Computational Photography

* Study the basics of computation and its impact on the entire workflow of photography, from capturing, manipulating and collaborating on, and sharing photographs.

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Feature Detection and Matching

* methods for Detecting Features in Images that can be matched for Registration and Alignment.

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1. Benefits of Feature Detection and matching in images
2. Characteristics of Good Features
3. Corners are Good Features
4. Harris Corner Detector Algorithm
5. Stages of a SIFT detector

Recall: Detection and Matching

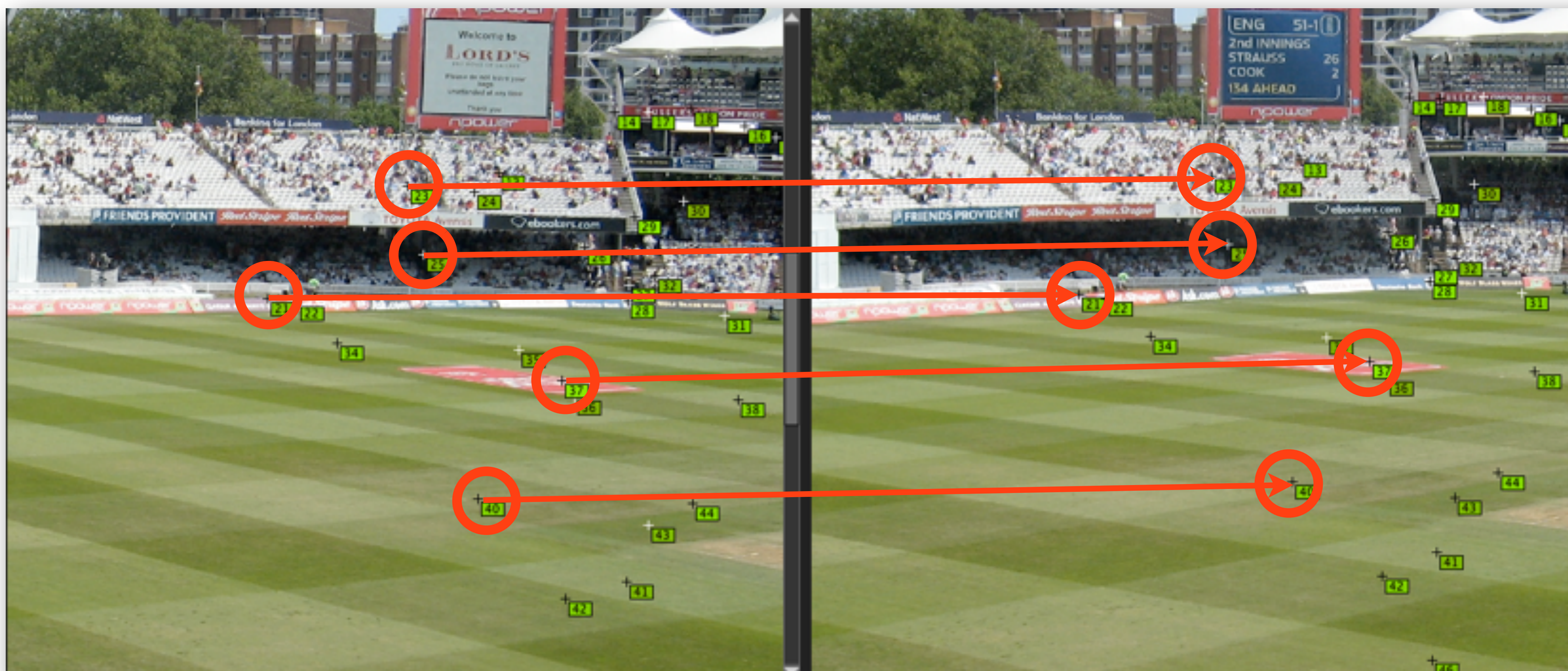
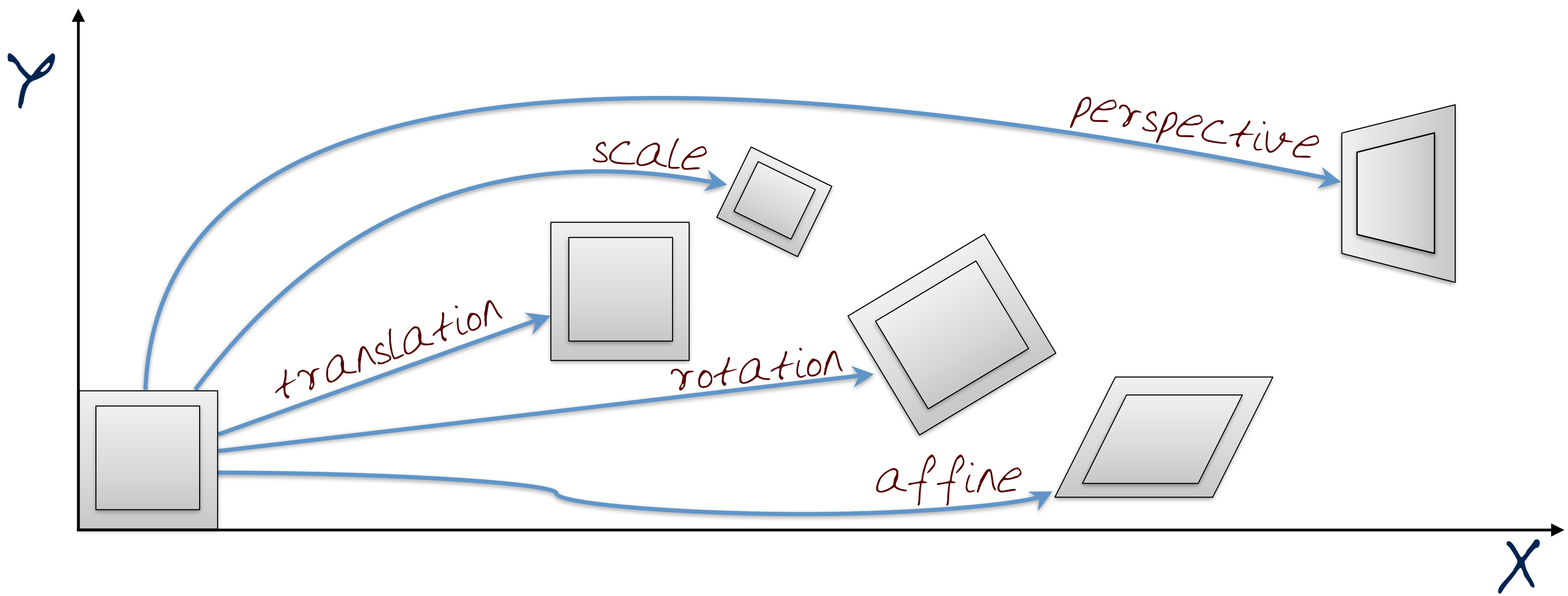
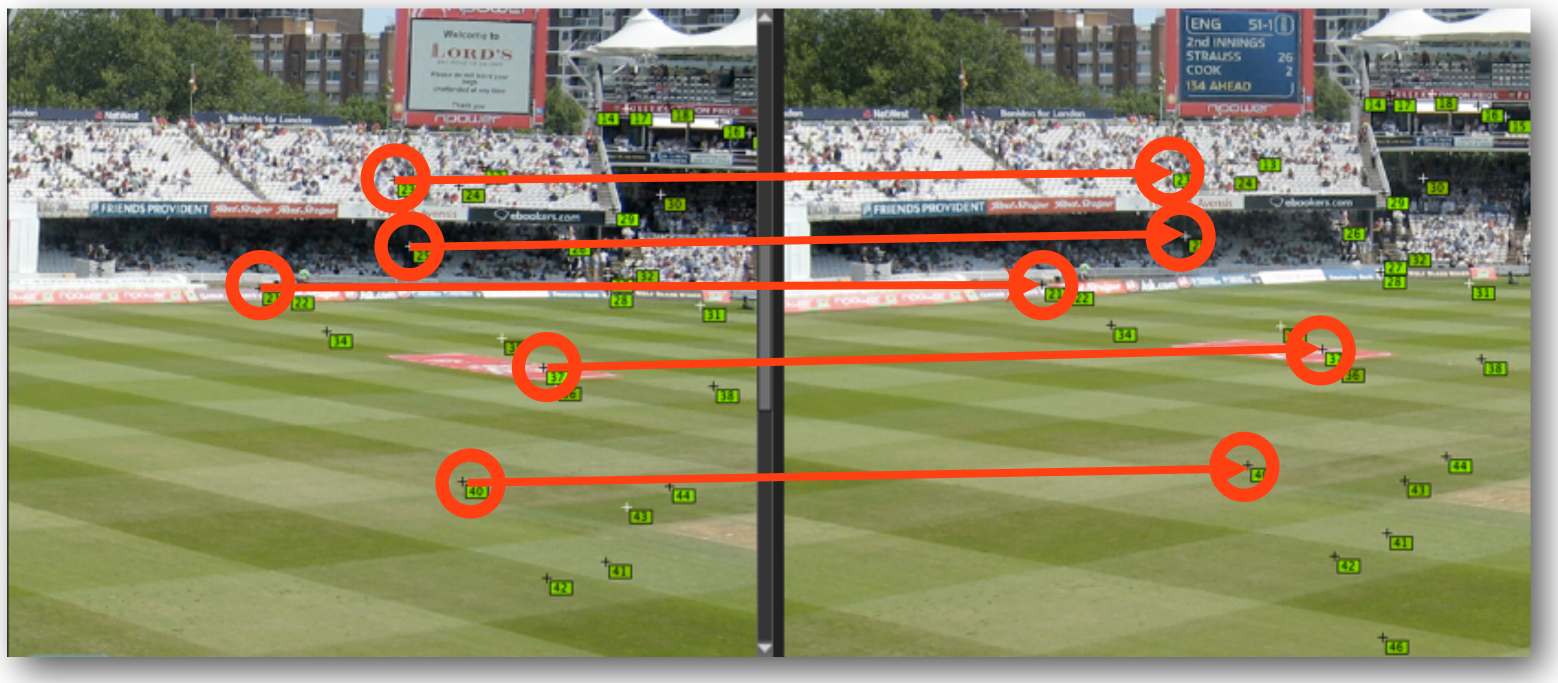


