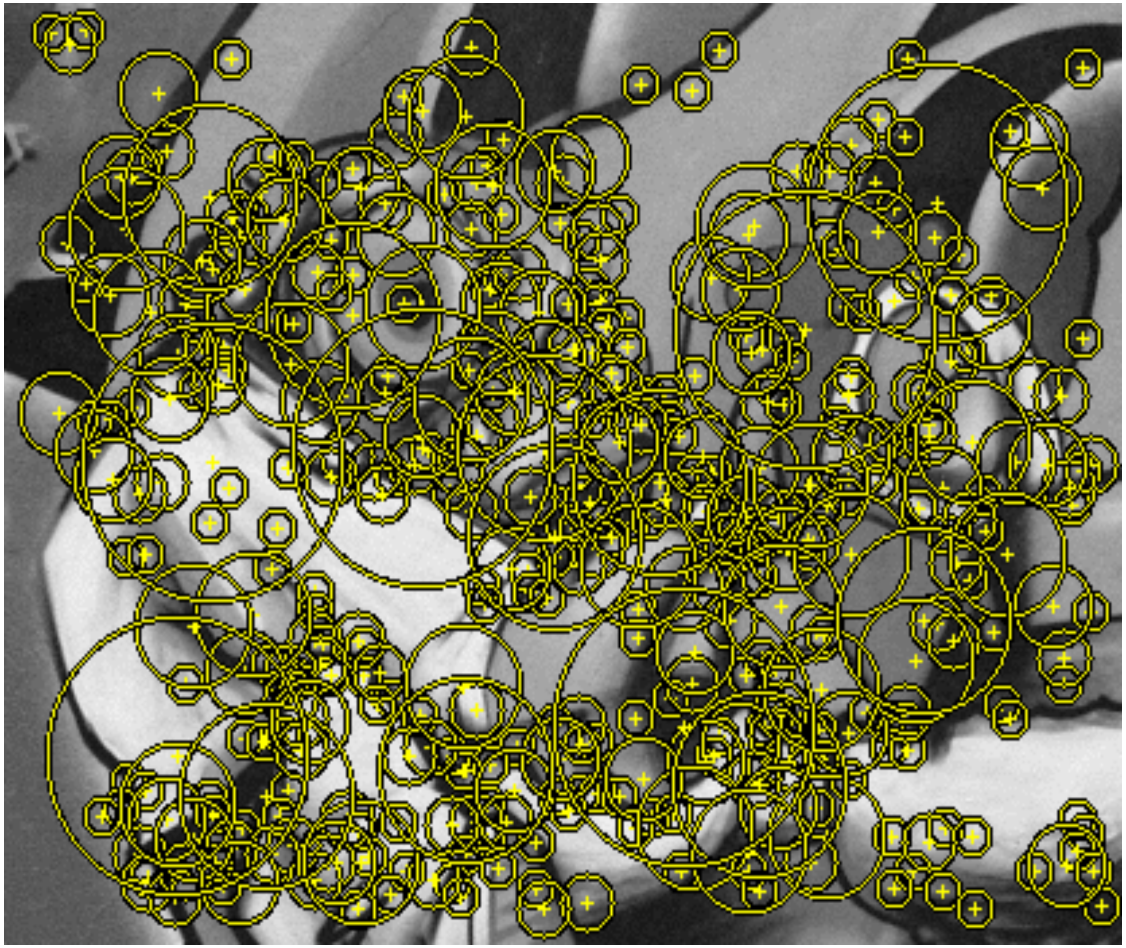
Scale

In practice the image is downsampled for larger sigmas.



Lowe, 2004.

