Digital Image Processing (CSE/ECE 478)

Lecture # 11:Interest point detection and description

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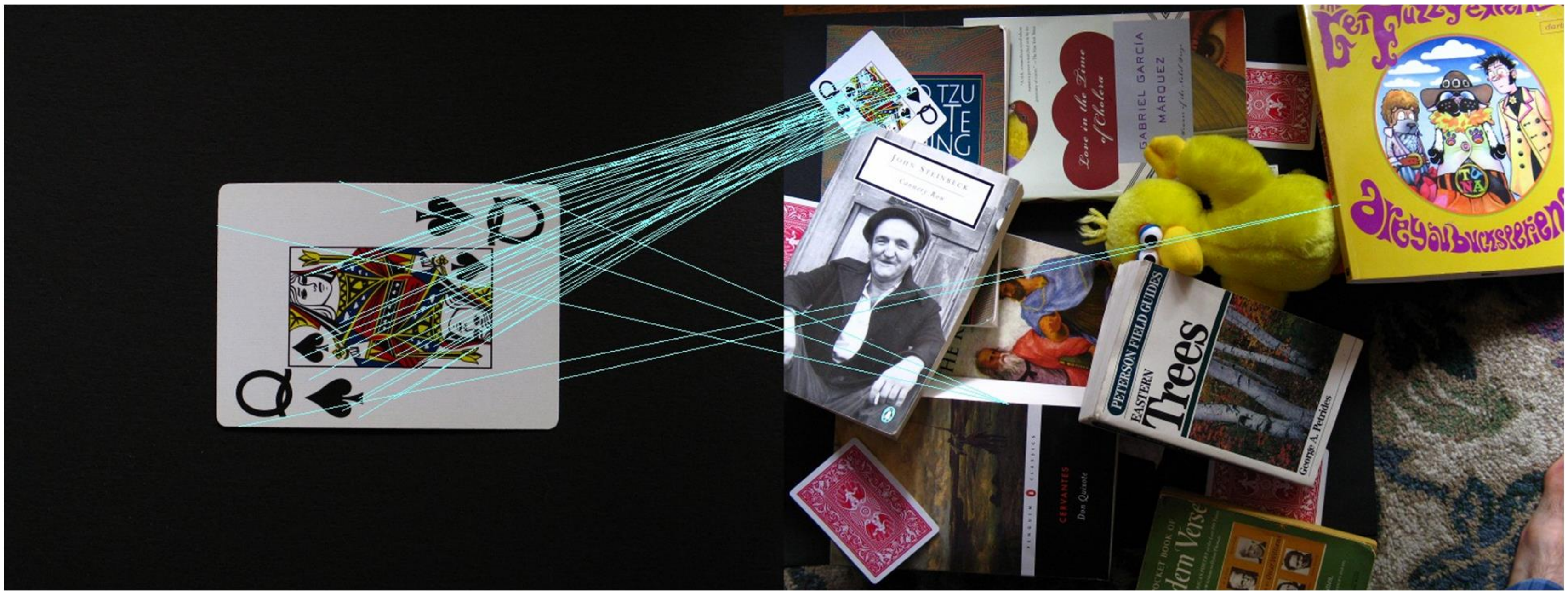
Applications:Feature matching

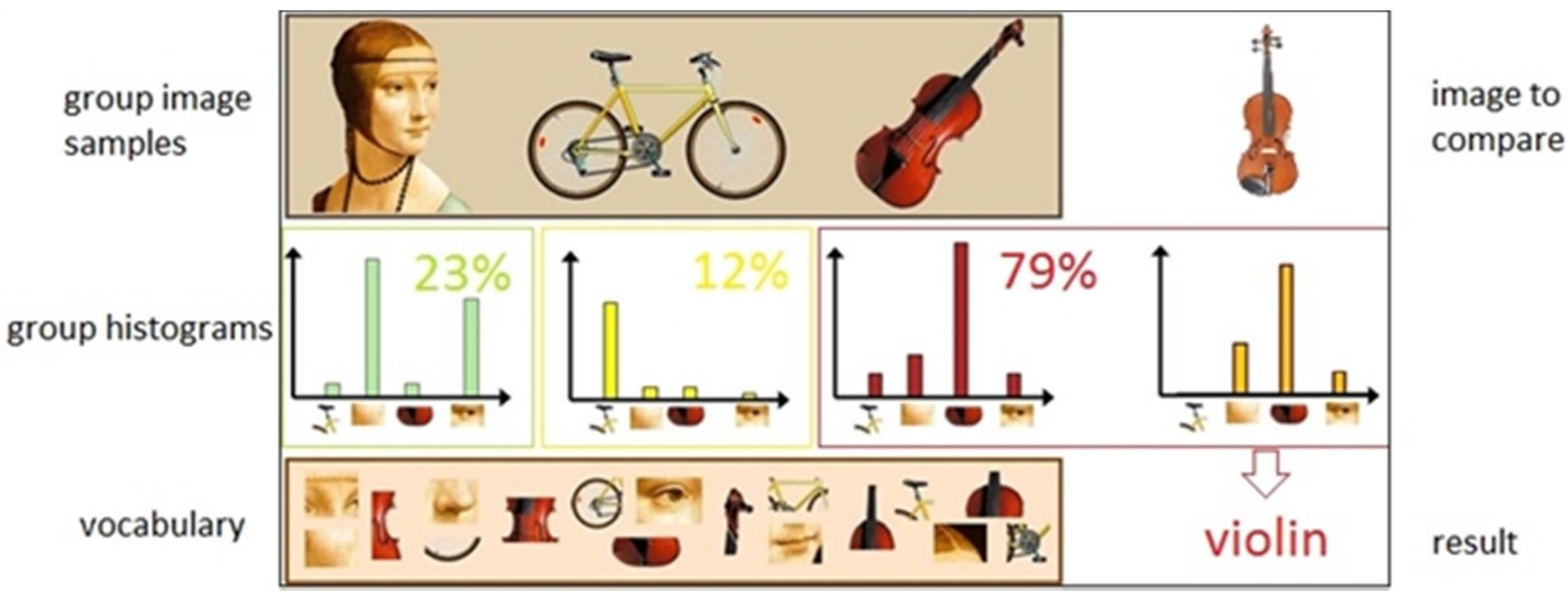
Invariance: image transformations + illumination changes

Applications:Feature matching

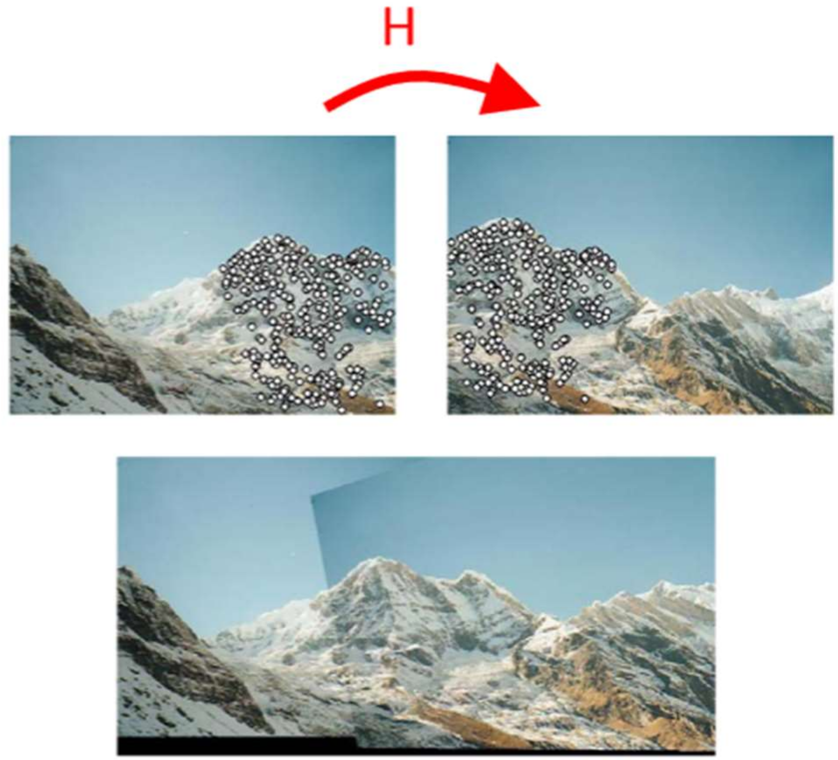


Applications: Object Detection

Applications: Object Recognition



Applications: Image stitching



Applications: Image puzzles

Applications: Image stitching

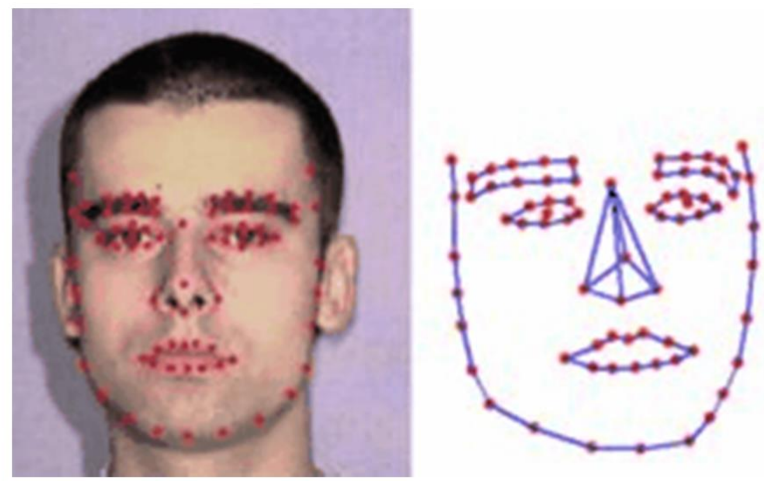
Applications: Augmented Reality

(a)

(b)

Applications: Face landmark detection

Figure 1. Results of our face part localizer.

