

CSCE 4603

Fundamentals of Computer Vision

Harris Corner Detector

Dr. Mahmoud Khalil
Fall 2025

Text Book

- Computer Vision: Algorithms and Applications,
Richard Szeliski, Springer, 2011.
- <http://szeliski.org/Book/>
- Section: 4.1.1

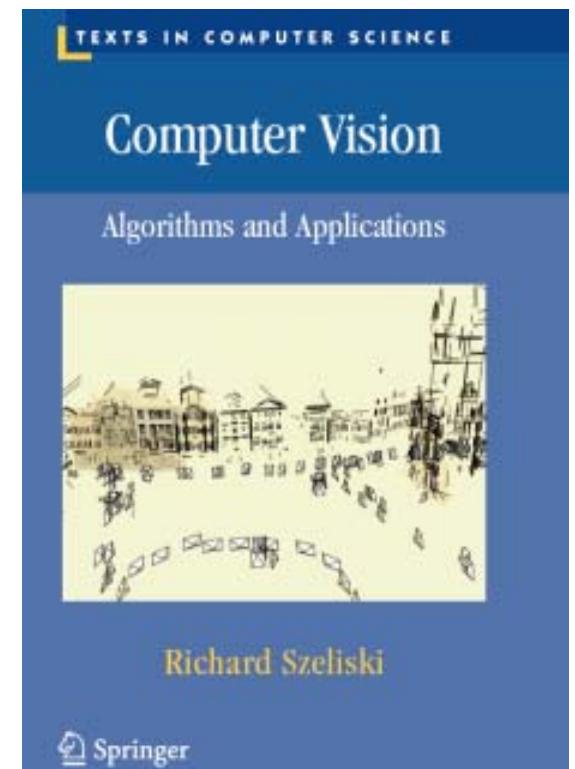


Image Matching



by [Diva Sian](#)



by [swashford](#)

Harder Case

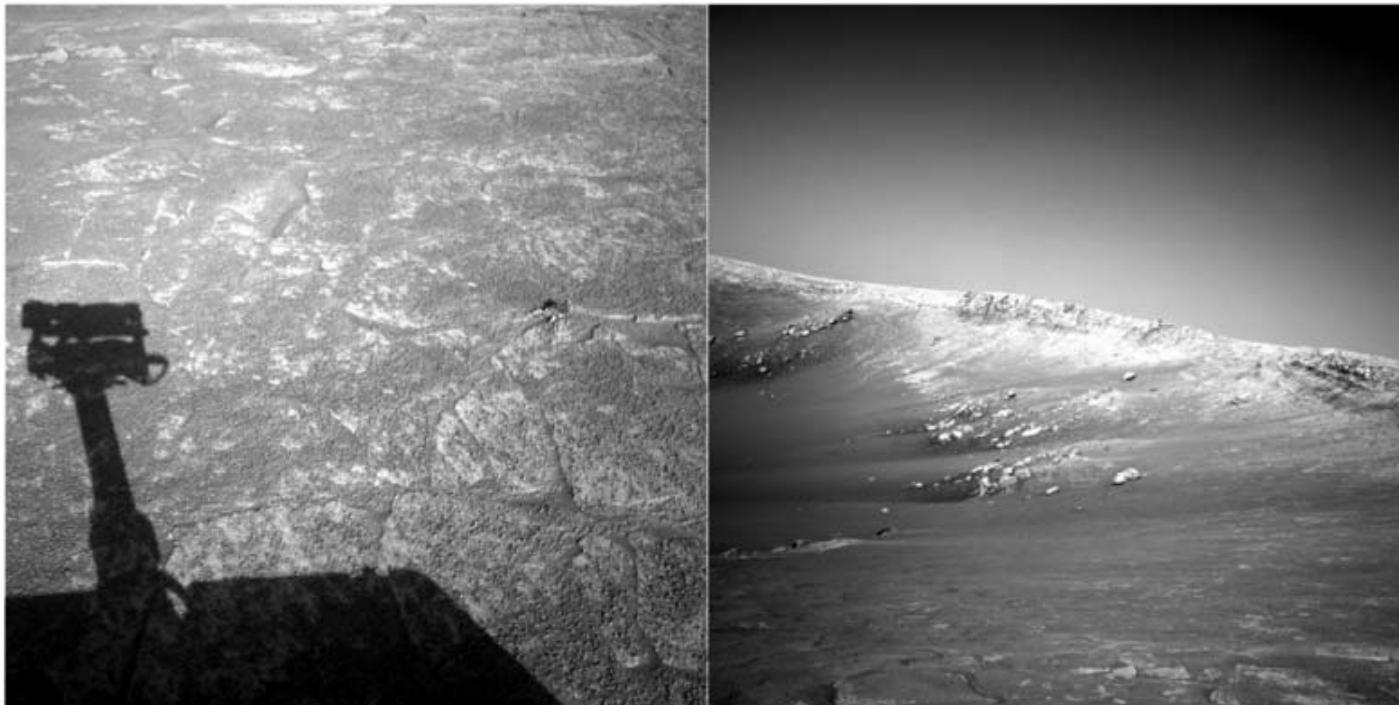


by [Diva Sian](#)



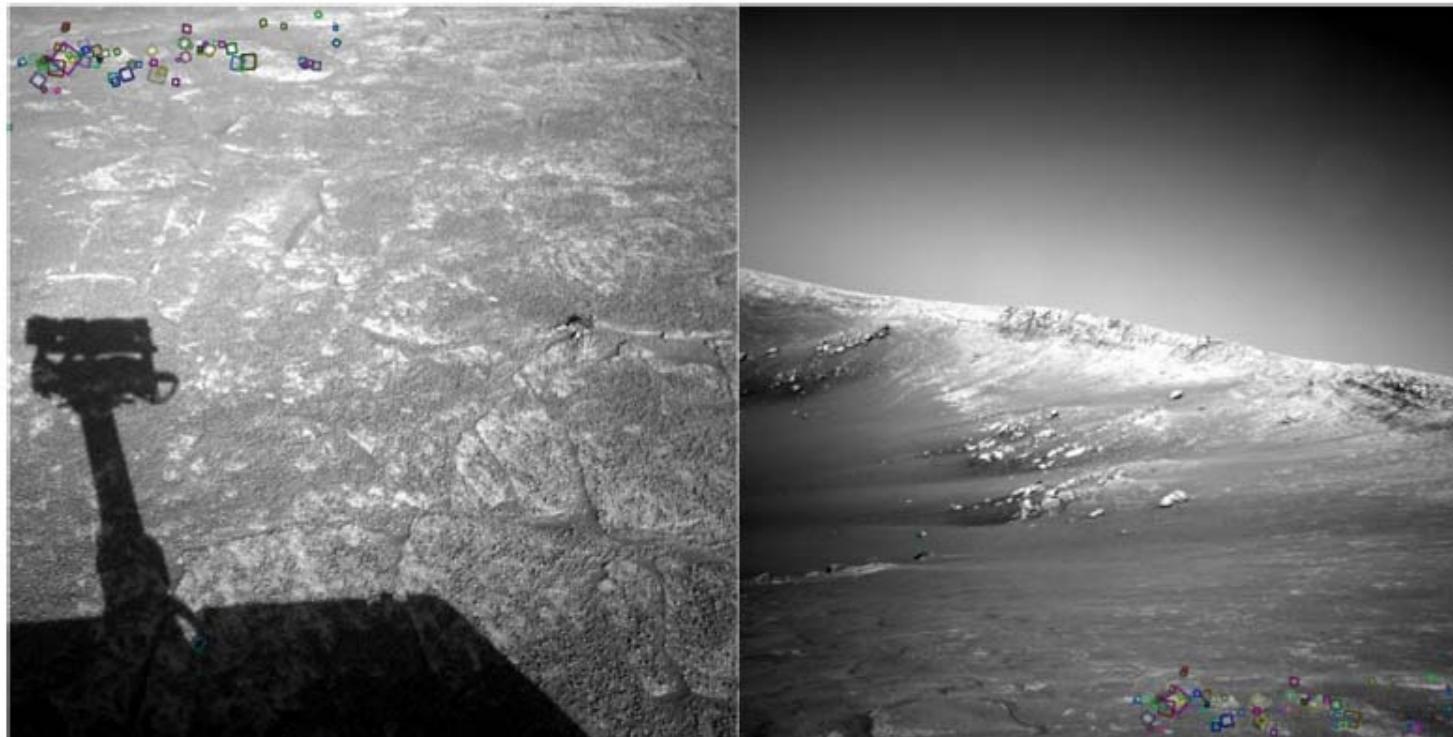
by [scgbt](#)

Still Harder



NASA Mars Rover images

Harder Case



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

Image Stitching



Image Stitching

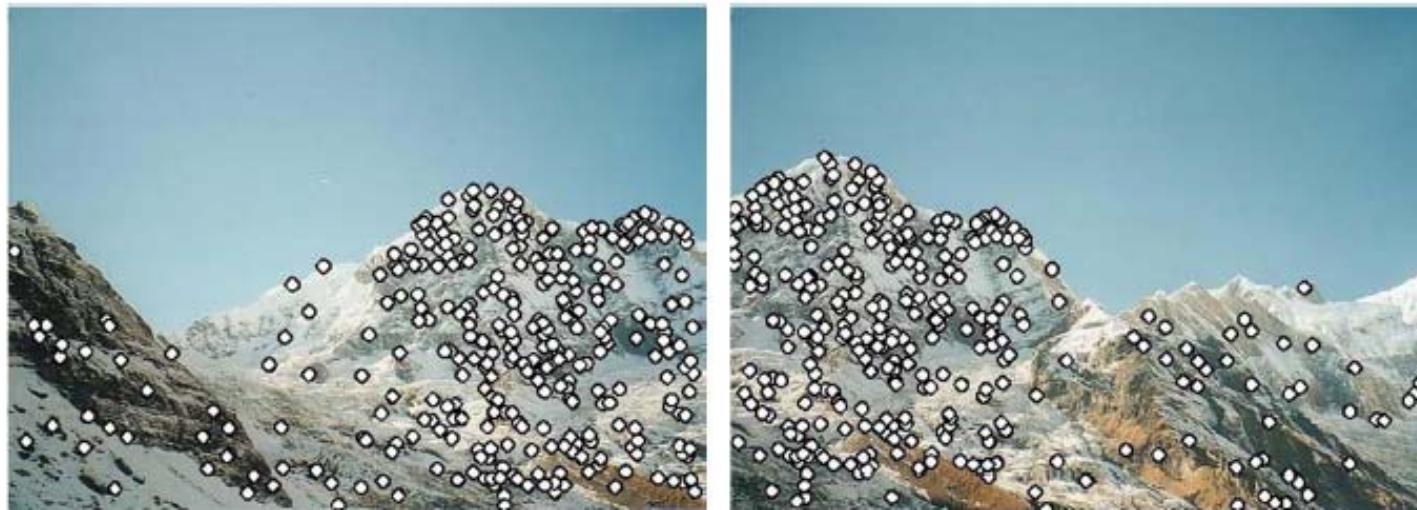


Image Stitching

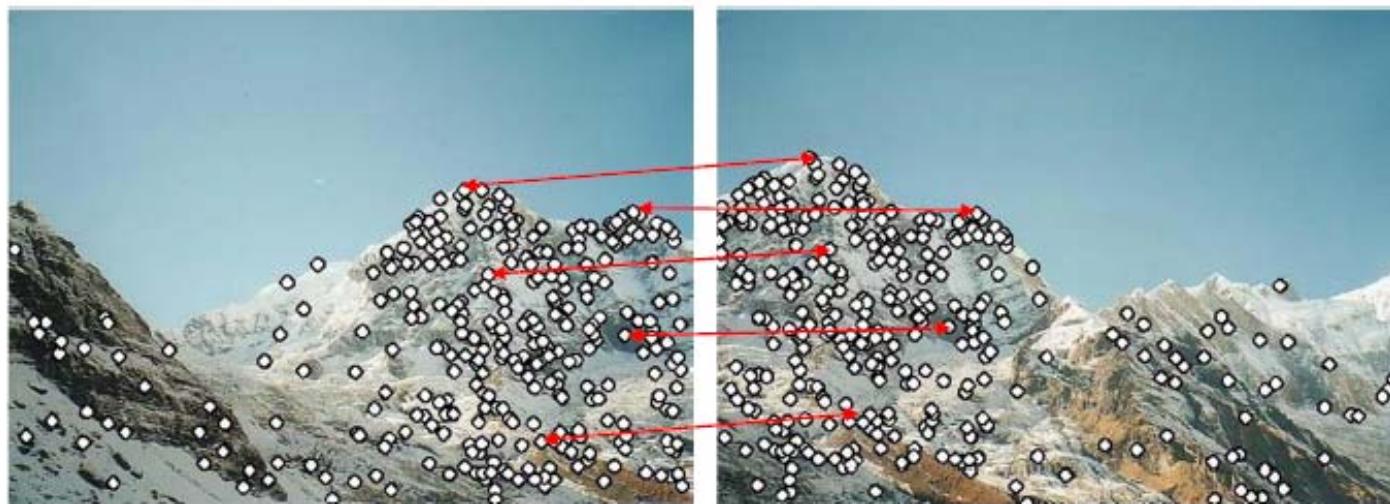


Image Stitching



Building a Panorama



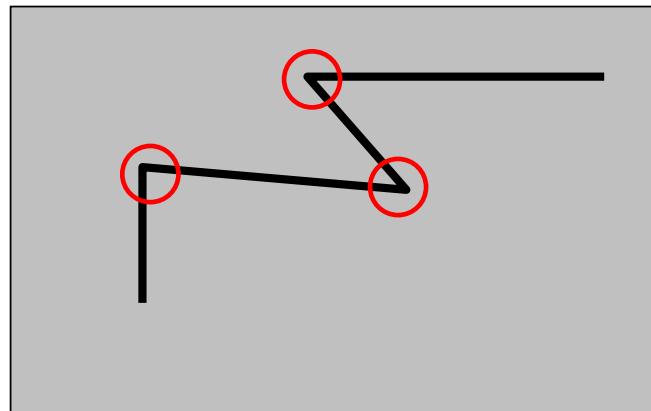
Applications

- Feature points are used for:
 - Image alignment
 - 3D reconstruction
 - Motion tracking
 - Robot navigation
 - Indexing and database retrieval
 - Object recognition

