

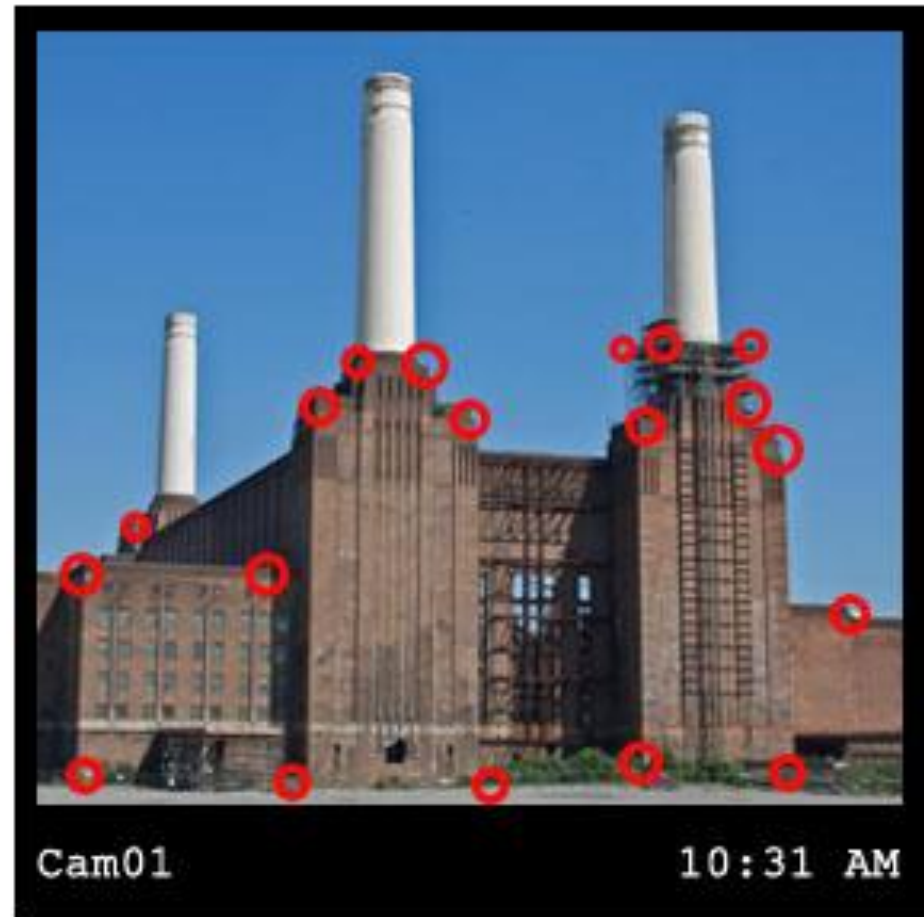
COMPUTER VISION LECTURE 8 – CORNER DETECTION

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2018-09-28

Cam01

10:31 AM

A: Original image



B: Detected image

WHAT WE WILL LEARN TODAY

- Intro to Features
- Keypoint localization
 - Harris corner detector



Some background reading:

Rick Szeliski, Chapter 4.1.1; David Lowe, IJCV 2004

Problem 1:

- Detect the same point *independently* in both images



No chance to match!

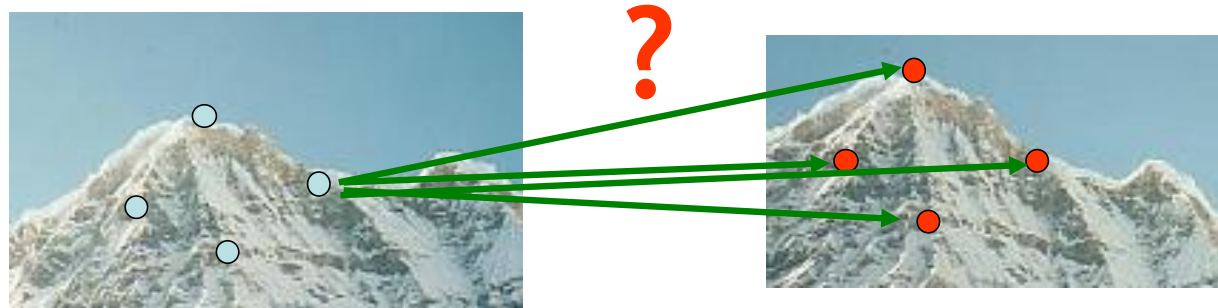
We need a repeatable detector!

Problem 1:

- Detect the same point *independently* in both images

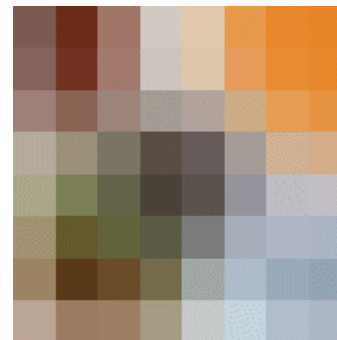
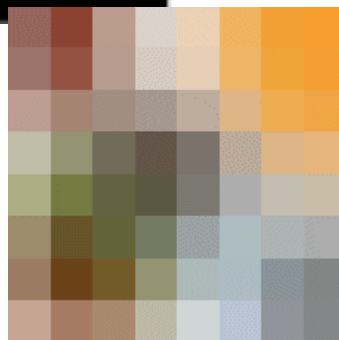
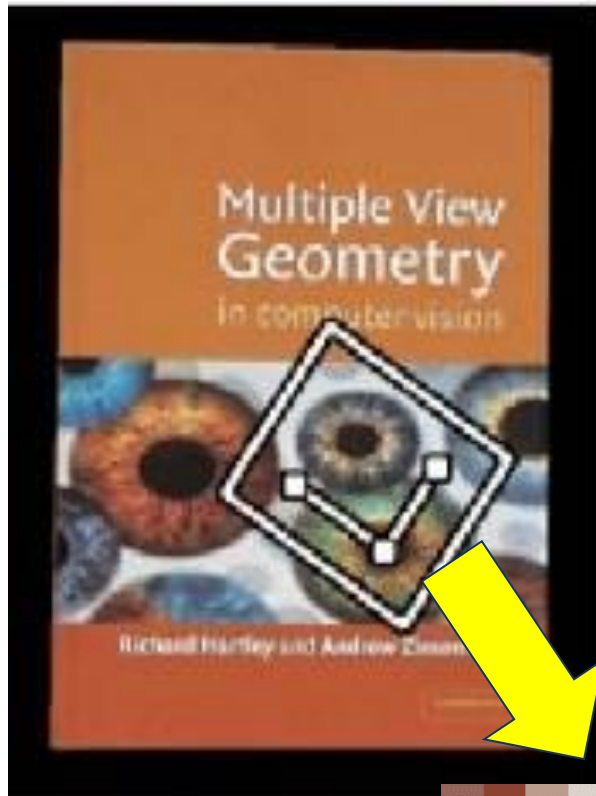
Problem 2:

