



Harris Corner Detector

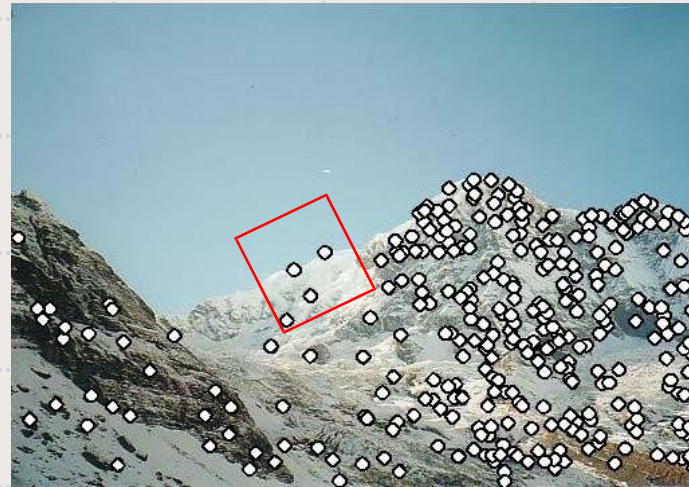
Interest Point Detection

Objective



Local features: main components

- Detection
- Description
- Matching



Application areas

Automate
object tracking

Point matching
for computing
disparity

Stereo
calibration

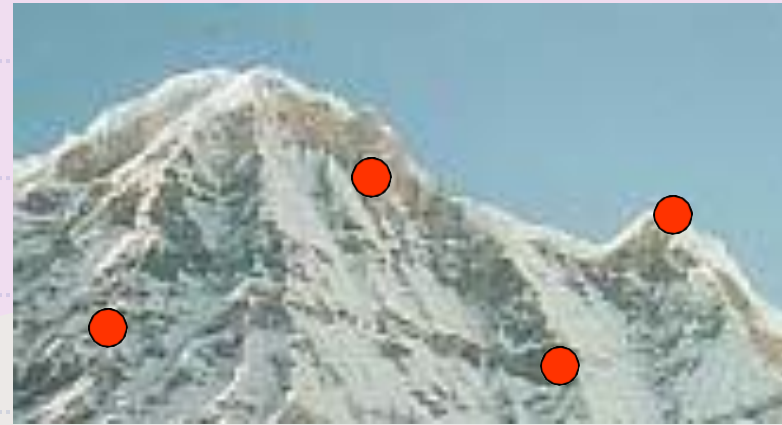
Motion based
segmentation

Recognition

3D object
reconstruction

Robot
navigation

Image retrieval
and indexing

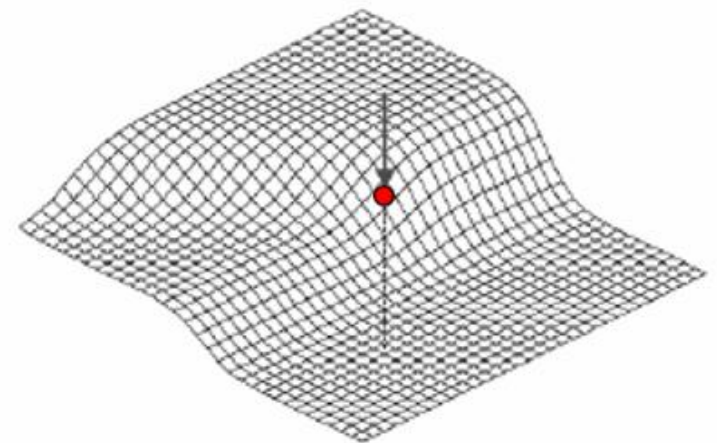
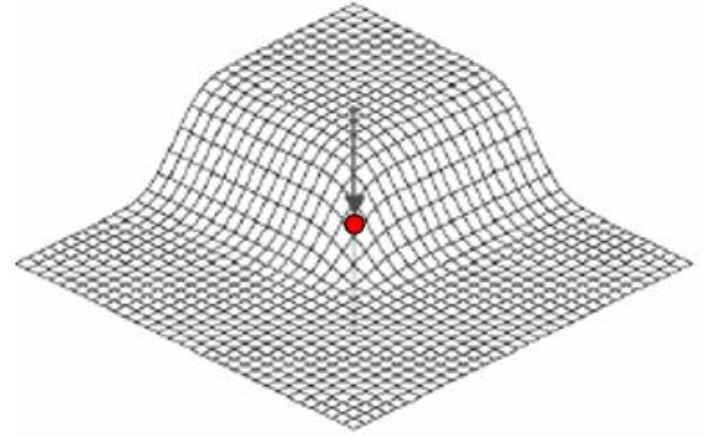


Goal: interest
operator
repeatability

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

What is an interest point

- Expressive texture
- The point at which the direction of the boundary of object changes abruptly
- Intersection point between two or more edge segments



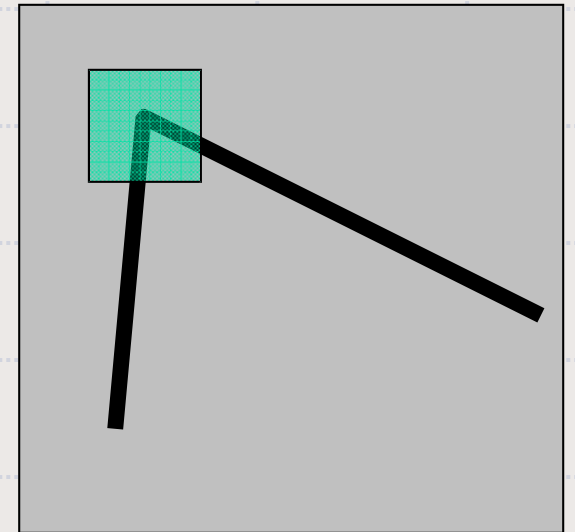


Properties of Interest Point Detectors

- Detect all (or most) true interest points
- No false interest points
- Well localized
- Robust with respect to noise
- Efficient detection

