Lecture:
Scale Selection, Local Descriptors, SIFT

Adapted from slides by Juan Carlos Niebles, and Ranjay Krishna

What we will learn today?

- Scale invariant keypoint detection
  - Automatic scale selection
  - Difference-of-Gaussian (DoG) detector
- SIFT: an image region descriptor

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Does scale matter?

- When detecting corners, the `scale` of the window you use can change the corners you detect.

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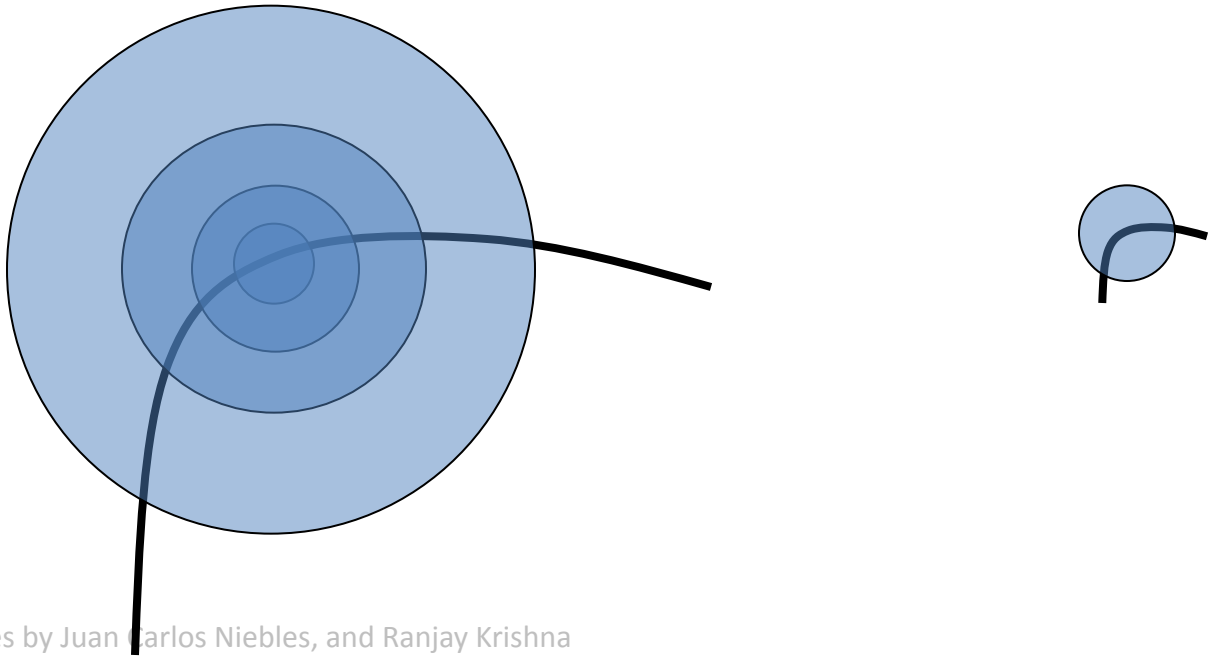
Scale Invariant Detection

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



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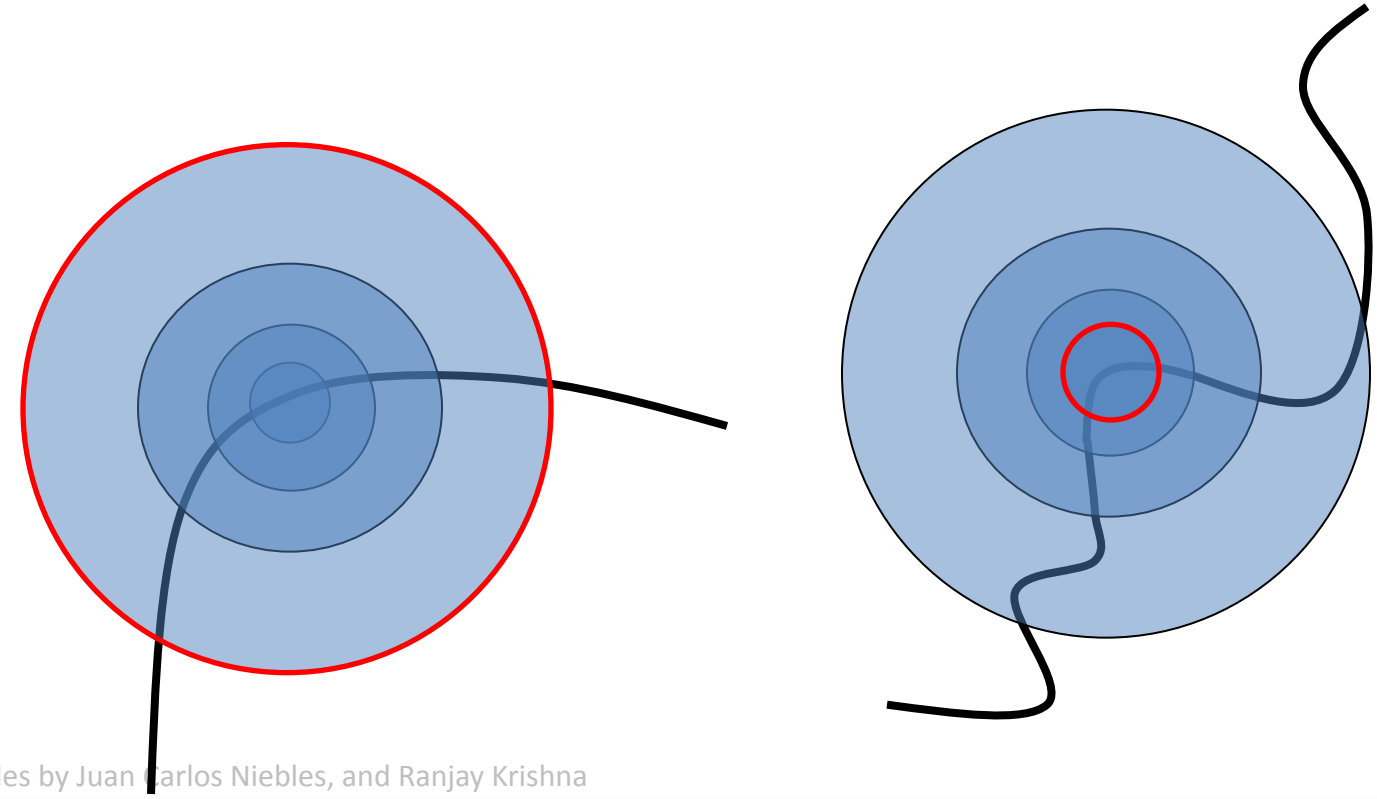
Scale Invariant Detection

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



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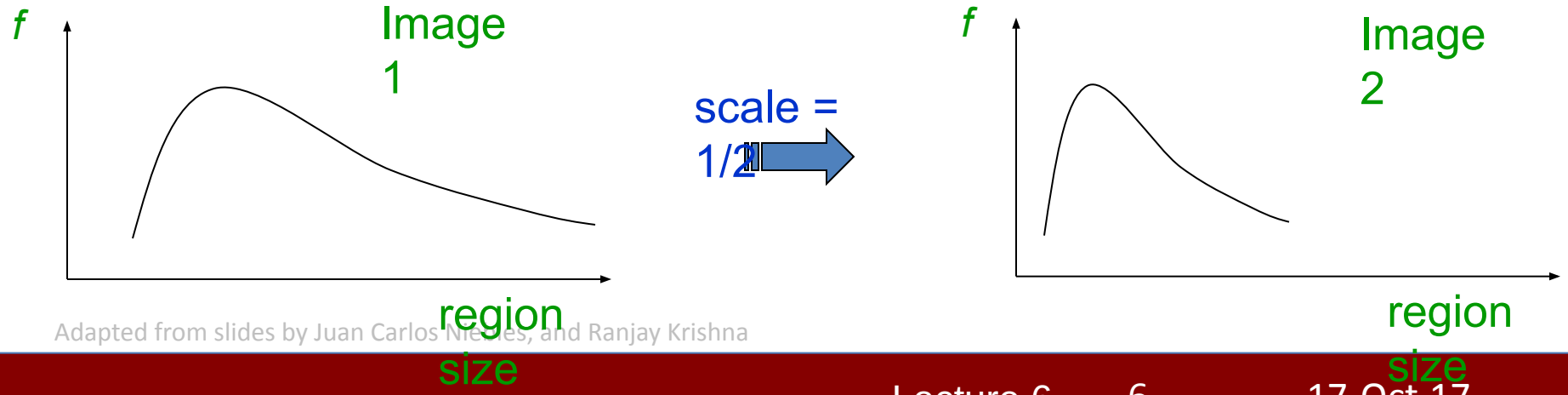
Scale Invariant Detection

- Solution:
  - Design a function on the region (circle), which is "scale invariant" in the following sense: the same for corresponding regions, even if they are at different scales)

Example: average intensity. For corresponding regions (even if regions have # of pixels), it will be the same.

