

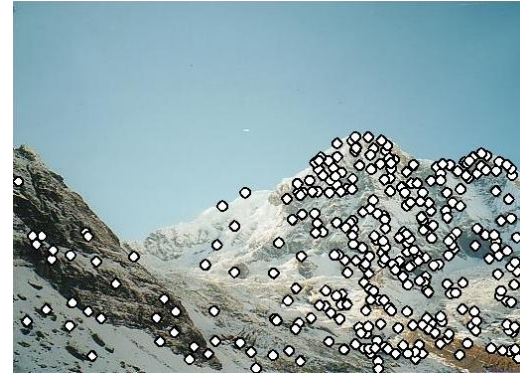


# Interest Point Detection

---

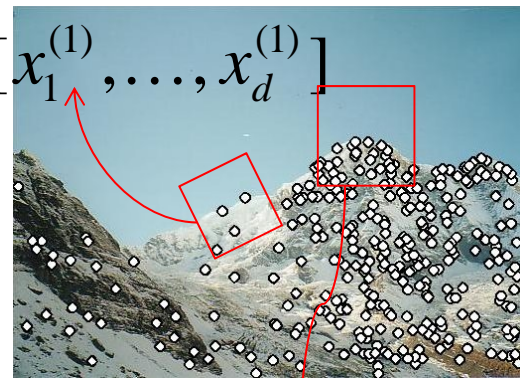
# Local features: main components

1) Detection: Identify the interest points



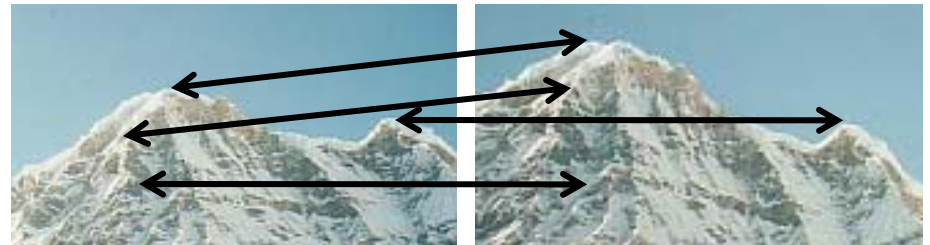
2) Description :Extract feature vector descriptor surrounding each interest point.

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



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

3) Matching: Determine correspondence between descriptors in two views





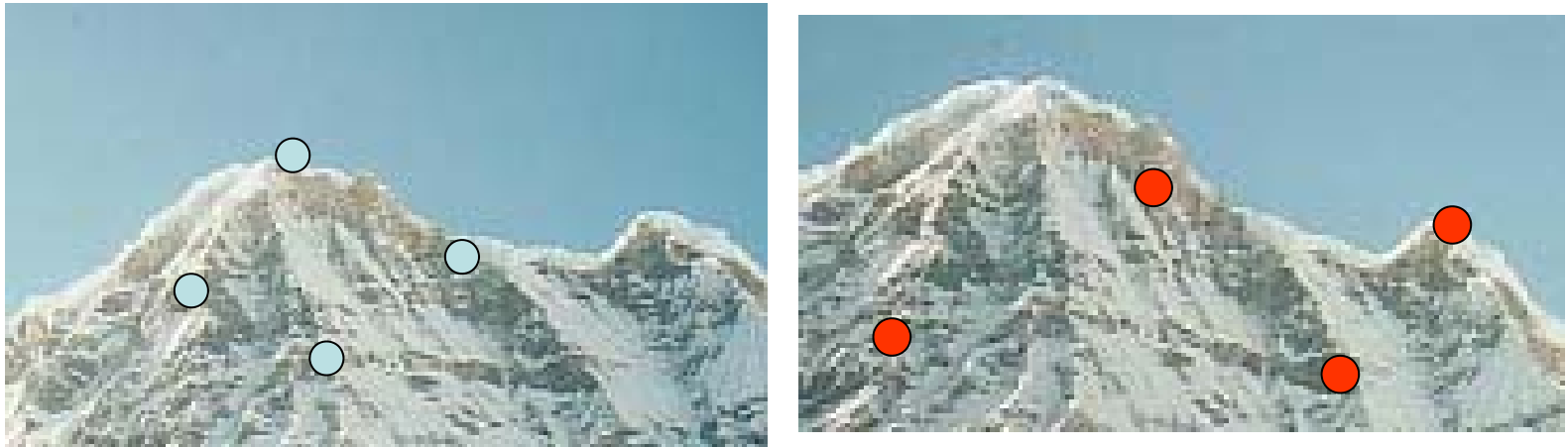
# Where can we use it?

---

- Automate object tracking
- Point matching for computing disparity
- Stereo calibration
  - Estimation of fundamental matrix
- 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.

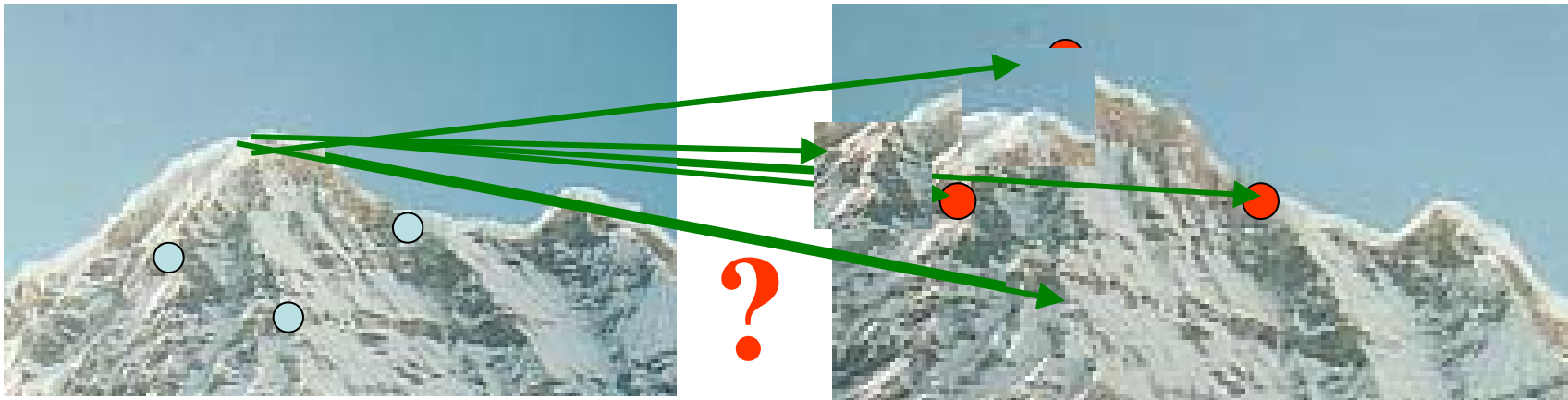


No chance to find true matches!

