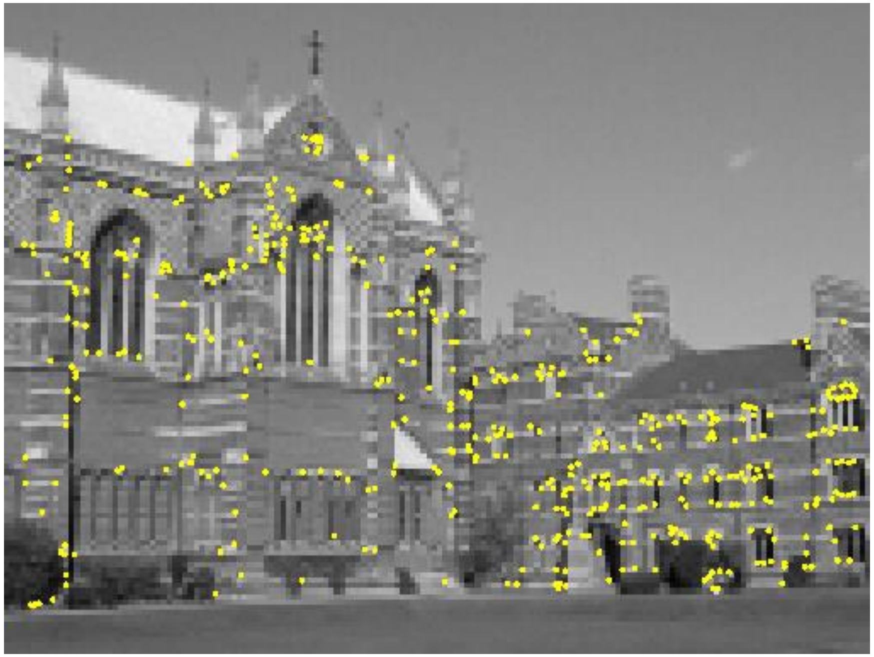
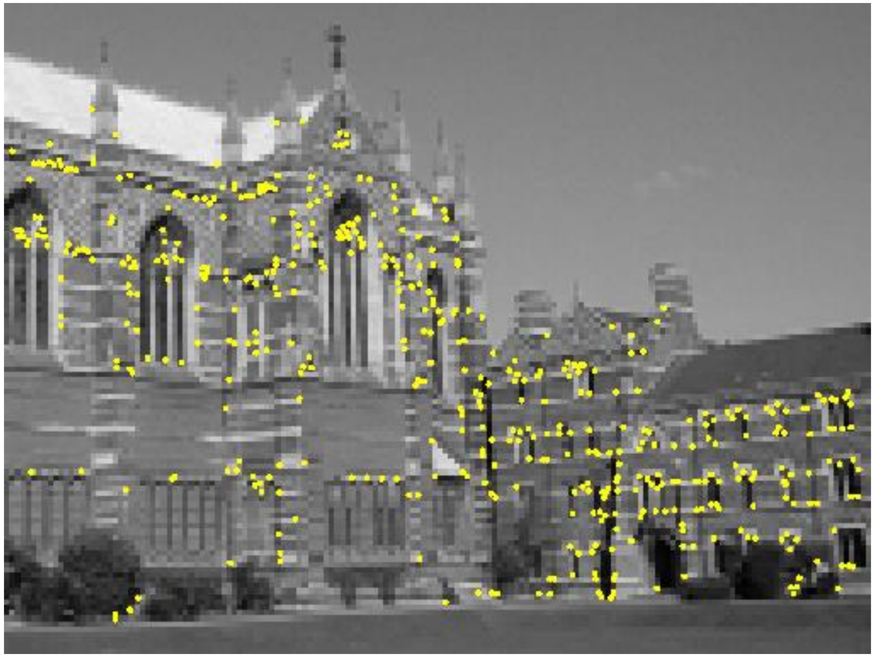
Interest Points

ECE/CSE 576
Linda Shapiro

Preview: Harris detector

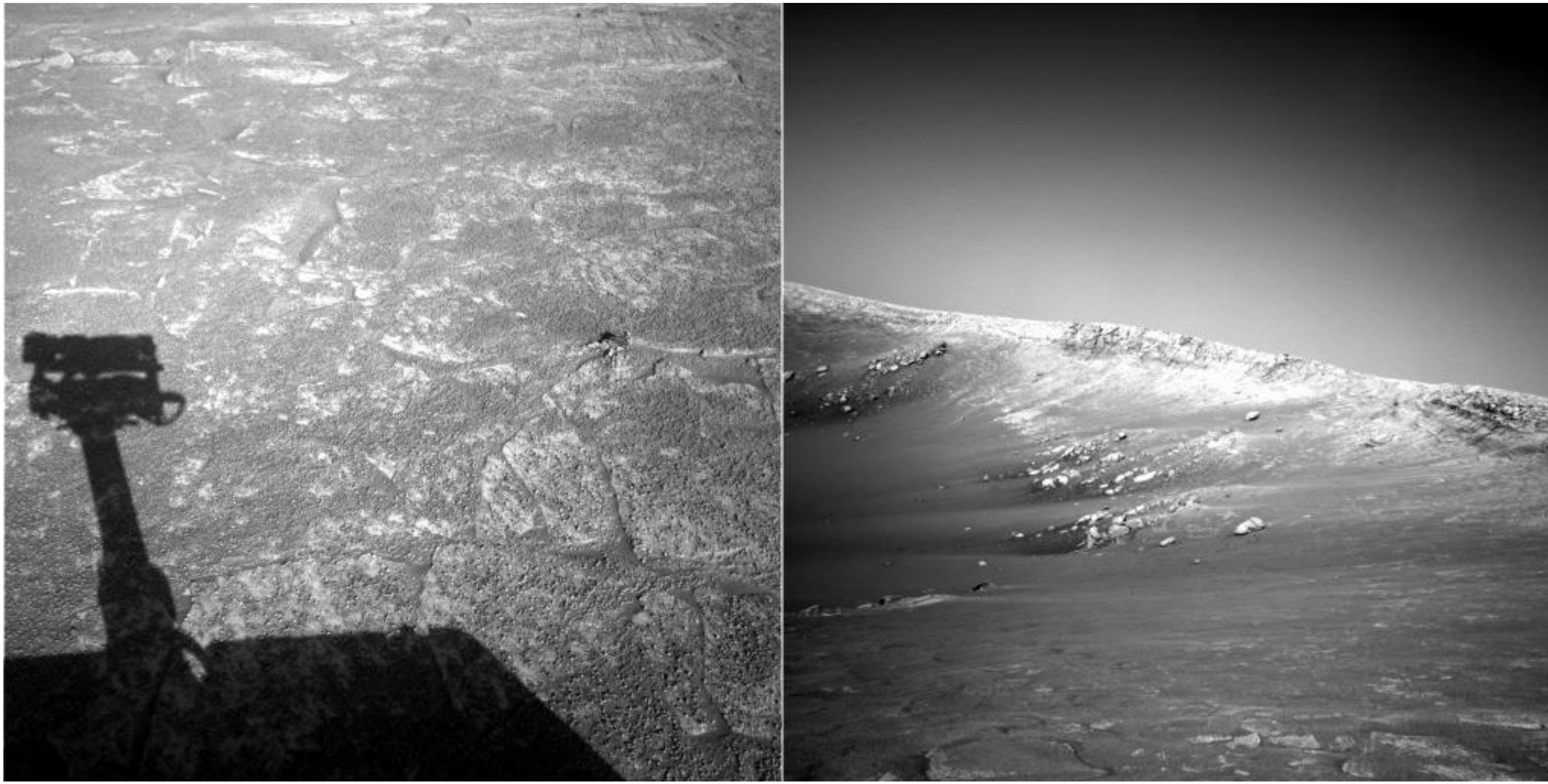




Interest points extracted with Harris (~ 500 points)

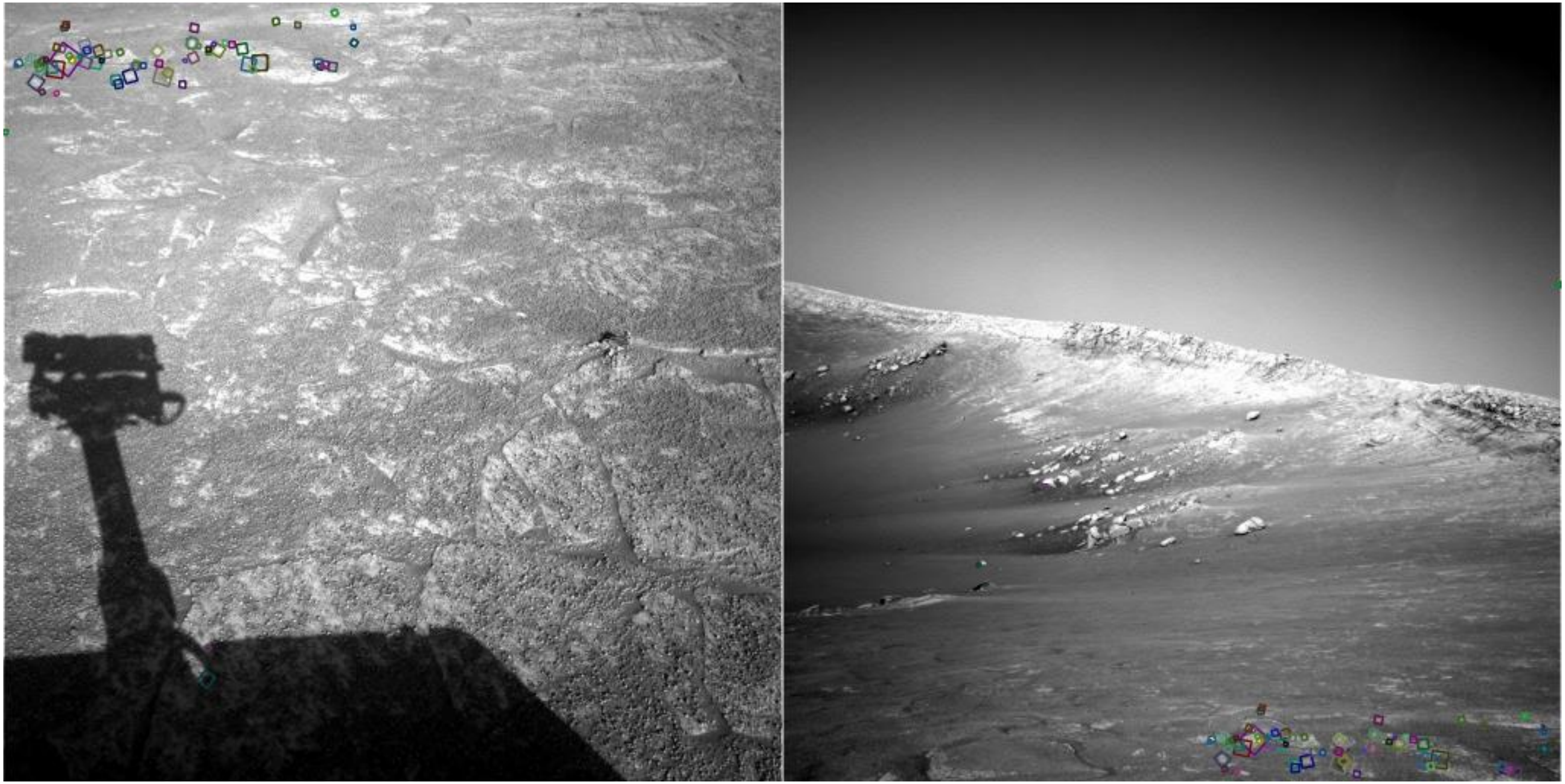
How can we find corresponding points?