  - For a point in one image, we can consider it as a function of region size (circle radius)

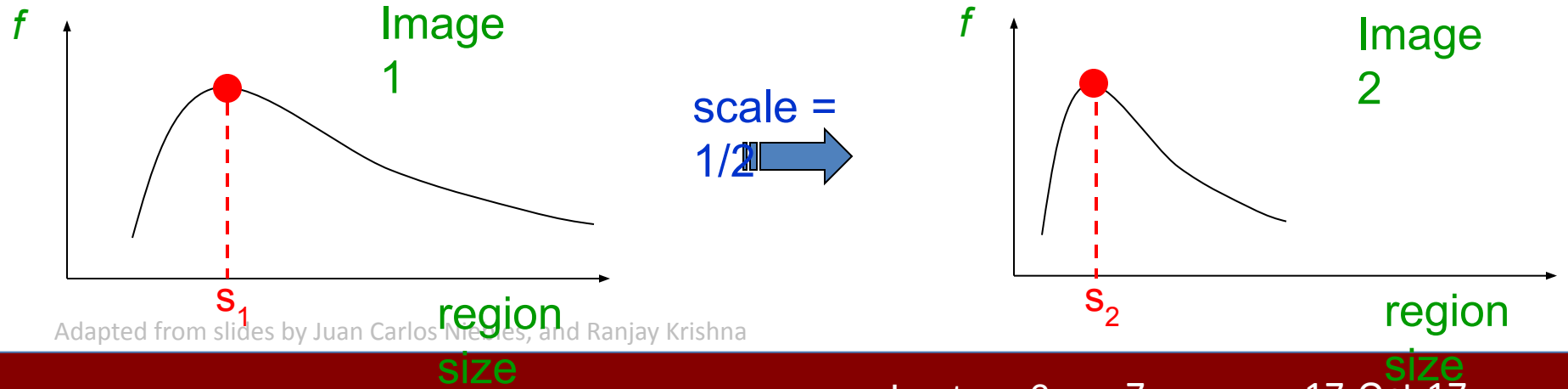


Scale Invariant Detection

- Common approach:
  Take a local maximum of this function

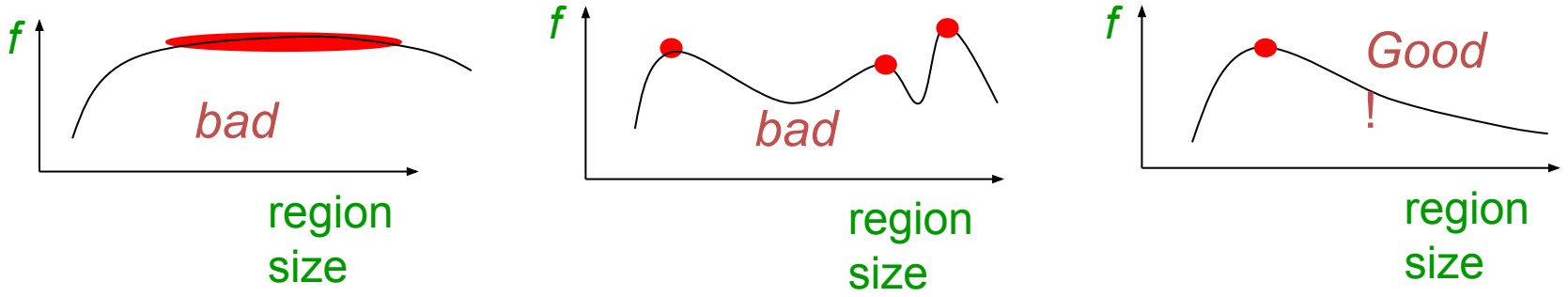
- Observation: region size, for which the maximum is achieved, should be *co-variant* with image scale.

Important: this scale invariant region size is found in each image independently!



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)

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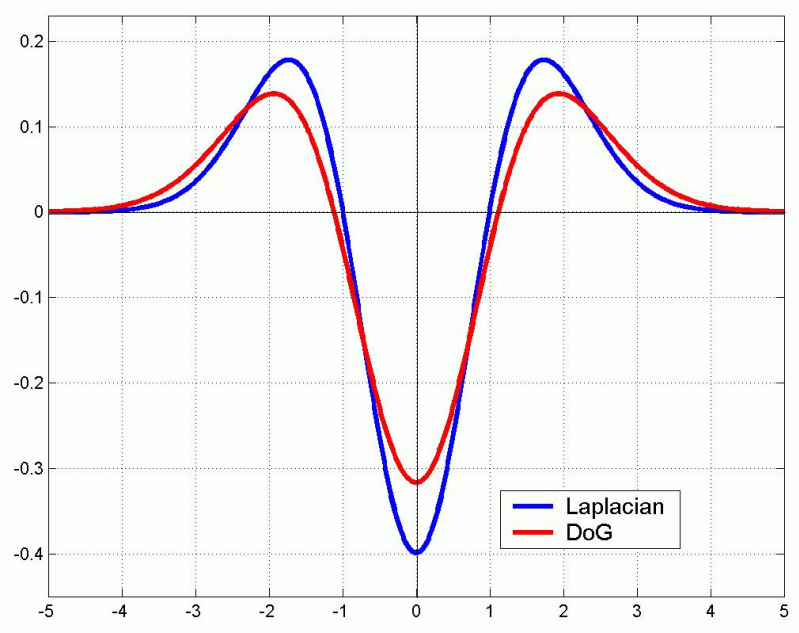
Scale Invariant Detection

- Functions for determining scale $f = \text{Kernel} * \text{Image}$

Kernels:

$$L = \sigma^2 \left(G_{xx}(x, y, \sigma) + G_{yy}(x, y, \sigma) \right)$$

(Laplacian)



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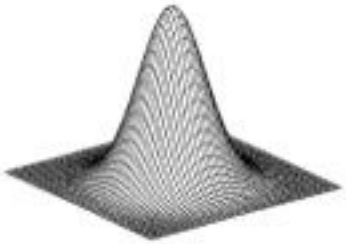
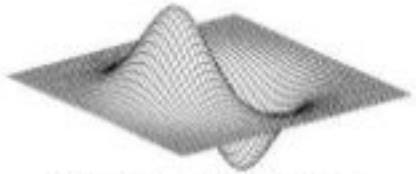
Derivative-of-Gaussian versus Laplacian-of-Gaussian

2D edge detection filters



Gaussian

$$h_\sigma(u,v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{2\sigma^2}}$$



derivative of Gaussian

$$\frac{\partial}{\partial x} h_\sigma(u,v)$$

Laplacian of Gaussian

$$\nabla^2 h_\sigma(u,v)$$

∇^2 is the **Laplacian** operator:

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

24

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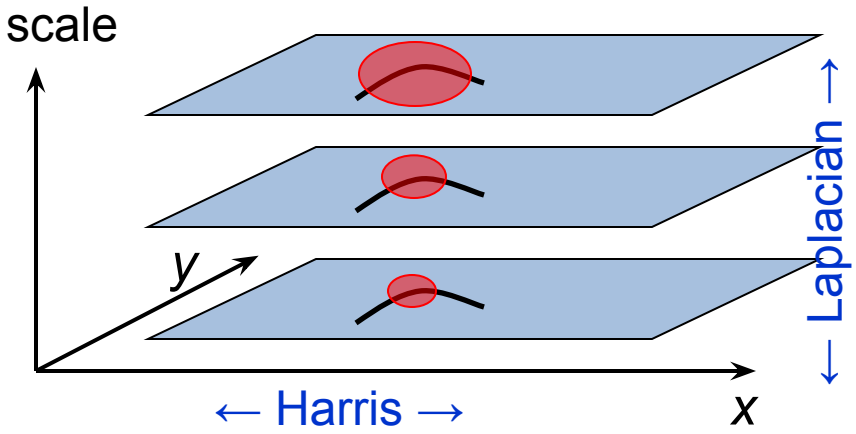
Scale Invariant Detectors

- Harris-Laplacian[1]
  Find local maximum of:
  - Harris corner detector in **space** (image coordinates)
  - Laplacian in **scale**



[1] K.Mikolajczyk, C.Schmid. "Indexing Based on Scale Invariant Interest Points". ICCV 2001
[2] D.Lowe. "Distinctive Image Features from Scale-Invariant Keypoints". IJCV 2004

