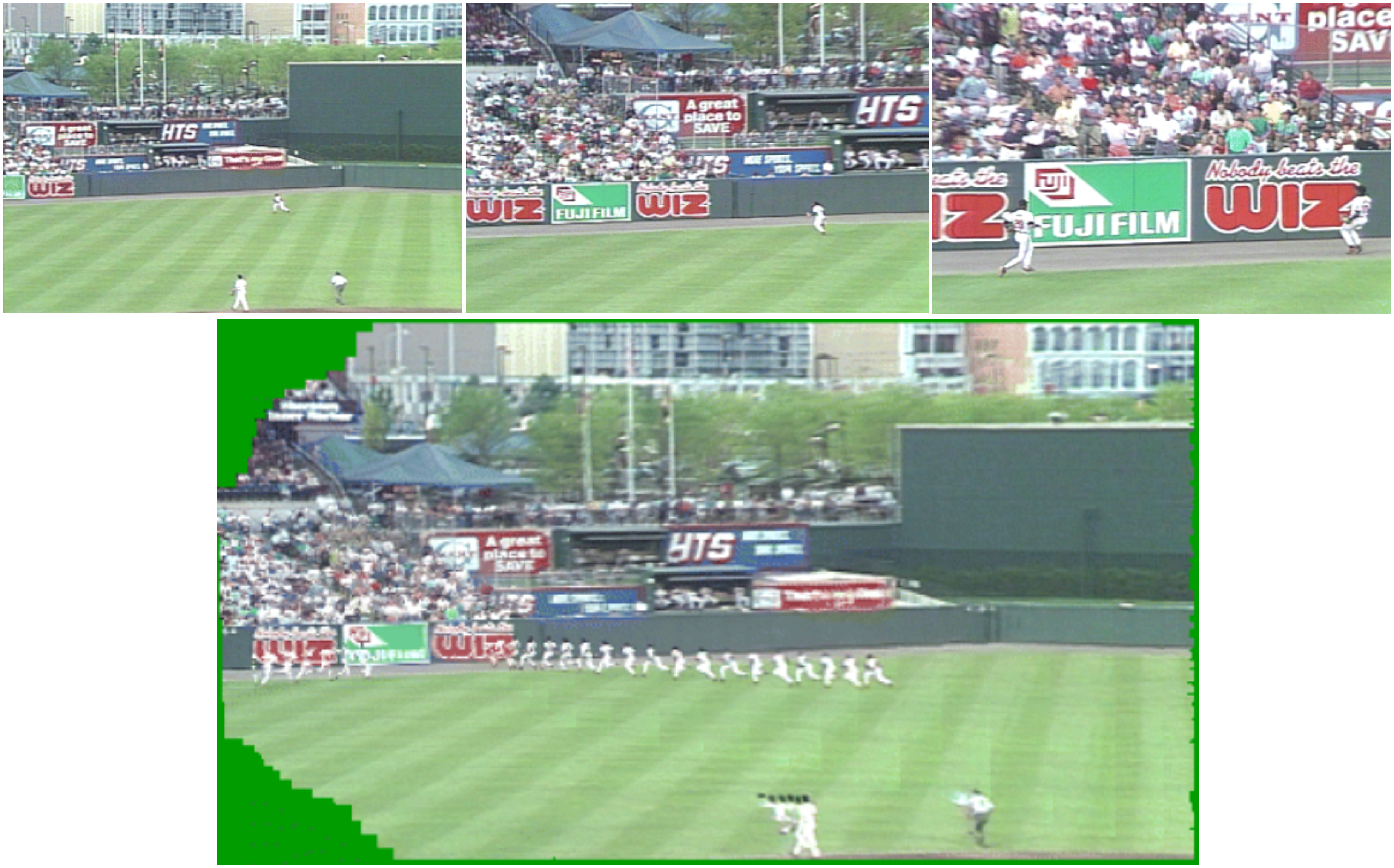
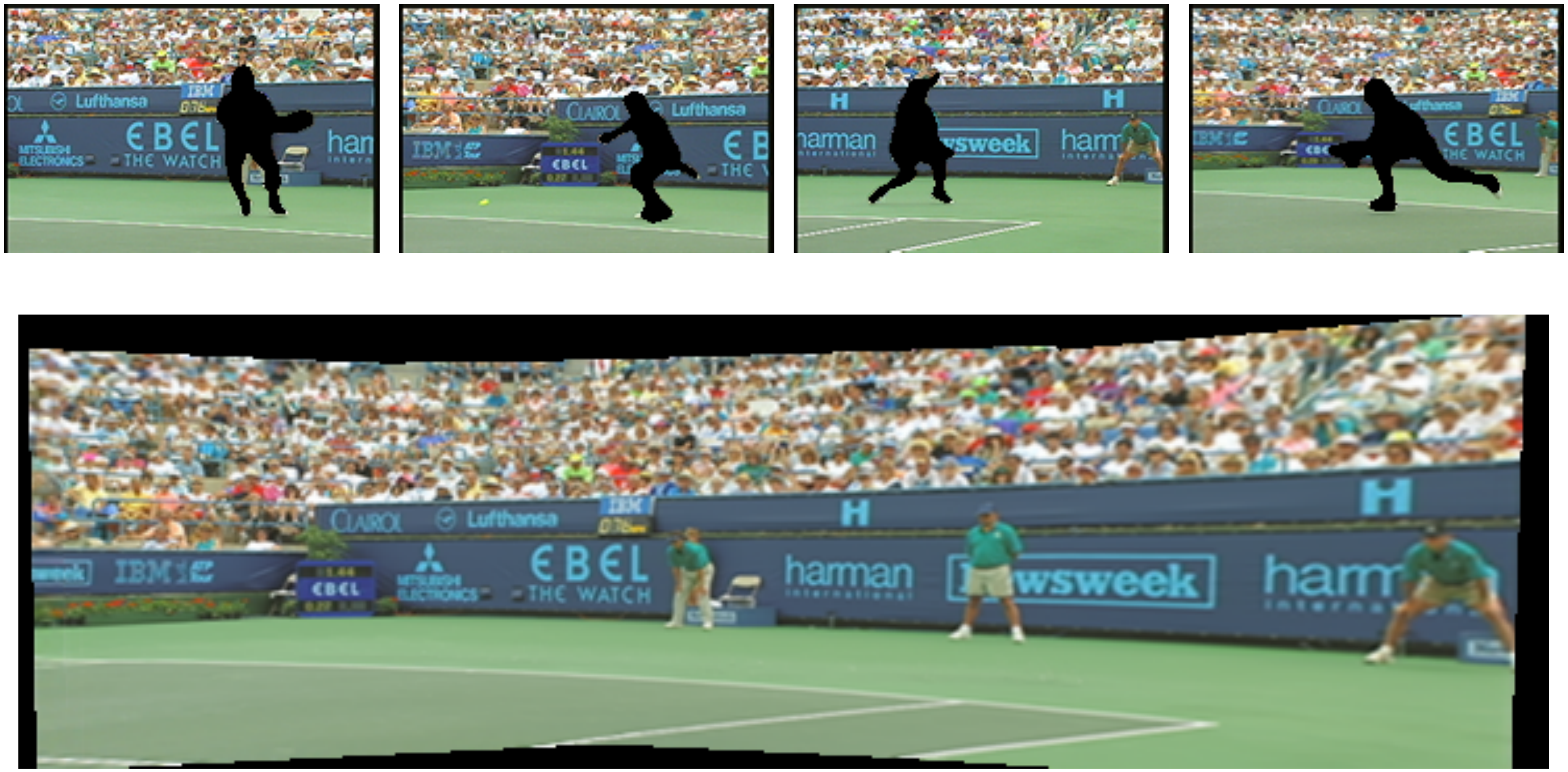
Video Summarization



Video compression



Magic: ghost removal

M. Uyttendaele, A. Eden, and R. Szeliski.
***Eliminating ghosting and exposure artifacts in image mosaics*.**
In Proceedings of the Interational Conference on Computer Vision and Pattern Recognition, volume 2, pages 509--516, Kauai, Hawaii, December 2001.

Magic: ghost removal

M. Uyttendaele, A. Eden, and R. Szeliski.
***Eliminating ghosting and exposure artifacts in image mosaics*.**
In Proceedings of the Interational Conference on Computer Vision and Pattern Recognition, volume 2, pages 509--516, Kauai, Hawaii, December 2001.