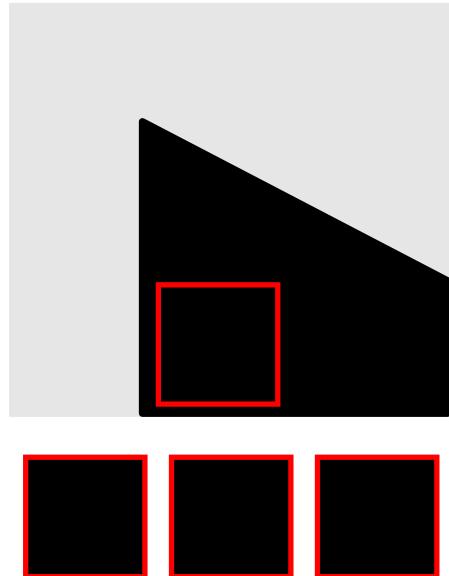


Moravec corner detector (1980)

- 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

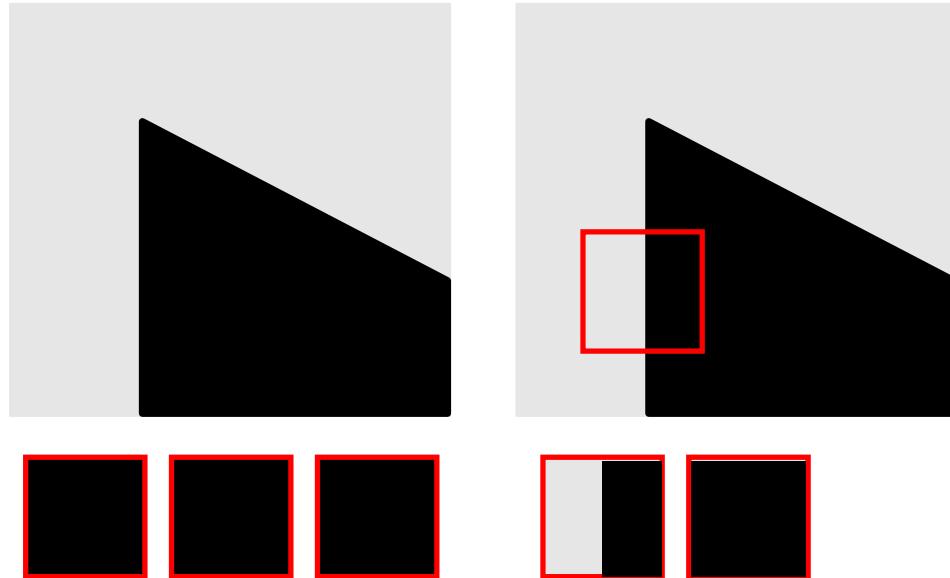


Moravec corner detector



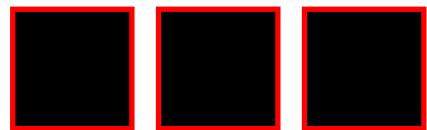
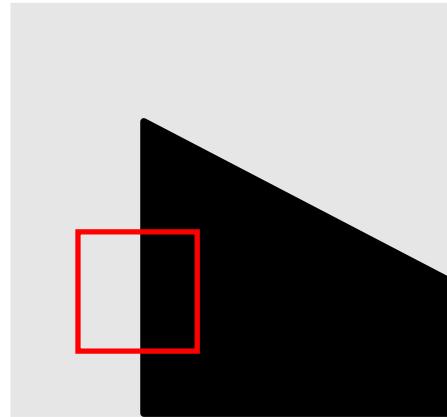
flat

Moravec corner detector

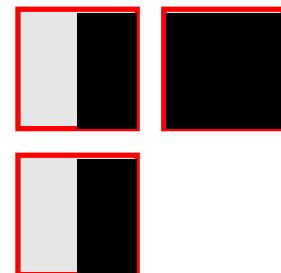


flat

Moravec corner detector

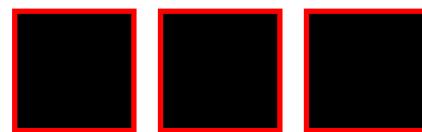


flat

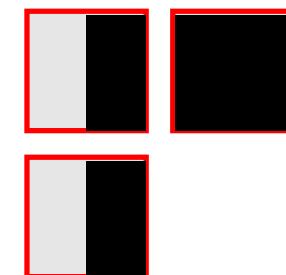


edge

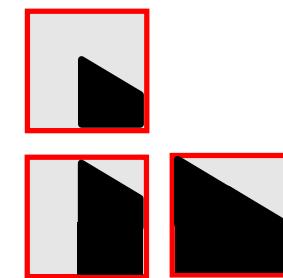
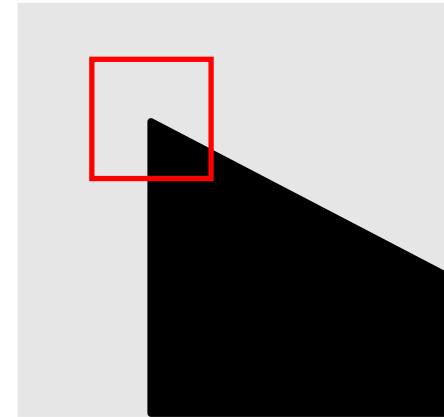
Moravec corner detector



flat



edge

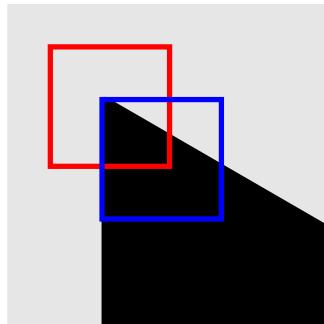


corner
isolated point

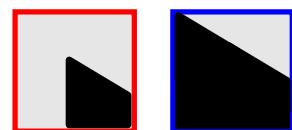
Moravec corner detector

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

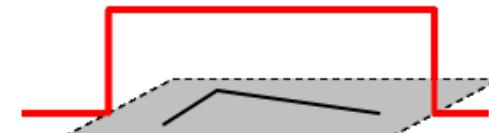
$$E(u,v) = \sum_{x,y} w(x,y)[I(x+u, y+v) - I(x, y)]^2$$



window
function



Window function $w(x,y) =$



1 in window, 0 outside

Four shifts: $(u,v) = (1,0), (1,1), (0,1), (-1, 1)$
Look for local maxima in $\min\{E\}$

Problems of Moravec detector

- Noisy response due to a binary window function
- Only a set of shifts at every 45 degree is considered
- Only minimum of E is taken into account

⇒ Harris corner detector (1988) solves these problems.

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

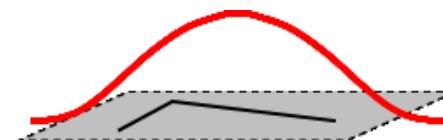
Harris corner detector

Noisy response due to a binary window function

- Use a Gaussian function

$$w(x, y) = \exp\left(-\frac{(x^2 + y^2)}{2\sigma^2}\right)$$

Window function $w(x, y) =$



Gaussian

Taylor Series for 2D Functions

$$f(x+u, y+v) = f(x, y) + u f_x(x, y) + v f_y(x, y) +$$

First partial derivatives

$$\frac{1}{2!} [u^2 f_{xx}(x, y) + uv f_{xy}(x, y) + v^2 f_{yy}(x, y)] +$$

Second partial derivatives

$$\frac{1}{3!} [u^3 f_{xxx}(x, y) + u^2 v f_{xxy}(x, y) + u v^2 f_{xyy}(x, y) + v^3 f_{yyy}(x, y)]$$

Third partial derivatives

+ ... (Higher order terms)

First order approx

$$f(x+u, y+v) \approx f(x, y) + u f_x(x, y) + v f_y(x, y)$$

Harris corner detector

Only a set of shifts at every 45 degree is considered

- Consider all small shifts by Taylor's expansion

Harris corner detector

Only a set of shifts at every 45 degree is considered

➤ Consider all small shifts by Taylor's expansion

$$\begin{aligned} E(u, v) &\approx \sum_{x, y} w(x, y)[I(x, y) + uI_x + vI_y - I(x, y)]^2 \\ &= \sum_{x, y} w(x, y)[uI_x + vI_y]^2 \\ &= \sum_{x, y} w(x, y)(u - v) \begin{bmatrix} I_x I_x & I_x I_y \\ I_x I_y & I_y I_y \end{bmatrix} \begin{pmatrix} u \\ v \end{pmatrix} \end{aligned}$$

Harris corner detector

Equivalently, for small shifts $[u, v]$ we have a *bilinear* approximation:

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

, where \mathbf{M} is a 2×2 matrix computed from image derivatives:

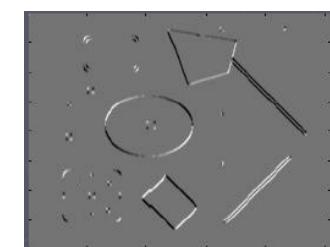
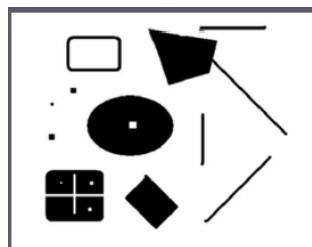
$$\mathbf{M} = \sum_{x,y} w(x, y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

\mathbf{M} is also called “structure tensor”

Harris corner detector

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

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



Notation:

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

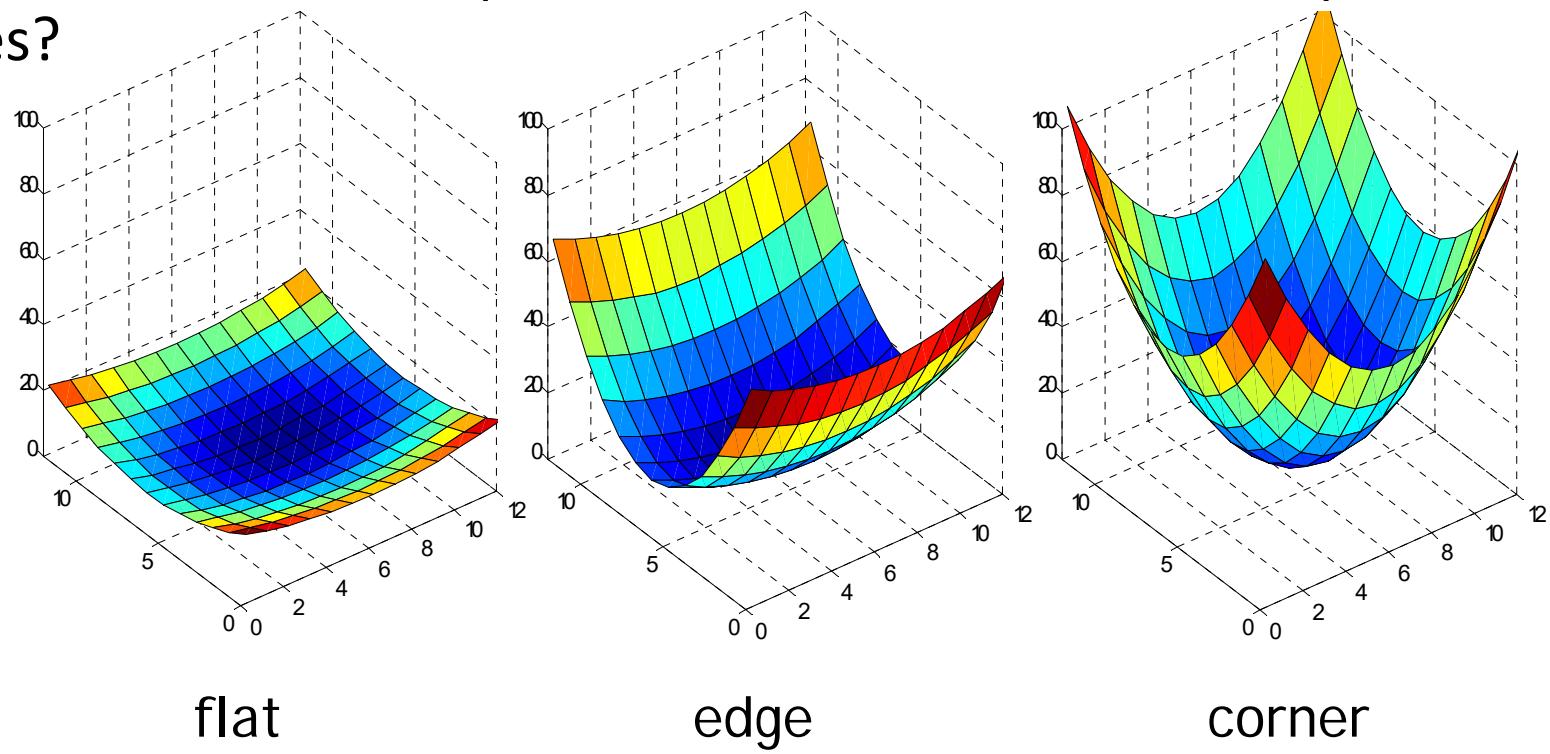
Harris corner detector

Only minimum of E is taken into account

- A new corner measurement by investigating the shape of the error function

Harris corner detector

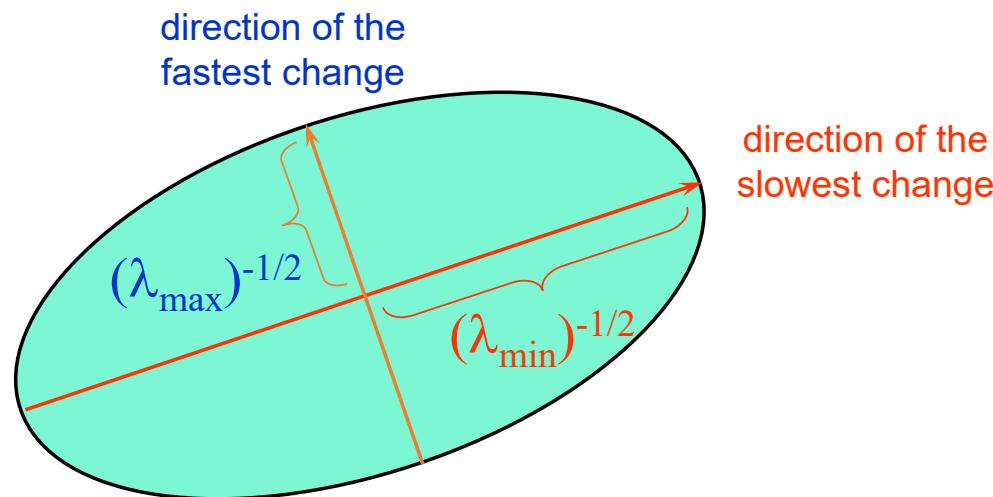
High-level idea: what shape of the error function will we prefer for features?



General Case

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

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



Harris corner detector

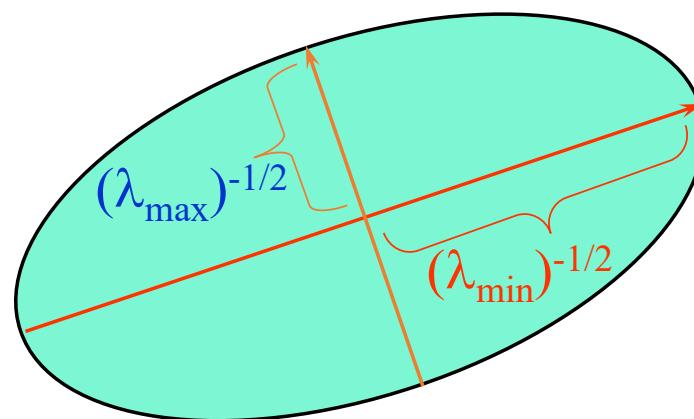
Intensity change in shifting window: eigenvalue analysis

$$E(u, v) \cong [u, v] \mathbf{M} \begin{bmatrix} u \\ v \end{bmatrix} \quad \lambda_1, \lambda_2 - \text{eigenvalues of } \mathbf{M}$$

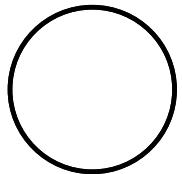
Ellipse $E(u, v) = \text{const}$

direction of the
fastest change

direction of the
slowest change

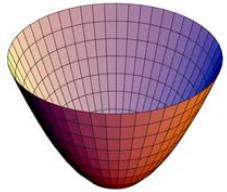


Visualizing quadratics



Equation of a circle

$$1 = x^2 + y^2$$



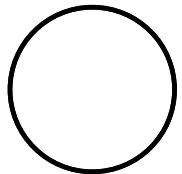
Equation of a 'bowl' (paraboloid)

$$f(x, y) = x^2 + y^2$$

If you slice the bowl at

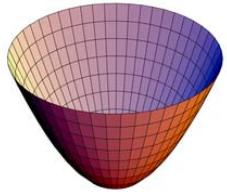
$$f(x, y) = 1$$

what do you get?



Equation of a circle

$$1 = x^2 + y^2$$



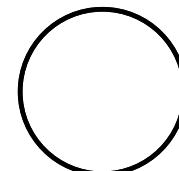
Equation of a 'bowl' (paraboloid)

$$f(x, y) = x^2 + y^2$$

If you slice the bowl at

$$f(x, y) = 1$$

what do you get?



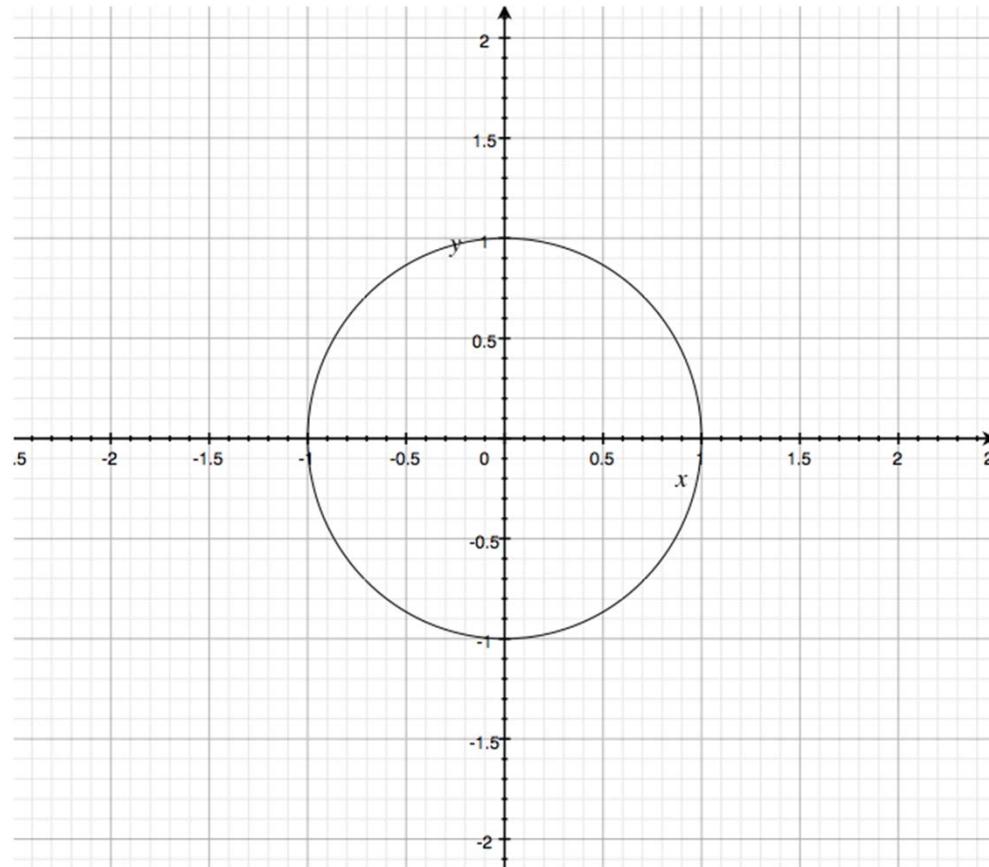
$$f(x, y) = x^2 + y^2$$

can be written in matrix form like this...

$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

'sliced at 1'



*What happens if you **increase** coefficient on **x**?*

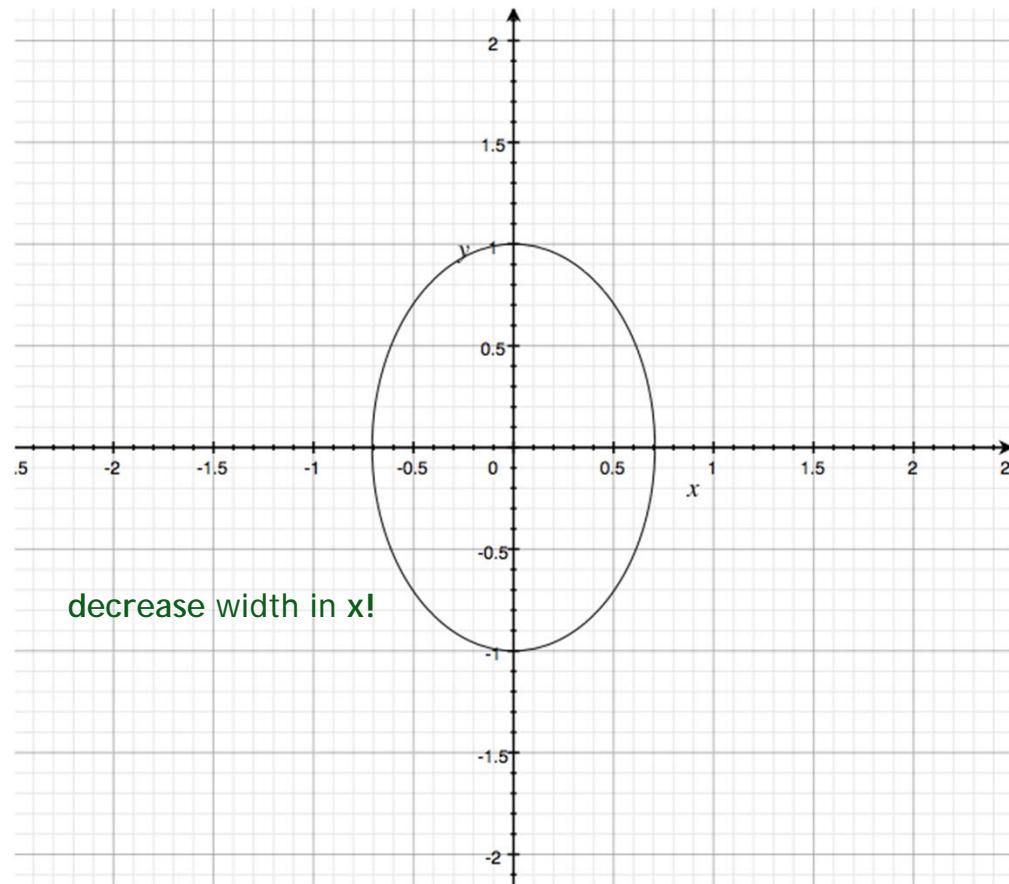
$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

and slice at 1

*What happens if you **increase** coefficient on **x**?*

$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

and slice at 1



*What happens if you **increase** coefficient on **y**?*

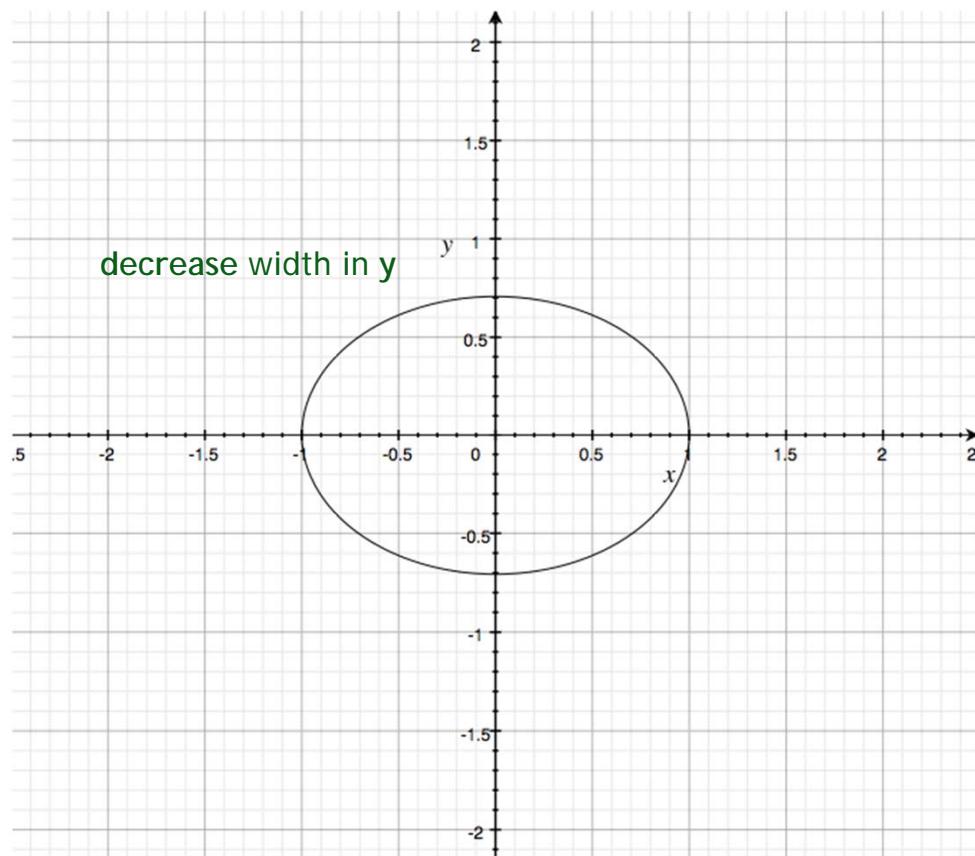
$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

and slice at 1

*What happens if you **increase** coefficient on y ?*

$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

and slice at 1



$$f(x, y) = x^2 + y^2$$

can be written in matrix form like this...

