Coner Features and Matching

Finding Local Features

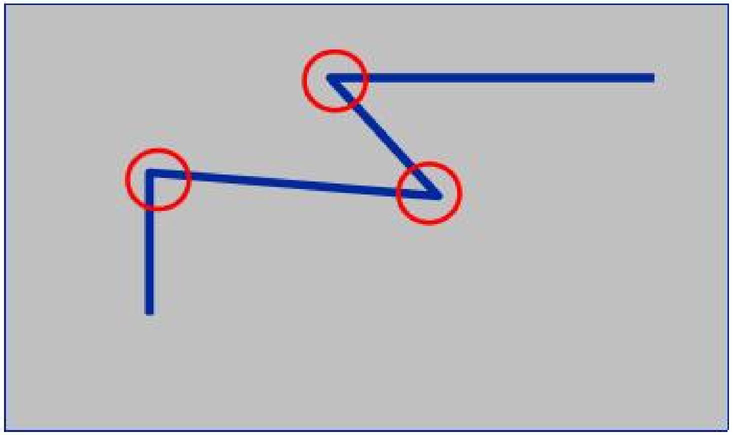
Applications of local feature matching:

Recognition, stereo calibration, motion tracking, 3D object reconstruction, auto calculation of epipolar geometry, etc…

Corners provide repeatable points for matching

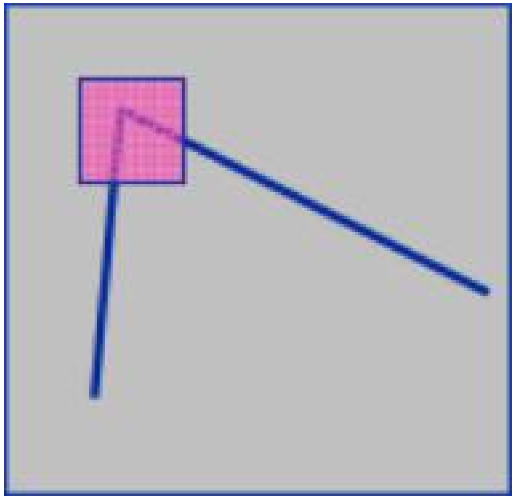
Harris (1988) corner detector:

- Exactly at a corner, gradient is ill defined.
- However, in the region around a corner, gradient has two or more different values.

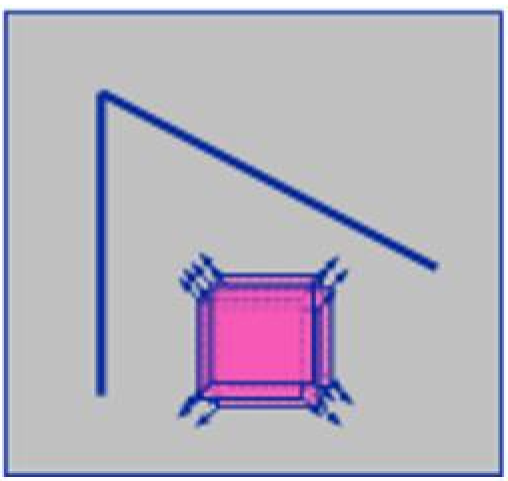


The Basic Idea

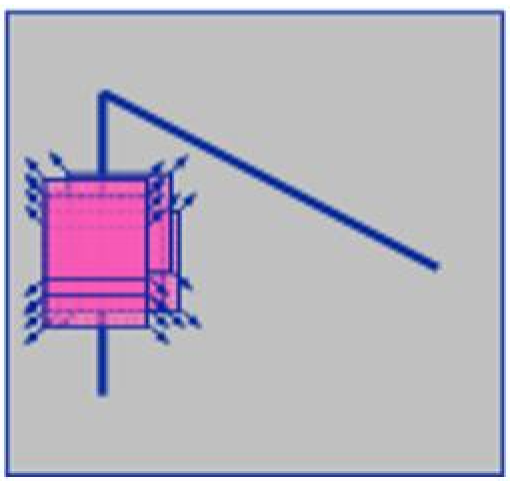
- We should easily recognize the point by looking through a small window
- Shifting a window in any direction should give a large change in response