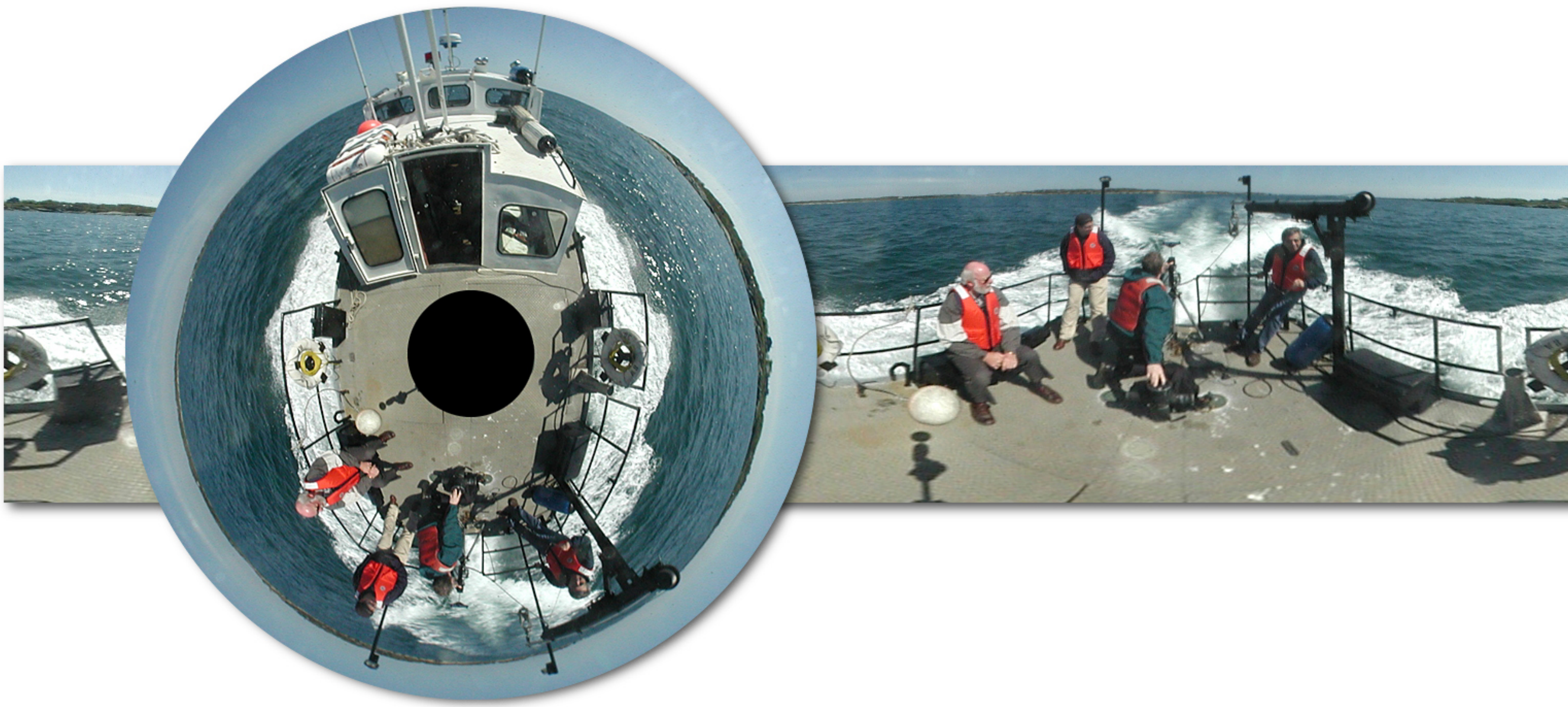
For dynamic Scenes

Point Grey Ladybug2

http://www.ptgrey.com/products/ladybug2/samples.asp

For dynamic scenes

http://www1.cs.columbia.edu/CAVE/projects/cat_cam_360/cat_cam_360.php




Video Conferencing

More and Blending

Cylindrical panorama

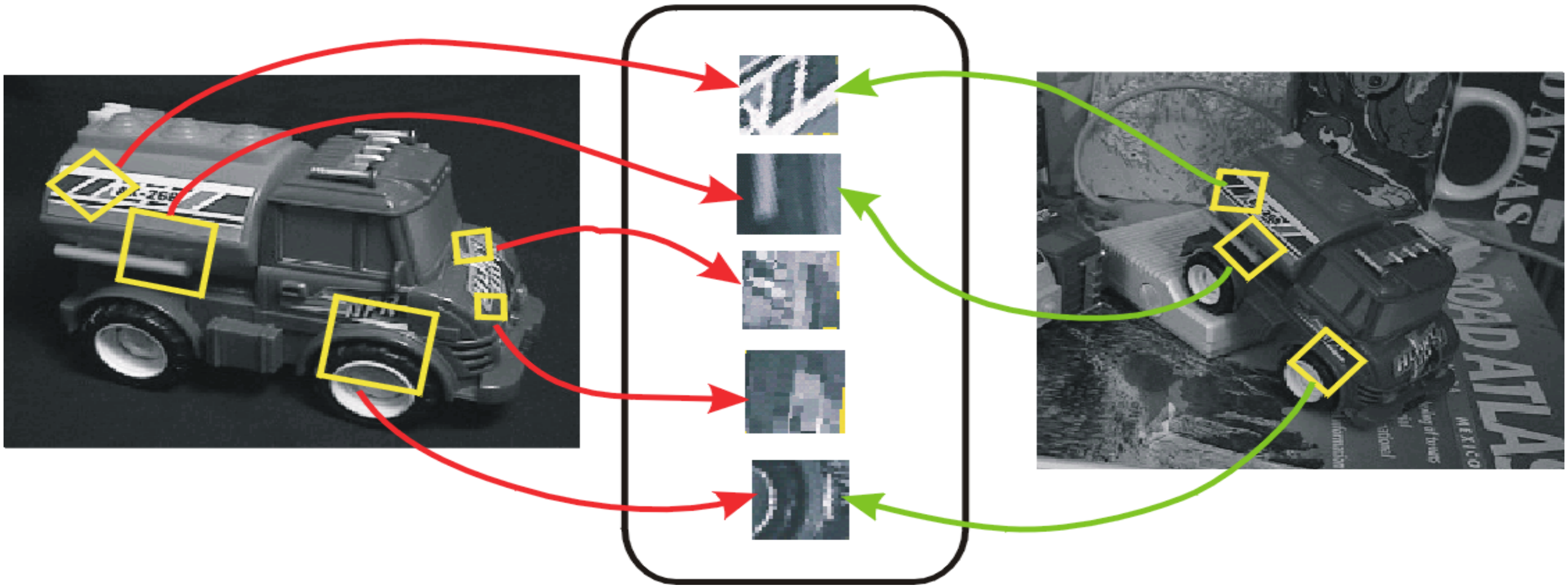
1. Take pictures on a tripod (or handheld)
2. Warp to cylindrical coordinate
3. Compute pairwise alignments
4. Fix up the end-to-end alignment
5. Blending
6. Crop the result and import into a viewer

Cylindrical panorama

1. Take pictures on a tripod (or handheld)
2. Warp to cylindrical coordinate
3. Compute pairwise alignments
4. Fix up the end-to-end alignment
5. Blending
6. Crop the result and import into a viewer

Invariant Local Features

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



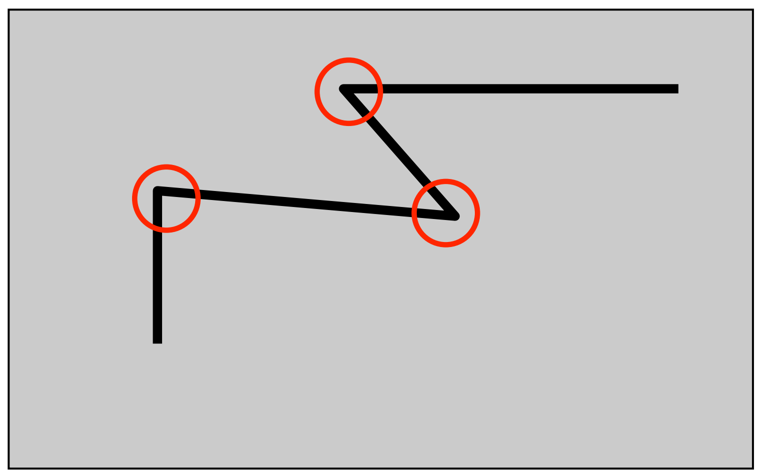
Features Descriptors

More motivation…

- Feature points are used for:
  - Image alignment (homography, fundamental matrix)
  - 3D reconstruction
  - Motion tracking
  - Object recognition
  - Indexing and database retrieval
  - Robot navigation
  - … other