- For each point correctly recognize the corresponding one

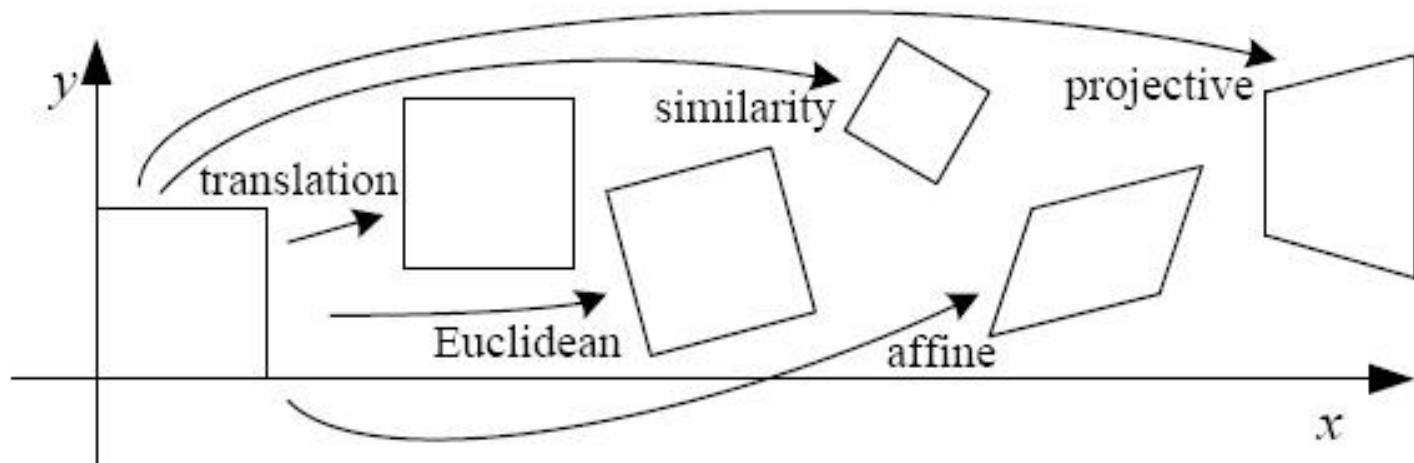


We need a reliable and distinctive descriptor!

INVARIANCE: GEOMETRIC TRANSFORMATIONS



LEVELS OF GEOMETRIC INVARIANCE



1. Region extraction needs to be **repeatable** and **accurate**

- **Invariant** to translation, rotation, scale changes
- **Robust** or **covariant** to out-of-plane (\approx affine) transformations
- **Robust** to lighting variations, noise, blur, quantization

2. **Locality**: Features are local, therefore robust to occlusion and clutter.

3. **Quantity**: We need a sufficient number of regions to cover the object.

4. **Distinctiveness**: The regions should contain “interesting” structure.

5. **Efficiency**: Close to real-time performance.

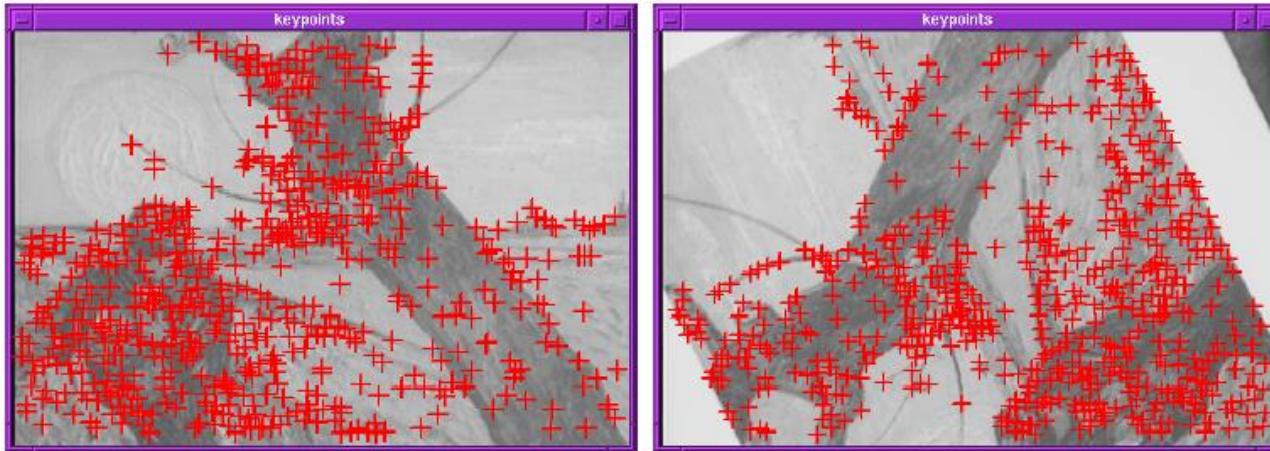
- Hessian & Harris
 - Laplacian, DoG
 - Harris-/Hessian-Laplace
 - Harris-/Hessian-Affine
 - EBR and IBR
 - MSER
 - Salient Regions
 - Others...
- [Beaudet '78], [Harris '88]
[Lindeberg '98], [Lowe '99]
[Mikolajczyk & Schmid '01]
[Mikolajczyk & Schmid '04]
[Tuytelaars & Van Gool '04]
[Matas '02]
[Kadir & Brady '01]
- *Those detectors have become a basic building block for many recent applications in Computer Vision.*



