

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

- * More details on Harris and SIFT Features



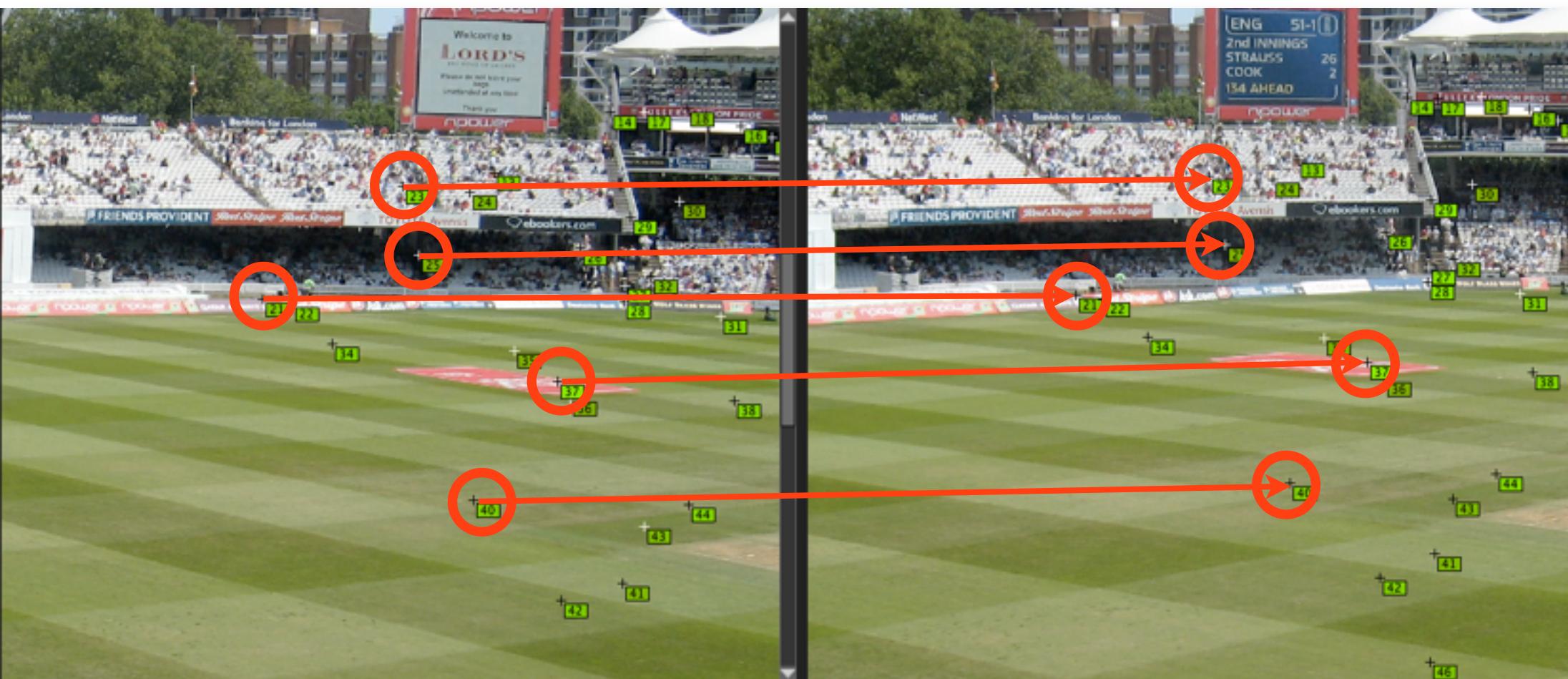
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Lesson Objectives

1. Harris Corner Detector Algorithm
2. SIFT

Recall: Detection and Matching



Recall: Corner Detection: Mathematics

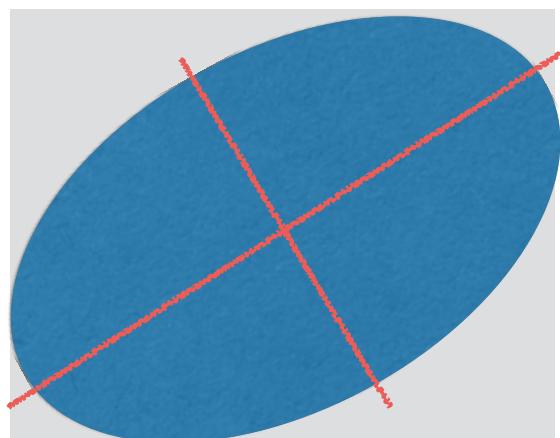
$$E(u, v) = \sum_{x, y} w(x, y) [I(x + u, y + v) - I(x, y)]^2$$

The quadratic approximation, following Taylor Expansion, simplifies to:

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

where M is a second moment matrix computed from image derivatives I_x and I_y :

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

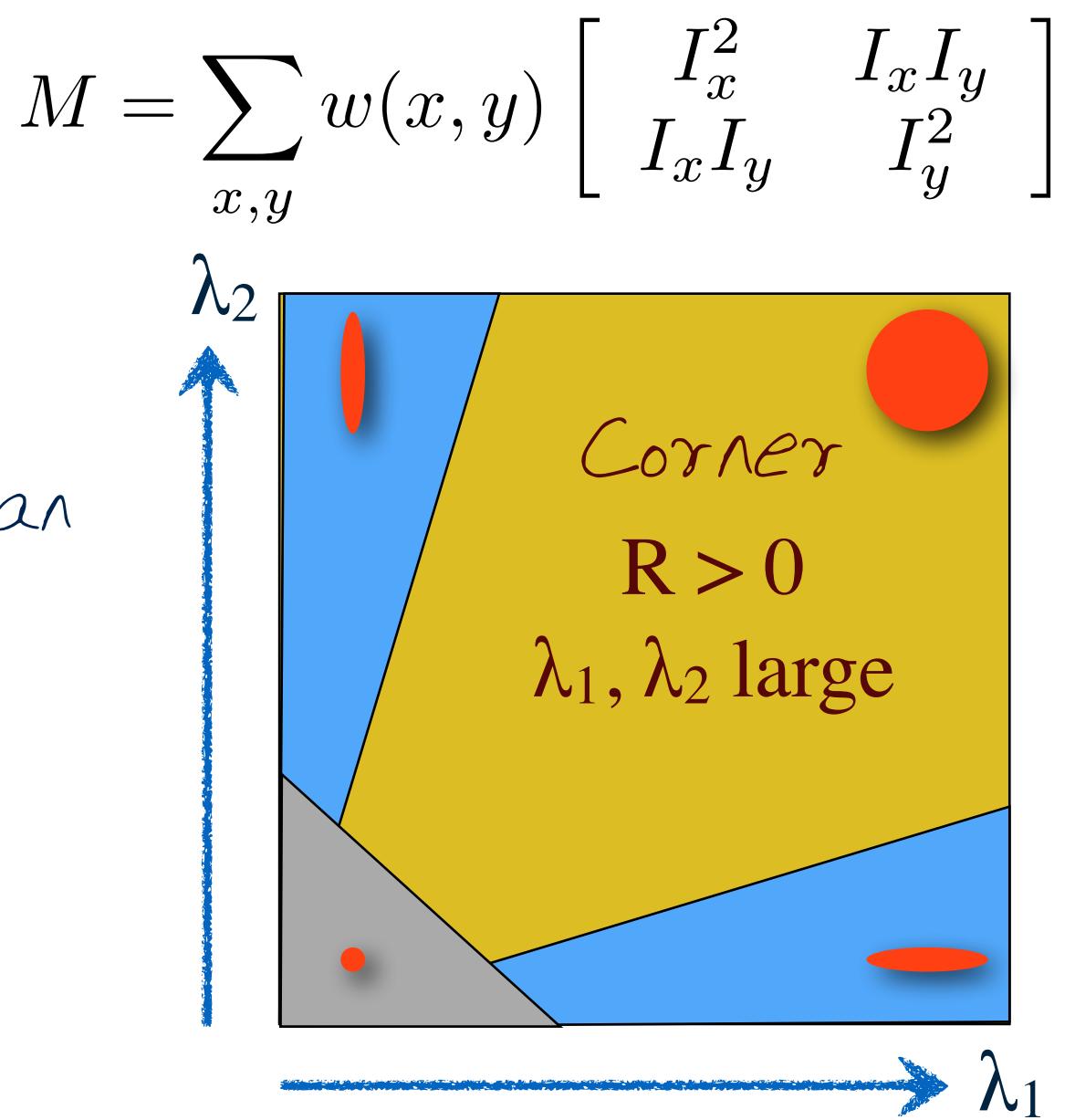


Recall: Harris Corner Response Function

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

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



Harris Detector: Step by Step

1. Compute horizontal and vertical derivatives of the image (convolve with derivative of Gaussians)
2. Computer outer products of gradients M
3. Convolve with larger Gaussian
4. Compute scalar interest measure R
5. Find local maxima above some threshold, detect features!

Harris Detector: Workflow

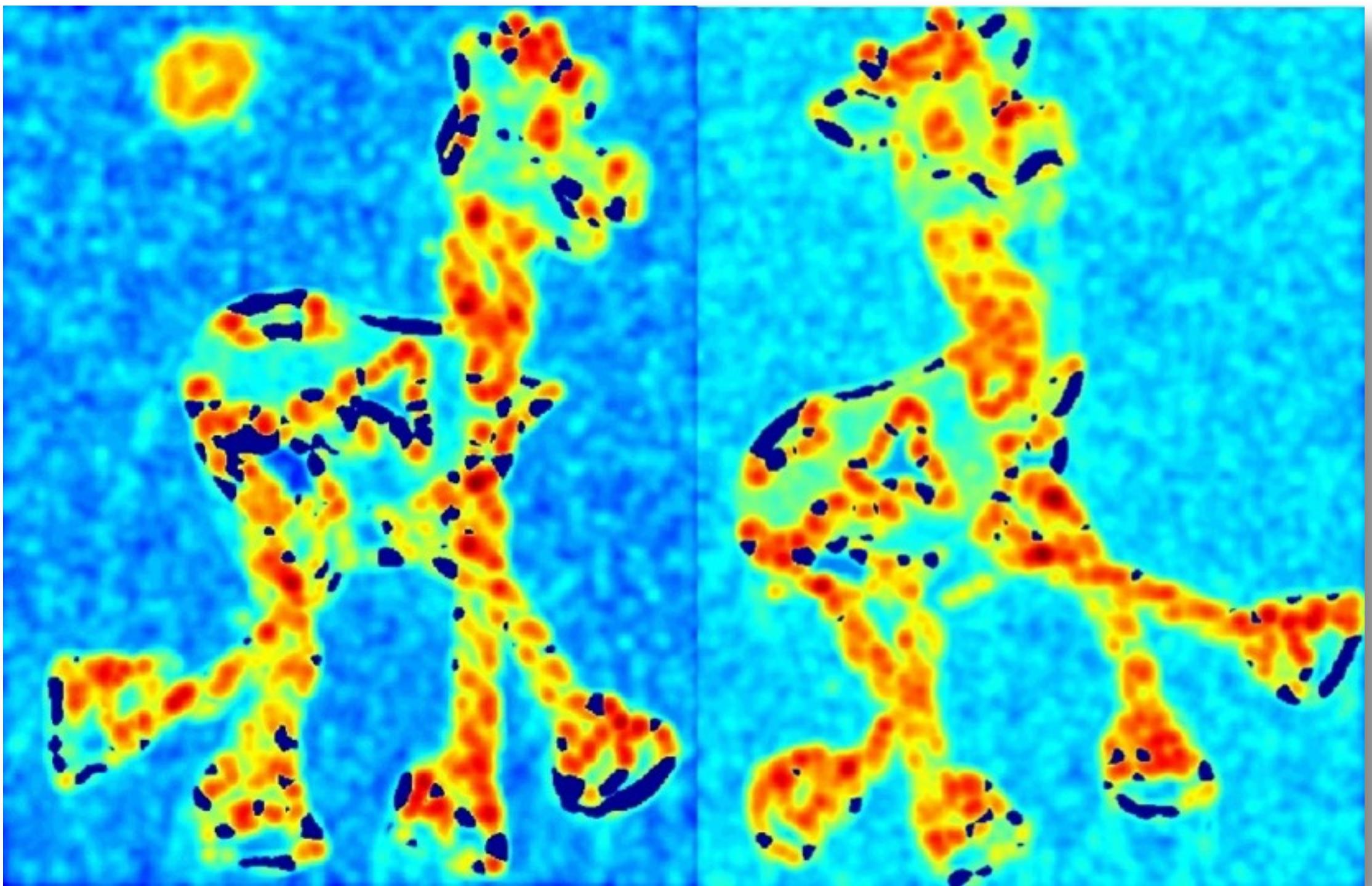
Image Pair



Slides adapted from Aaron Bobick, Alyosha Efros, etc.