Image Matching



Finding Features

* Goal – Find points in an image that can be:
  * Found in other images
  * Found precisely – well localized
  * Found reliably – well matched



Characteristics of Good Features

* Repeatability/Precision
* Saliency/matchability
* Compactness and efficiency
* Locality

Slide motivated by Aaron Bobick

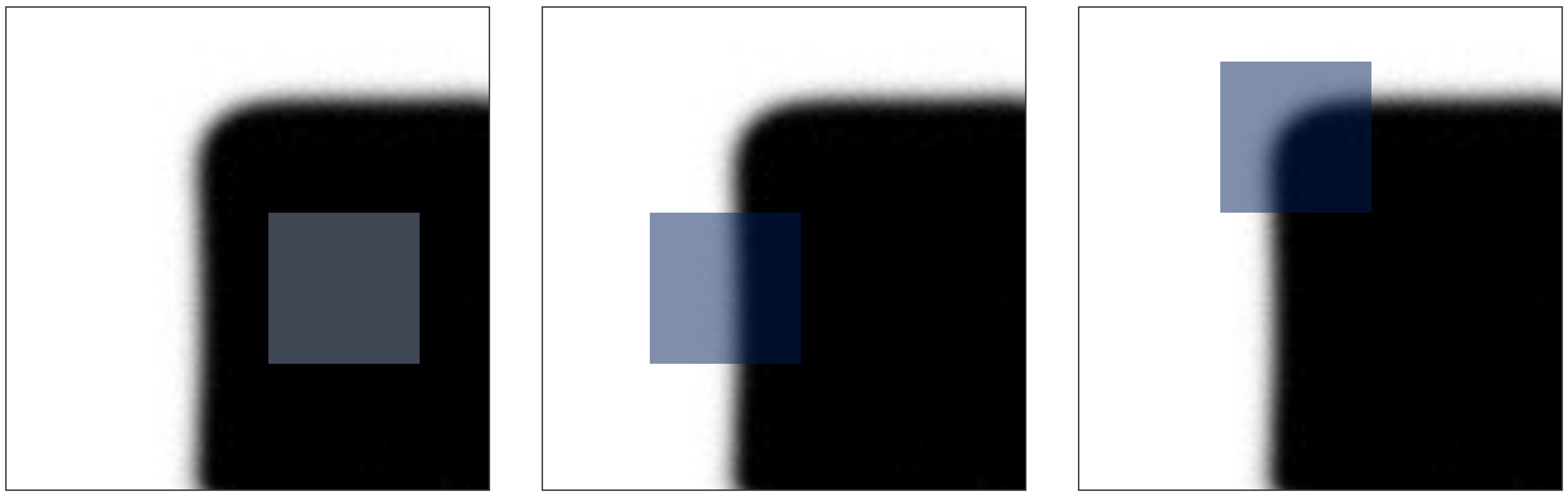
Find Corners

* Key property: In the region around a corner, image gradient has two or more dominant directions
* Corners are repeatable and distinctive

Harris and Stephens (1988)

Corner Detection: The Basics



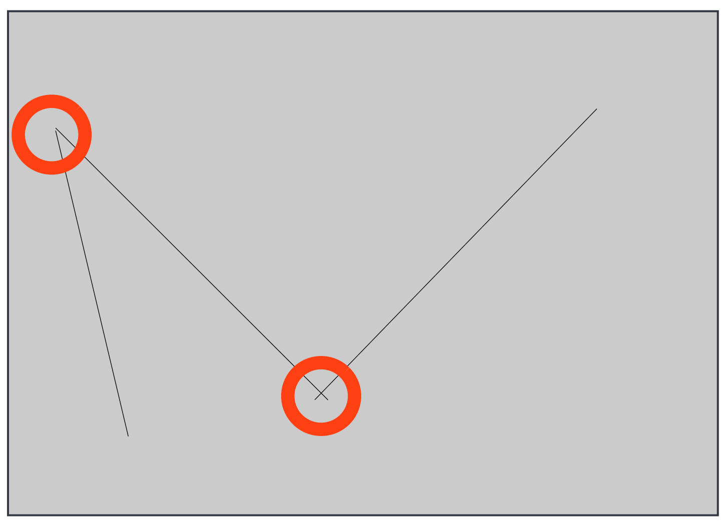
"flat"
No change in any directions

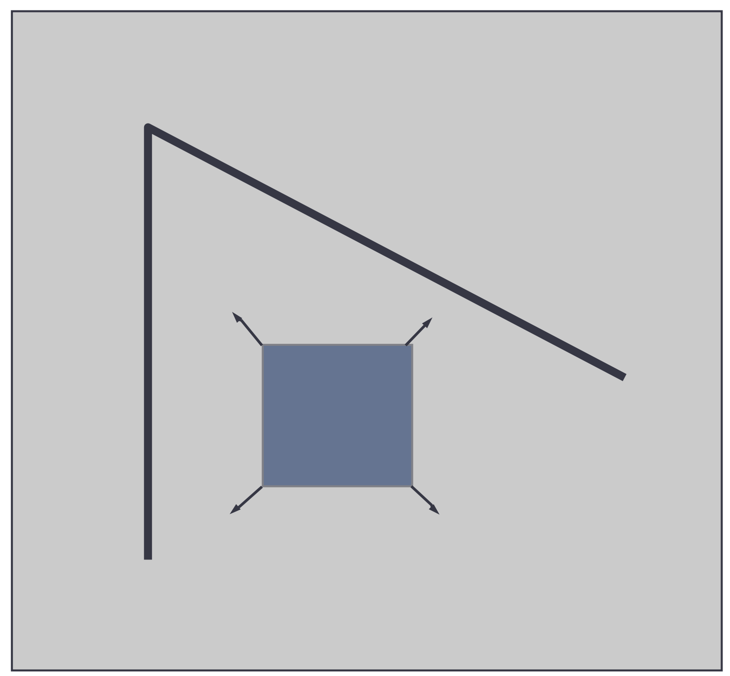
"edge"
No change along the edge direction

"corner"
Change in all directions

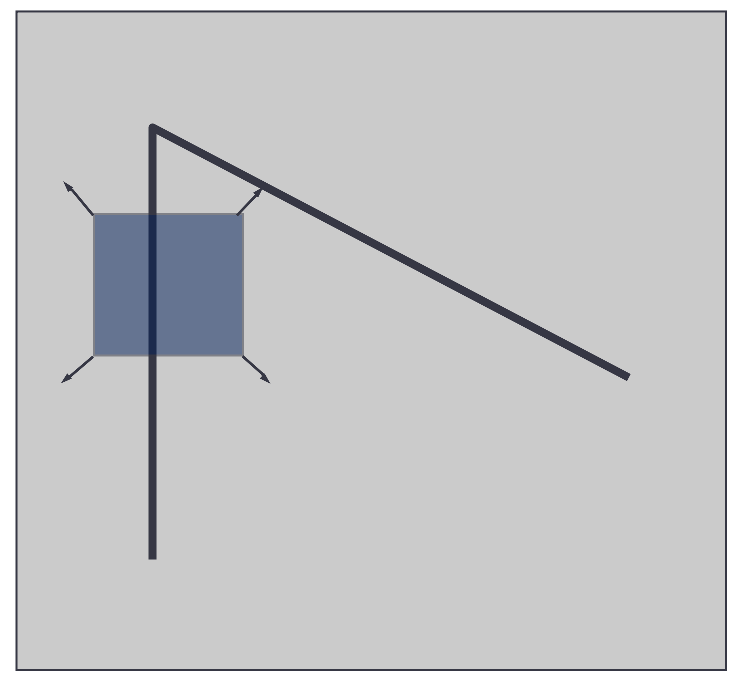
* Recognize a point by looking through a small window
* Shifting a window in any direction causes a large change in intensity