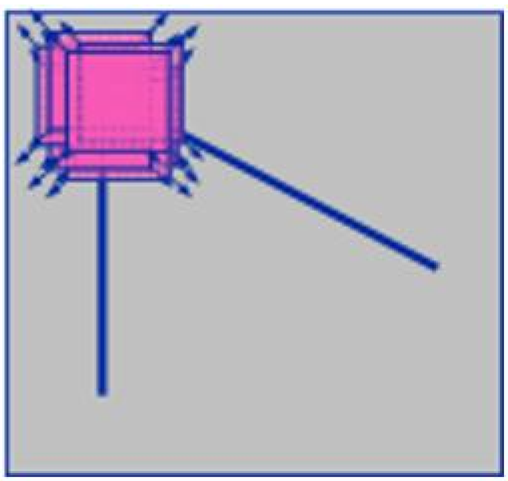
Harris Detector: Basic Idea



"flat" region:
no change in
all directions



"edge":
no change along
the edge direction



"corner":
significant change
in all directions

Harris Detector: Mathematics

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

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

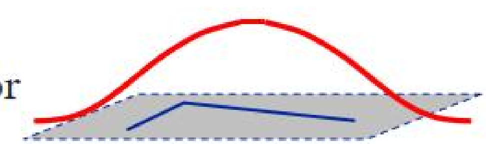
Window function

Shifted intensity

Intensity

Window function $w(x,y) =$

or



1 in window, 0 outside

Gaussian

Harris Detector: Mathematics

For small shifts $[u,v]$ we have a bilinear approximation:

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

where $\boldsymbol{M}$ is a 2×2 matrix computed from image derivatives:

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

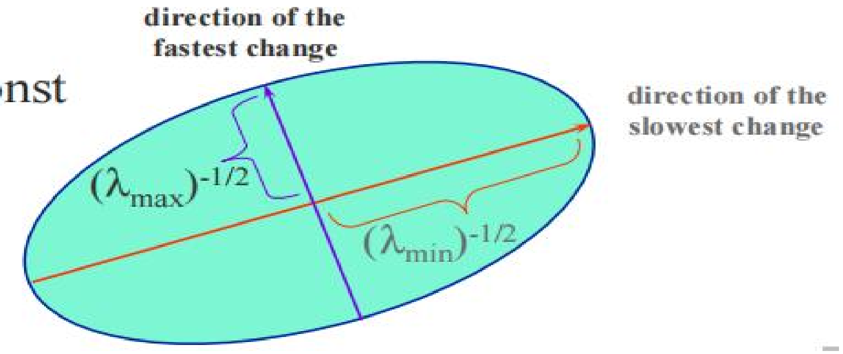
Harris Detector: Mathematics

Intensity change in shifting window: eigenvalue analysis

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

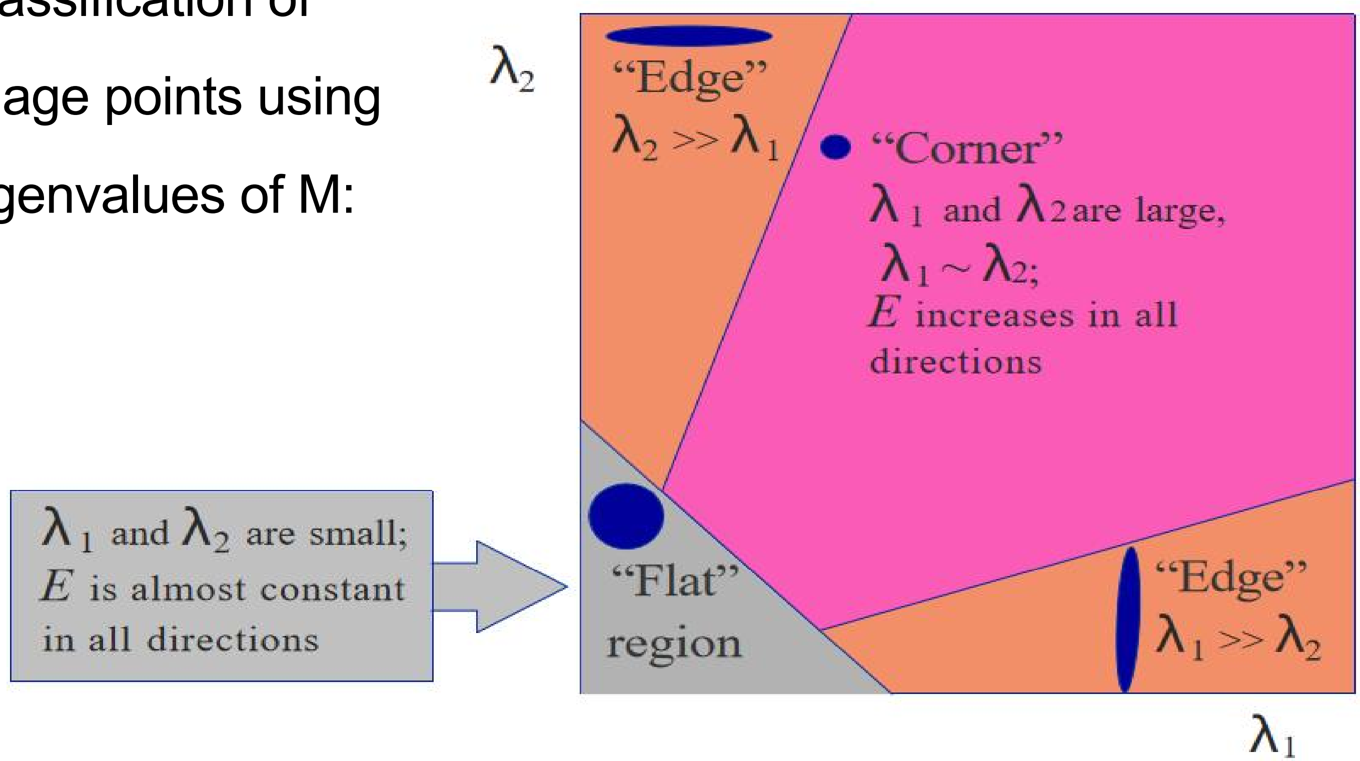
λ_1, λ_2 – eigenvalues of M

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



Harris Detector: Mathematics

Classification of image points using eigenvalues of M:



Harris Detector: Mathematics

Measure of corner response:

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

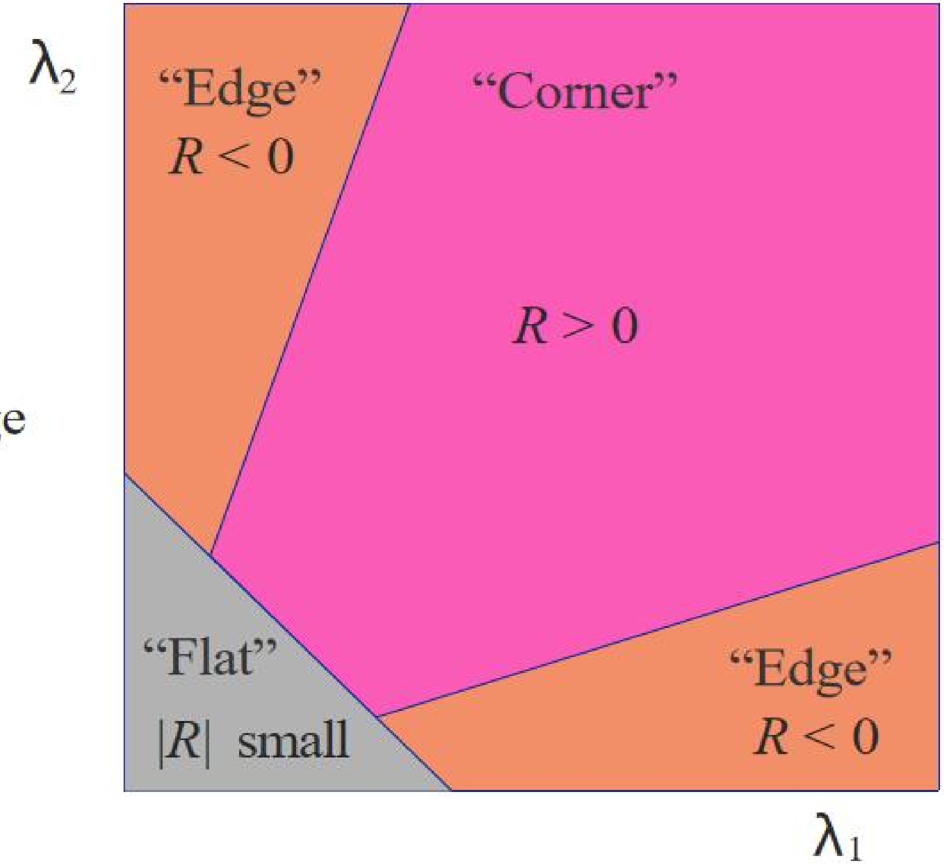
(where k is an empirically determined constant; k = 0.04 - 0.06)