$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

What's the shape?

What are the eigenvectors?

What are the eigenvalues?

$$f(x, y) = x^2 + y^2$$

can be written in matrix form like this...

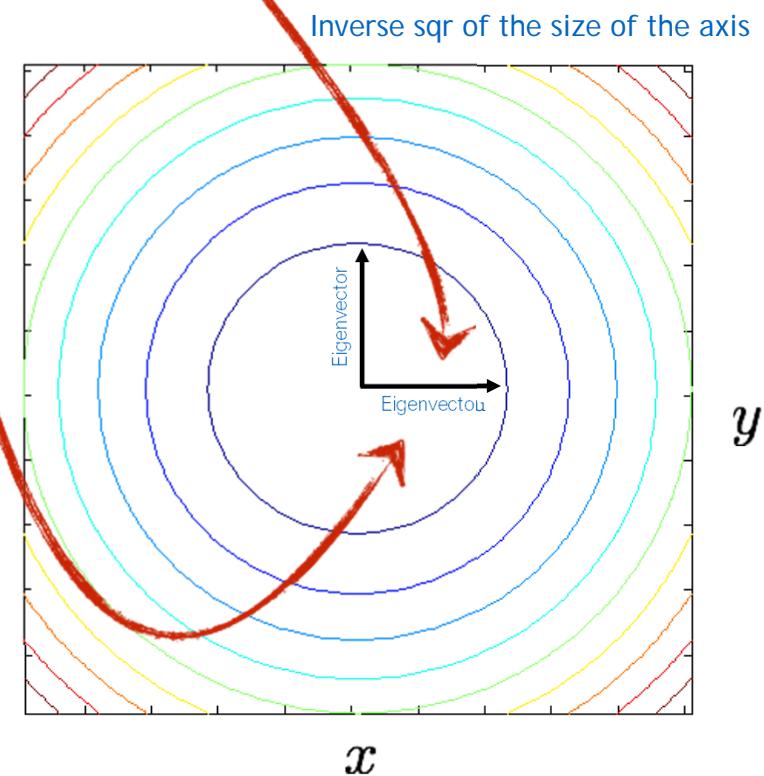
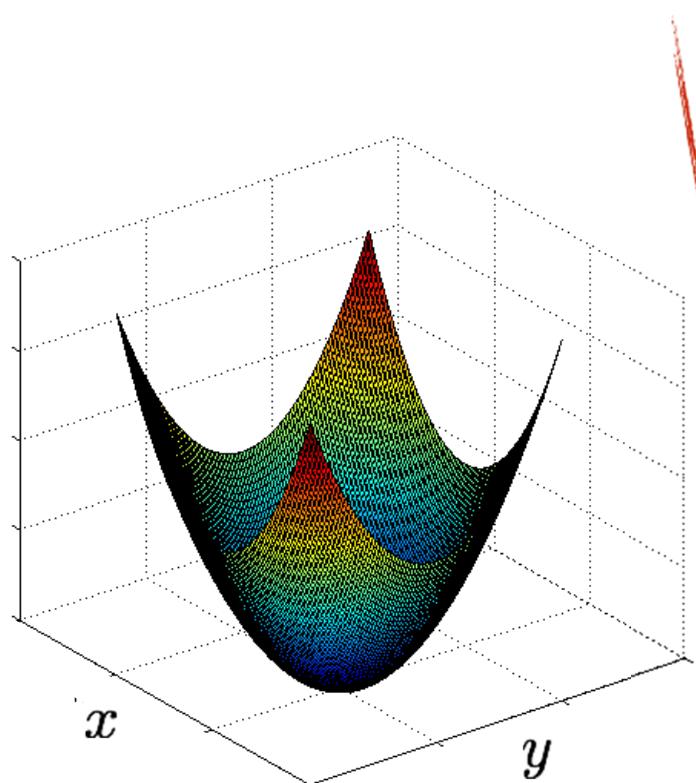
$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Result of Singular Value Decomposition (SVD)

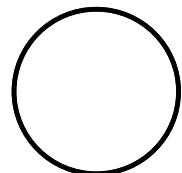
$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} \text{eigenvectors} \\ \text{axis of the 'ellipse slice'} \end{bmatrix} \begin{bmatrix} \text{eigenvalues along diagonal} \\ \text{Inverse sqrt of length of the quadratic along the axis} \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}^\top$$

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}^T$$

Eigenvectors Eigenvalues



Recall:



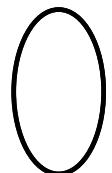
$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

you can smash this bowl in the y direction



$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 4 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

you can smash this bowl in the x direction

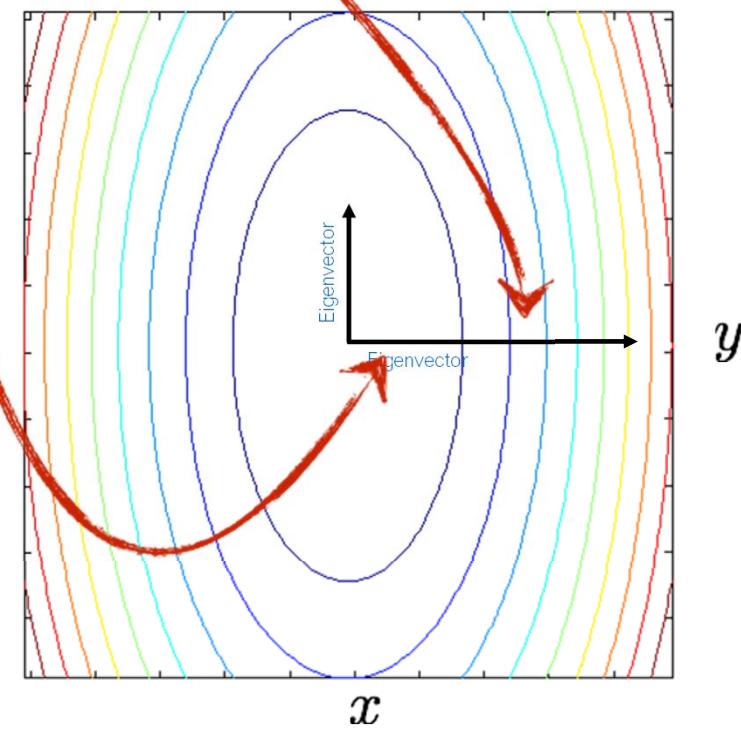
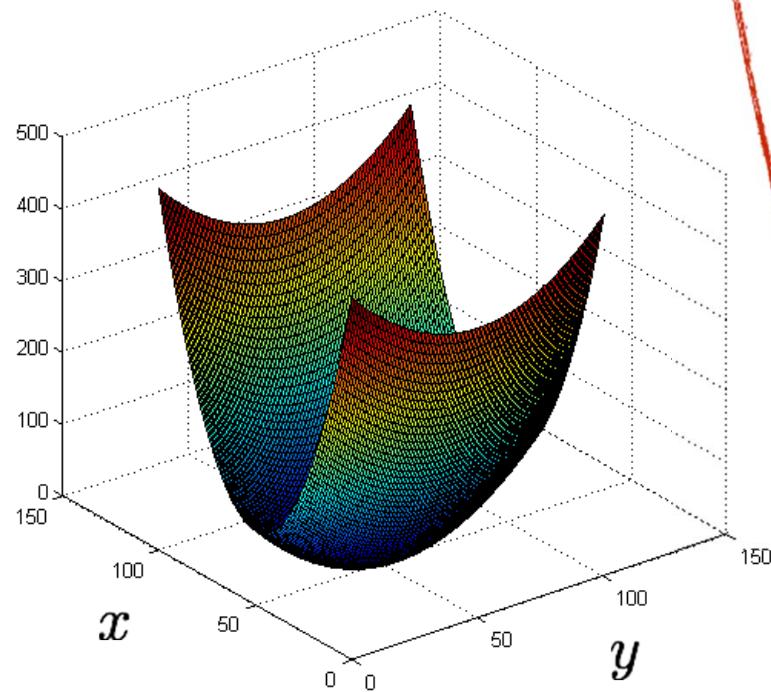


$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

$$A = \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}^T$$

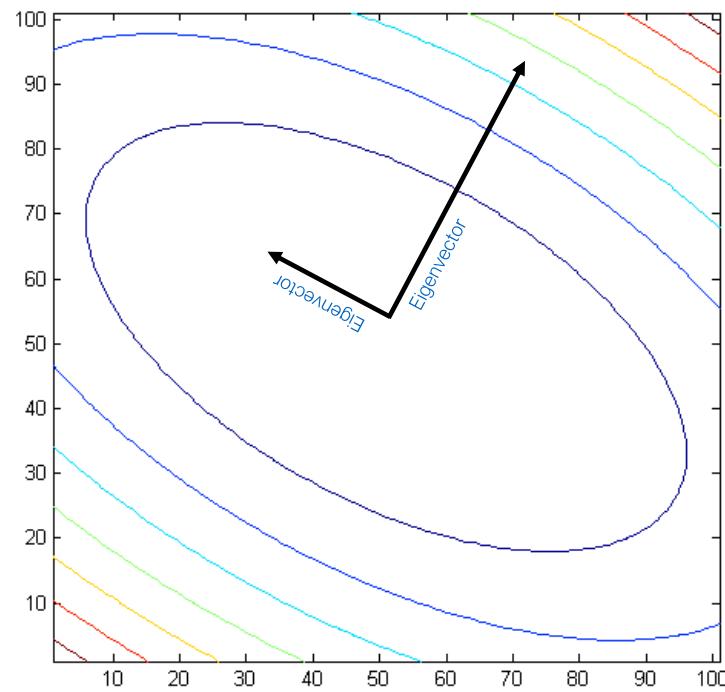
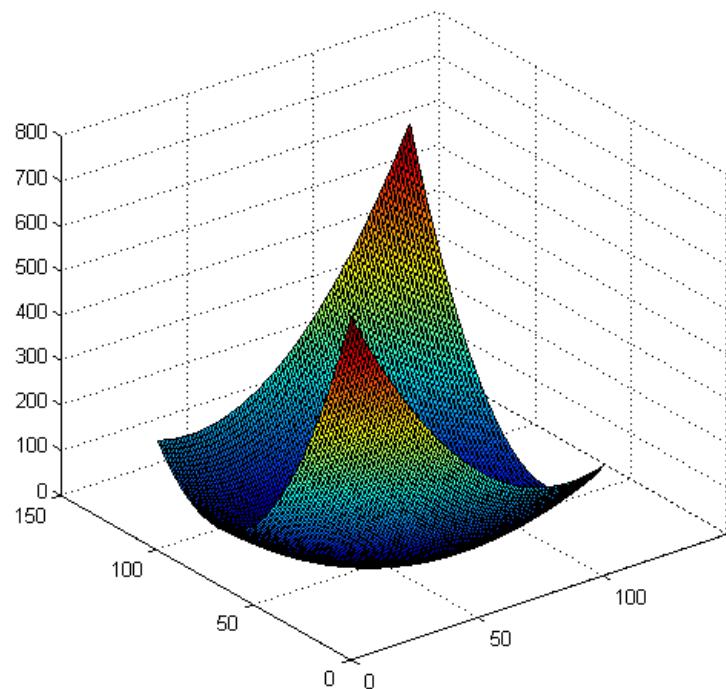
Eigenvalues
Eigenvectors
Eigenvectors