Corner Detection: The Basics

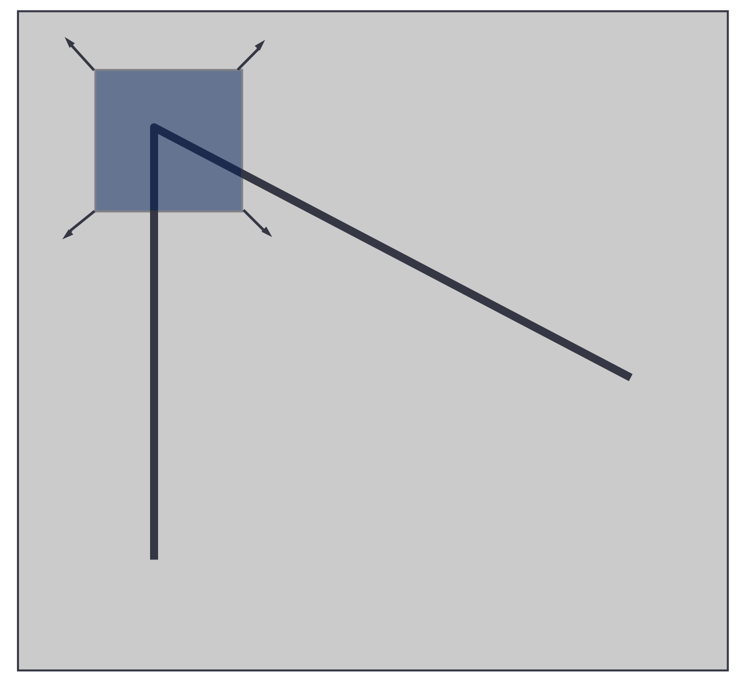




"flat"
No change in any directions



"edge"
No change along the edge direction



"corner"
Change in all directions

Harris and Stephens (1988)

Corner Detection: Mathematics

Compute the change in appearance by shifting the window by u,v:

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

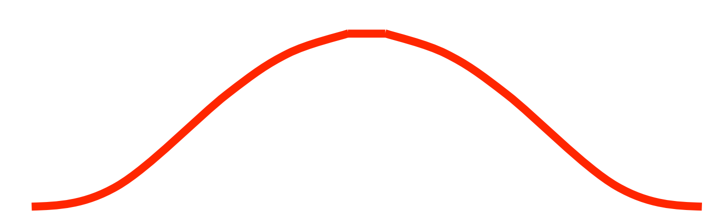
change in appearance

window function

shifted intensity

intensity

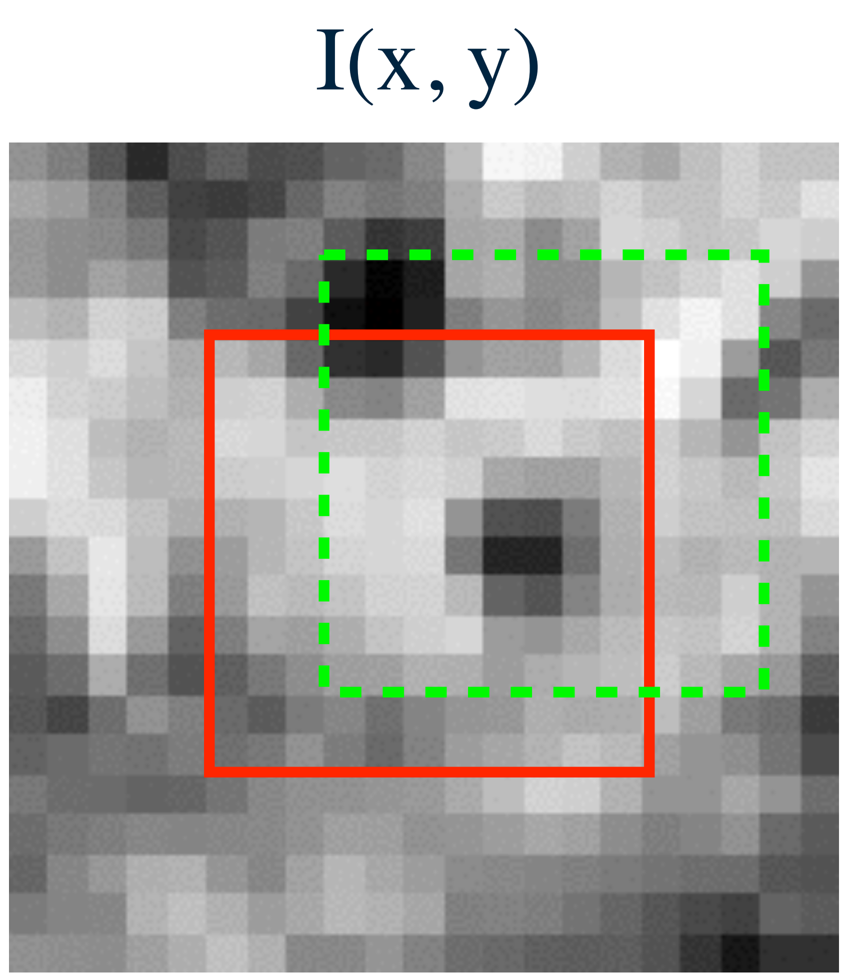
$$w(x,y) \begin{cases} \text{box function} \\ \text{a Gaussian} \end{cases}$$

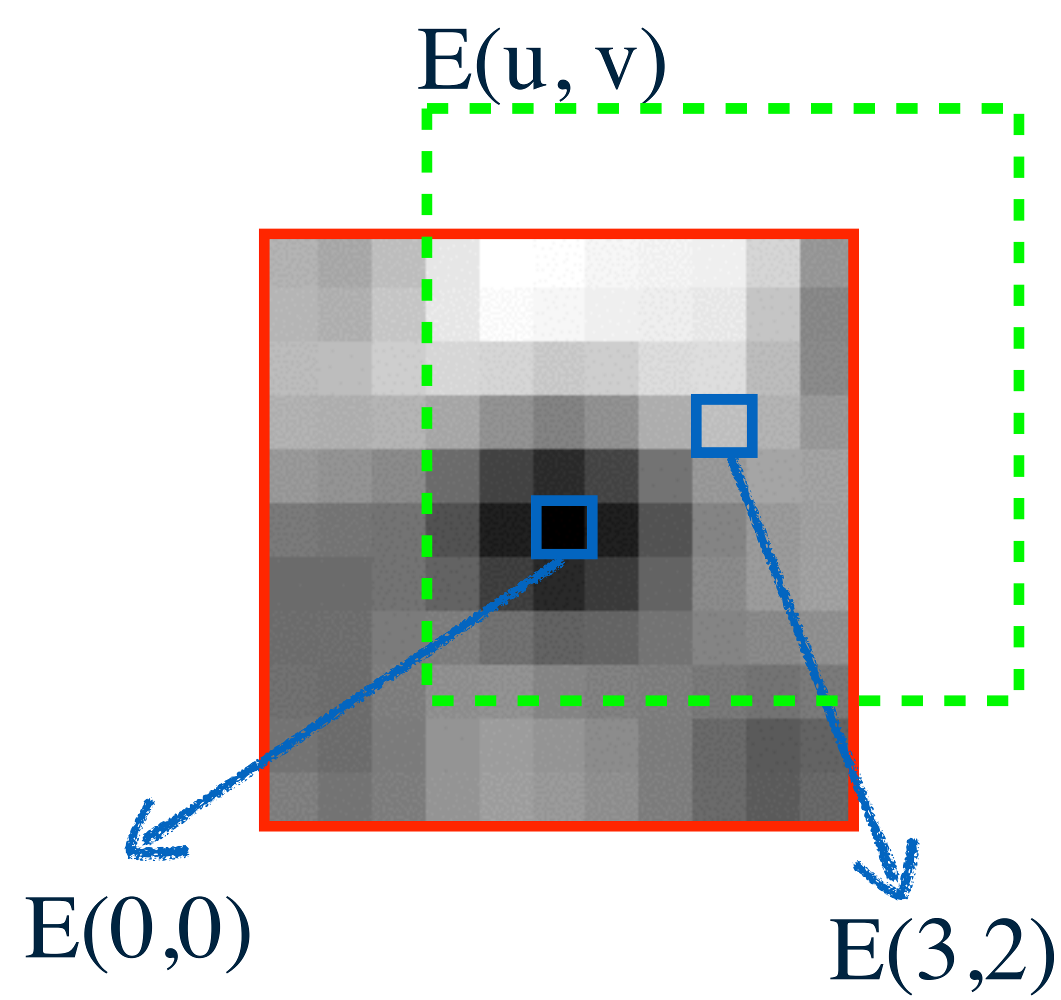


Corner Detection: Mathematics

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

Computation of the change in appearance by shifting the window by u,v:





Slide motivated by Alyosha Efros

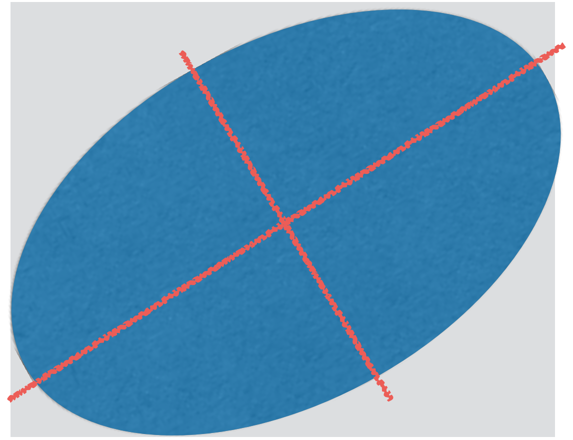
Corner Detection: Mathematics

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

The quadratic approximation, following Taylor Expansion, simplifies to:

$$E(u,v) \approx \left[\begin{array}{cc} u & v \end{array} \right] M \left[\begin{array}{c} u \\ v \end{array} \right]$$

where **M** is a second moment matrix computed from image derivatives $\mathbf{I}_x$ and $\mathbf{I}_y$:



$$M = \sum_{x,y} w(x,y) \left[\begin{array}{cc} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{array} \right]$$

Corner Detection: Mathematics

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

$$E(u,v) = \sum_{x,y} \omega(x,y) \left(u^2 I_x^2 + 2uvI_xI_y + v^2 I_y^2\right)$$

The surface E(u,v) is locally approximated by a quadratic form

Corner Detection: Mathematics

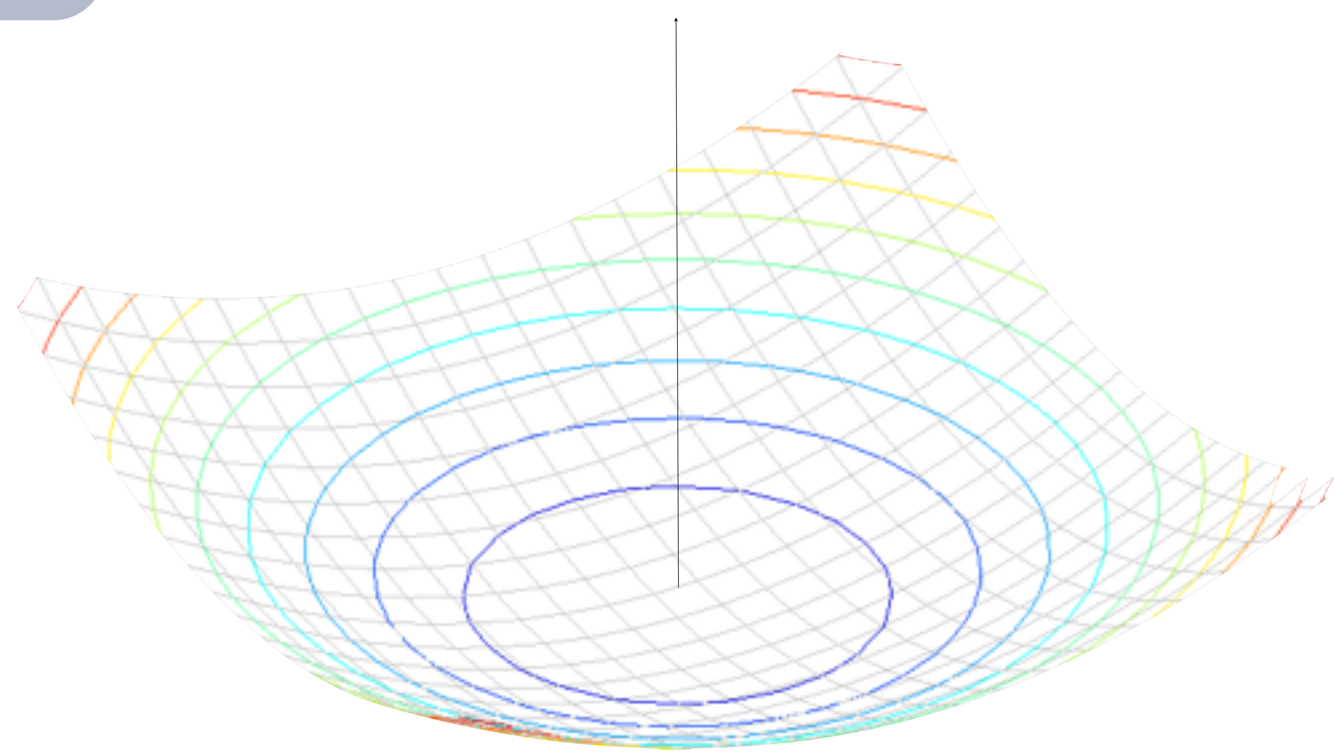
$$E(u,v) = \sum_{x,y} \omega(x,y) \left(u^2 I_x^2 + 2uvI_xI_y + v^2 I_y^2\right)$$

The surface E(u,v) is locally approximated by a quadratic form.

$$E(u, v) = \sum_{x,y} \omega(x, y) \left(u^2 I_x^2 + 2uvI_xI_y + v^2 I_y^2\right)$$

consider a "slice" :

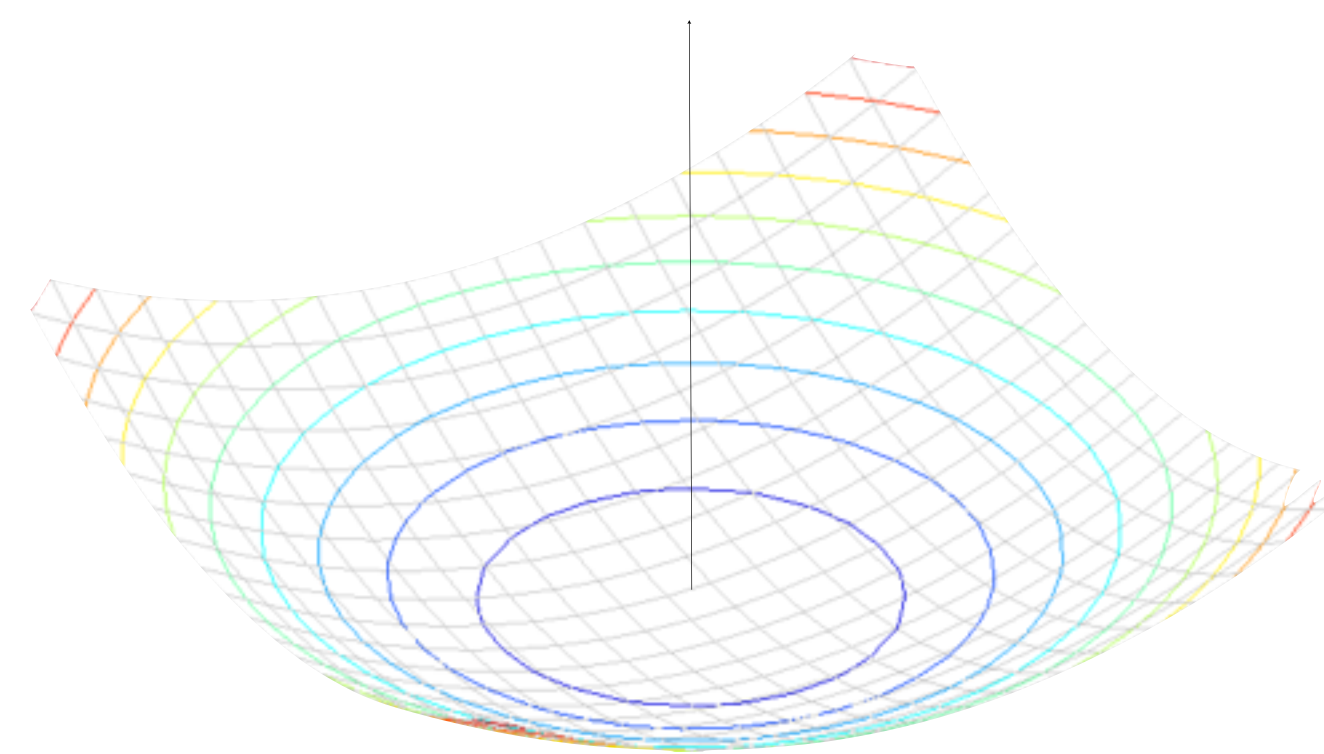
$$u^2 I_x^2 + 2uvI_xI_y + v^2 I_y^2 = k$$



which is an equation of an ellipse

The surface E(u,v) is locally approximated by a quadratic form.