$$\det M = \lambda_1 \lambda_2$$

$$\operatorname{trace} M = \lambda_1 + \lambda_2$$

Harris Detector: Mathematics

- 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



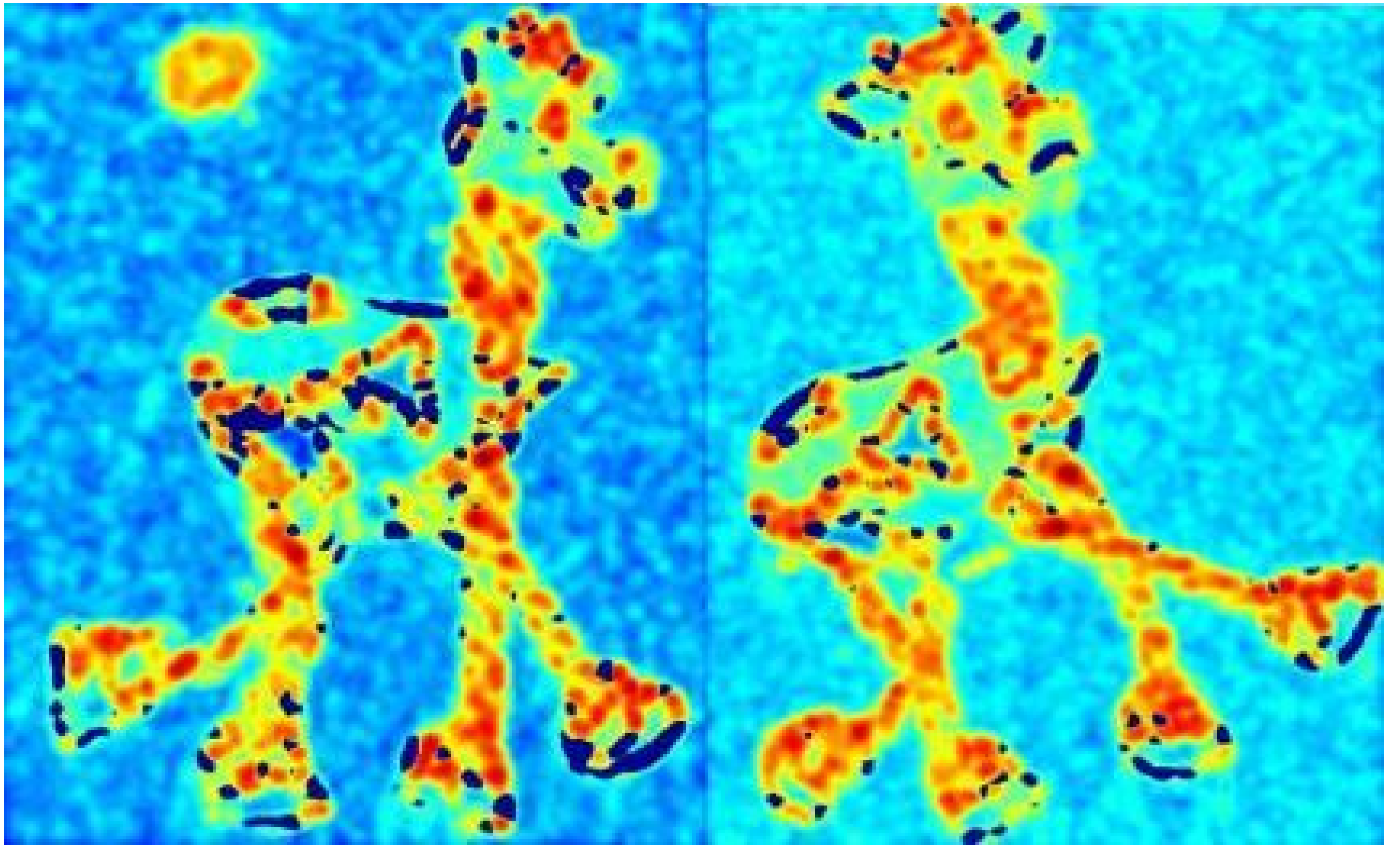
Harris Detector Summary:

- Filter image with Gaussian to reduce noise
- Compute magnitude of the x and y gradients at each pixel
- Construct $\boldsymbol{M}$ in a window around each pixel (Harris uses a Gaussian window – just blur) and then R
- Find points with large corner response function R (R > threshold)
- Take the points of local maxima of R