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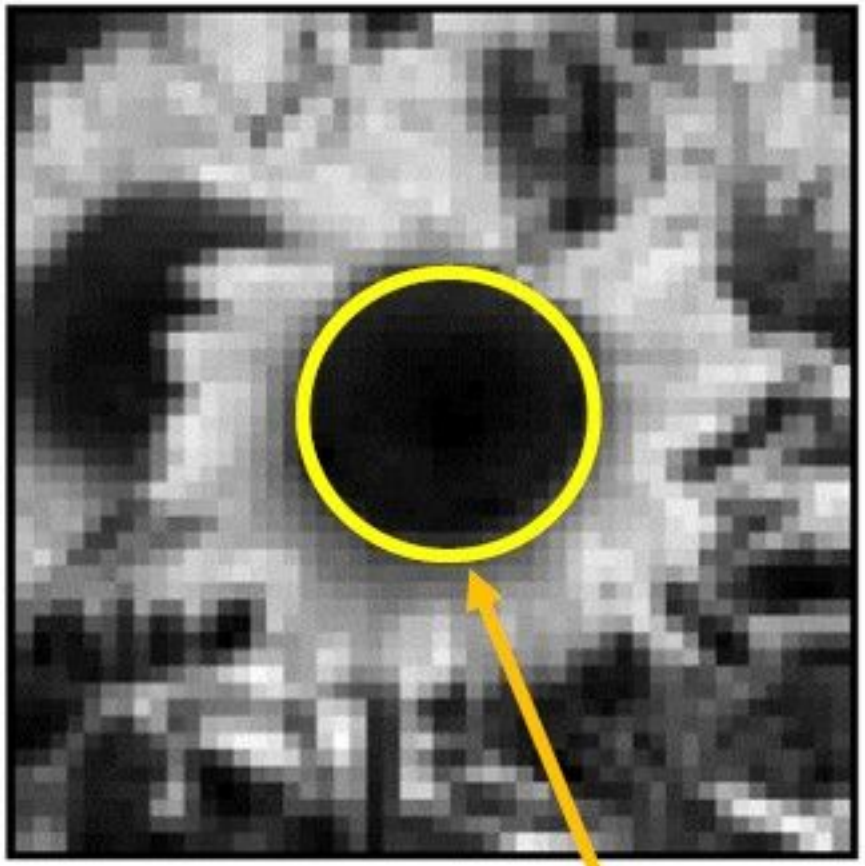
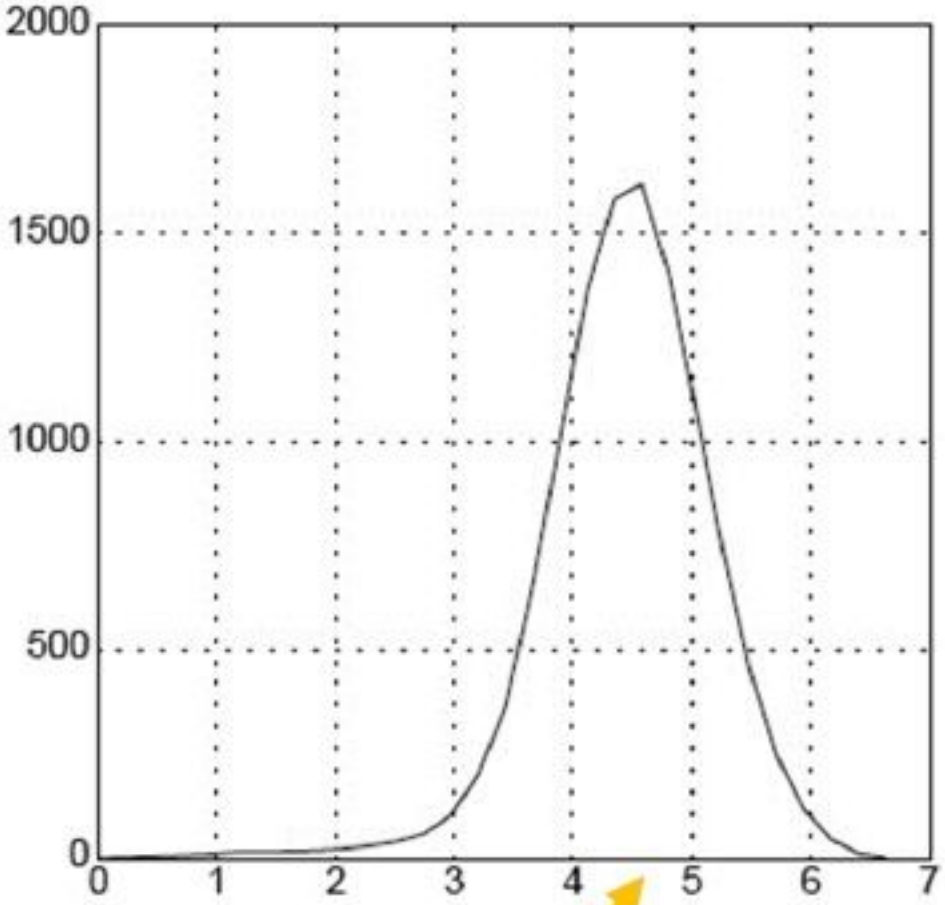
Laplacian





Characteristic scale

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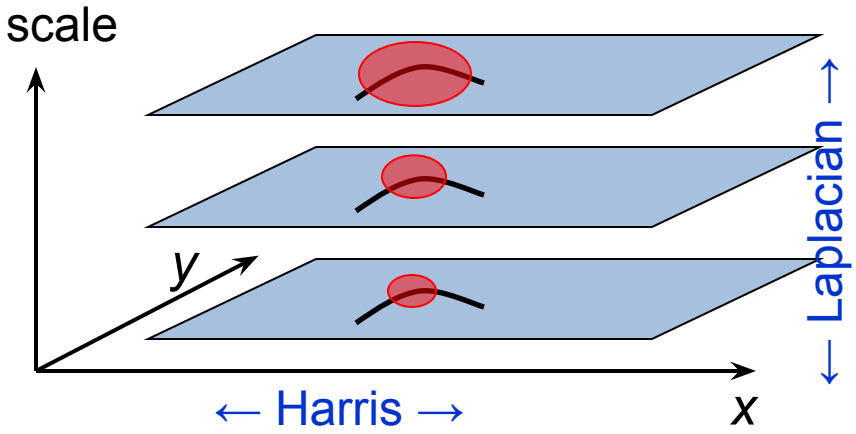
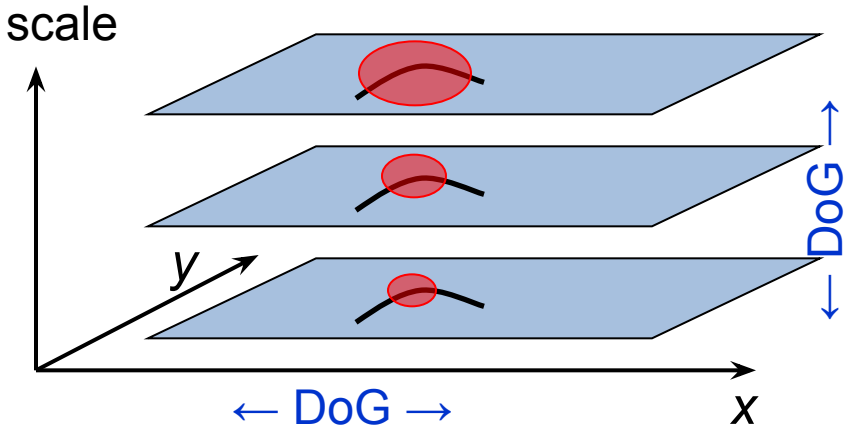
Scale Invariant Detectors

- Harris-Laplacian[1]
  Find local maximum of:
  - Harris corner detector in **space** (image coordinates)
  - Laplacian in **scale**



- SIFT (Lowe)[2]
  Find local maximum of:
  - Difference of Gaussians **in space and scale**



[1] K.Mikolajczyk, C.Schmid. "Indexing Based on Scale Invariant Interest Points". ICCV 2001
[2] D.Lowe. "Distinctive Image Features from Scale-Invariant Keypoints". IJCV 2004

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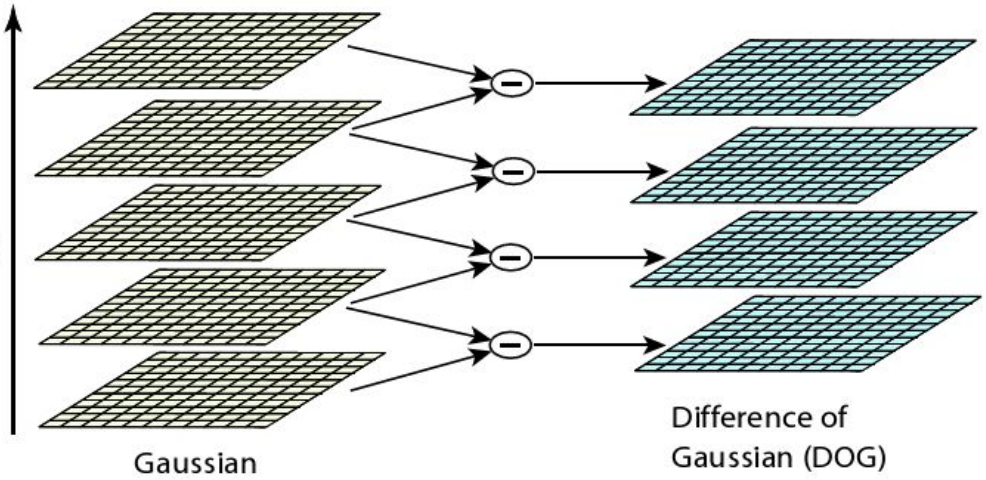
Difference-of-Gaussians