Not always easy



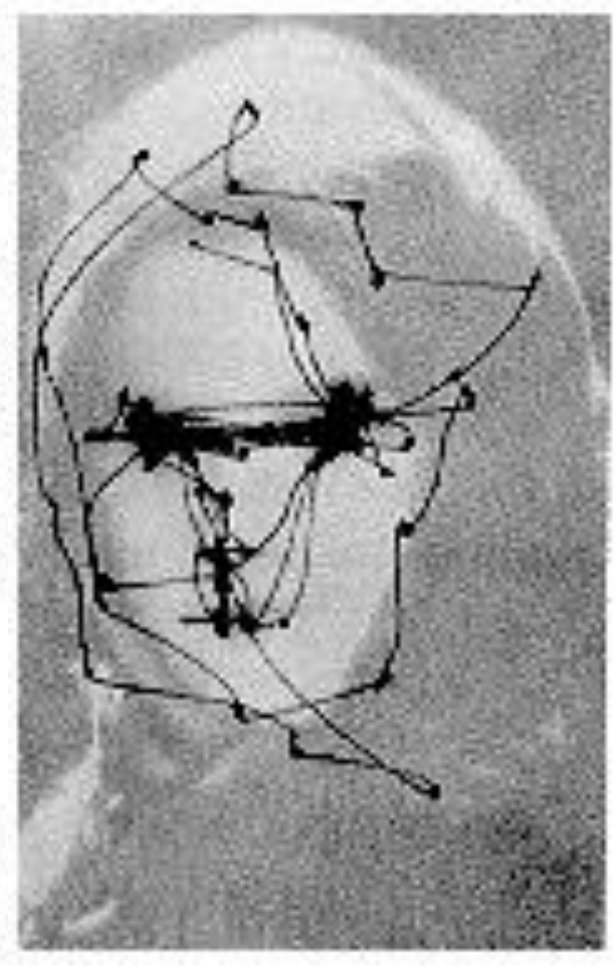
NASA Mars Rover images

Answer below (look for tiny colored squares…)



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

Human eye movements

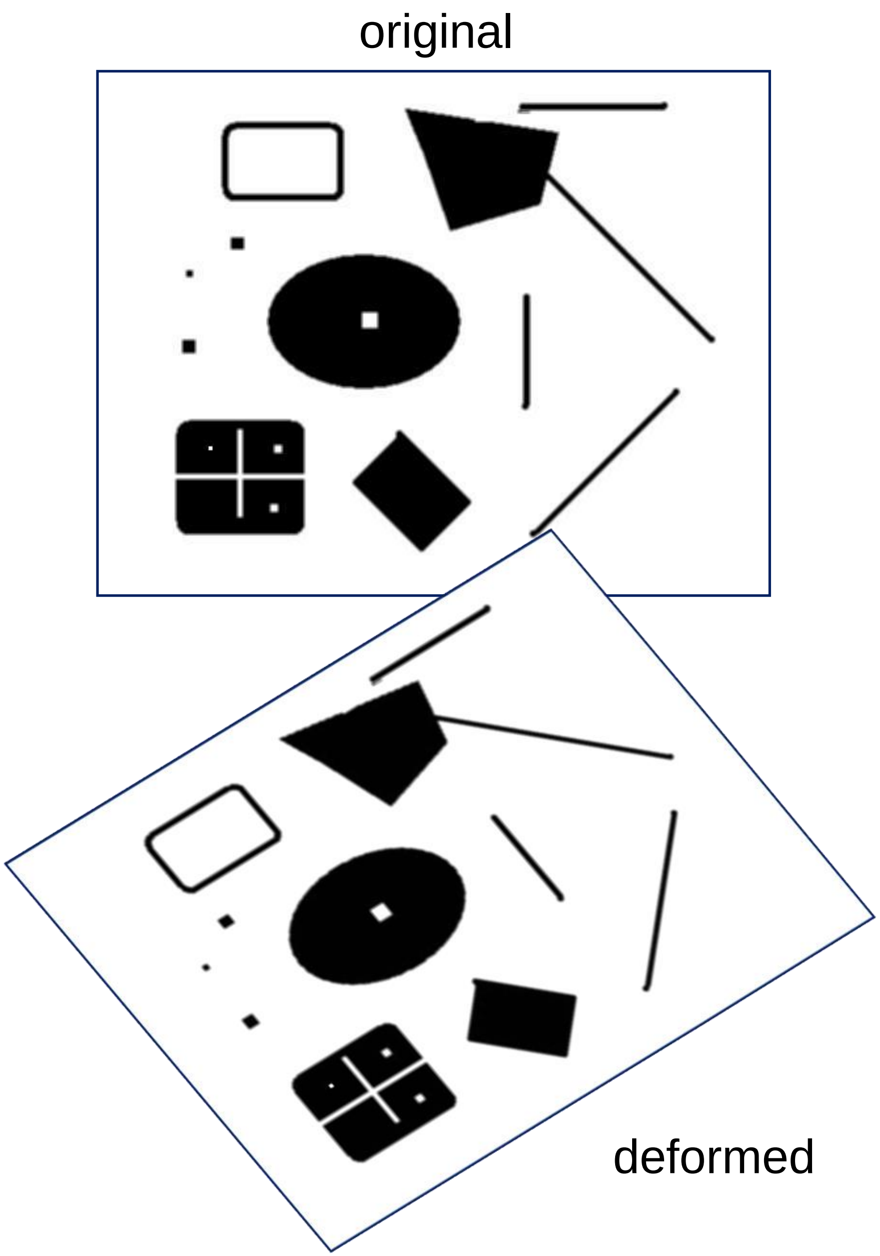


Yarbus eye tracking

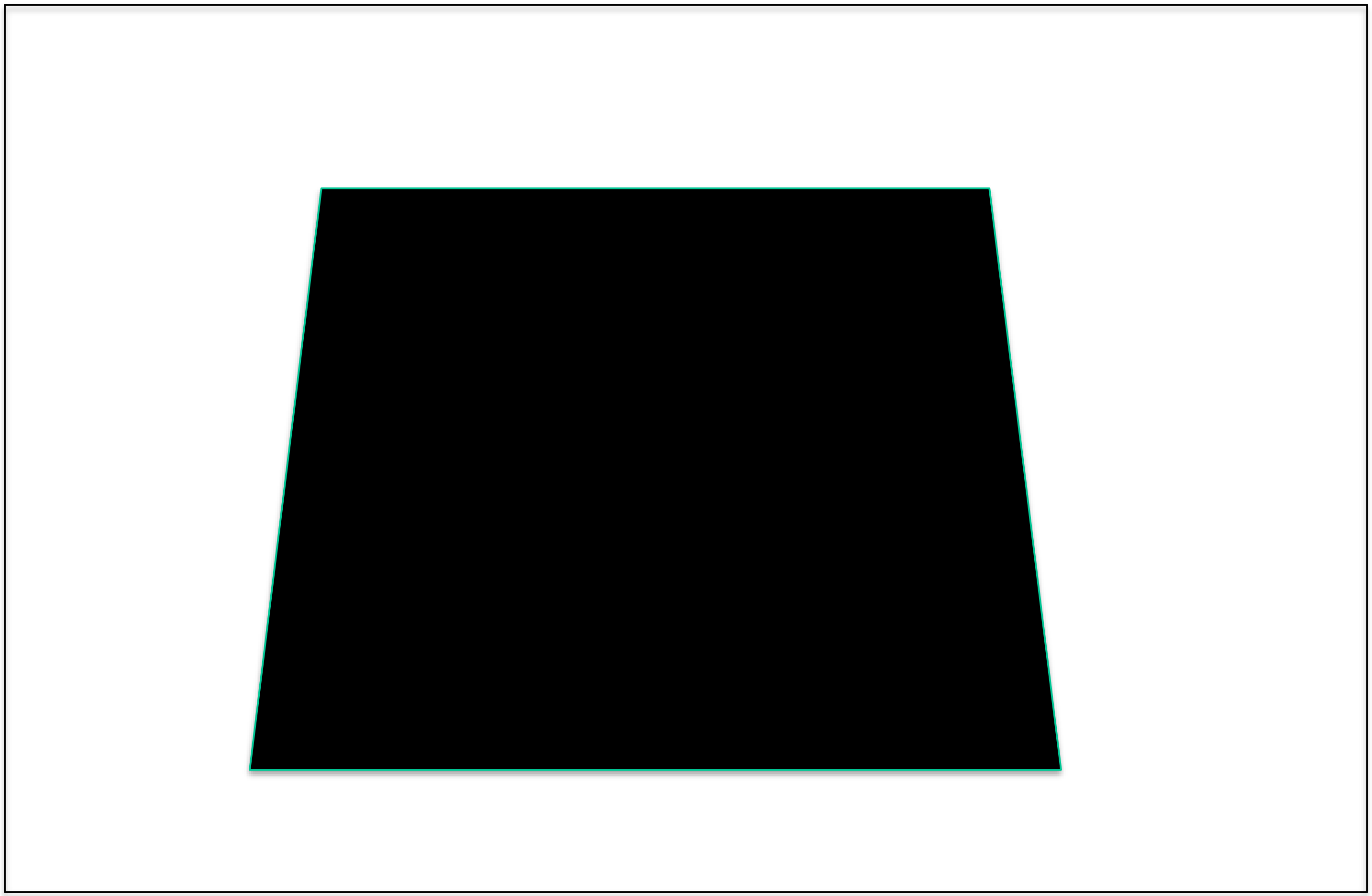
What catches your interest?

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?