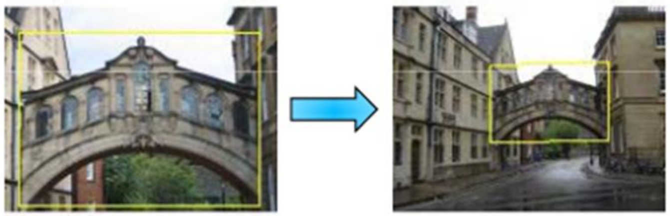


Belhumeur et al. 2011

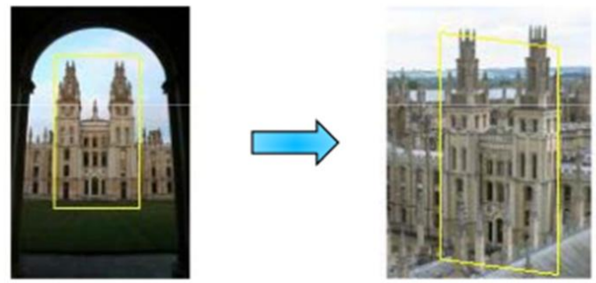
Applications: Take a picture, get related content

Source: Cordelia Schmid

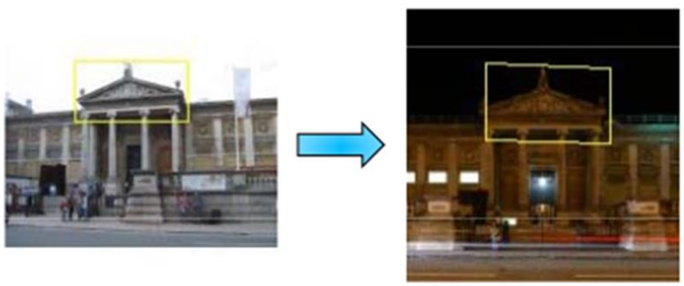
Example Challenges (recognition)



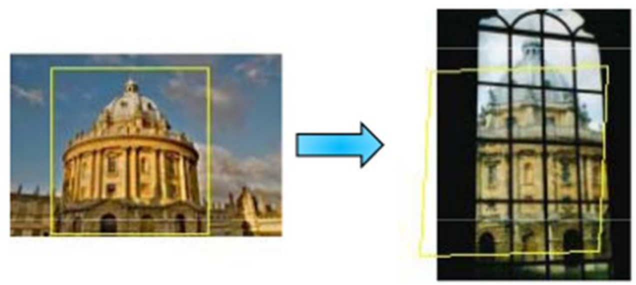
Scale



Viewpoint



Lighting



Occlusion

Today's Lecture

Three tasks gain importance in most of these applications:

- Feature Detection
- Feature Extraction
- Feature Matching

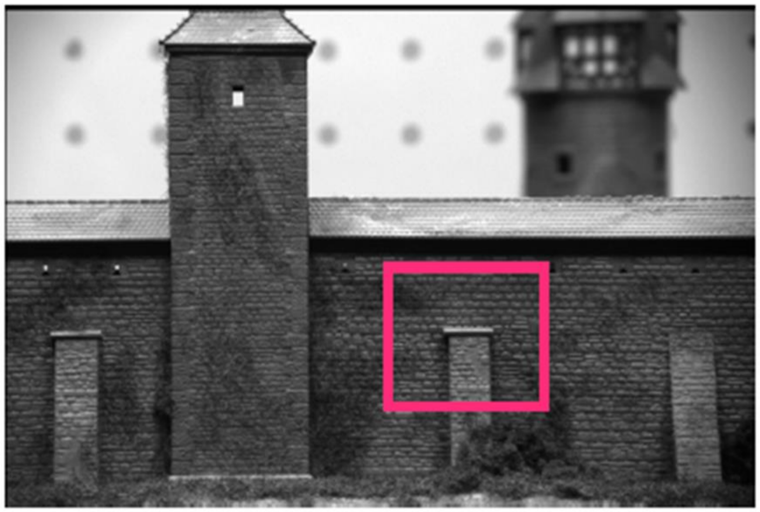
We will discuss the first two in detail!

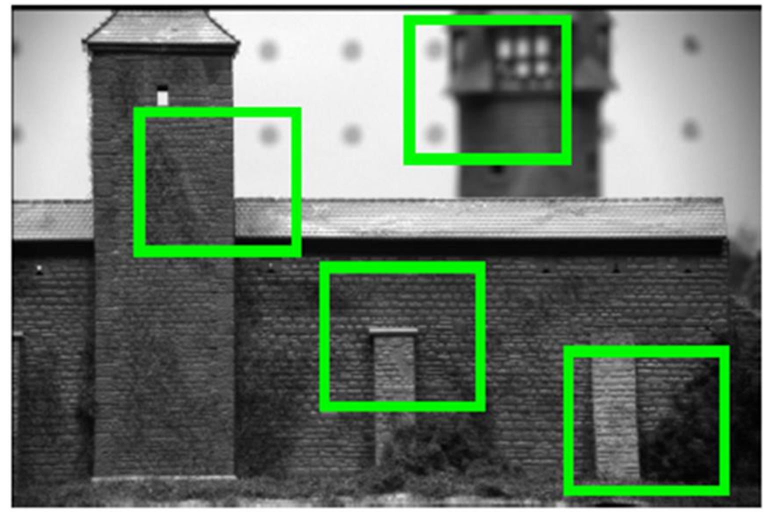
Today's Lecture

- Feature detection
  - Harris feature detector
  - SIFT feature detector

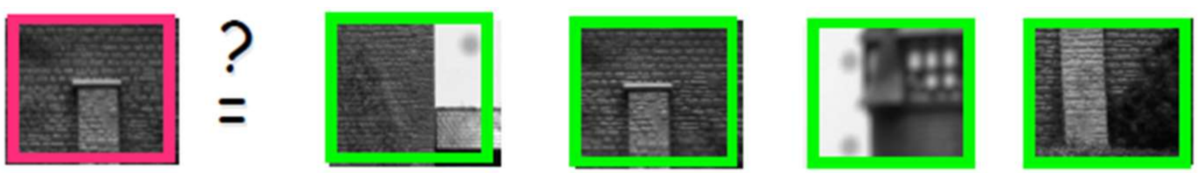
- Feature Descriptors
  - SIFT feature descriptor

Matching patches, why interest points (corners)?





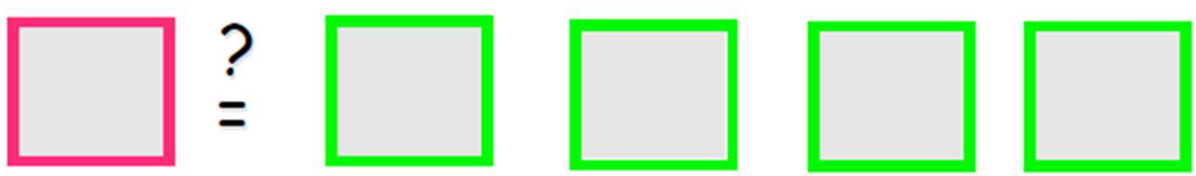
Task: find the most similar patch in the second image



Source: Robert Collins

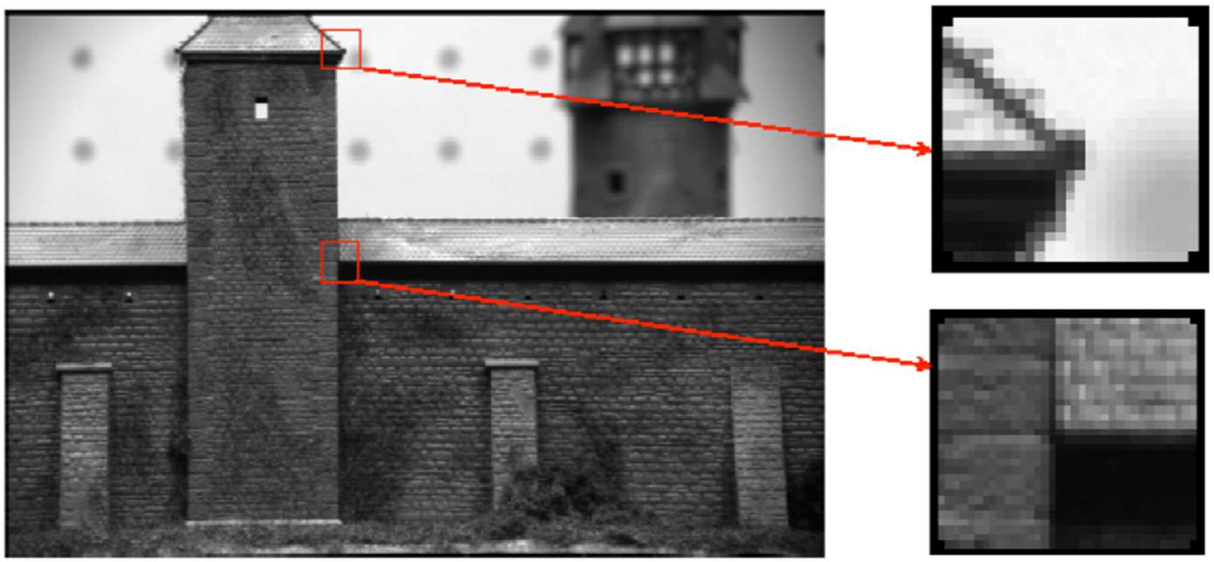
Matching patches, why interest points (corners)?

Task: find the most similar patch in the second image



Source: Robert Collins

What interest points (corners)?

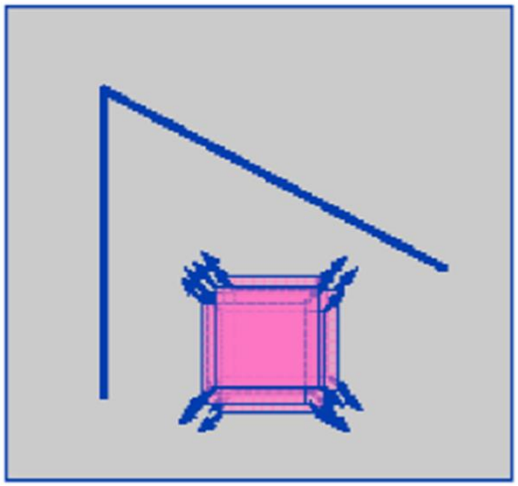


- Junctions of contours
- Generally more stable over changes of viewpoint
- Large variations in neighbourhood of the point in all directions
- Good features to match!

