Feature point detection

IN4393 – Computer Vision

Image matching

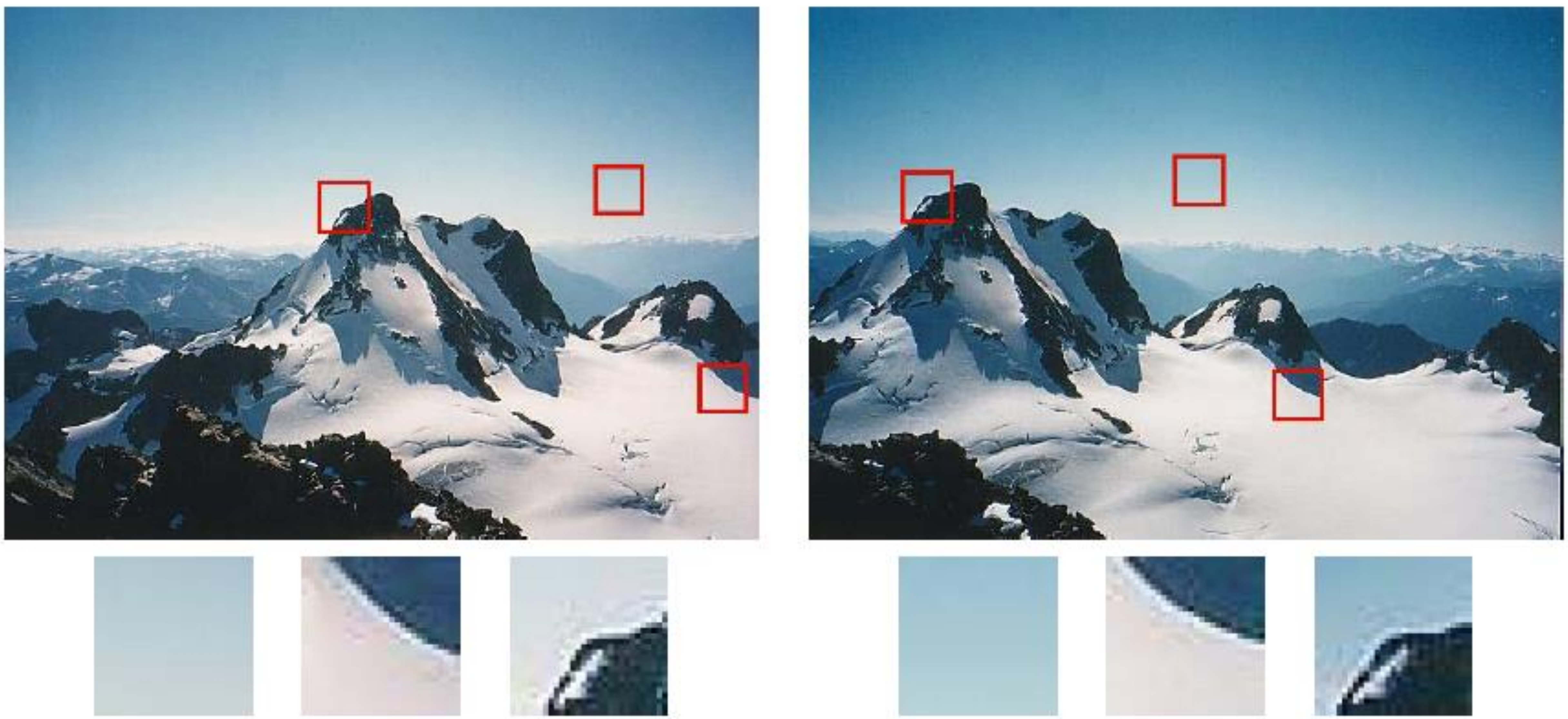
- What feature can we use to establish *correspondences* between images?

Feature point detection

- The goal is to find locations that are stable under *image transformations*
- Feature points are frequently used in, among others:
    - Stereo matching
    - Image stitching
    - Video stabilization
    - Instance or object recognition

Feature point detection

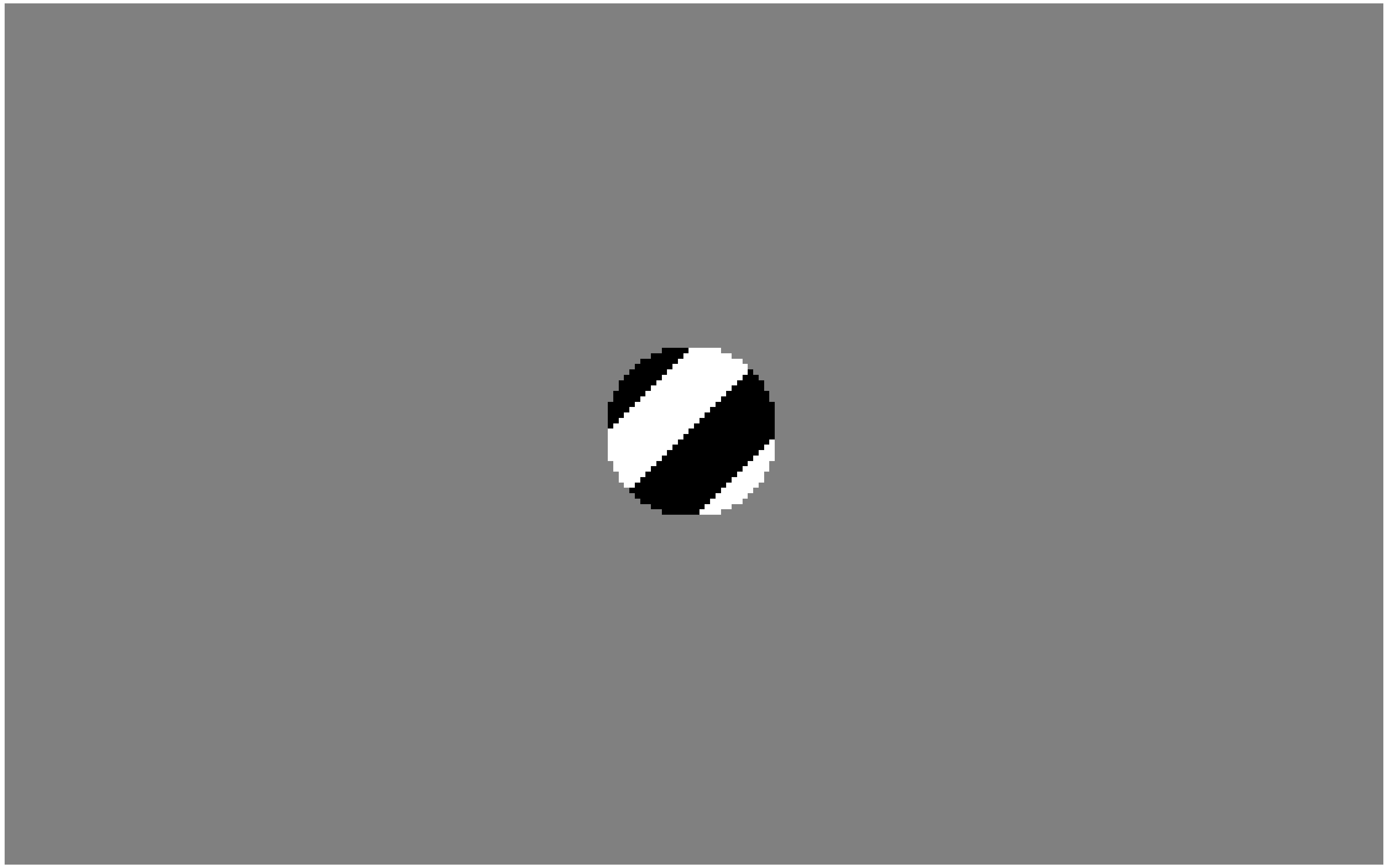
- Some feature points can be matched more accurately than others:



Feature point detection

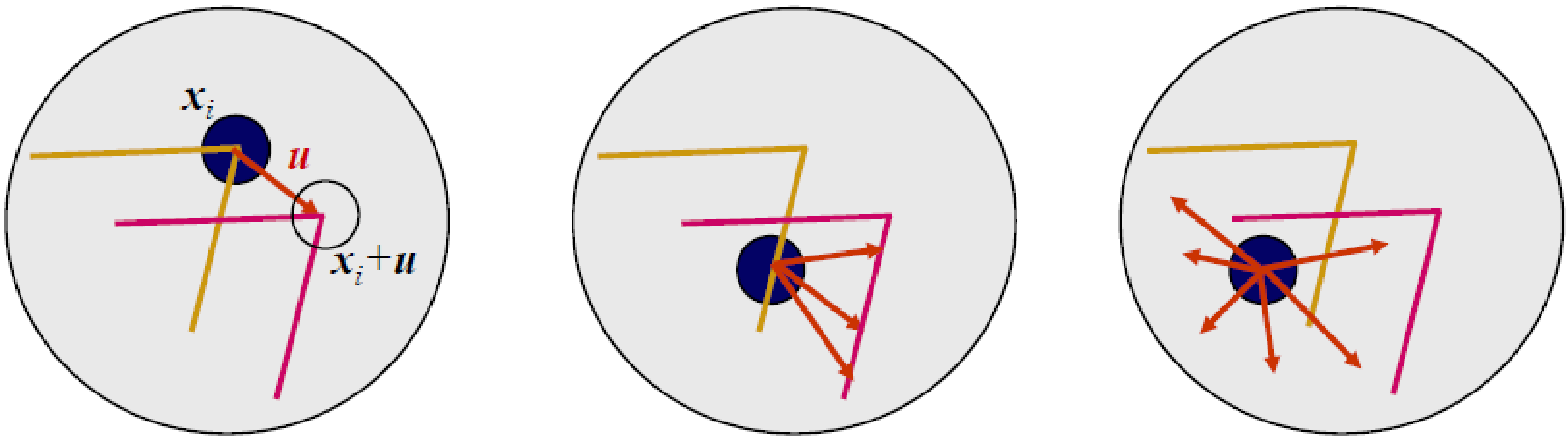
- Patches with large contrast changes are easier to localize

- However, straight lines with a single orientation suffer from *aperture problem*:



Feature point detection

- The most reliable points for matching are *“corner”*-like points:

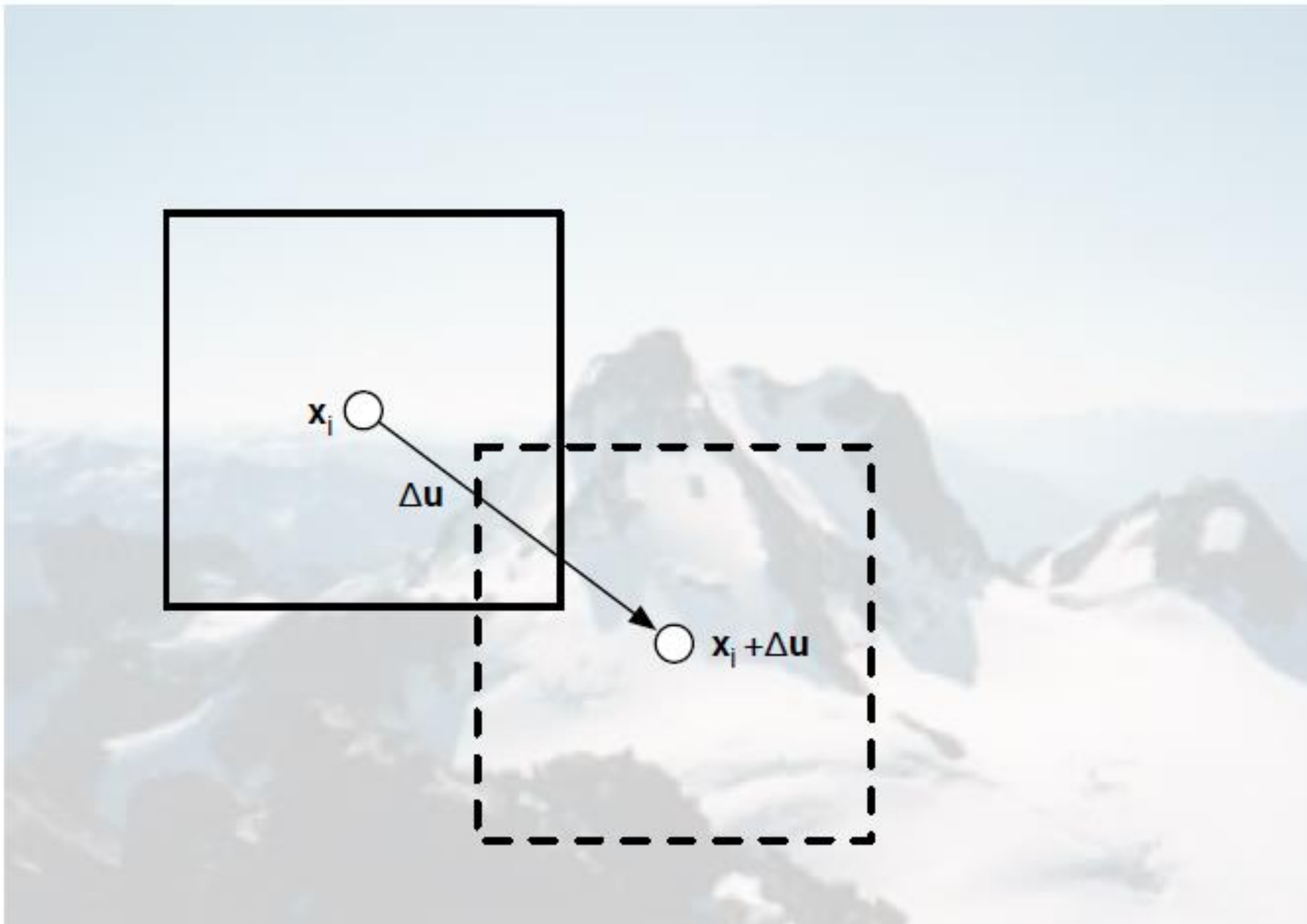


- We can formalize these intuitions by looking at the *autocorrelation function*:

$$E_{AC}(\Delta\mathbf{u}) = \sum_i w(\mathbf{x}_i)[I_0(\mathbf{x}_i + \Delta\mathbf{u}) - I_0(\mathbf{x}_i)]^2$$

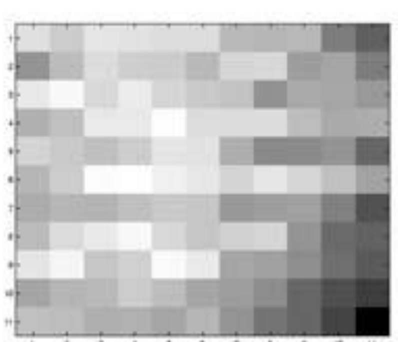
Local weighting function: the summation over the window

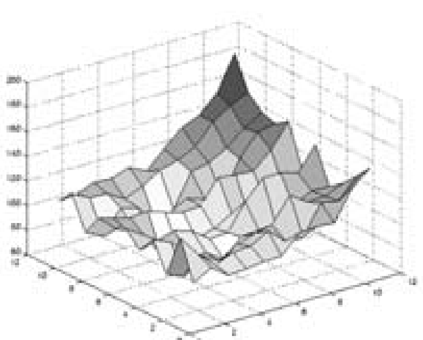
Autocorrelation function



$$E_{AC}(\Delta \mathbf{u}) = weighted\ SSE(\square, \square)$$

Autocorrelation surfaces



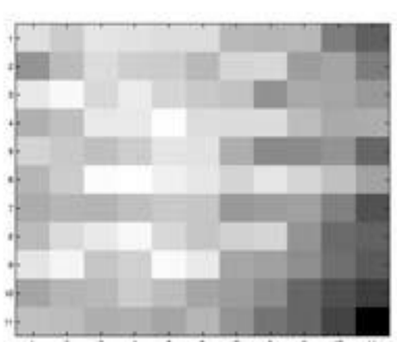


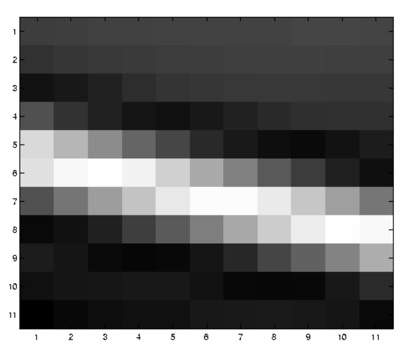
- For homogeneous regions, there is no clear minimum