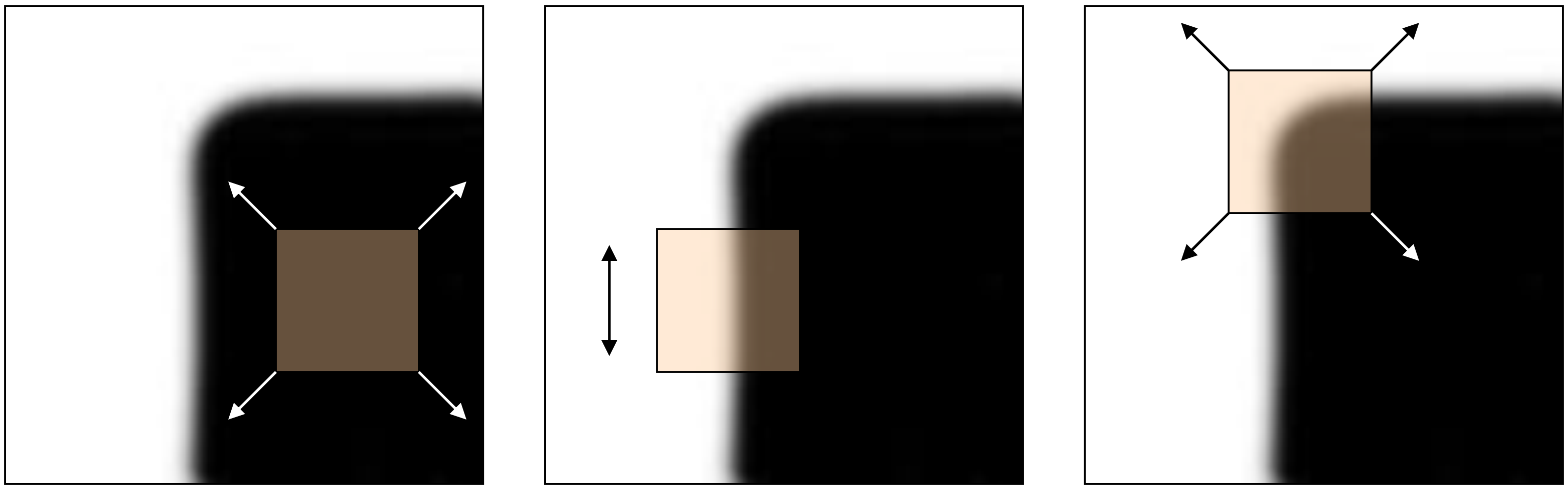


Intuition



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



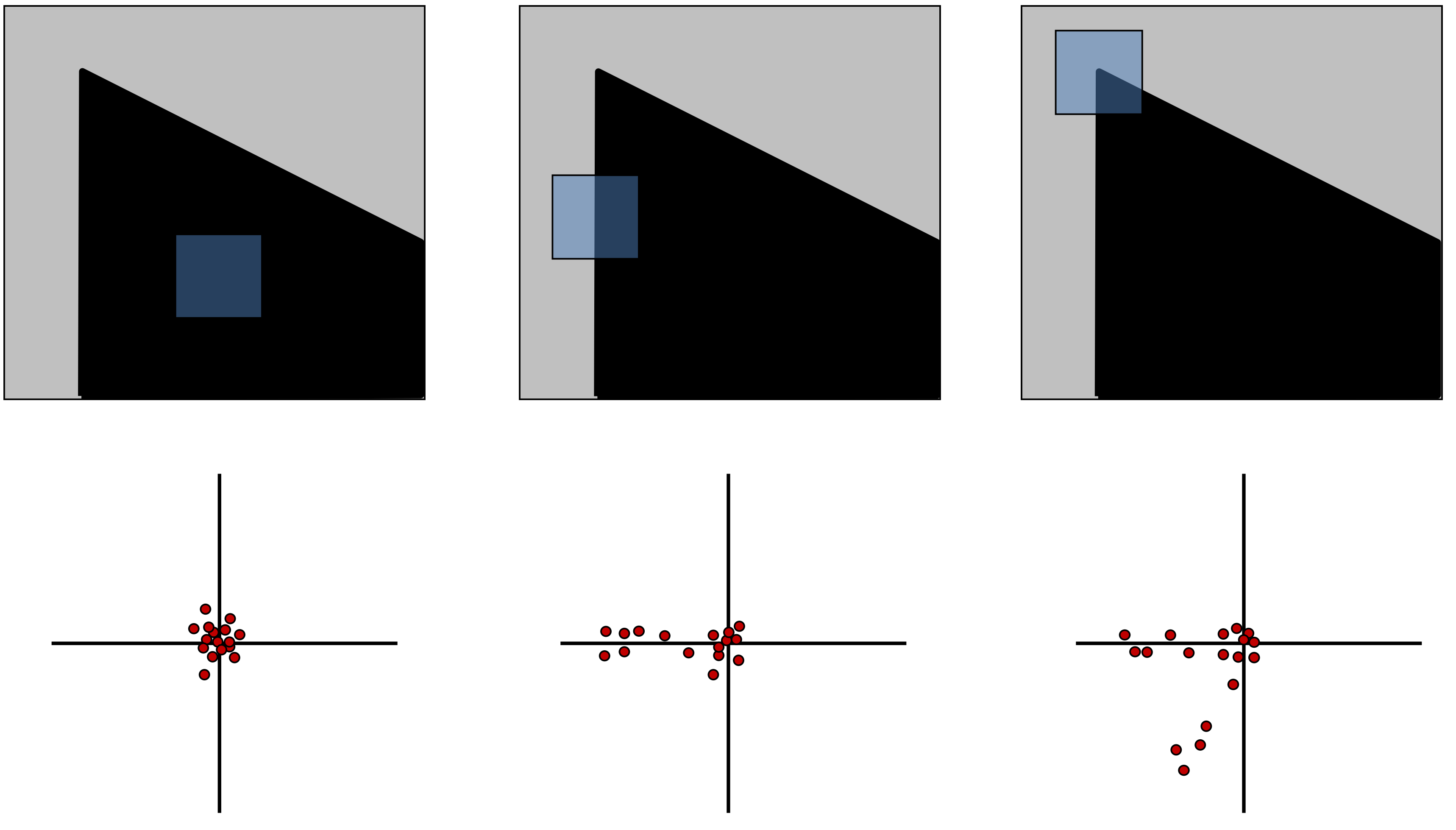
"flat" region: no change in all directions

"edge": no change along the edge direction

"corner": significant change in all directions

Source: A. Efros

Let's look at the gradient distributions



Principal Component Analysis

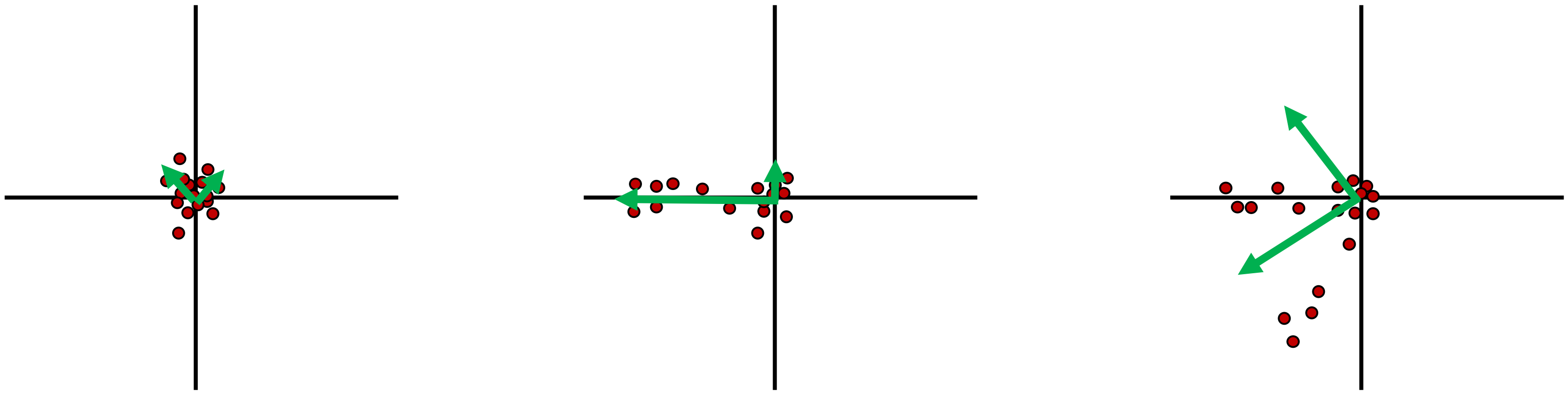
Principal component is the direction of highest variance.

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

How to compute PCA components:

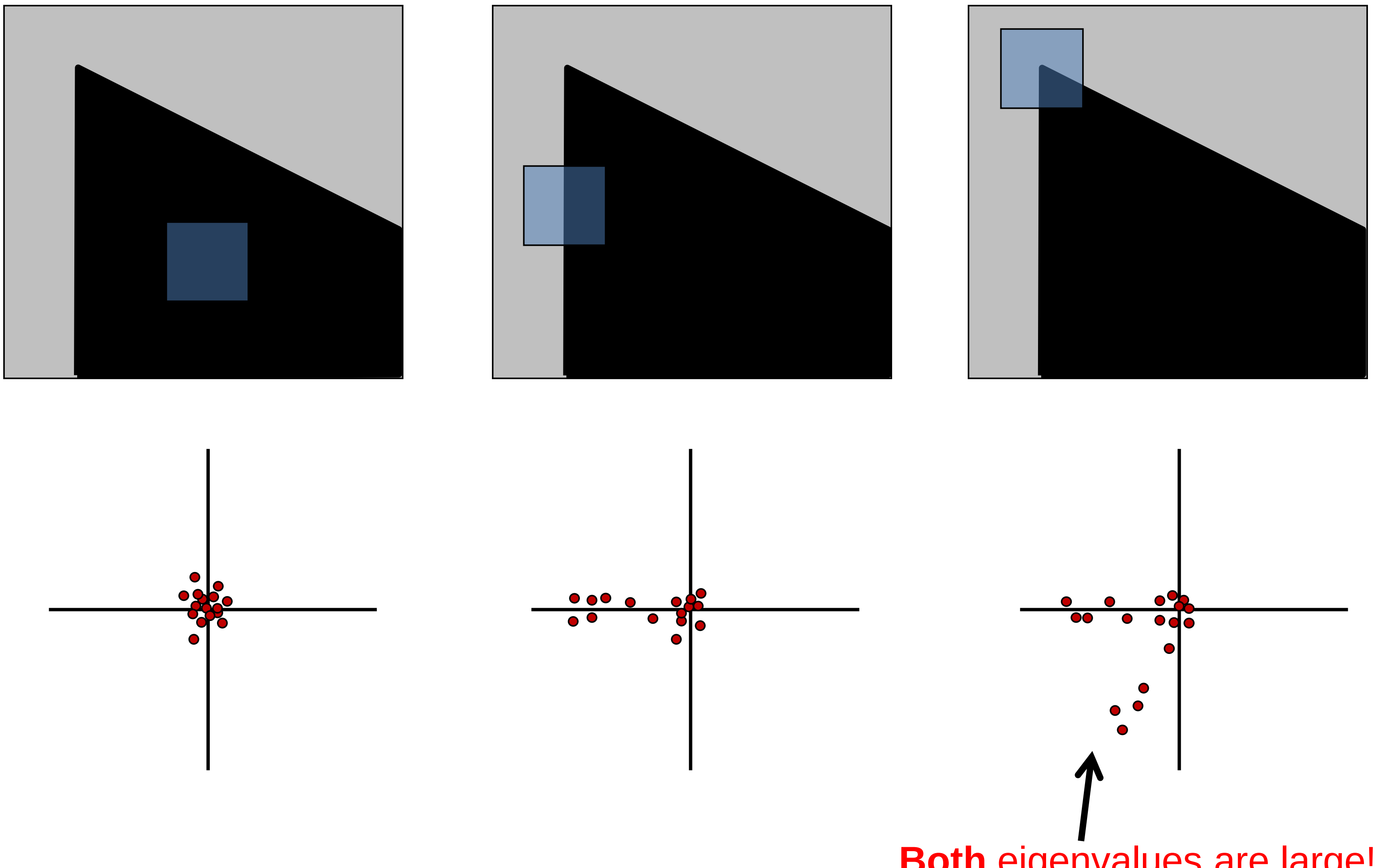
1. Subtract off the mean for each data point.
2. Compute the covariance matrix.
3. Compute eigenvectors and eigenvalues.
4. The components are the eigenvectors ranked by the eigenvalues.

$$Hx = \lambda x$$



Definition: A scalar λ is called an eigenvalue of the n×n matrix A if there is a nontrivial solution x of Ax=λx. Such x is called an eigenvector corresponding to the eigenvalue λ.