- Yet we have to be able to run the detection procedure *independently* per image.

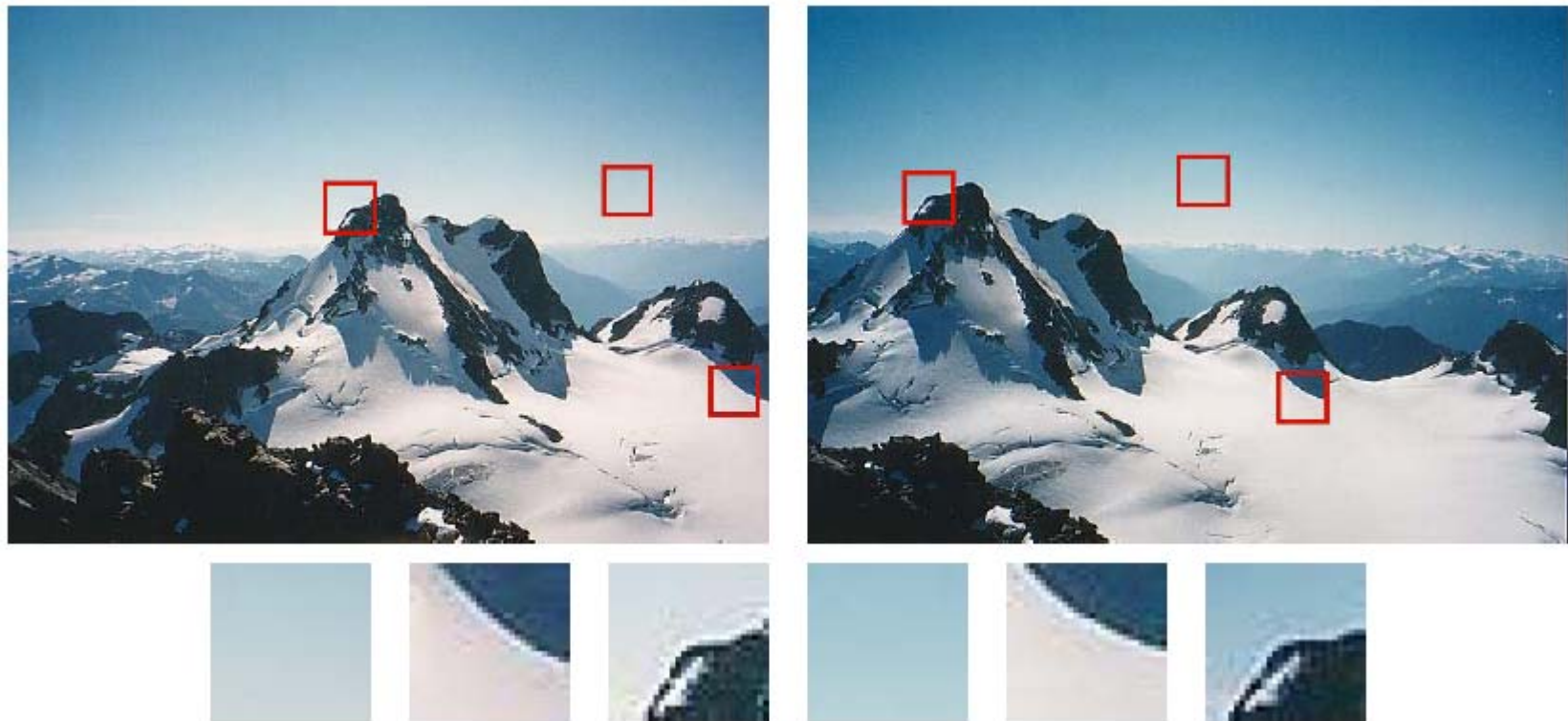
# Goal: descriptor distinctiveness

- We want to be able to reliably determine which point goes with which.



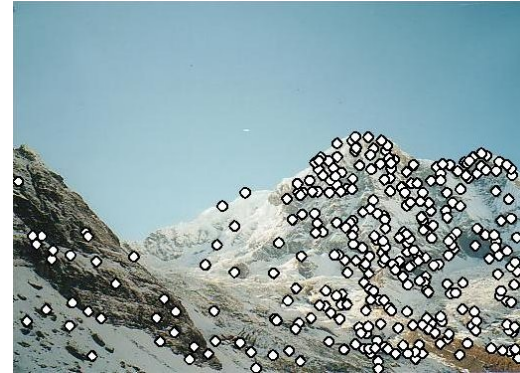
- Must provide some **invariance** to **geometric** and **photometric** differences between the two views.

Some patches can be localized or matched with higher accuracy than others.