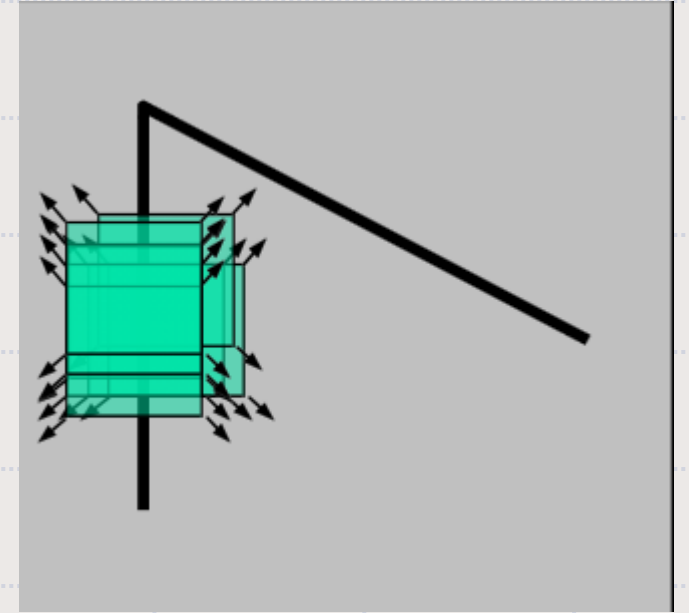
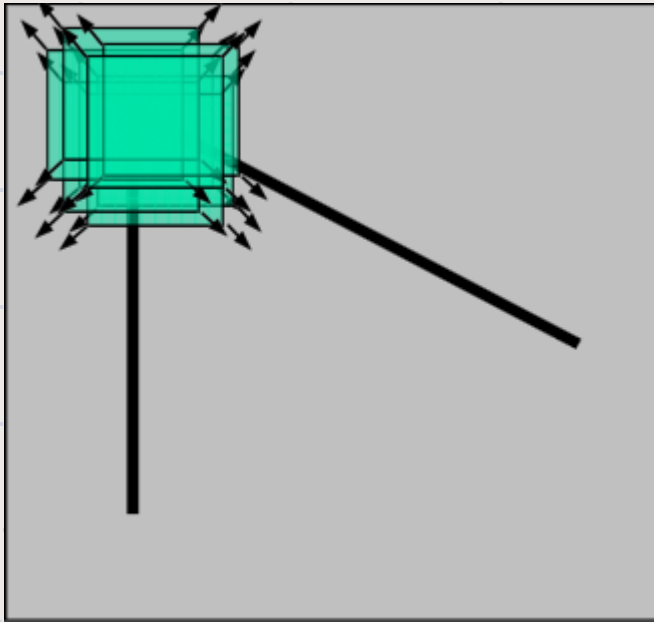
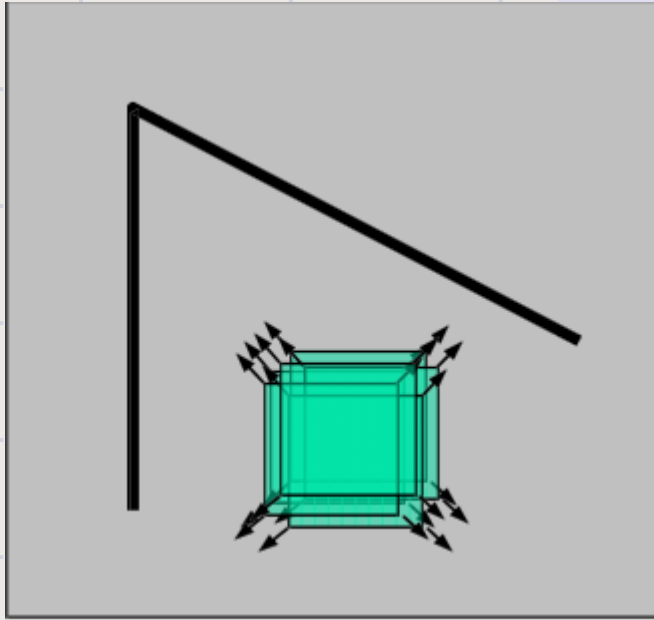
Harris Corner Detector

- Corner point can be recognized in a window
- Shifting a window in any direction should give a large change in intensity



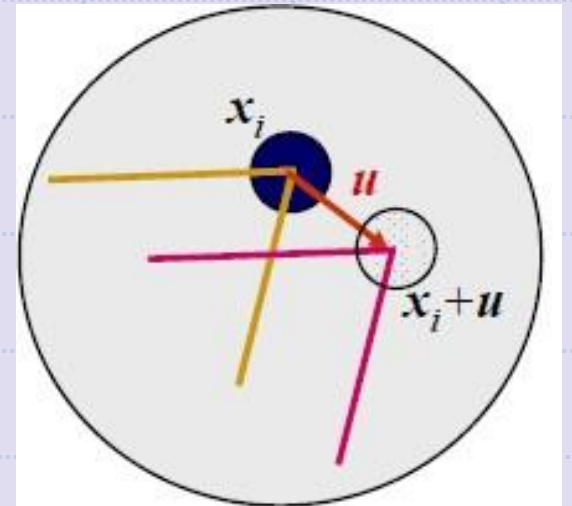
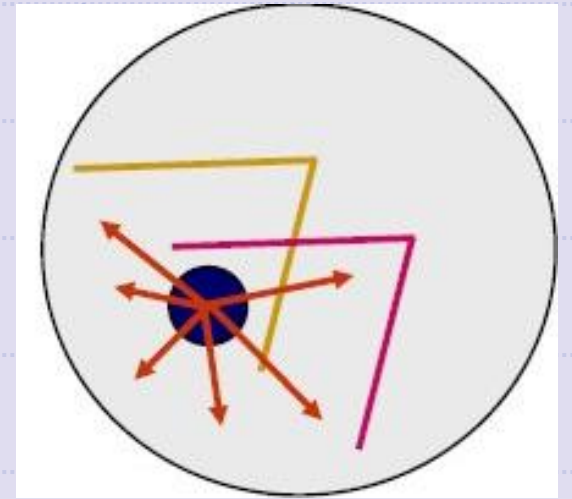
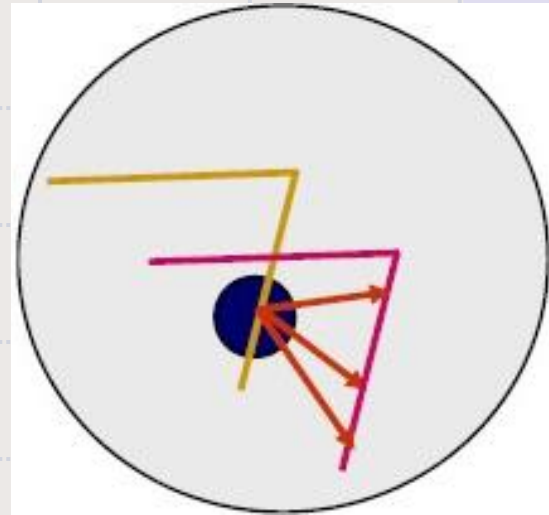
The thought!