Harris Detector: Workflow

Compute corner
response R

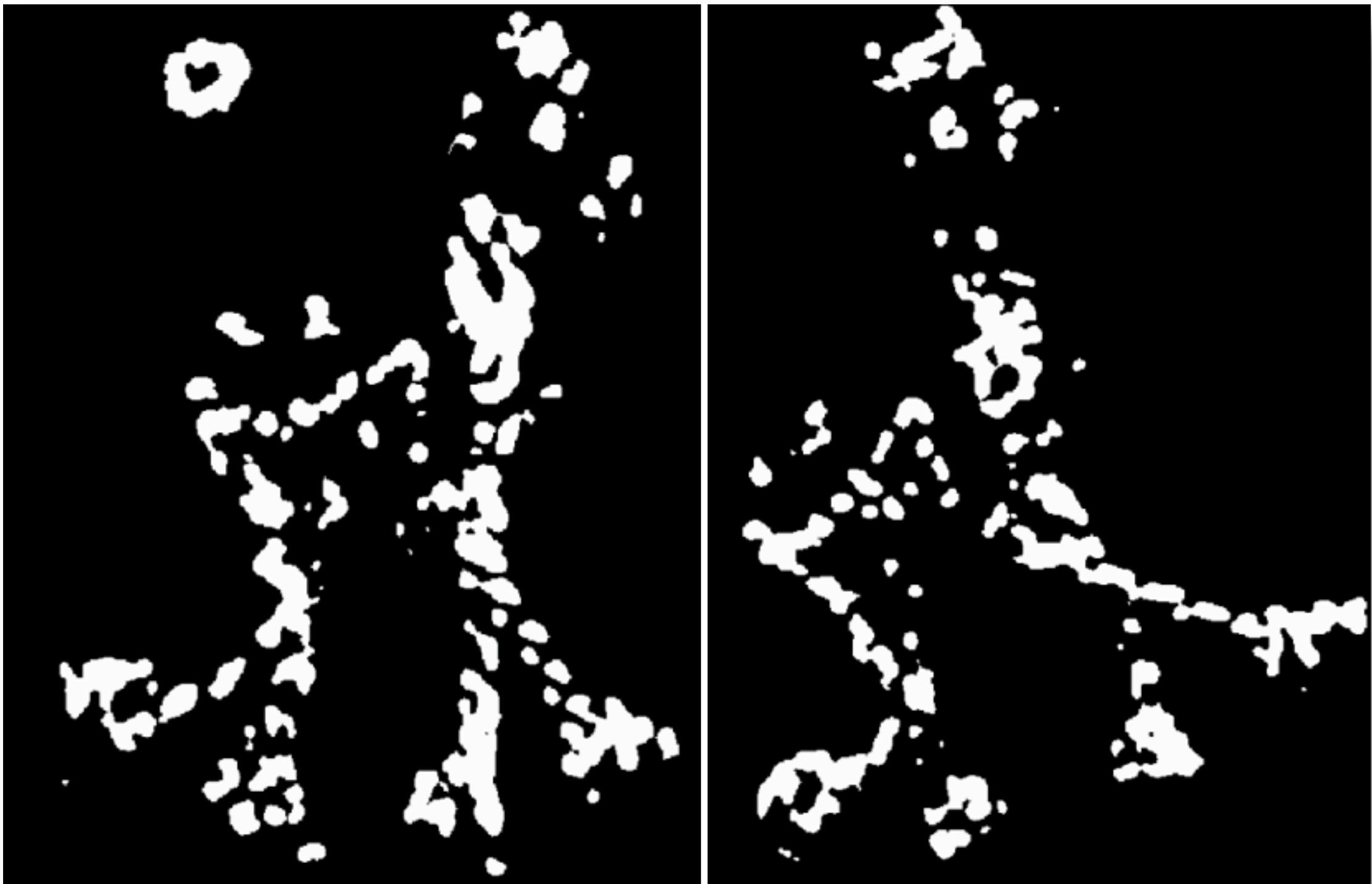


Slides adapted from Aaron Bobick, Alyosha Efros, etc.

Harris Detector: Workflow

Find points
with large
corner response.

$R > \text{threshold}$



Slides adapted from Aaron Bobick, Alyosha Efros, etc.

Harris Detector: Workflow

Take only the
points of local
maxima of R



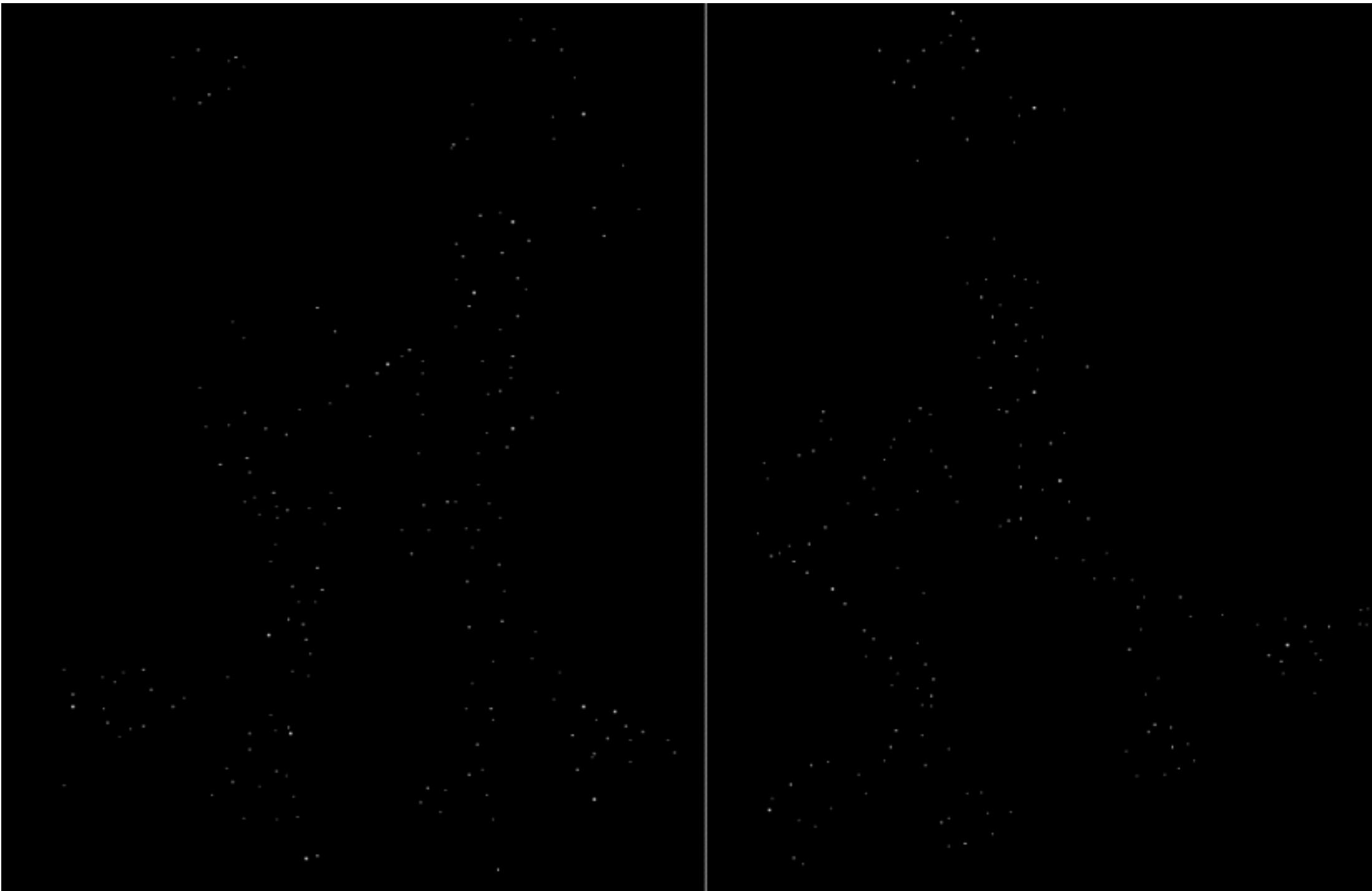
Slides adapted from Aaron Bobick, Alyosha Efros, etc.

Harris Detector: Workflow

Take only the
points of local
maxima of R



Slides adapted from Aaron Bobick, Alyosha Efros, etc.



Harris Detector: Workflow

Output



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)

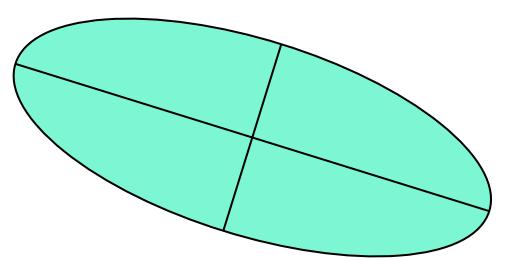
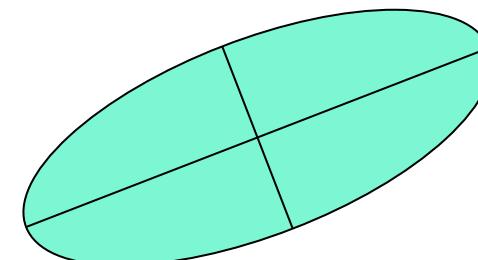
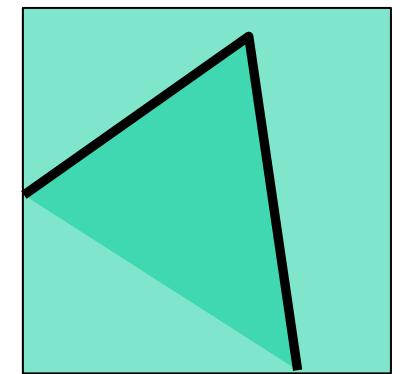
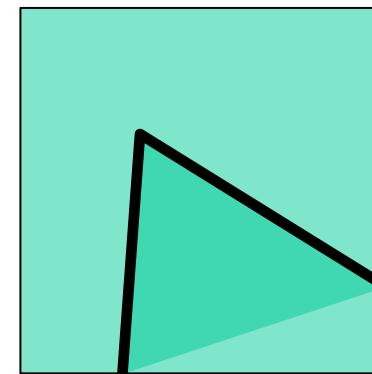


Harris Detector: Some Properties

- * Invariant to Rotation?
- * Invariance to image intensity?
- * Invariant to image scale?

Harris Detector: Some Properties

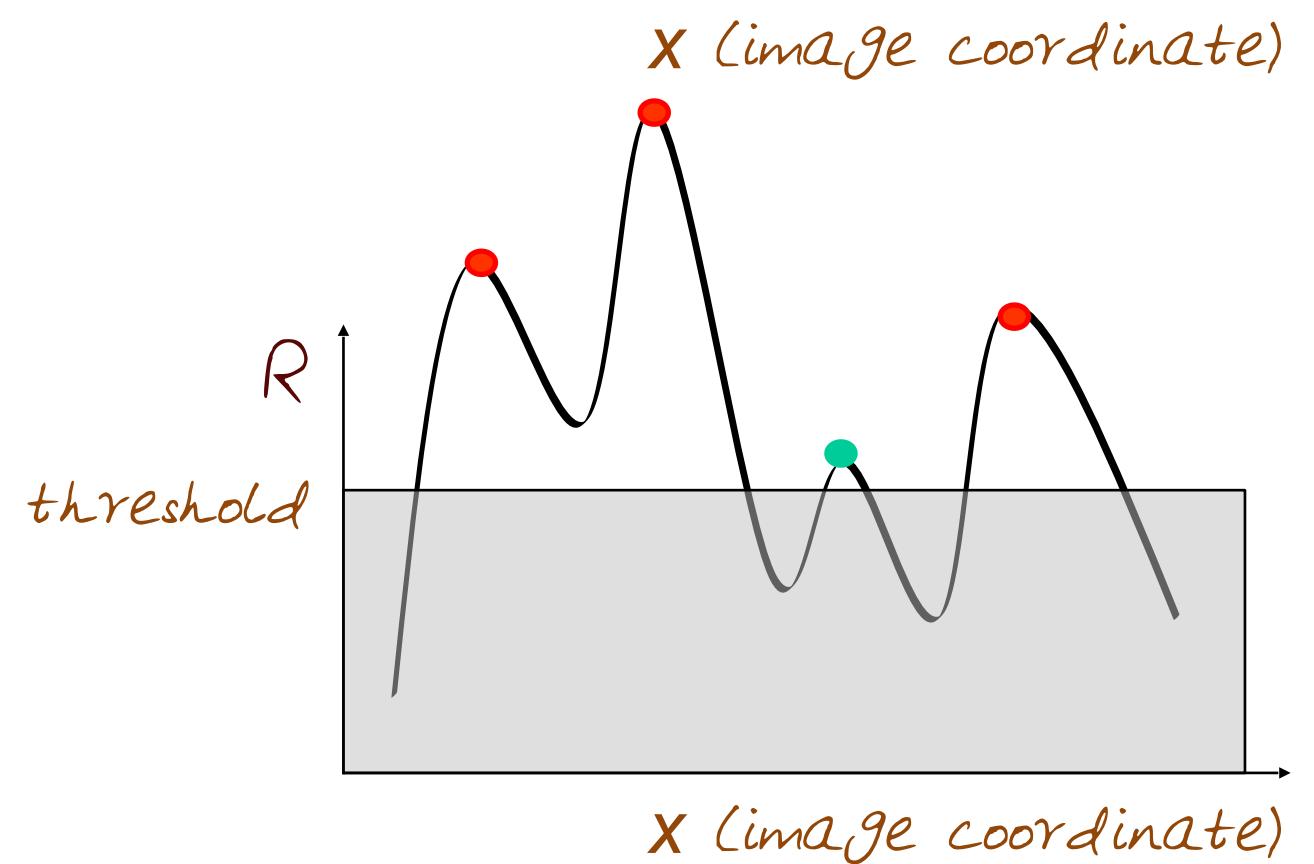
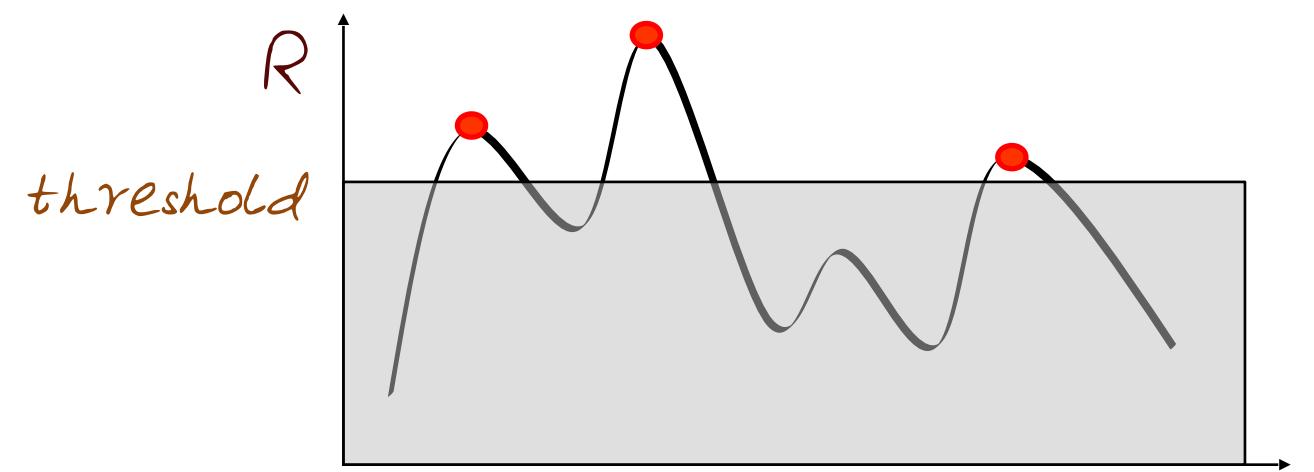
- * Invariant to Rotation?
- * Ellipse rotates but its shape (i.e. eigenvalues) remains the same
- * Corner response R is invariant to image rotation