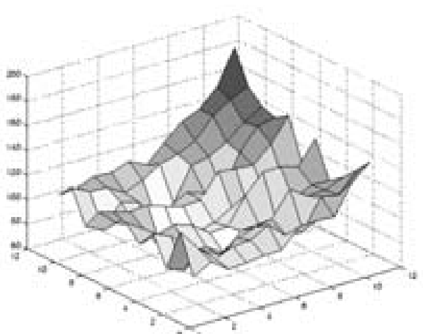
Autocorrelation surfaces

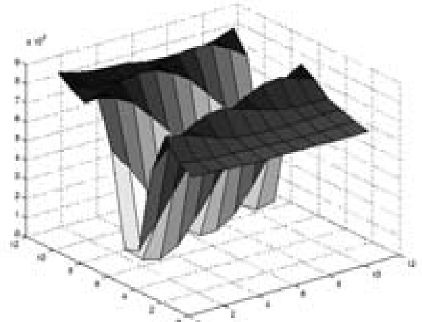
- For homogeneous regions, there is no clear minimum

- For lines, there is an ambiguity



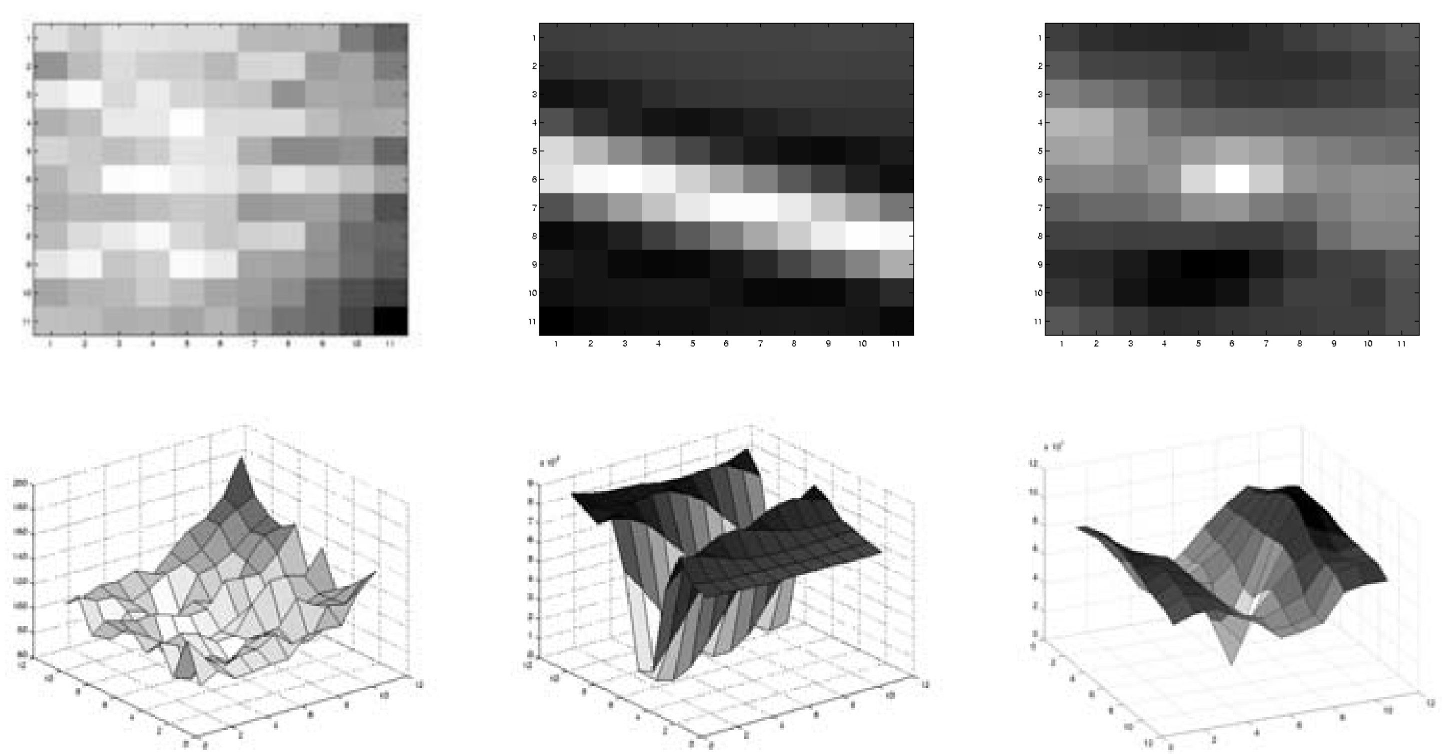






Autocorrelation surfaces

- For homogeneous regions, there is no clear minimum
- For lines, there is an ambiguity
- The flower does have a clear minimum (= easy to localize!)



Harris corner detector

- We can approximate the autocorrelation via a Taylor expansion* of the image:

$$
\begin{aligned}
E_{AC}(\Delta\mathbf{u}) &= \sum_i w(\mathbf{x}_i)[I_0(\mathbf{x}_i + \Delta\mathbf{u}) - I_0(\mathbf{x}_i)]^2 \\
&\approx \sum_i w(\mathbf{x}_i)[I_0(\mathbf{x}_i) + \nabla I_0(\mathbf{x}_i)\cdot\Delta\mathbf{u} - I_0(\mathbf{x}_i)]^2 \\
&= \sum_i w(\mathbf{x}_i)[\nabla I_0(\mathbf{x}_i)\cdot\Delta\mathbf{u}]^2 \\
&= \Delta\mathbf{u}^{\mathrm{T}}\mathbf{A}\Delta\mathbf{u}
\end{aligned}
$$

- Here, we define the *autocorrelation matrix* (aka *second-moment matrix* or *structure tensor*):

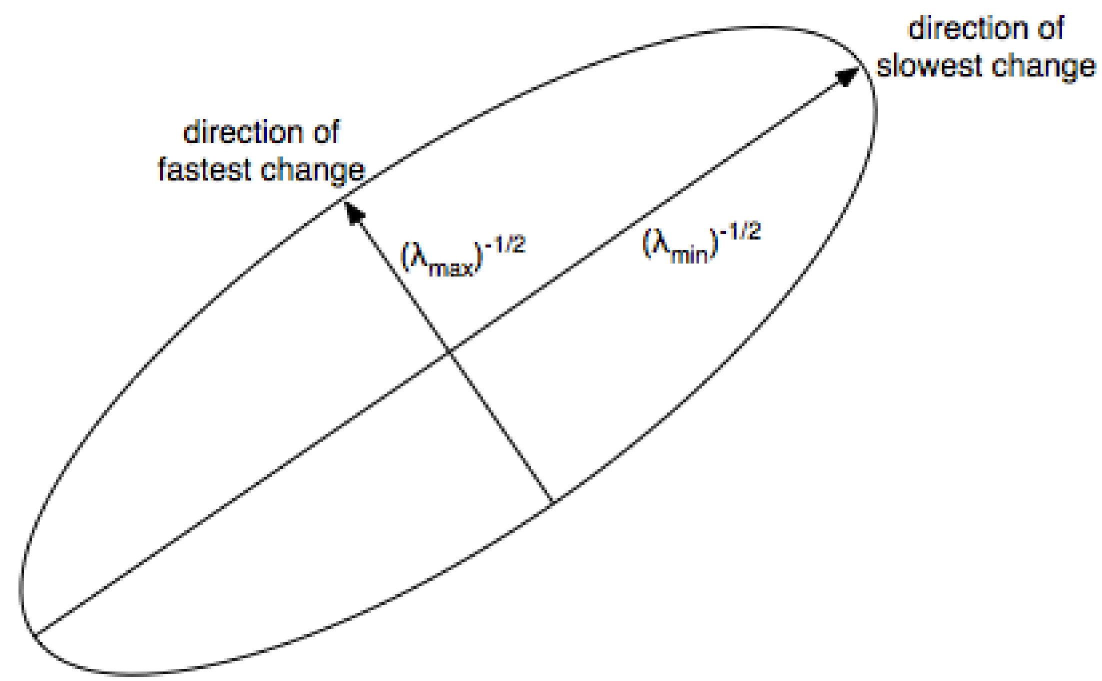
$$\mathbf{A} = w \times \begin{bmatrix} I_x^2 & I_xI_y \\ I_xI_y & I_y^2 \end{bmatrix}$$