- Flat
- Edge
- Corner



Aperture Problem

- Flat
- Edge
- Corner



Correlation

- f = image
- h = Kernel

$$f \otimes h = \sum_k \sum_l f(k, l) h(i + k, j + l)$$

f

f_1	f_2	f_3
f_4	f_5	f_6
f_7	f_8	f_9

\otimes

h

h_1	h_2	h_3
h_4	h_5	h_6
h_7	h_8	h_9

$$\begin{aligned} f * h &= f_1 h_1 + f_2 h_2 + f_3 h_3 \\ &\quad + f_4 h_4 + f_5 h_5 + f_6 h_6 \\ &\quad + f_7 h_7 + f_8 h_8 + f_9 h_9 \end{aligned}$$

Correlation

- Cross correlation

$$f \otimes h = \sum_k \sum_l f(k, l) h(i + k, j + l)$$

- Auto correlation

$$f \otimes f = \sum_k \sum_l f(k, l) f(i + k, j + l)$$

Correlation v/s SSD

minimize $SSD = \sum_k \sum_l (f(k,l) - h(k,l))^2$ Sum of Squares Difference

minimize $SSD = \sum_k \sum_l (\cancel{f(k,l)}^2 - 2h(k,l)\cancel{f(k,l)} + \cancel{h(k,l)}^2)$

$SSD = \sum_k \sum_l (-2h(k,l)f(k,l))$ These terms do not depend on correlation

maximize $SSD = \sum_k \sum_l (2\cancel{h(k,l)}f(k,l))$

maximize $Correlation = \sum_k \sum_l (h(k,l)f(k,l))$

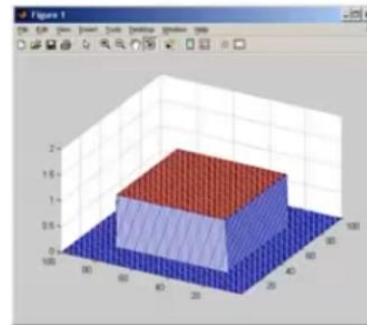
Harris Corner Detector

- Change of intensity for shift (u,v)

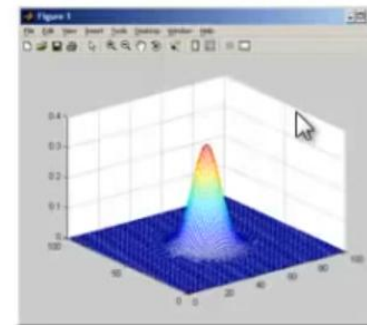
$$E(u,v) = \sum_{x,y} \underbrace{w(x,y)}_{\text{window function}} \underbrace{[I(x+u, y+v) - I(x,y)]}_{\text{shifted intensity}}^2 \underbrace{1}_{\text{intensity}}$$