Inverse sqrt of length of axis



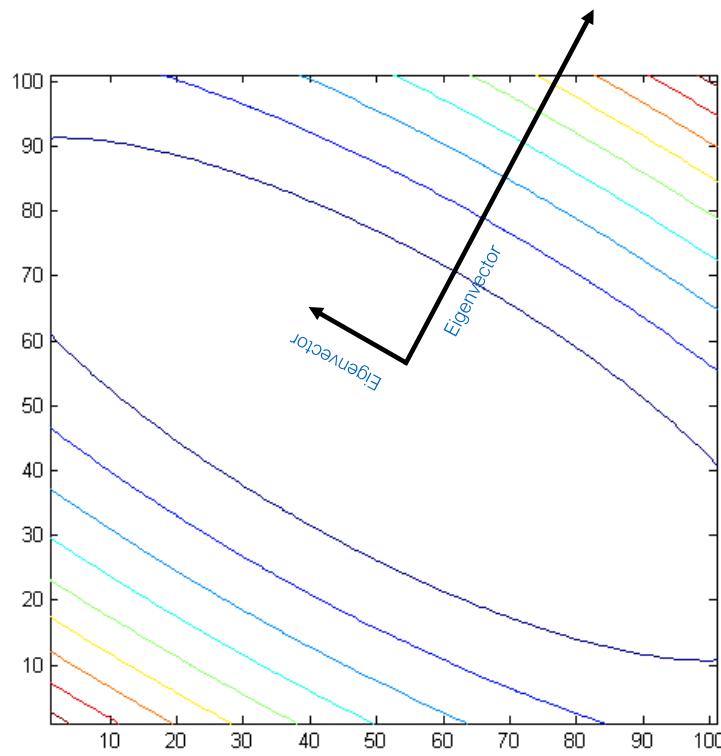
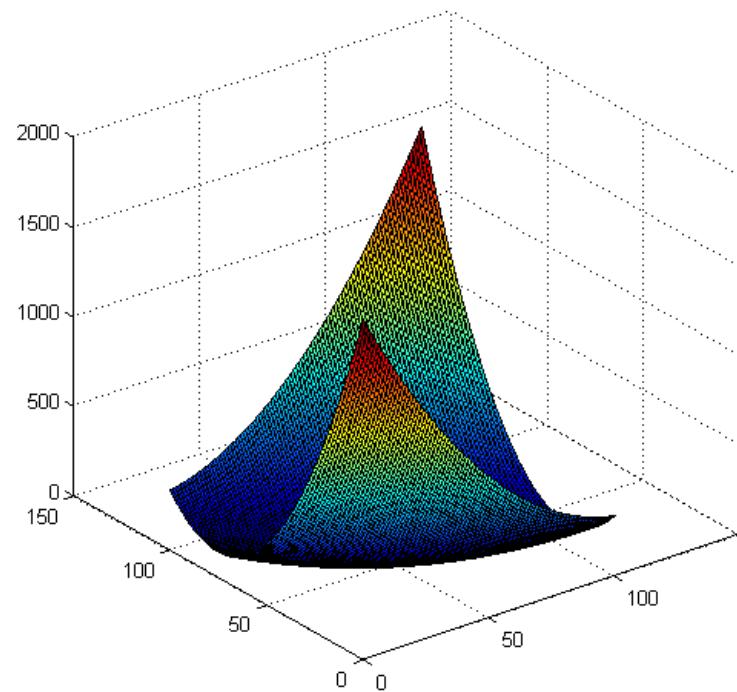
$$A = \begin{bmatrix} 3.25 & 1.30 \\ 1.30 & 1.75 \end{bmatrix} = \begin{bmatrix} 0.50 & -0.87 \\ -0.87 & -0.50 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 4 \end{bmatrix} \begin{bmatrix} 0.50 & -0.87 \\ -0.87 & -0.50 \end{bmatrix}^T$$

Eigenvalues
Eigenvectors Eigenvectors



$$A = \begin{bmatrix} 7.75 & 3.90 \\ 3.90 & 3.25 \end{bmatrix} = \begin{bmatrix} 0.50 & -0.87 \\ -0.87 & -0.50 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 10 \end{bmatrix} \begin{bmatrix} 0.50 & -0.87 \\ -0.87 & -0.50 \end{bmatrix}^T$$

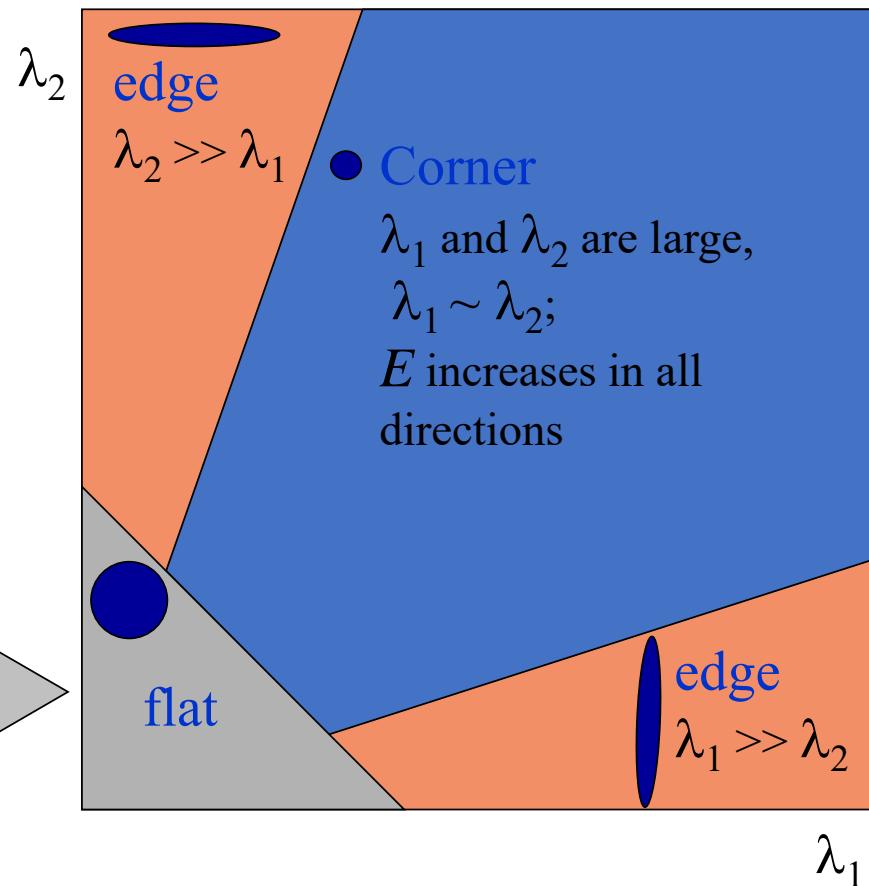
Eigenvalues Eigenvectors Eigenvectors



Harris corner detector

Classification of image points using eigenvalues of M :

λ_1 and λ_2 are small;
 E is almost constant in all directions



Harris corner detector

$$\lambda = \frac{a_{00} + a_{11} \pm \sqrt{(a_{00} - a_{11})^2 + 4a_{10}a_{01}}}{2}$$

Only for reference,
you do not need
them to compute R

Measure of corner response:

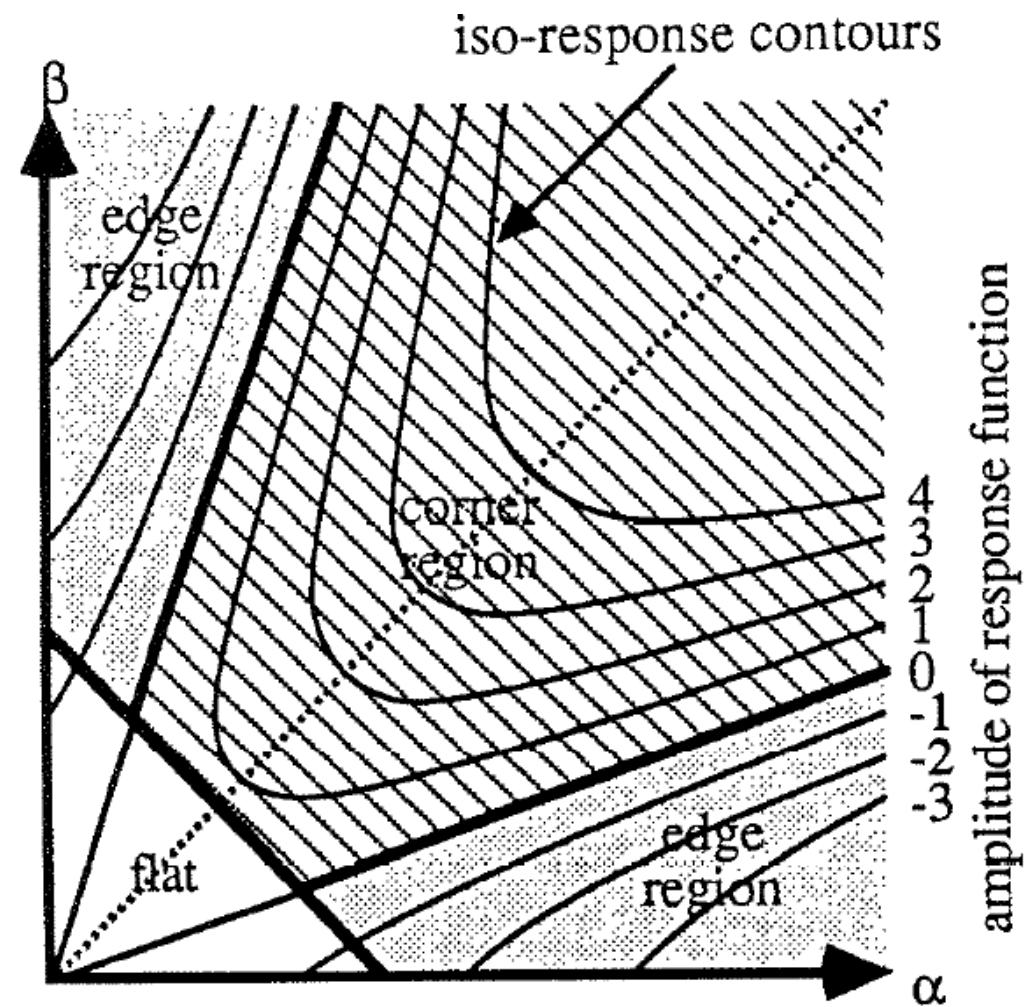
$$R = \lambda_1 \lambda_2 - k(\lambda_1 + \lambda_2)^2$$

(k - empirical constant, $k = 0.04-0.06$)

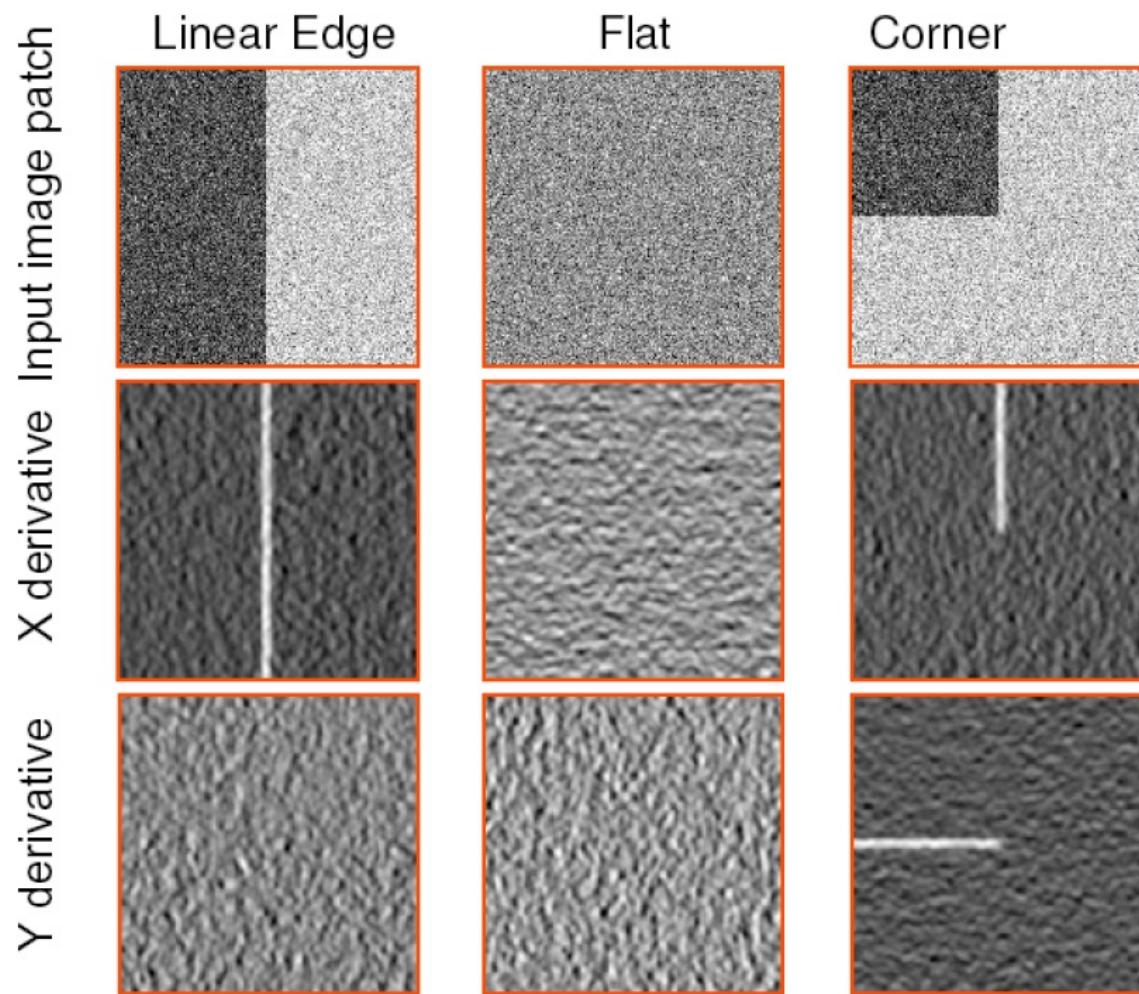
$$\begin{aligned}\det \mathbf{M} &= \lambda_1 \lambda_2 \\ \text{trace } \mathbf{M} &= \lambda_1 + \lambda_2\end{aligned}$$