Goals:

- Repeatable detection
- Precise localization
- Interesting content

⇒ *Look for two-dimensional signal changes*



Key property:

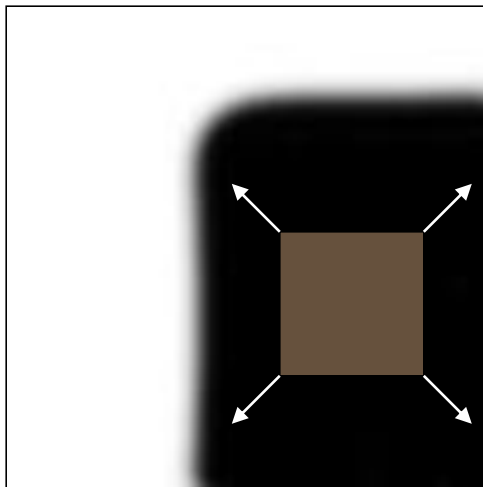
- In the region around a corner, image gradient has two or more dominant directions

Corners are *repeatable* and *distinctive*

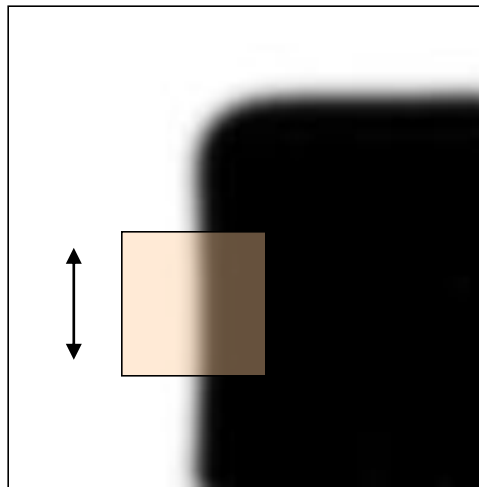
C.Harris and M.Stephens. "A Combined Corner and Edge Detector."
Proceedings of the 4th Alvey Vision Conference, 1988.

Design criteria

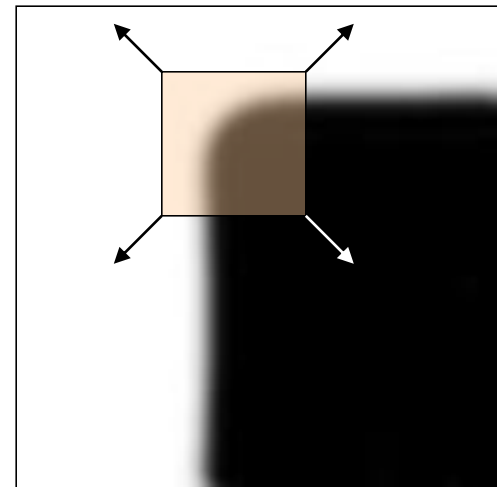
- We should easily recognize the point by looking through a small window (*locality*)
- Shifting the window in *any direction* should give a *large change* in intensity (*good localization*)



“flat” region:
no change in all
directions

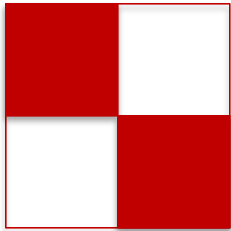


“edge”:
no change along
the edge direction



“corner”:
significant change
in all directions

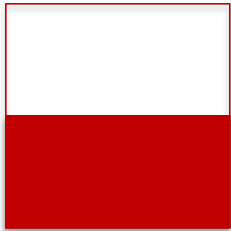
CORNERS VERSUS EDGES



$$\sum I_x^2 \longrightarrow \text{Large}$$

$$\sum I_y^2 \longrightarrow \text{Large}$$

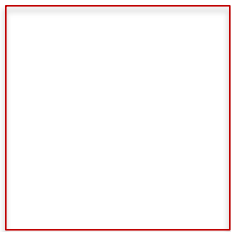
Corner



$$\sum I_x^2 \longrightarrow \text{Small}$$

$$\sum I_y^2 \longrightarrow \text{Large}$$

Edge

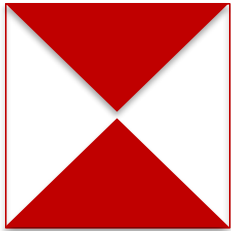


$$\sum I_x^2 \longrightarrow \text{Small}$$

$$\sum I_y^2 \longrightarrow \text{Small}$$

Nothing

CORNERS VERSUS EDGES



$$\sum I_x^2 \longrightarrow ??$$

$$\sum I_y^2 \longrightarrow ??$$

Corner

Change of intensity for the shift $[u,v]$:

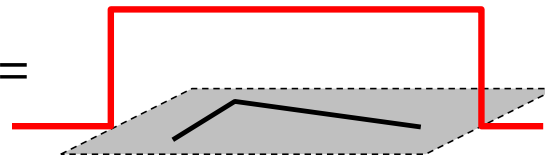
$$E(u, v) = \sum_{x,y} w(x, y) [I(x + u, y + v) - I(x, y)]^2$$

x, y
Window
function

Shifted
intensity

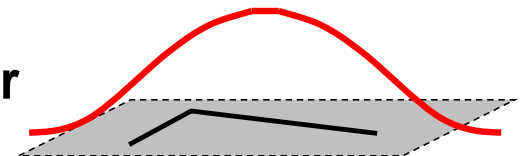
Intensity

Window function $w(x, y) =$



1 in window, 0 outside

or



Gaussian

HARRIS DETECTOR FORMULATION

This measure of change can be approximated by:

$$E(u, v) \approx [u \ v] M \begin{bmatrix} u \\ v \end{bmatrix}$$

where M is a 2×2 matrix computed from image derivatives:

$$M = \sum_{x,y} w(x, y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

Sum over image region – the area we are checking for corner

Gradient with respect to x , times gradient with respect to y

$$M = \begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix} = \sum \begin{bmatrix} I_x \\ I_y \end{bmatrix} [I_x \ I_y]$$

HARRIS DETECTOR FORMULATION

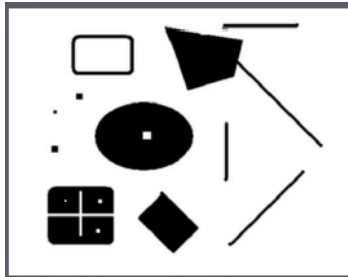
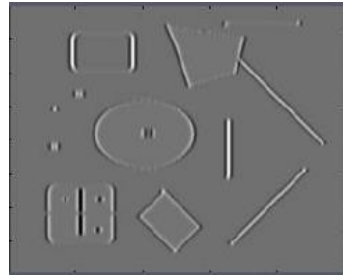
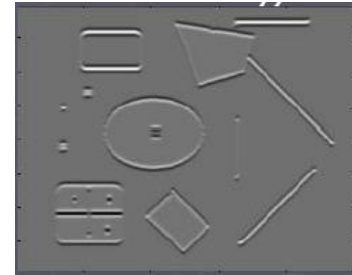


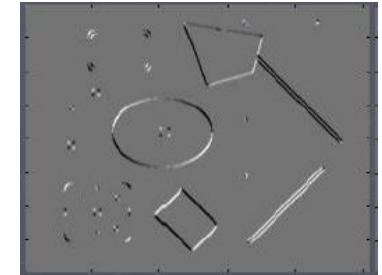
Image I



I_x



I_y



$I_x I_y$

where M is a 2×2 matrix computed from image derivatives:

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

Sum over image region – the area we are checking for corner

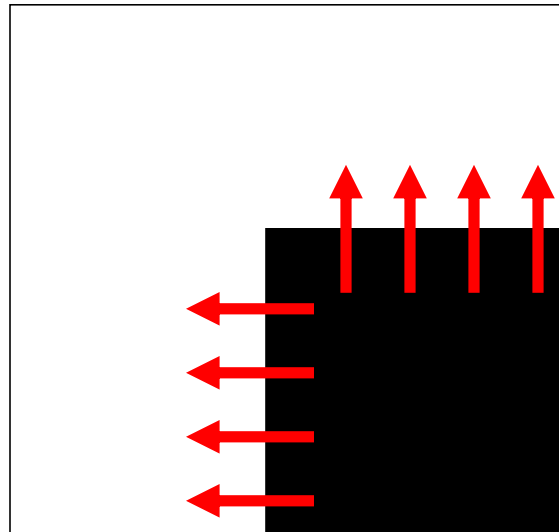
Gradient with respect to x , times gradient with respect to y

$$M = \begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix} = \sum \begin{bmatrix} I_x \\ I_y \end{bmatrix} [I_x \ I_y]$$

WHAT DOES THIS MATRIX REVEAL?

First, let's consider an axis-aligned corner:

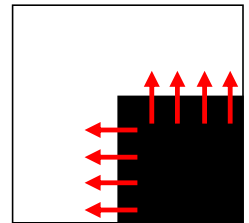
$$M = \begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$



WHAT DOES THIS MATRIX REVEAL?

First, let's consider an axis-aligned corner:

$$M = \begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$



This means:

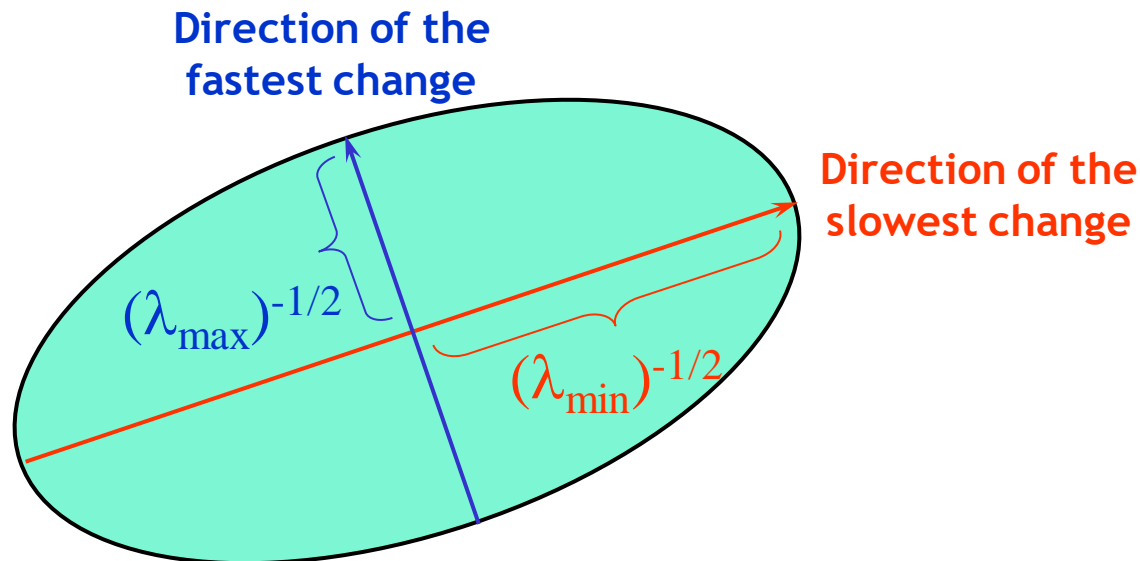
- Dominant gradient directions align with x or y axis
- If either λ is close to 0, then this is not a corner, so look for locations where both are large.