Slides adapted from Aaron Bobick

Harris Detector: Some Properties

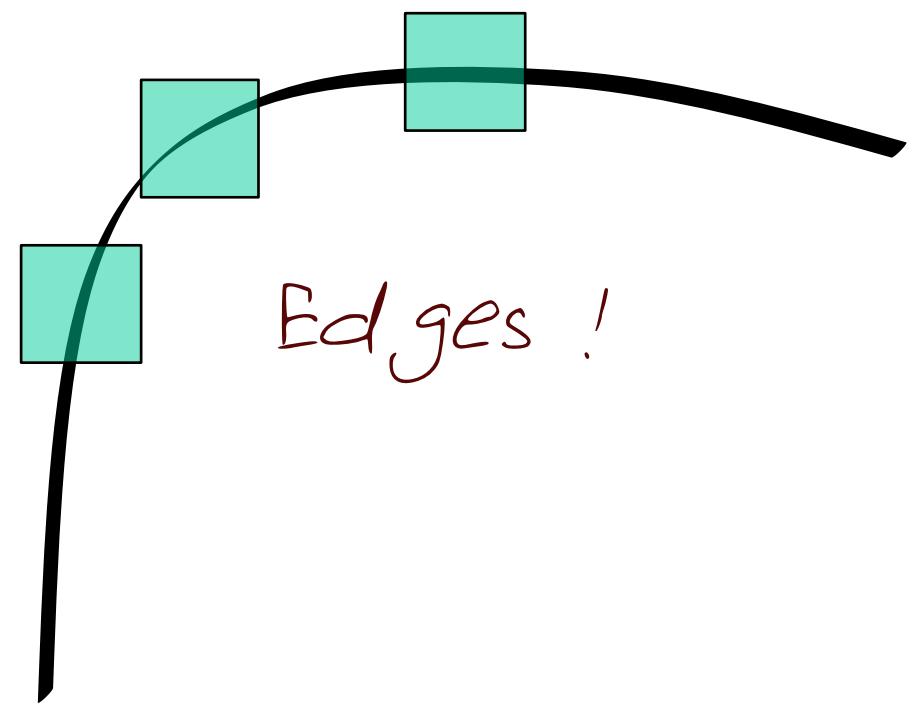
- * Invariance to image intensity?
- * Mostly invariant to additive and multiplicative intensity changes
- * Only derivatives are used
- * Invariance to intensity shift:
 - * $I \rightarrow I + b$
 - * Intensity scale:
 - * $I \rightarrow a I$



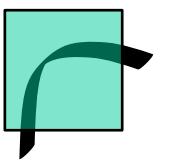
Slides adapted from Aaron Bobick

Harris Detector: Some Properties

- * Invariant to image scale?
- * Not Invariant to image scale,
- * But can we do something about this?



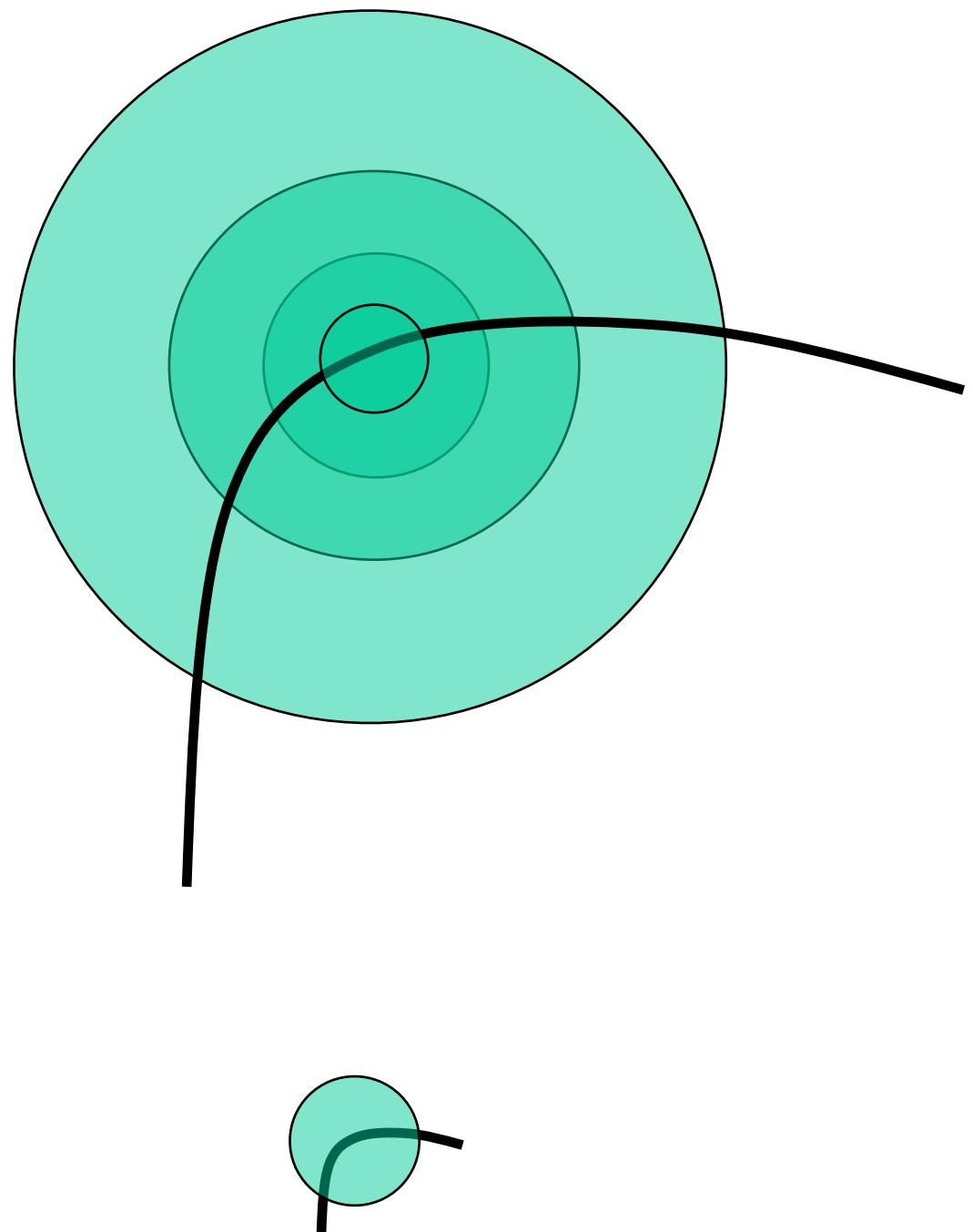
Edges !



Corner !