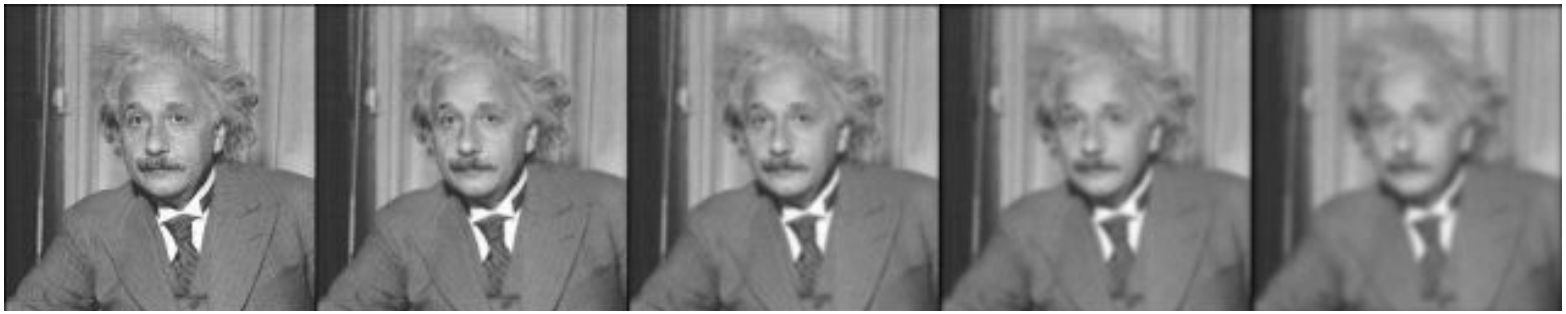
$G(k^2\sigma) * I$

$G(k\sigma) * I$

$G(\sigma) * I$



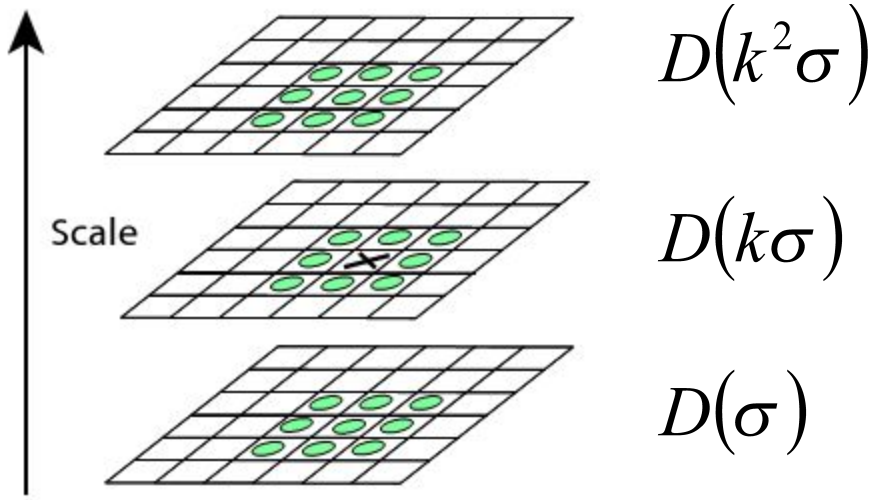
$D(\sigma) \equiv (G(k\sigma) - G(\sigma)) * I$



Adapted from

Scale-Space Extrema

- Choose all extrema within 3x3x3 neighborhood.



X is selected if it is larger or smaller than all 26 neighbors

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DoG approximates Laplacian

- Functions for determining scale $f = \text{Kernel} * \text{Image}$

Kernels:

$$L = \sigma^2 \left(G_{xx}(x, y, \sigma) + G_{yy}(x, y, \sigma) \right)$$

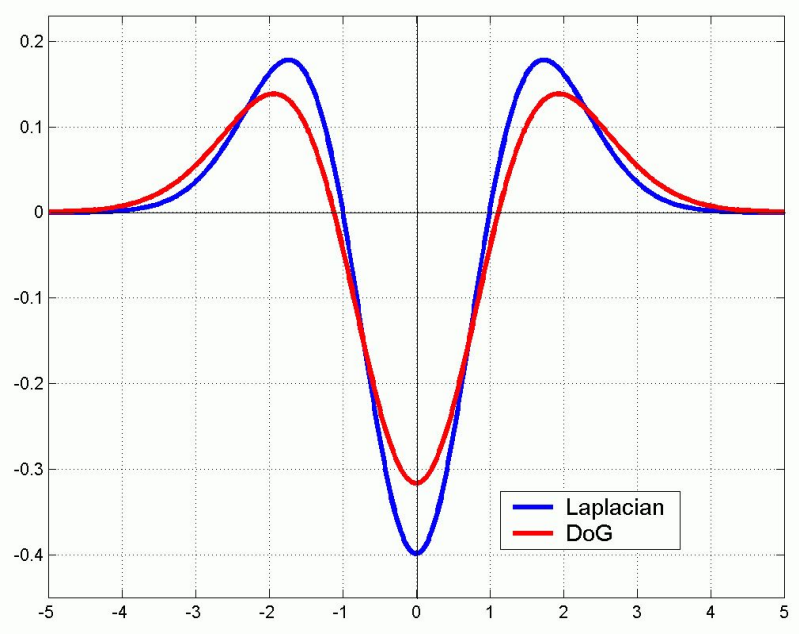
(Laplacian)

$$DoG = G(x, y, k\sigma) - G(x, y, \sigma)$$

(Difference of Gaussians)

where Gaussian

$$G(x, y, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2 + y^2}{2\sigma^2}}$$



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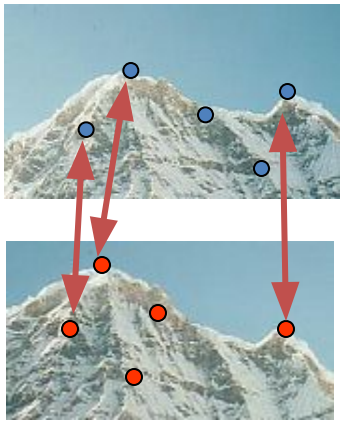
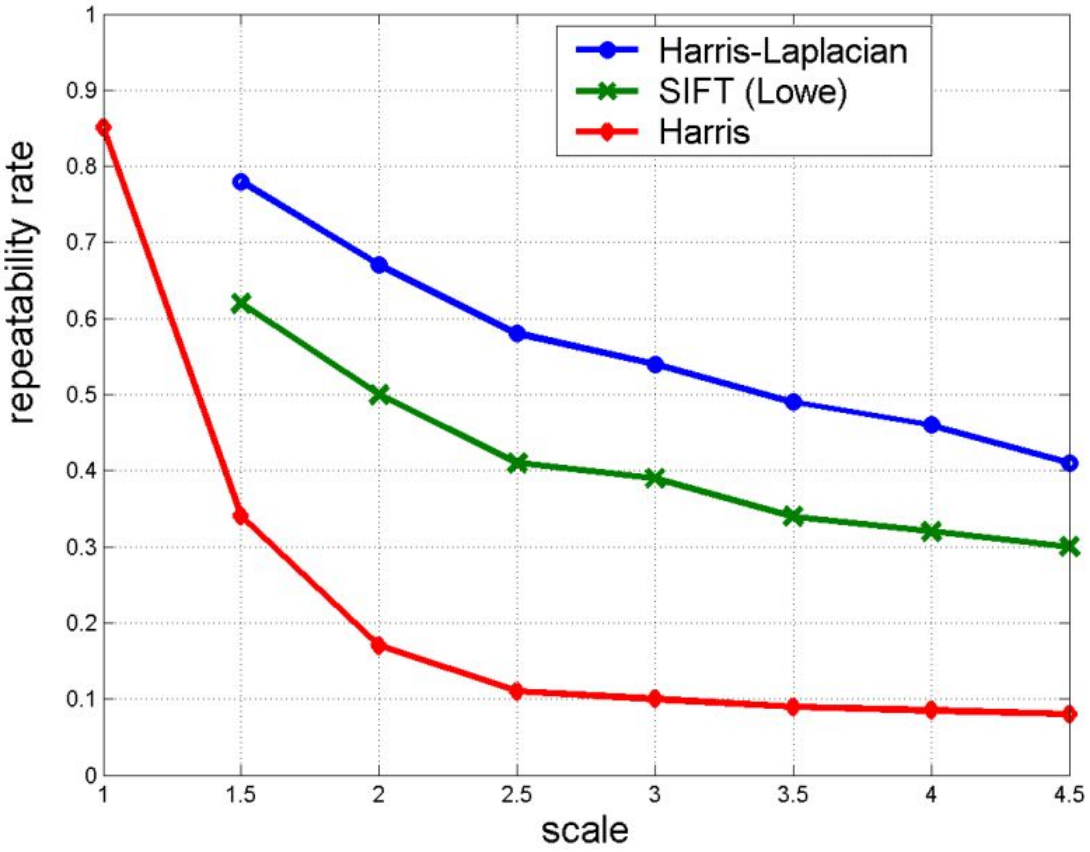
Scale Invariant Detectors

- Experimental evaluation of detectors w.r.t. scale change

Repeatability rate:

$$\frac{\#\ \text{correspondences}}{\#\ \text{possible correspondences}}$$





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

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Scale Invariant Detection: Summary

- Given: two images of the same scene with a large *scale difference* between them
- Goal: find *the same* interest points *independently* in each image
- Solution: search for *maxima* of suitable functions in *scale* and in *space* (over the image)

Methods:

1. Harris-Laplacian [Mikolajczyk, Schmid]: maximize Laplacian over scale, Harris' measure of corner response over the image
2. SIFT [Lowe]: maximize Difference of Gaussians over scale and space

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What's next?

So we have can detect keypoints at varying scales. But what can we do with those keypoints?

Things we would like to do:

- Search:
  - We would need to find similar key points in other images
- Panorama
  - Match keypoints from one image to another.
- Etc…

For all such applications, we need a way of `describing` the keypoints.

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What we will learn today?