Auto-correlation

Window functions →

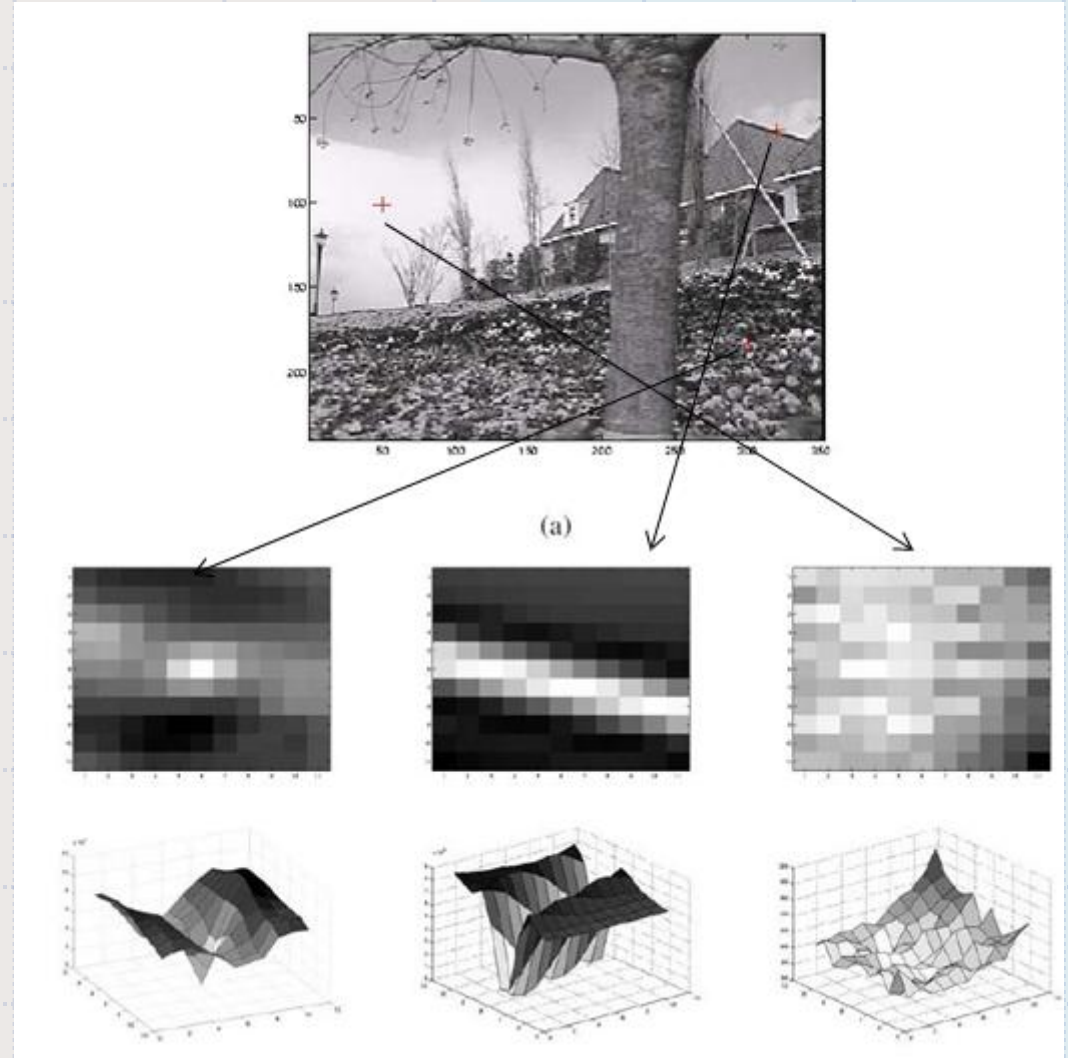


UNIFORM



GAUSSIAN

Auto- Correlation



Taylor Series

$f(x)$ can be represented at point a in terms of its derivatives

$$f(a) + \frac{f'(a)}{1!}(x-a) + \frac{f''(a)}{2!}(x-a)^2 + \frac{f^{(3)}(a)}{3!}(x-a)^3 + \dots$$

Harris Corner Detector

$$E(u, v) = \sum_{x,y} \underbrace{w(x, y)}_{\text{window function}} \underbrace{[I(x+u, y+v) - I(x, y)]}_{\text{shifted intensity}} \underbrace{]}_{\text{intensity}}^2$$

$$E(u, v) = \sum_{x,y} \underbrace{w(x, y)}_{\text{window function}} \underbrace{[I(x, y) + uI_x + vI_y - I(x, y)]}_{\text{shifted intensity}} \underbrace{]}_{\text{intensity}}^2 \quad \text{Taylor Series}$$

$$E(u, v) = \sum_{x,y} w(x, y) [uI_x + vI_y]^2$$

$$E(u, v) = \sum_{x,y} w(x, y) \left[(u \quad v) \begin{pmatrix} I_x \\ I_y \end{pmatrix} \right]^2$$

$$E(u, v) = \sum_{x,y} w(x, y) (u \quad v) \begin{pmatrix} I_x \\ I_y \end{pmatrix} (I_x \quad I_y) \begin{pmatrix} u \\ v \end{pmatrix}$$

$$E(u, v) = (u \quad v) \left[\sum_{x,y} w(x, y) \begin{pmatrix} I_x \\ I_y \end{pmatrix} (I_x \quad I_y) \right] \begin{pmatrix} u \\ v \end{pmatrix} \quad E(u, v) = (u \quad v) M \begin{pmatrix} u \\ v \end{pmatrix}$$

Harris Corner Detector

$E(u,v)$ is an equation of an ellipse

Let λ_1 and λ_2 be eigenvalues of M

$$E(u,v) = \begin{pmatrix} u & v \end{pmatrix} M \begin{pmatrix} u \\ v \end{pmatrix}$$

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

Eigen Vector and Eigen Values

The eigen vector, x , of a matrix A is a special vector, with the following property

$$Ax = \lambda x$$

Where λ is called eigen value

To find eigen values of a matrix A first find the roots of:

$$\det(A - \lambda I) = 0$$

Then solve the following linear system for each eigen value to find corresponding eigen vector