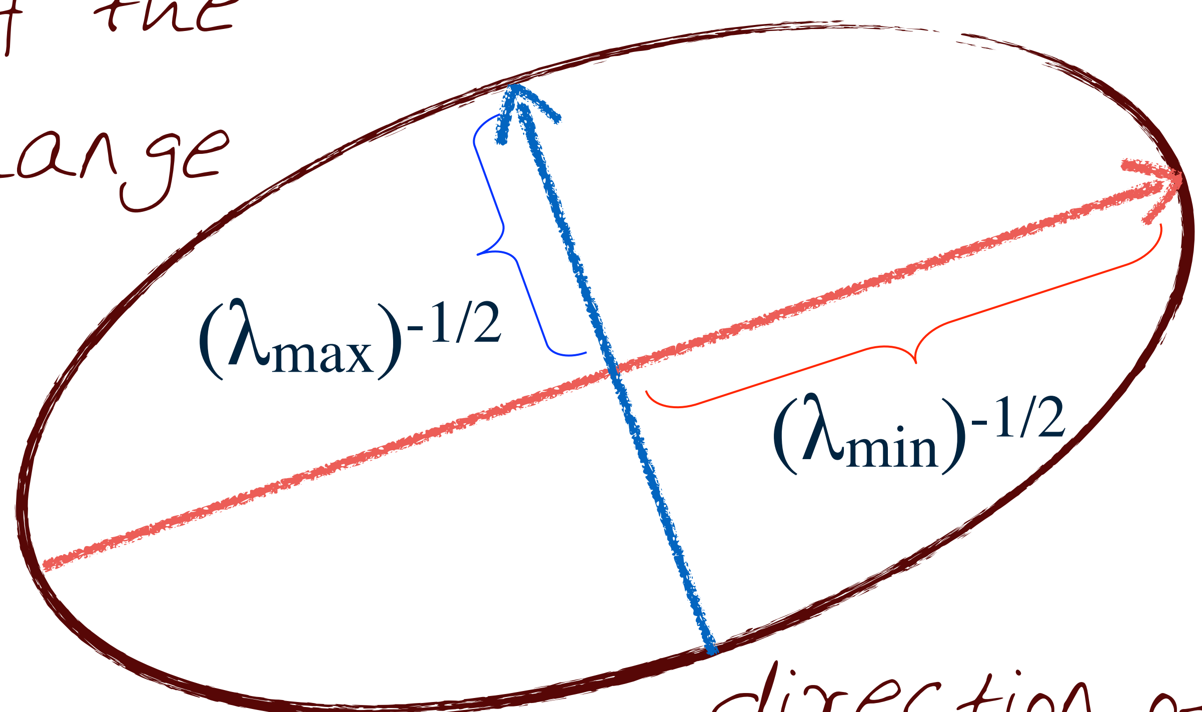
$$u^2 I_x^2 + 2uvI_xI_y + v^2 I_y^2 = k$$



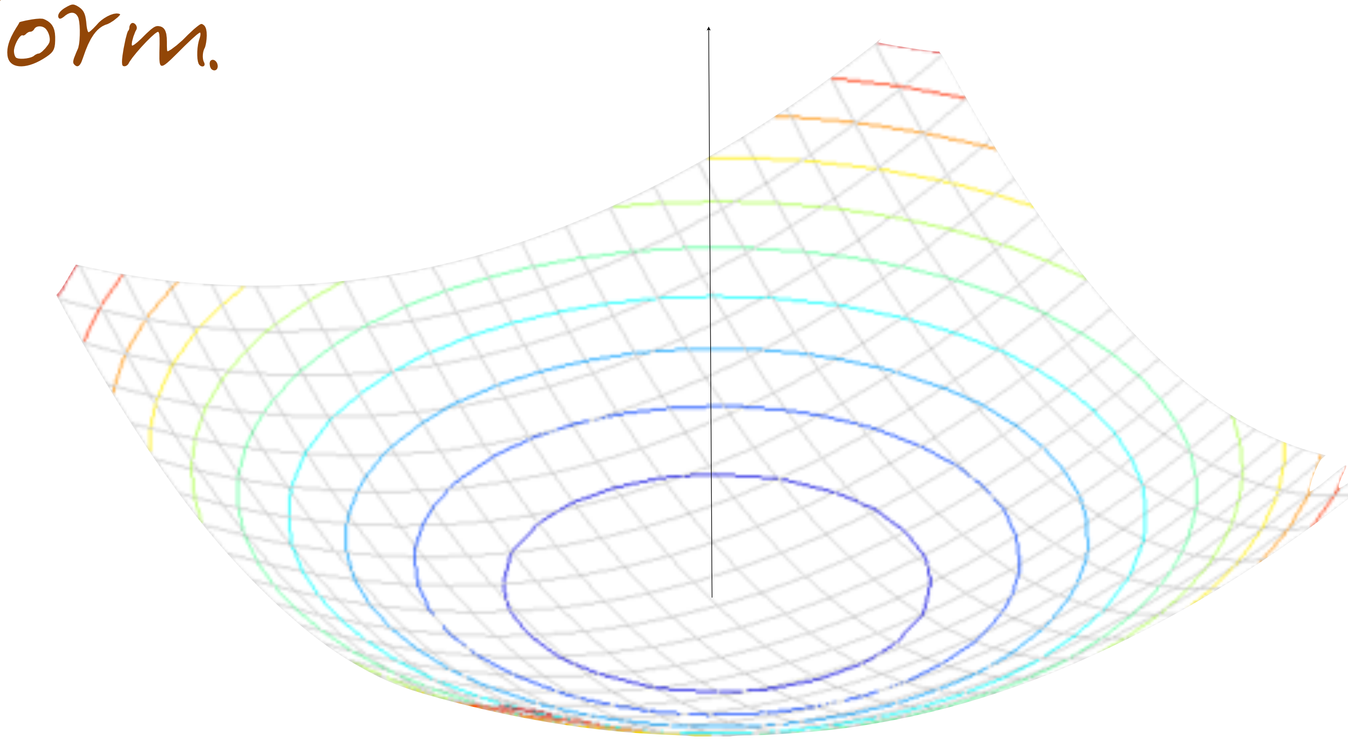
The surface E(u,v) is locally approximated by a quadratic form.

$$u^2 I_x^2 + 2uvI_xI_y + v^2 I_y^2 = k$$

direction of the fastest change



direction of the slowest change



Eigenvalue Analysis:

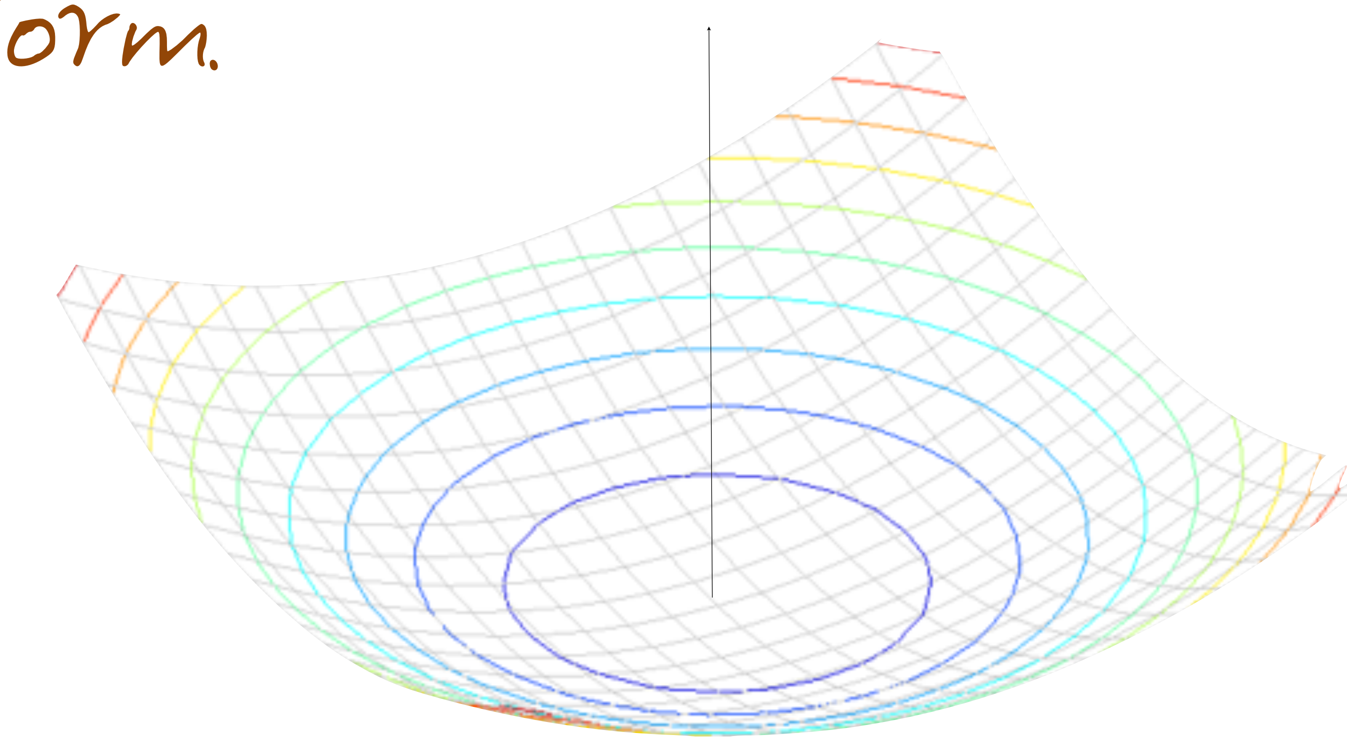
- Axis lengths ⇒ Eigenvalues
- Orientation ⇒ Eigenvectors

Slide motivated by Aaron Bobick

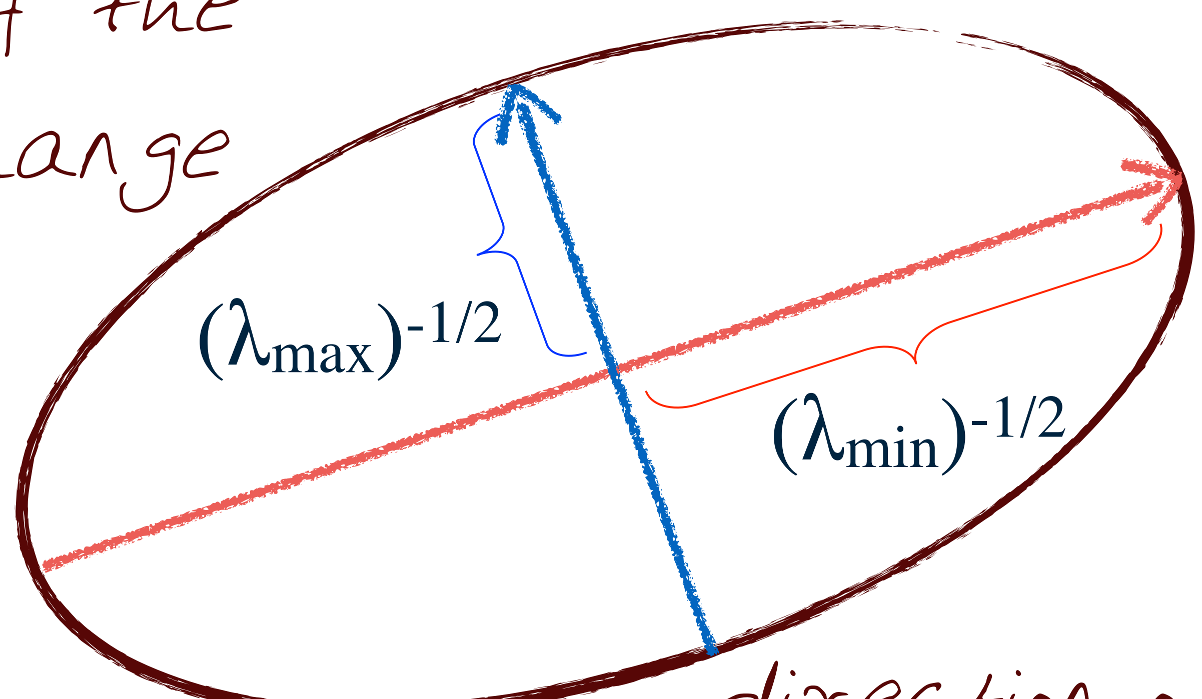
The surface E(u,v) is locally approximated by a quadratic form.

$$u^2 I_x^2 + 2uvI_xI_y + v^2 I_y^2 = k$$

$$\begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix} = k$$



direction of the fastest change



direction of the slowest change

M is a diagonal matrix

$$M = R^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$$

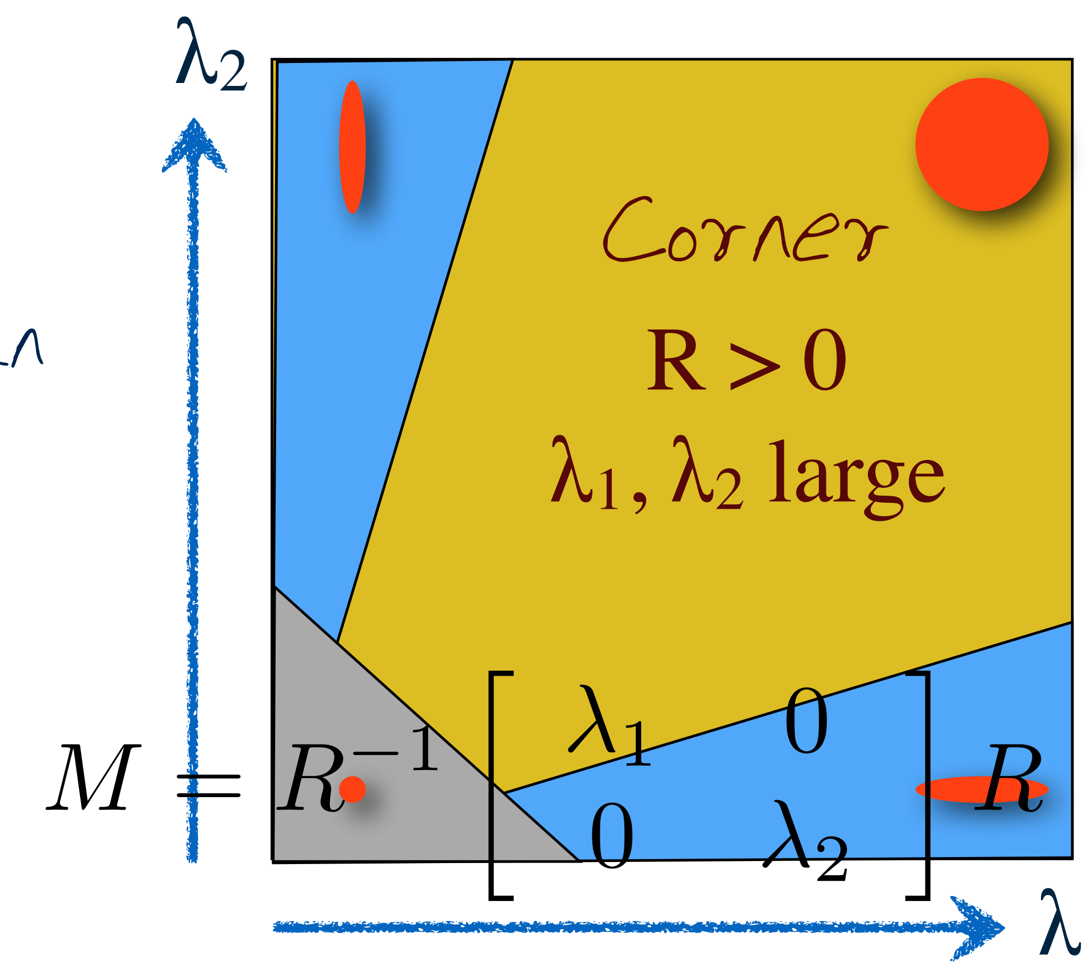
Slide motivated by Aaron Bobick

Eigenvalues

$$R = \det(M) - \alpha \,\mathrm{trace}(M)^2 = \lambda_1\lambda_2 - \alpha(\lambda_1 + \lambda_2)^2$$

α: constant (0.04 to 0.06)