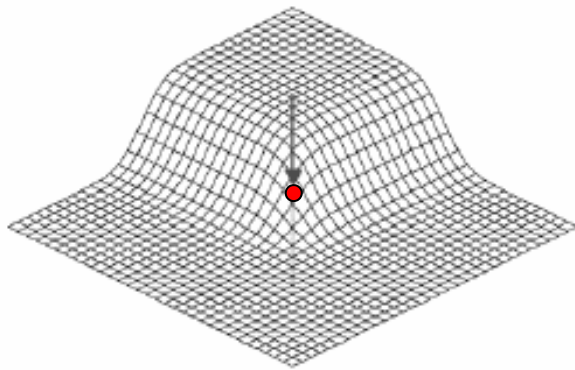
# Local features: main components

- 1) Detection: Identify the interest points
- 2) Description: Extract vector feature descriptor surrounding each interest point.
- 3) Matching: Determine correspondence between descriptors in two views



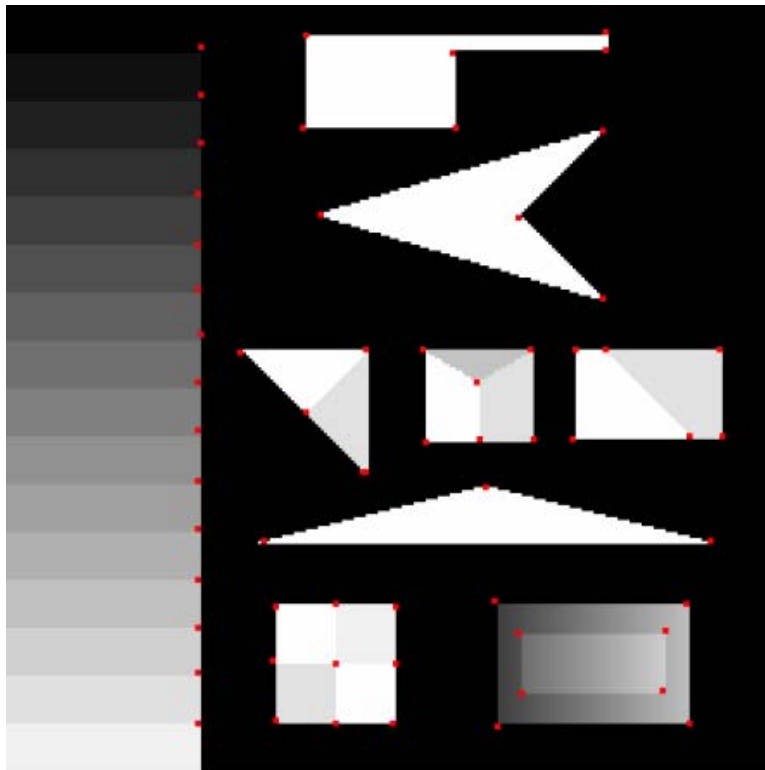
# What is an interest point

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





# Synthetic & Real Interest Points



Corners are indicated in red

# 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



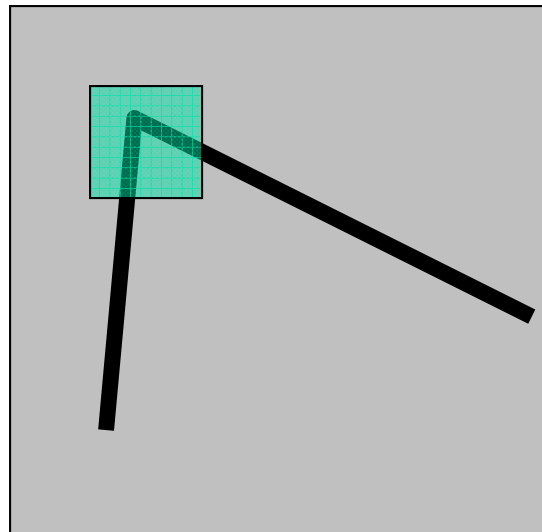
# Possible Approaches to Corner Detection

---

- Based on brightness of images
  - Usually image derivatives
- Based on boundary extraction
  - First step edge detection
  - Curvature analysis of edges

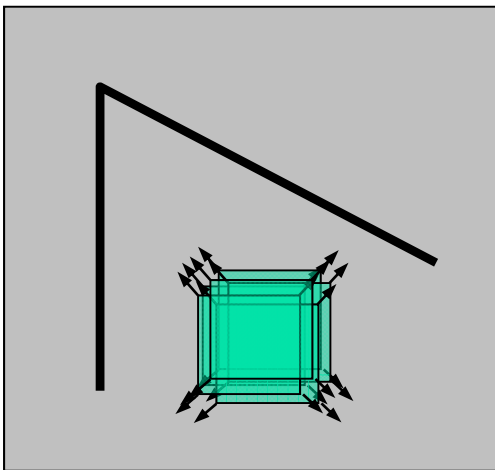
# Harris Corner Detector

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

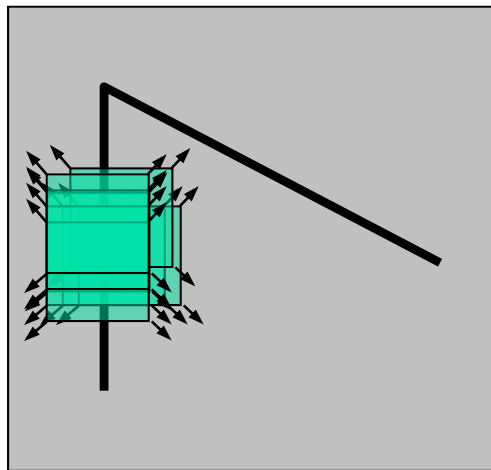


C.Harris, M.Stephens. “A Combined Corner and Edge Detector”. 1988

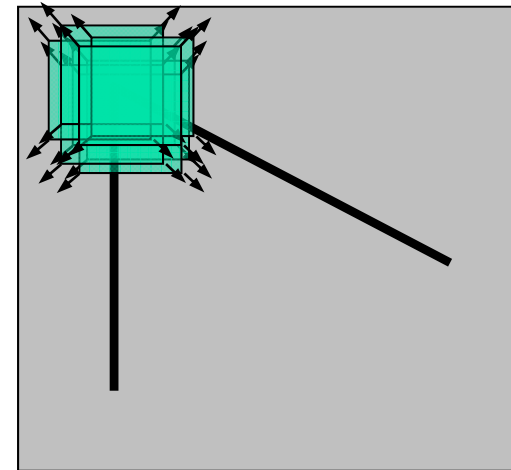
# Basic Idea



“flat” region:  
no change in  
all directions

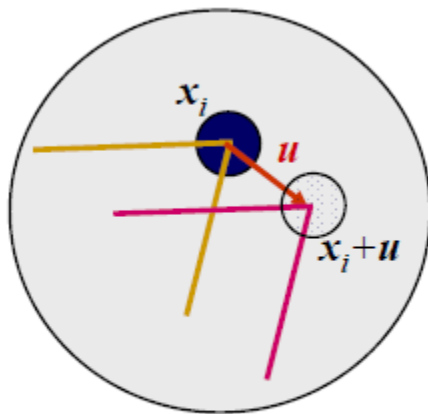


“edge”:  
no change along  
the edge direction



“corner”:  
significant change  
in all directions

# Aperture Problem



(a)