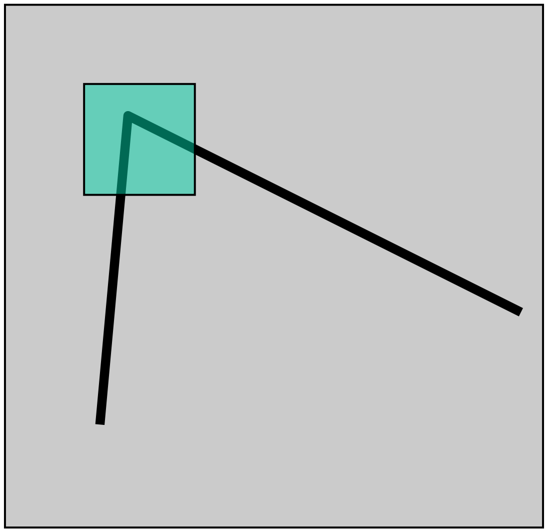
Corner detector

- C.Harris, M.Stephens. “A Combined Corner and Edge Detector”. 1988

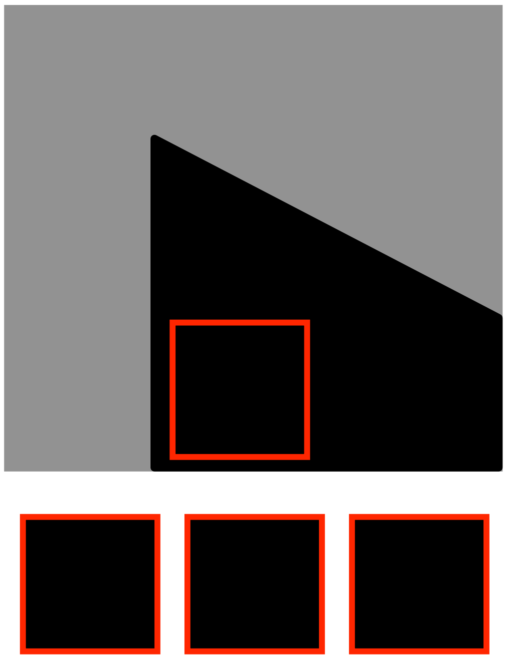


The Basic Idea

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

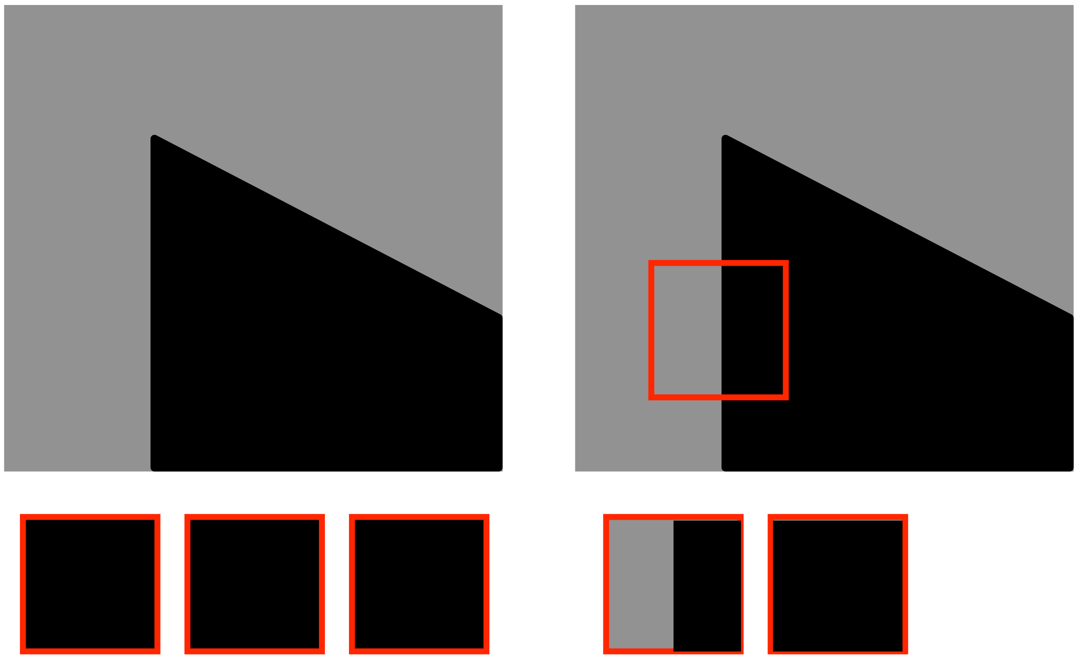


Moravec corner detector



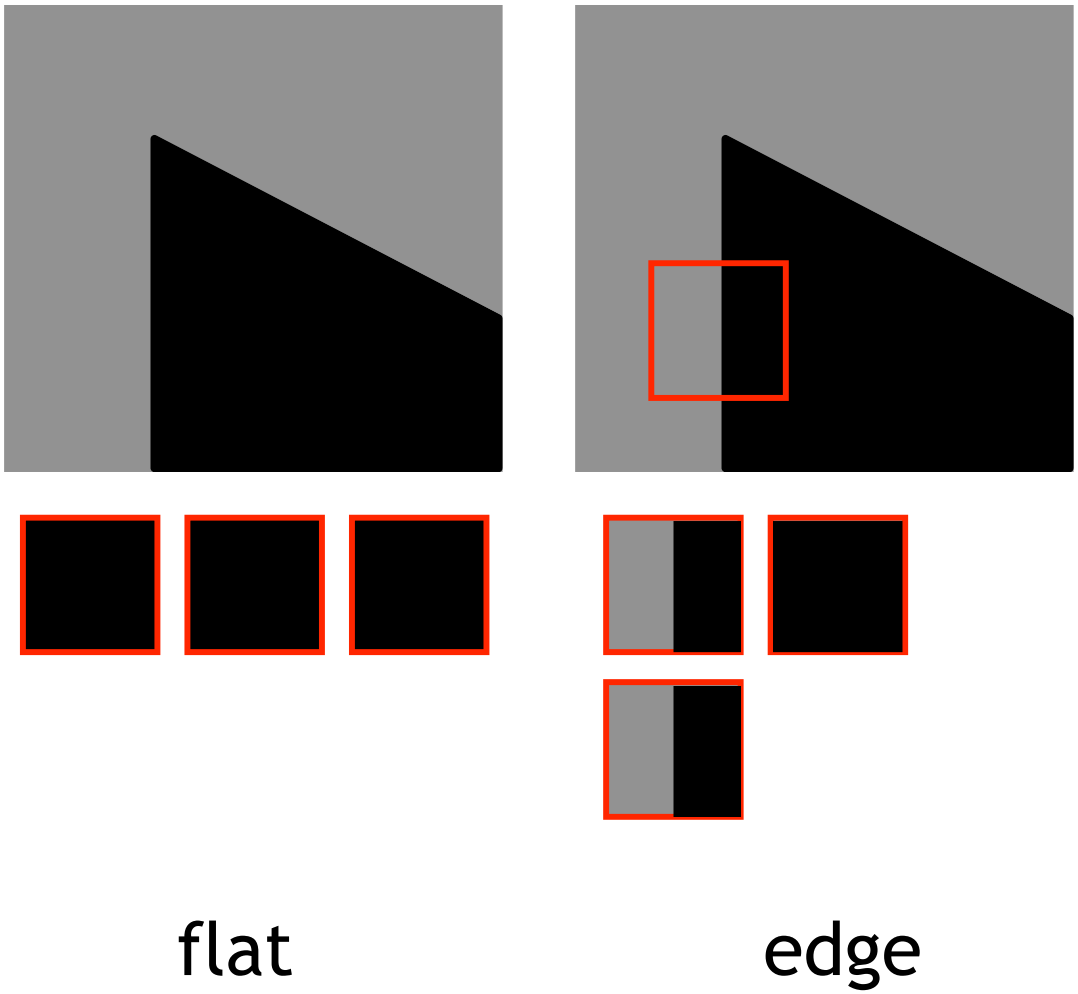
flat

Moravec corner detector

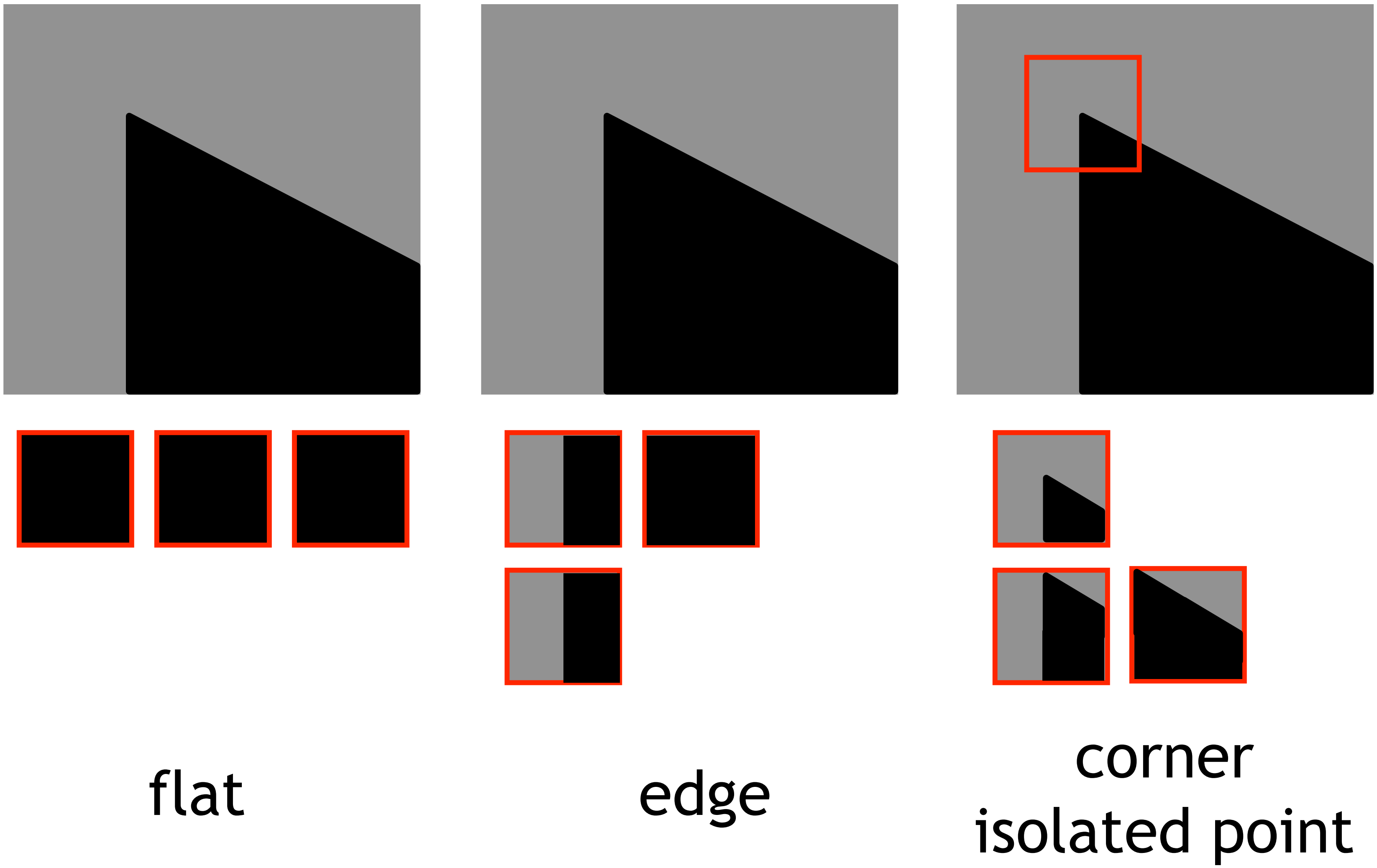


flat

Moravec corner detector



Moravec corner detector



Moravec corner detector

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

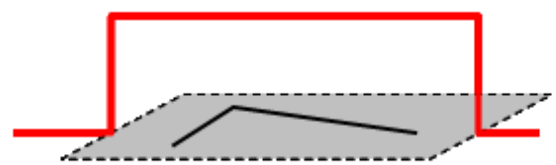
$$E(u,v) = \sum_{x,y} w(x,y)\left[I(x+u, y+v) - I(x,y)\right]^2$$

Window function

Shifted intensity

Intensity

Window function $w(x,y)$ =



1 in window, 0 outside

Four shifts: (u,v) = (1,0), (1,1), (0,1), (-1, 1)

Look for local maxima in *min{E}*

When does this idea fail?

Problems of Moravec detector

- Only a set of shifts at every 45 degree is considered

- Only minimum of E is taken into account

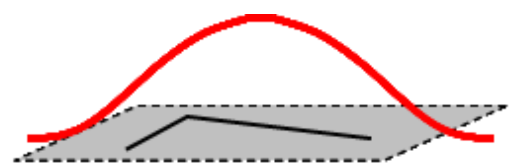
⇨ Harris corner detector (1988) solves these problems.

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

Harris corner detector

Only a set of shifts at every 45 degree is considered

- Consider all small shifts by Taylor's expansion

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

$$E(u,v)=Au^2+2Cuv+Bv^2$$

$$A=\sum_{x,y} w(x,y)I_x^2(x,y)$$

$$B=\sum_{x,y} w(x,y)I_y^2(x,y)$$

$$C=\sum_{x,y} w(x,y)I_x(x,y)I_y(x,y)$$

Harris corner detector

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

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

, where *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 corner detector

Only minimum of E is taken into account

- A new corner measurement

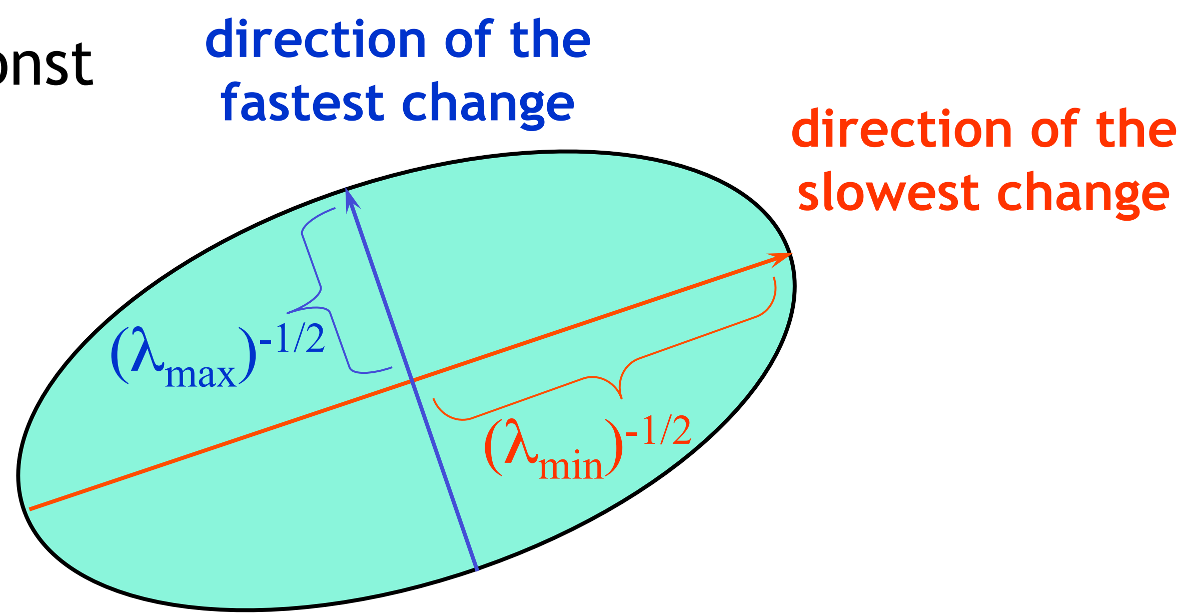
Harris corner detector

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

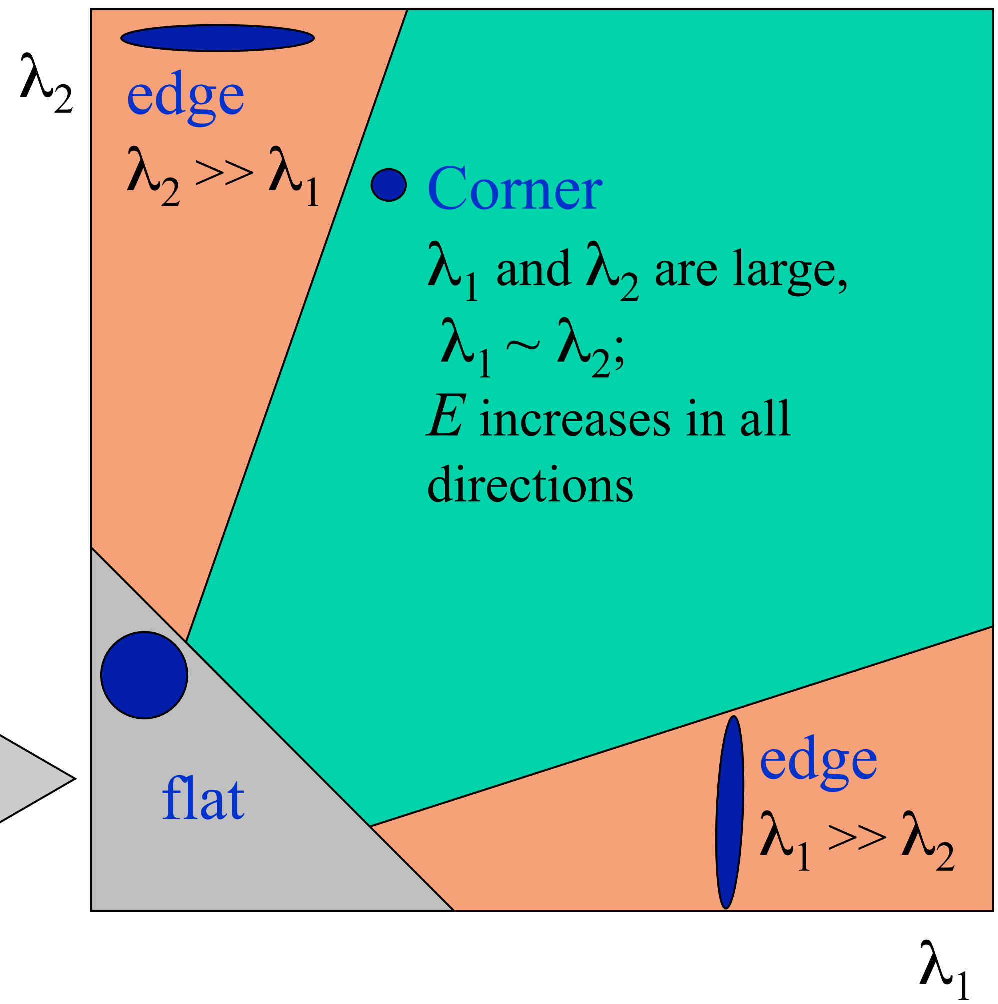
Ellipse *E(u,v)* = const



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

Measure of corner response:

$$R = \frac{\lambda_1 \lambda_2}{\lambda_1 + \lambda_2} = \frac{\det M}{\operatorname{Trace} M}$$

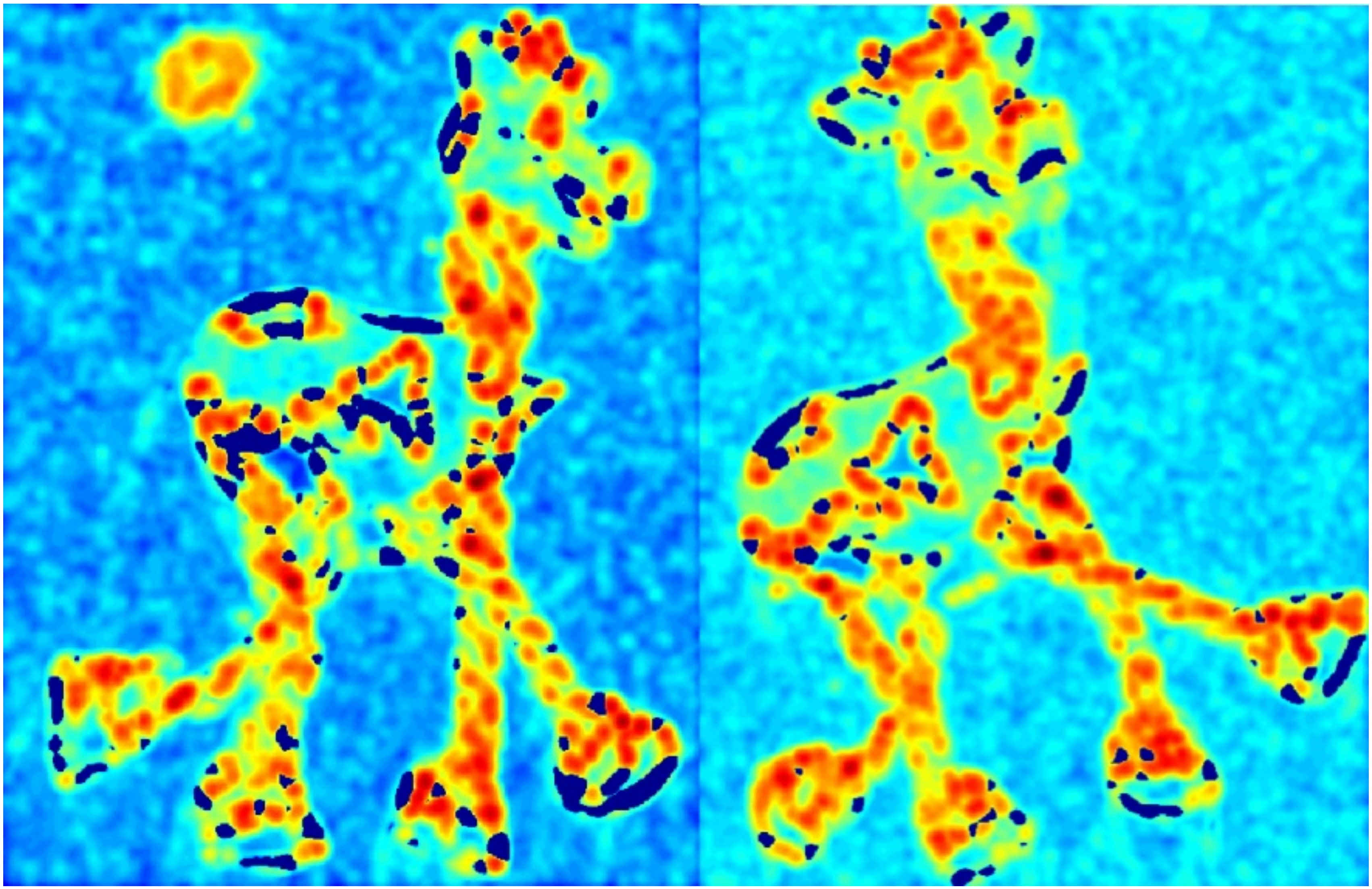
Harris Detector

- The Algorithm:
  - Find points with large corner response function R (R > threshold)
  - Take the points of local maxima of R