Harris Detector: Example

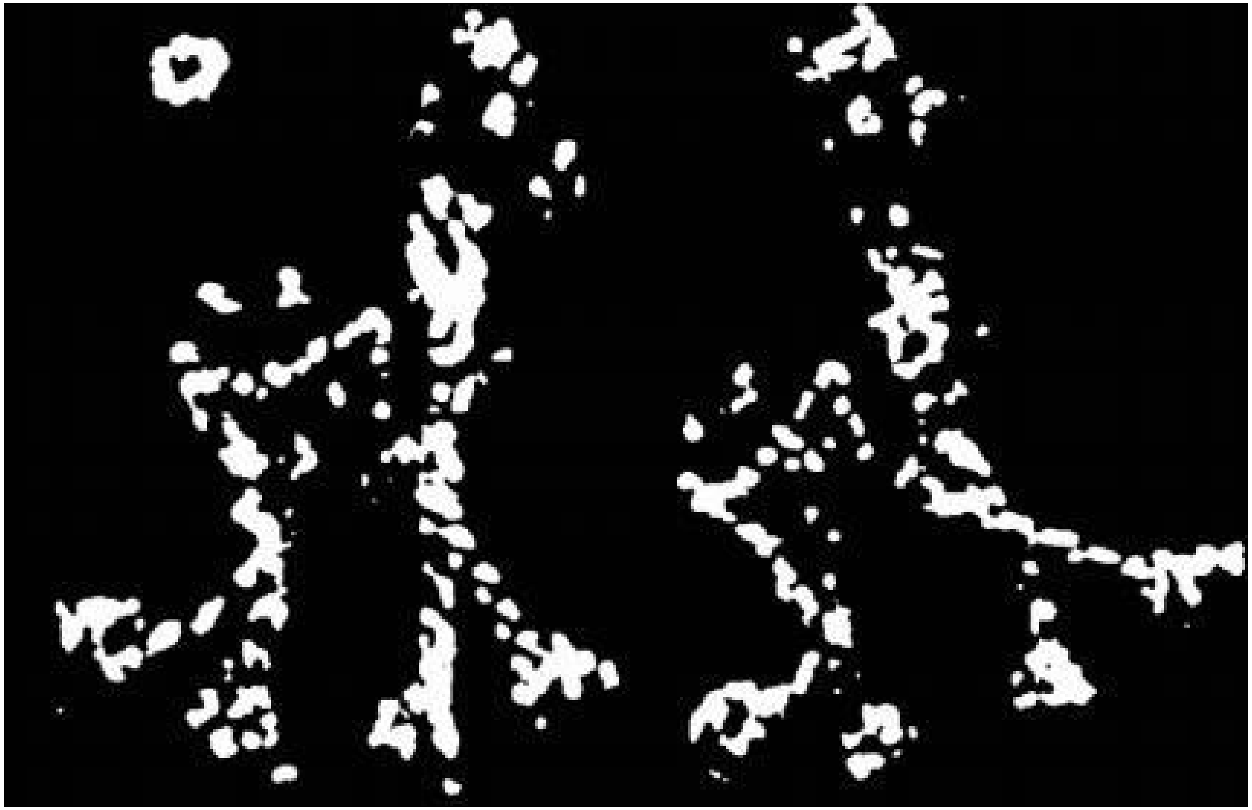
Harris Detector: Example

Compute corner response R



Harris Detector: Example

Find points with large corner response: R>threshold

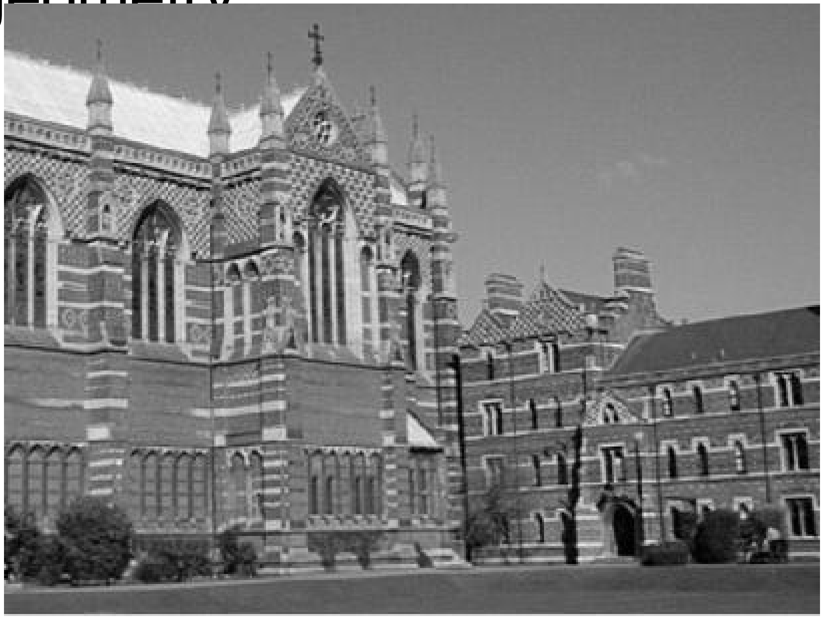


Harris Detector: Example

Take only the points of local maxima of *R*

Automatic Matching of Images

- How to get correct correspondences without human intervention?
- Can be used for image stitching or automatic determination of epipolar geometry