# Correlation

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

$f$  = Image

$h$  = Kernel

$f$

$f_1$	$f_2$	$f_3$
$f_4$	$f_5$	$f_6$
$f_7$	$f_8$	$f_9$

$\otimes$

$h$

$h_1$	$h_2$	$h_3$
$h_4$	$h_5$	$h_6$
$h_7$	$h_8$	$h_9$

$\rightarrow$

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



# Correlation

---

$$f \otimes h = \sum_k \sum_l f(k, l) h(i + k, j + l) \quad \text{Cross correlation}$$

$$f \otimes f = \sum_k \sum_l f(k, l) f(i + k, j + l) \quad \text{Auto correlation}$$





# Correlation Vs SSD

$$\underset{\text{minimize}}{SSD} = \sum_k \sum_l (f(k, l) - h(i + k, j + l))^2 \quad \text{Sum of Squares Difference}$$

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

$$\underset{\text{minimize}}{SSD} = \sum_k \sum_l (-2h(i + k, j + l)f(k, l))$$

$$\underset{\text{maximize}}{SSD} = \sum_k \sum_l (2h(i + k, j + l)f(k, l))$$

$$\underset{\text{maximize}}{Correlation} = \sum_k \sum_l (h(i + k, j + l)f(k, l))$$

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

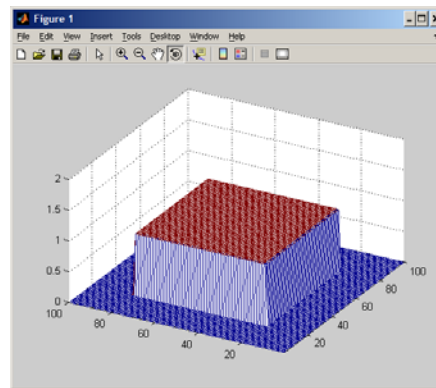
# Mathematics of Harris Detector

- Change of intensity for the shift (u,v)

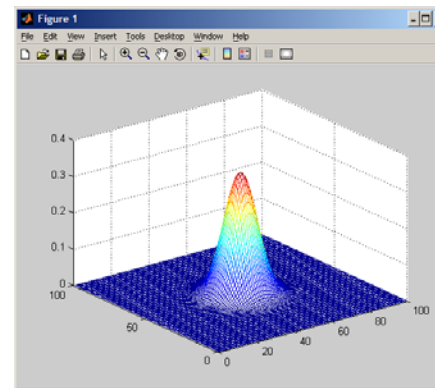
$$E(u, v) = \sum_{x, y} \underbrace{[I(x + u, y + v)]}_{\text{shifted intensity}} - \underbrace{I(x, y)}_{\text{intensity}}]^2$$