- Scale invariant region selection
  - Automatic scale selection
  - Difference-of-Gaussian (DoG) detector
- SIFT: an image region descriptor

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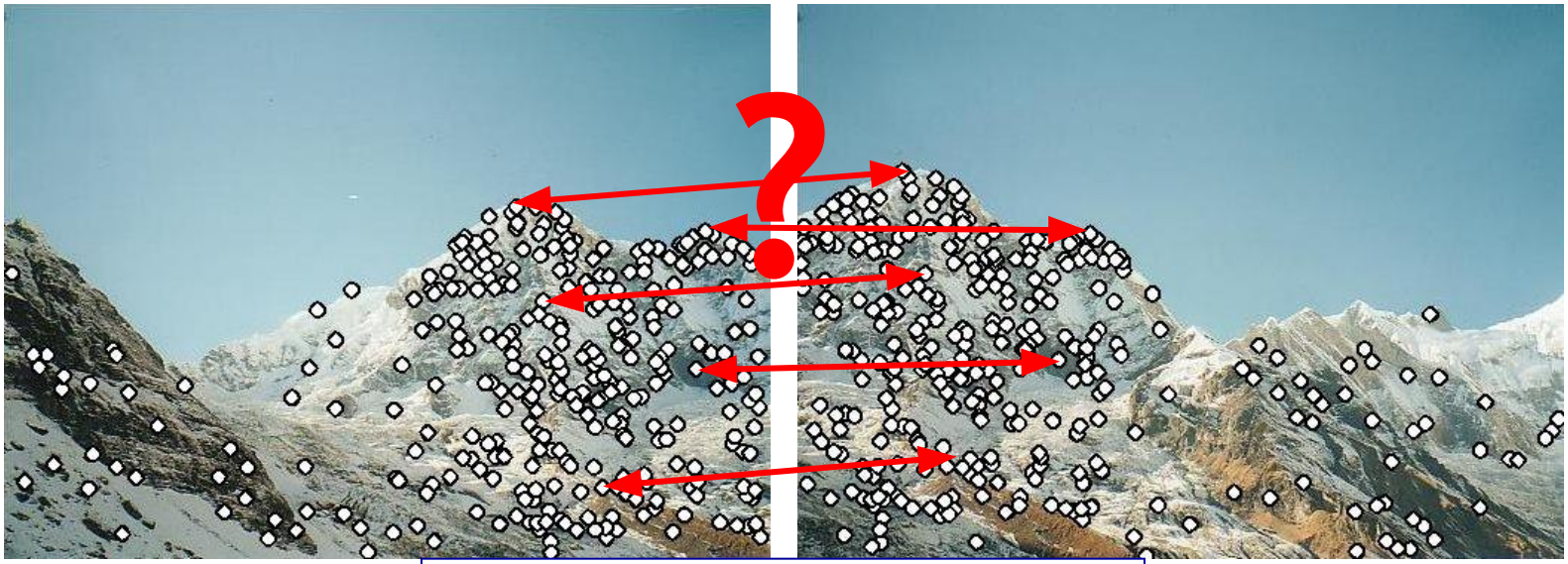
Local Descriptors

- We know how to detect points
- Next question:

How to *describe* them for matching?



Point descriptor should be:

1. **Invariant**
2. **Distinctive**

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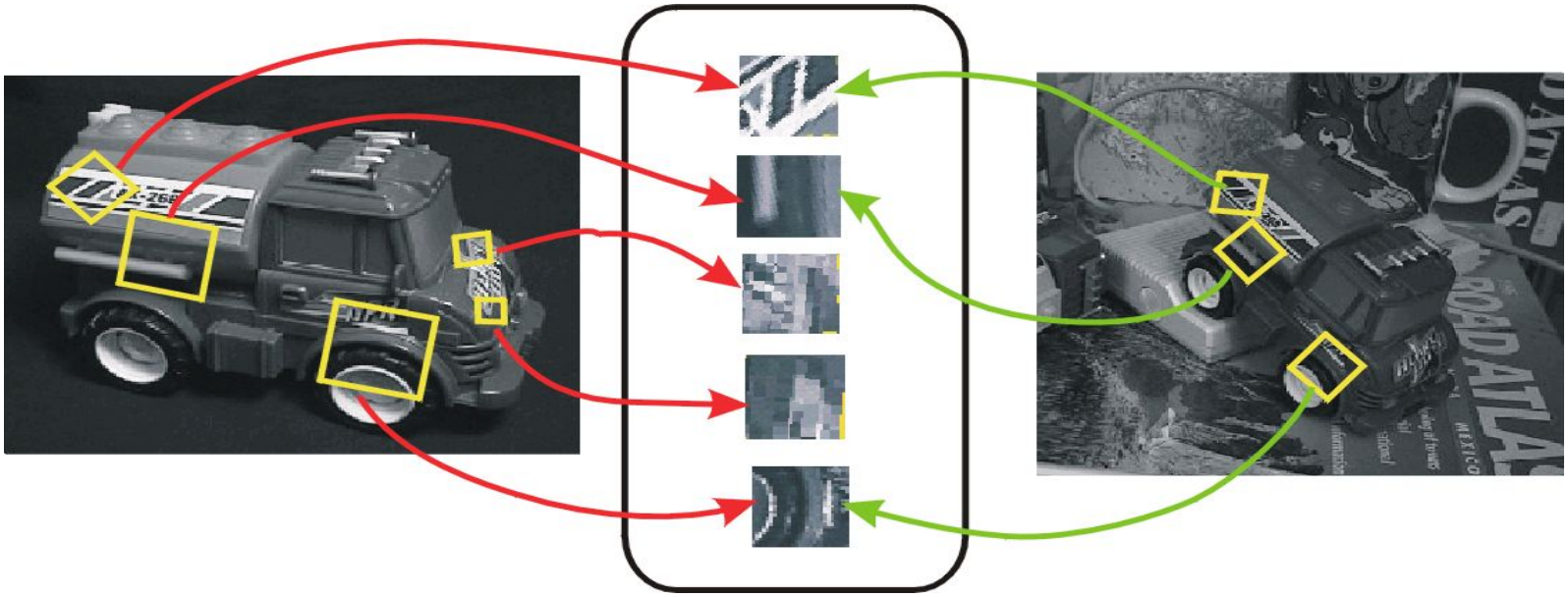
Slide credit: Kristen Grauman

Invariant Local Features

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



Following slides credit: CVPR 2003 Tutorial on **Recognition and Matching Based on Local Invariant Features** David Lowe

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Advantages of invariant local features

- **Locality:** features are local, so robust to occlusion and clutter (no prior segmentation)
- **Distinctiveness:** individual features can be matched to a large database of objects
- **Quantity:** many features can be generated for even small objects
- **Efficiency:** close to real-time performance
- **Extensibility:** can easily be extended to wide range of differing feature types, with each adding robustness

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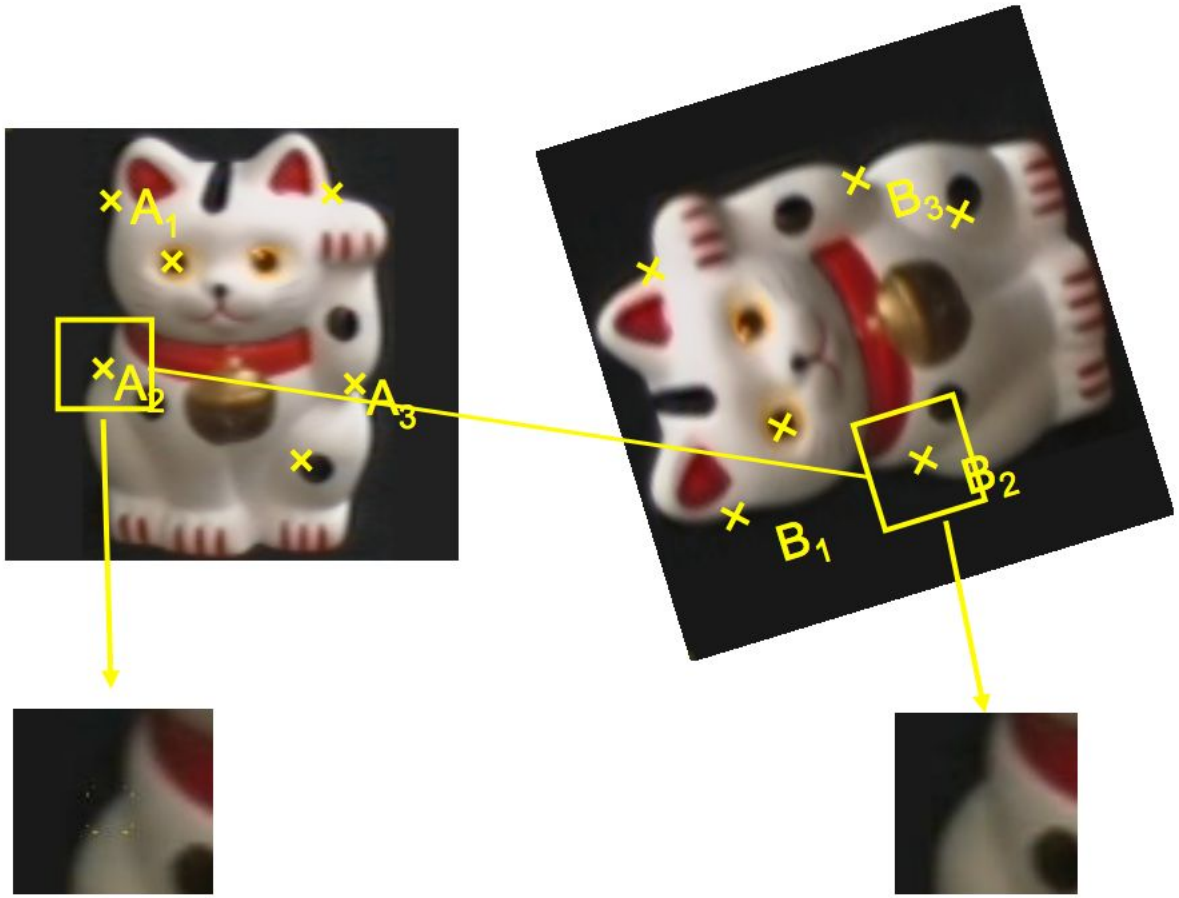
Becoming rotation invariant