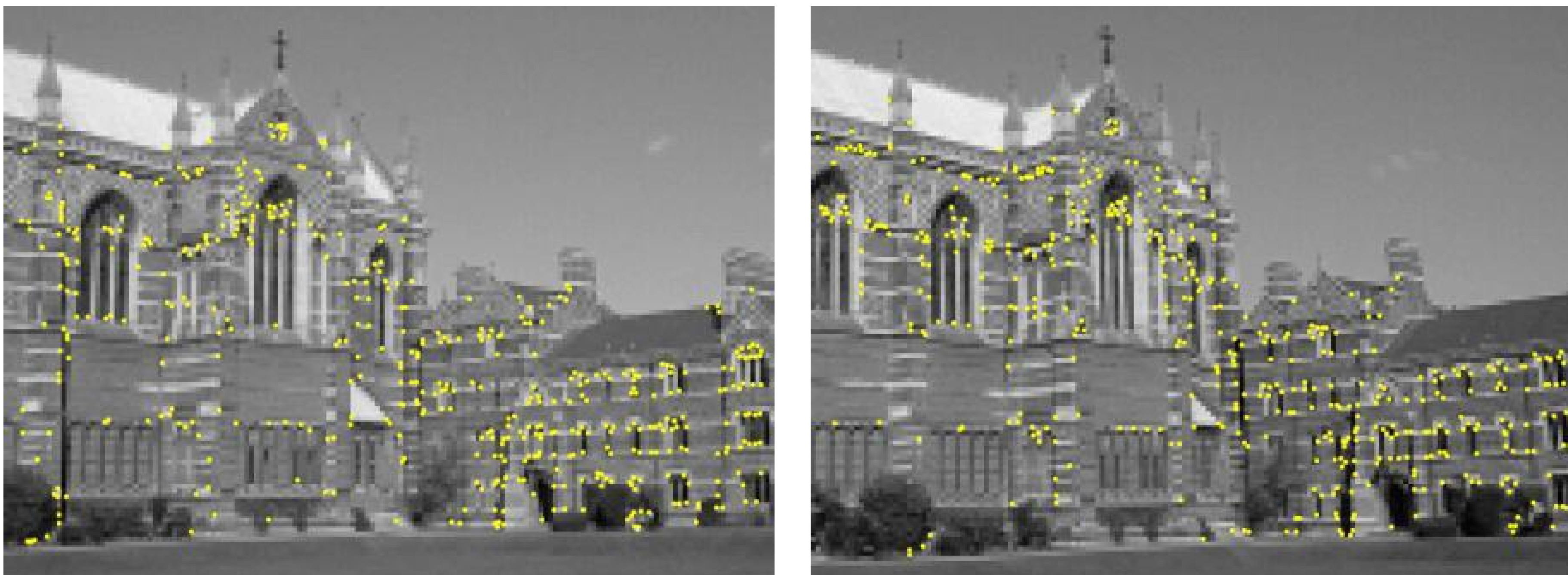



from Hartley & Zisserman

Slide credit: Christopher Rasmussen

Feature Extraction

- Find features in pair of images using Harris corner detector
- Assumes images are roughly the same scale