Corners have …

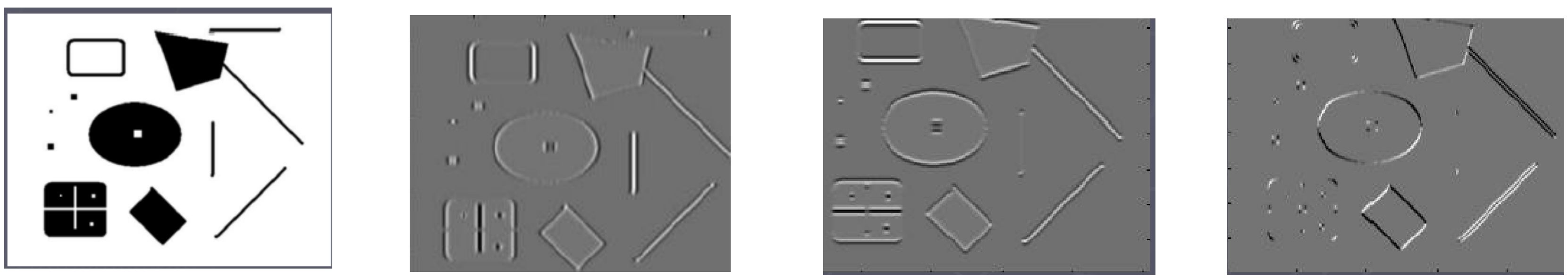


Both eigenvalues are large!

Second Moment Matrix or Harris Matrix

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

2 x 2 matrix of image derivatives smoothed by Gaussian weights.



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

- First compute I_x, I_y, and $I_x I_y$ as 3 images; then apply Gaussian to each.
- OR, first apply the Gaussian and then compute the derivatives.

The math

To compute the eigenvalues:

1. Compute the Harris matrix over a window.

$$H = \sum_{(u,v)} w(u,v) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

$$I_x = \frac{\partial f}{\partial x}, I_y = \frac{\partial f}{\partial y}$$

Typically Gaussian weights

What does this equation mean in practice?

$$\begin{bmatrix} \Sigma\text{smoothed } I_x^2 & \Sigma\text{smoothed } I_x I_y \\ \Sigma\text{smoothed } I_x I_y & \Sigma\text{smoothed } I_y^2 \end{bmatrix}$$

2. Compute eigenvalues from that.

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

Corner Response Function

- Computing eigenvalues are expensive
- Harris corner detector used 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 derivatives I_x, I_y and I_xI_y at each pixel and smooth them with a Gaussian. (Or smooth first and then derivatives.)

2. Compute the Harris matrix H in a window around each pixel

3. Compute corner response function *R*

4.Threshold *R*

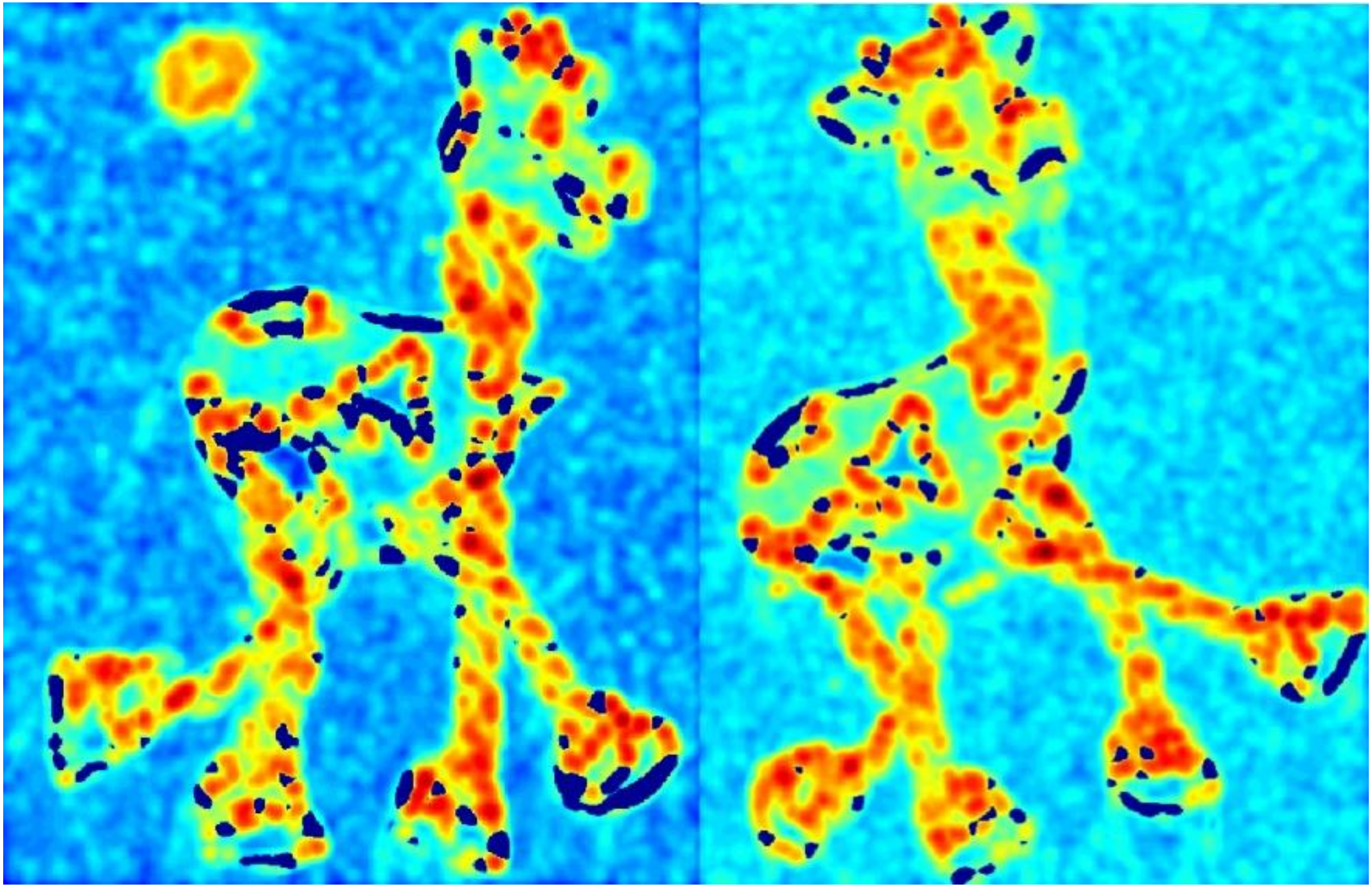
5.Find local maxima of response function (nonmaximum suppression)

C.Harris and M.Stephens. *Proceedings of the 4th Alvey Vision Conference*: pages 147—151, 1988.