* R depends only on eigenvalues of M
* $R \Rightarrow$ large for a corner
* $R \Rightarrow$ negative with large magnitude for an edge
* $|R| \Rightarrow$ small for a flat region
* Note: No explicit computation of eigenvalues required



$$M = R^{-1}\begin{bmatrix}\lambda_1 & 0 \\ 0 & \lambda_2\end{bmatrix}R$$

Harris Detector Algorithm (Preview)

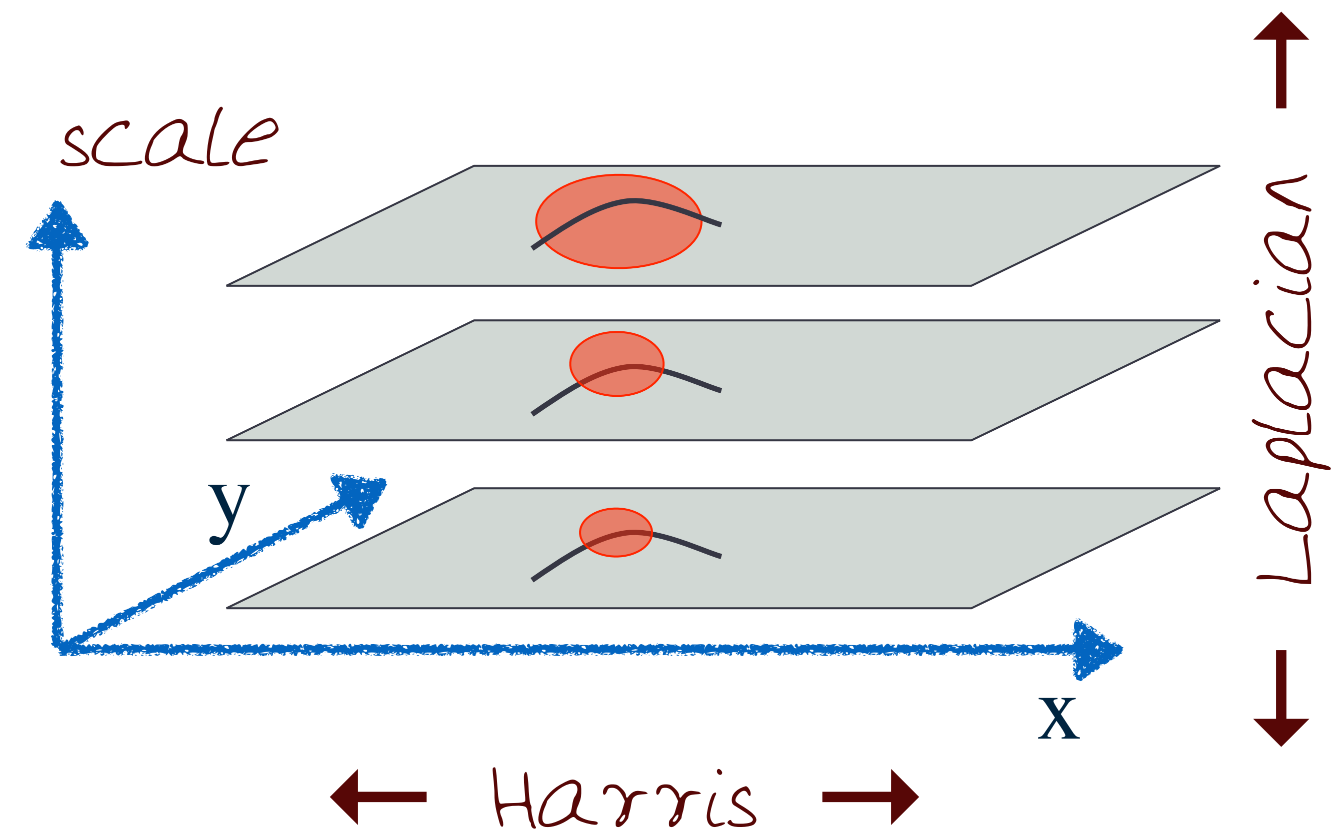
- Compute Gaussian derivatives at each pixel
- Compute second moment matrix M in a Gaussian window around each pixel
- Compute corner response function R
- Threshold R
- Find local maxima of response function (non-maximum suppression)

Properties of the Harris Detector

* Rotation Invariant?
  * Ellipses rotate, but shape (eigenvalues) remain same
  * Corner Response R is invariant
* Intensity Invariant?
  * Partial invariance to additive and multiplicative intensity changes (threshold issue for multiplicative)
  * Only Image derivatives are used
* Scale Invariant
  * NO! Dependent on Window Size!
  * USE Pyramids (or Frequency Domain!)

Scale Invariant Detectors

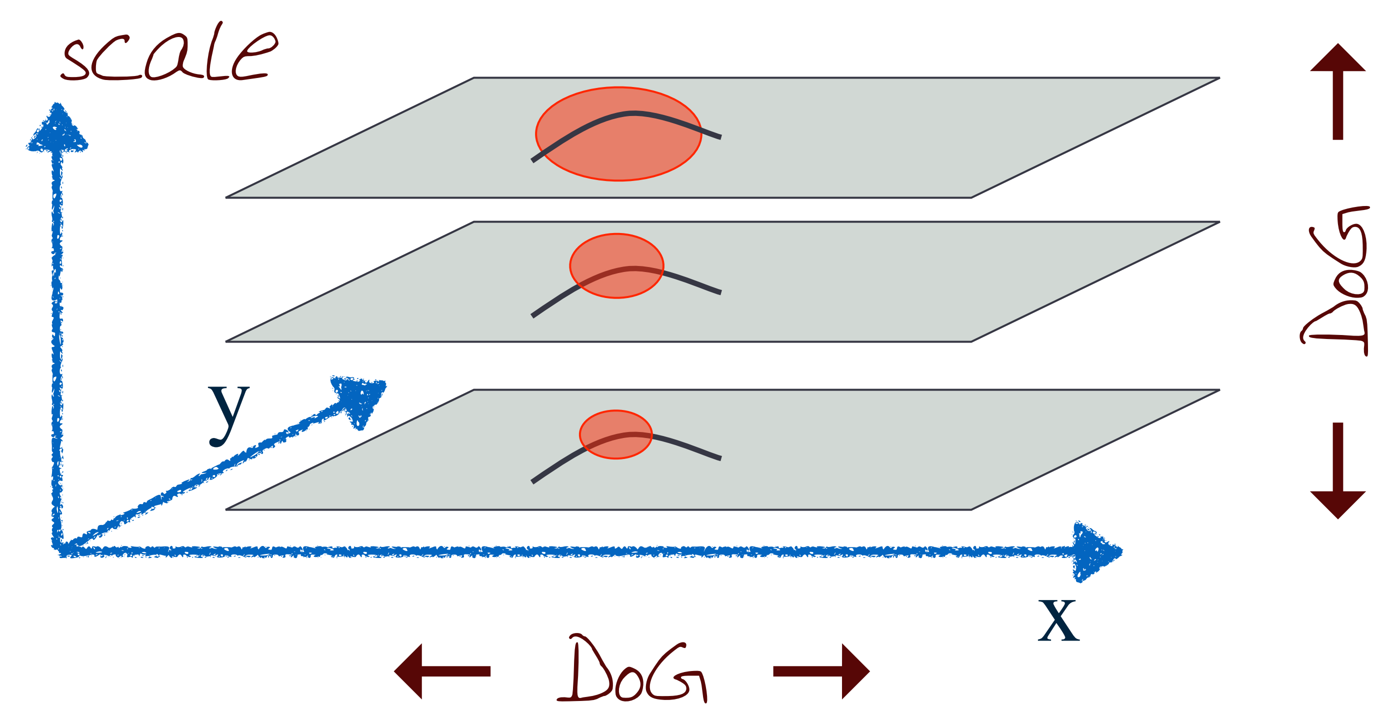
* Harris-Laplacian
* Find local maximum of:
    * Harris corner detector in space (image coordinates)
    * Laplacian in scale



(Mikolajczyk and Schmid, 2001)

Scale Invariant Detectors

* SIFT (Lowe, 2004)
* Find local maximum of:
    * Difference of Gaussians (DoG) in space and scale
    * DoG is simply a pyramid of the difference of Gaussians within each octave



Lowe 2004

SIFT (Scale-Invariant Feature Transform)

* Orientation assignment
  * Compute best orientation(s) for each keypoint region.
* Keypoint description
  * Use local image gradients at selected scale and rotation to describe each keypoint region.