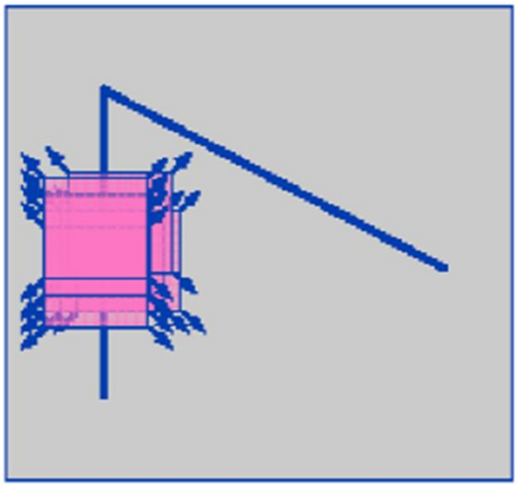
Source: Robert Collins

Corner detection: basic idea

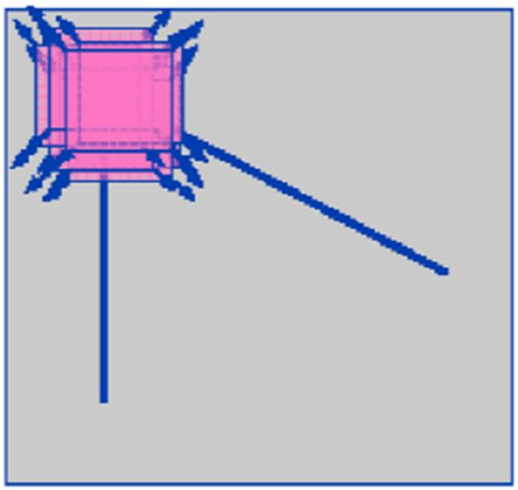
Take a window around the point of interest and move around



“flat” region: no change in all directions



“edge”: no change along edge direction

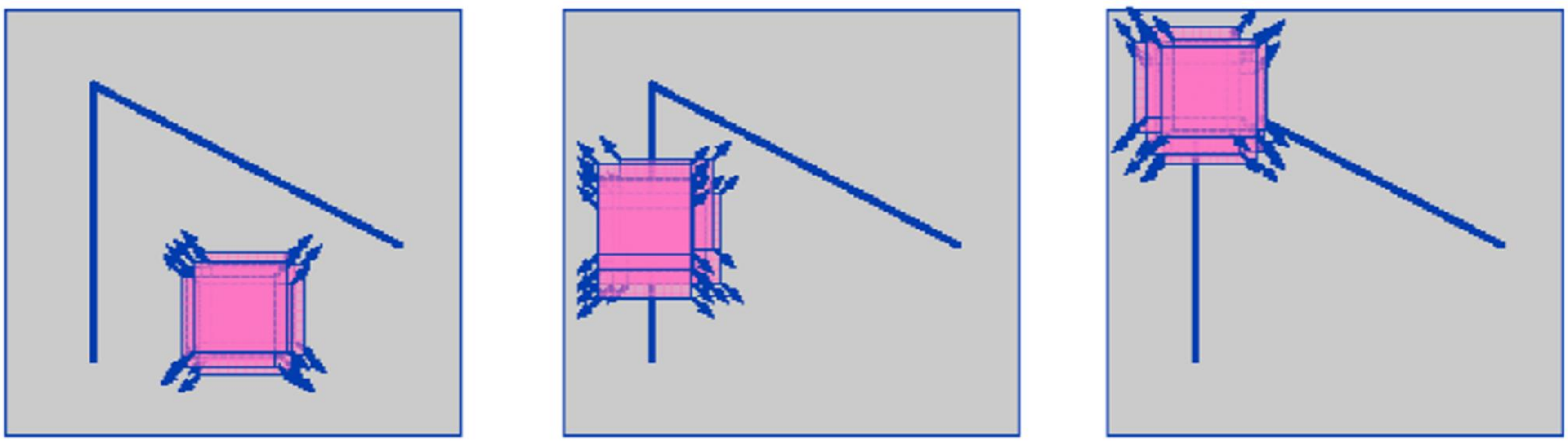


“corner”: significant change in all directions

Source: Robert Collins

Harris corner detection

Harris and Stephens* proposed a mathematical approach to determine which case holds

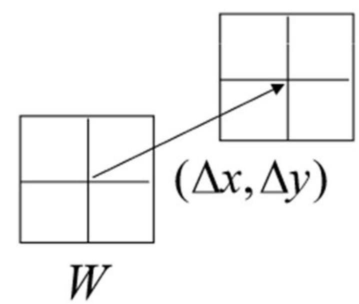


**C. Harris and M. Stephens (1988). ["A combined corner and edge detector"](). Proceedings of the 4th Alvey Vision Conference. pp. 147–151*

Harris corner detection: Auto-correlation function

- Auto-correlation function for a point (x, y) and a shift $(\Delta x, \Delta y)$

$$A(x,y) = \sum_{W(x,y)} \left(I(x,y) - I(x + \Delta x, y + \Delta y)\right)^2$$



$$A(x,y) \begin{cases} \text{small in all directions} & \rightarrow \text{uniform region} \\ \text{large in one directions} & \rightarrow \text{contour} \\ \text{large in all directions} & \rightarrow \text{interest point} \end{cases}$$

Taylor series expansion

- Taylor series expansion (1D)

$$F(x_0 + \Delta x) \approx F(x_0) + F'(x_0)\Delta x + \frac{1}{2!}F''(x_0)\Delta x^2 + \frac{1}{3!}F^{(3)}(x_0)\Delta x^3 + \ldots + \frac{1}{n!}F^{(n)}(x_0)\Delta x^n$$

Taylor series expansion

- Taylor series expansion (2D)

$$F(x_0 + \Delta x, y_0 + \Delta y) \approx F(x_0, y_0) + F_x(x_0, y_0)\Delta x + F_y(x_0, y_0)\Delta y +$$

First partial derivative

$$\frac{1}{2!}[F_{xx}(x_0, y_0)\Delta x^2 + F_{xy}(x_0, y_0)\Delta x \Delta y + F_{yy}(x_0, y_0)\Delta y^2] +$$

Second partial derivative

$$\frac{1}{3!}[F_{xxx}(x_0, y_0)\Delta x^3 + F_{xxy}(x_0, y_0)\Delta x^2 \Delta y + F_{xyy}(x_0, y_0)\Delta x \Delta y^2 + F_{yy}\ \ (x_0, y_0)\Delta y^3]$$

Third partial derivative

…. + higher order terms

Harris corner detection: Auto-correlation function

$$A(x,y) = \sum_{W(x,y)} \left(I(x,y) - I(x+\Delta x, y+\Delta y)\right)^2$$

$$I(x+\Delta x, y+\Delta y) \approx I(x,y) + I_x(x,y)\Delta x + I_y(x,y)\Delta y$$

First order approximation

$$A(x,y) \approx \sum \left(I(x,y) - I(x,y) - I_x(x,y)\Delta x - I_y(x,y)\Delta y\right)^2$$

$$= \sum (I_x\Delta x)^2 + \left(I_y\Delta y\right)^2 + 2\, I_x I_y \Delta x \Delta y$$

$$= [\Delta x \;\; \Delta y]\left(\sum \begin{bmatrix} {I_x}^2 & I_x I_y \\ I_x I_y & {I_y}^2 \end{bmatrix}\right)\begin{bmatrix}\Delta x \\ \Delta y\end{bmatrix}$$

$$A(x,y) = [\Delta x \;\; \Delta y] M \begin{bmatrix}\Delta x \\ \Delta y\end{bmatrix}$$

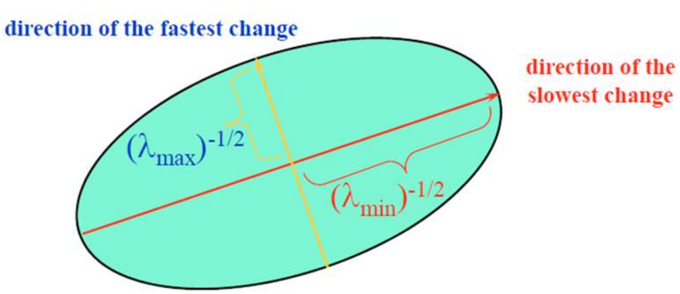
Equation of an ellipse, where M is the covariance matrix

Harris corner detection: Auto-correlation matrix

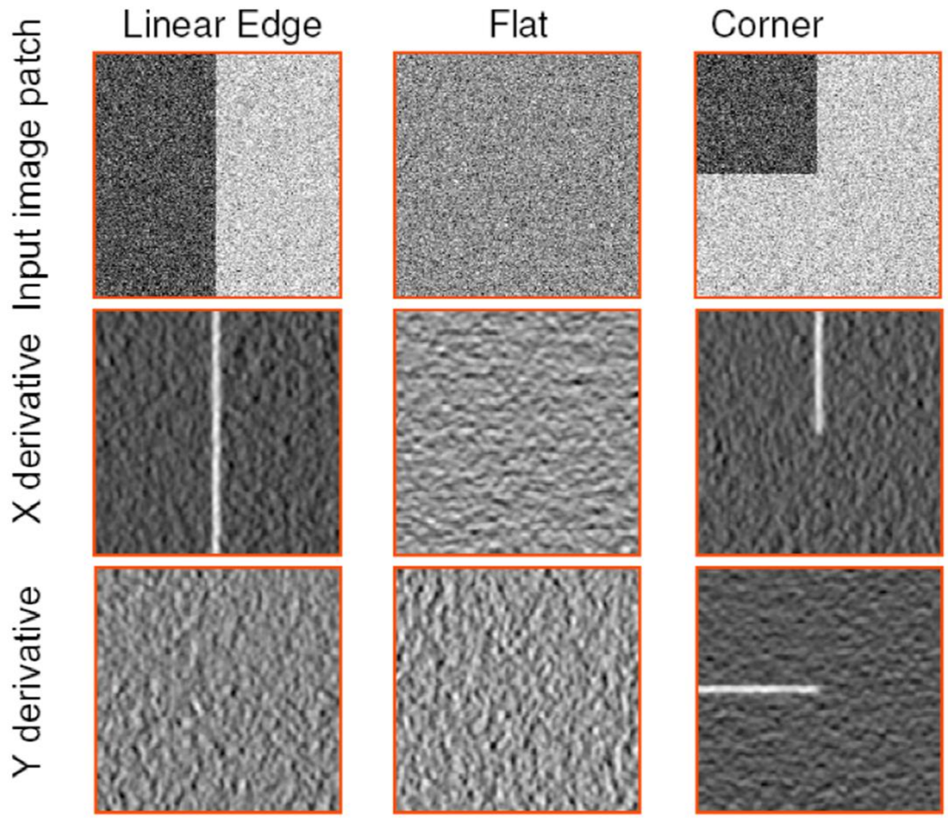
$$M = \begin{bmatrix} \sum {I_x}^2 & \sum I_x I_y \\ \sum I_x I_y & \sum {I_y}^2 \end{bmatrix}$$

- M is a 2×2 covariance matrix computed from image derivatives.
- It is also common practice to smooth each individual component before computing the sum.