Results: Difference-of-Gaussian



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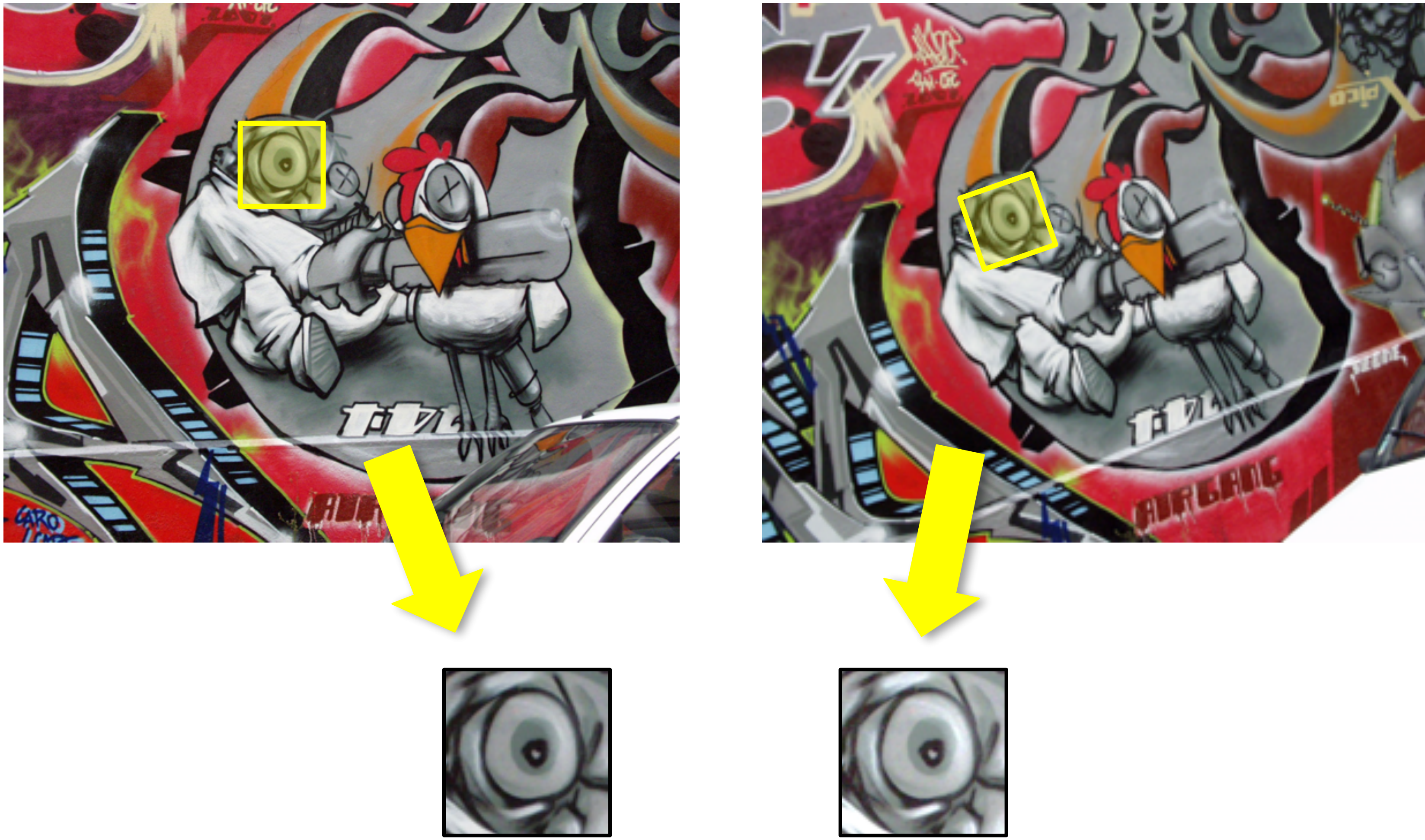
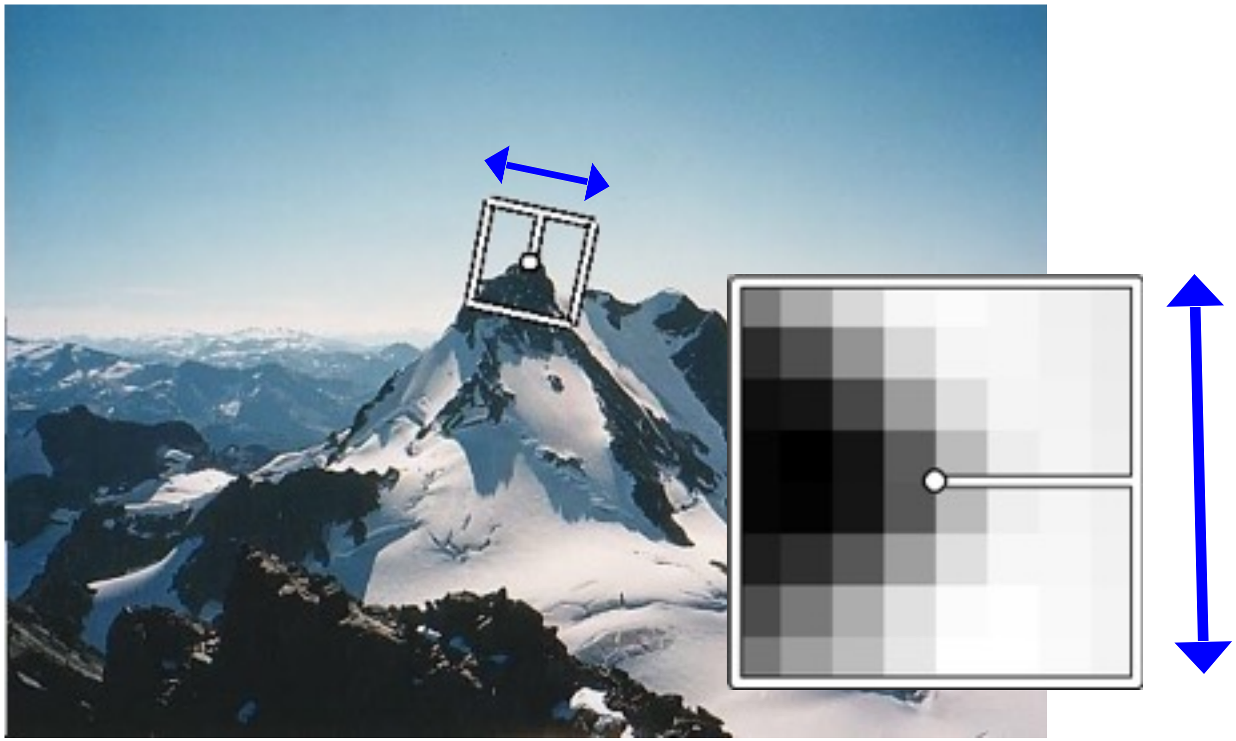
How can we find correspondences?



Similarity transform

Rotation invariance



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

Image from Matthew Brown

Orientation Normalization

- Compute orientation histogram
- Select dominant orientation
- Normalize: rotate to fixed orientation

[Lowe, SIFT, 1999]