* A Taylor expansion of $f(x)$ around a is given by: $\sum_{n=0}^{\infty} \frac{f^{(n)}(a)}{n!}(x-a)^n$

Harris corner detector

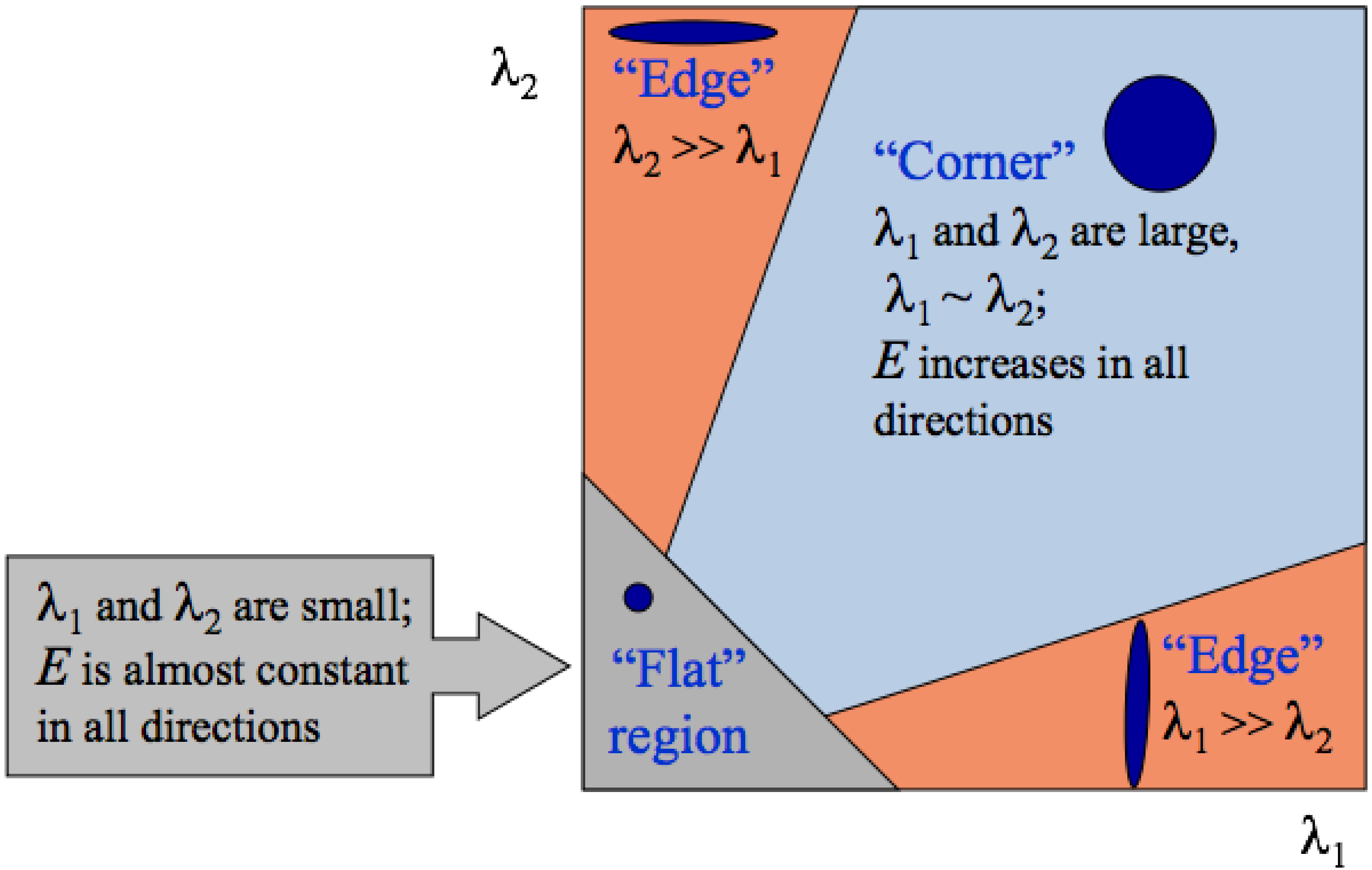
- Corners correspond to large changes in E_{AC} in all directions
- *Eigenanalysis* of autocorrelation matrix reveals direction and speed of change:

$$\mathbf{A}\mathbf{v} = \lambda\mathbf{v}$$



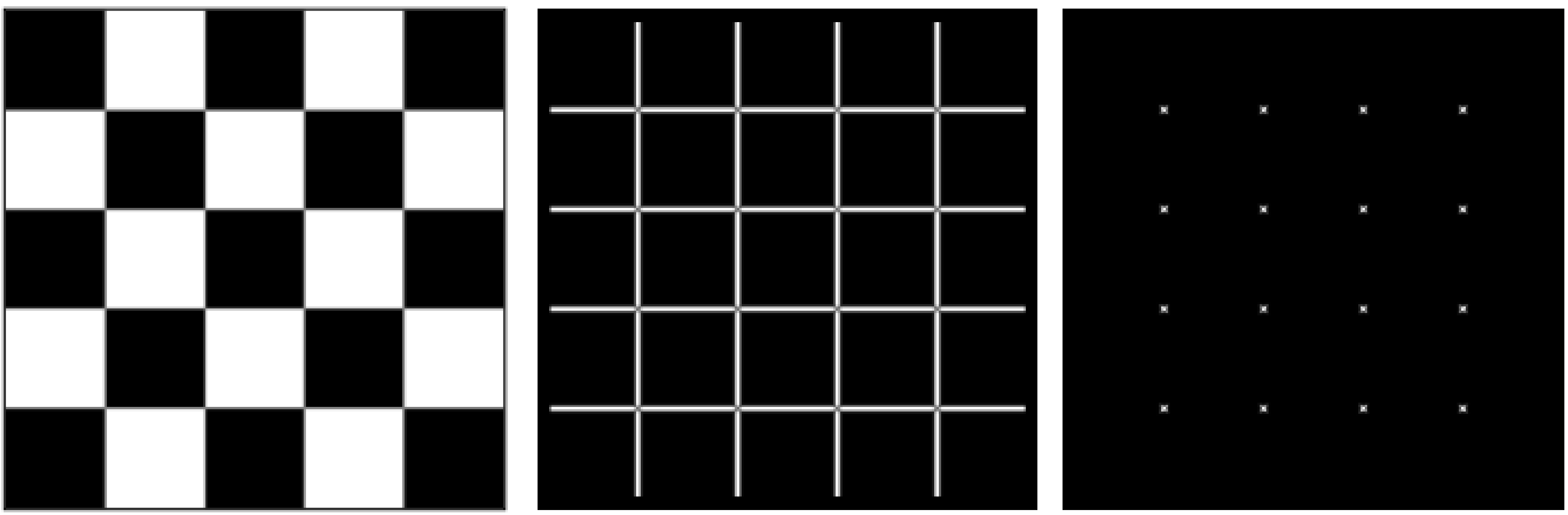
- Harris detector finds local maxima of: $\det(\mathbf{A}) - \alpha\,\mathrm{trace}(\mathbf{A})^2 = \lambda_0\lambda_1 - \alpha(\lambda_0 + \lambda_1)^2$
- Shi and Tomasi detector finds local maxima in the smallest eigenvalue λ_0