Harris Detector: Workflow

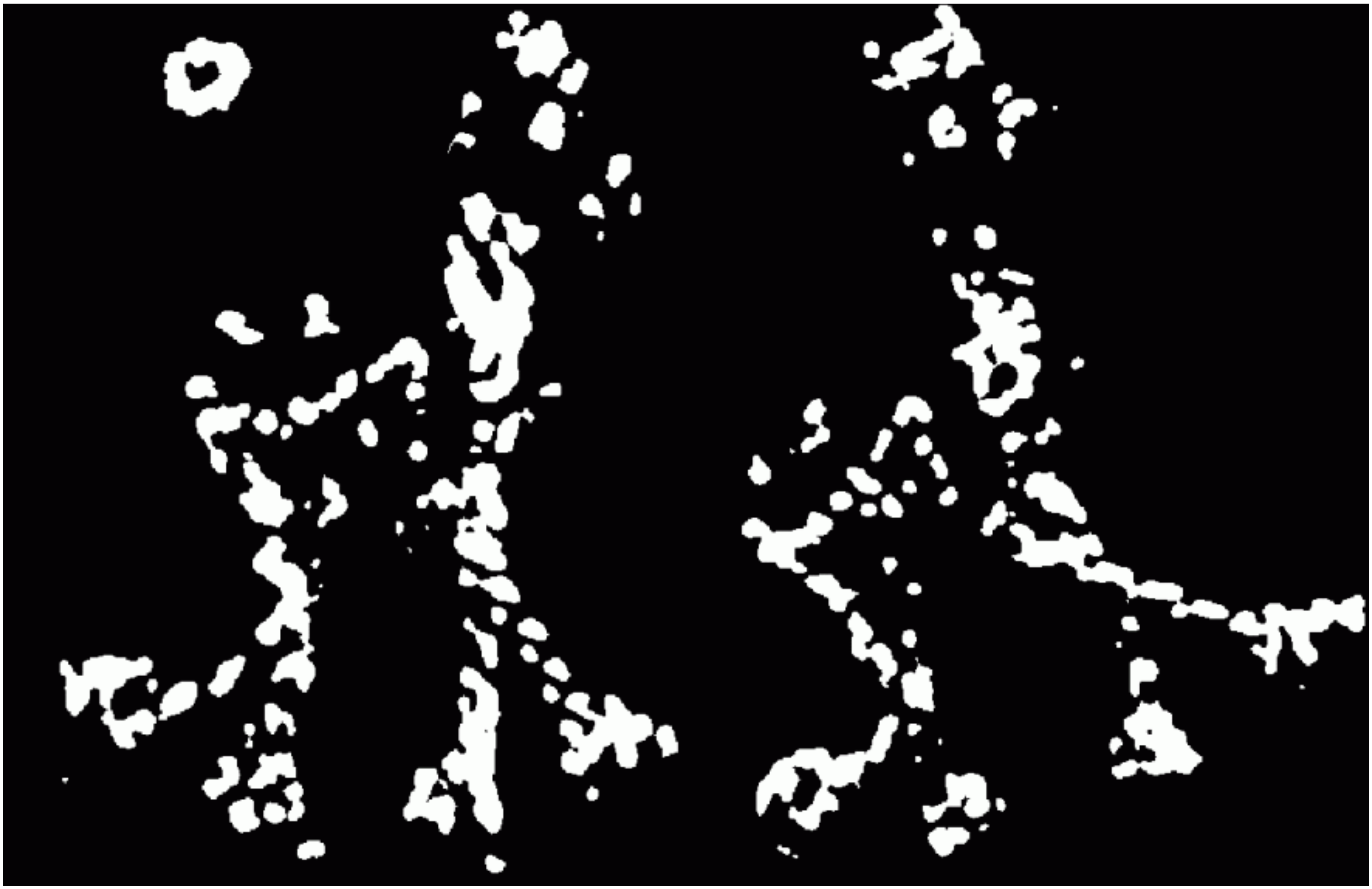
Harris Detector: Workflow

Compute corner response R



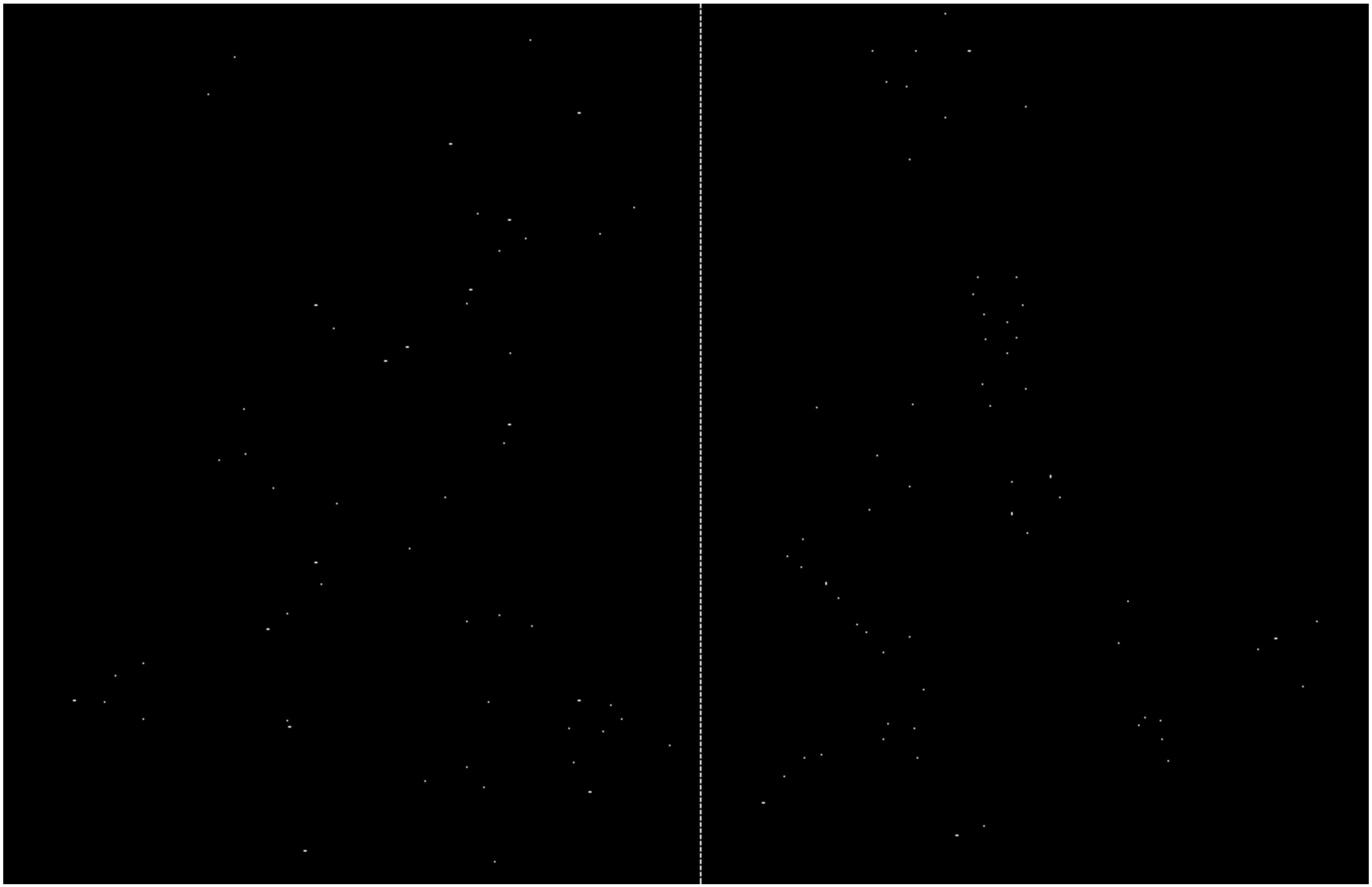
Harris Detector: Workflow

Find points with large corner response: R>threshold

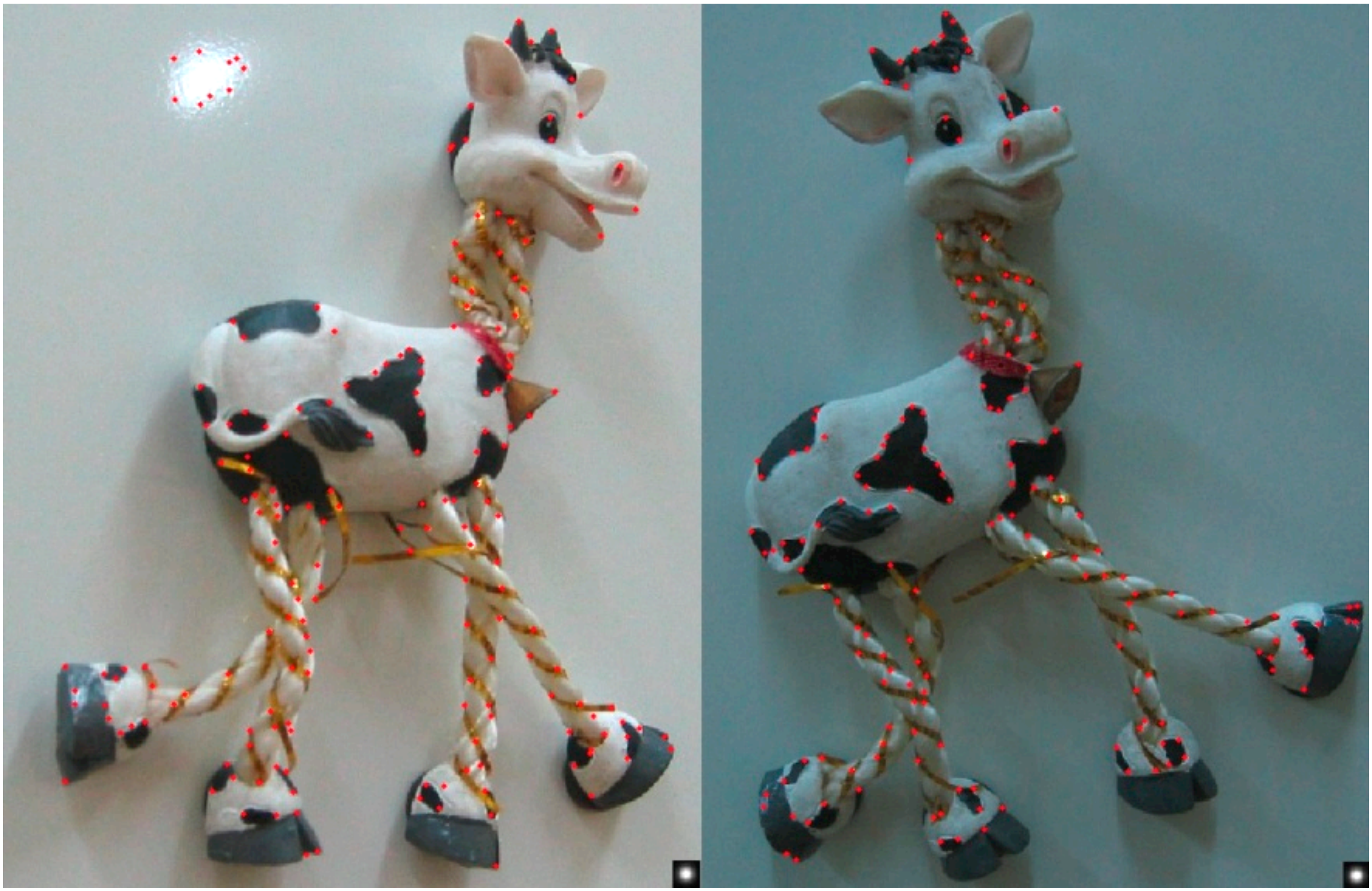


Harris Detector: Workflow

Take only the points of local maxima of R

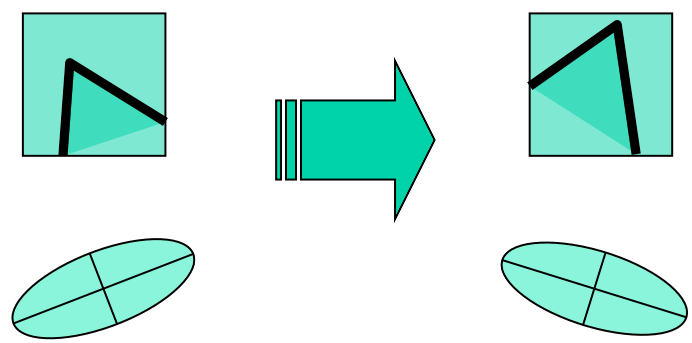


Harris Detector: Workflow



Harris Detector: Some Properties

- Rotation invariance



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

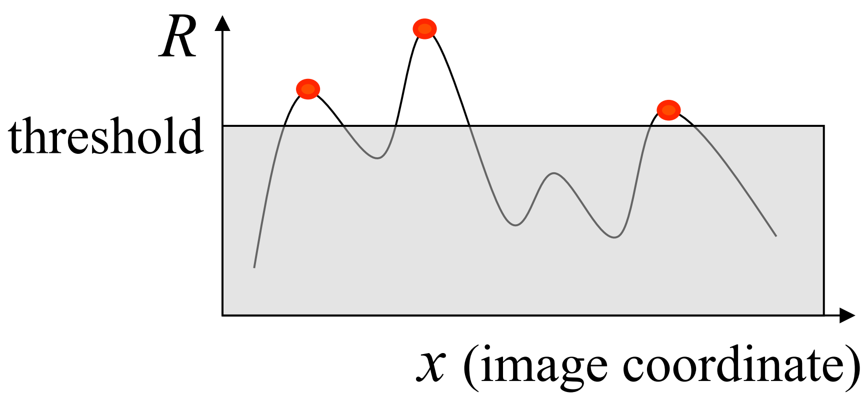
Corner response R is invariant to image rotation