$$(A - \lambda I)x = 0$$

Harris Corner Detector

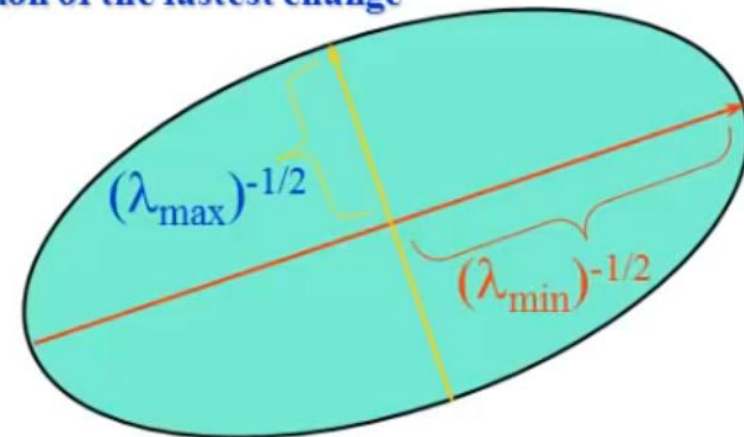
$E(u,v)$ is an equation of an ellipse

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

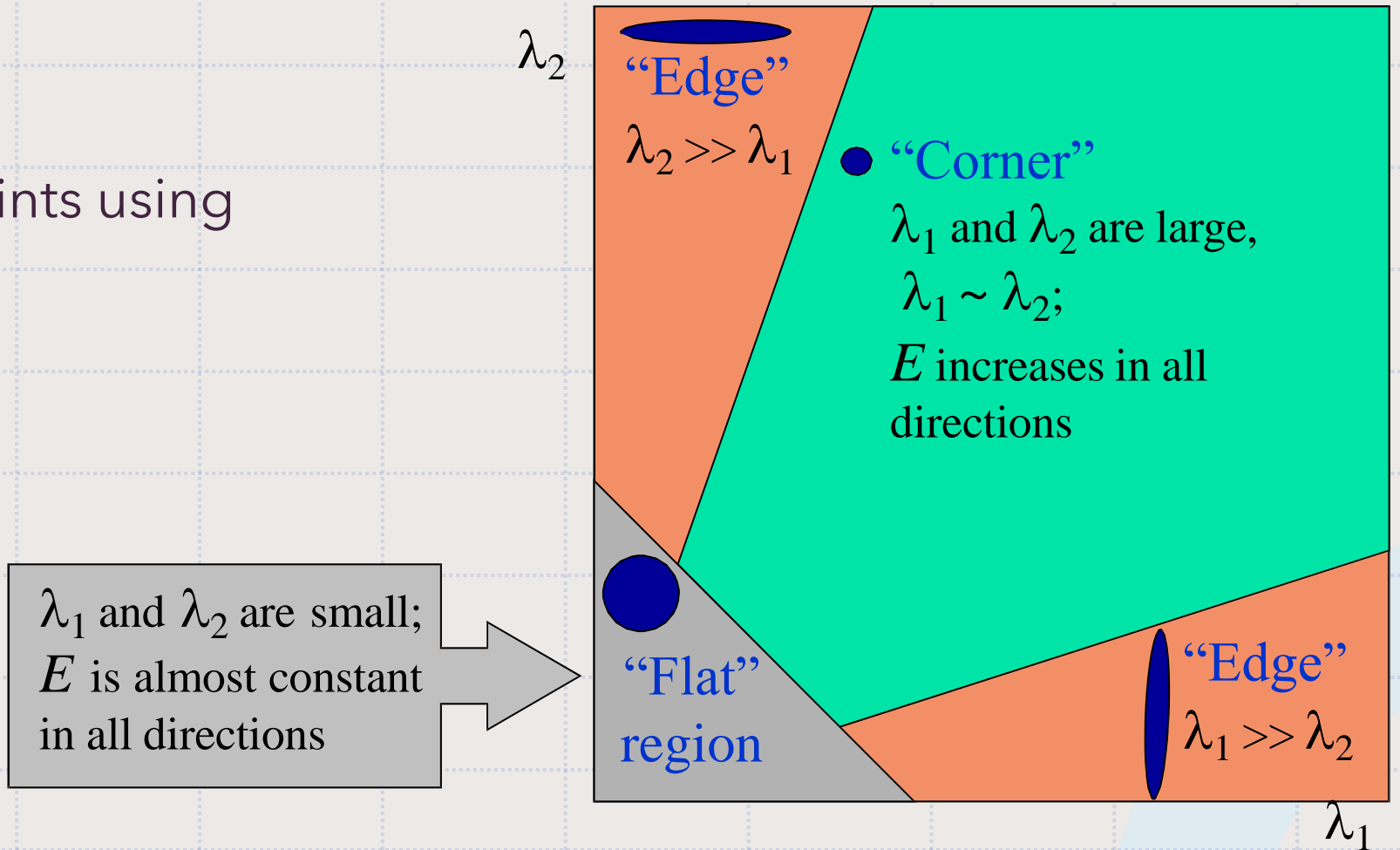
direction of the fastest change



direction of the slowest change

Harris Corner Detector

Classification of image points using eigenvalues of M



Harris Corner Detector

Measure of cornerness in terms of λ_1 and λ_2

$$R = \det D - k(\text{trace } D)^2$$