Harris Detector: Steps

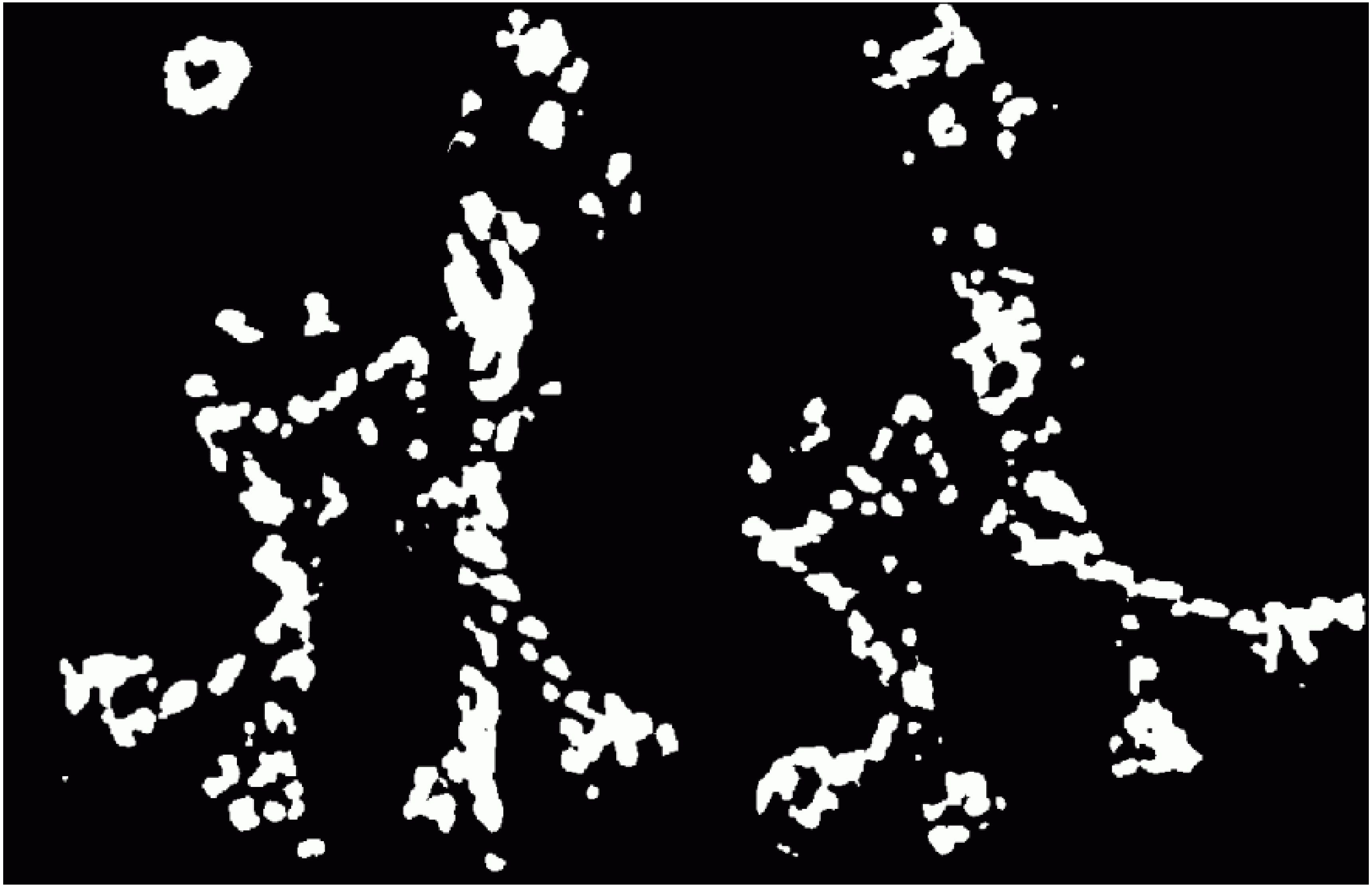
Harris Detector: Steps

Compute corner response R



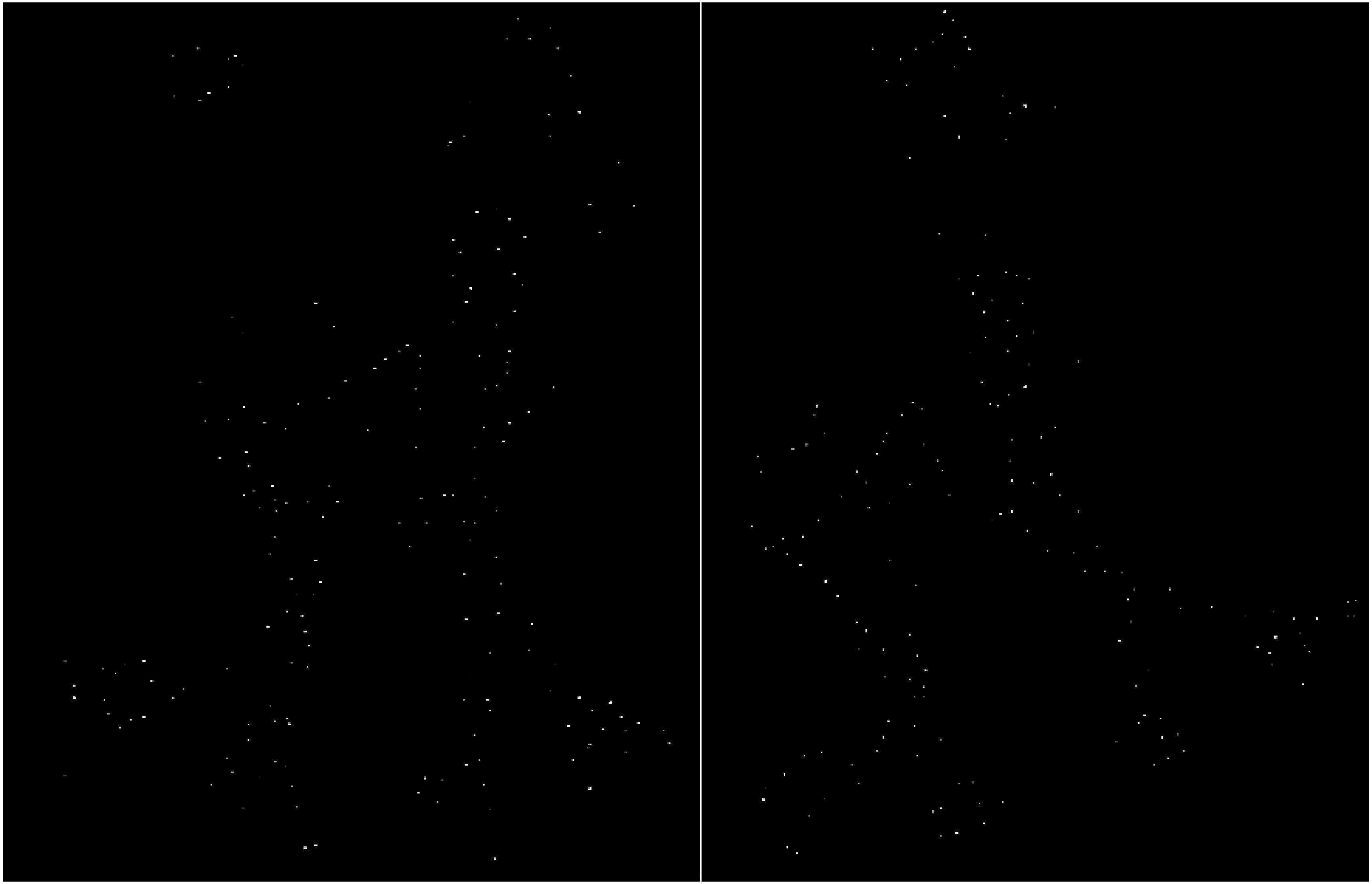
Harris Detector: Steps

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



Harris Detector: Steps

Take only the points of local maxima of R



Harris Detector: Results

Simpler Response Function

Instead of

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

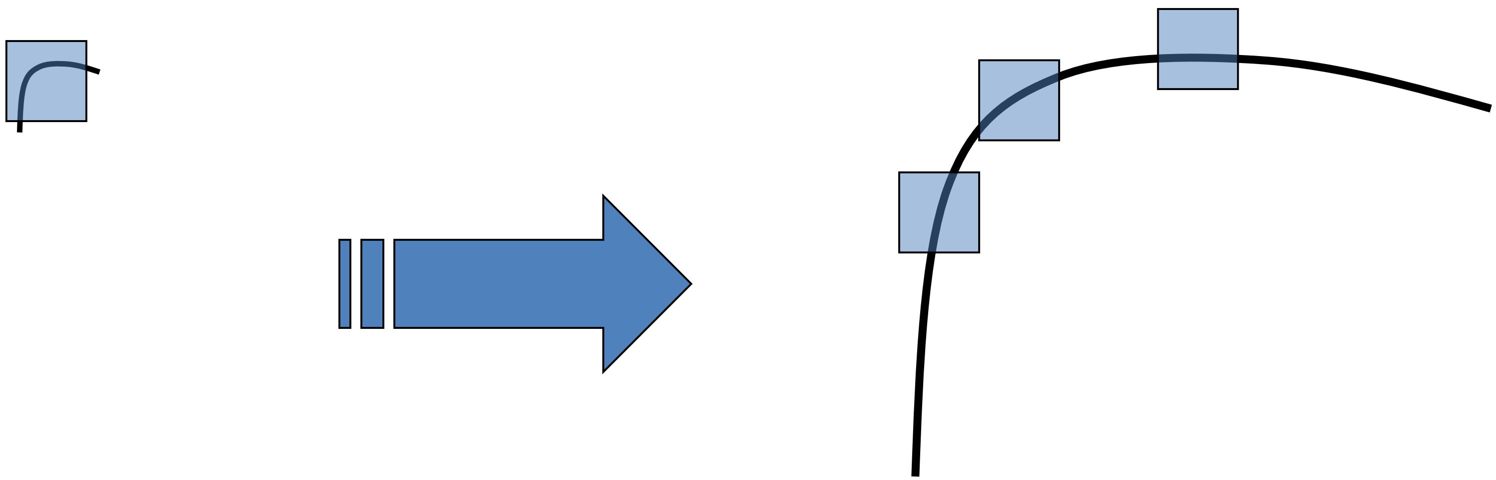
We can use

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

Properties of the Harris corner detector

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

What's the problem?



Corner !

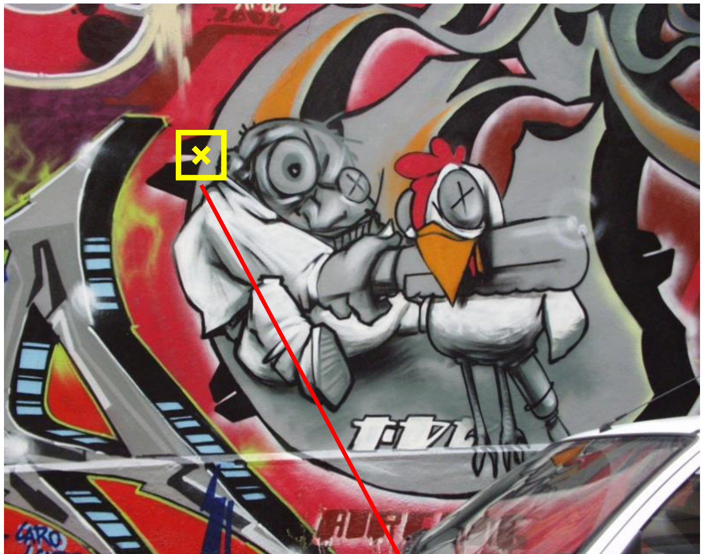
All points will be classified as edges

Scale

Let’s look at scale first:

What is the “best” scale?

Scale Invariance

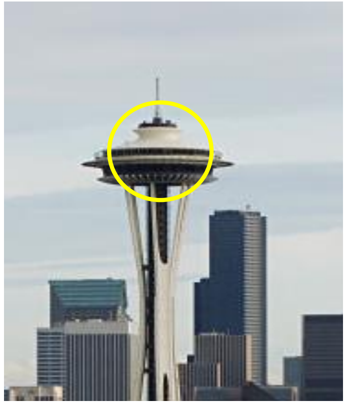


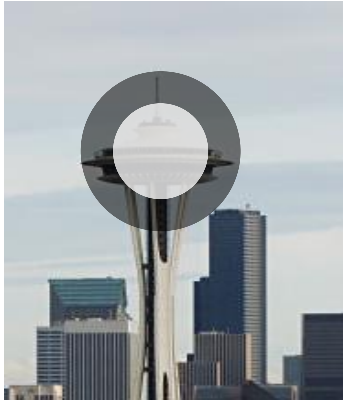
$$f(I_{i_1\ldots i_m}(x,\sigma)) = f(I_{i_1\ldots i_m}(x',\sigma'))$$

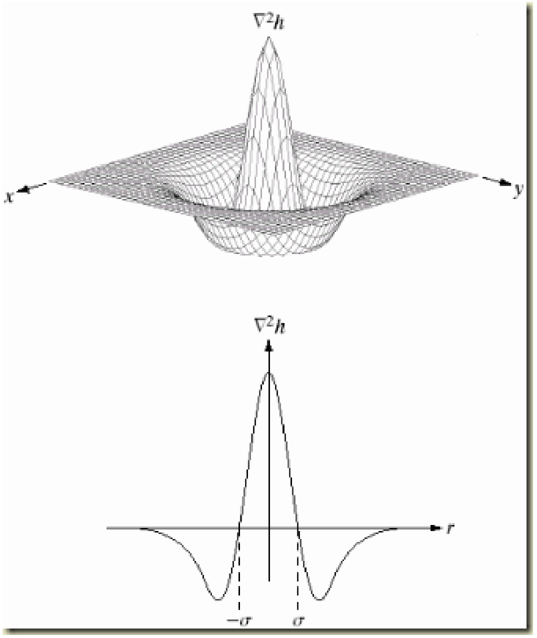
How can we independently select interest points in each image, such that the detections are repeatable across different scales?