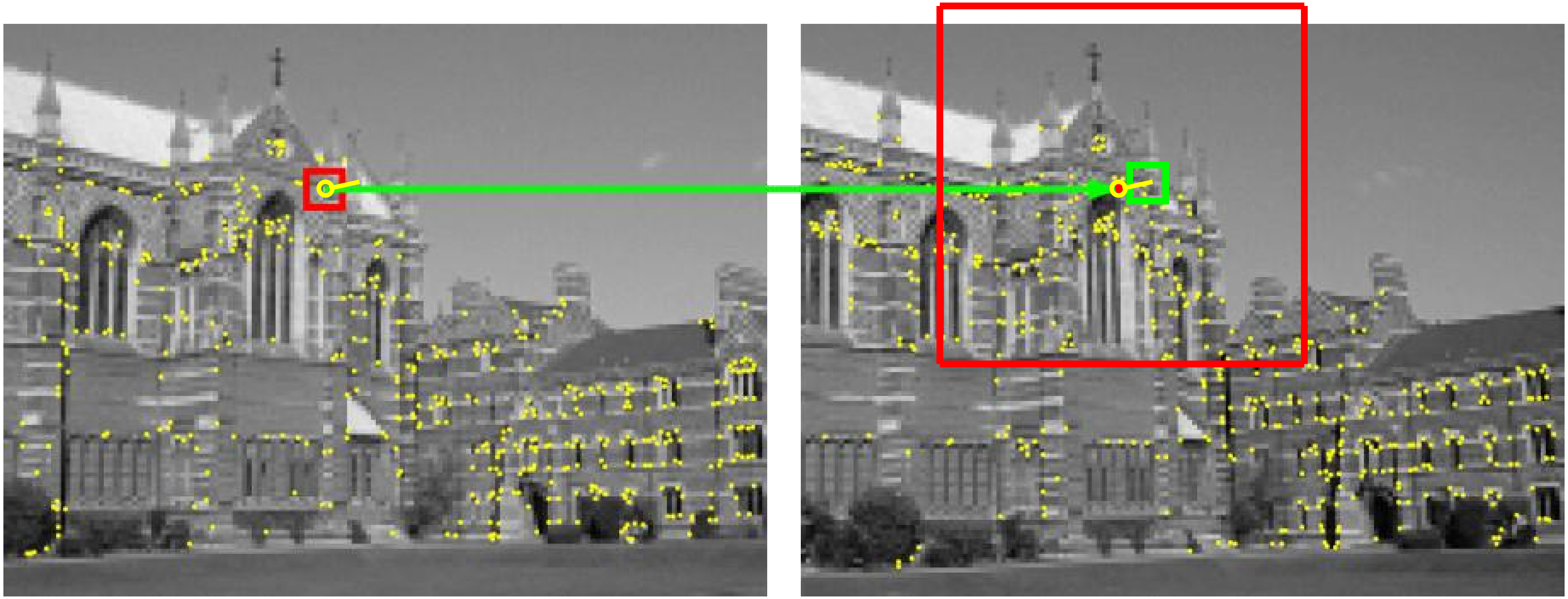
from Hartley & Zisserman

~500 features found

Slide credit: Christopher Rasmussen

Finding Feature Matches

- Select best match over threshold within a square search window (here 300 pixels²) using SSD or normalized cross-correlation (NCC) for small patch around the corner



Finding Feature Matches

- SSD(Sum of Squared Difference)

$$SSD(I, J) = \Sigma(I(x, y) - J(x, y))^2$$

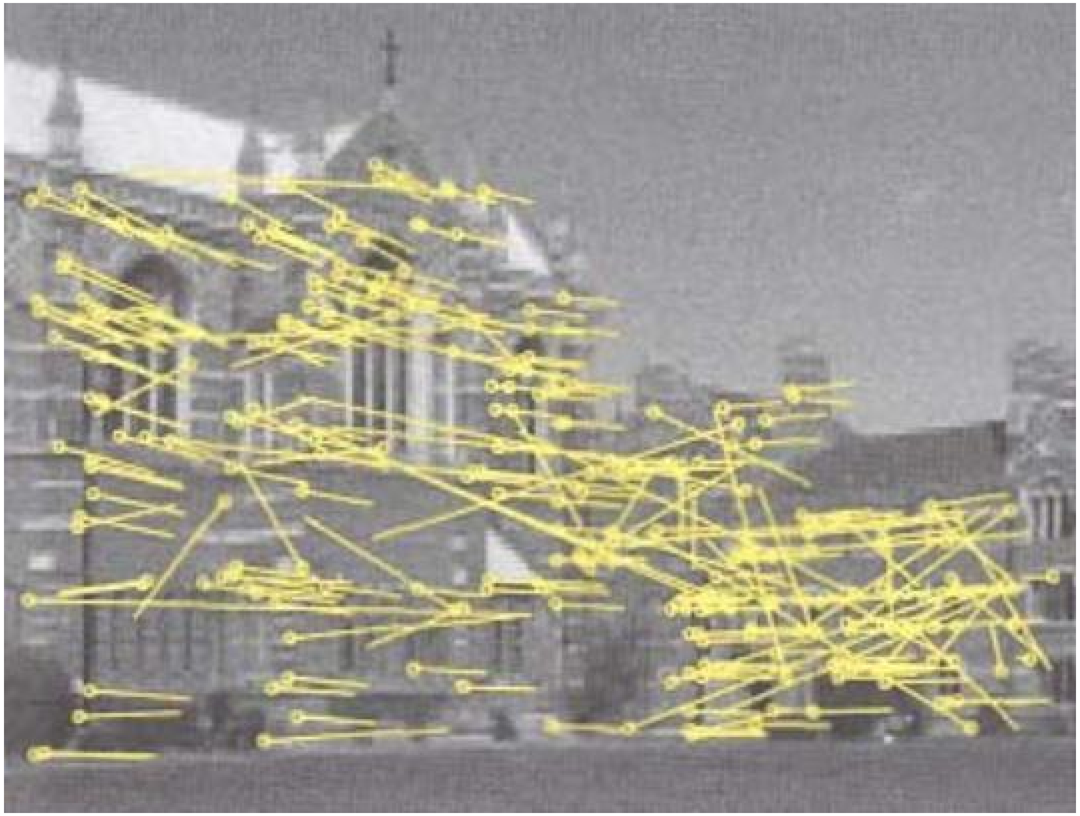
The SSD values closer to 0 indicate a higher similarity between the two images.