What if we have a corner that is not aligned with the image axes?

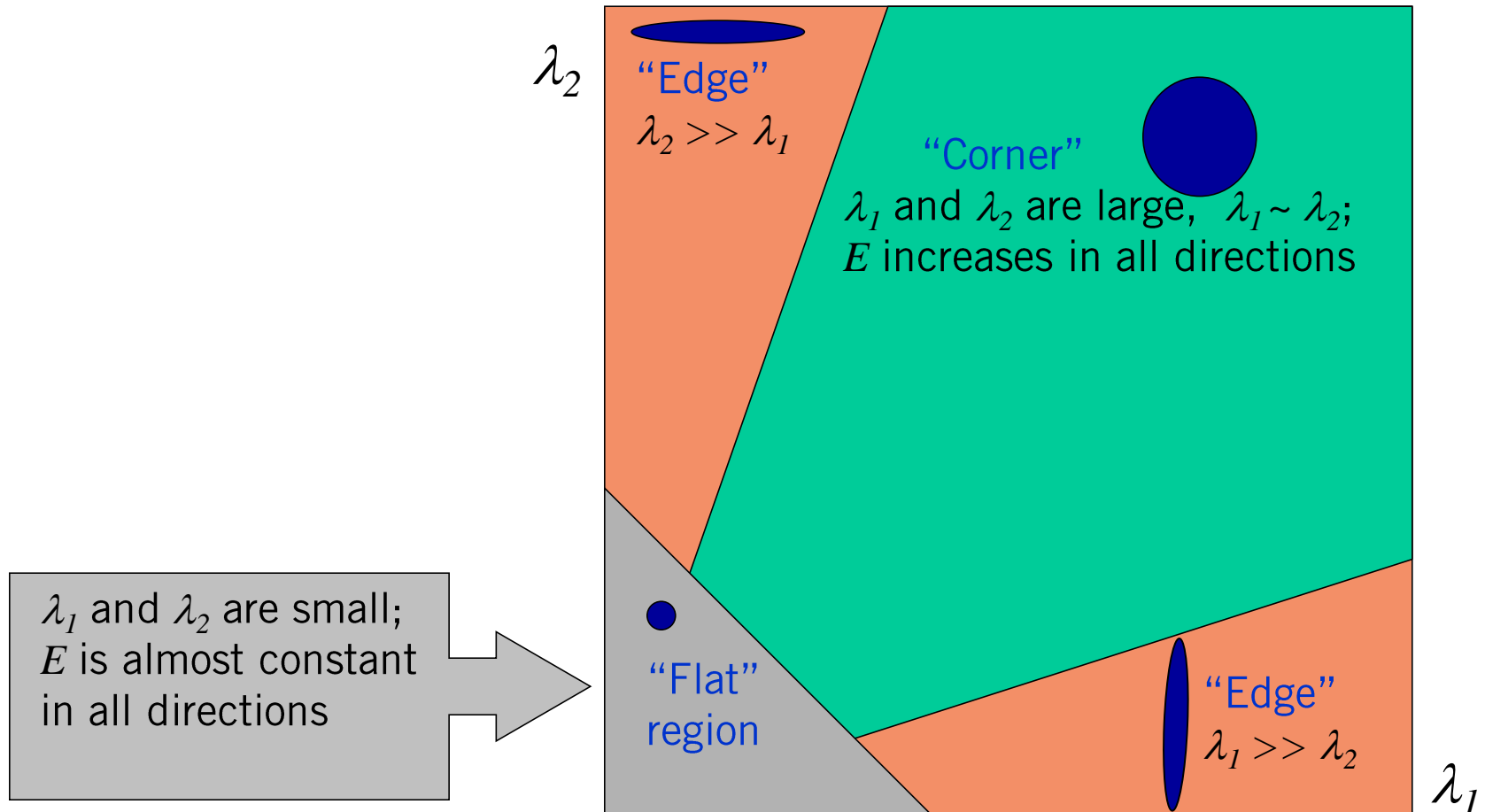
- Since M is symmetric, we have
$$M = R^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$$

(Eigenvalue decomposition)

- We can visualize M as an ellipse with axis lengths determined by the eigenvalues and orientation determined by R