K. Grauman, B. Leibe

Differences between Inside and Outside







1. We can use a Laplacian function

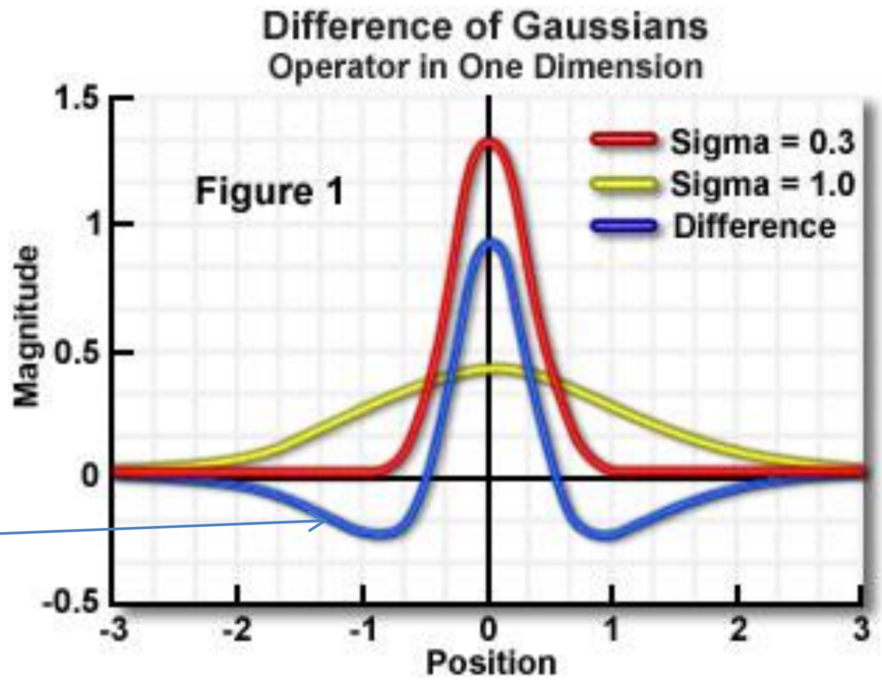
Scale

But we use a Gaussian.

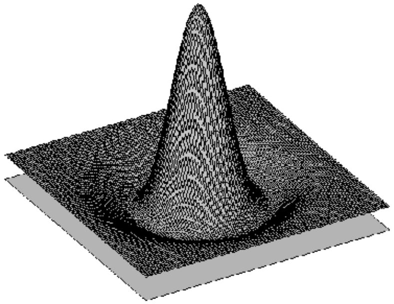
Why Gaussian?

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)



G1 - G2 = DoG

-

=

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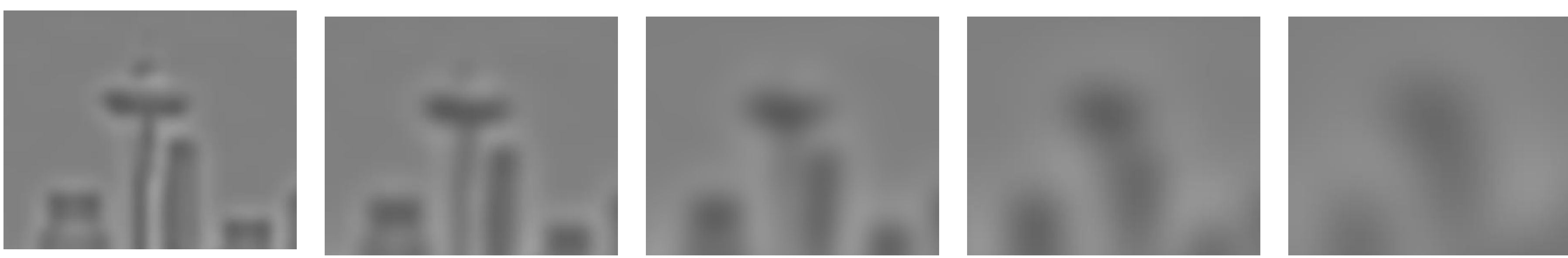
DoG example

Take Gaussians at multiple spreads and uses DoGs.

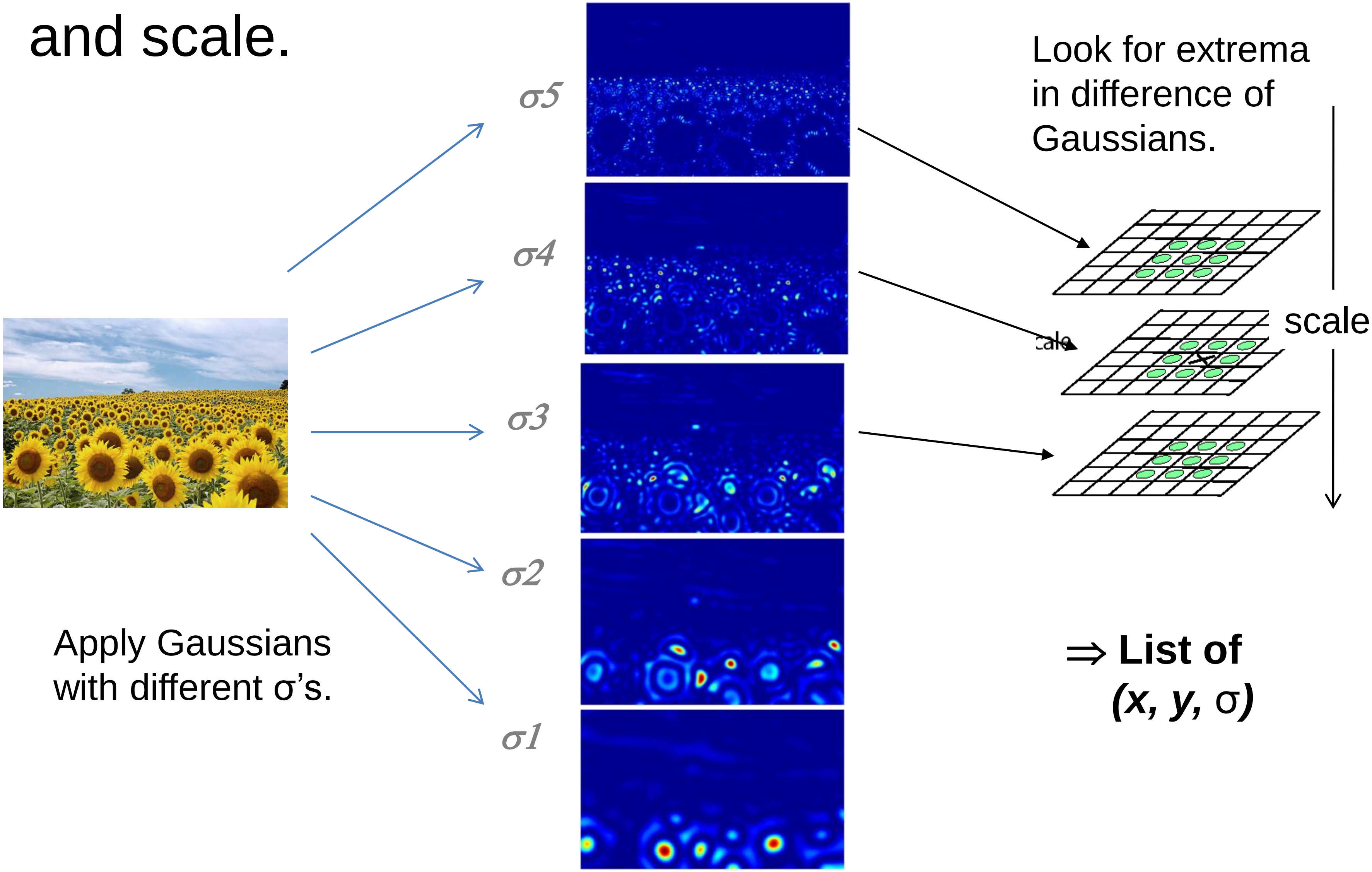
σ = 1



σ = 66

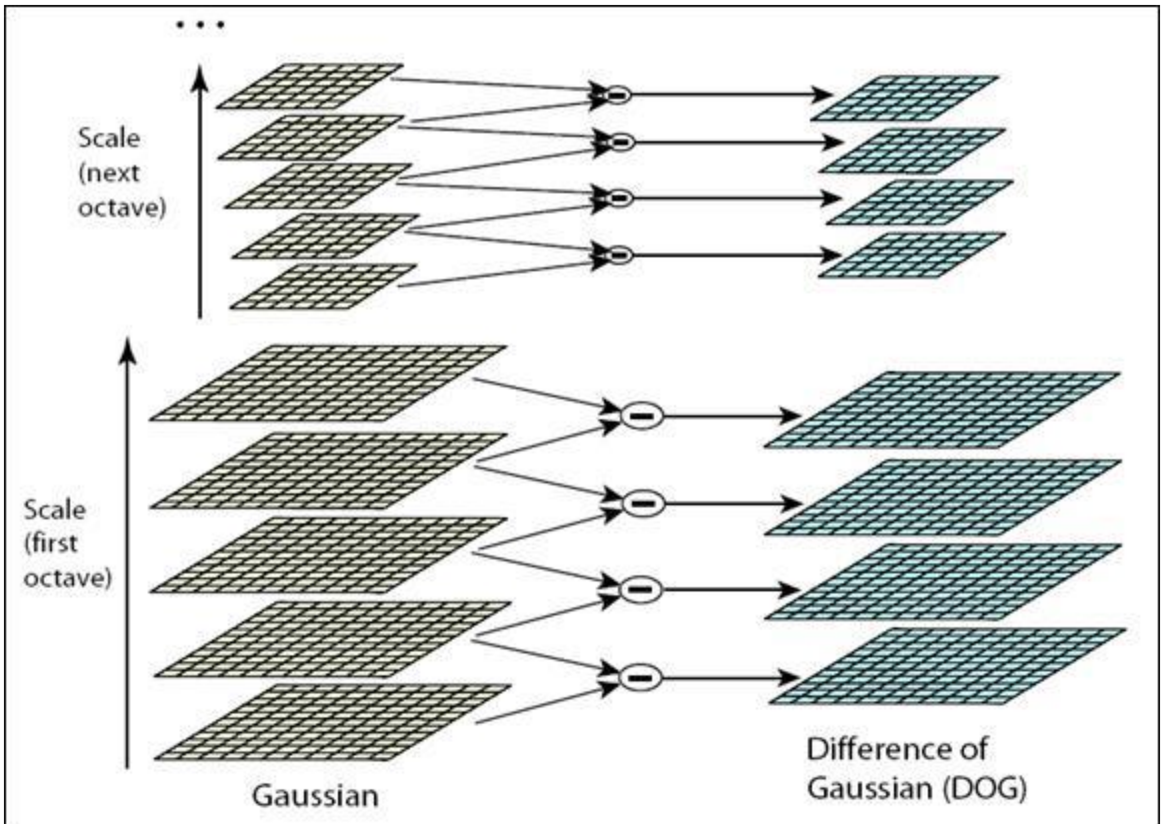
Scale invariant interest points

Interest points are local maxima in both position and scale.