$$R = \lambda_1 \lambda_2 - k(\lambda_1 + \lambda_2)^2$$

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

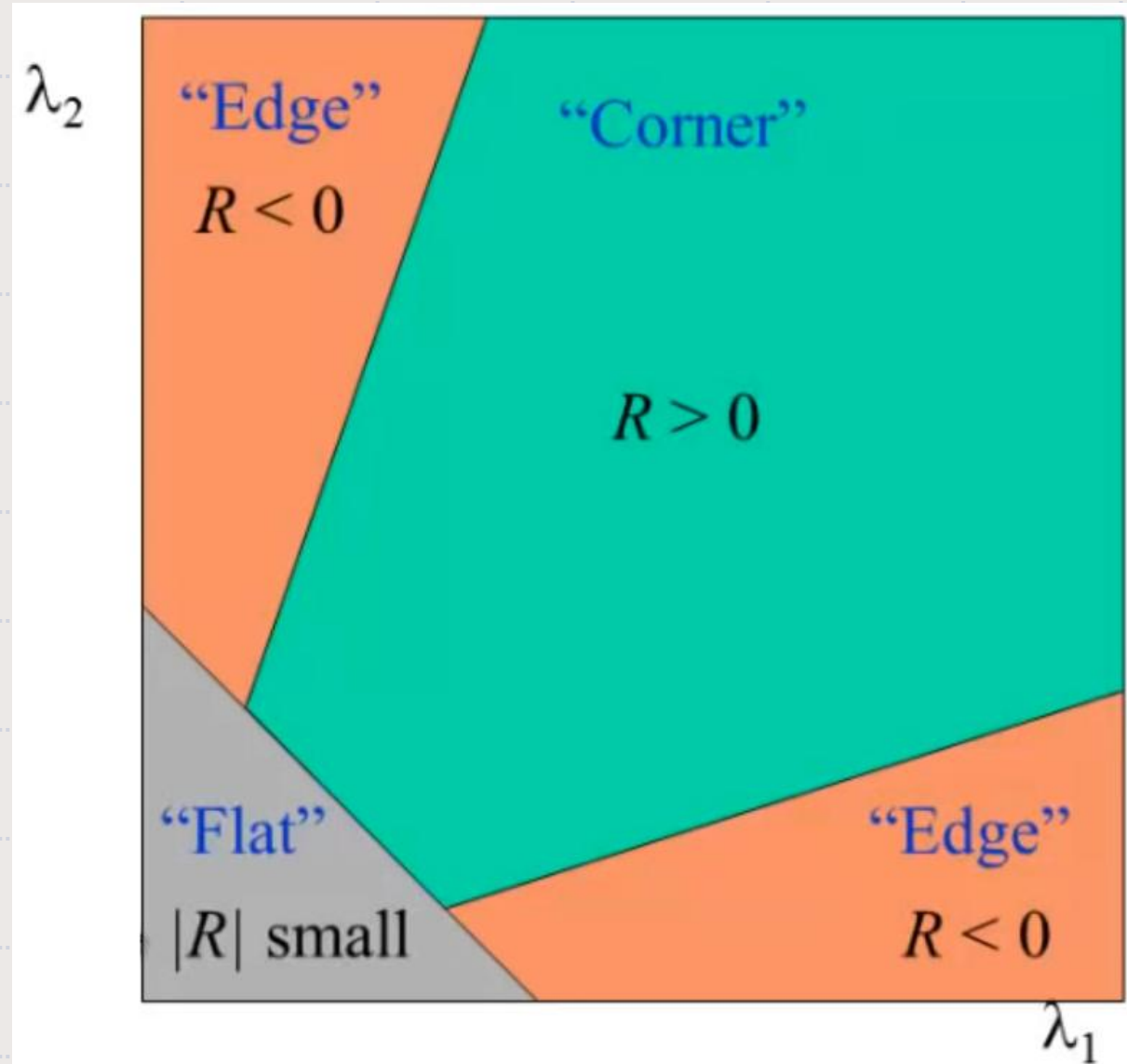
Harris Corner Detector

R depends only on eigenvalues of M

R is large for a corner

R is negative with large magnitude for an edge

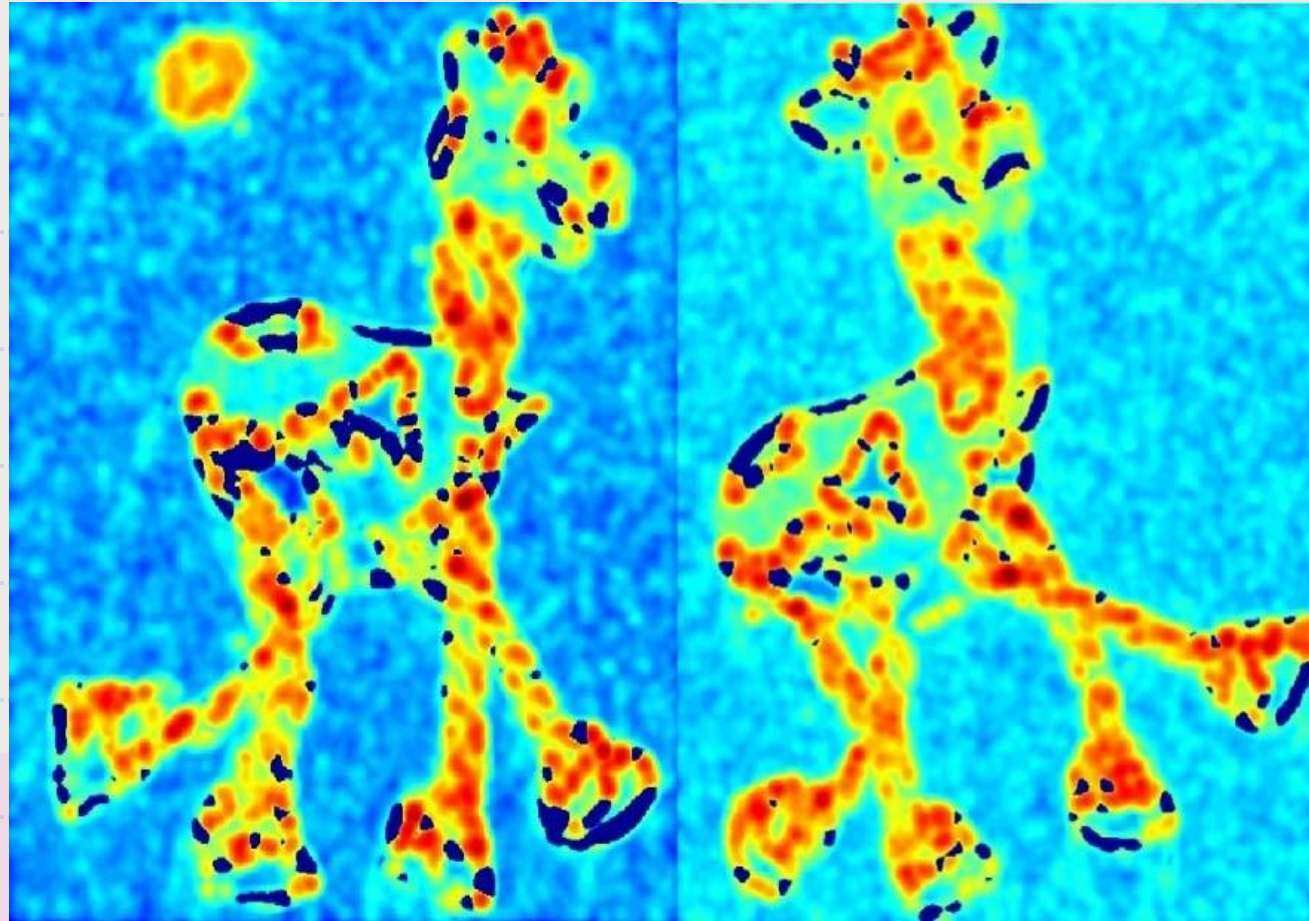
$|R|$ is small for a flat region



Harris Corner Detector

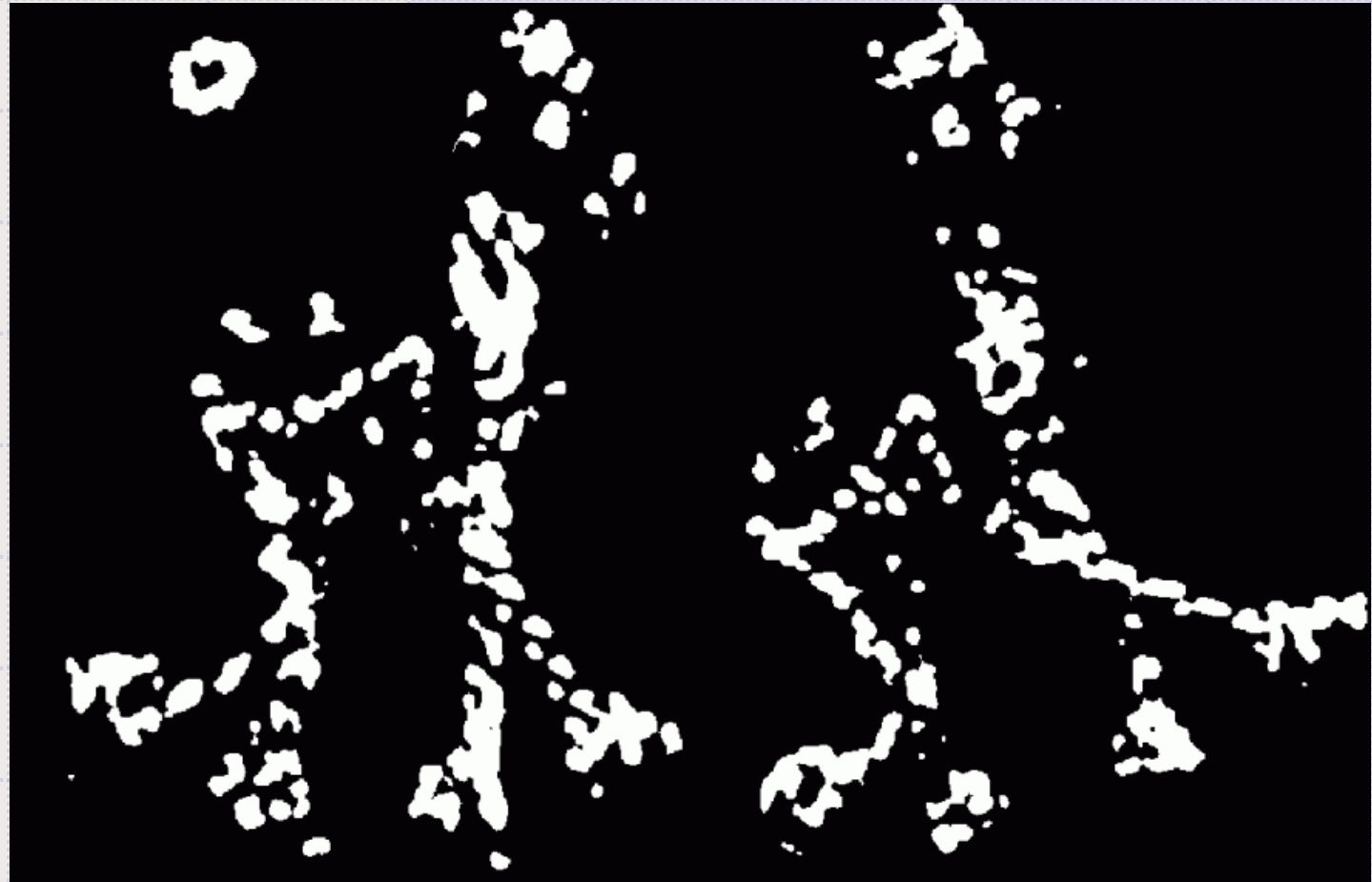


Harris Corner Detector