- Captures the structure of the local neighbourhood
- Measure based on Eigen values of this matrix
  - 2 strong eigenvalues → interest point
  - 1 strong eigenvalue → line (contour)
  - 0 strong eigenvalue → uniform region

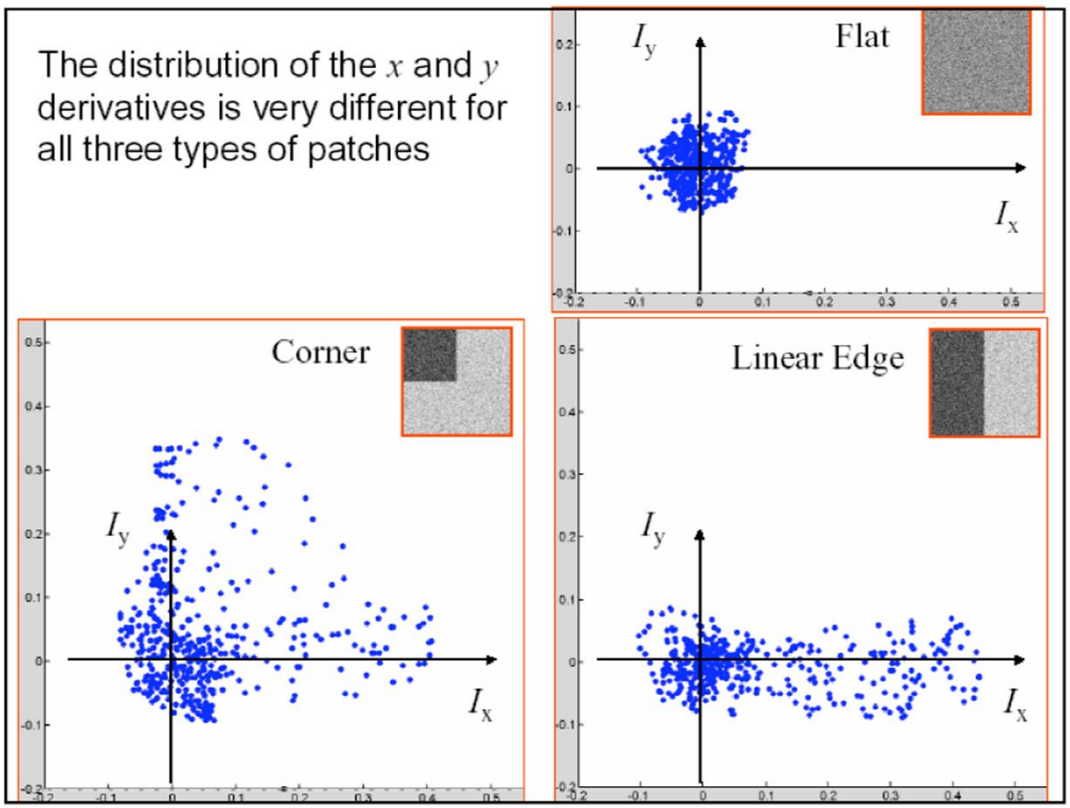


Harris corner detection: Intuition



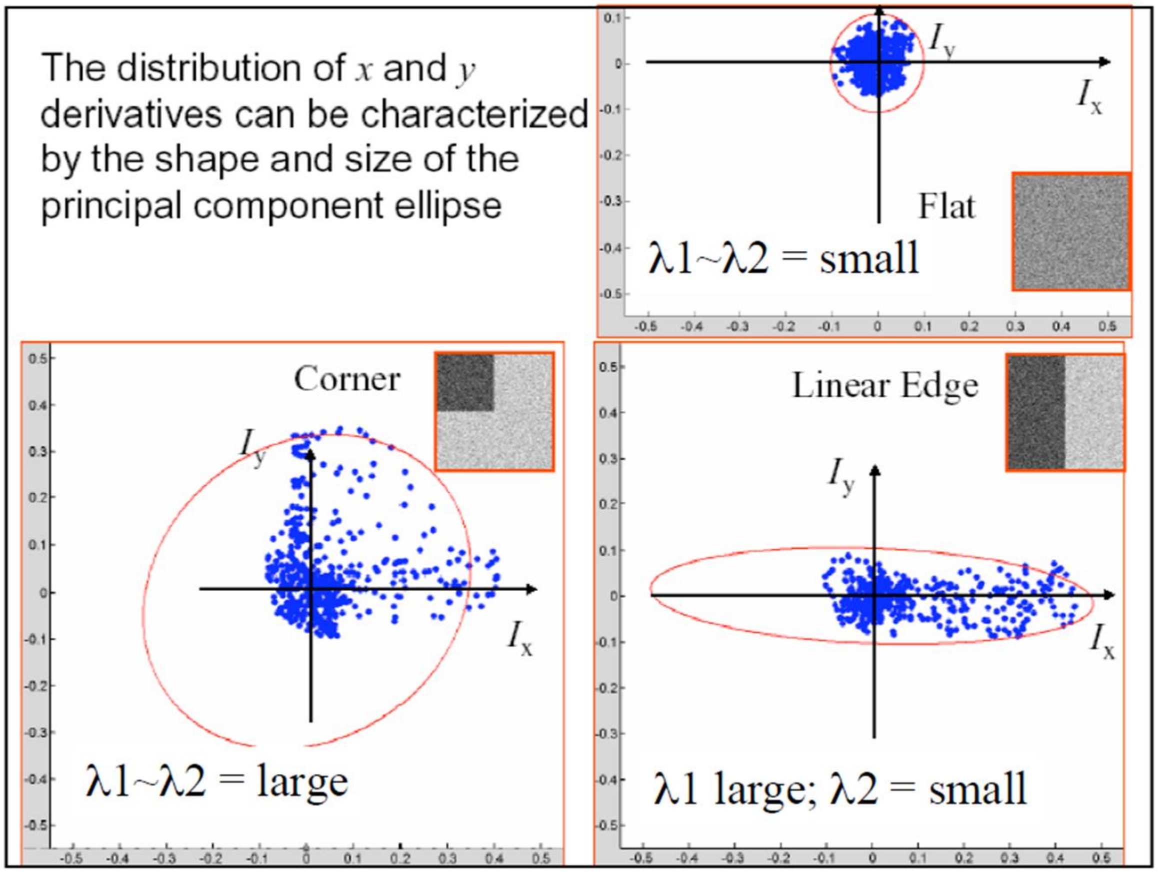
Source: Robert Collins

Harris corner detection: Intuition



Source: Robert Collins

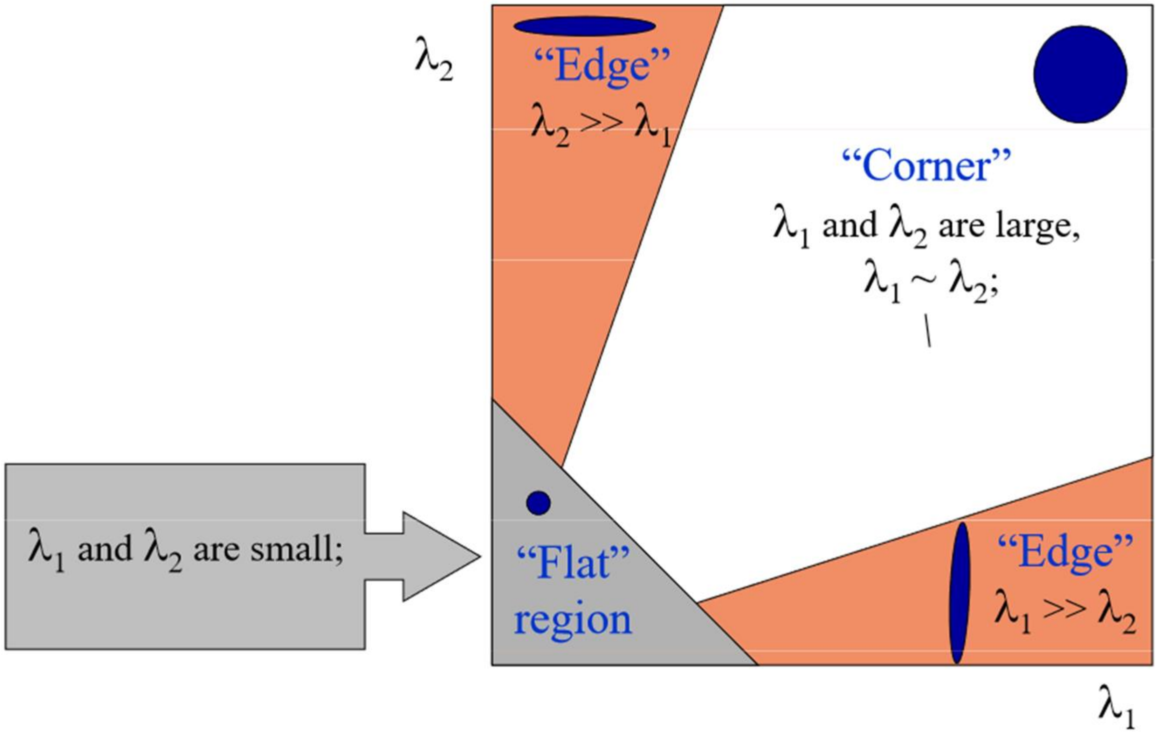
Harris corner detection: Intuition



Source: Robert Collins

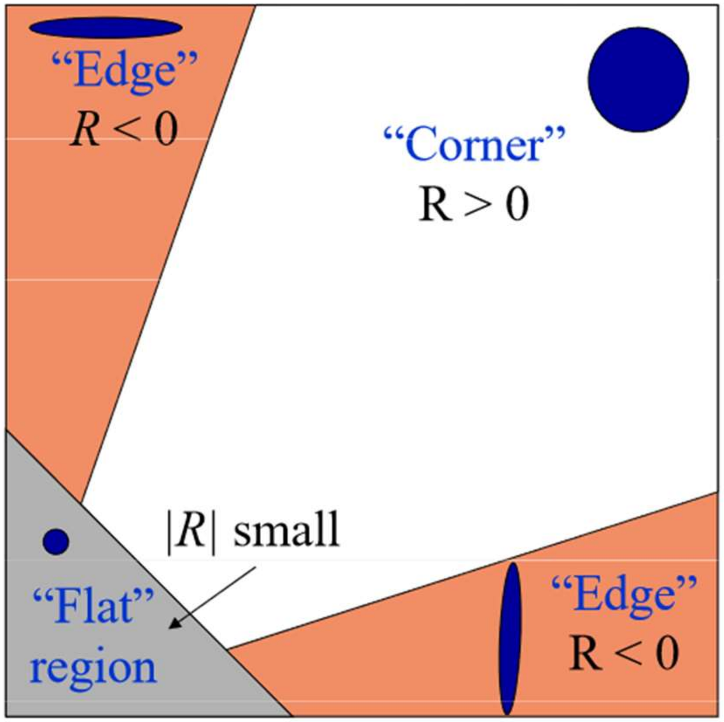
Interpreting the eigenvalues

- Classification of image points using eigenvalues of autocorrelation matrix



Corner response function

$$R = \det(M) - \alpha\left(\text{trace}(M)\right)^2 = \lambda_1\lambda_2 - \alpha(\lambda_1 + \lambda_2)^2$$



Harris Detector: Steps

1. Compute horizontal and vertical derivatives of an image (I_x , I_y)
2. Compute products of derivatives at every pixel

   $I_{xx} = I_x.I_x$ $\quad$ $I_{yy} = I_y.I_y$ $\quad$ $I_{xy} = I_x.I_y$
3. Compute local sum at each pixel (often weighted by gaussian)