Auto-correlation

Window functions →

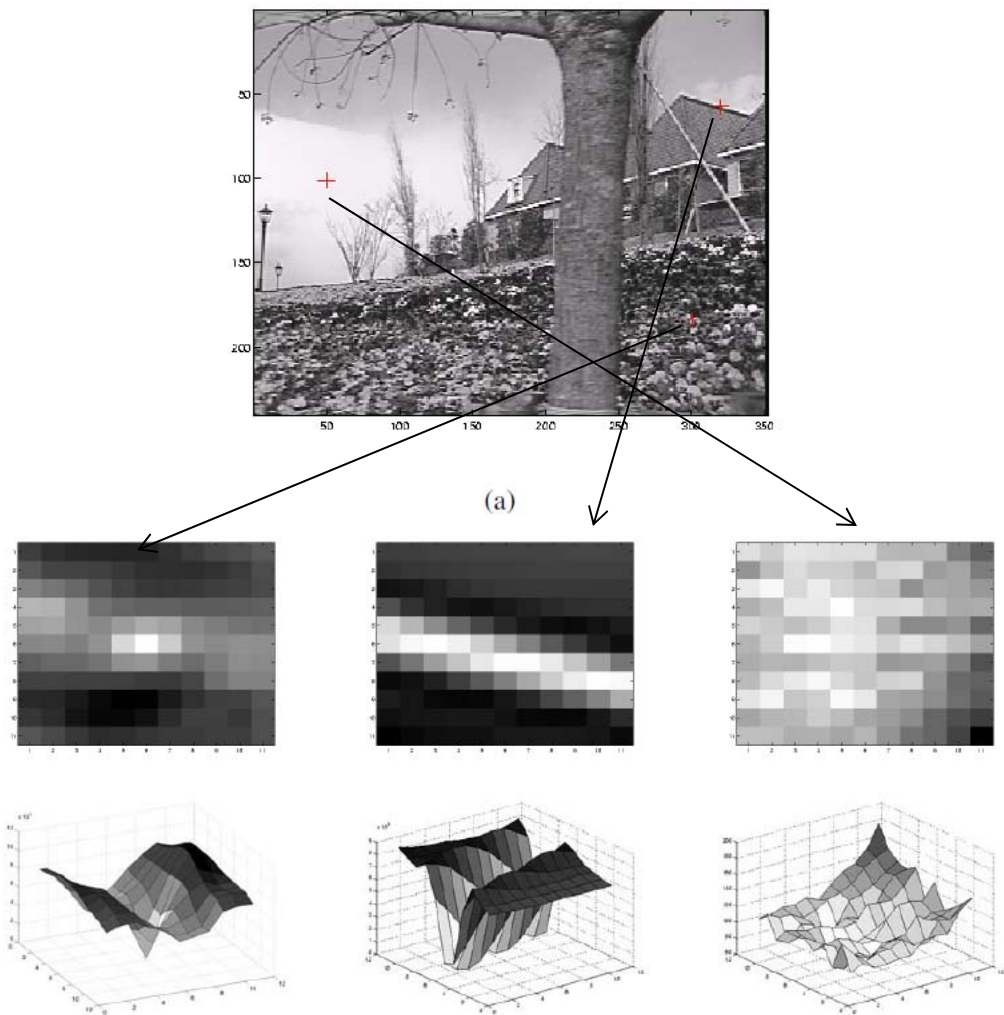


UNIFORM



GAUSSIAN

# Auto-Correlation





# Taylor Series

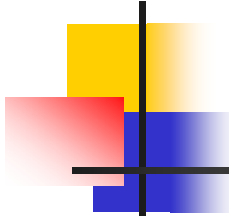
---

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

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

# Mathematics of Harris

## Detector



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

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

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

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

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

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

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

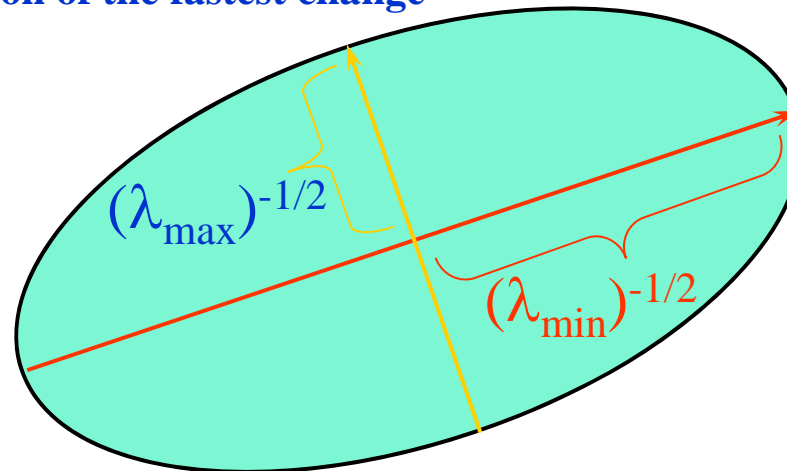
# Mathematics of Harris Detector

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

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

- $E(u, v)$  is an equation of an ellipse, where  $M$  is the covariance
- Let  $\lambda_1$  and  $\lambda_2$  be eigenvalues of  $M$

direction of the fastest change



direction of the  
slowest change

# Eigen Vectors and Eigen Values

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

$$Ax = \lambda x \quad \text{Where } \lambda \text{ is called eigen value}$$

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

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

# Example

$$A = \begin{bmatrix} -1 & 2 & 0 \\ 0 & 3 & 4 \\ 0 & 0 & 7 \end{bmatrix}$$

Eigen Values

$$\lambda_1 = 7, \lambda_2 = 3, \lambda_3 = -1$$

$$\mathbf{x}_1 = \begin{bmatrix} 1 \\ 4 \\ 4 \end{bmatrix}, \mathbf{x}_2 = \begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix}, \mathbf{x}_3 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

Eigen Vectors



# Eigen Values

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

$$\det\left(\begin{bmatrix} -1 & 2 & 0 \\ 0 & 3 & 4 \\ 0 & 0 & 7 \end{bmatrix} - \lambda \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}\right) = 0$$

$$\det\left(\begin{bmatrix} -1-\lambda & 2 & 0 \\ 0 & 3-\lambda & 4 \\ 0 & 0 & 7-\lambda \end{bmatrix}\right) = 0$$

$$(-1-\lambda)((3-\lambda)(7-\lambda)-0) = 0$$

$$(-1-\lambda)(3-\lambda)(7-\lambda) = 0$$

$$\lambda = -1, \quad \lambda = 3, \quad \lambda = 7$$

# Eigen Vectors

$$\lambda = -1$$

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

$$\begin{pmatrix} \begin{bmatrix} -1 & 2 & 0 \\ 0 & 3 & 4 \\ 0 & 0 & 7 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 & 2 & 0 \\ 0 & 4 & 4 \\ 0 & 0 & 8 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