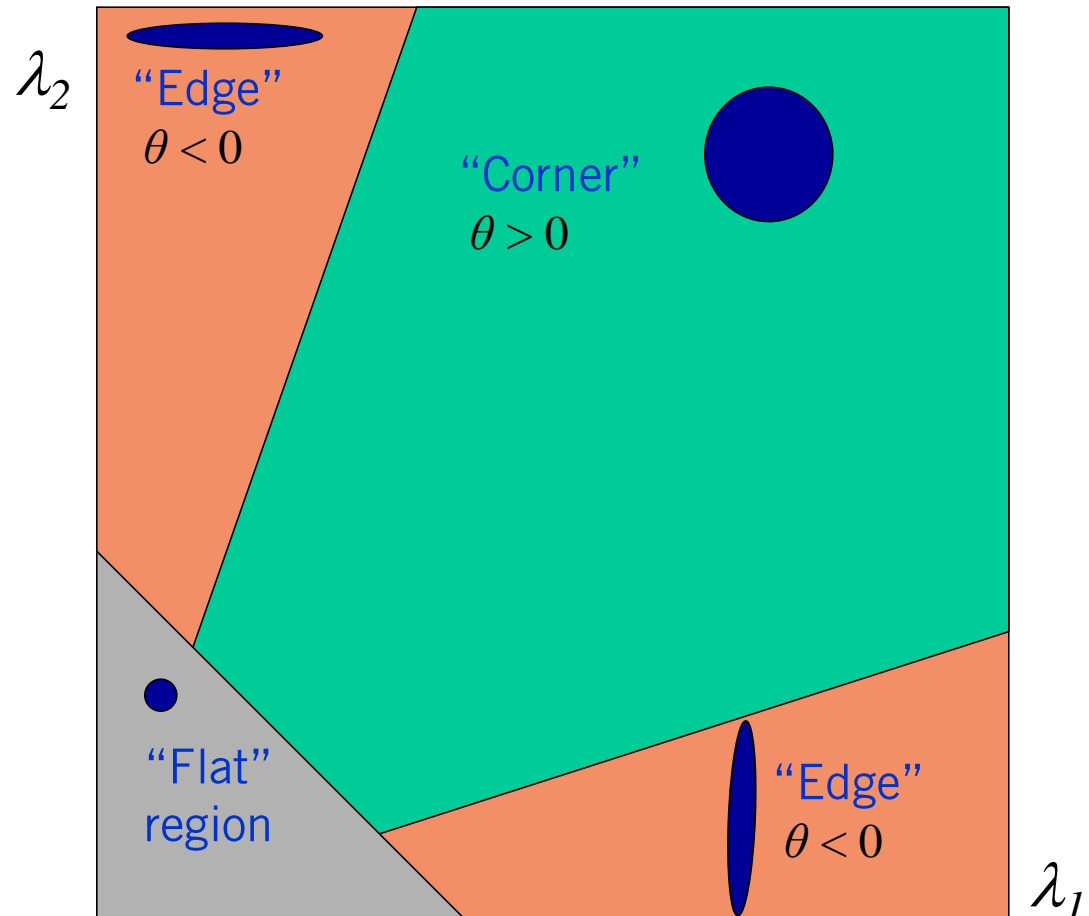


Classification of image points using eigenvalues of M :



CORNER RESPONSE FUNCTION

$$q = \det(M) - a \operatorname{trace}(M)^2 = l_1 l_2 - a(l_1 + l_2)^2$$



Fast approximation

- Avoid computing the eigenvalues
- α : constant (0.04 to 0.06)

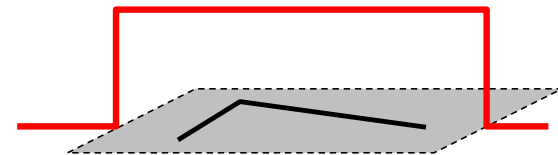
$$M = \sum_{x,y} w(x, y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

Option 1: uniform window

- Sum over square window

$$M = \sum_{x,y} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

- Problem: not rotation invariant



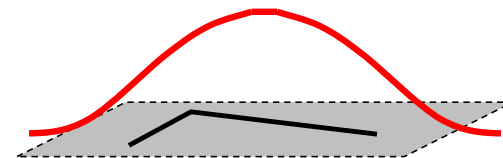
1 in window, 0 outside

Option 2: Smooth with Gaussian

- Gaussian already performs weighted sum

$$M = g(\sigma) * \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

- Result is rotation invariant



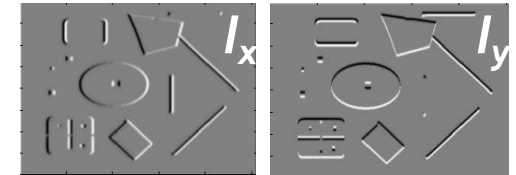
Gaussian

SUMMARY: HARRIS DETECTOR

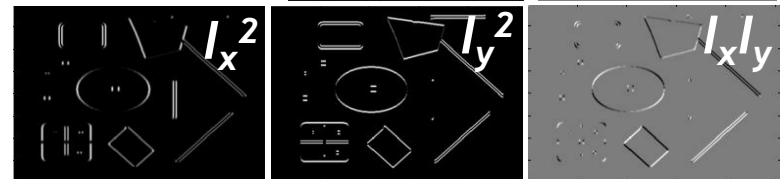
Compute second moment matrix
(autocorrelation matrix)

$$M(\sigma_I, \sigma_D) = g(\sigma_I) * \begin{bmatrix} I_x^2(\sigma_D) & I_x I_y(\sigma_D) \\ I_x I_y(\sigma_D) & I_y^2(\sigma_D) \end{bmatrix}$$