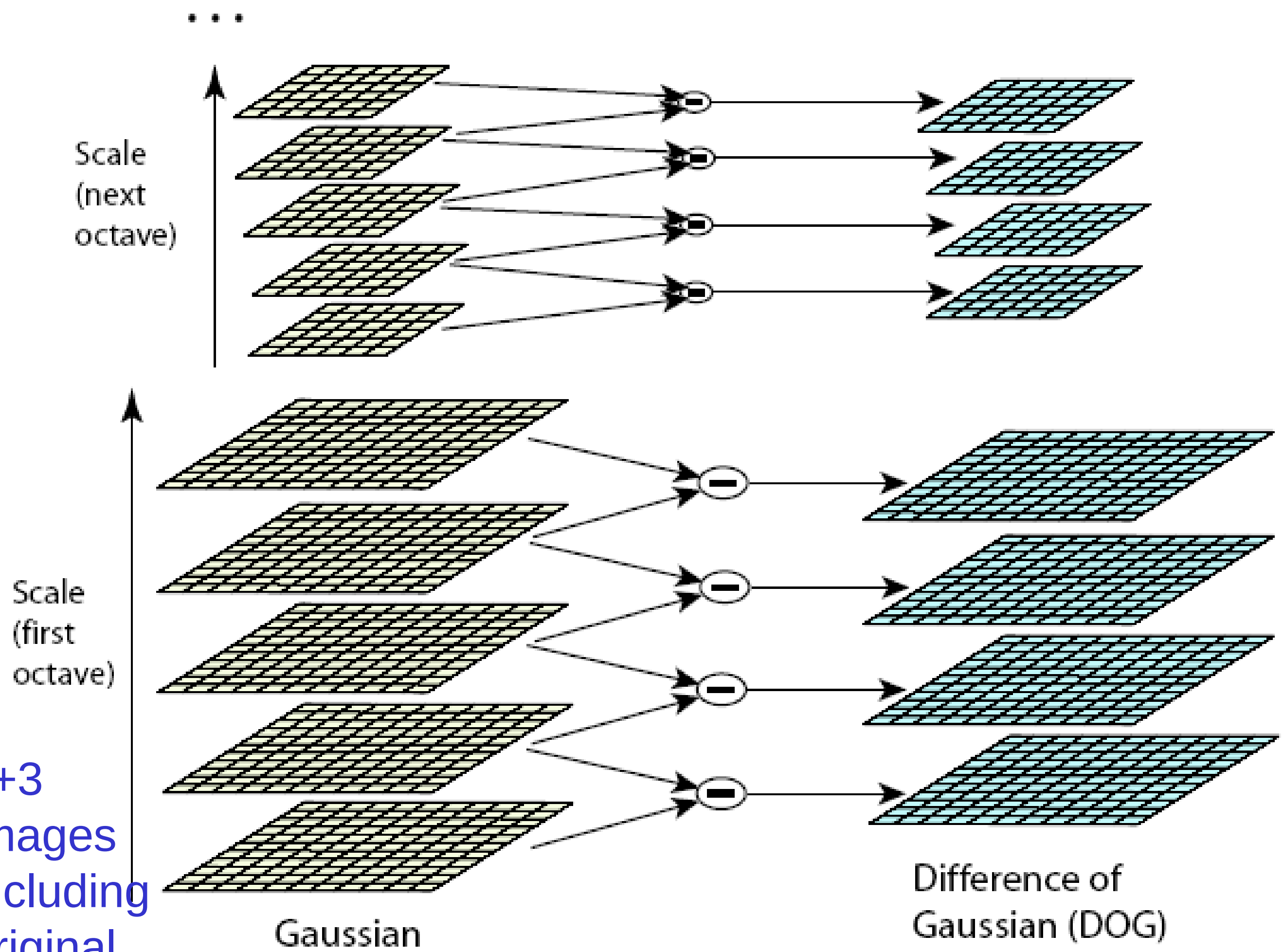
Scale

In practice the image is downsampled for larger sigmas.



Lowe, 2004.

Lowe's Pyramid Scheme



s+2 filters

$\sigma_{s+1}=2^{(s+1)/s}\sigma_0$

.

.

$\sigma_i=2^{i/s}\sigma_0$

.

.

$\sigma_2=2^{2/s}\sigma_0$

$\sigma_1=2^{1/s}\sigma_0$

σ_0

s+3 images including original

s+2 differ-ence images

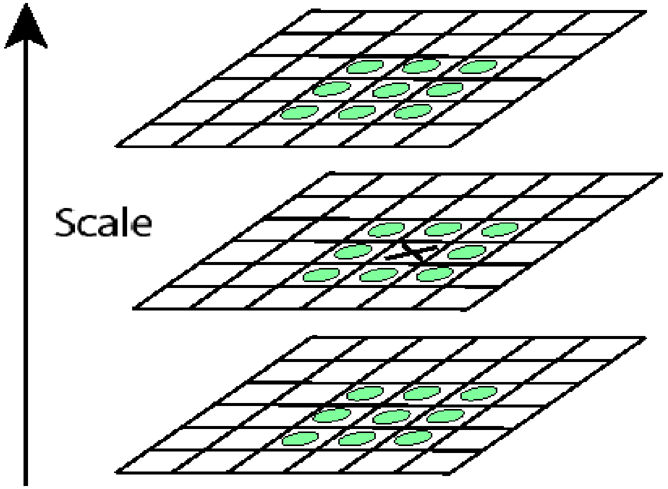
The parameter **s** determines the number of images per octave.

Key point localization

s+2 difference images.
top and bottom ignored.
s planes searched.

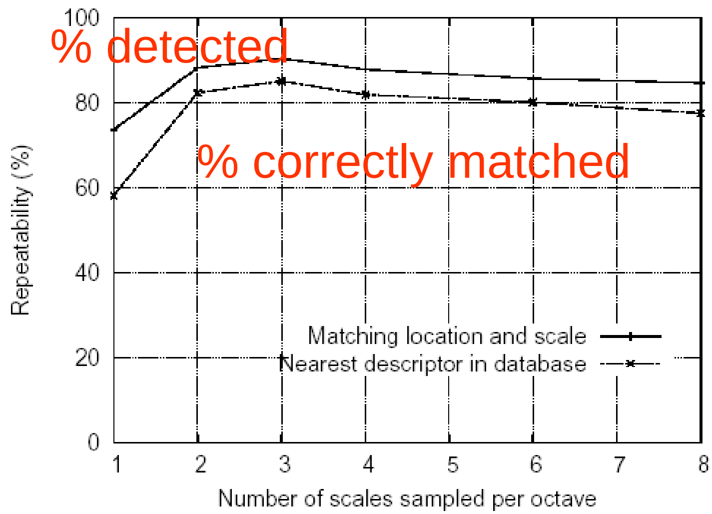
Detect maxima and minima of difference-of-Gaussian in scale space

Each point is compared to its 8 neighbors in the current image and 9 neighbors each in the scales above and below

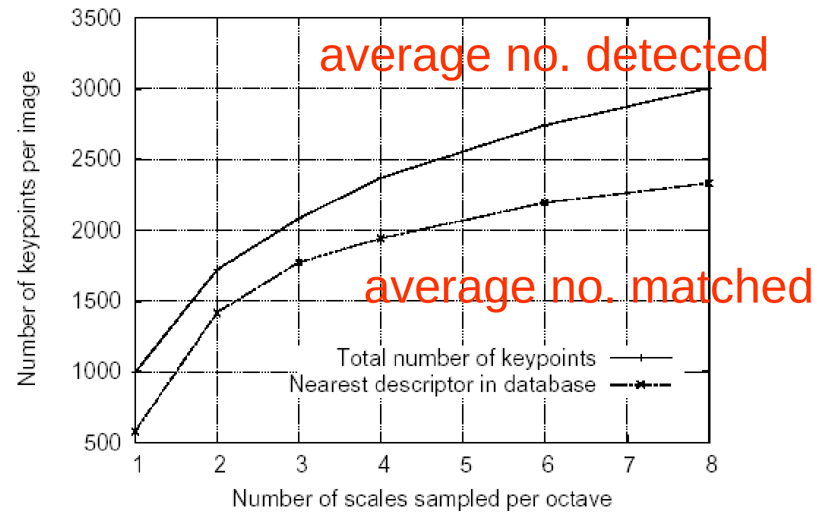


For each max or min found, output is the **location** and the **scale**.

Scale-space extrema detection: experimental results over 32 images that were synthetically transformed and noise added.



Stability



Expense

Sampling in scale for efficiency

How many scales should be used per octave? S=?

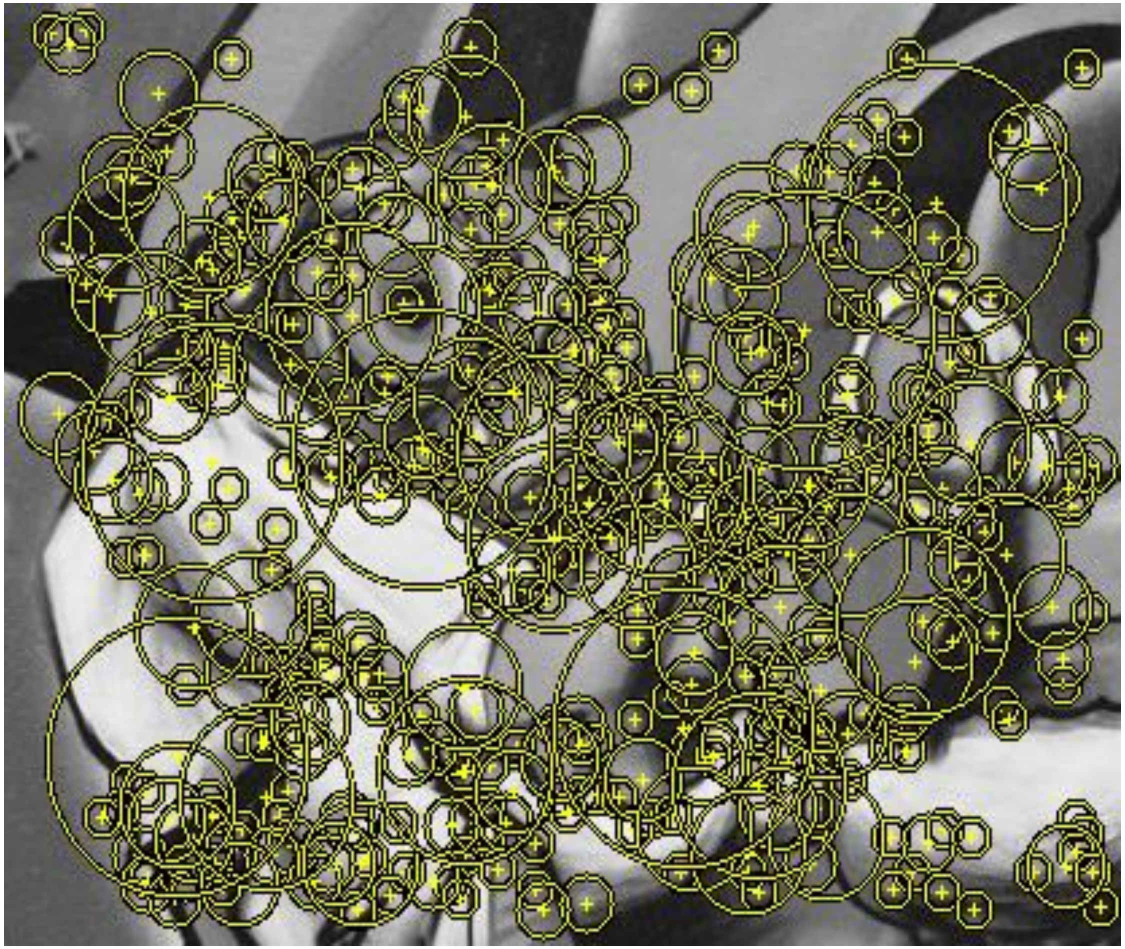
More scales evaluated, more keypoints found