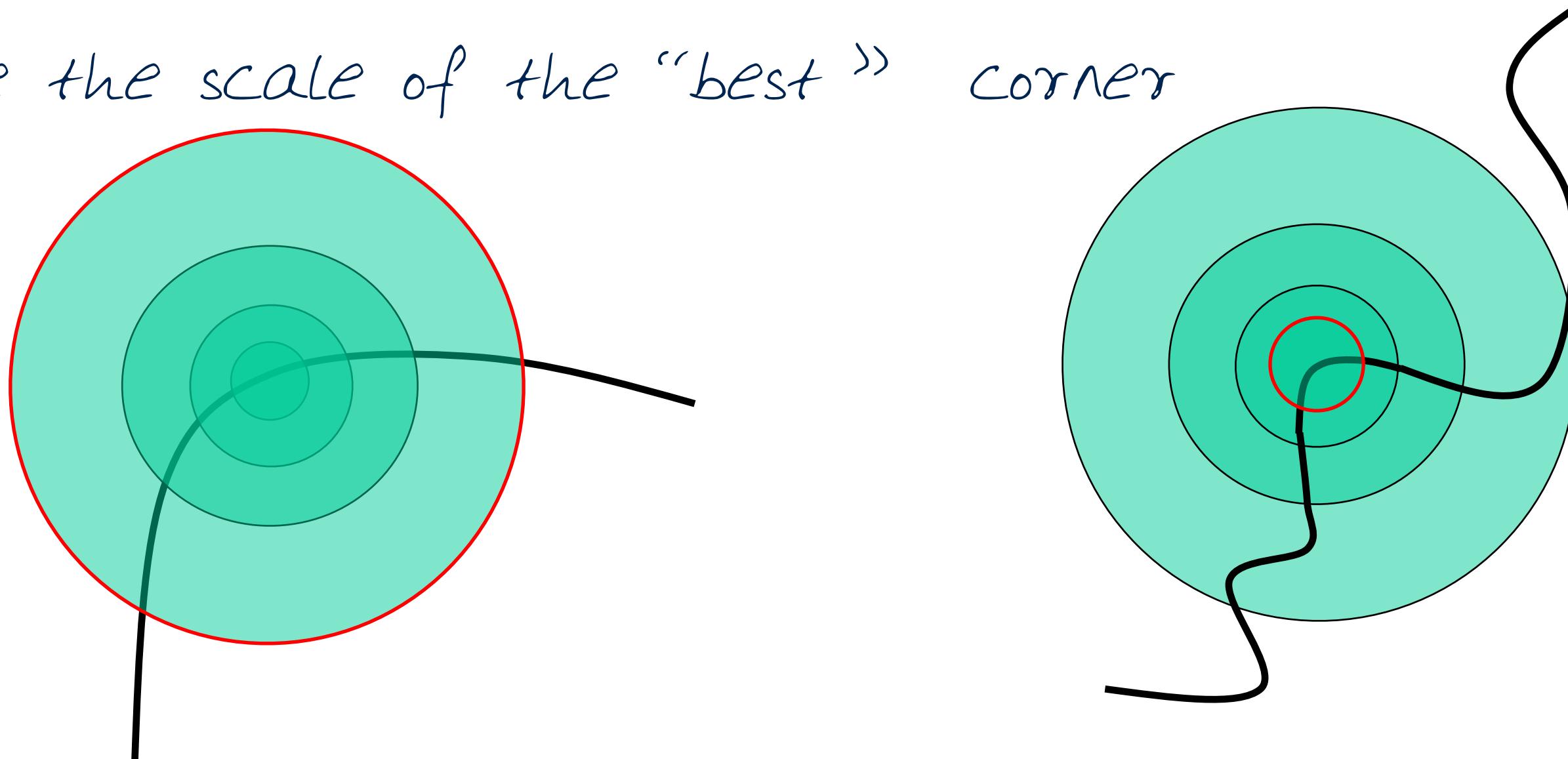
Scale Invariant Detection

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



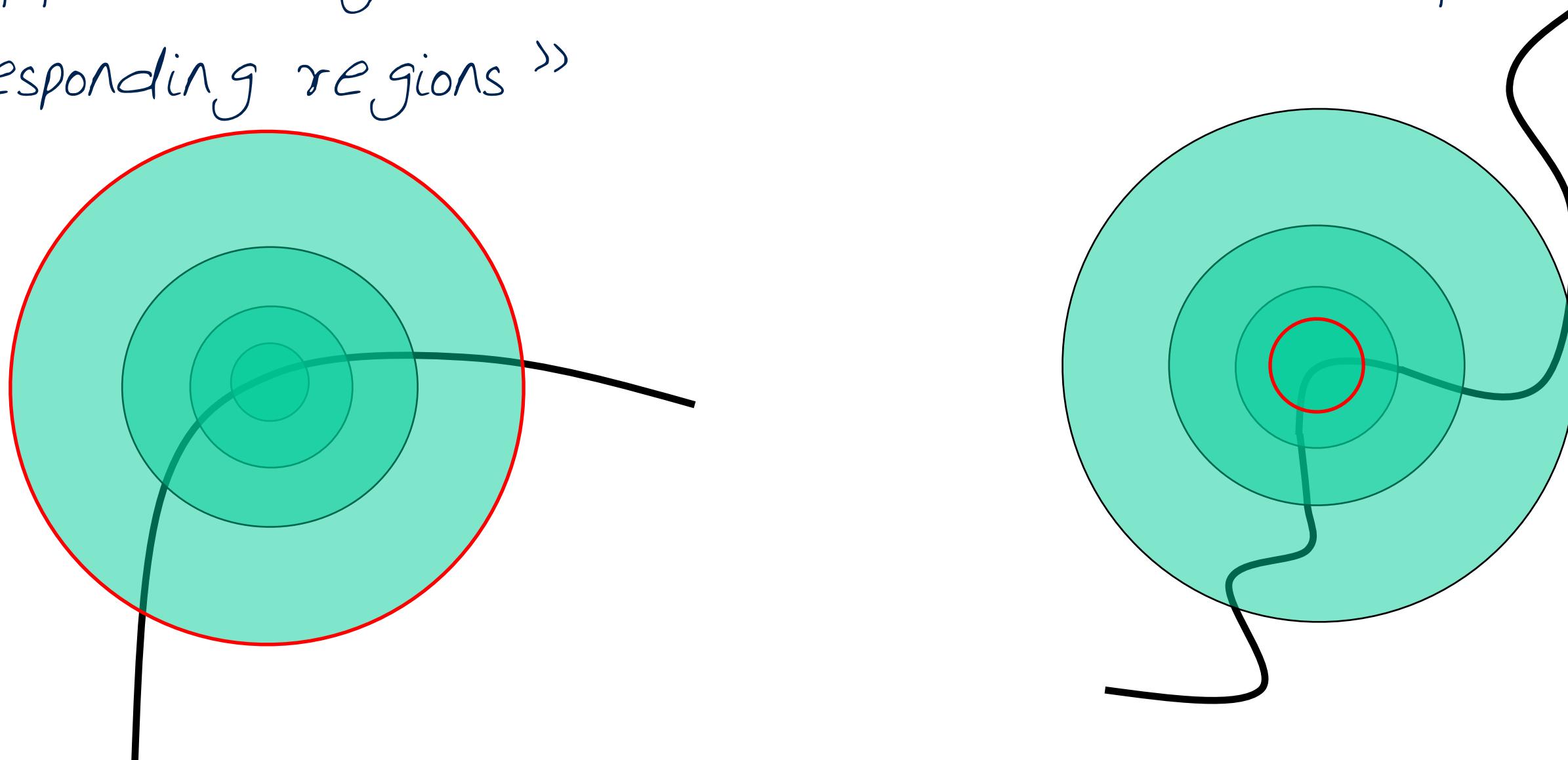
Scale Invariant Detection

- * The problem: how do we choose corresponding circles independently in each image?
- * Choose the scale of the “best” corner



Scale Invariant Detection

- * A region (circle), which is "scale invariant"
- * Not affected by the size but will be the same for "corresponding regions"

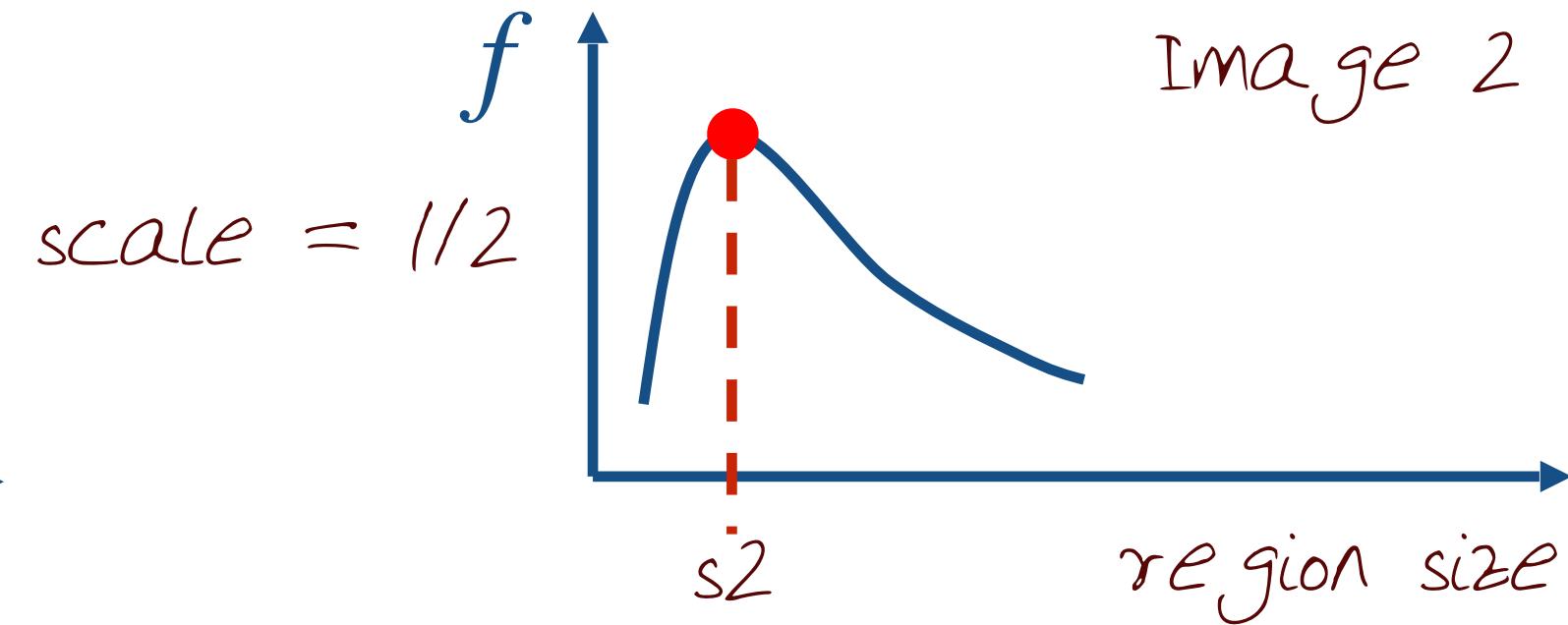
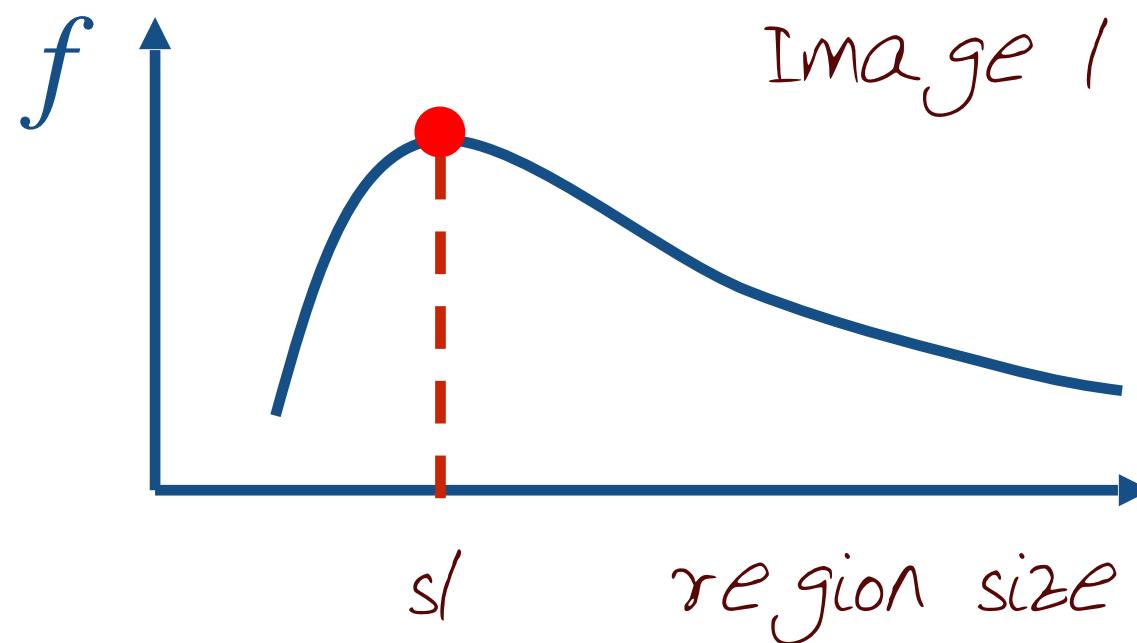


Scale Invariant Detection

- * A region (circle), which is "scale invariant"
- * Not affected by the size but will be the same for "corresponding regions"
- * Example: Average intensity. For corresponding regions (even of different sizes) it will be the same

Scale Invariant Detection

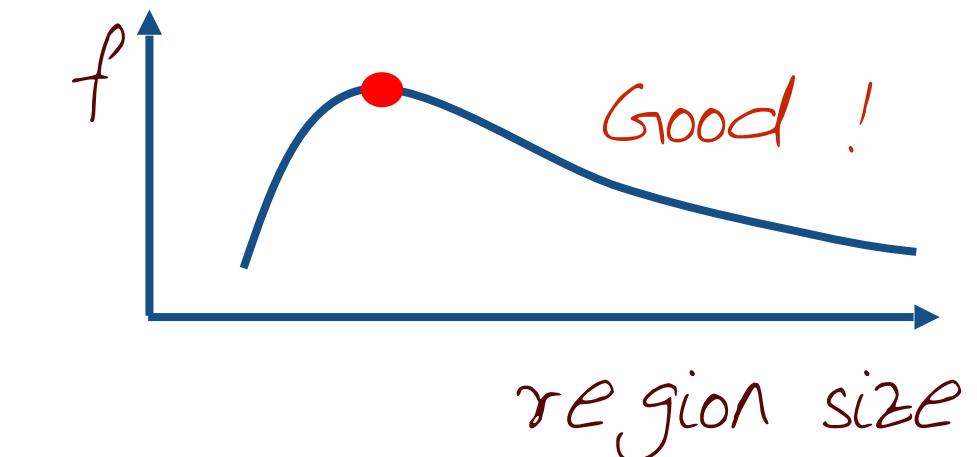
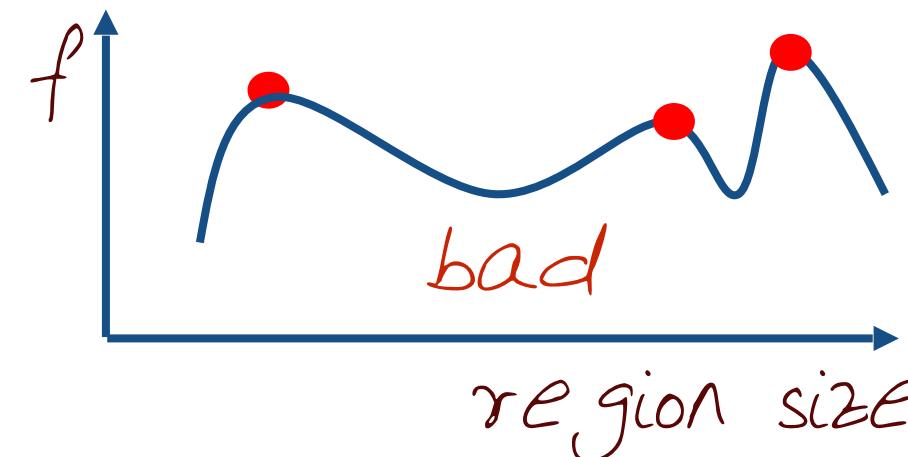
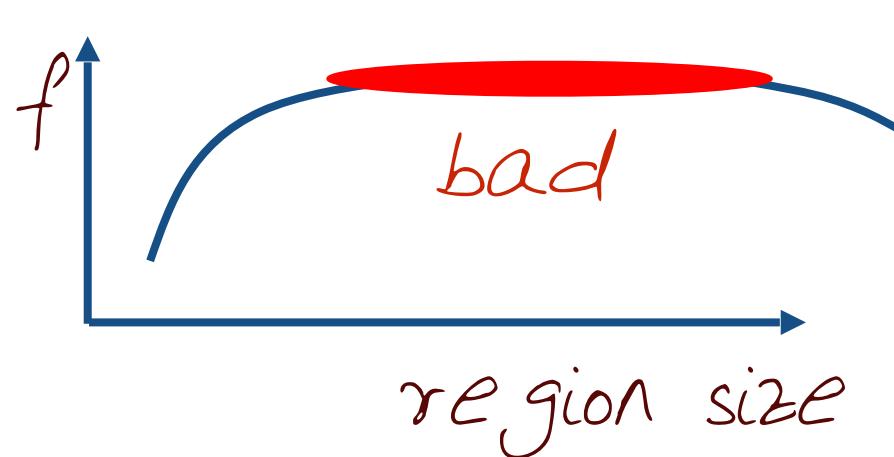
- * At a point, compute the scale invariant function over different size neighborhoods (different scales)
- * Choose the scale for each image at which the function is a maximum