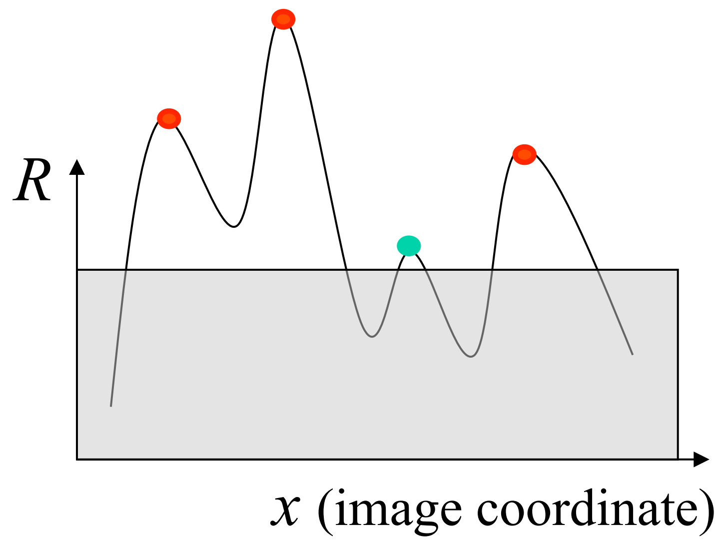
Harris Detector: Some Properties

- Partial invariance to *affine intensity* change

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

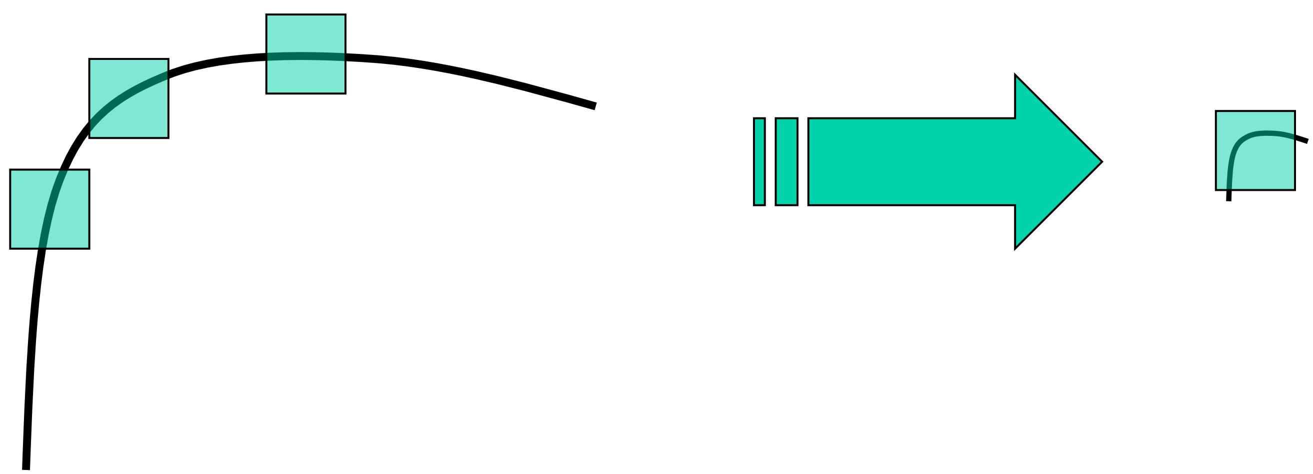
✓ Intensity scale: $I \rightarrow a\, I$





Harris Detector: Some Properties

- But: non-invariant to *image scale*!

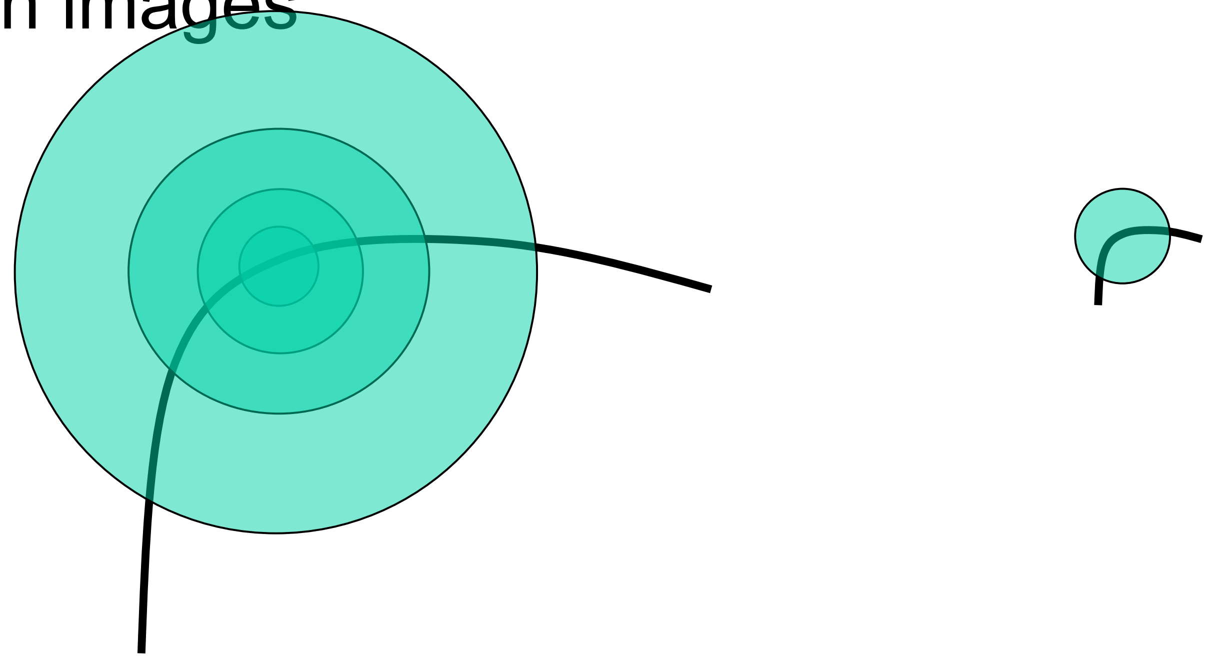


All points will be classified as edges

Corner !

Scale Invariant Detection

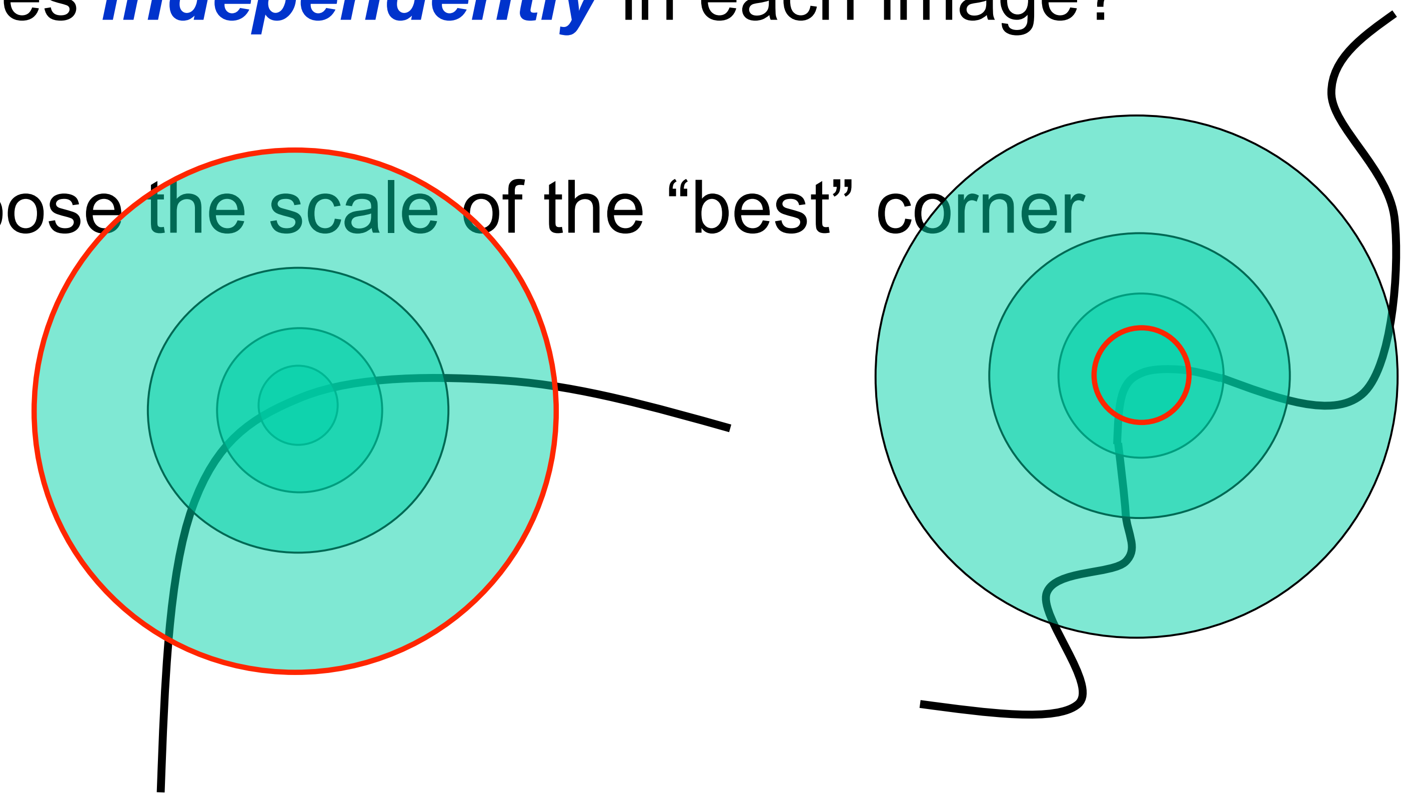
- Consider regions (e.g. circles) of different sizes around a point
- Regions of corresponding sizes will look the same in both images



Scale Invariant Detection

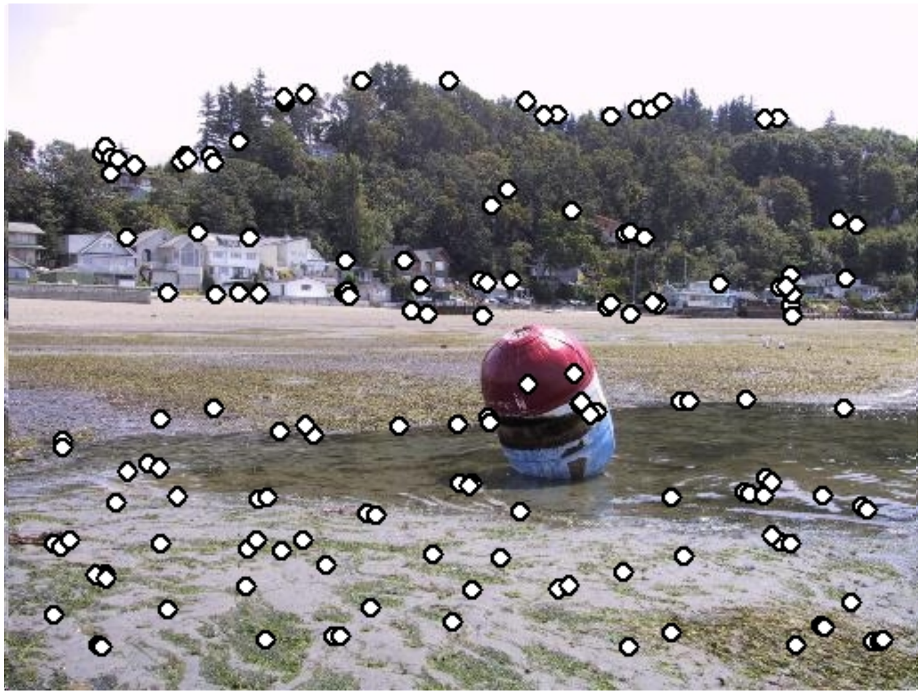
- The problem: how do we choose corresponding circles ***independently*** in each image?