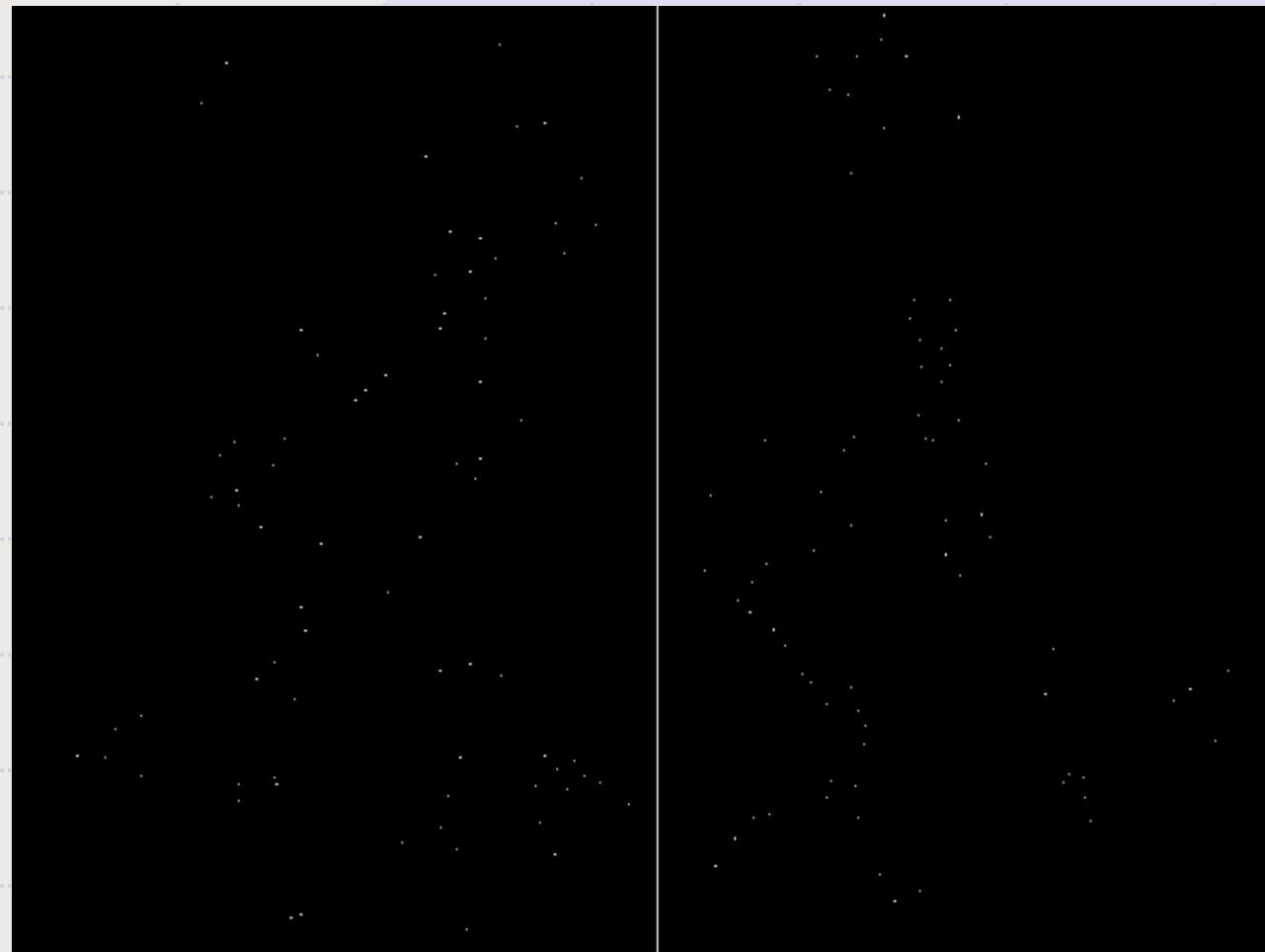
Harris Corner Detector

Find points with large corner response: $R > \text{threshold}$



Harris Corner Detector

Take only the points of local maxima of R



Harris Corner Detector



Other Version of Harris Detectors

$$R = \lambda_1 - \alpha \lambda_2$$

Triggs

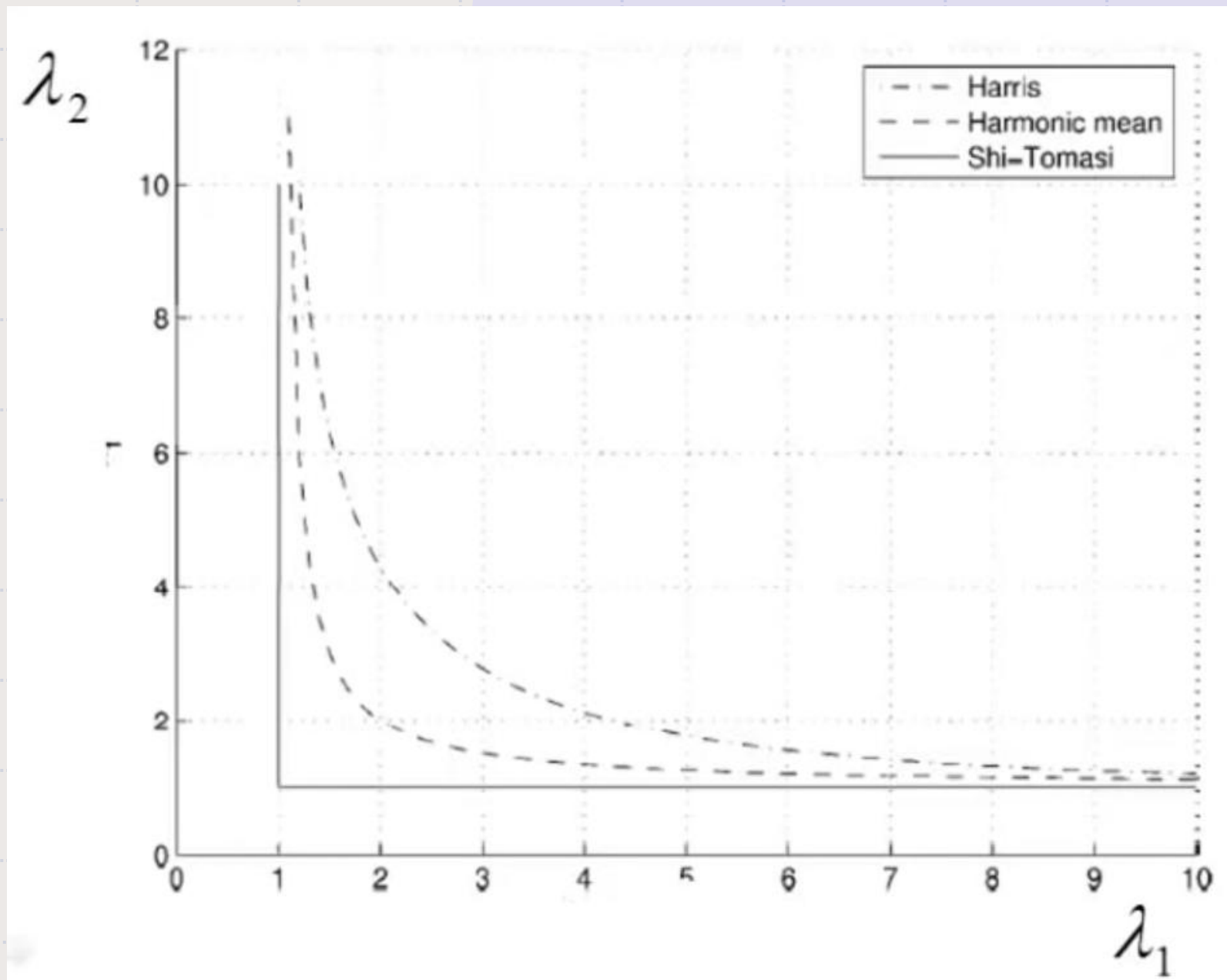
$$R = \frac{\det(D)}{\text{trace}(D)} = \frac{\lambda_1 \lambda_2}{\lambda_1 + \lambda_2}$$

Szeliski (Harmonic mean)

$$R = \lambda_1$$

Shi-Tomasi

Performance analysis



Algorithm

- Compute horizontal and vertical derivatives of image I_x and I_y .
- Compute three images corresponding to three terms in matrix M .
- Convolve these three images with a larger Gaussian (window).
- Compute scalar cornerness value using one of the R measures.
- Find local maxima above some threshold as detected interest points.

Practical

Write a program for Corner detection using:

1. Harris
2. Triggs
3. Szeliski
4. Shi-Tomasi