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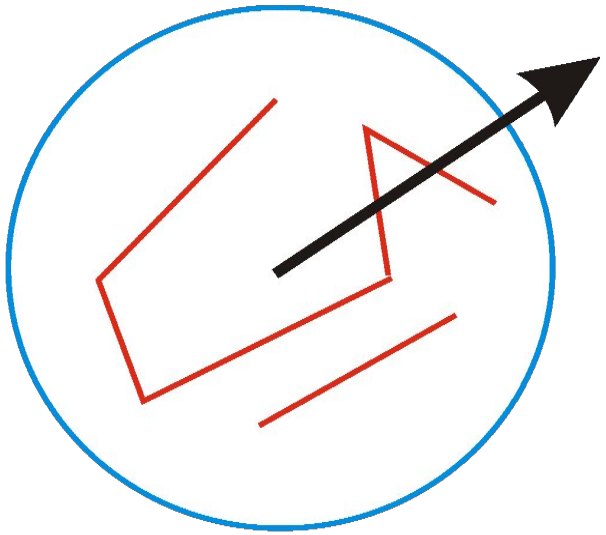
Becoming rotation invariant

- We are given a keypoint and its scale from DoG
- We will select a characteristic orientation for the keypoint (based on the most prominent gradient there; discussed next slide)
- We will describe all features **relative** to this orientation
- Causes features to be rotation invariant!
  - If the keypoint appears rotated in another image, the features will be the same, because they're **relative** to the characteristic orientation



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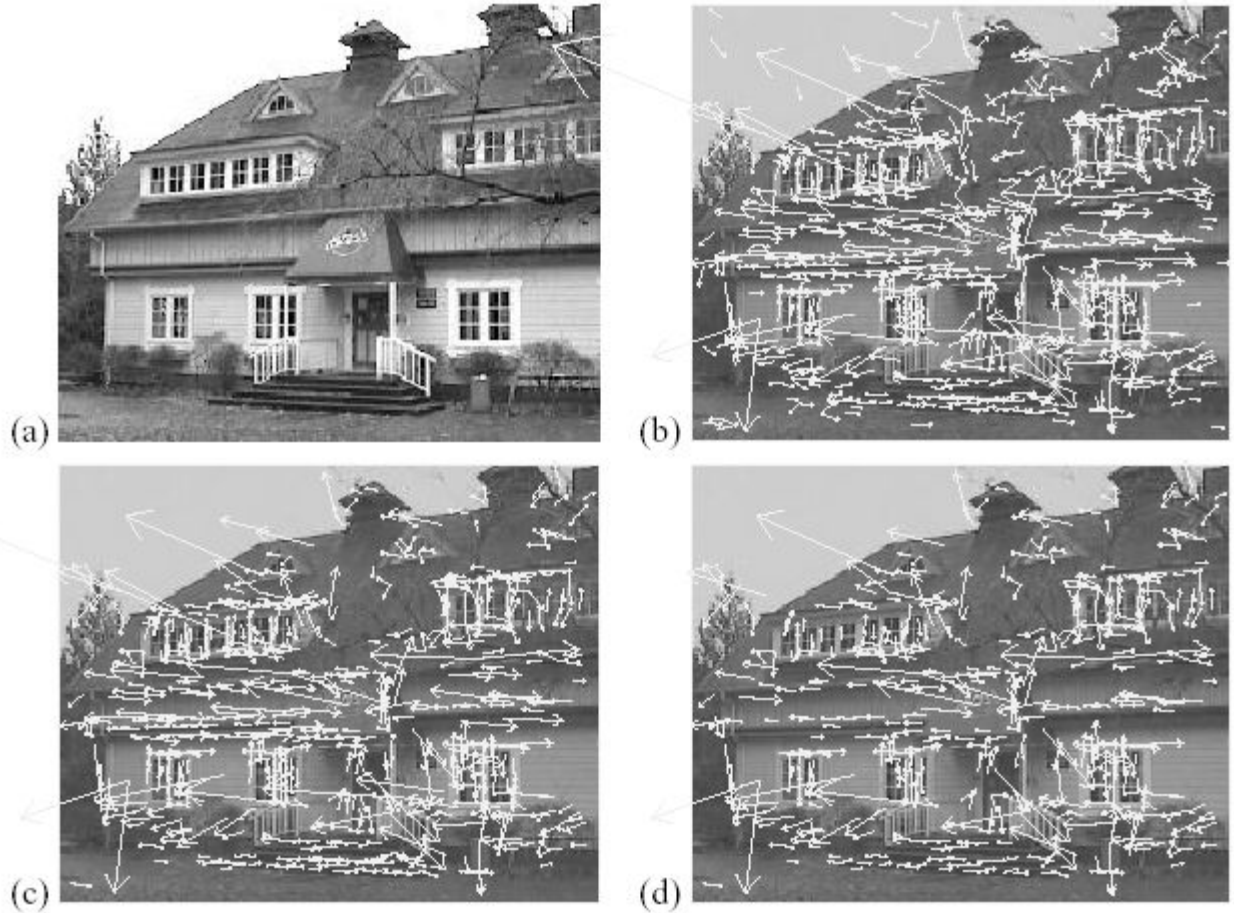
Example of keypoint detection

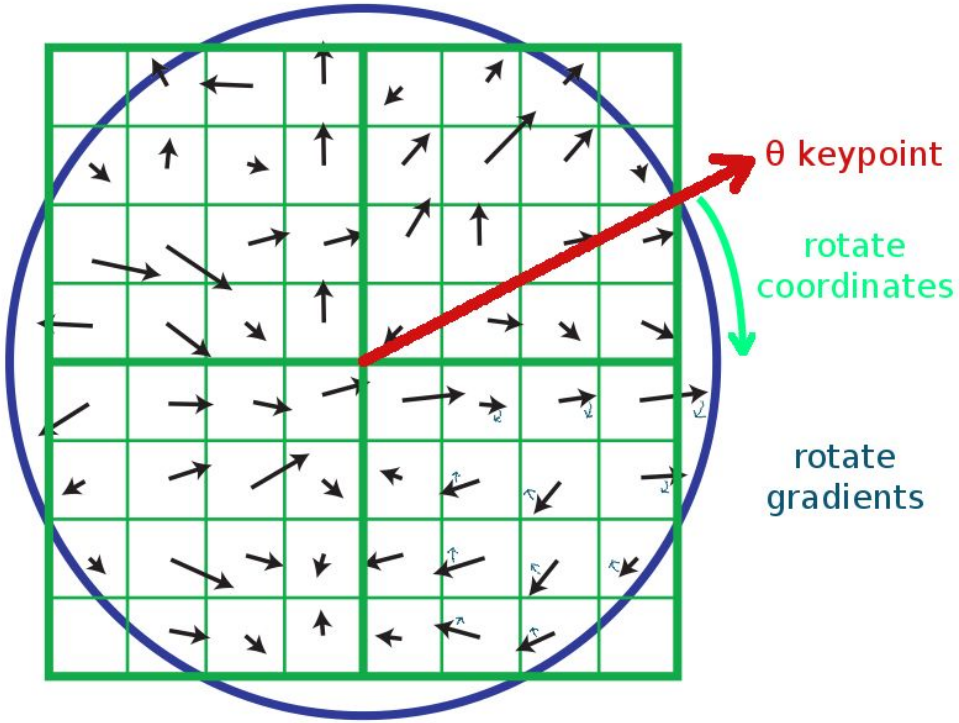
Threshold on value at DOG peak and on ratio of principle curvatures (Harris approach)



(a) 233x189 image
(b) 832 DOG extrema
(c) 729 left after peak value threshold
(d) 536 left after testing ratio of principle curvatures (Harris-like measure to suppress edges)

Vectors indicate scale, orientation and location.

SIFT descriptor formation



- Use the blurred image associated with the keypoint's scale
- Take image gradients over the keypoint neighborhood.
- To become rotation invariant, rotate the gradient directions AND locations by (-keypoint orientation)
  - Now we've cancelled out rotation and have gradients expressed at locations **relative** to keypoint orientation θ
  - We could also have just rotated the whole image by -θ, but that would be slower.

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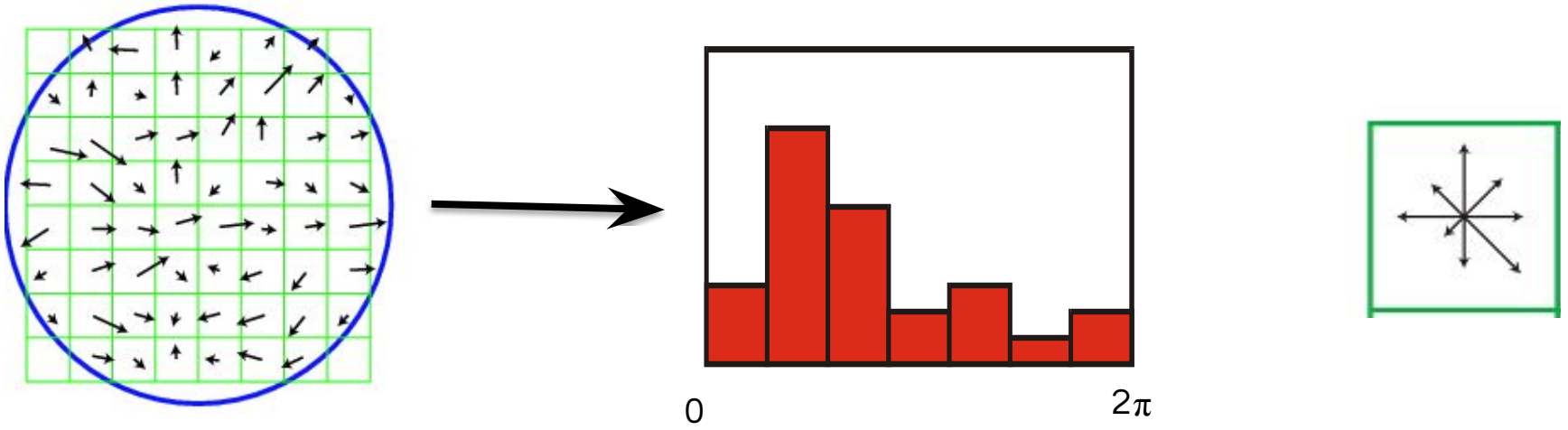
SIFT descriptor formation