- Choose the scale of the “best” corner



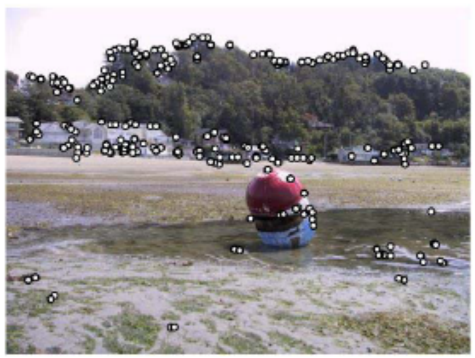
Feature selection

- Distribute points evenly over the image

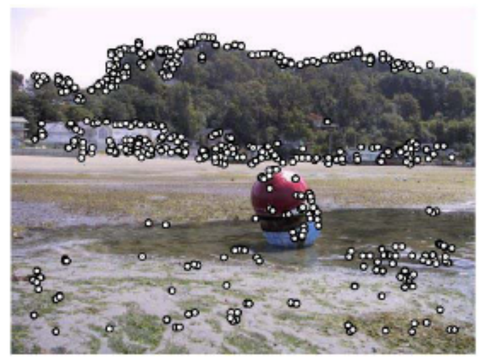


Adaptive Non-maximal Suppression

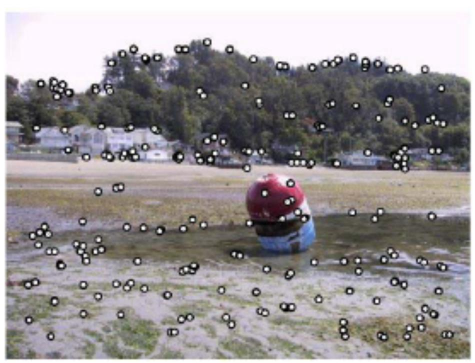
- Desired: Fixed # of features per image
  - Want evenly distributed spatially…
  - Sort ponts by non-maximal suppression radius [Brown, Szeliski, Winder, CVPR'05]



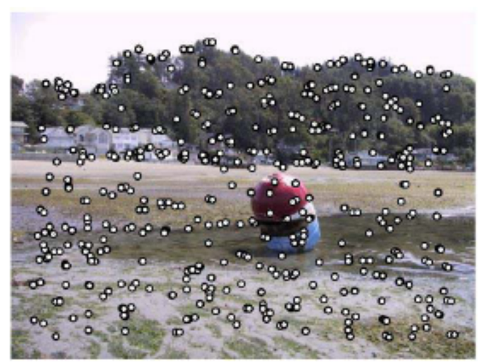
(a) Strongest 250



(b) Strongest 500



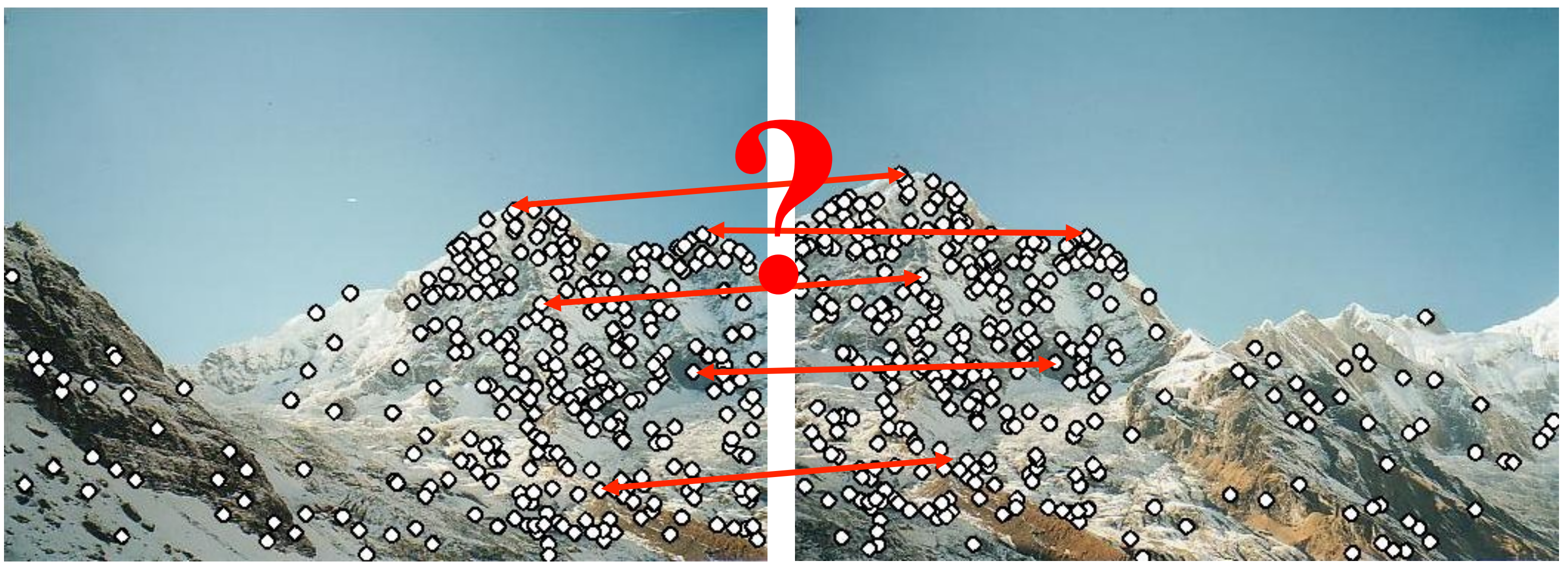
(c) ANMS 250, $r = 24$



(d) ANMS 500, $r = 16$

Feature descriptors

- We know how to detect points
- Next question: **How to match them?**



Point descriptor should be:

1. Invariant
2. Distinctive

Descriptors Invariant to Rotation

- Find local orientation

Dominant direction of gradient

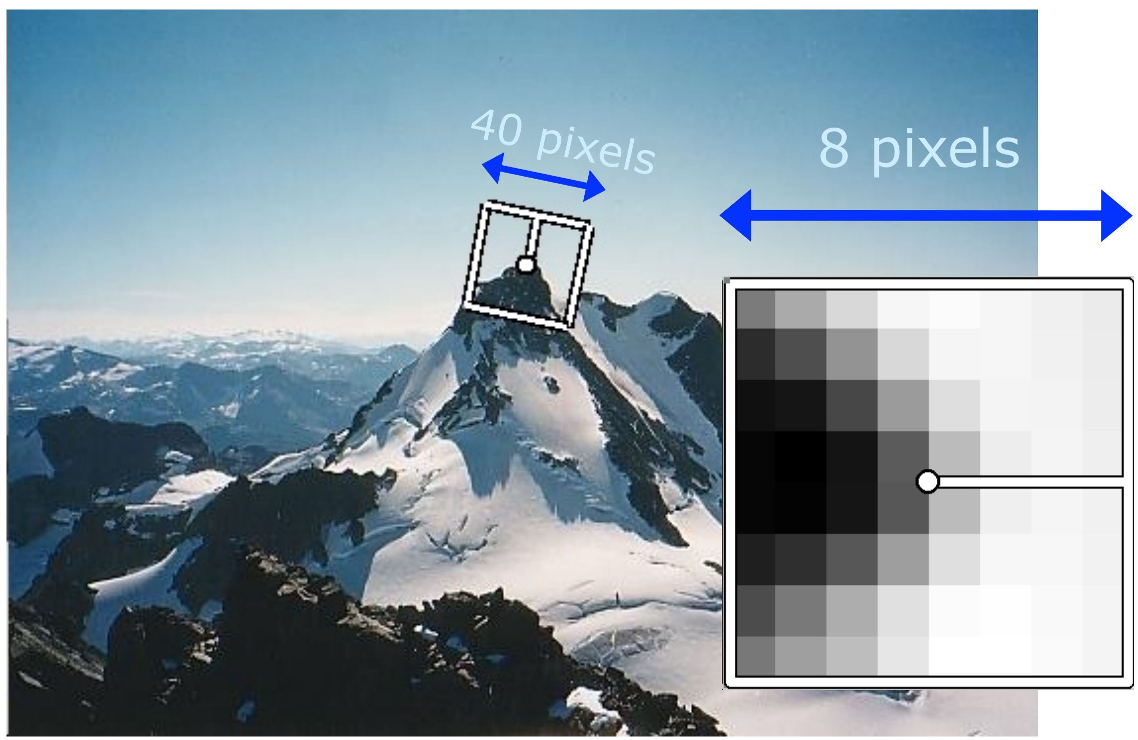
- Extract image patches relative to this orientation

Descriptor Vector

- Rotation Invariant Frame
- Orientation = blurred gradient

MOPS descriptor vector

- 8x8 oriented patch
  - Sampled at 5 x scale
- Bias/gain normalisation: $I' = (I - \mu)/\sigma$



Detections at multiple scales

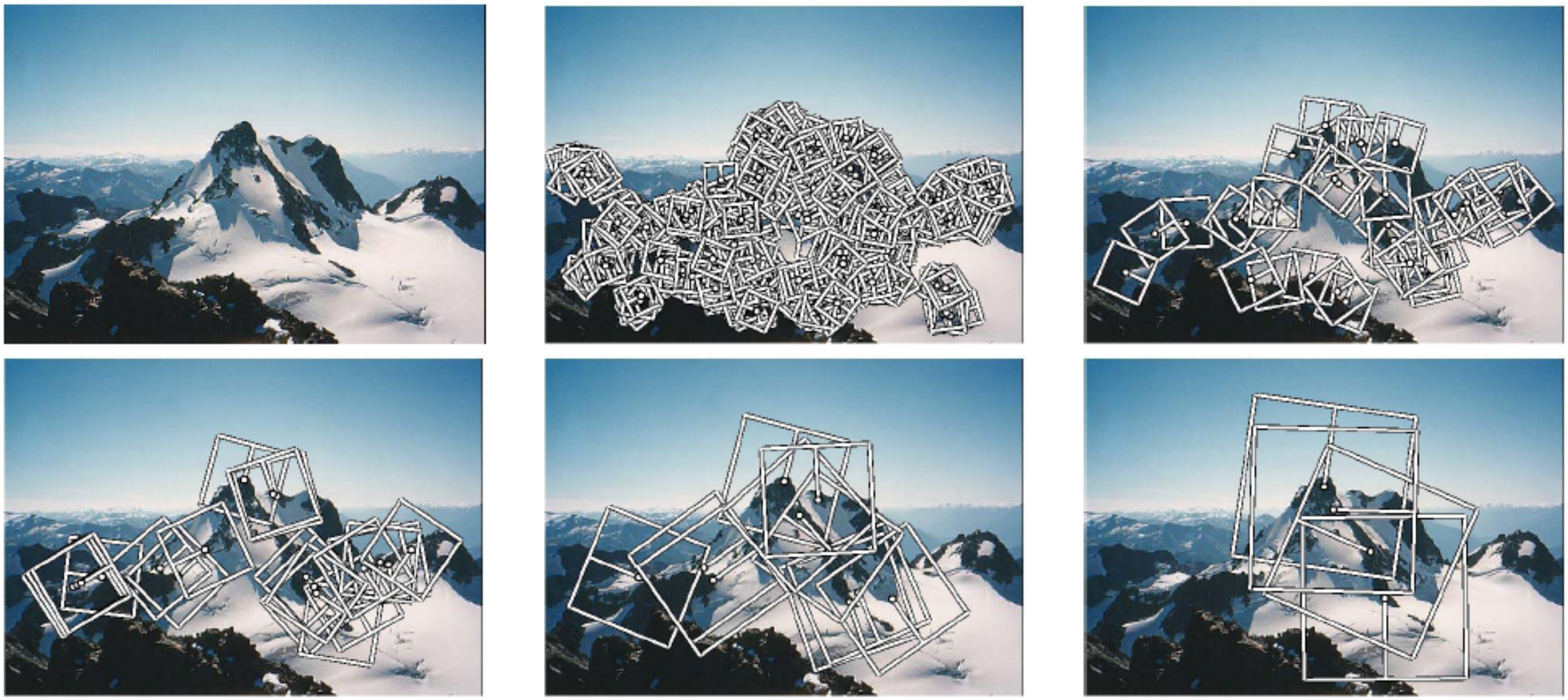
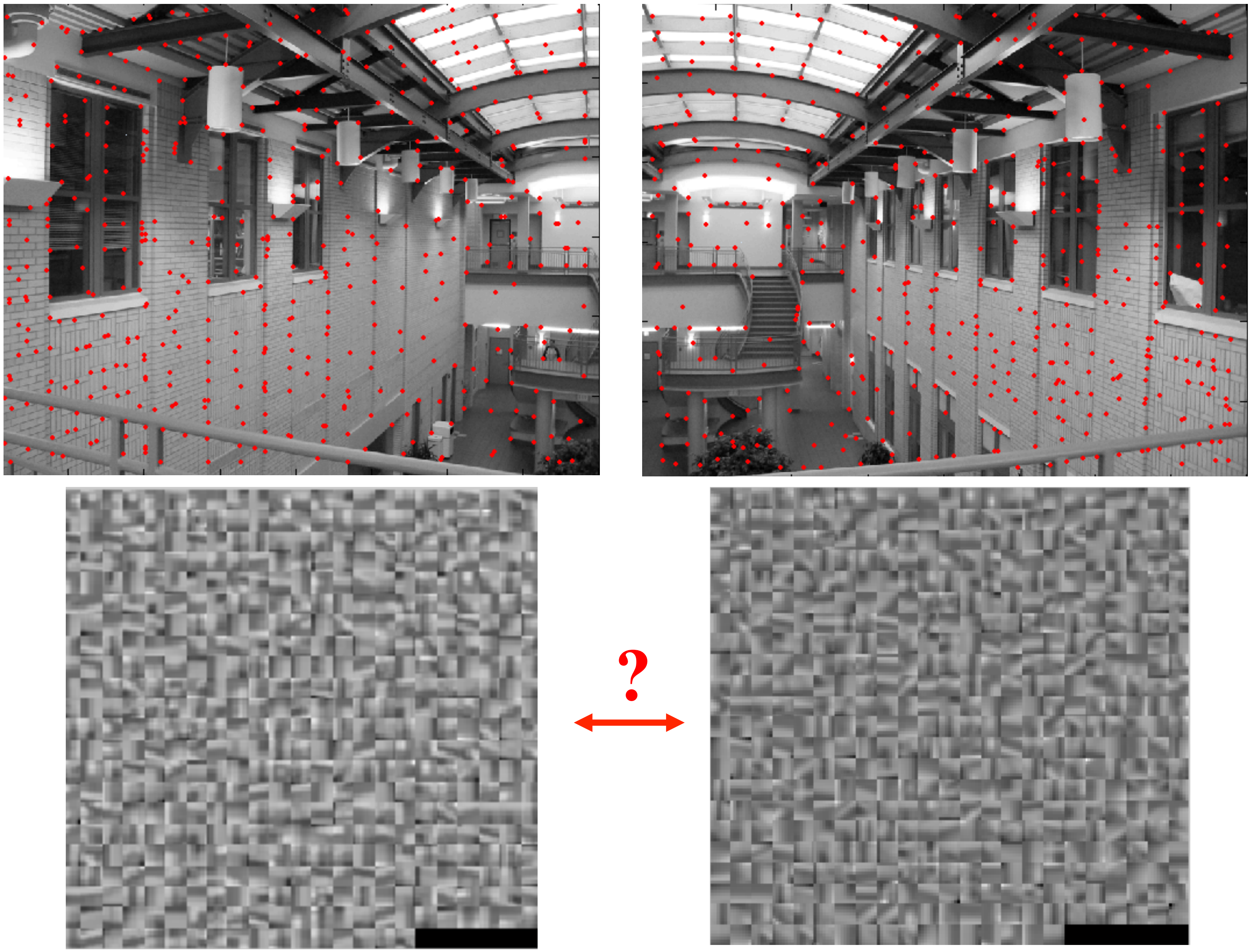