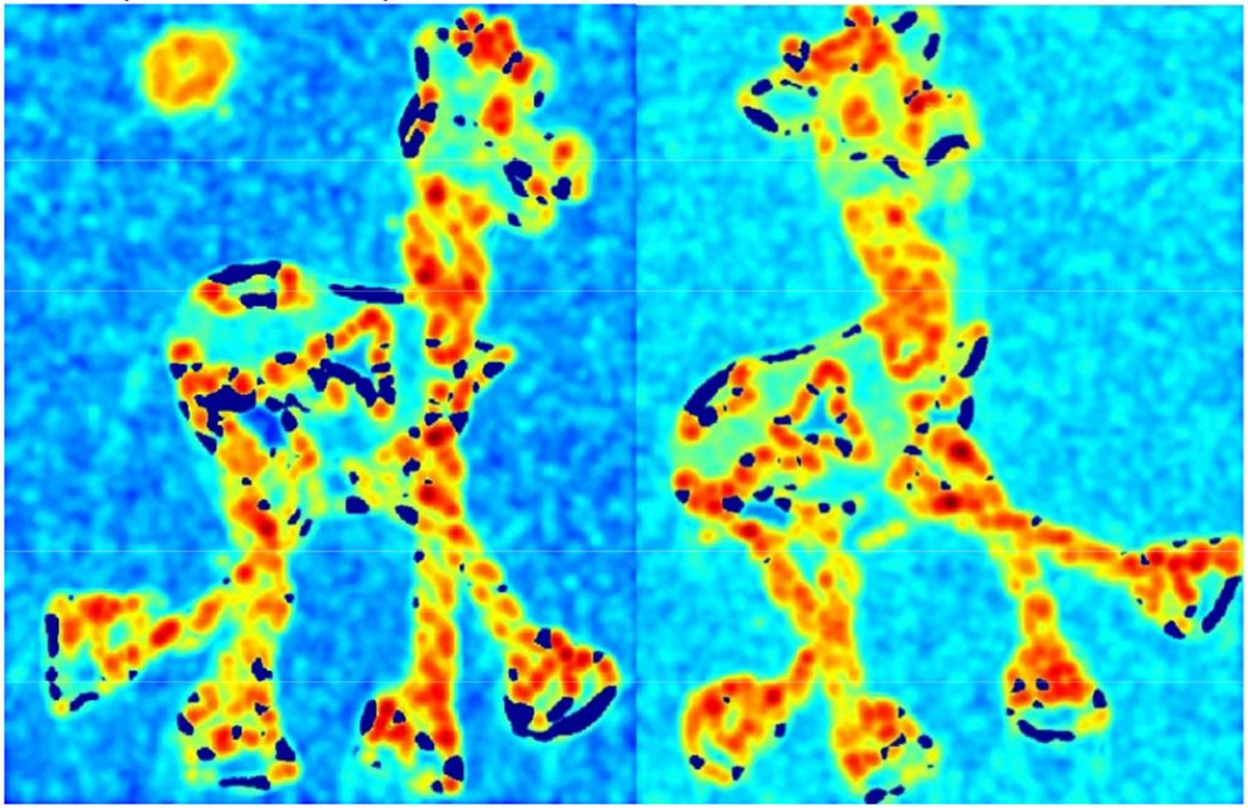
   $S1 = G * I_{xx}$ $\quad$ $S2 = G * I_{yy}$ $\quad$ $S3 = G * I_{xy}$
4. For each pixel define R matrix

   $\mathrm{R} = [S1\ S3; S3\ S2]$
5. Compute the corner response function at each pixel
6. Threshold the resulting matrix then compute non maximal supression