http://en.wikipedia.org/wiki/File:Sift_keypoints_filtering.jpg

Invariant Local Features

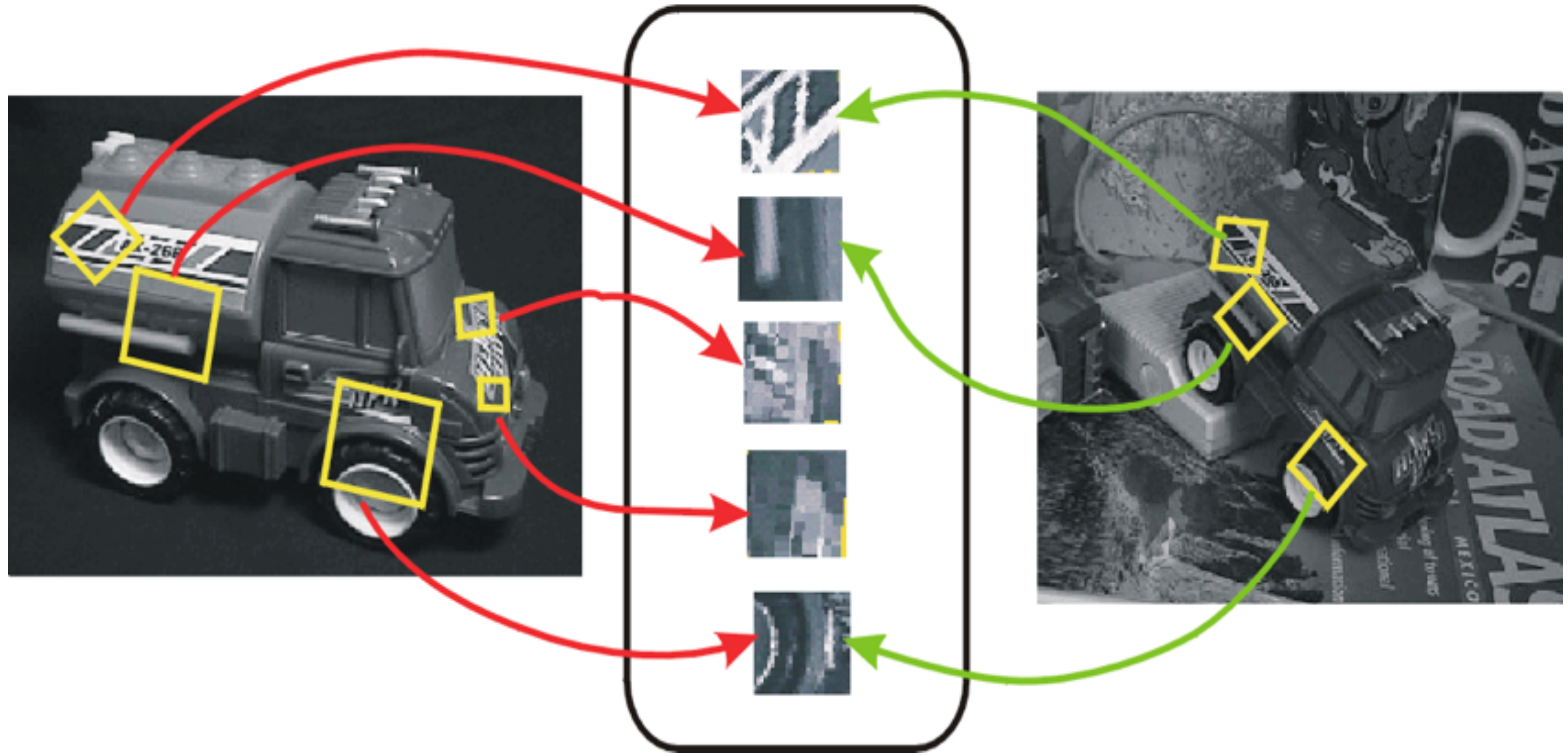


Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters

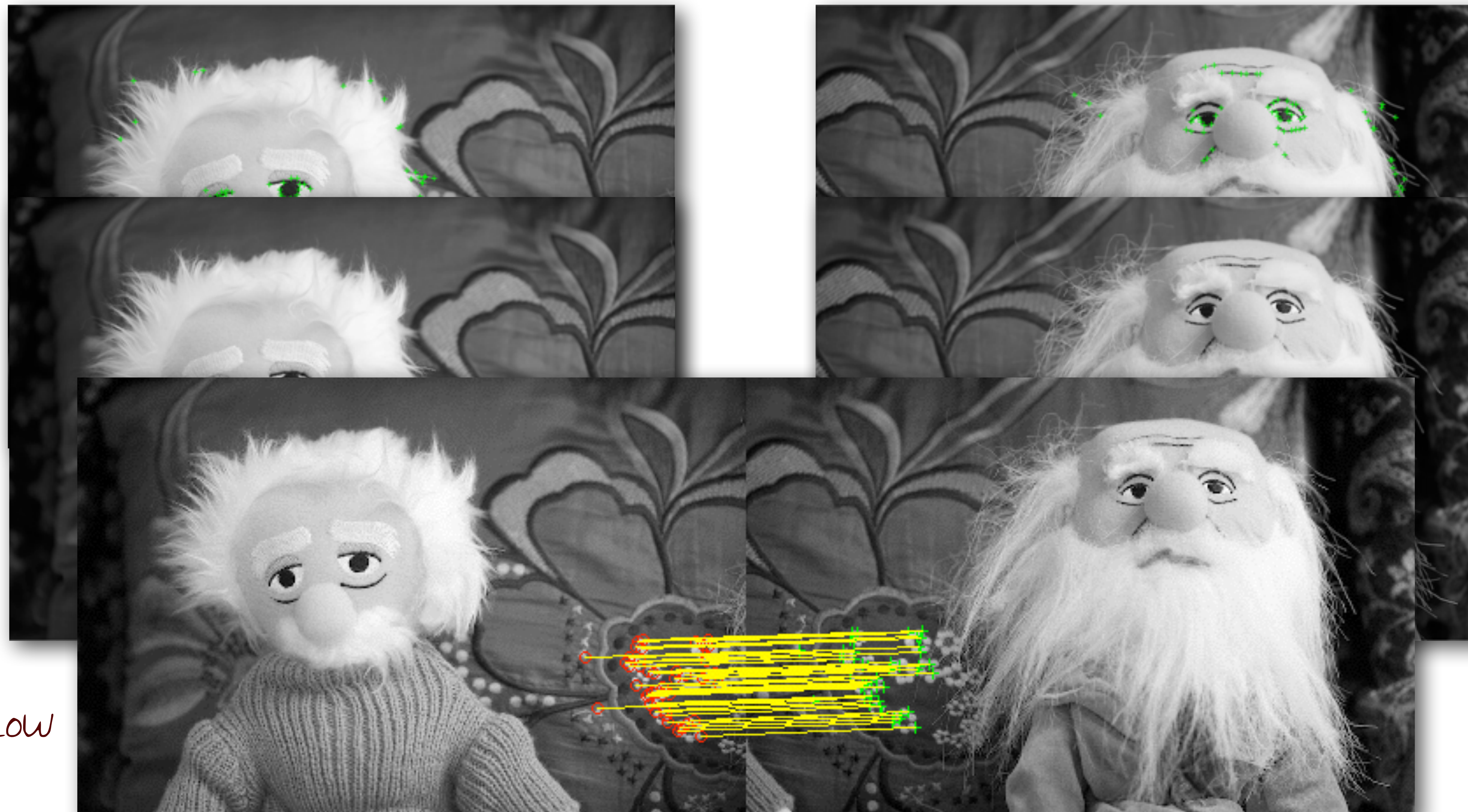
Lowe 2004

Results

Detect

Match

Show



Summary

* Introduced Feature Detection and matching for images
* Discussed the four (4) Characteristics of Good Features
* Introduced the Harris Corner Detector Framework
* Introduced the SIFT detector

Further Reading

* Harris and Stephens (1988) "A Combined Corner and Edge Detector." Proceedings of the 4th Alvey Vision Conference, 1988, [PDF][DOI]
* Mikolajczyk and Schmid (2001). "Indexing Based on Scale Invariant Interest Points". ICCV 2001
* Lowe (2004) "Distinctive Image Features from Scale-Invariant Keypoints". IJCV 2004
* Search for "Features" on OpenCV site

Next Class

* More details on SIFT and Harris Corner Detectors!

Credits

* For more information, see:
  * Richard Szeliski (2010) Computer Vision: Algorithms and Applications, Springer
* Some concepts in slides motivated by similar slides by A. Efros and J. Hays
* Some images retrieved from
  * http://commons.wikimedia.org/
  * List will be available on website

Computational Photography

* Study the basics of computation and its impact on the entire workflow of photography, from capturing, manipulating and collaborating on, and sharing photographs.

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