Slides adapted from Aaron Bobick

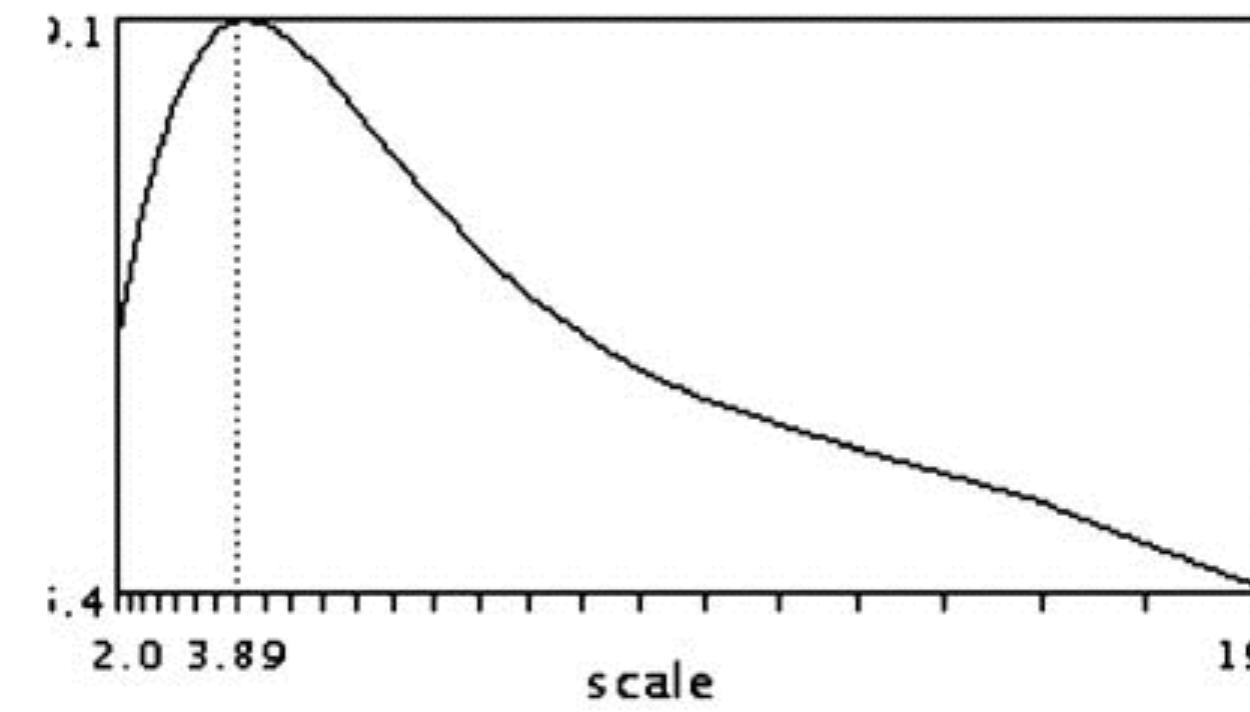
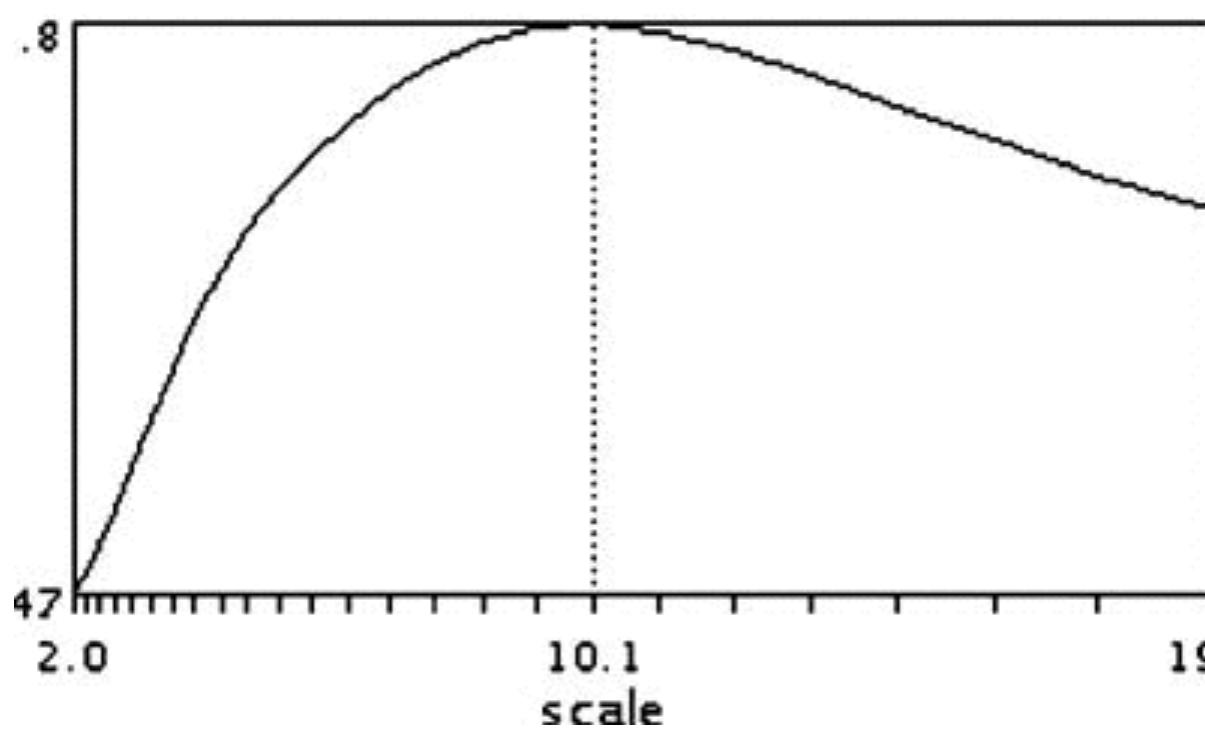
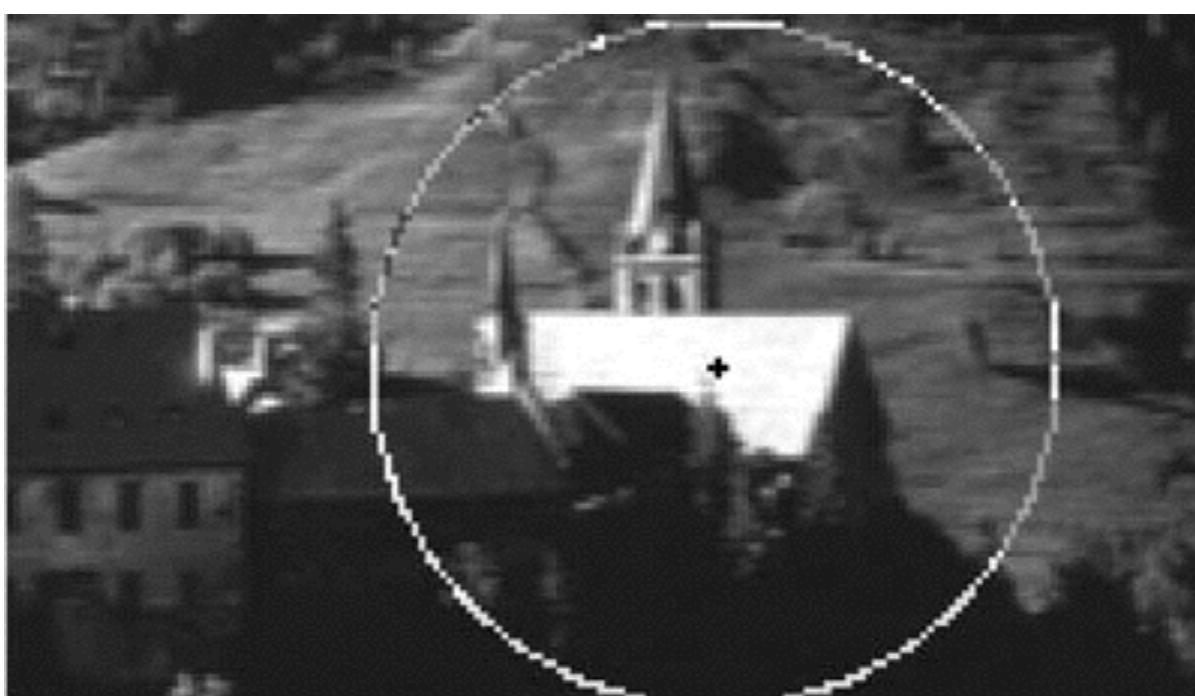
Scale Invariant Detection

- * A “good” function for scale detection has one stable sharp peak



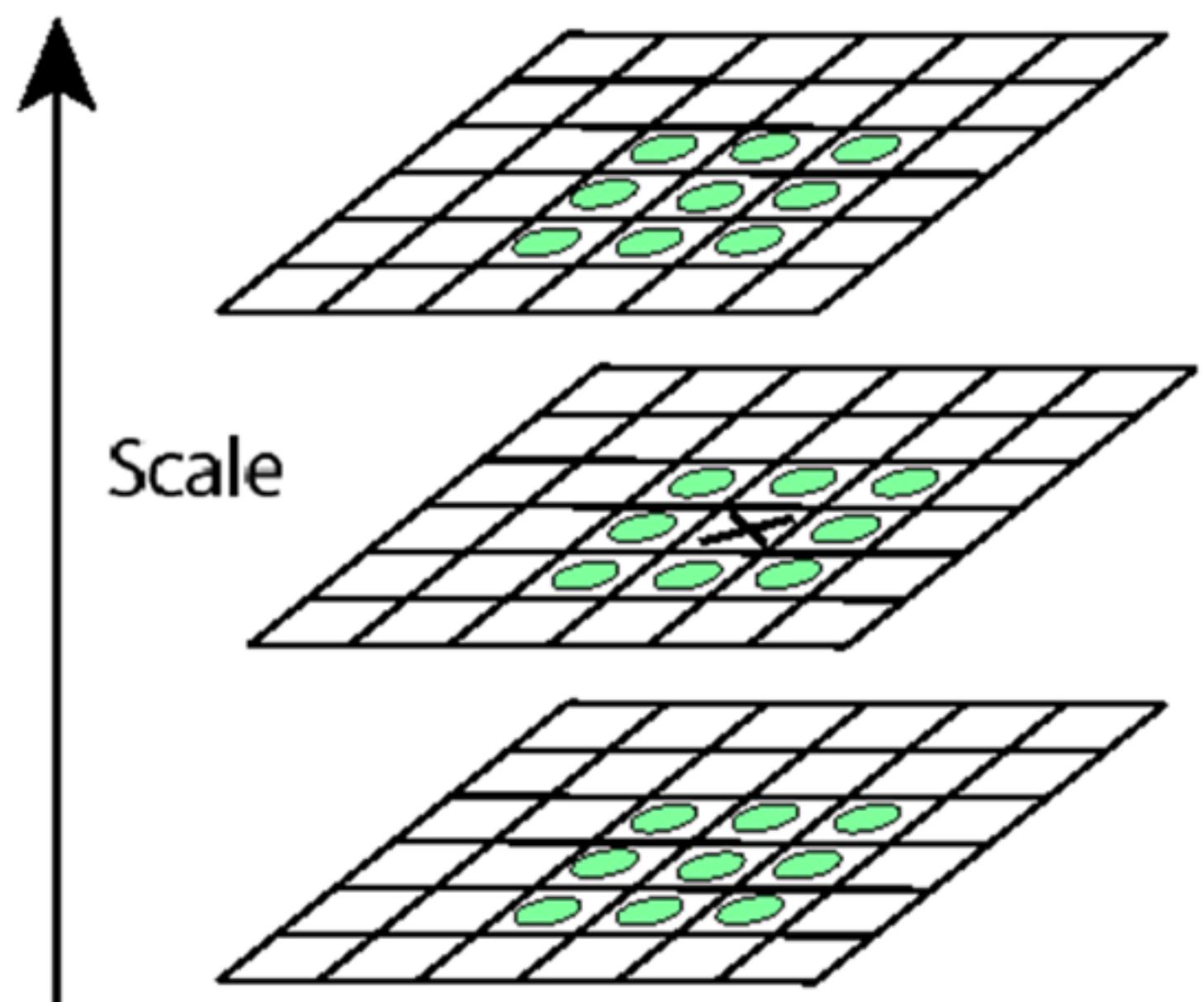
- * For usual images, a good function would be one which responds to contrast (sharp local intensity change)