Harris Detector: Steps

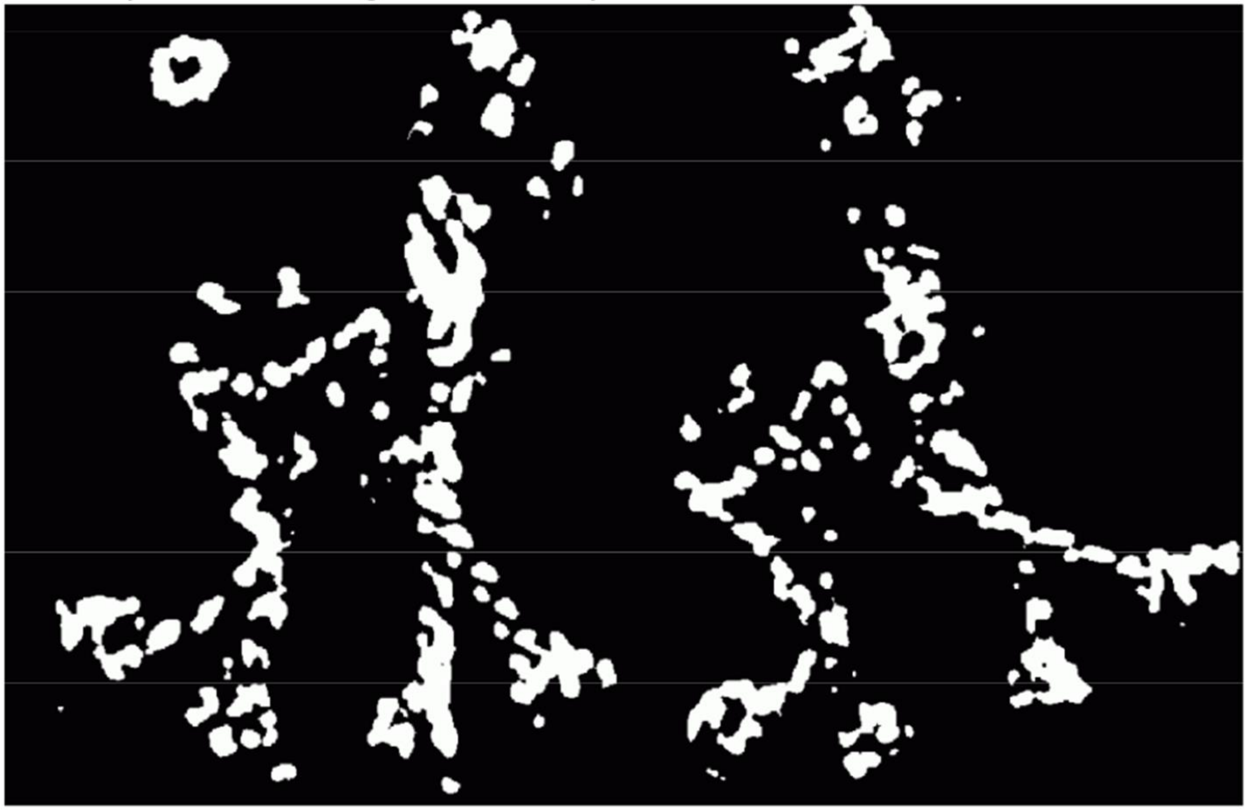
Harris Detector: Steps

Compute corner response R



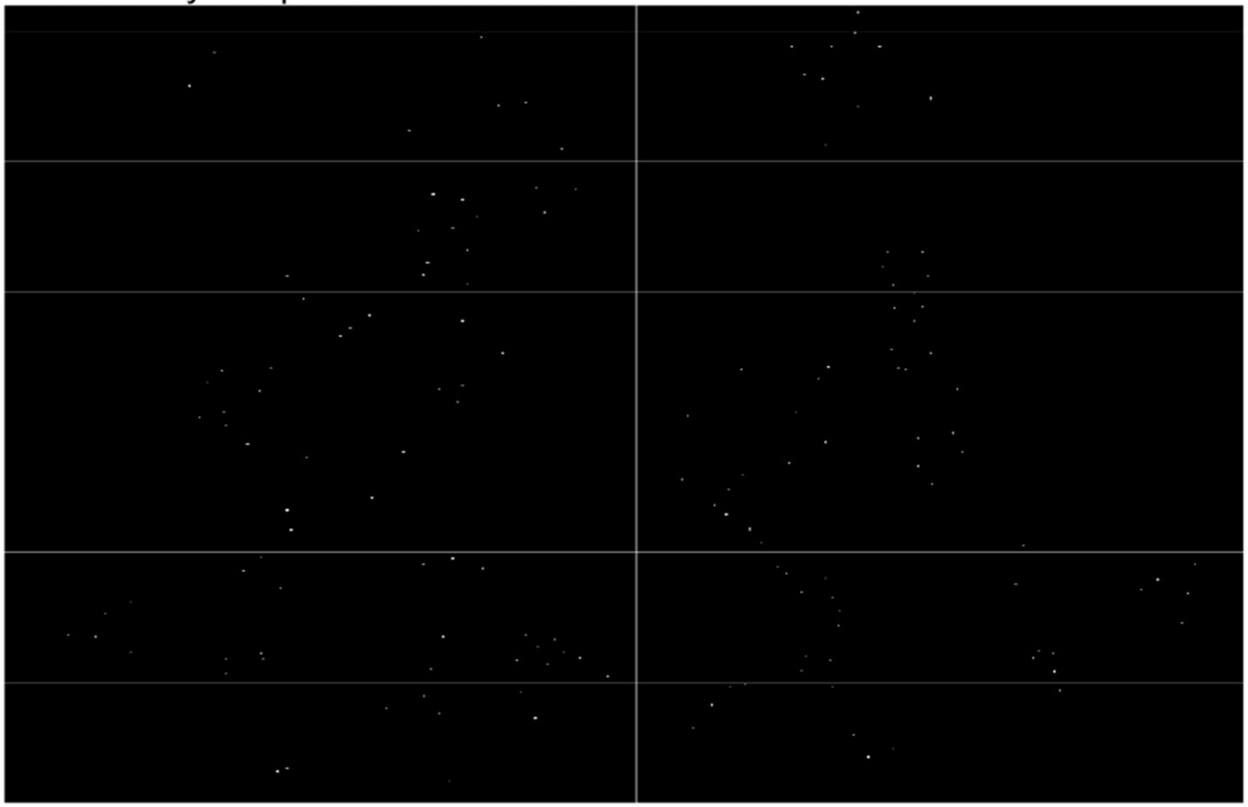
Harris Detector: Steps

Find points with large corner response: R>threshold

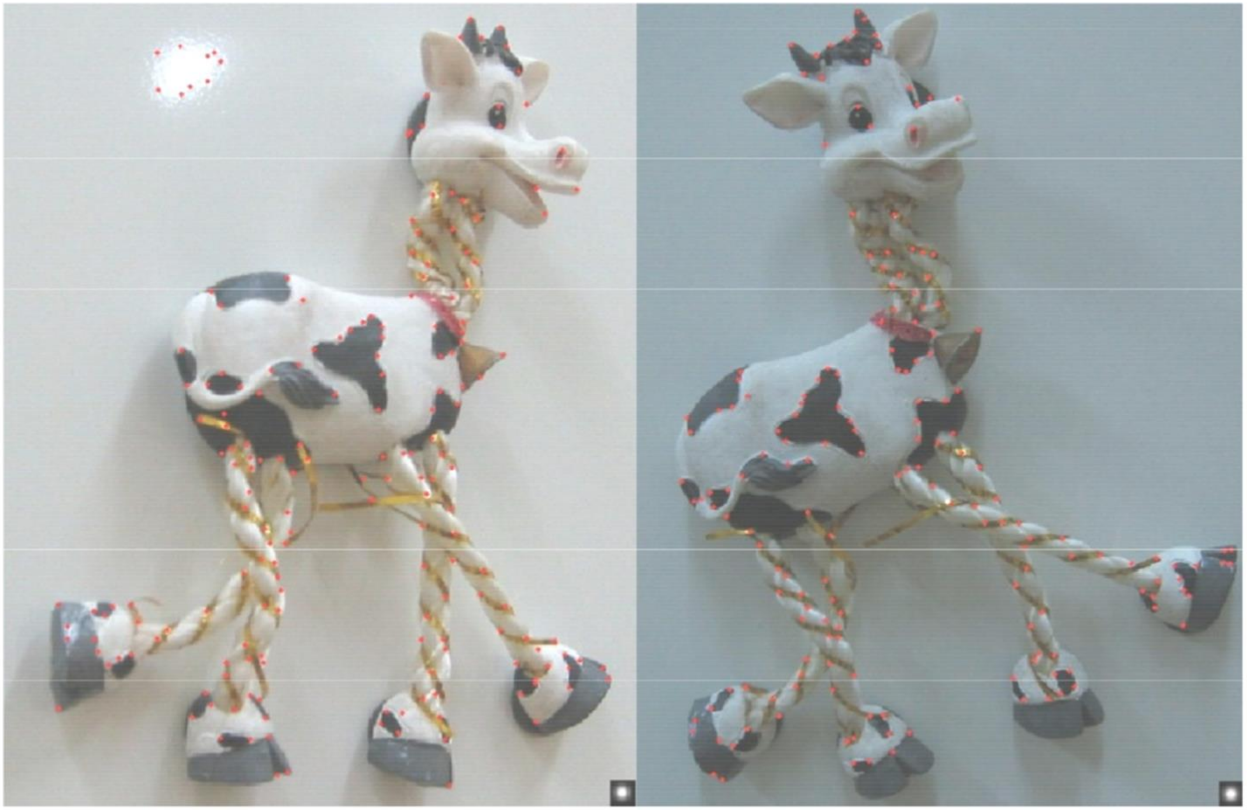


Harris Detector: Steps

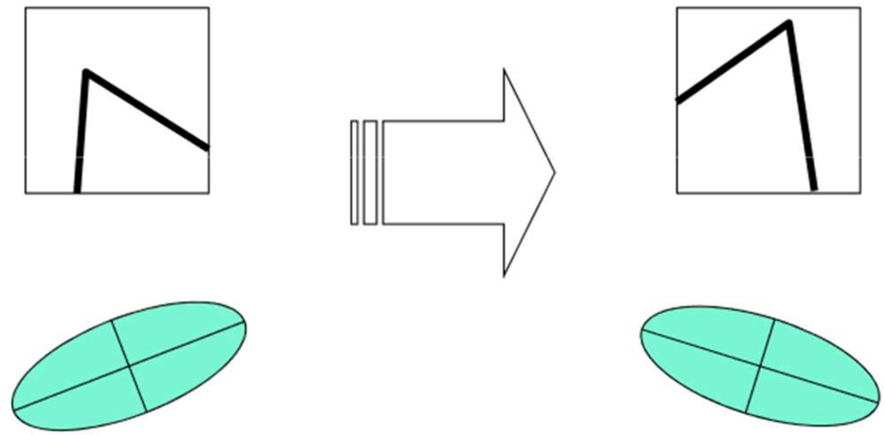
Take only the points of local maxima of R



Harris Detector: Steps



Invariance properties: Rotation



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

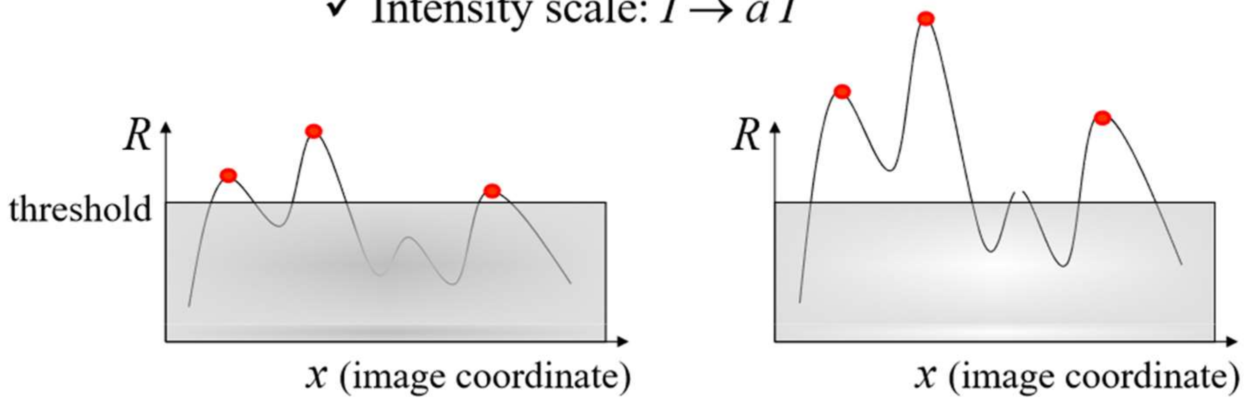
Corner response R is invariant of rotation

Source: Cordelia Schmid

Invariance properties: Intensity Scaling

✓ Only derivatives are used => invariance to intensity shift $I \rightarrow I + b$

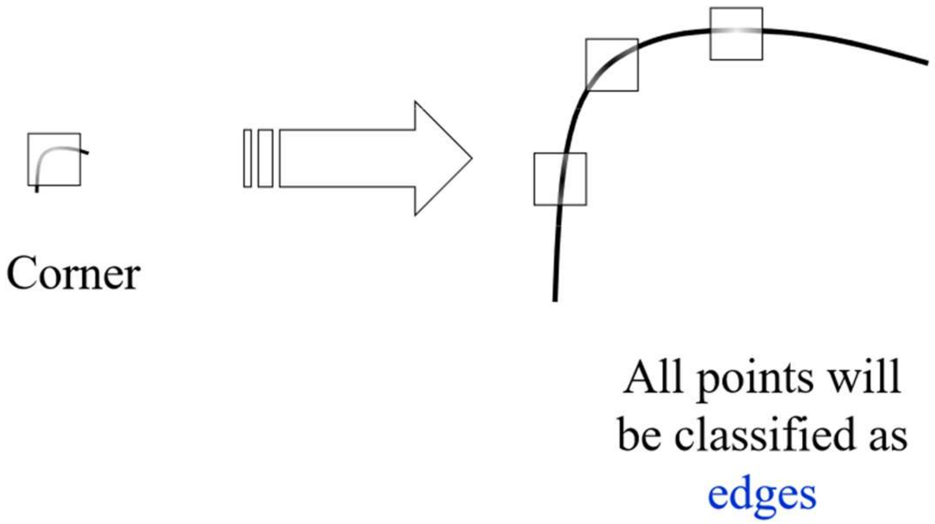
✓ Intensity scale: $I \rightarrow a\, I$



Partially invariant to affine intensity change

Source: Cordelia Schmid

Invariance properties: Scaling



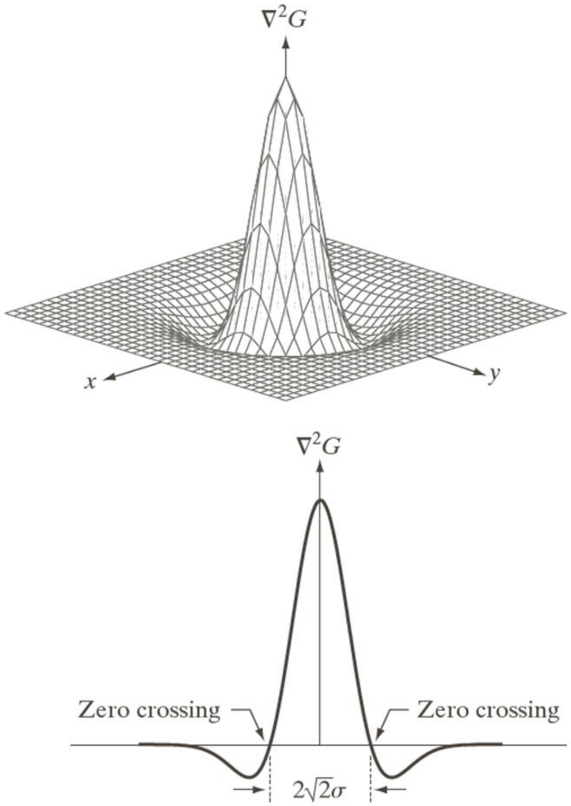
Corner response R is not invariant of scaling

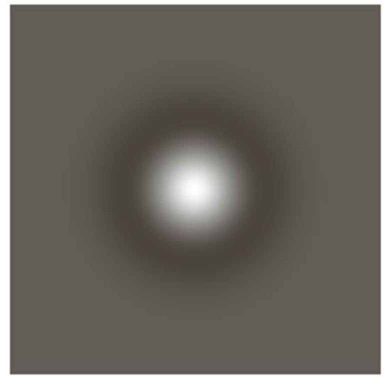
Source: Cordelia Schmid

SIFT interest point detector

- Formulates scale invariance
- We go back to the ideas of scale space!

Revision: Laplacian of a Gaussian





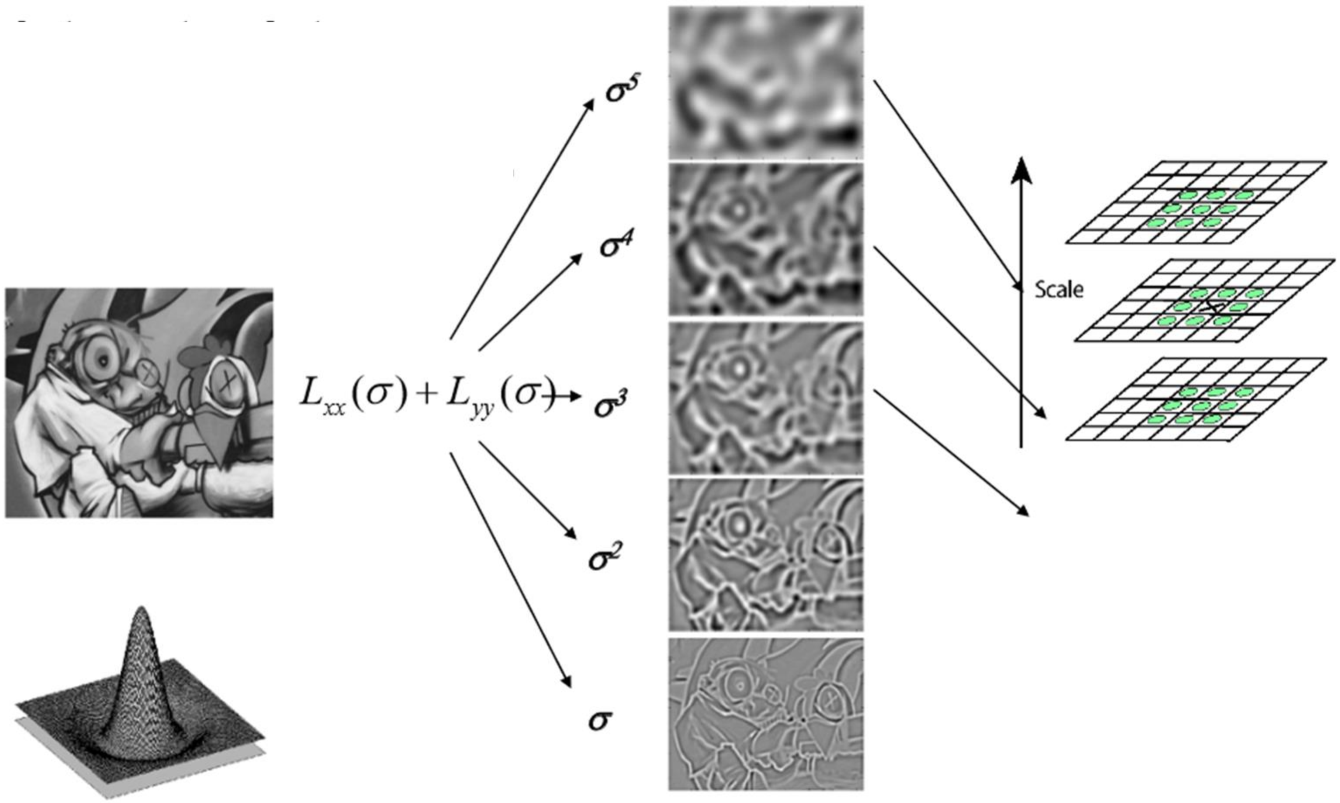
0	0	−1	0	0
0	−1	−2	−1	0
−1	−2	16	−2	−1
0	−1	−2	−1	0
0	0	−1	0	0