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

Harris corner detector

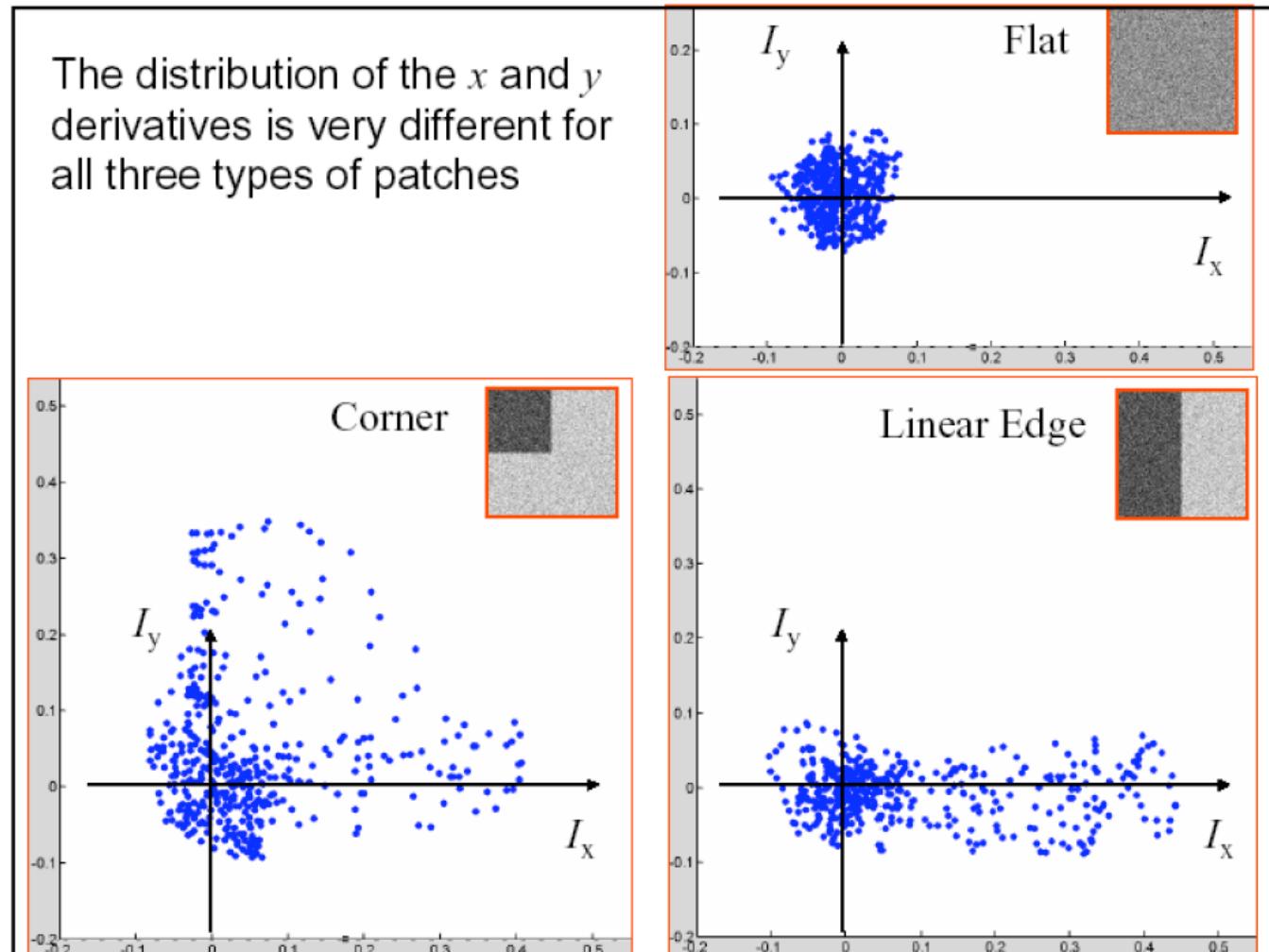


Another view



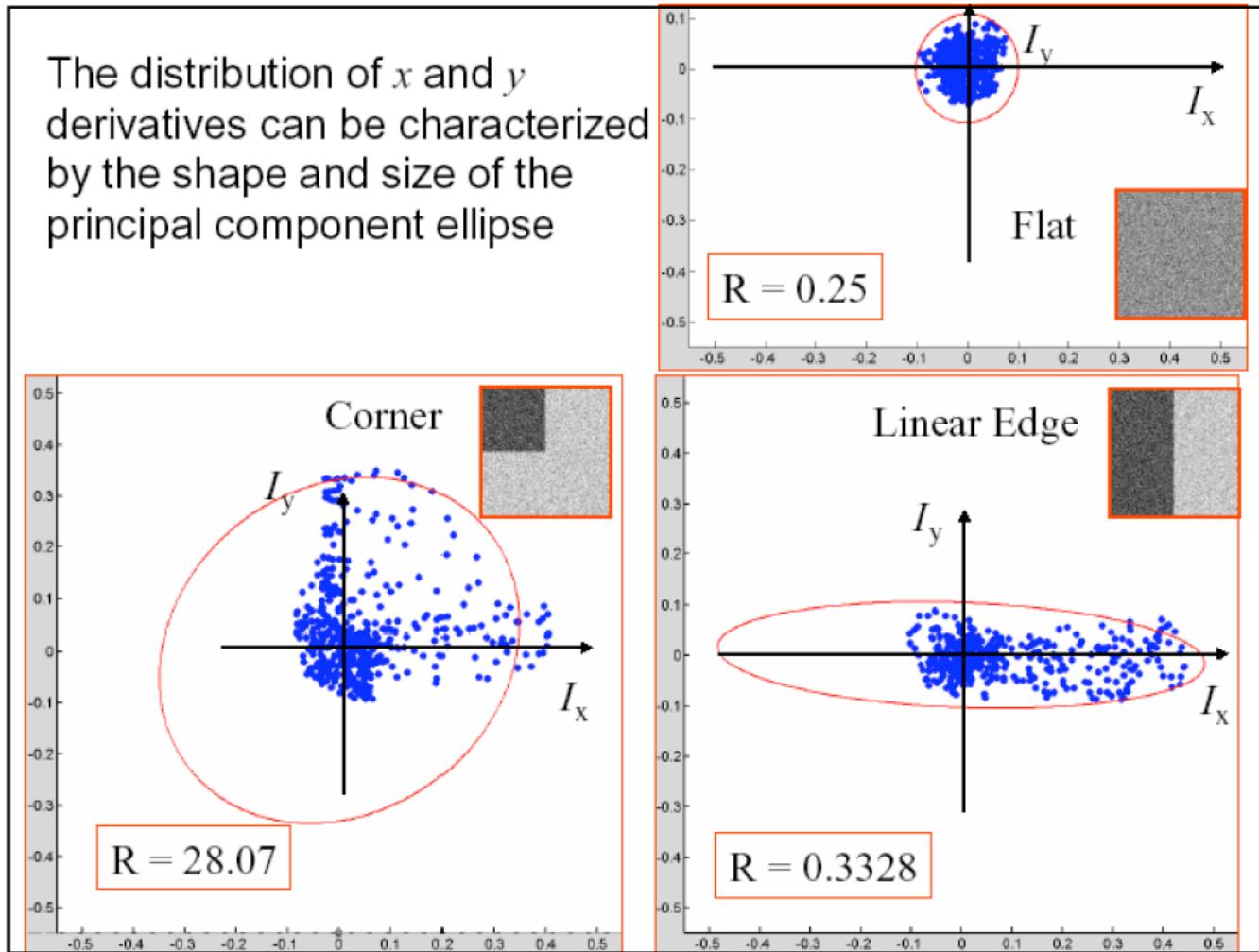
Another view

The distribution of the x and y derivatives is very different for all three types of patches



Another view

The distribution of x and y derivatives can be characterized by the shape and size of the principal component ellipse



Summary of Harris detector

1. Compute x and y derivatives of image

$$I_x = G_\sigma^x * I \quad I_y = G_\sigma^y * I$$

2. Compute products of derivatives at every pixel

$$I_{x^2} = I_x \cdot I_x \quad I_{y^2} = I_y \cdot I_y \quad I_{xy} = I_x \cdot I_y$$

3. Compute the sums of the products of derivatives at each pixel

$$S_{x^2} = G_{\sigma'} * I_{x^2} \quad S_{y^2} = G_{\sigma'} * I_{y^2} \quad S_{xy} = G_{\sigma'} * I_{xy}$$

Summary of Harris detector

4. Define the matrix at each pixel

$$M(x, y) = \begin{bmatrix} S_{x^2}(x, y) & S_{xy}(x, y) \\ S_{xy}(x, y) & S_{y^2}(x, y) \end{bmatrix}$$