- Using precise gradient locations is fragile. We'd like to allow some "slop" in the image, and still produce a very similar descriptor ⇒ HISTOGRAM!
- Create array of orientation histograms (1 histogram is shown)
- Put the rotated gradients into their local orientation histograms

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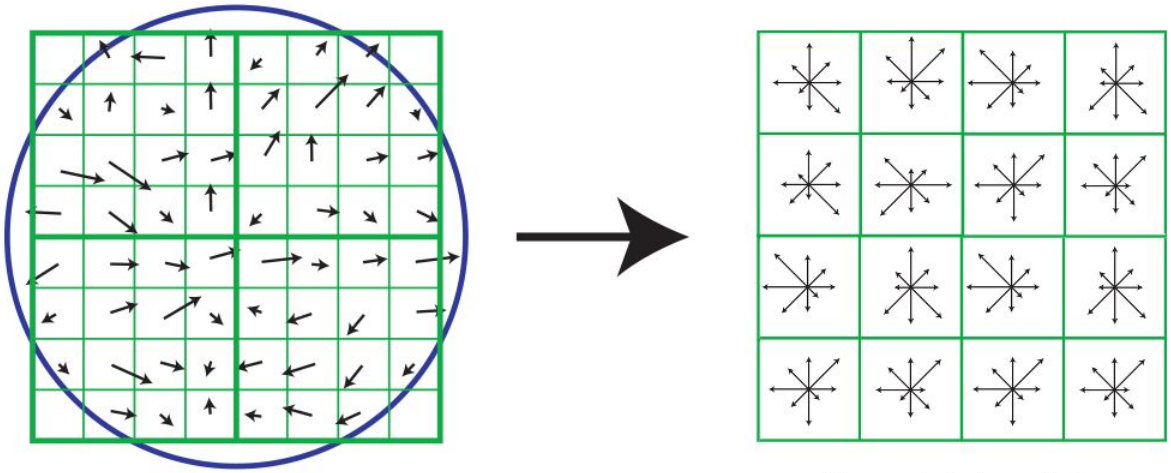
SIFT descriptor formation



- Example with 4x4 spatial grid is shown
- Put the rotated gradients into their local orientation histograms
  - A gradients's contribution is divided among the nearby histograms based on distance. If it's halfway between two histogram locations, it gives a half contribution to both.
  - Also, scale down gradient contributions for gradients far from the center
- The SIFT authors found that best results were with 8 orientation bins per histogram, and a 4x4 histogram array.

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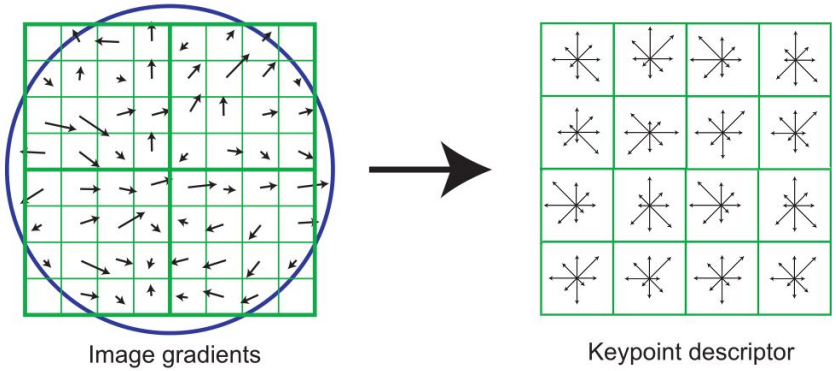
SIFT descriptor formation



- 8 orientation bins per histogram, and a 4x4 histogram array, yields 8 x 4x4 = 128 numbers.
- So a SIFT descriptor is a length 128 vector, which is invariant to rotation (because we rotated the descriptor) and scale (because we worked with the scaled image from DoG)
- We can compare each vector from image A to each vector from image B to find matching keypoints!
  - Euclidean “distance” between descriptor vectors gives a good measure of keypoint similarity

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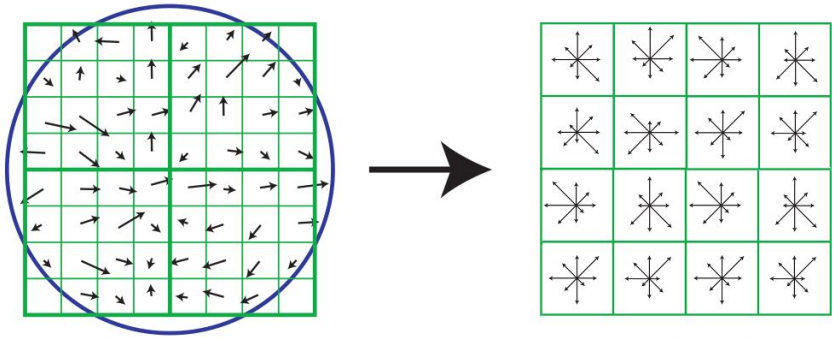
SIFT descriptor formation



- Adding robustness to illumination changes:
- Remember that the descriptor is made of gradients (differences between pixels), so it's already invariant to changes in brightness (e.g. adding 10 to all image pixels yields the exact same descriptor)
- A higher-contrast photo will increase the magnitude of gradients linearly. So, to correct for contrast changes, **normalize the vector** (scale to length 1.0)
- Very large image gradients are usually from unreliable 3D illumination effects (glare, etc). So, to reduce their effect, **clamp all values in the vector to be ≤ 0.2 (an experimentally tuned value). Then normalize the vector again.**
- Result is a vector which is fairly invariant to illumination changes.

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Sensitivity to number of histogram orientations

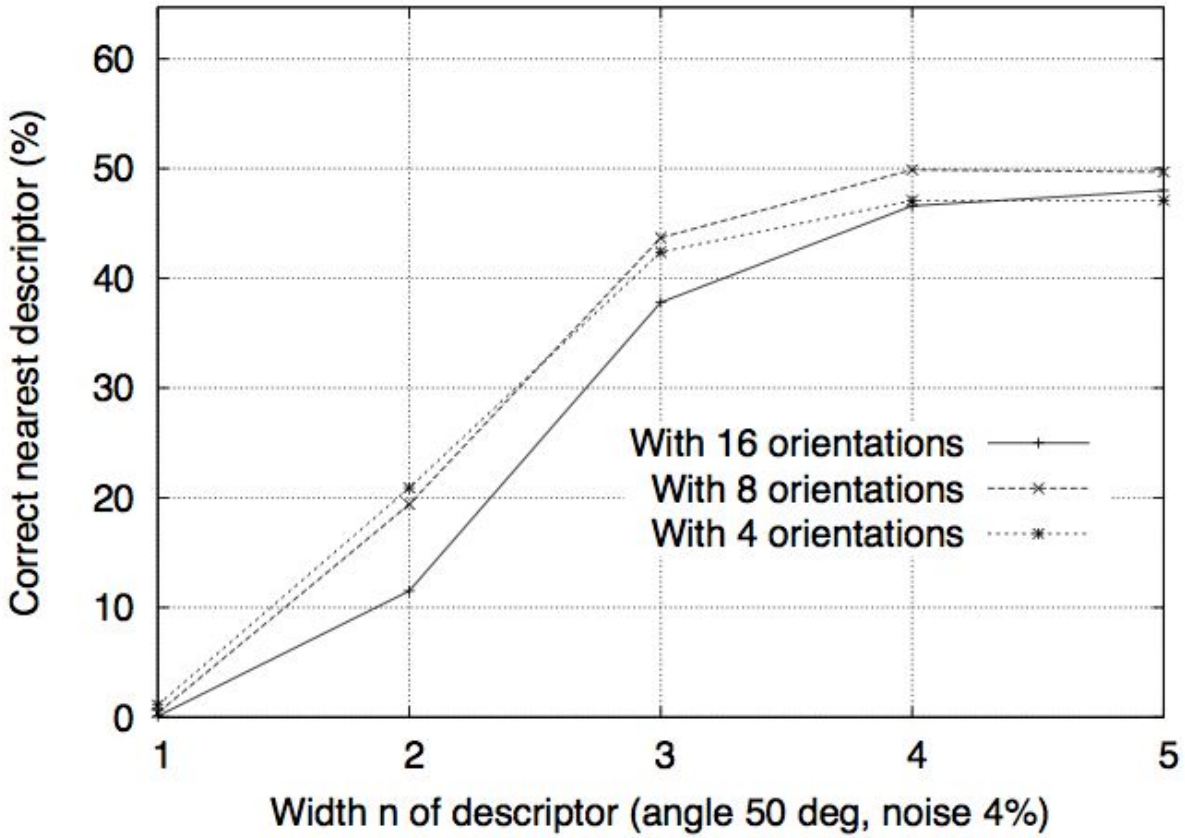

Figure 8: This graph shows the percent of keypoints giving the correct match to a database of 40,000 keypoints as a function of width of the $n \times n$ keypoint descriptor and the number of orientations in each histogram. The graph is computed for images with affine viewpoint change of 50 degrees and addition of 4% noise.