Figure 1. Multi-scale Oriented Patches (MOPS) extracted at five pyramid levels from one of the Matier images. The boxes show the feature orientation and the region from which the descriptor vector is sampled.

Multi-Scale Oriented Patches (Summary)

- Interest points
  - Multi-scale Harris corners
  - Orientation from blurred gradient
  - Geometrically invariant to rotation
- Descriptor vector
  - Bias/gain normalized sampling of local patch (8x8)
  - Photometrically invariant to affine changes in intensity
- [Brown, Szeliski, Winder, CVPR'2005]

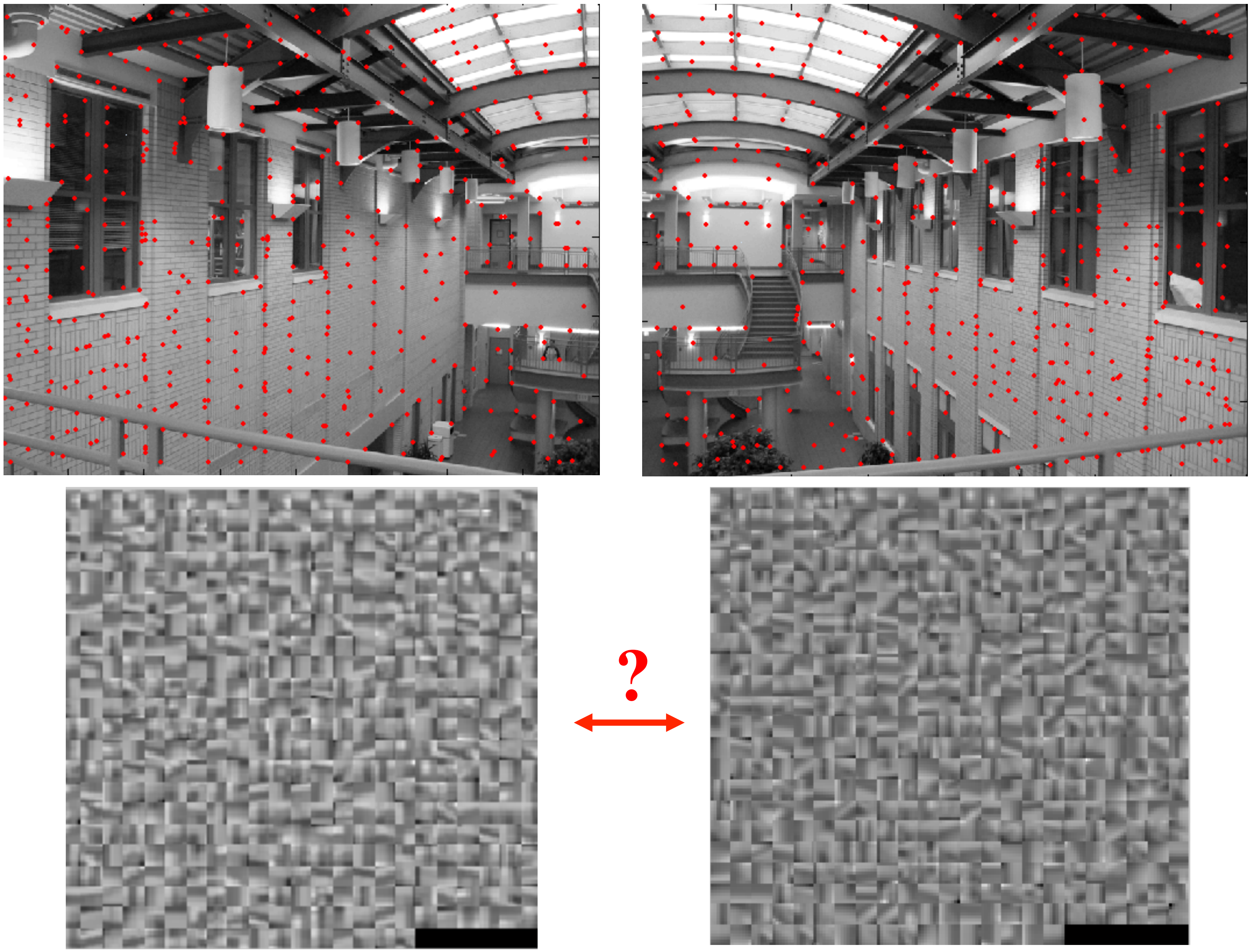
Feature matching



Feature matching

- Exhaustive search
  - for each feature in one image, look at *all* the other features in the other image(s)
- Hashing
  - compute a short descriptor from each feature vector, or hash longer descriptors (randomly)
- Nearest neighbor techniques
  - *kd*-trees and their variants

What about outliers?



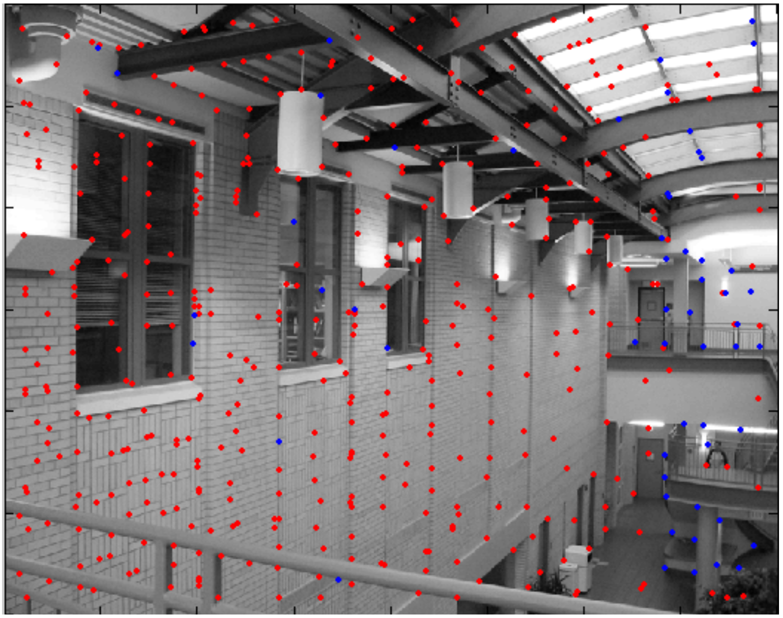
Feature-space outlier rejection

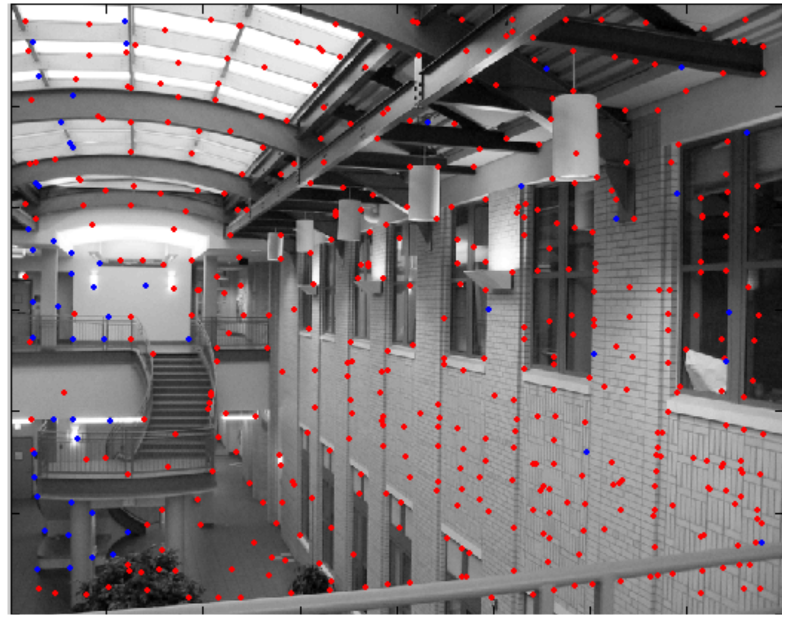
- Let’s not match all features, but only these that have “similar enough” matches?
- How can we do it?
  - SSD(patch1,patch2) < threshold
  - How to set threshold?

Feature-space outlier rejection

- A better way [Lowe, 1999]:
  - 1-NN: SSD of the closest match
  - 2-NN: SSD of the <u>second-closest</u> match
  - Look at how much better 1-NN is than 2-NN, e.g. 1-NN/2-NN
  - That is, is our best match so much better than the rest?