5. Compute the response of the detector at each pixel

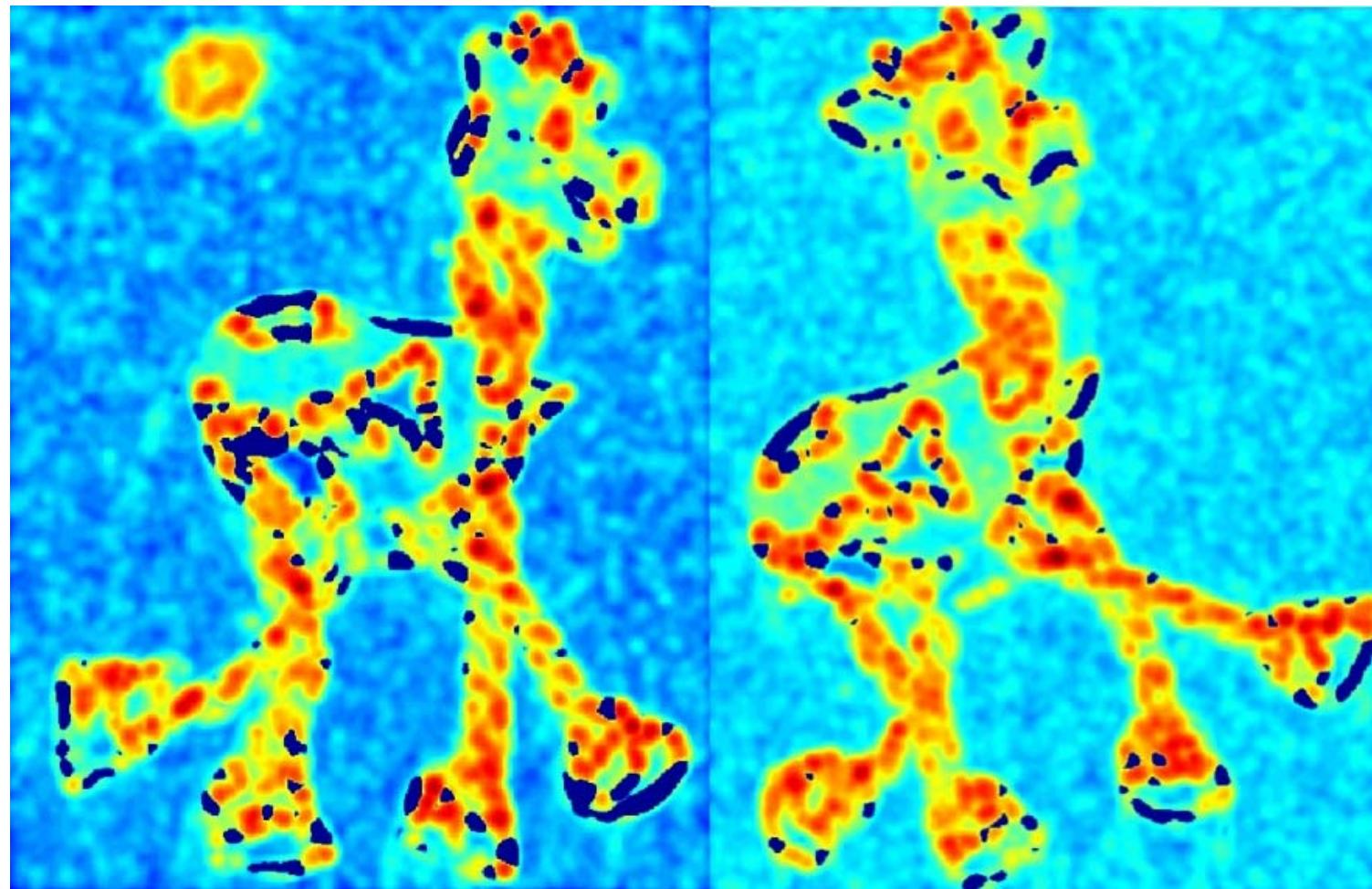
$$R = \det M - k(\text{trace} M)^2$$

6. Threshold on value of R; compute nonmax suppression.

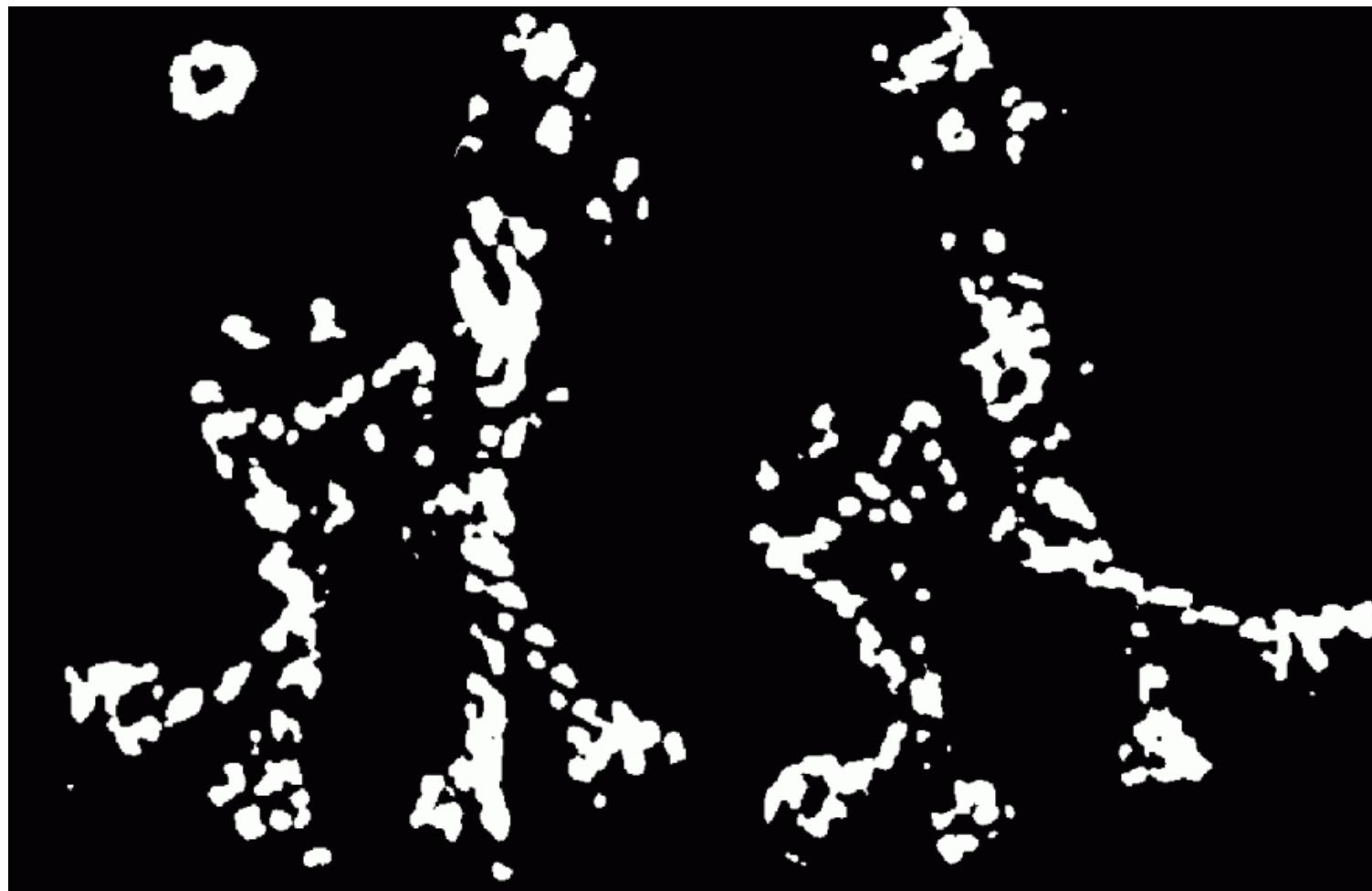
Harris corner detector (input)



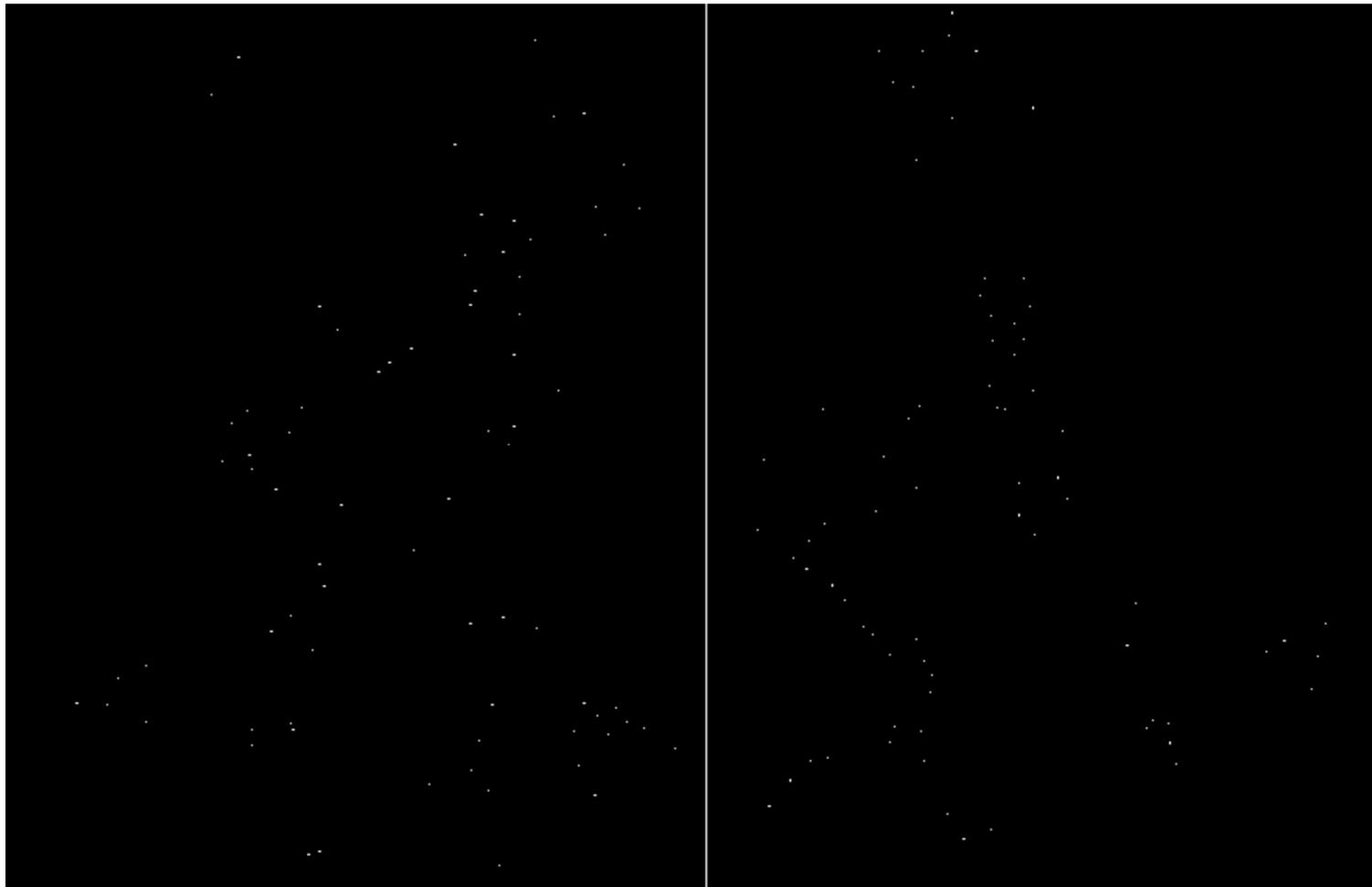
Corner response R



Threshold on R



Local maximum of R



Harris corner detector



Harris detector: summary

- Average intensity change in direction $[u, v]$ can be expressed as a bilinear form:

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

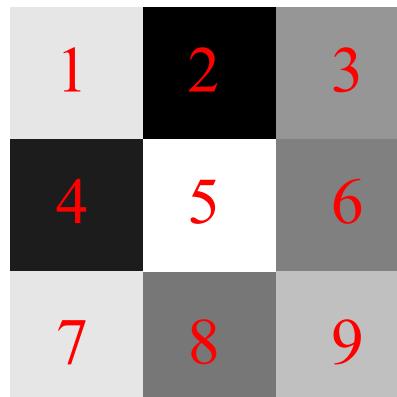
- Describe a point in terms of eigenvalues of M :
measure of corner response

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

- A good (corner) point should have a *large intensity change in all directions*, i.e. R should be large positive

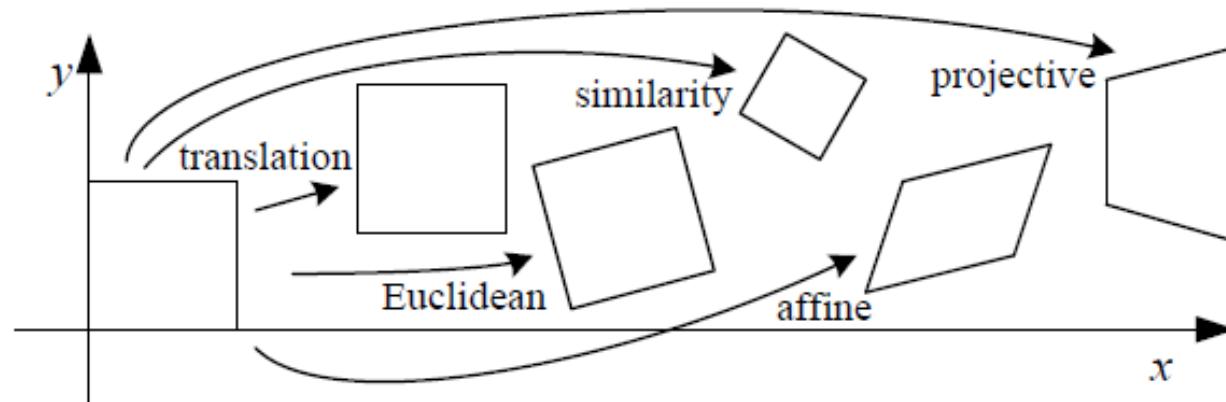
Now we know where features are

- But, how to match them?
- What is the descriptor for a feature? The simplest solution is the intensities of its spatial neighbors. This might not be robust to brightness change or small shift/rotation.