Scale Sensitive Response



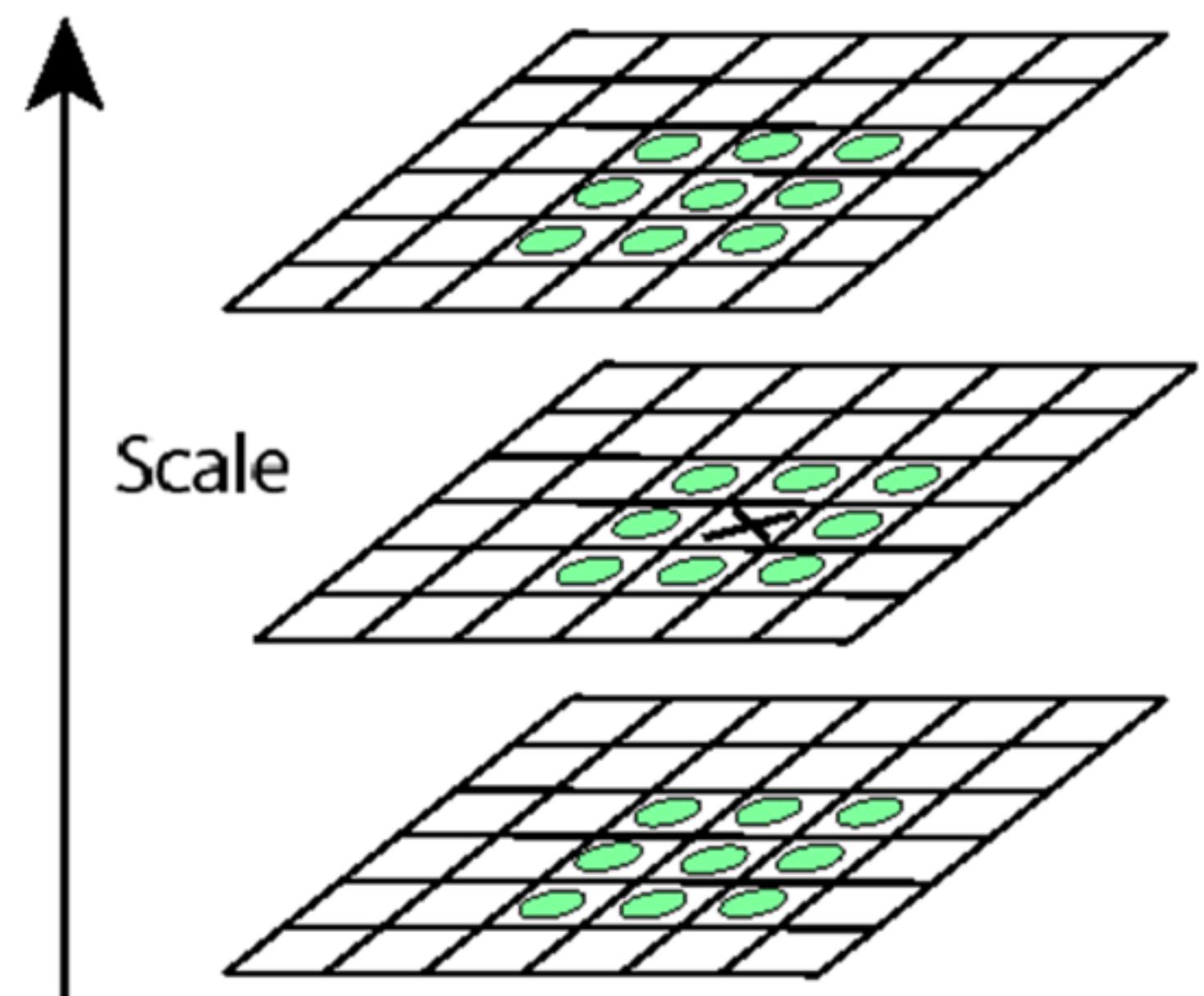
Key Point Localization in SPACE

- * Find robust extremum
(maximum or minimum) both
in space and in scale



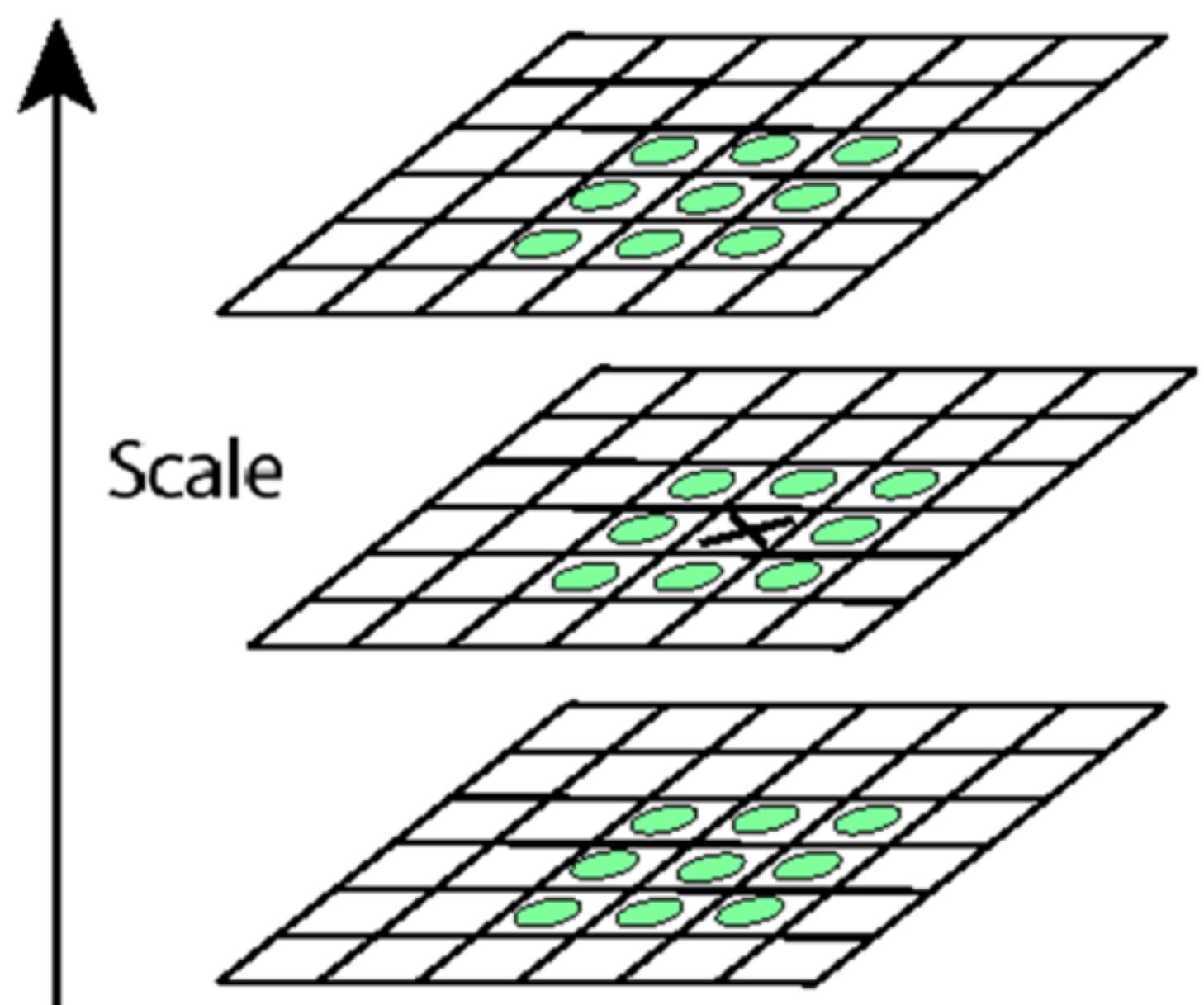
Key Point Localization

- * SIFT: Scale Invariant Feature Transform
- * Specific suggestion: use pyramid to find maximum values (remember edge detection?) – then eliminate “edges” and pick only corners

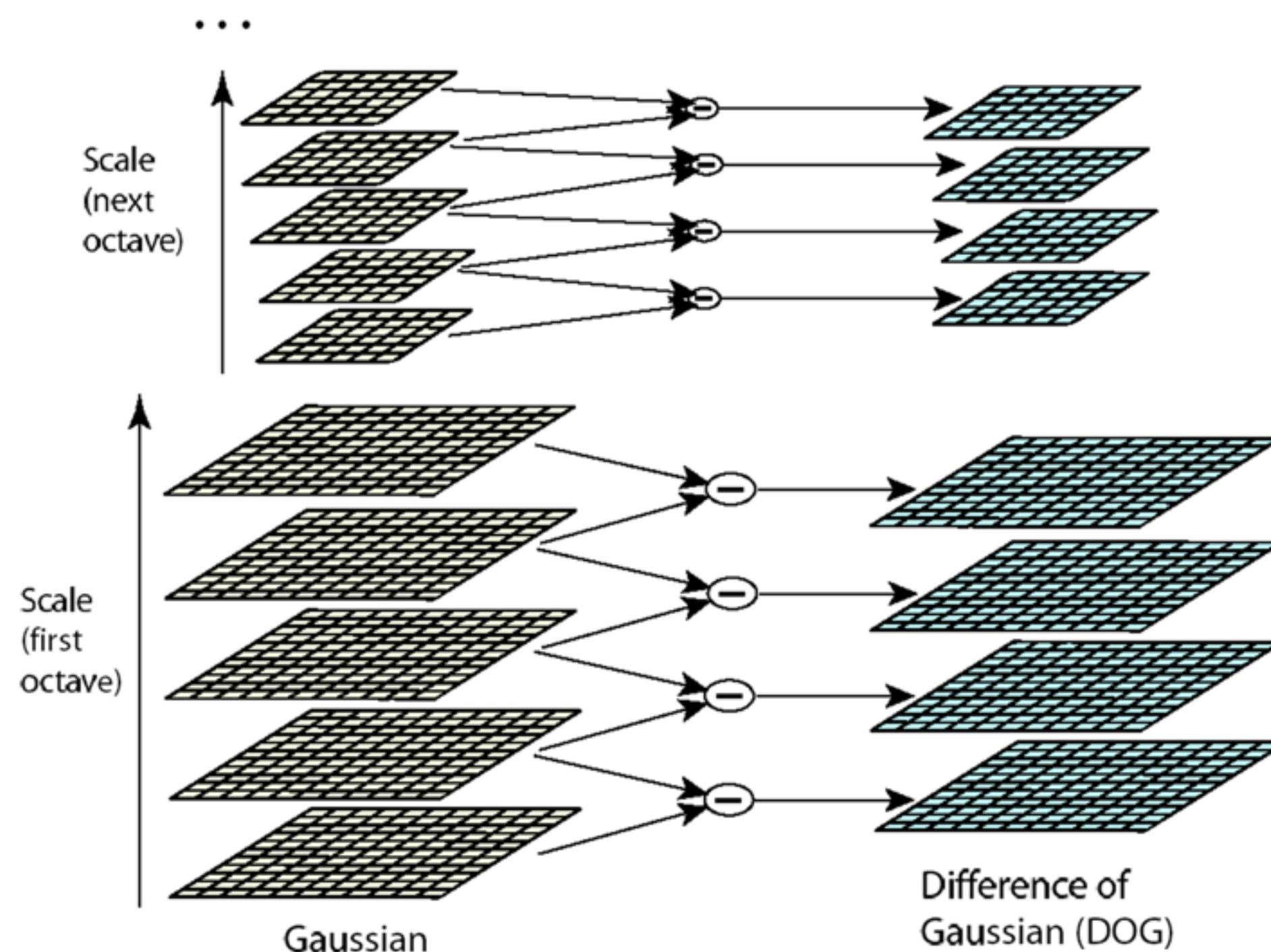


Key Point Localization

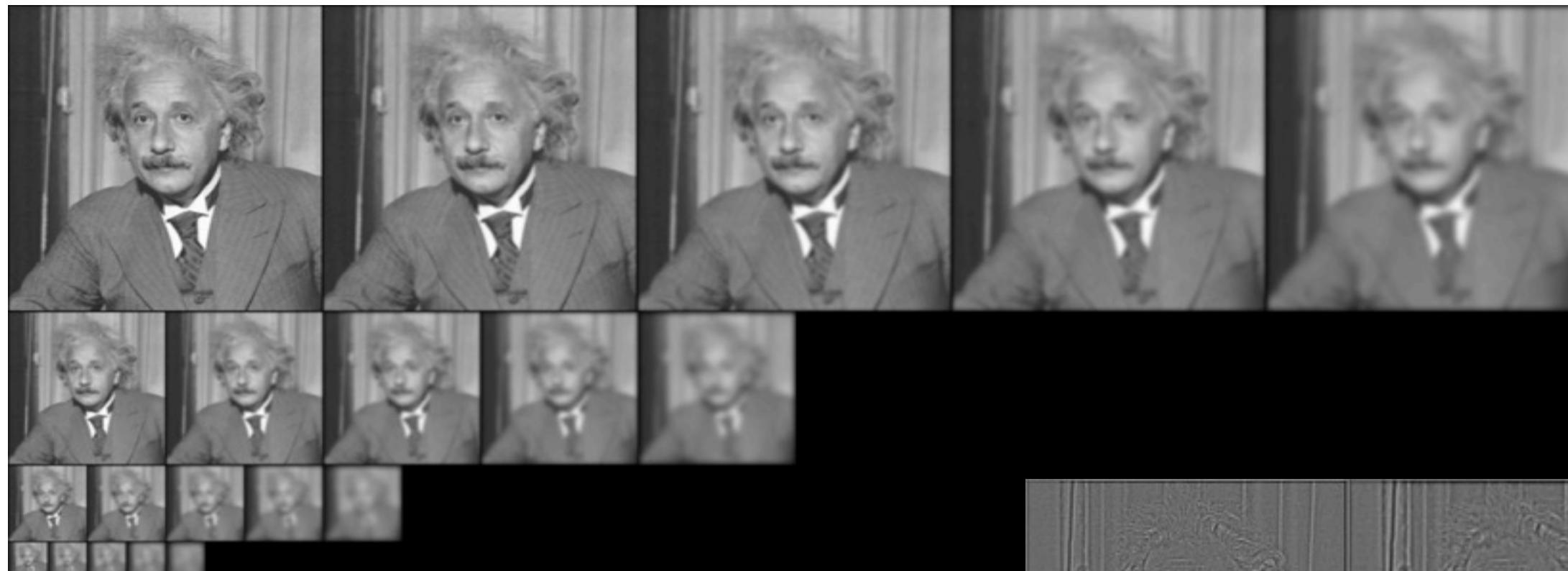
- * Each point is compared to its 8 neighbors in the current image and 9 neighbors each in the scales above and below)