1. Image
derivatives



2. Square of
derivatives



3. Gaussian
filter $g(\sigma_I)$



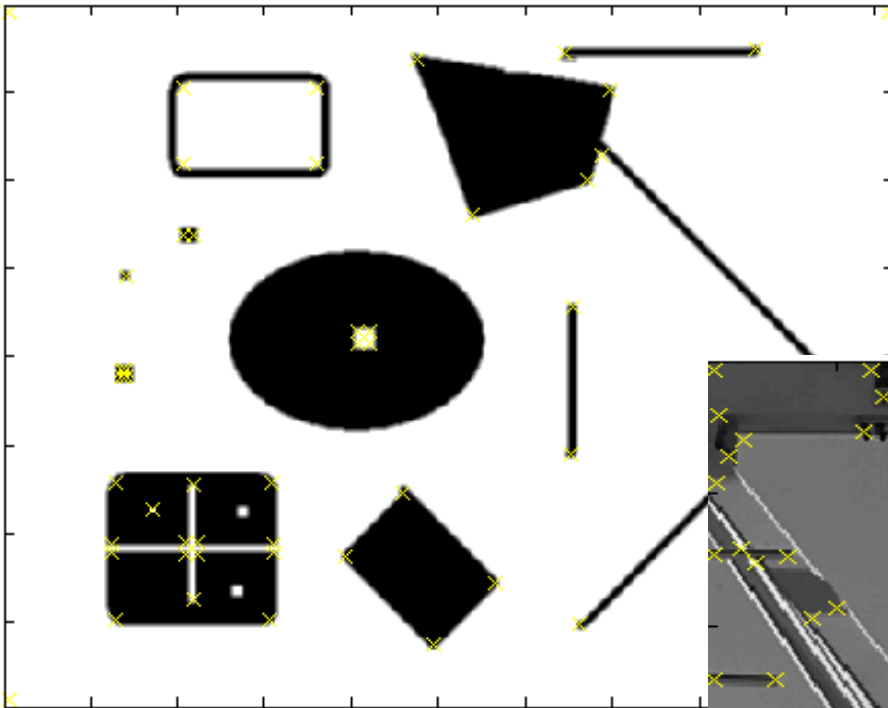
4. Cornerness function - two strong eigenvalues

$$\begin{aligned} q &= \det[M(S_I, S_D)] - \alpha[\text{trace}(M(S_I, S_D))]^2 \\ &= g(I_x^2)g(I_y^2) - [g(I_x I_y)]^2 - \alpha[g(I_x^2) + g(I_y^2)]^2 \end{aligned}$$

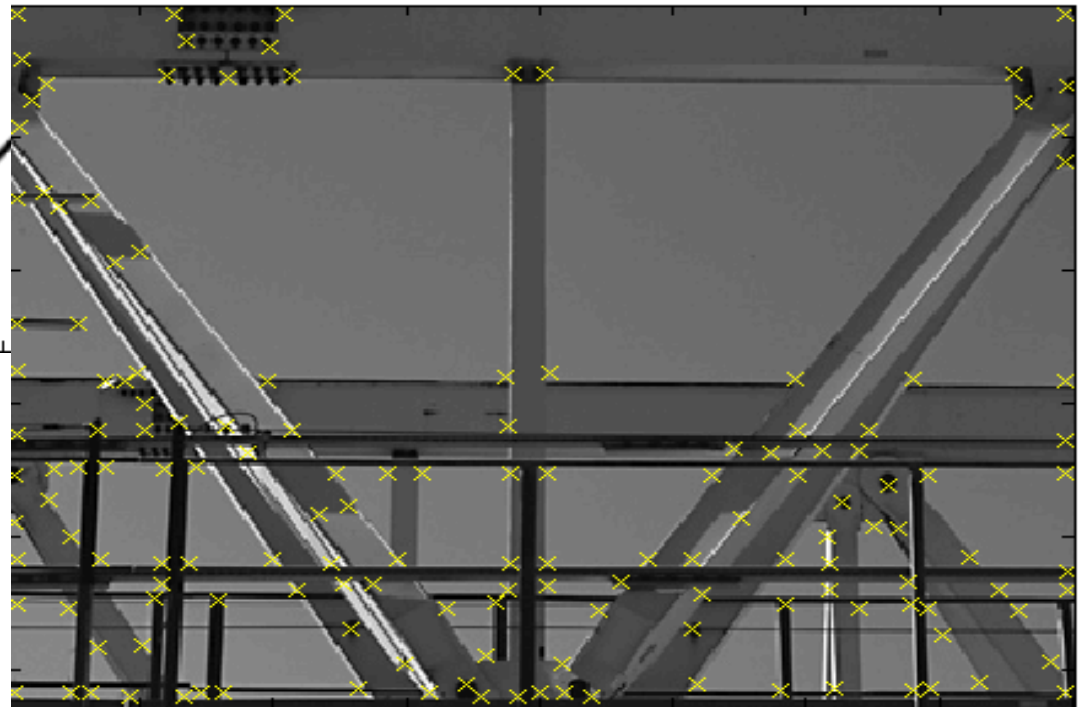
5. Perform non-maximum suppression



HARRIS DETECTOR - RESPONSES



Effect: A very precise corner detector.