a b
c d

FIGURE 10.21
(a) Three-dimensional plot of the *negative* of the LoG. (b) Negative of the LoG displayed as an image. (c) Cross section of (a) showing zero crossings. (d) 5×5 mask approximation to the shape in (a). The negative of this mask would be used in practice.

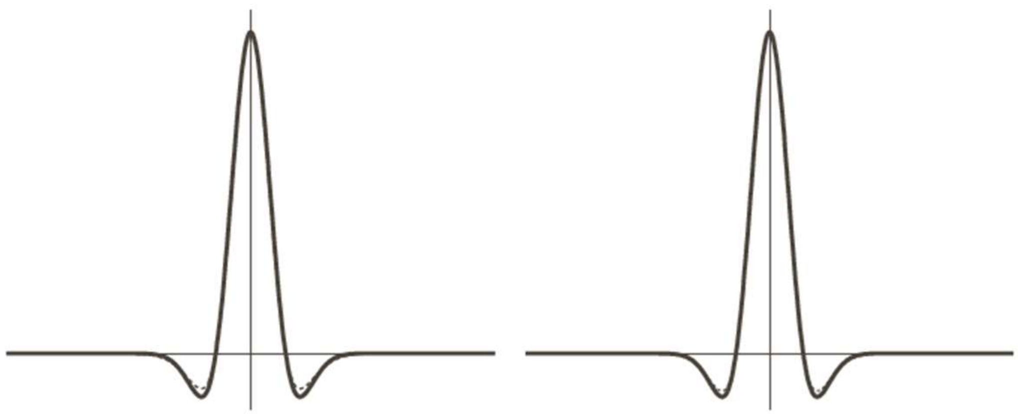
$$\nabla^2 G(x, y) = \left[\frac{x^2+y^2-2\sigma^2}{\sigma^4}\right] e^{-\frac{x^2+y^2}{2\sigma^2}}$$

SIFT interest point detector



K. Grauman, B. Leibe

Laplacian of a Gaussian Vs Difference of Gaussian

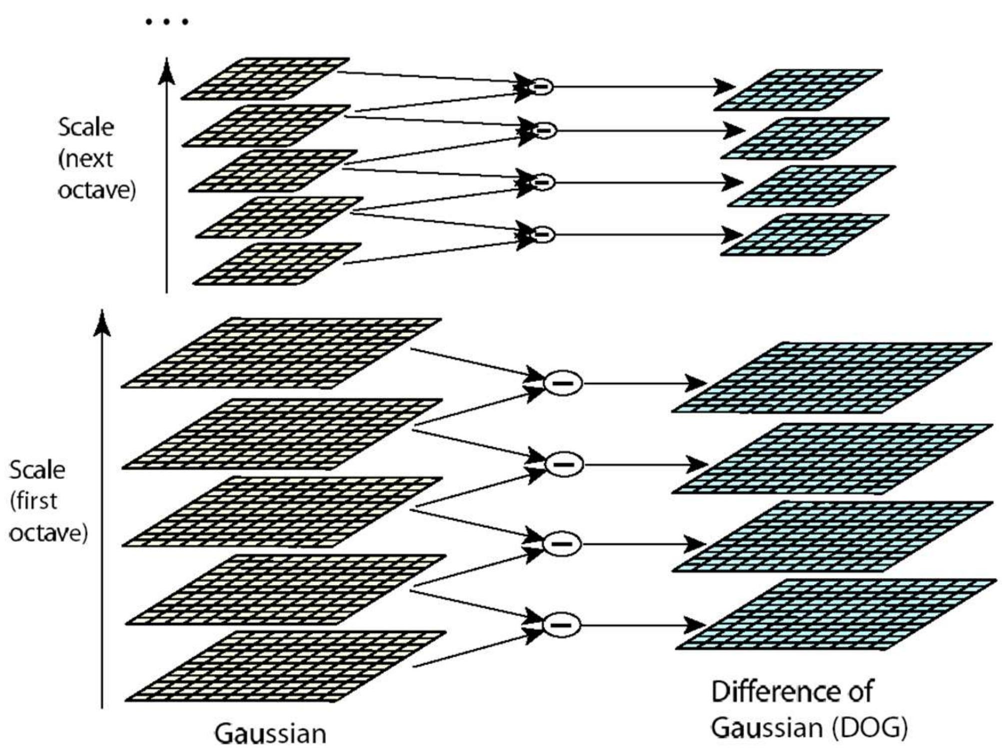


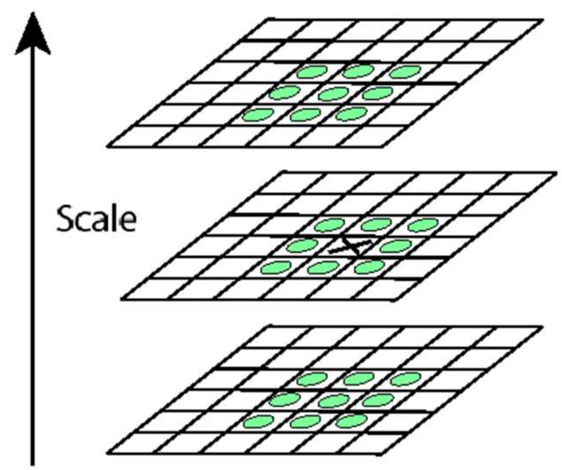
a b

FIGURE 10.23
(a) Negatives of the LoG (solid) and DoG (dotted) profiles using a standard deviation ratio of 1.75:1.
(b) Profiles obtained using a ratio of 1.6:1.

$$\mathrm{DoG}(x, y) = \frac{1}{2\pi{\sigma_1}^2} e^{-\frac{x^2 + y^2}{2{\sigma_1}^2}} - \frac{1}{2\pi{\sigma_2}^2} e^{-\frac{x^2 + y^2}{2{\sigma_2}^2}}$$