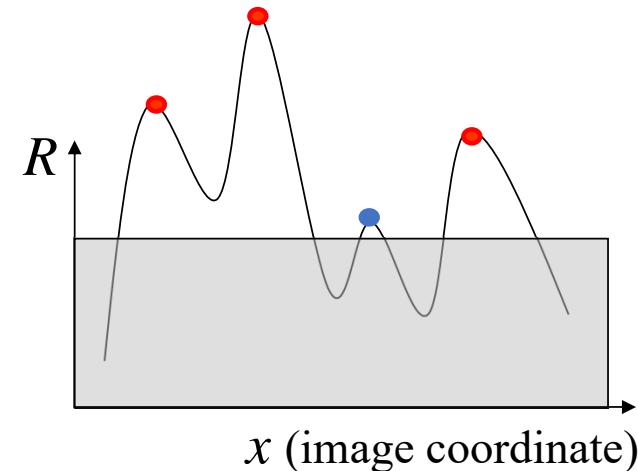
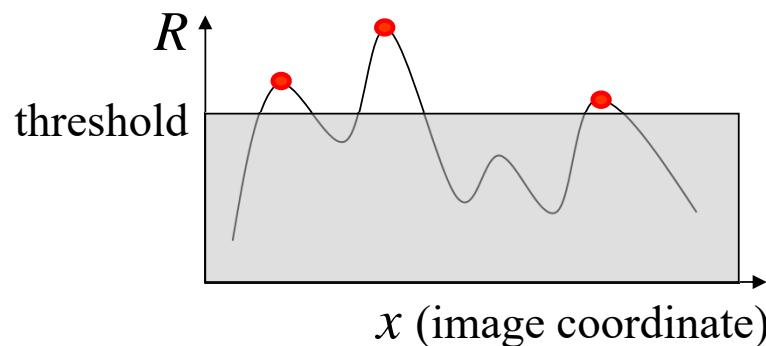
$$\left(\begin{array}{ccccccccc} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 \end{array} \right)$$

2D Geometric Transformations



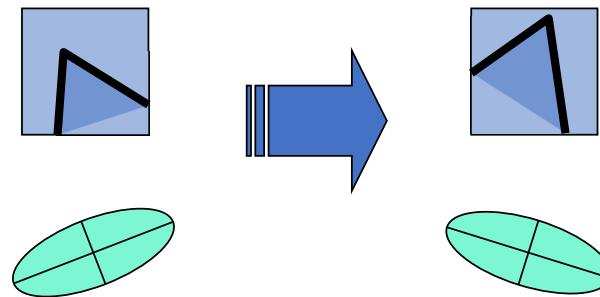
Harris detector: some properties

- Partial invariance to affine intensity change
 - ✓ Only derivatives are used => invariance to intensity shift $I \rightarrow I + b$
 - ✓ Intensity scale: $I \rightarrow a I$



Harris Detector: Some Properties

- Rotation invariance



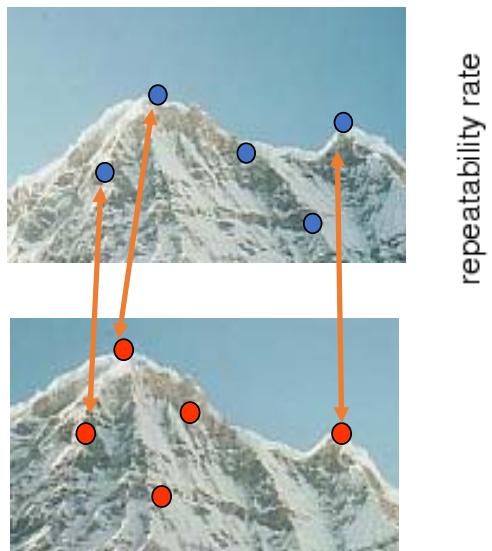
Ellipse rotates but its shape (i.e. eigenvalues) remains the same

Corner response R is invariant to image rotation

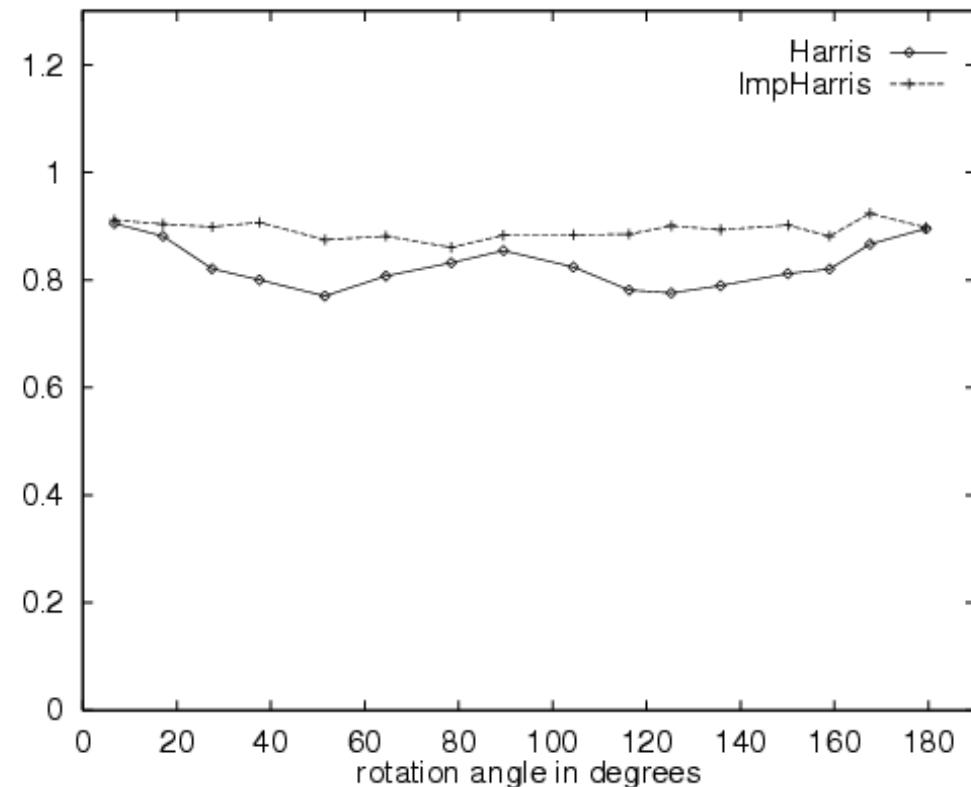
Harris Detector is rotation invariant

Repeatability rate:

$$\frac{\# \text{ correspondences}}{\# \text{ possible correspondences}}$$



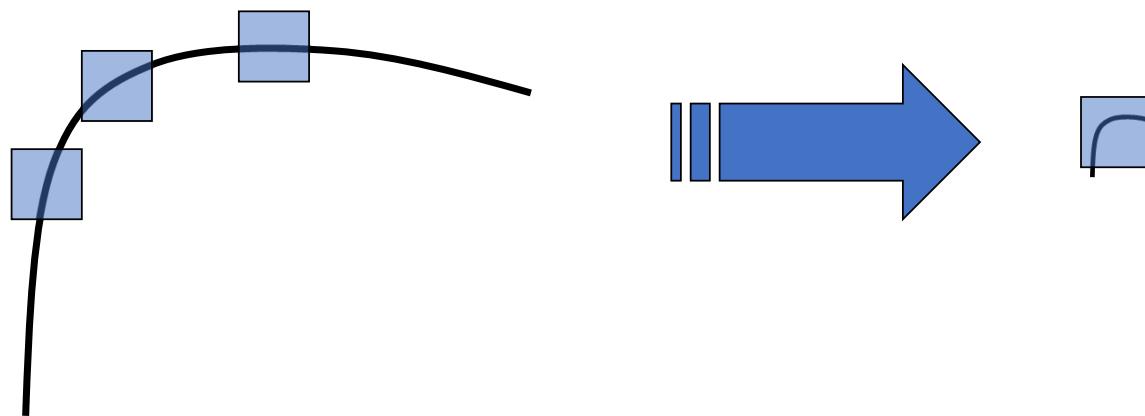
repeatability rate



C.Schmid et.al. "Evaluation of Interest Point Detectors". IJCV 2000

Harris Detector: Some Properties

- But: not invariant to *image scale*!



All points will be
classified as **edges**

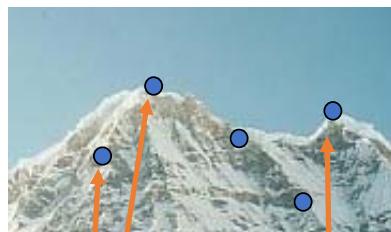
Corner !

Harris detector: some properties

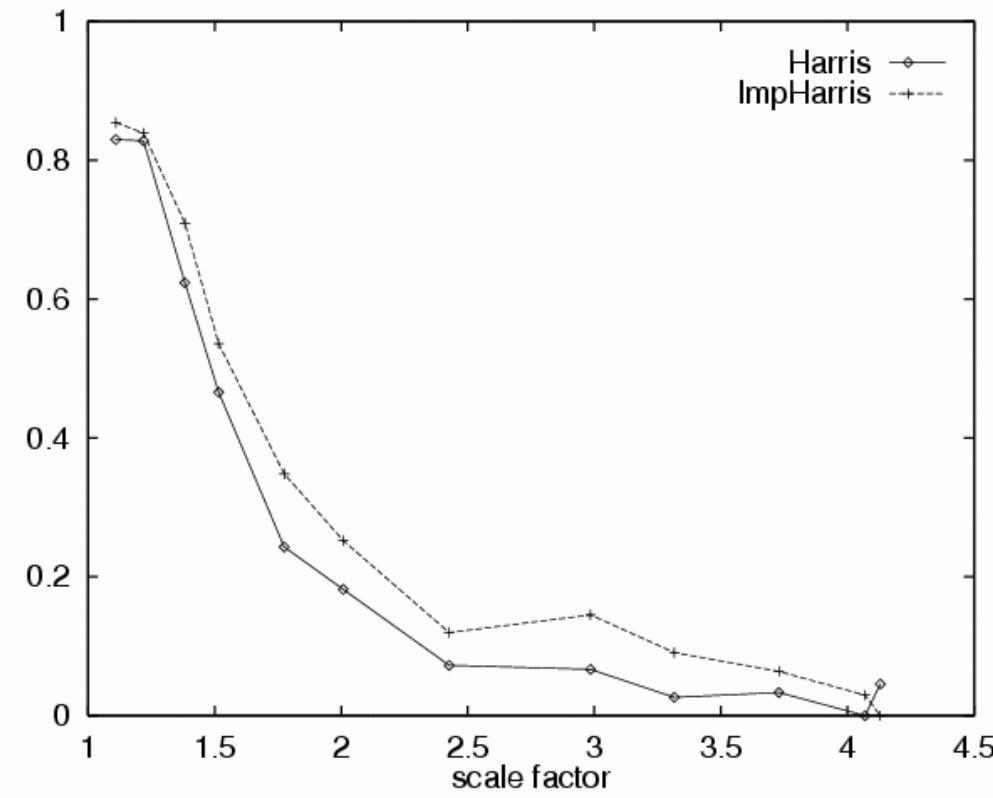
- Quality of Harris detector for different scale changes

Repeatability rate:

$$\frac{\# \text{ correspondences}}{\# \text{ possible correspondences}}$$

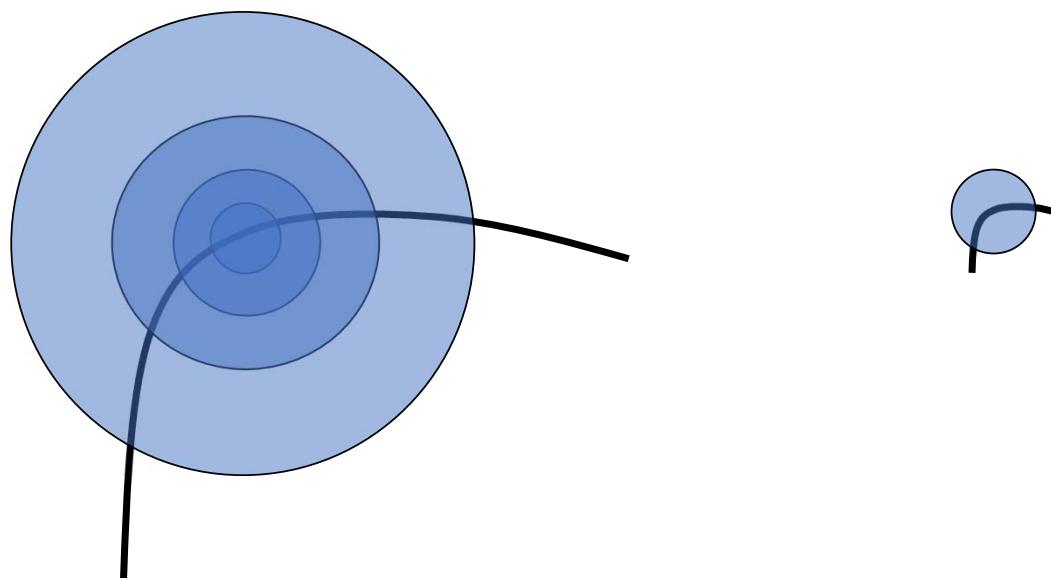


repeatability rate



Scale invariant detection

- Consider regions (e.g. circles) of different sizes around a point
- Regions of corresponding sizes will look the same in both images



References

- Chris Harris, and Mike Stephens, “A Combined Corner and Edge Detector”, 4th Alvey Vision Conference, pp.147-151, 1988.
- Cordelia Schmid, Roger Mohr and Christian Bauckhage, “Evaluation of Interest Point Detectors”. International Journal of Computer Vision, Volume 37, Number 2, pp. 151-172, 2000.
- Steffen Gauglitz, Tobias Höllerer and Matthew Turk, “Evaluation of Interest Point Detectors and Feature Descriptors for Visual Tracking ”. International Journal of Computer Vision, Volume 94, Number 3, pp. 335-360, 2011.