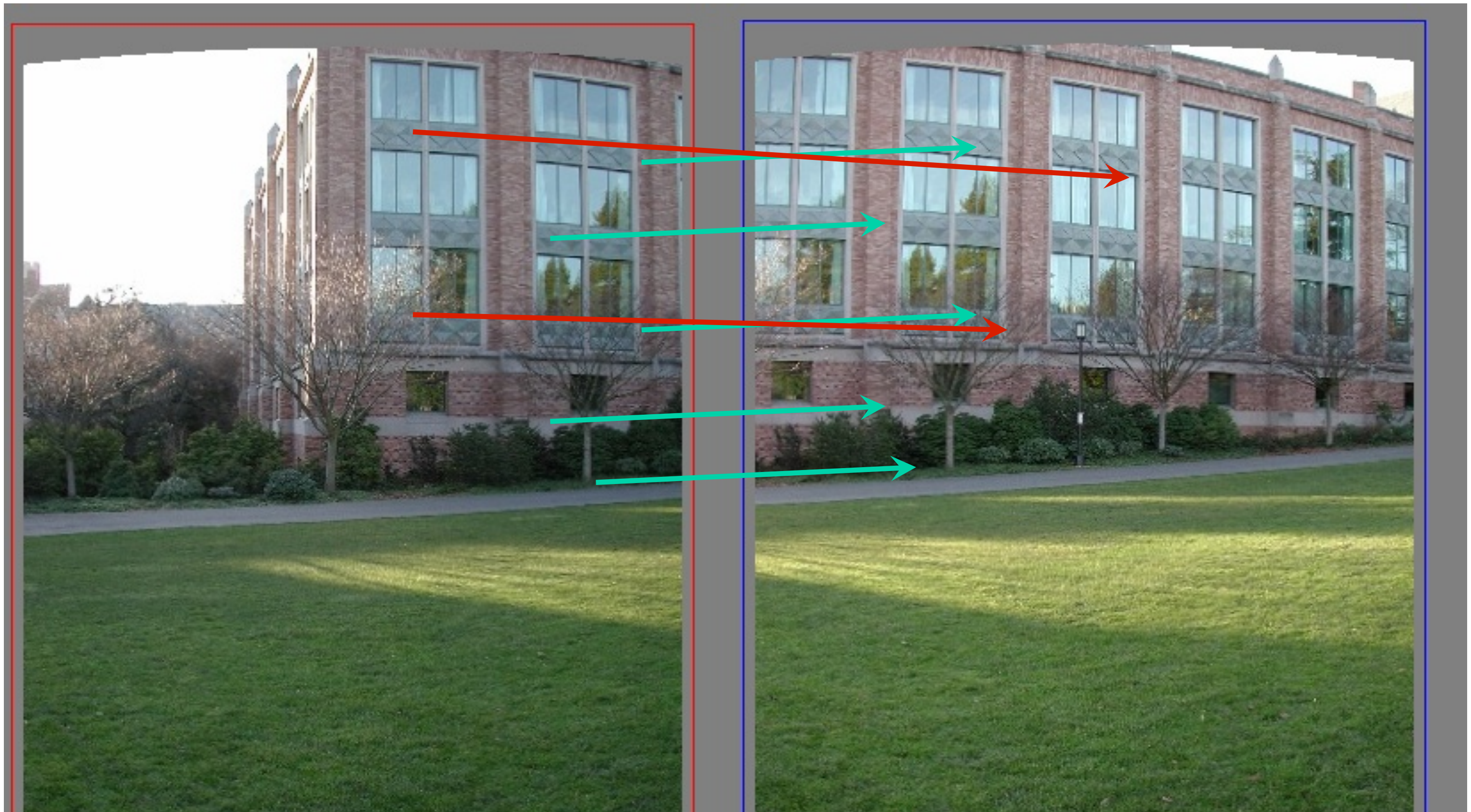
Feature-space outliner rejection





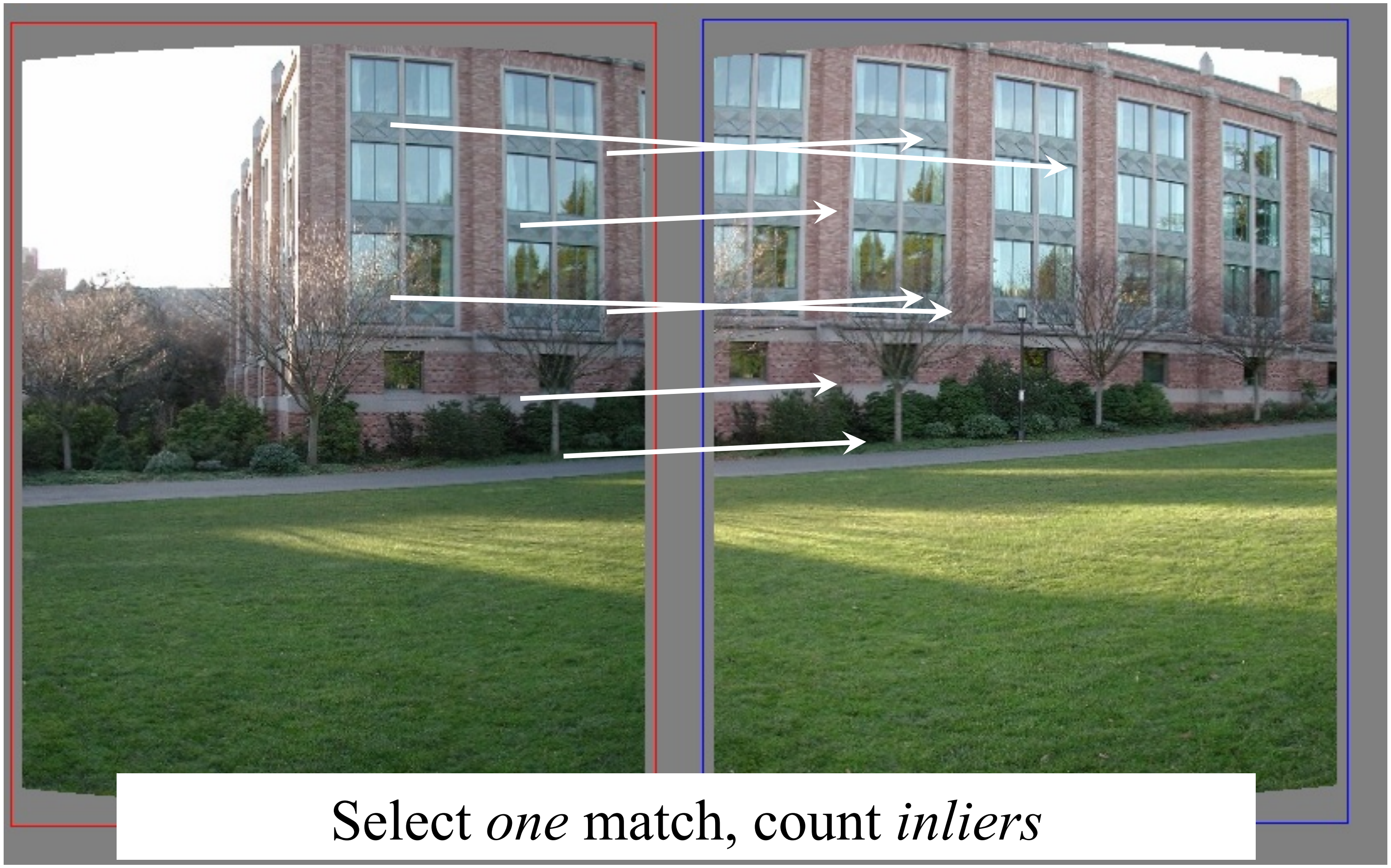
- Can we now compute H from the blue points?
  - No! Still too many outliers…
  - What can we do?

Matching features



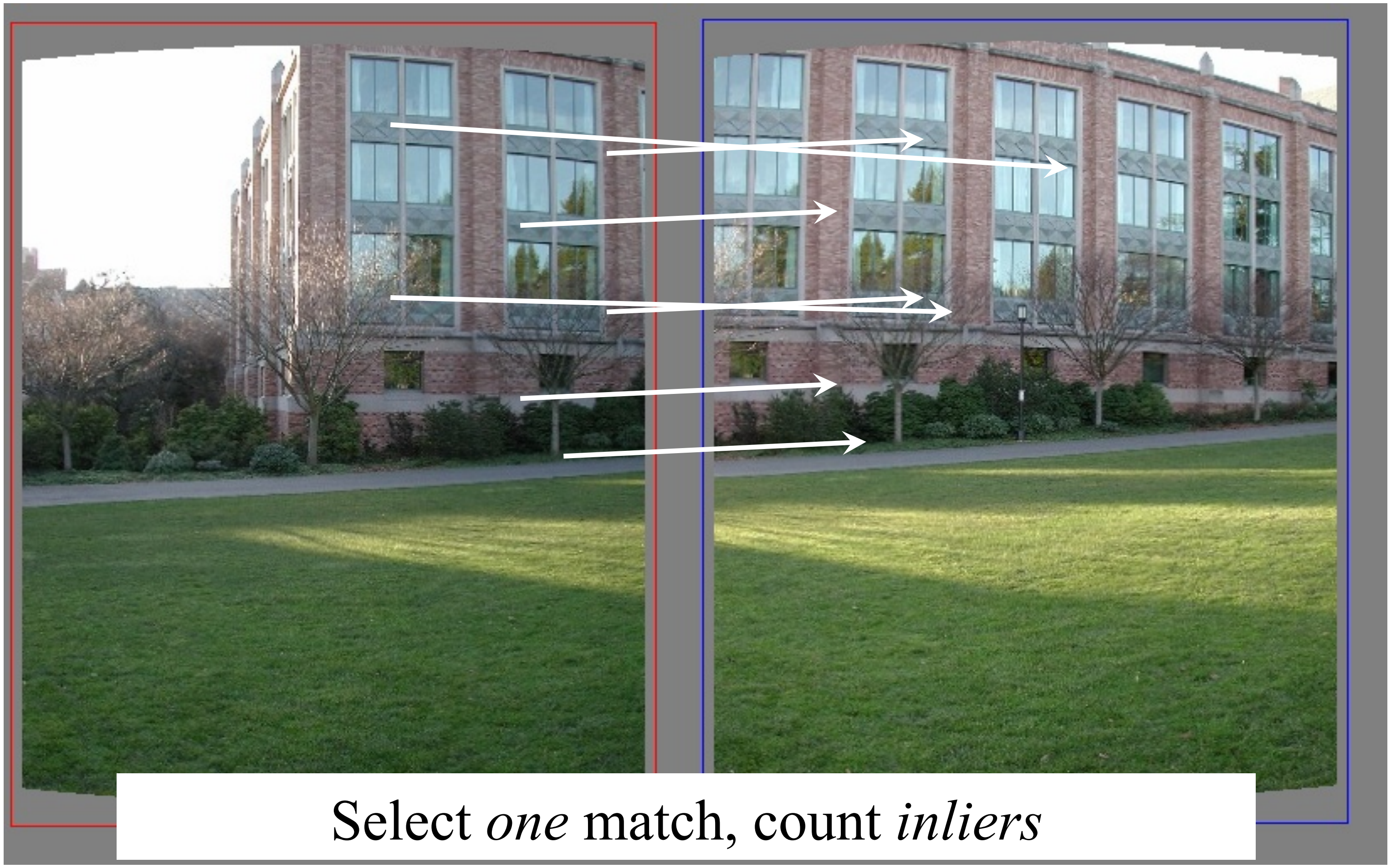
What do we do about the “bad” matches?

RAndom SAmple Consensus

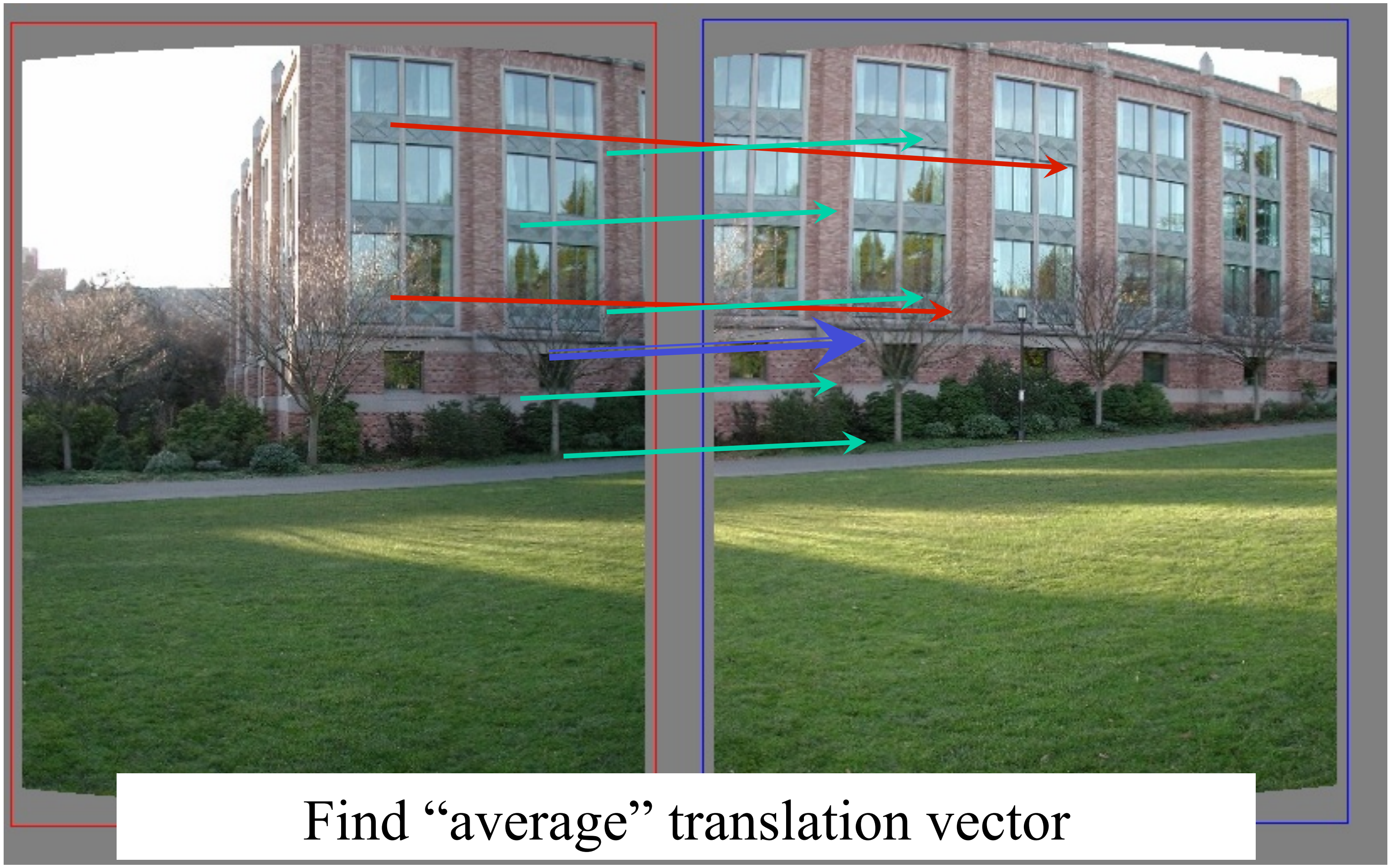


Select *one* match, count *inliers*

RAndom SAmple Consensus



Least squares fit



Find “average” translation vector