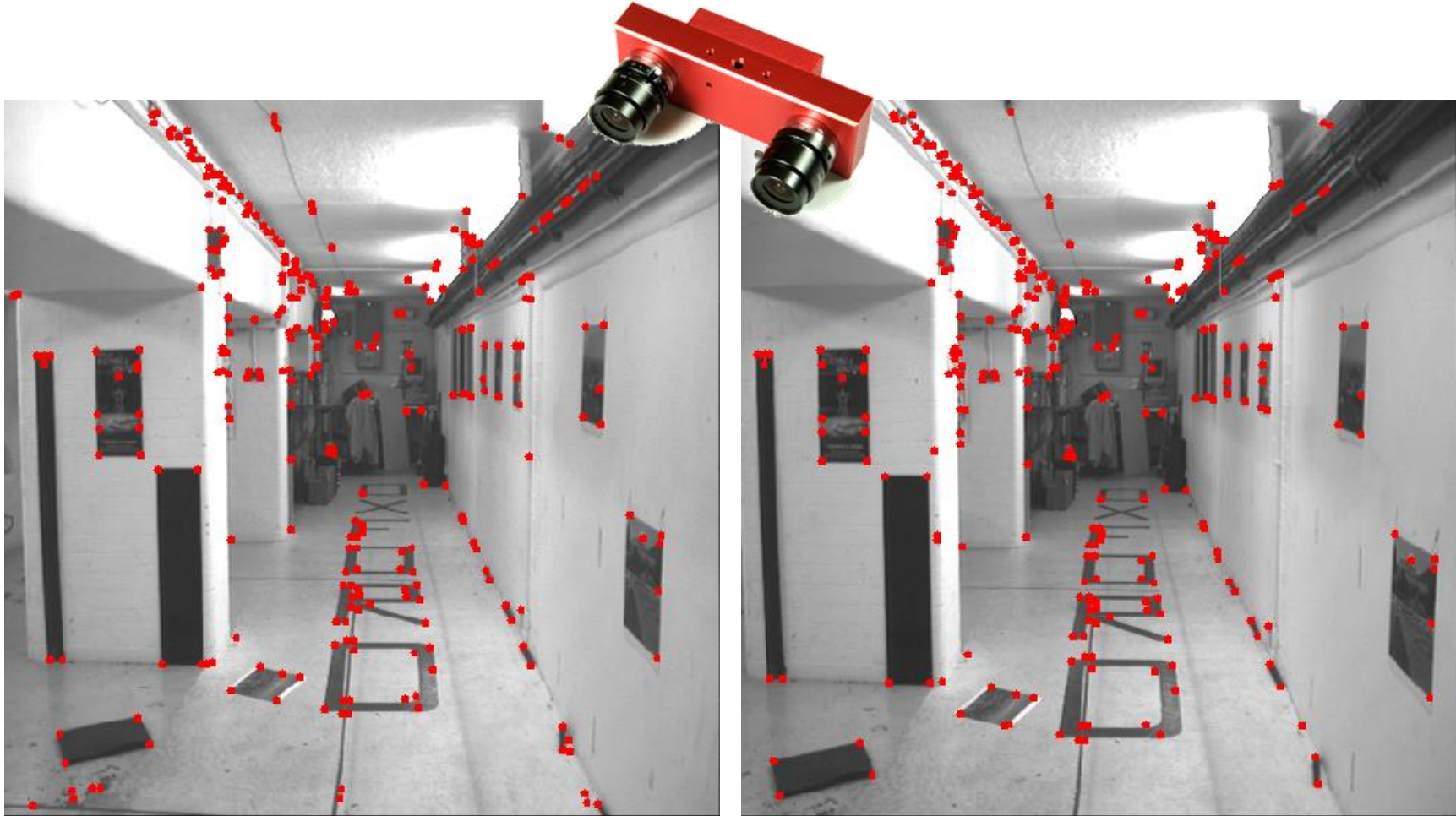


HARRIS DETECTOR - RESPONSES



Slide credit: Krystian Mikolajczyk

HARRIS DETECTOR - RESPONSES

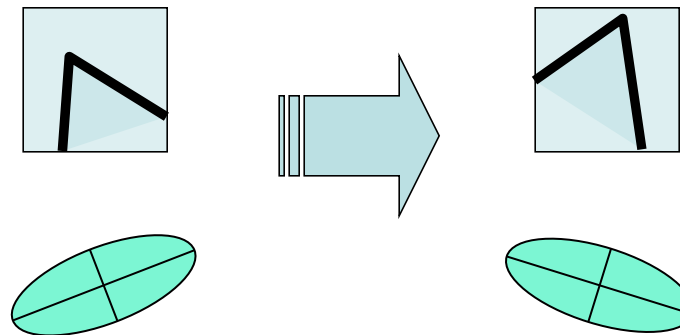


1. Results are well suited for finding stereo correspondences

HARRIS DETECTOR - PROPERTIES

1. Translation invariance?

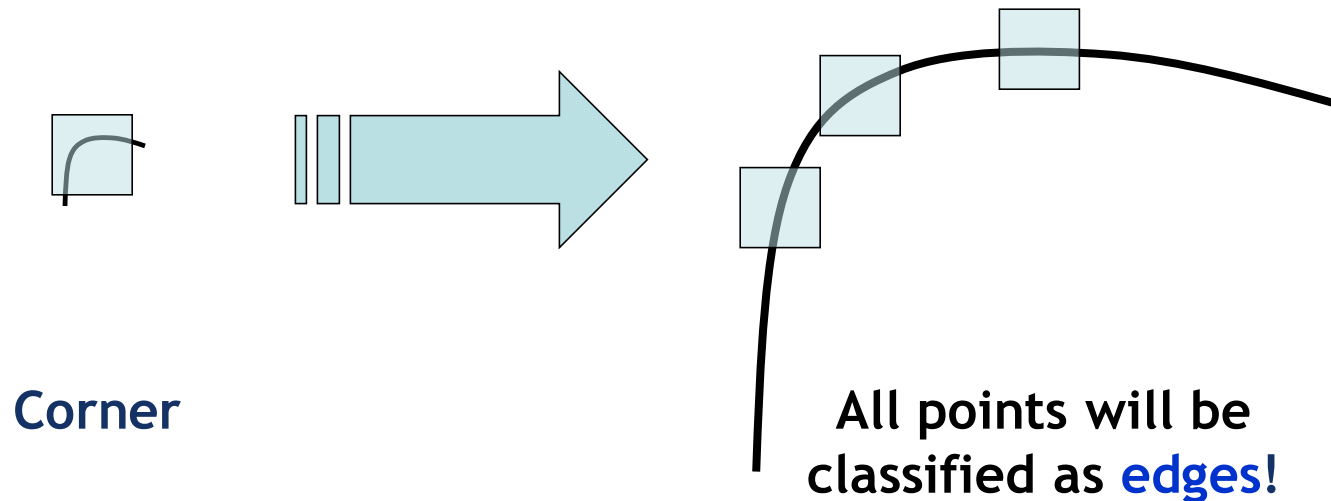
1. Translation invariance
2. Rotation invariance?



Ellipse rotates but its shape (i.e. eigenvalues) remains the same

Corner response θ is invariant to image rotation

1. Translation invariance
2. Rotation invariance
3. Scale invariance?



Not invariant to image scale!