- NCC (Normalized Cross Correlation)

$$NCC(I, J) = \Sigma(I(x, y) * J(x, y)) / \sqrt{(\Sigma I(x, y)^2 * \Sigma J(x, y)^2)}$$

The NCC value ranges from -1 to 1, and the closer the value is to 1, the higher the similarity between the two images.

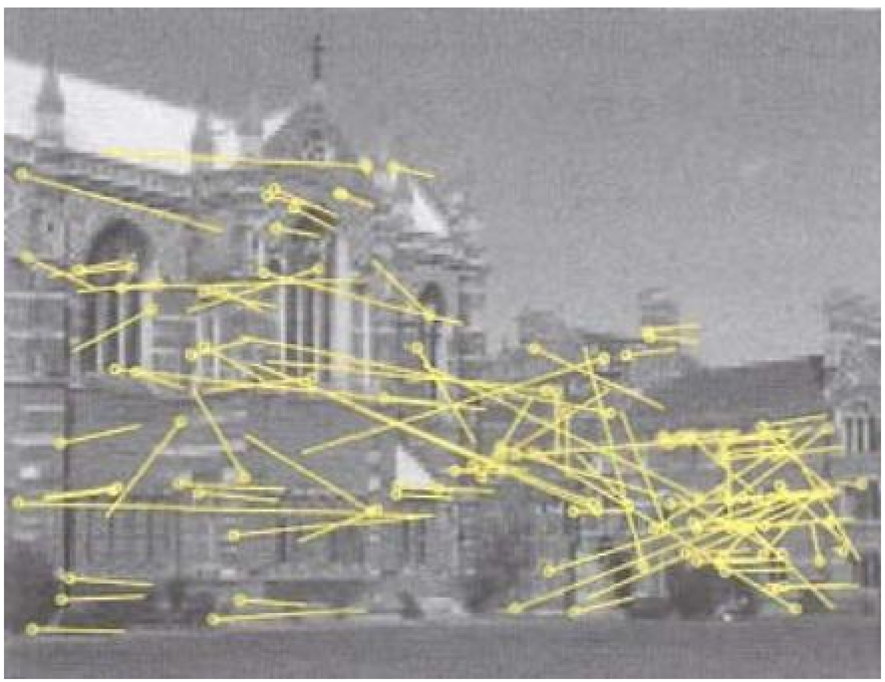
Initial Match Hypotheses

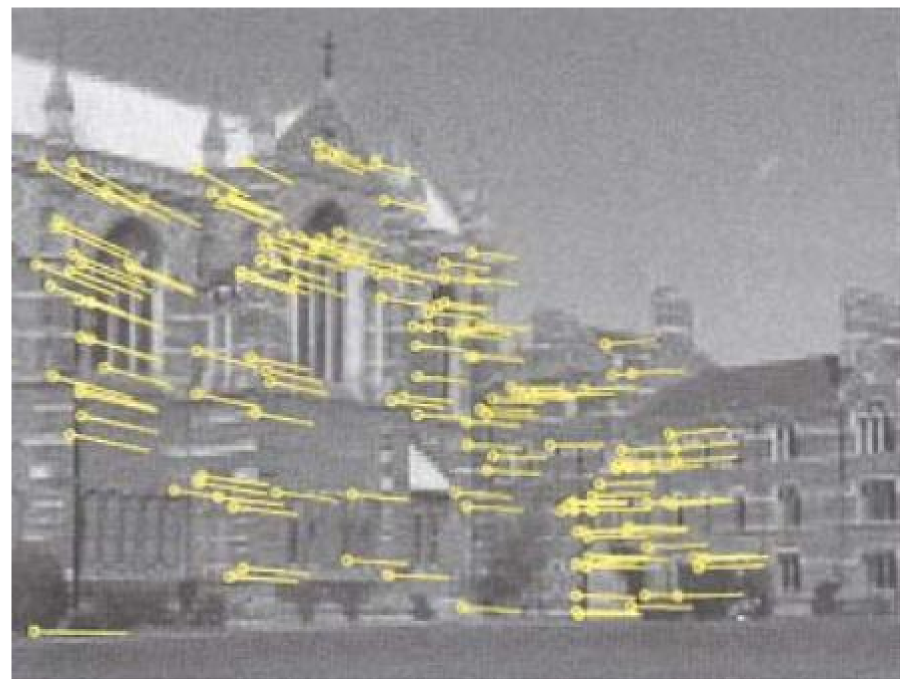


268 matched features (over SSD threshold) in left image pointing to locations of corresponding right image features

Outliers & Inliers after RANSAC

- n is 4 for this problem (a homography relating 2 images)
- Assume up to 50% outliers
- 43 samples used with t = 1.25 pixels





from Hartley & Zisserman

117 outliers

151 inliers