Interpreting the eigenvalues



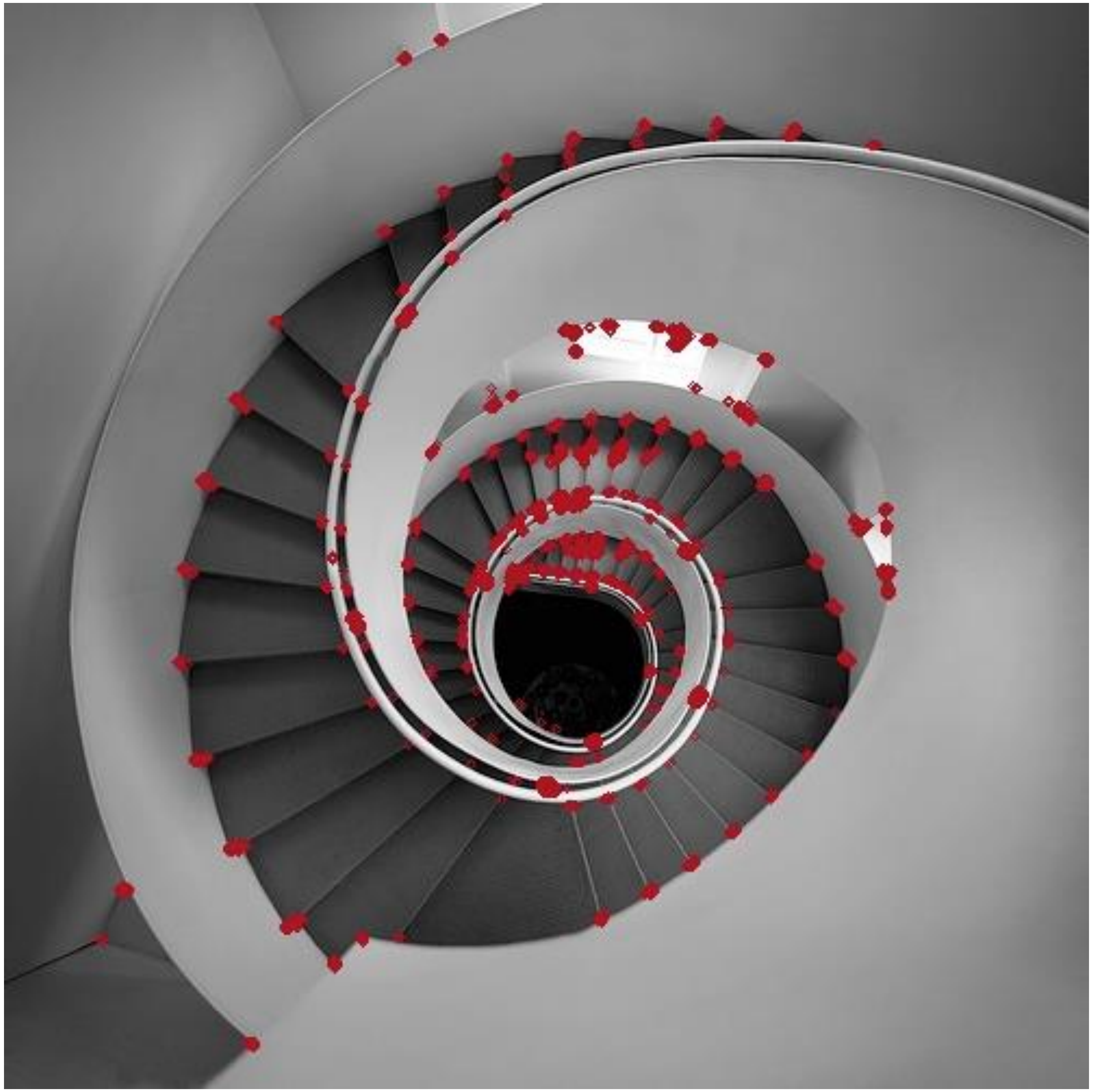
Harris corner detector

- Perform *eigendecomposition* of the second-moment matrix at each location
- Find local maxima in the field of the smallest eigenvalues:



I λ_{max} λ_{min}

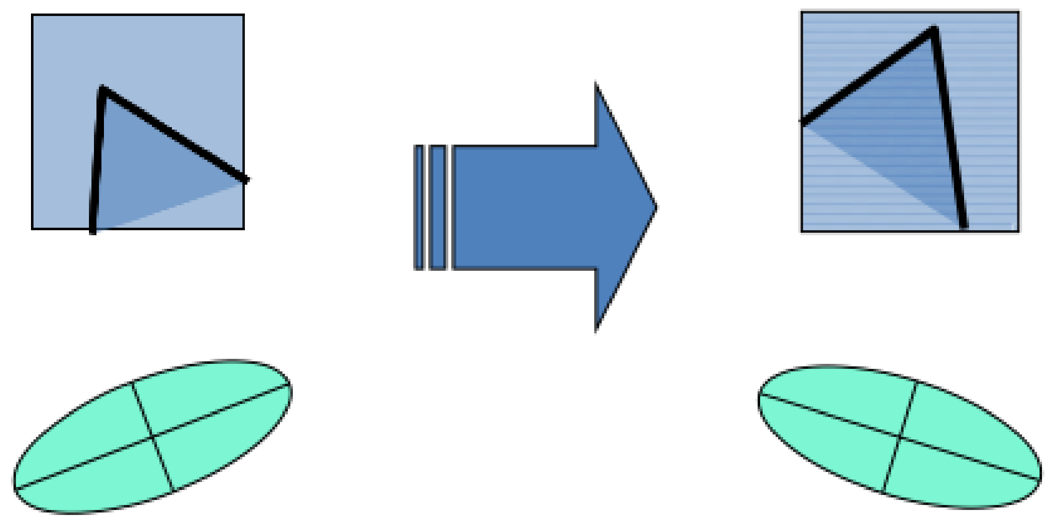
Example: Harris corner detector



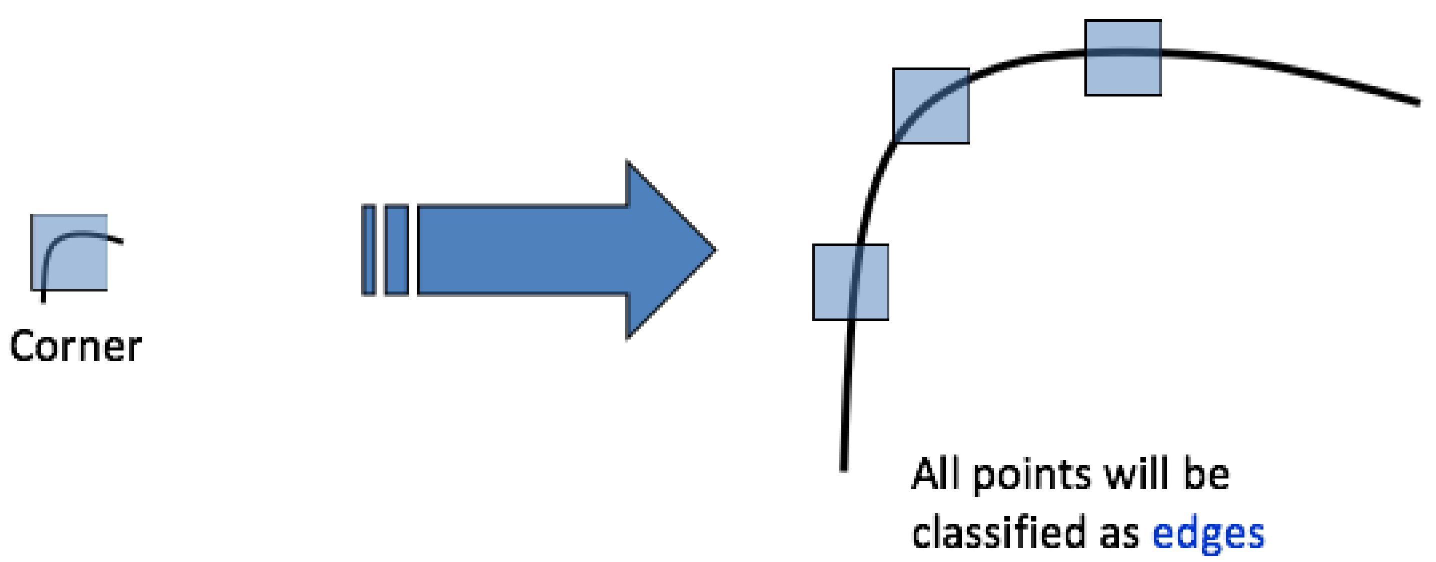
Example: Harris corner detector

Invariances of Harris detector

- The Harris detector is invariant to *rotations*:



- The Harris detector is not invariant to *scale changes*:



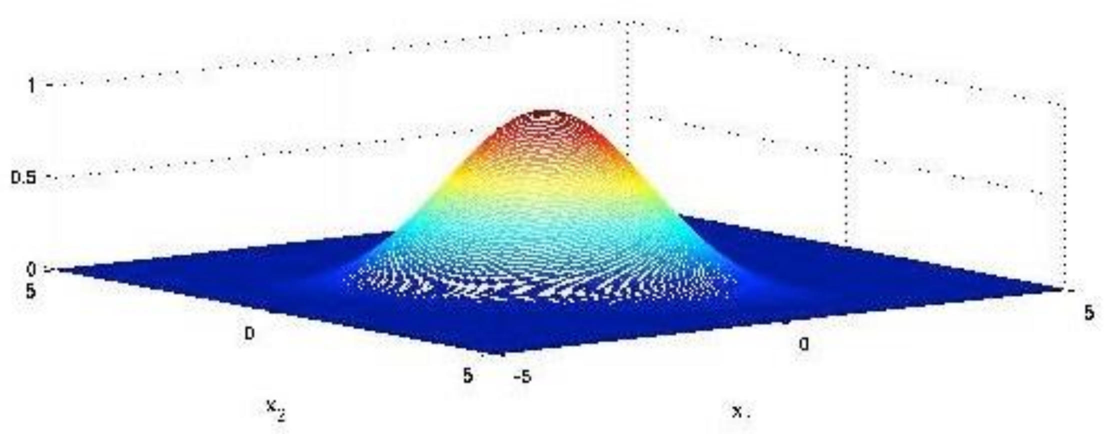
Scale-Invariant Feature Transform

- In contrast to Harris corners, SIFT features are stable in location and *scale*

- Overview of the SIFT feature point detector:
  - Perform *band-pass filtering* on a wide range of image scales
  - *Non-maxima suppression* to find candidate keypoints in location <u>and</u> scale
  - Remove candidate keypoints in low-contrast regions and keypoints on edges

Scale-Invariant Feature Transform

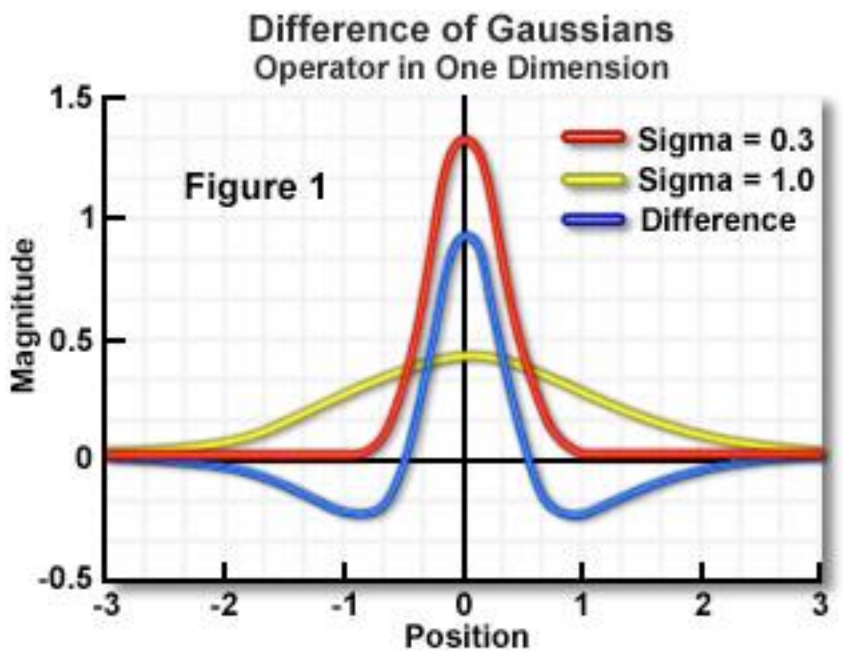
- Gaussian scale space removes features at fine scales via repeated blurring:

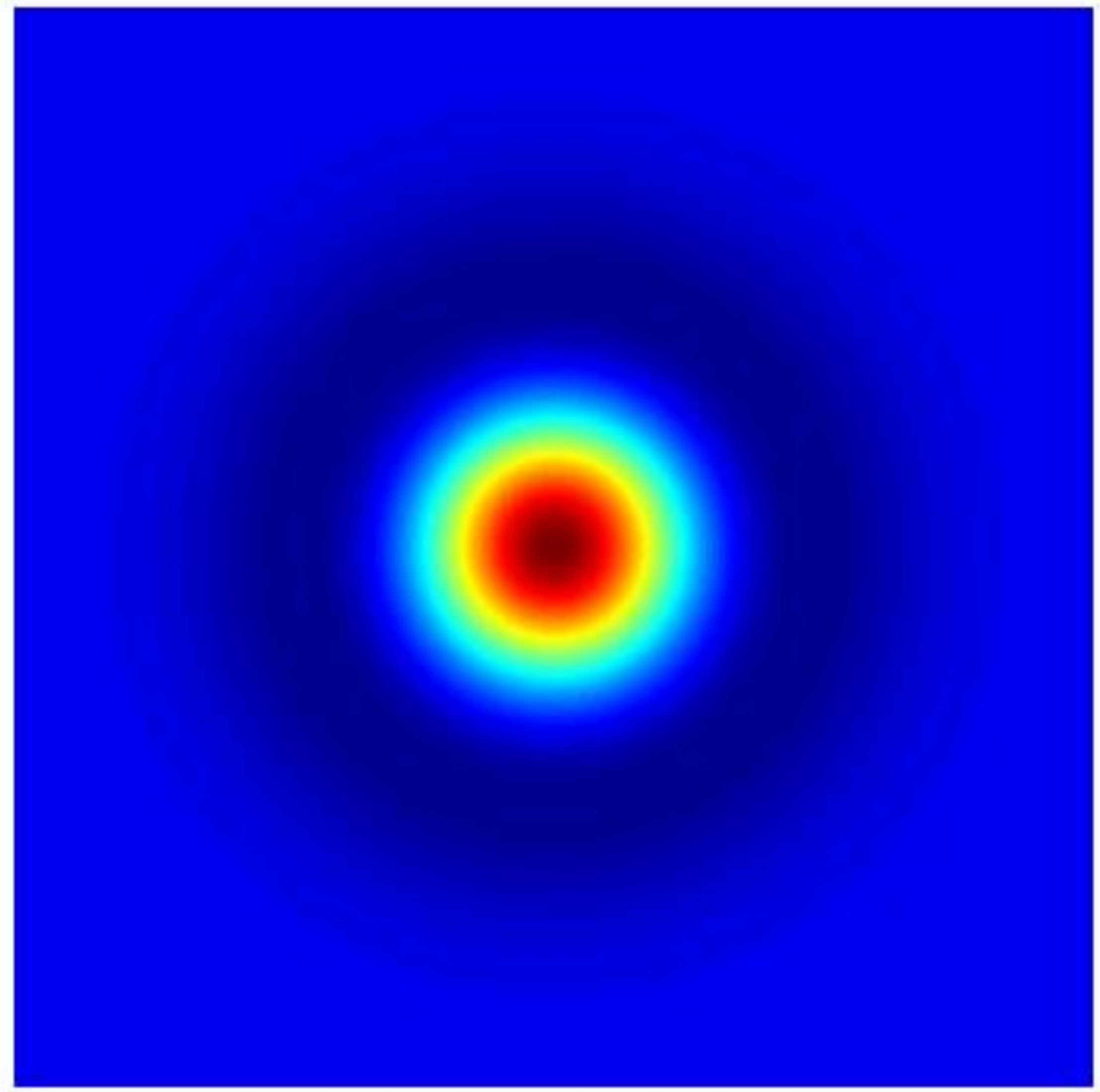


larger sigma / coarser scale →

Scale-Invariant Feature Transform

- SIFT performs filtering using *difference-of-Gaussian* (DoG) filters:

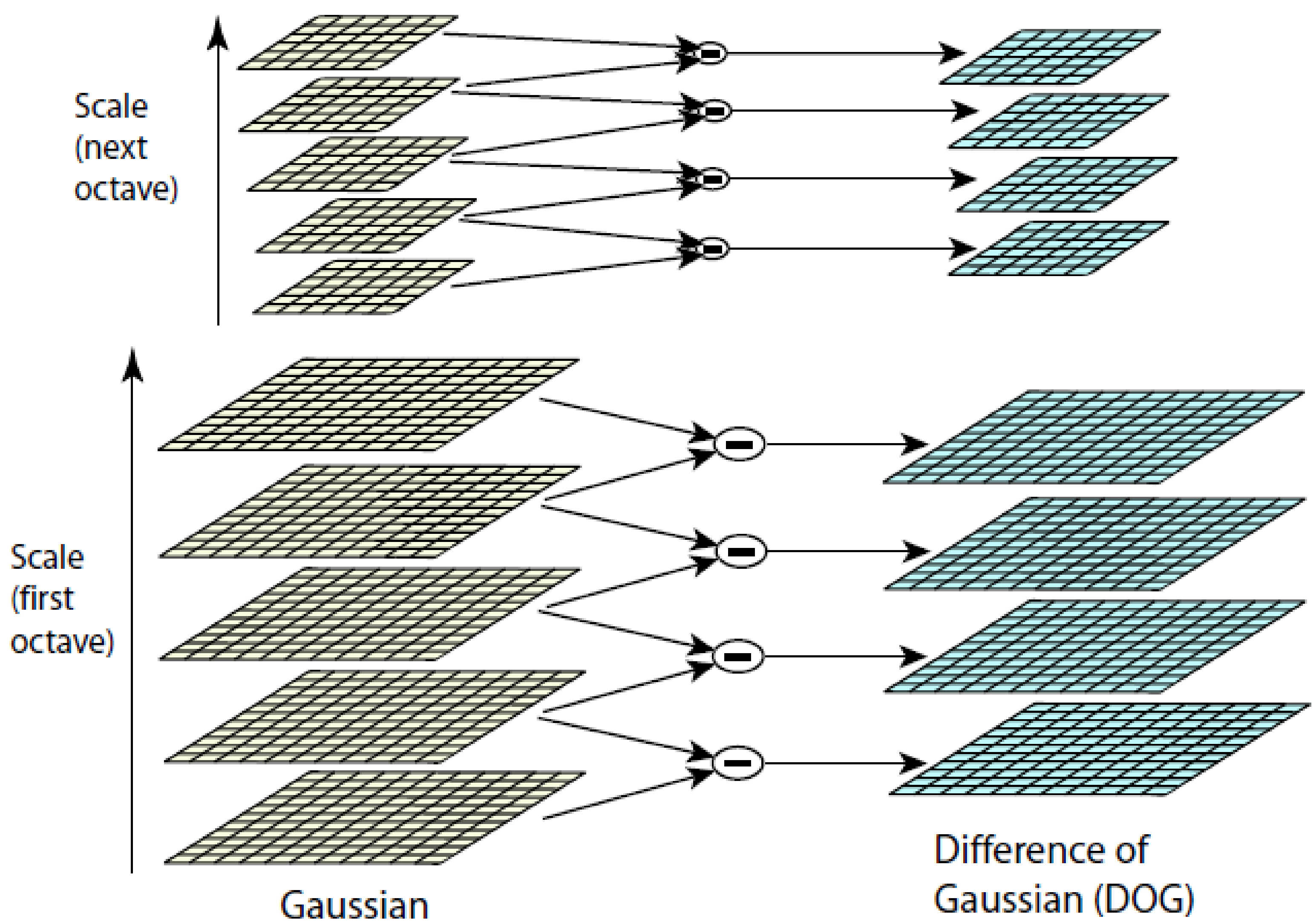


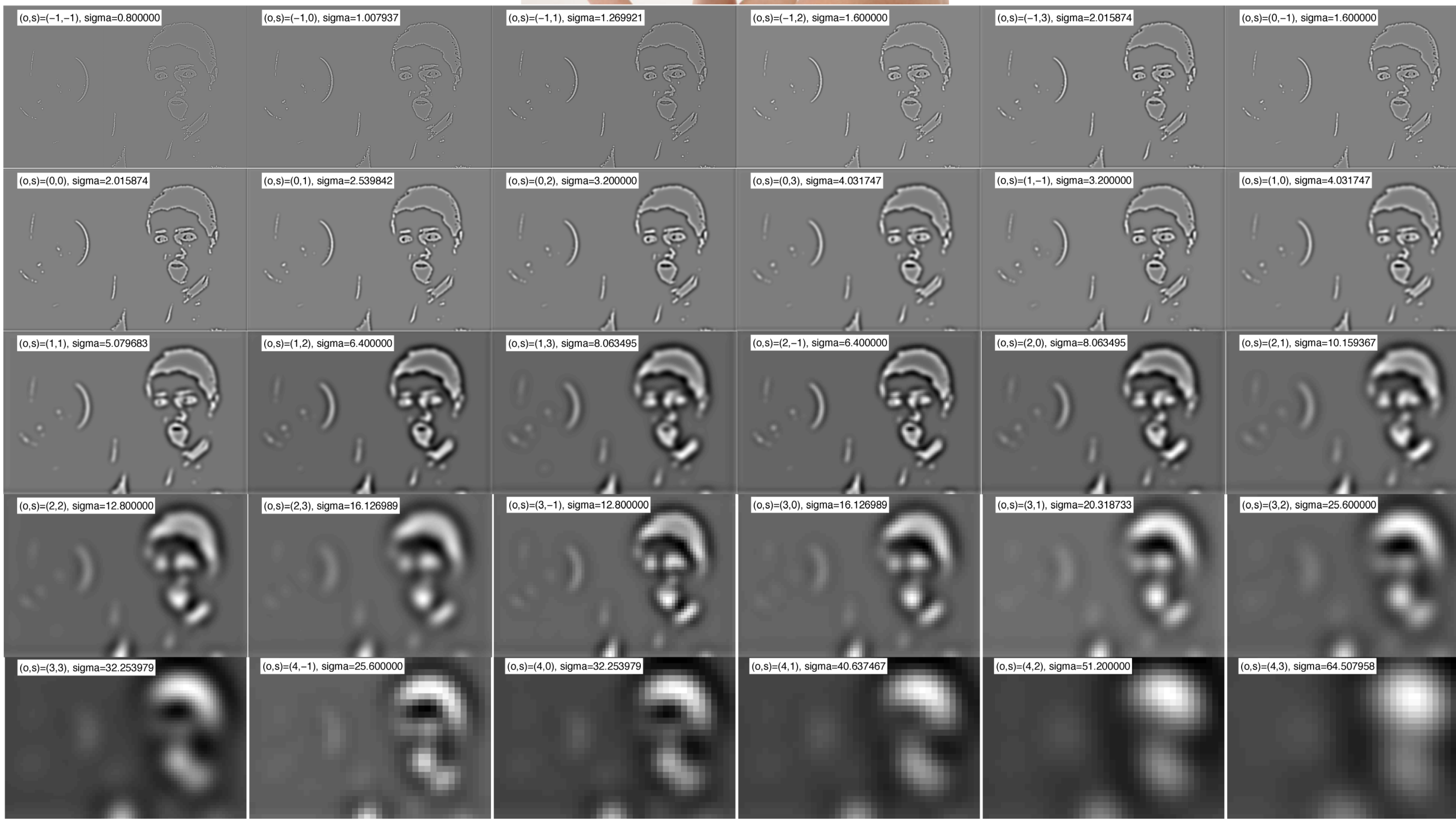


- This is a *band-pass filter* that only retains particular spatial frequencies

Scale-Invariant Feature Transform

- Efficiently computing difference-of-Gaussian response images:

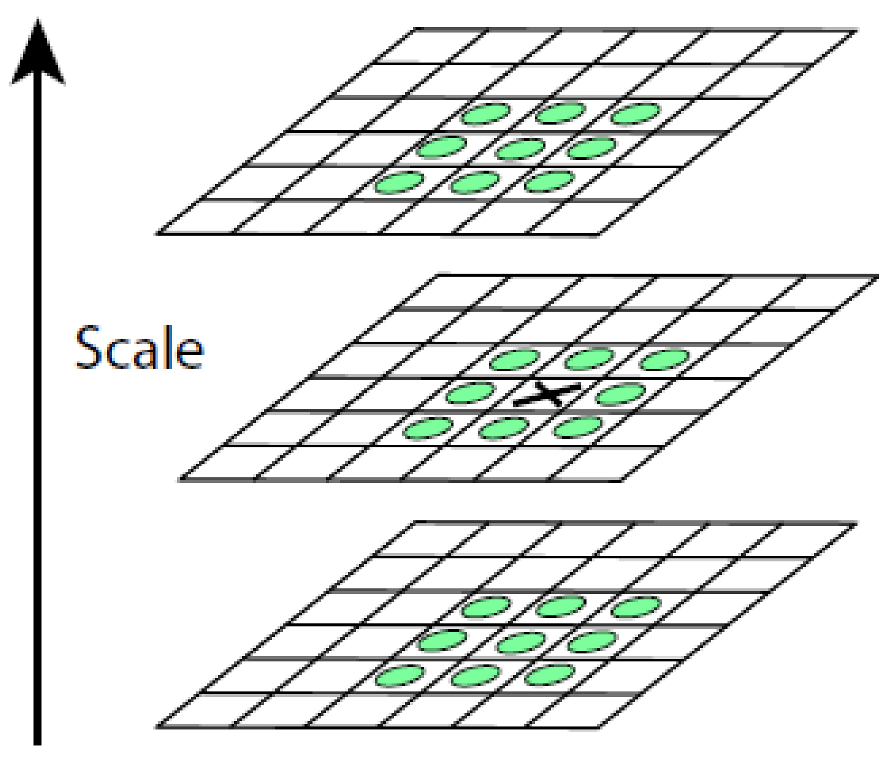



(o,s)=(−1,−1), sigma=0.800000
(o,s)=(−1,0), sigma=1.007937
(o,s)=(−1,1), sigma=1.269921
(o,s)=(−1,2), sigma=1.600000
(o,s)=(−1,3), sigma=2.015874
(o,s)=(0,−1), sigma=1.600000
(o,s)=(0,0), sigma=2.015874
(o,s)=(0,1), sigma=2.539842
(o,s)=(0,2), sigma=3.200000
(o,s)=(0,3), sigma=4.031747
(o,s)=(1,−1), sigma=3.200000
(o,s)=(1,0), sigma=4.031747
(o,s)=(1,1), sigma=5.079683
(o,s)=(1,2), sigma=6.400000
(o,s)=(1,3), sigma=8.063495
(o,s)=(2,−1), sigma=6.400000
(o,s)=(2,0), sigma=8.063495
(o,s)=(2,1), sigma=10.159367
(o,s)=(2,2), sigma=12.800000
(o,s)=(2,3), sigma=16.126989
(o,s)=(3,−1), sigma=12.800000
(o,s)=(3,0), sigma=16.126989
(o,s)=(3,1), sigma=20.318733
(o,s)=(3,2), sigma=25.600000
(o,s)=(3,3), sigma=32.253979
(o,s)=(4,−1), sigma=25.600000
(o,s)=(4,0), sigma=32.253979
(o,s)=(4,1), sigma=40.637467
(o,s)=(4,2), sigma=51.200000
(o,s)=(4,3), sigma=64.507958

Scale-Invariant Feature Transform

- Keypoints are found as local maxima and minima of the DoG responses

- Search for maxima in eight-pixel spatial neighborhood across three scales:



Scale-Invariant Feature Transform

- Candidate keypoints with low contrast or that lie on edges are removed

- This is done based on the *local Hessian* of the response $D(x, y, \sigma)$:

$$\mathbf{H} = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}$$

- Eigenvalues of the local Hessian are proportional to the *principal curvature*

- SIFT looks at the ratio of the two eigenvalues $r = \frac{\lambda_1}{\lambda_2}$; it rejects whenever:

$$\frac{(r+1)^2}{r} = \frac{\mathrm{trace}(\mathbf{H})^2}{\det(\mathbf{H})} > 10$$

Scale-Invariant Feature Transform

- Example of removing unstable candidate feature points:

Scale-Invariant Feature Transform

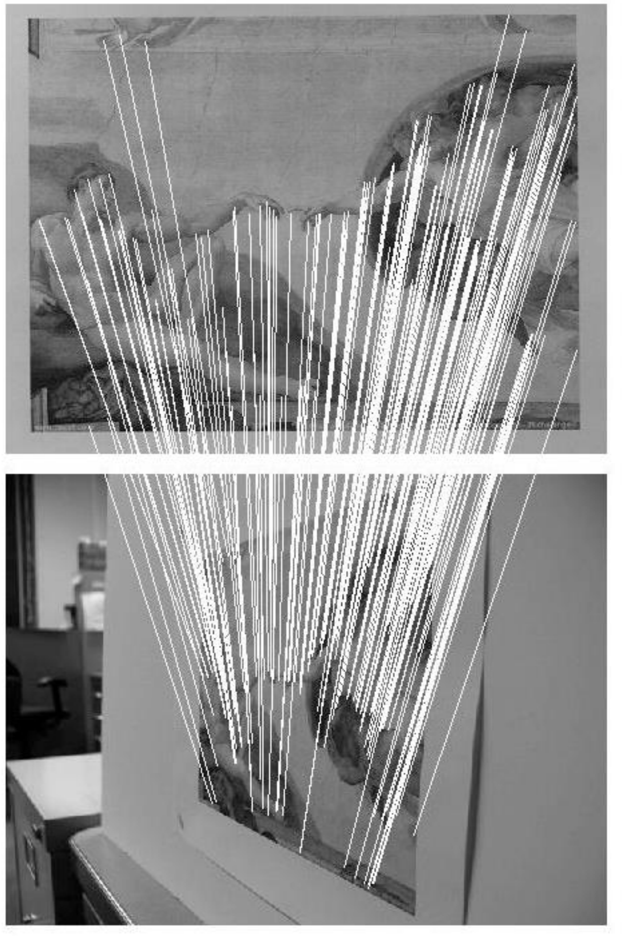
- Feature points in low-contrast regions are removed:

Scale-Invariant Feature Transform

- Feature points that lie on edges are removed:

What have we learned in this lecture?

- Feature points are stable in location, rotation, and preferably also scale
- Harris performs spectral analysis of second-moment matrix / structure tensor
- By contrast, SIFT inspects the local Hessian of difference images
- Next: Feature description and matching



Reading material: Section 3 and 4.1.1