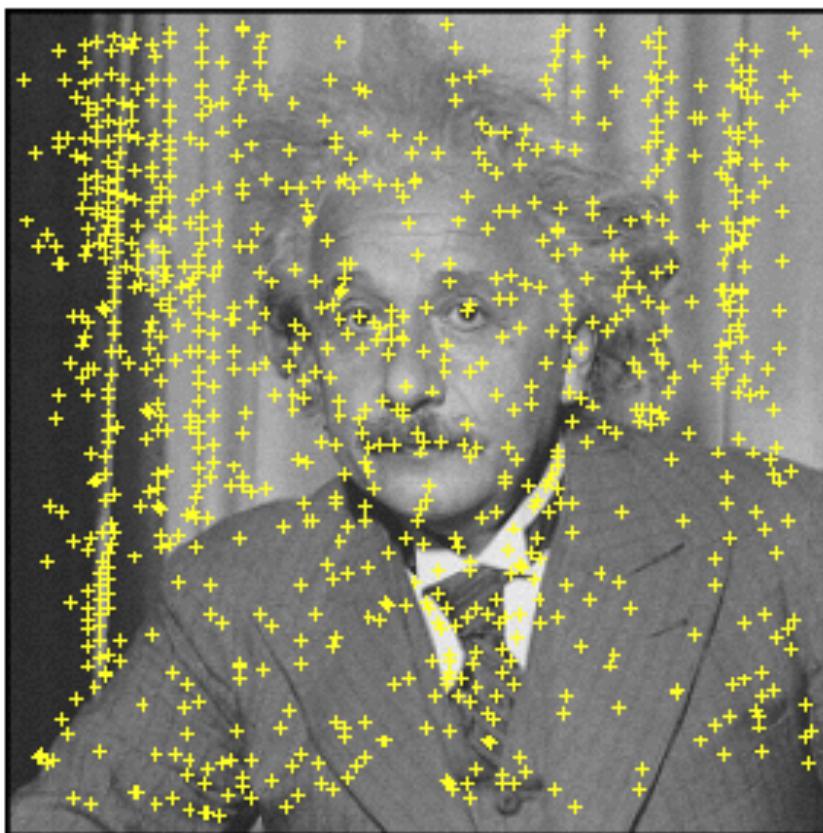
Scale Space Processed One Octave at a Time



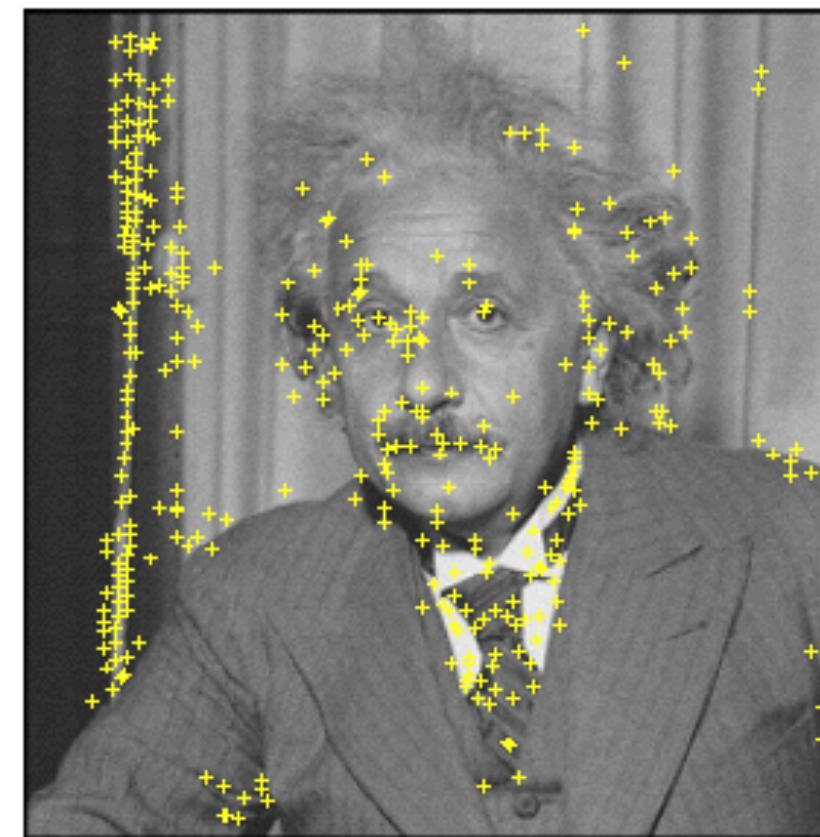
Extrema at Different Scales



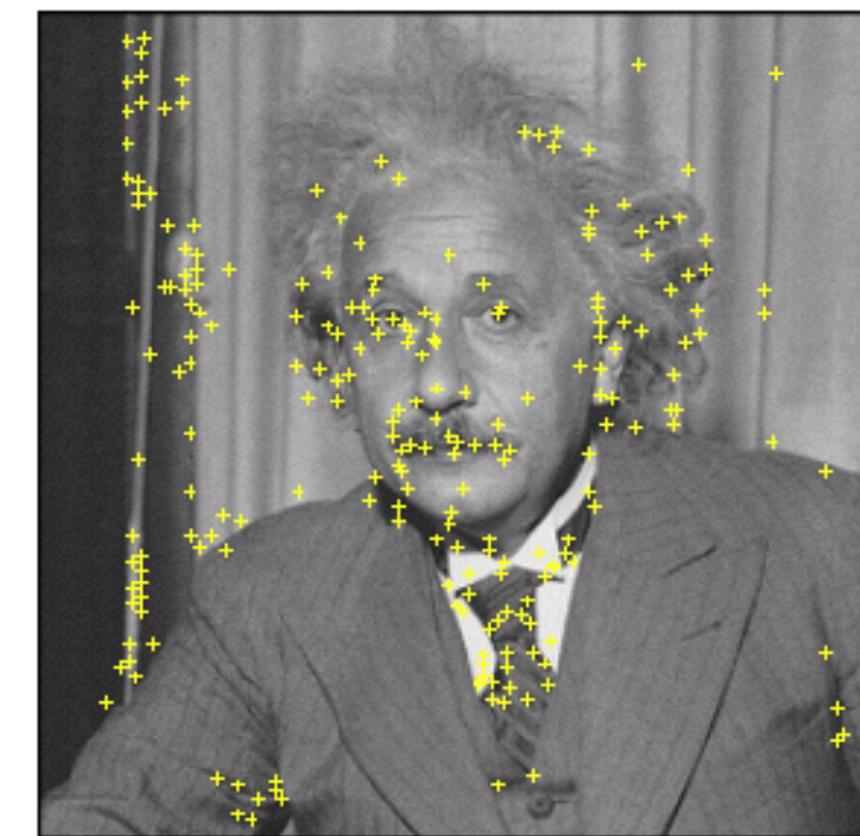
Remove Low Contrast, Edge Bound



Extrema points



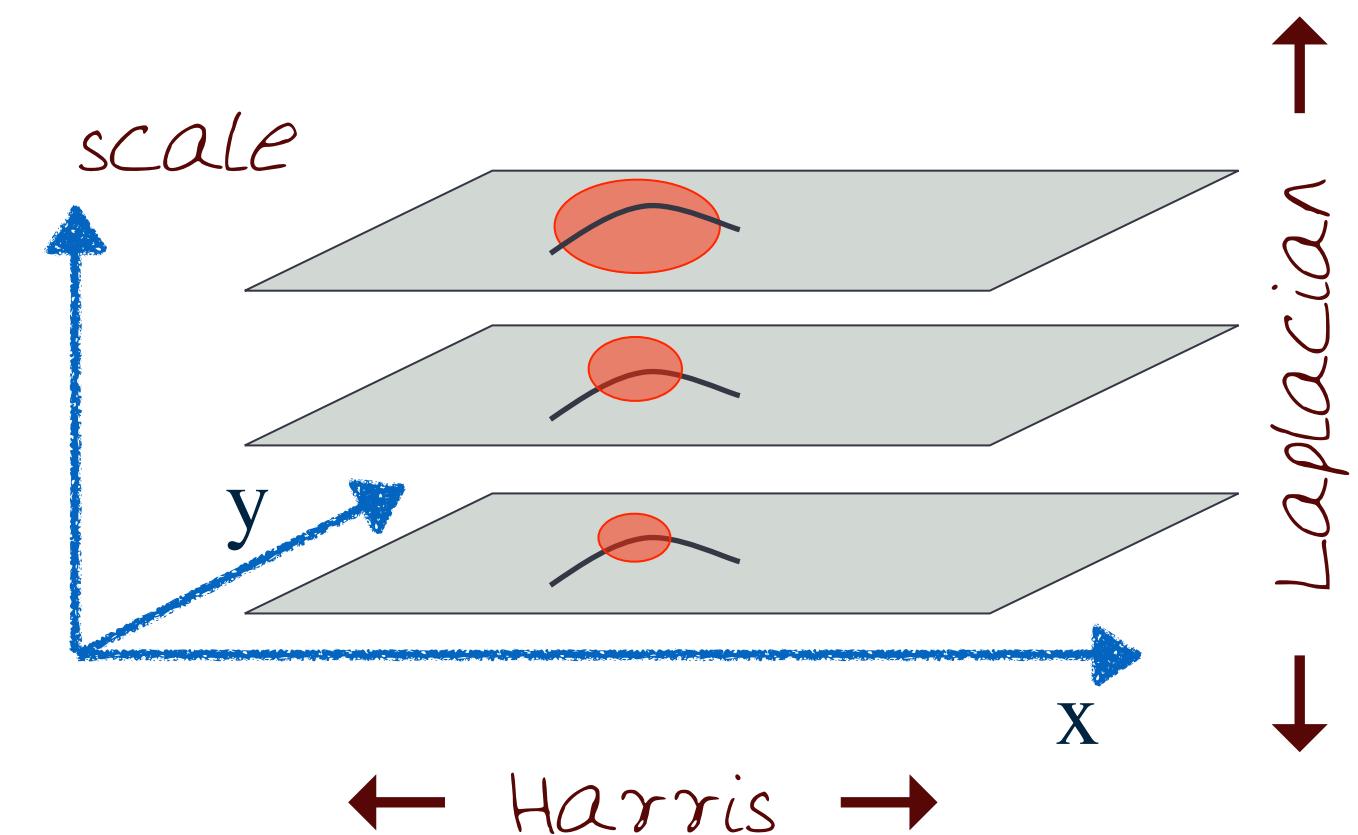
Contrast > C



Not on edge

Scale Invariant Detectors

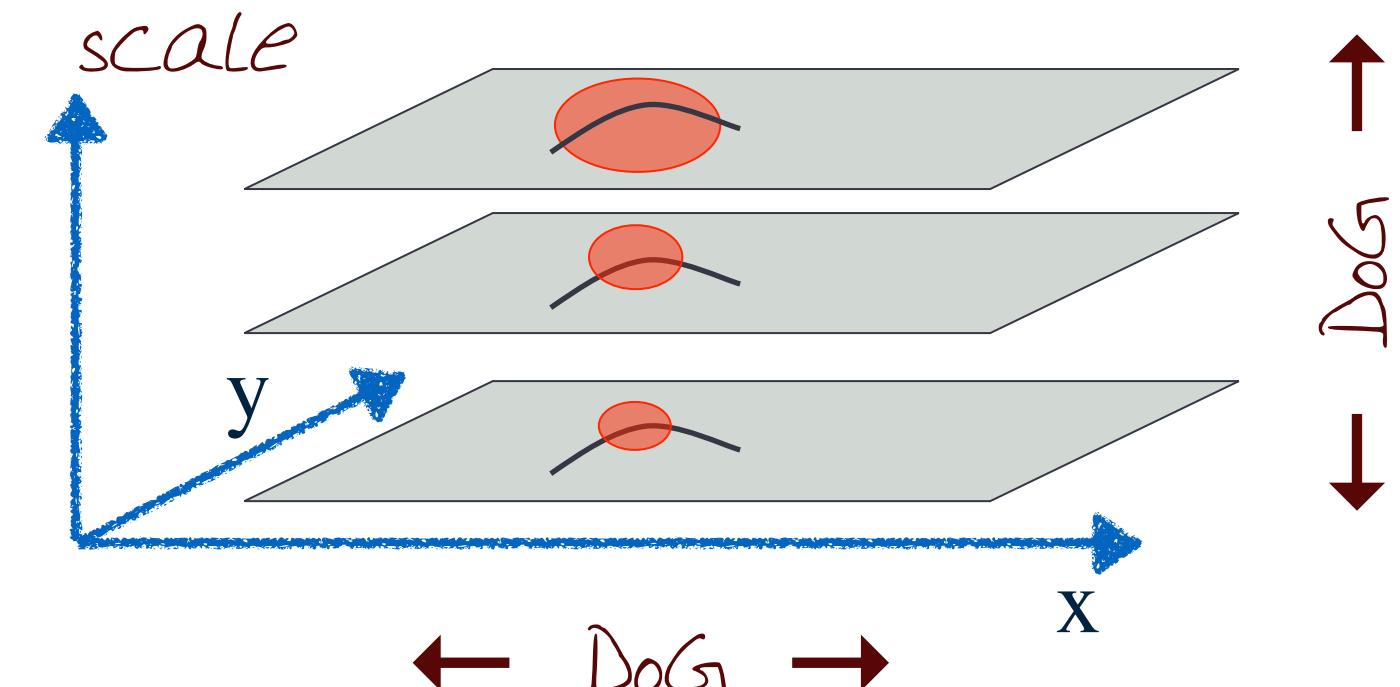
- * Harris-Laplacian
- * Find local maximum of:
 - * Harris corner detector in space (image coordinates)
 - * Laplacian in scale



(mikolajczyk and schmid, 2001)