$$0 + 2x_2 + 0 = 0$$

$$0 + 4x_2 + 4x_3 = 0$$

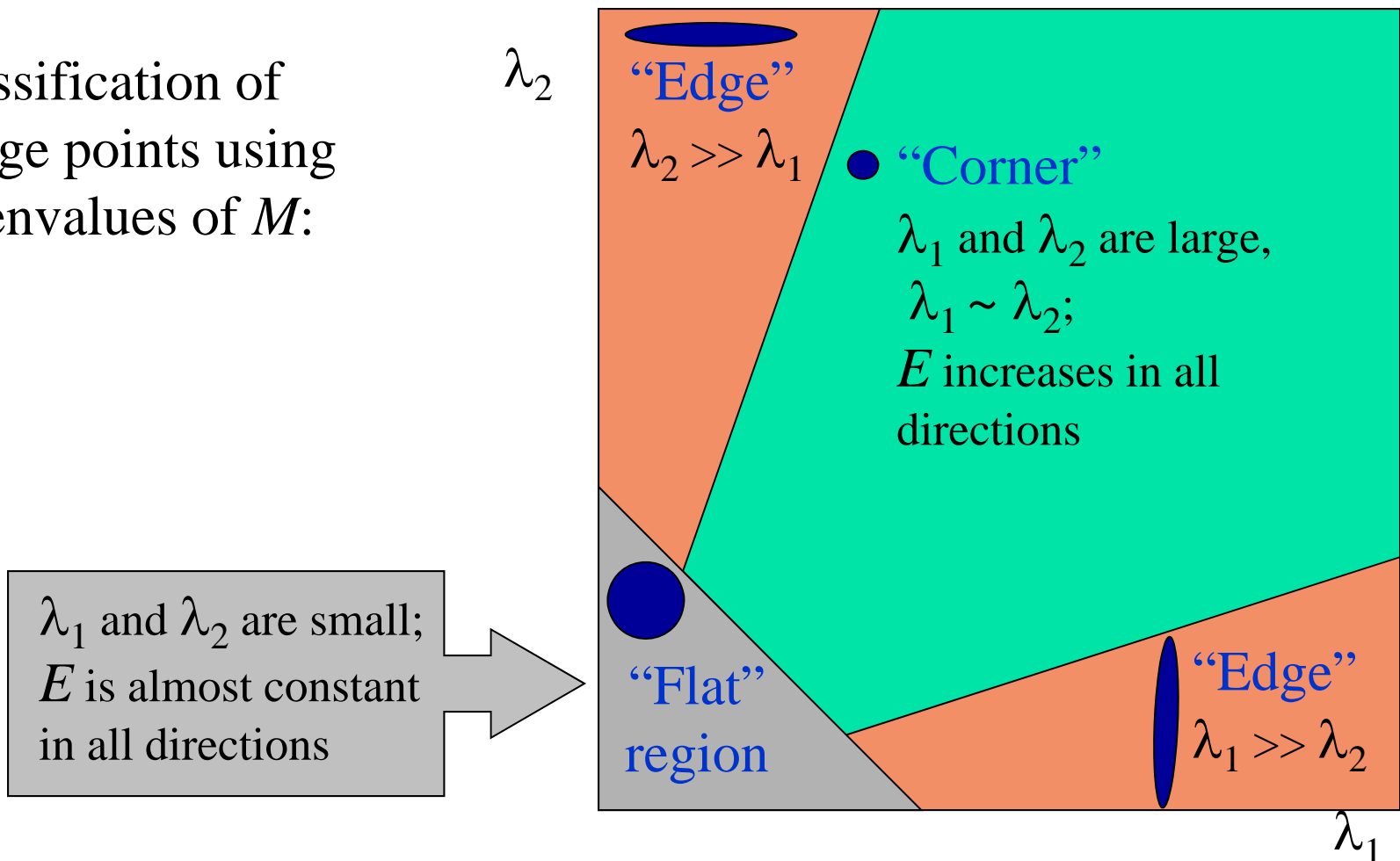
$$0 + 0 + 8x_3 = 0$$

$$x_1 = 1, \quad x_2 = 0, \quad x_3 = 0$$

$$\mathbf{x}_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

# Mathematics of Harris Detector

Classification of  
image points using  
eigenvalues of  $M$ :





# Mathematics of Harris Detector

---

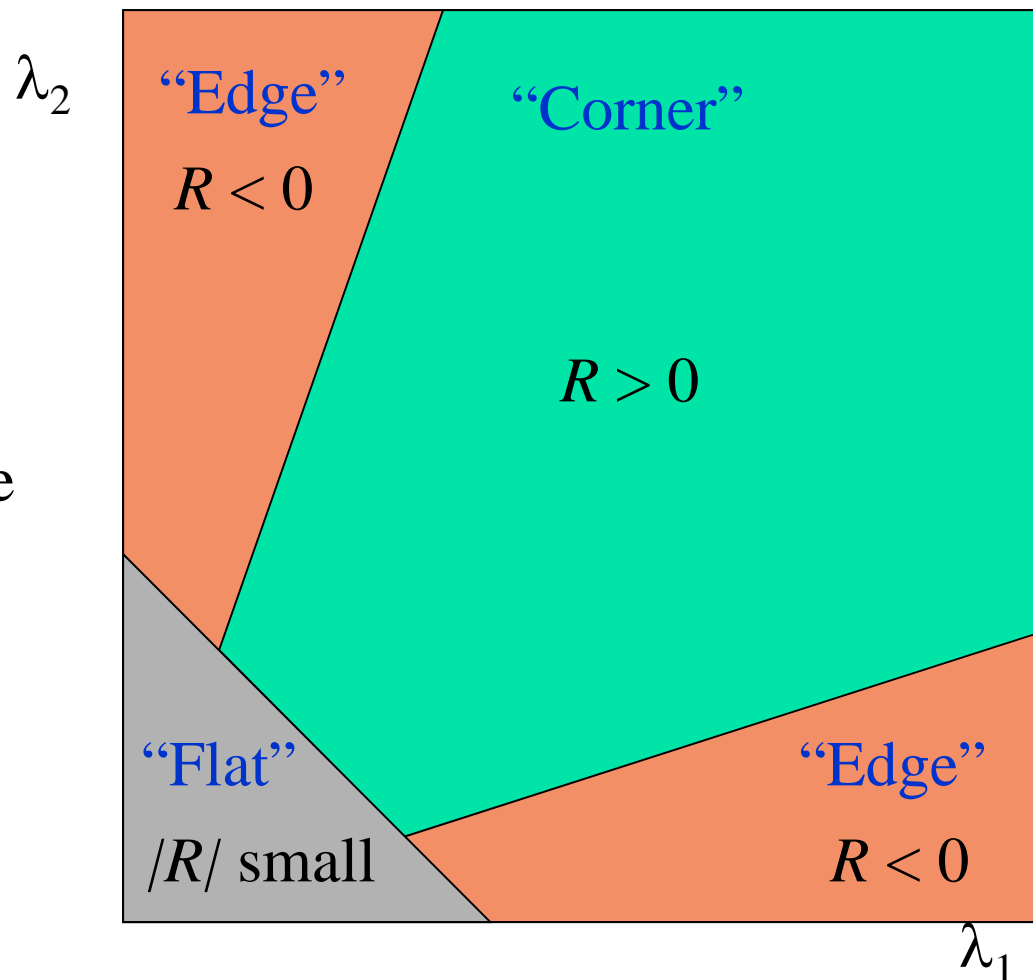
- Measure of corneriness in terms of  $\lambda_1, \lambda_2$

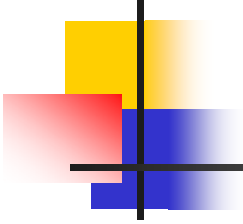
$$M = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

$$R = \det M - k(\text{trace} M)^2 \qquad R = \lambda_1 \lambda_2 - k(\lambda_1 + \lambda_2)^2$$