S < 3, stable keypoints increased too

S > 3, stable keypoints decreased

S = 3, maximum stable keypoints found

Results: Difference-of-Gaussian



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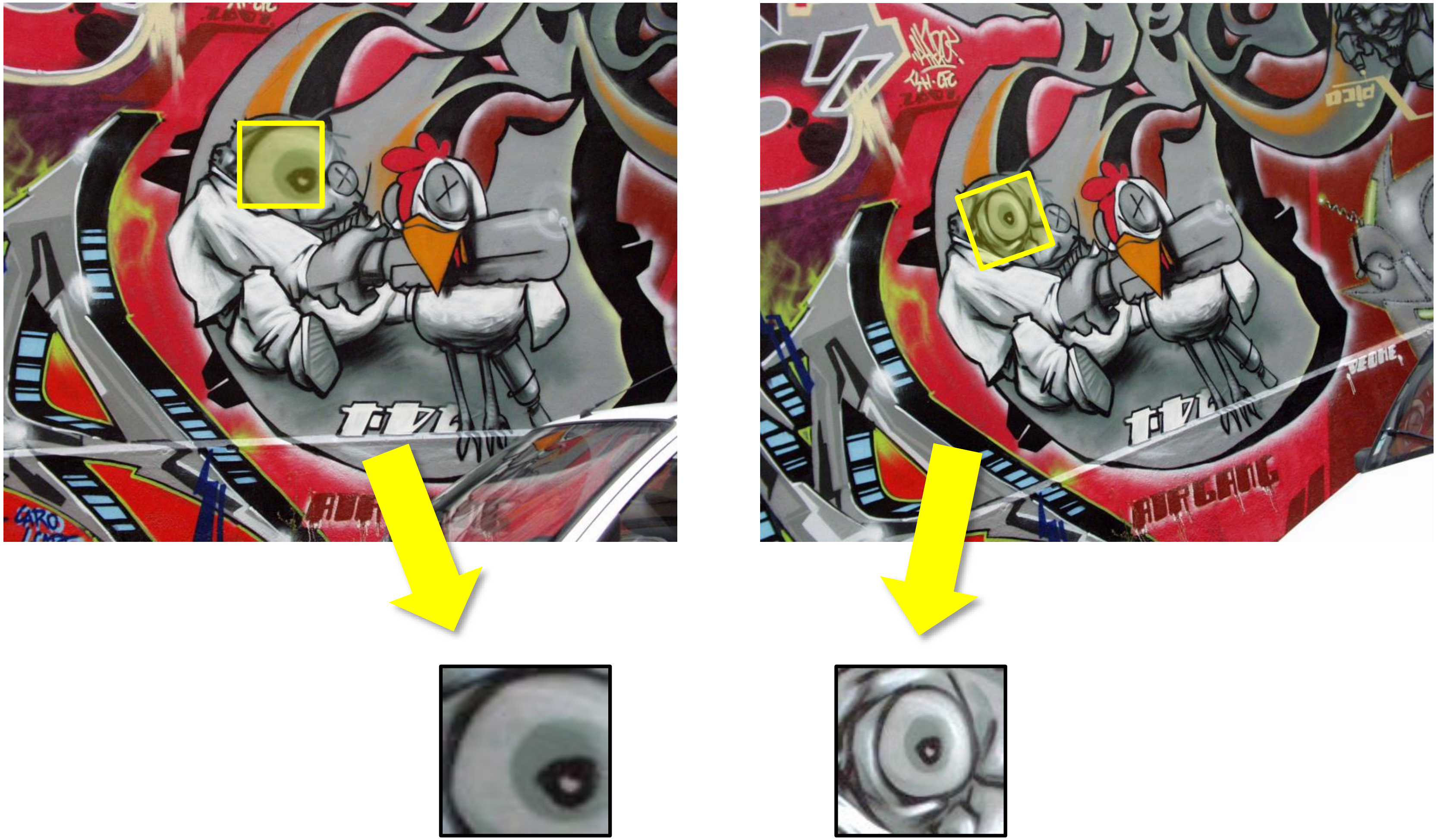
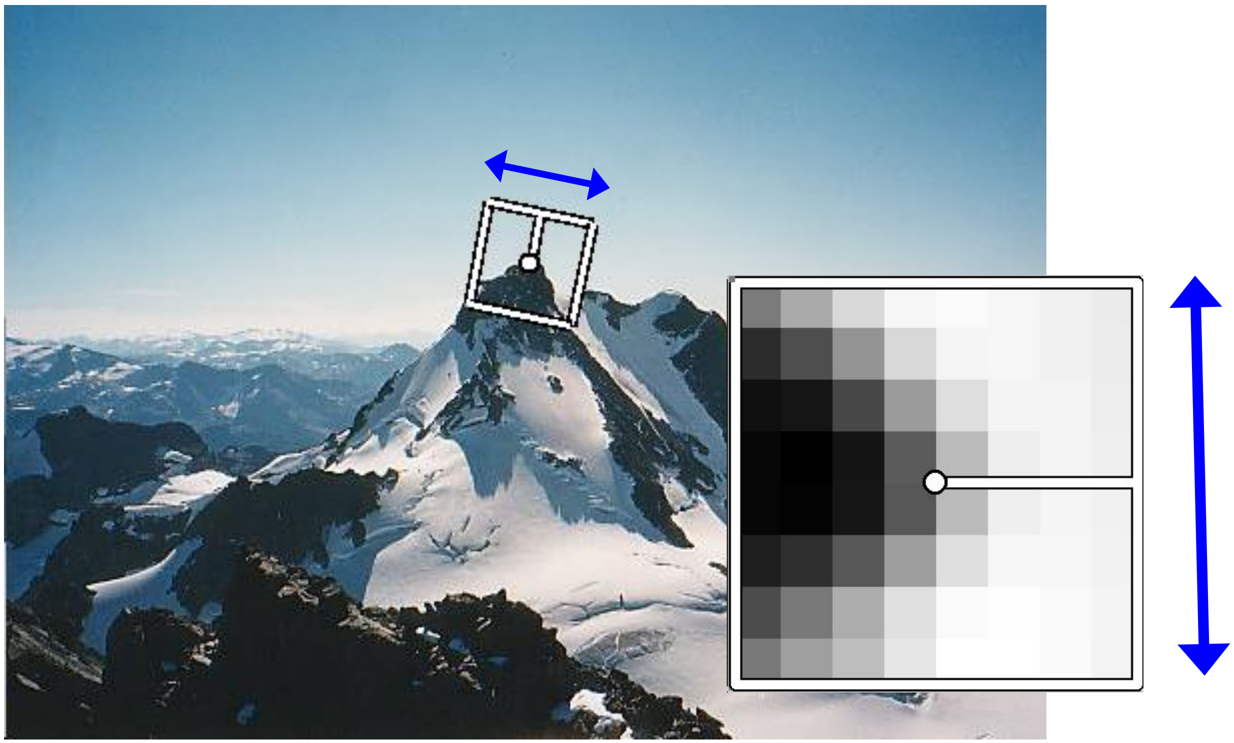
How can we find correspondences?



Similarity transform

Rotation invariance



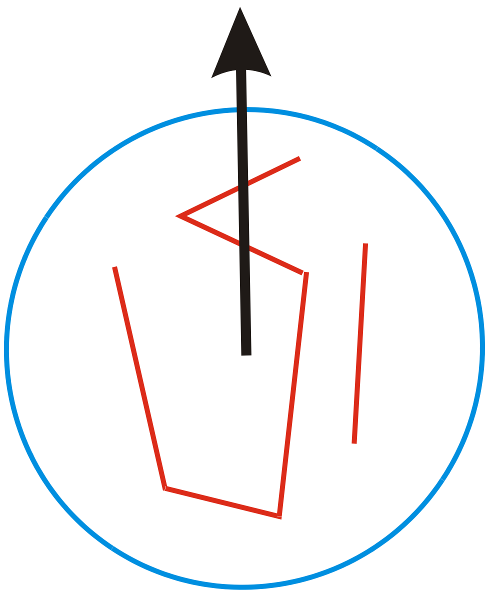
- Rotate patch according to its dominant gradient orientation
- This puts the patches into a canonical orientation.

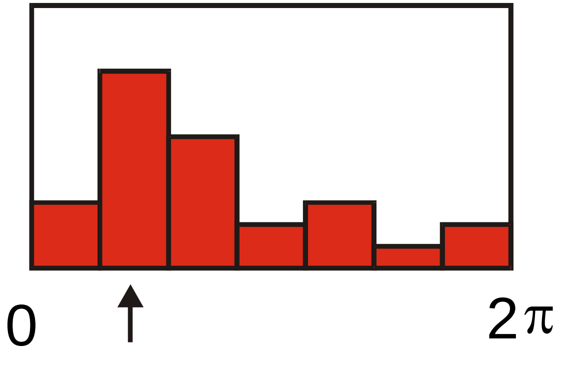
Image from Matthew Brown

Orientation Normalization

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

[Lowe, SIFT, 1999]

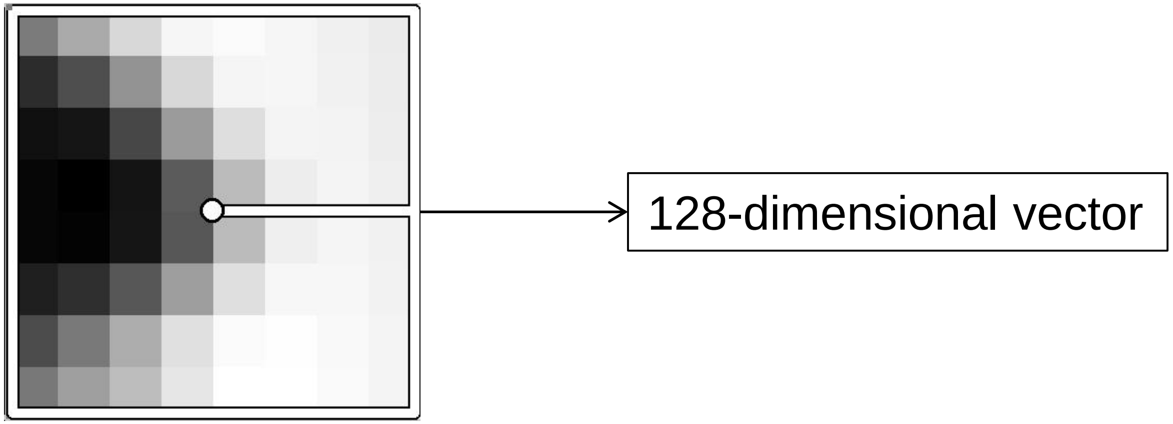




What's next?

Once we have found the keypoints and a dominant orientation for each,

we need to describe the (rotated and scaled) neighborhood about each.



Important Point

- People just say “SIFT”.

- But there are TWO parts to SIFT.

1. an interest point detector

2. a region descriptor

- They are independent. Many people use the region descriptor without looking for the points.