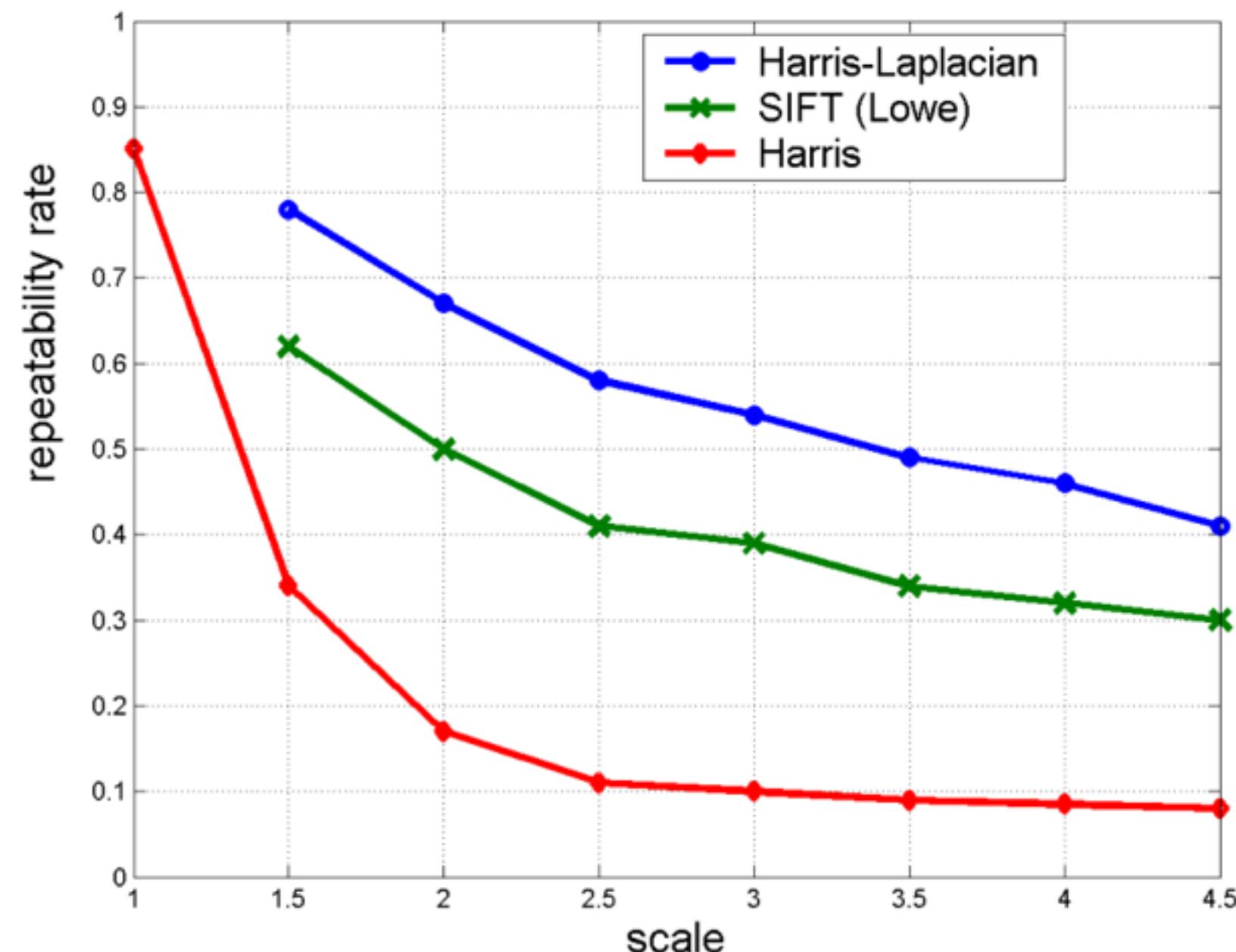
Scale Invariant Detectors

- * 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

Scale Invariant Detectors



K. Mikolajczyk, C. Schmid (2001) "Indexing Based on Scale Invariant Interest Points" . ICCV 2001

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.



Invariant Local Features

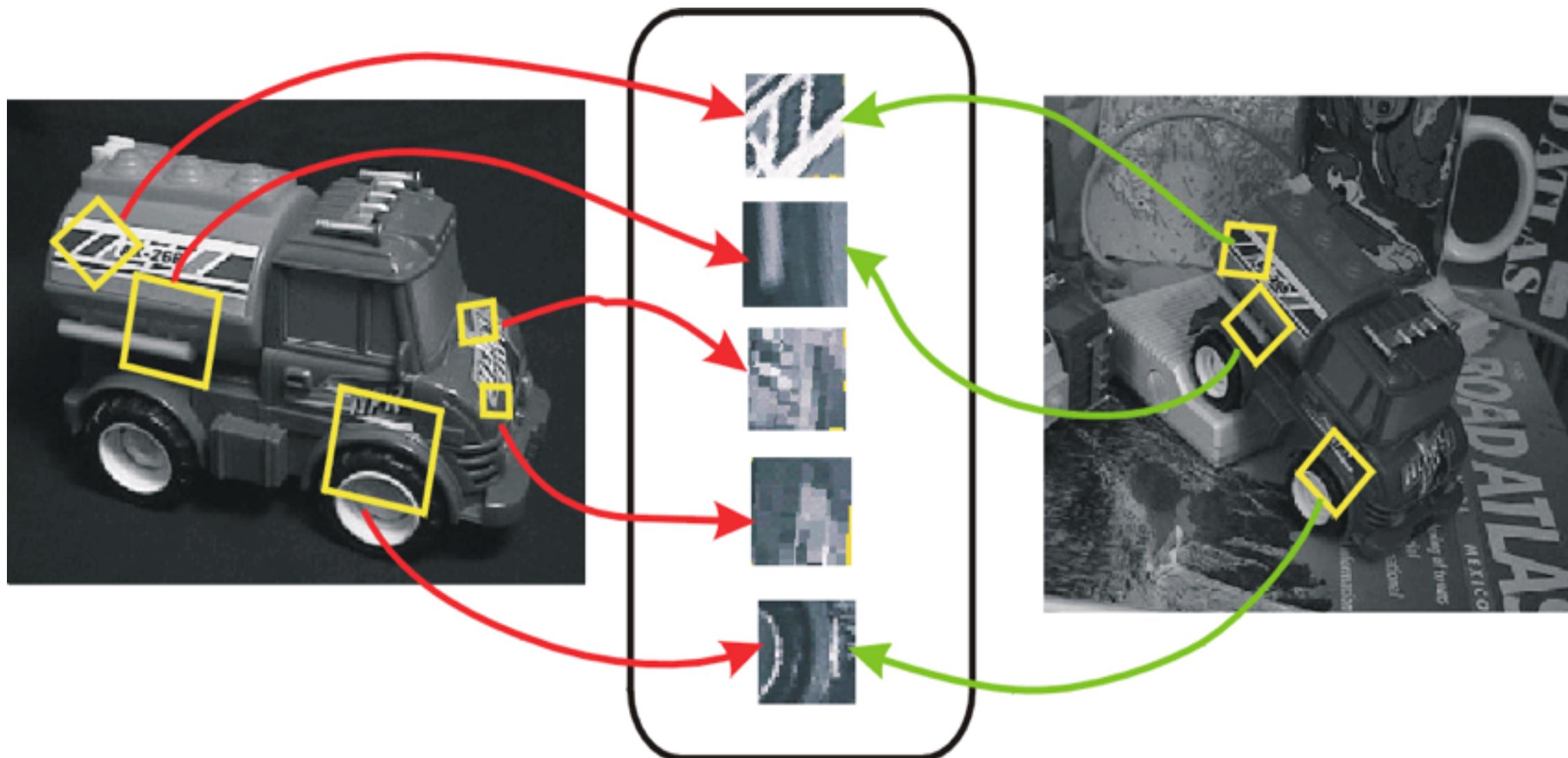
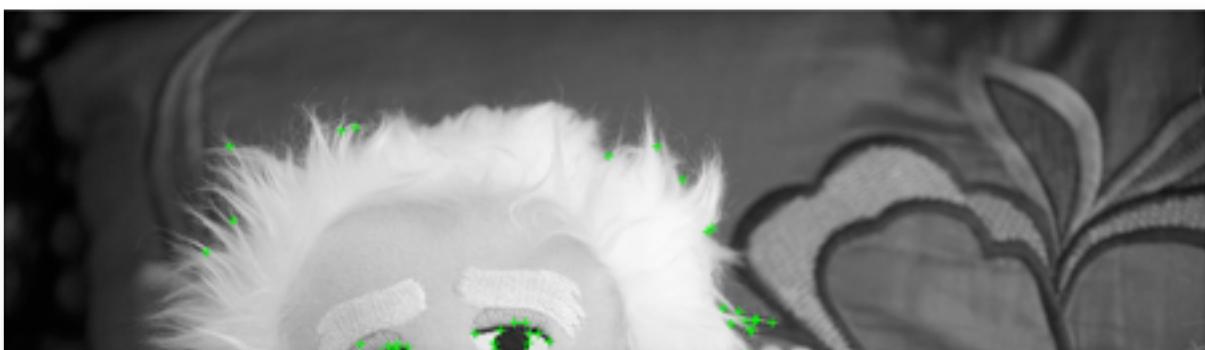


Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters

Lowe 2004

Results

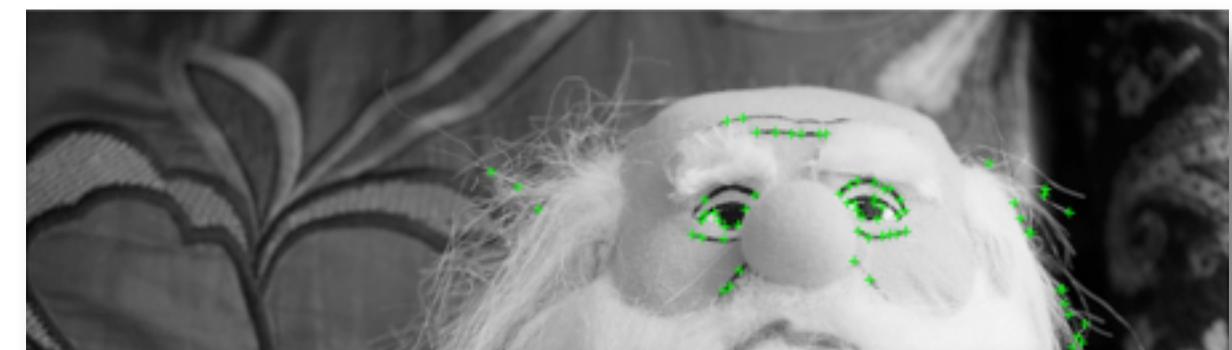
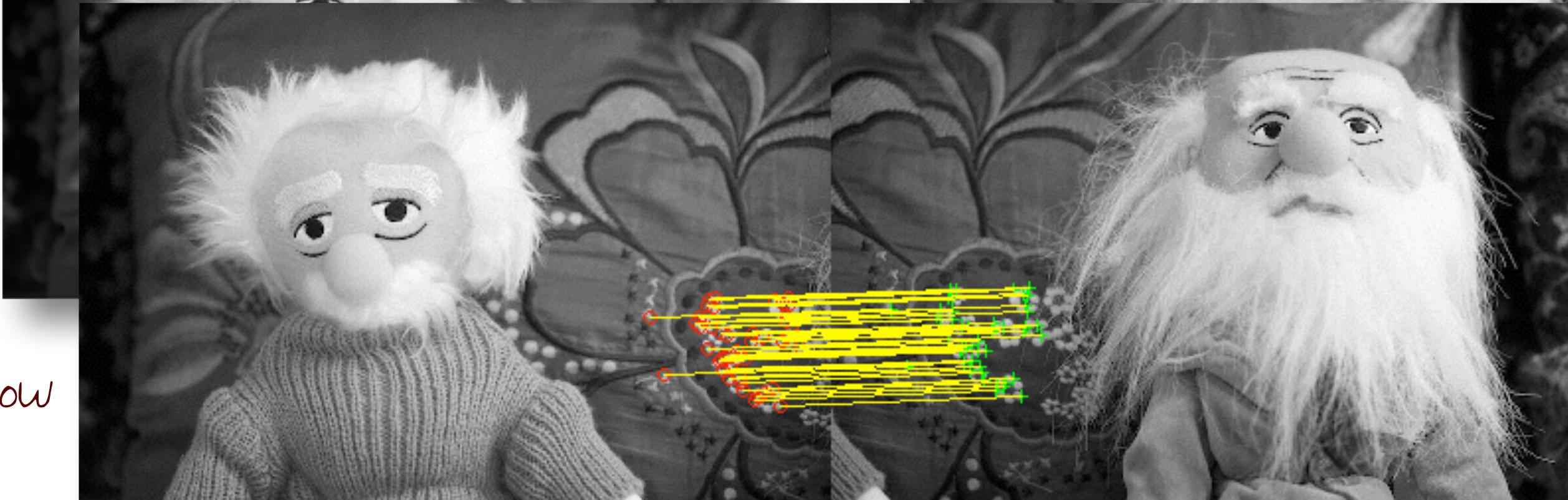
Detect



match



Show



Summary



- * Discussed invariants
for feature
detection
- * Harris Corner
Detector Framework
- * SIFT detector

Further Reading



- * Harris and Stephens (1988) "A Combined Corner and Edge Detector." Proceedings of the 4th Alvey Vision Conference, 1988,
- * 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

Neat Class

- * Moving on to more advanced topics



Credits



- * For more information, see:
 - * Richard Szeliski (2010) Computer Vision: Algorithms and Applications, Springer
- * Some concepts in slides motivated by similar slides by Aaron Bobick, Alysoha Efros and Greg Turk
- * Additional 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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