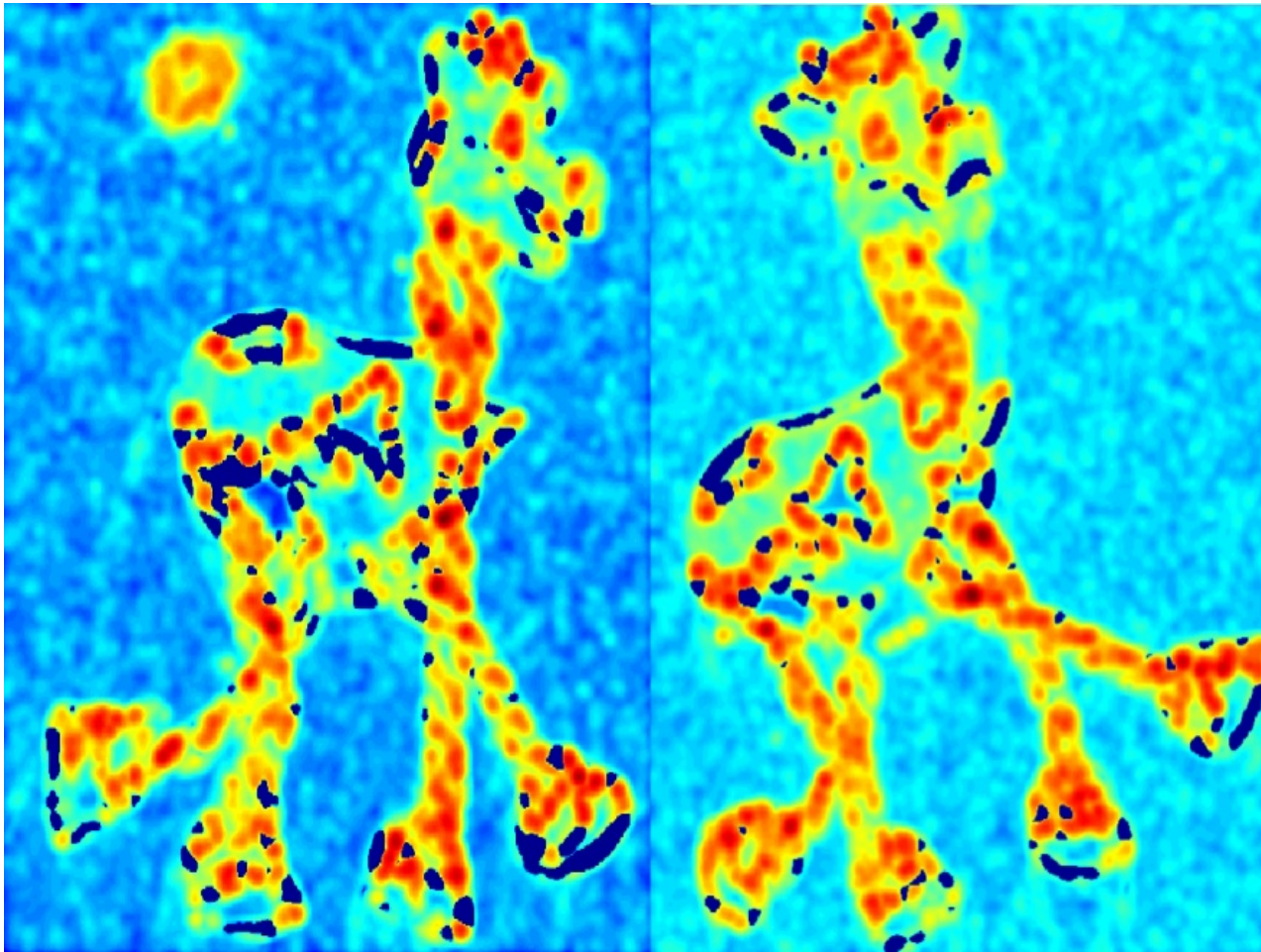
# Mathematics of Harris Detector

- $R$  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

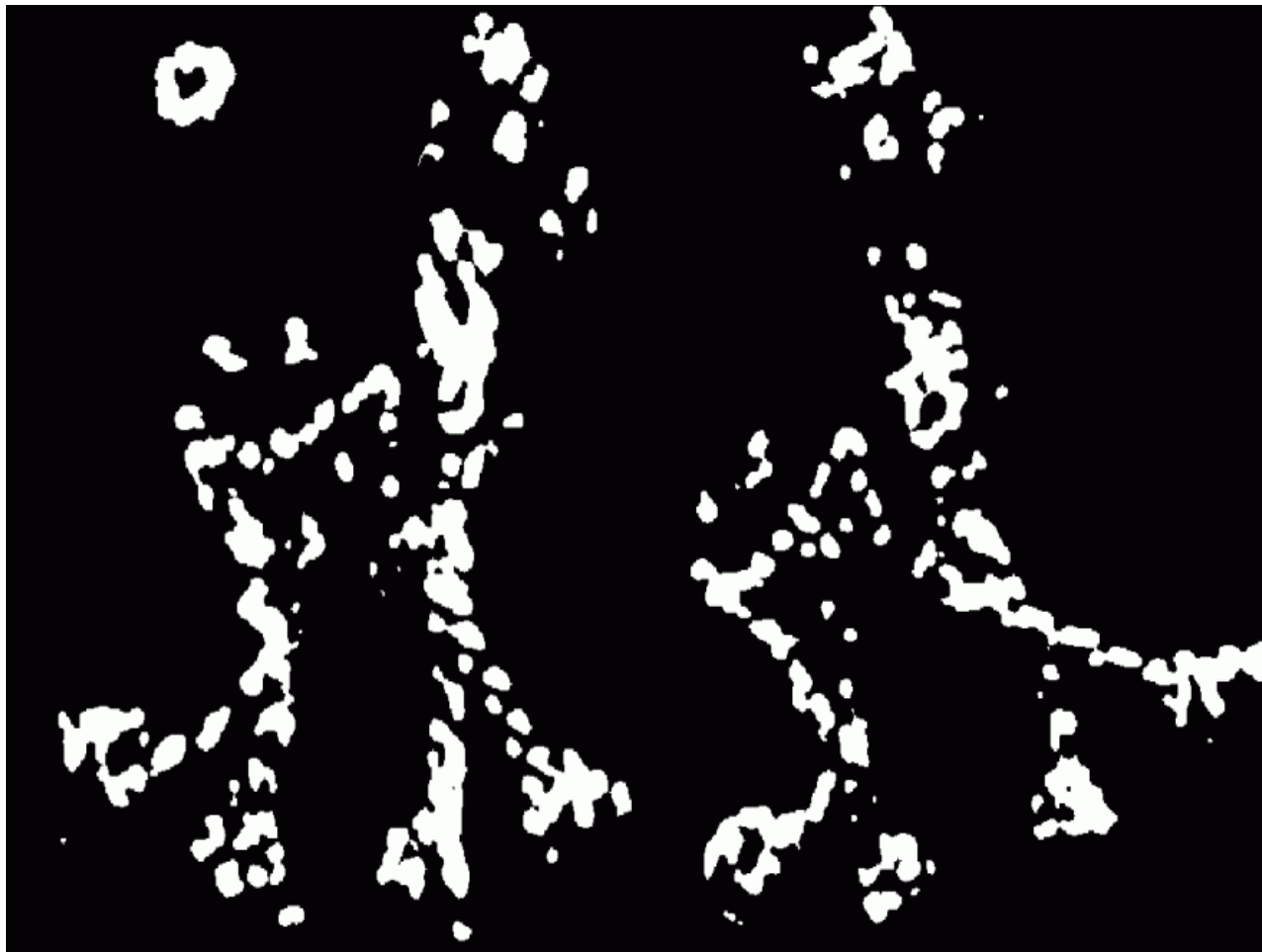




## Compute corner response



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



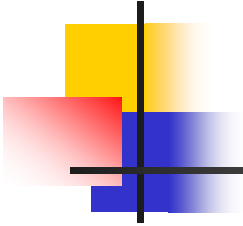




Take only the points of local maxima of  $R$



If pixel value is greater than its neighbors then it is a local maxima.