SIFT interest point detector

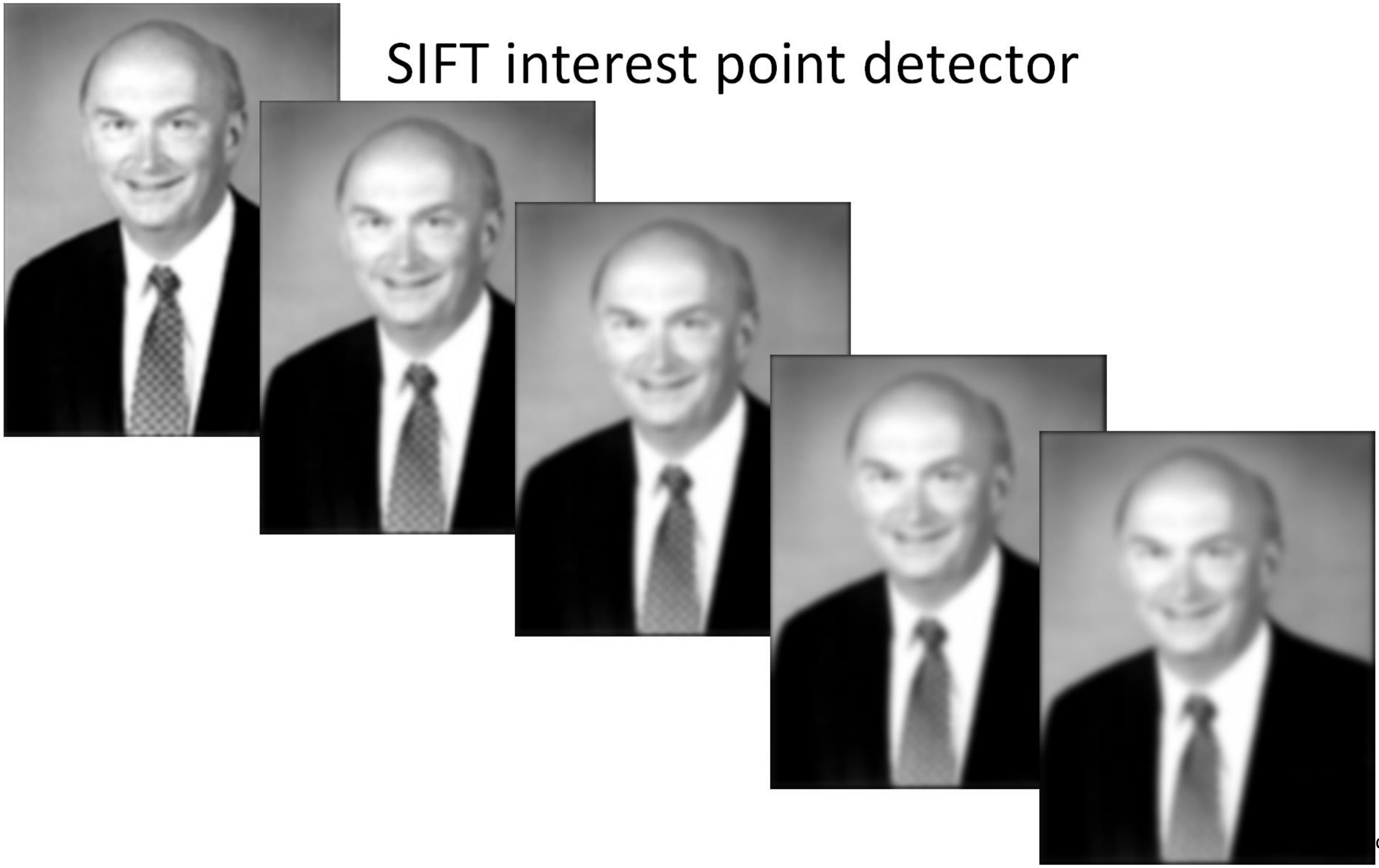




Compare with 26 Neighbors

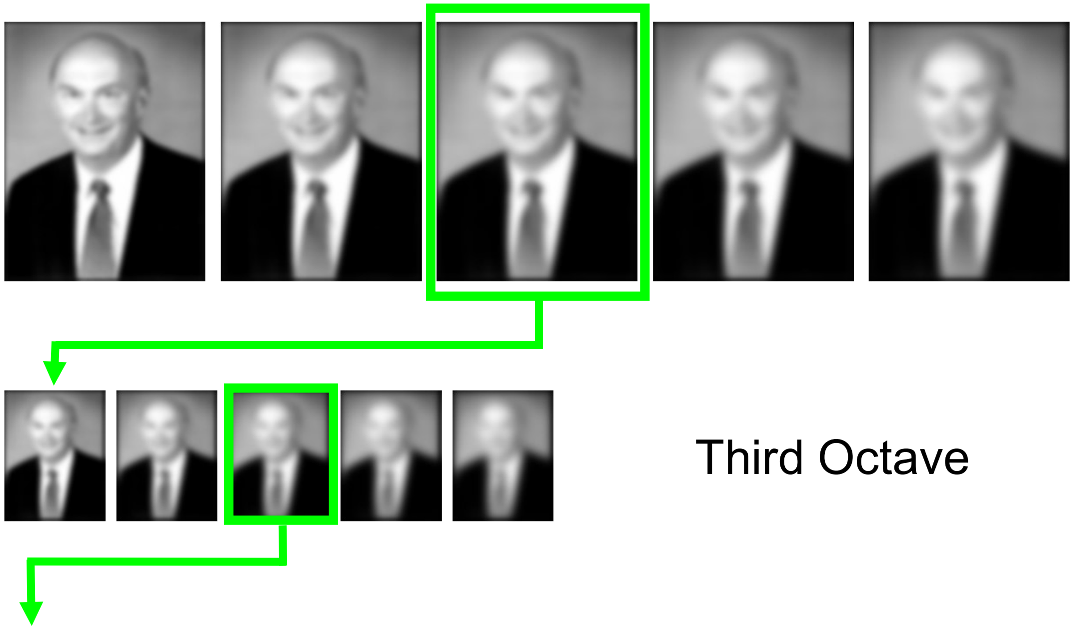
Source: David Lowe

SIFT interest point detector



ce: David Lowe

SIFT interest point detector



Second Octave

Third Octave

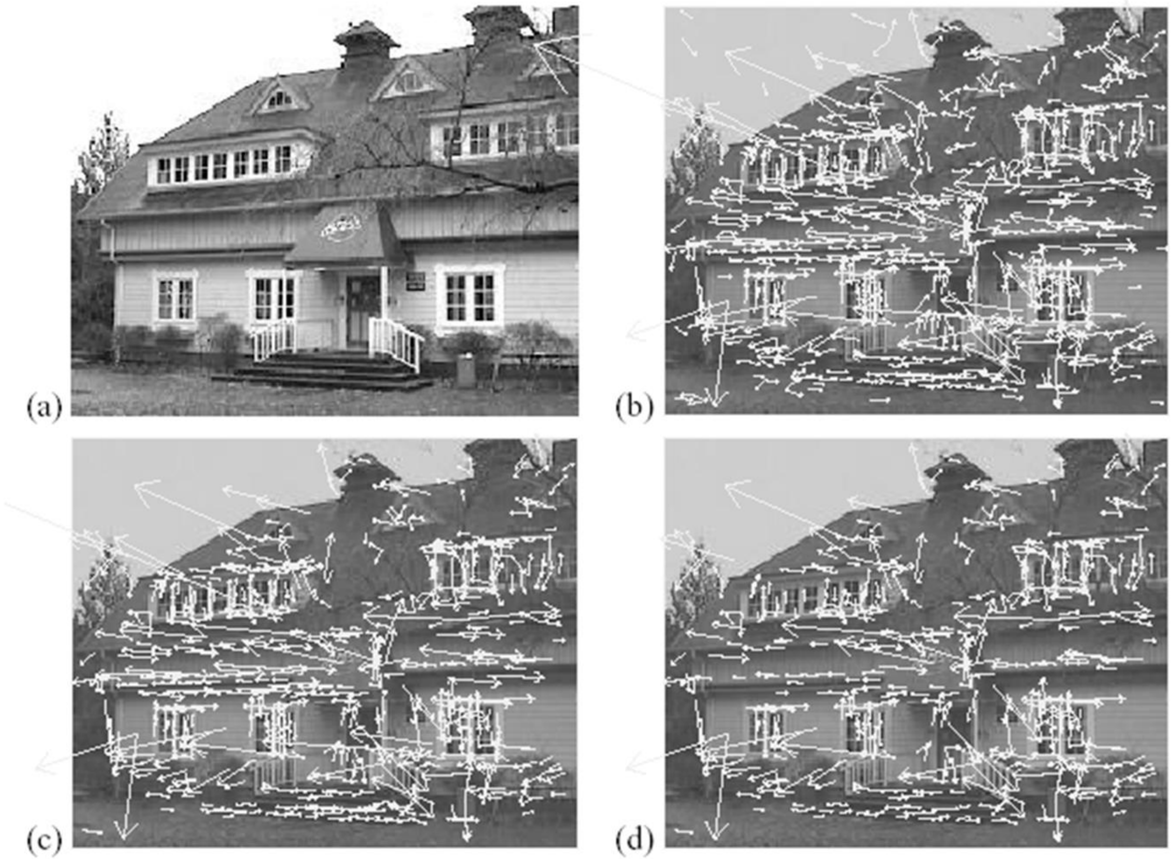
Fourth Octave

Source: David Lowe

SIFT interest point detector

: David Lowe

SIFT interest point detector



Source: David Lowe

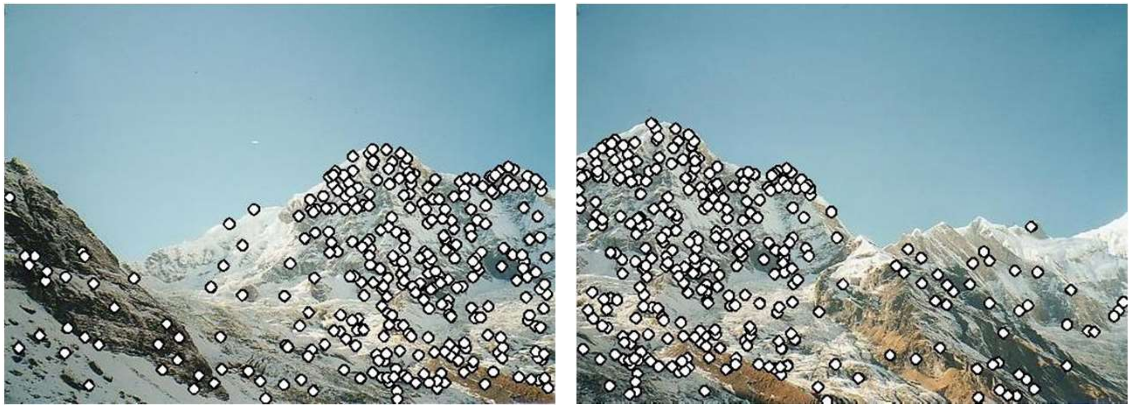
Today's Lecture

- Feature detection
  - Harris feature detector
  - SIFT feature detector

- Feature Descriptors
  - SIFT feature descriptor

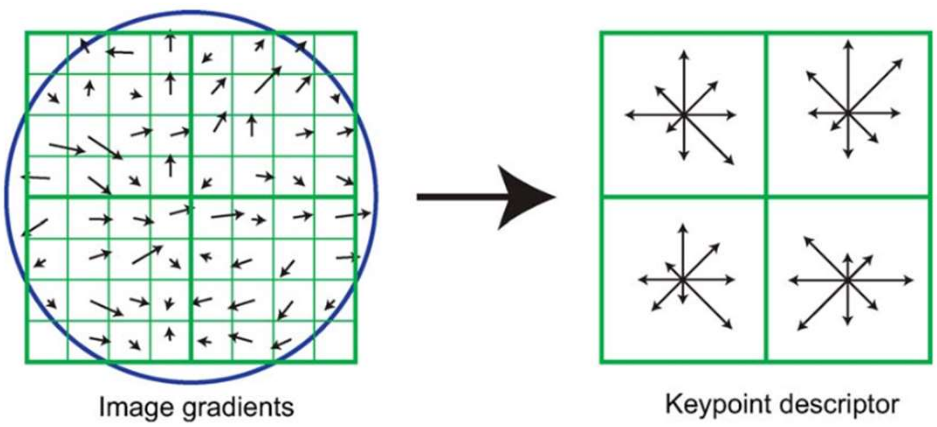
How to match the interest points across images?

- Keypoints give only the positions of strong features
- To match them across different images, we need a way to describe them
- Important to understand clear distinction between interest point detections and description
- Description is usually based on nearby image region
  - Intensity values
  - Moments
  - Derivatives
  - **SIFT**



SIFT descriptors

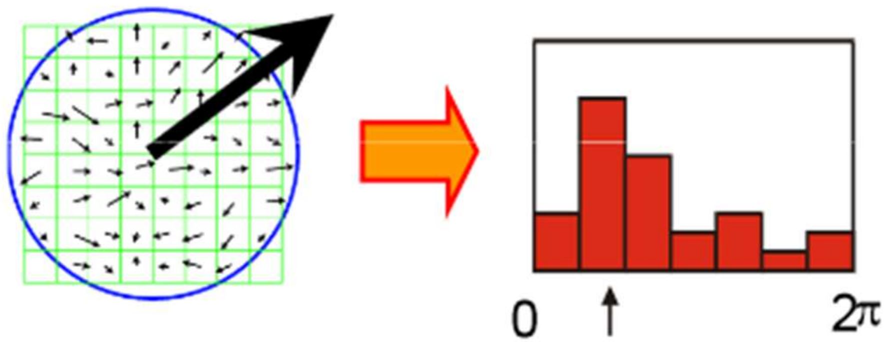
- Orientation of gradients
  - 8 orientations
  - 4×4 orientation grid
  - Dimension 128
  - Soft assignment
  - Weighted by a Gaussian



Source: David Lowe

SIFT descriptors: Rotation invariance

- Solution: Compute relative orientation



Compute the dominant orientation (peak in the histogram) and rotate the patch accordingly

Source: David Lowe

One final example

Source: David Lowe