# Other Version of Harris Detectors

---

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

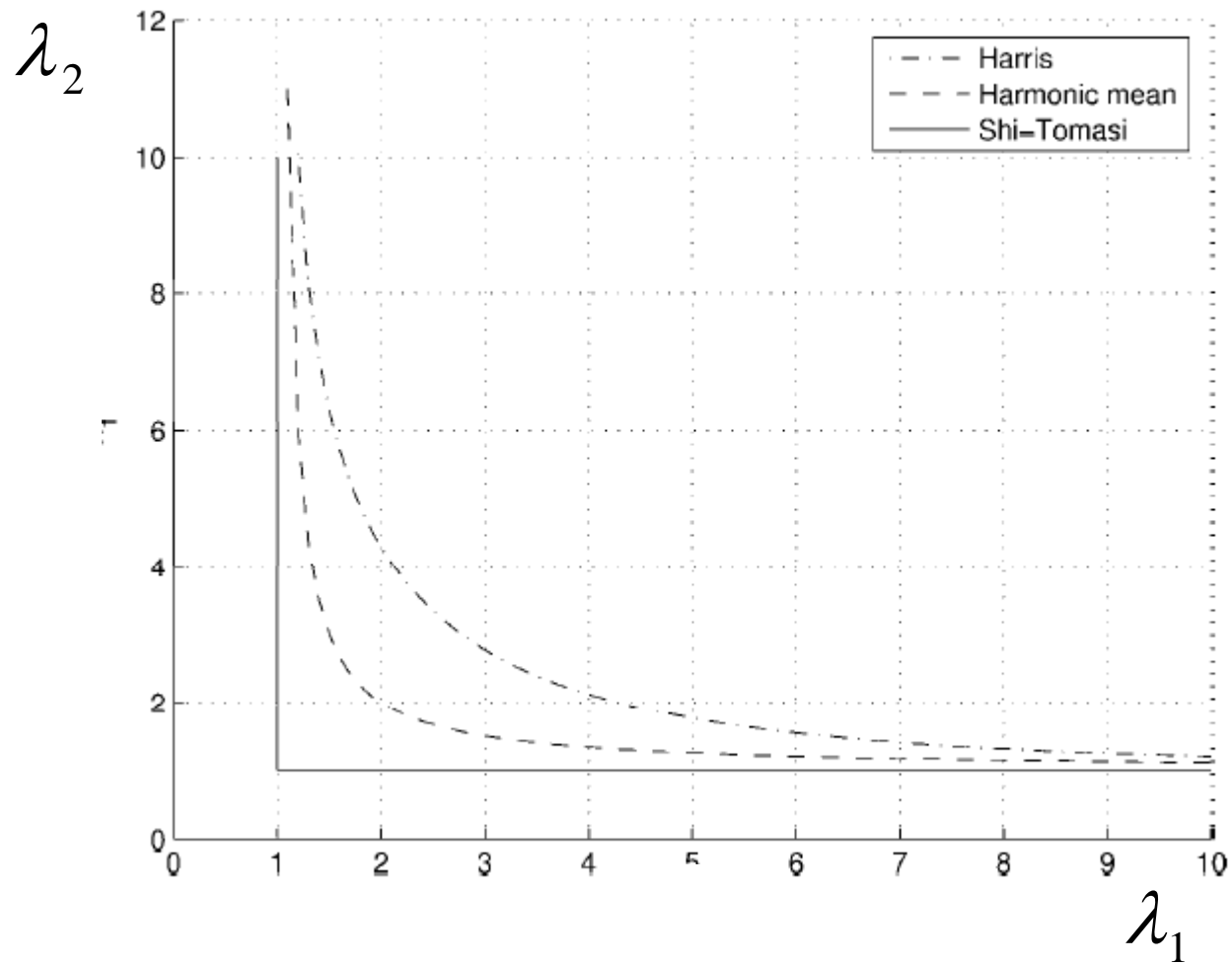
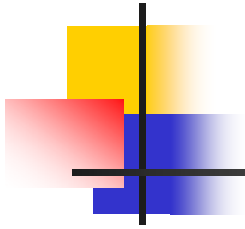
**Triggs**

$$R = \frac{\det(M)}{\text{trace}(M)_1} = \frac{\lambda_1 \lambda_2}{\lambda_1 + \lambda_2}$$

**Szeliski** (Harmonic mean)

$$R = \lambda_1$$

**Shi-Tomasi**





# 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.