David G. Lowe, "Distinctive image features from scale-invariant keypoints," International Journal of Computer Vision, 60, 2 (2004), pp. 91-110

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Ratio of distances can be used reliably for matching

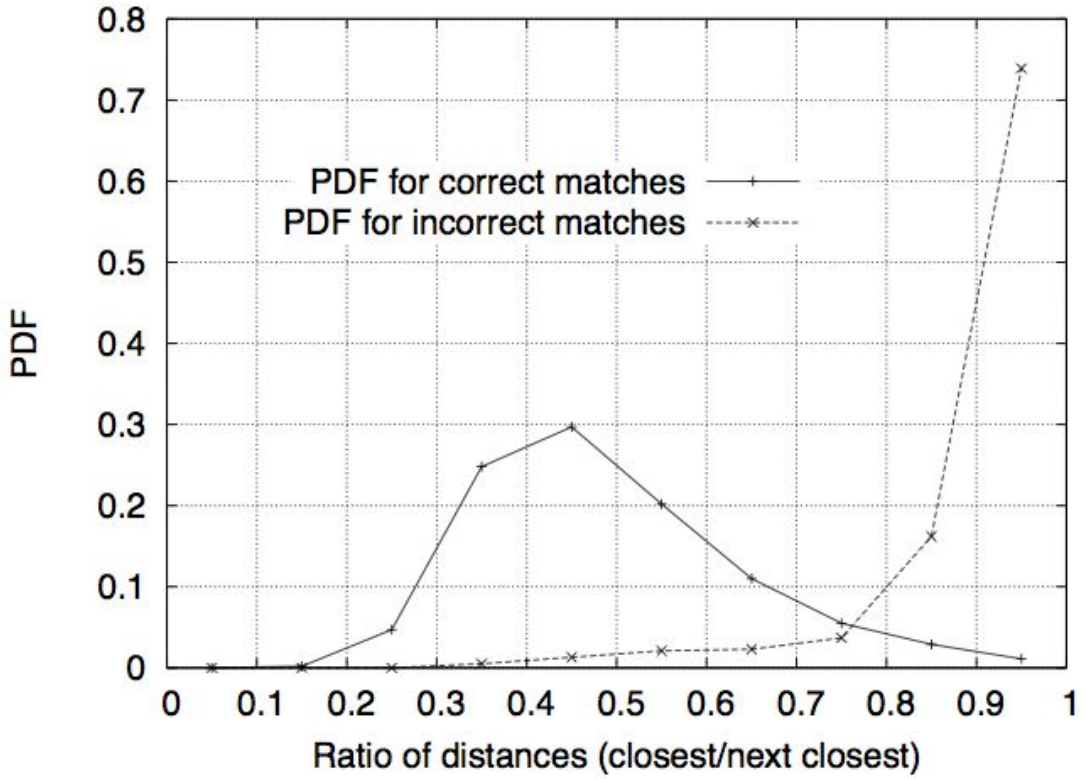

Figure 11: The probability that a match is correct can be determined by taking the ratio of distance from the closest neighbor to the distance of the second closest. Using a database of 40,000 keypoints, the solid line shows the PDF of this ratio for correct matches, while the dotted line is for matches that were incorrect.

Adapted from slides by Juan Carlos Niebles, and Ranjay Krishna

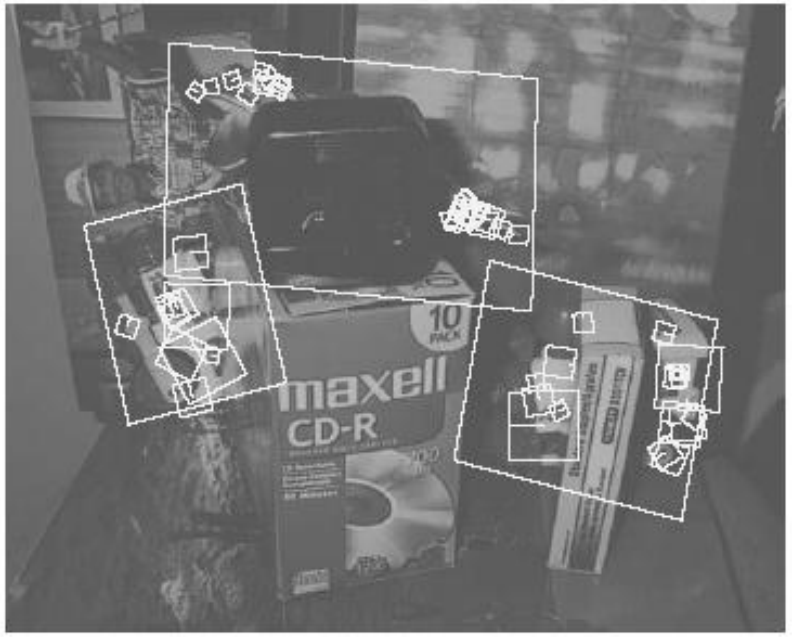

Figure 12: The training images for two objects are shown on the left. These can be recognized in a cluttered image with extensive occlusion, shown in the middle. The results of recognition are shown on the right. A parallelogram is drawn around each recognized object showing the boundaries of the original training image under the affi ne transformation solved for during recognition. Smaller squares indicate the keypoints that were used for recognition.

Adapted from slides by Juan Carlos Niebles, and Ranjay Krishna

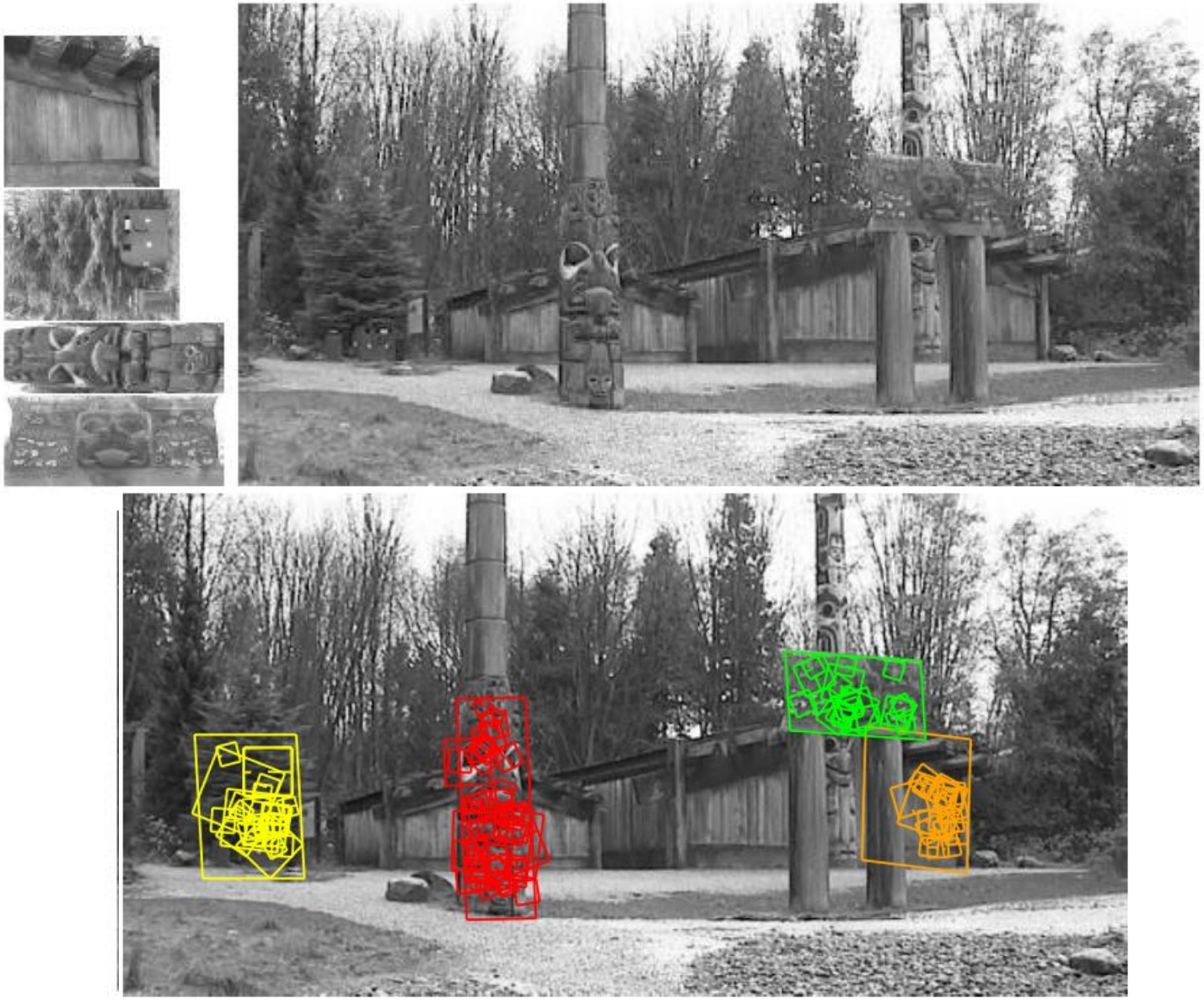

Figure 13: This example shows location recognition within a complex scene. The training images for locations are shown at the upper left and the 640x315 pixel test image taken from a different viewpoint is on the upper right. The recognized regions are shown on the lower image, with keypoints shown as squares and an outer parallelogram showing the boundaries of the training images under the affi ne transform used for recognition.

Required SIFT reading

- Wikipedia - well written, required reading): http://en.wikipedia.org/wiki/Scale-invariant_feature_transform

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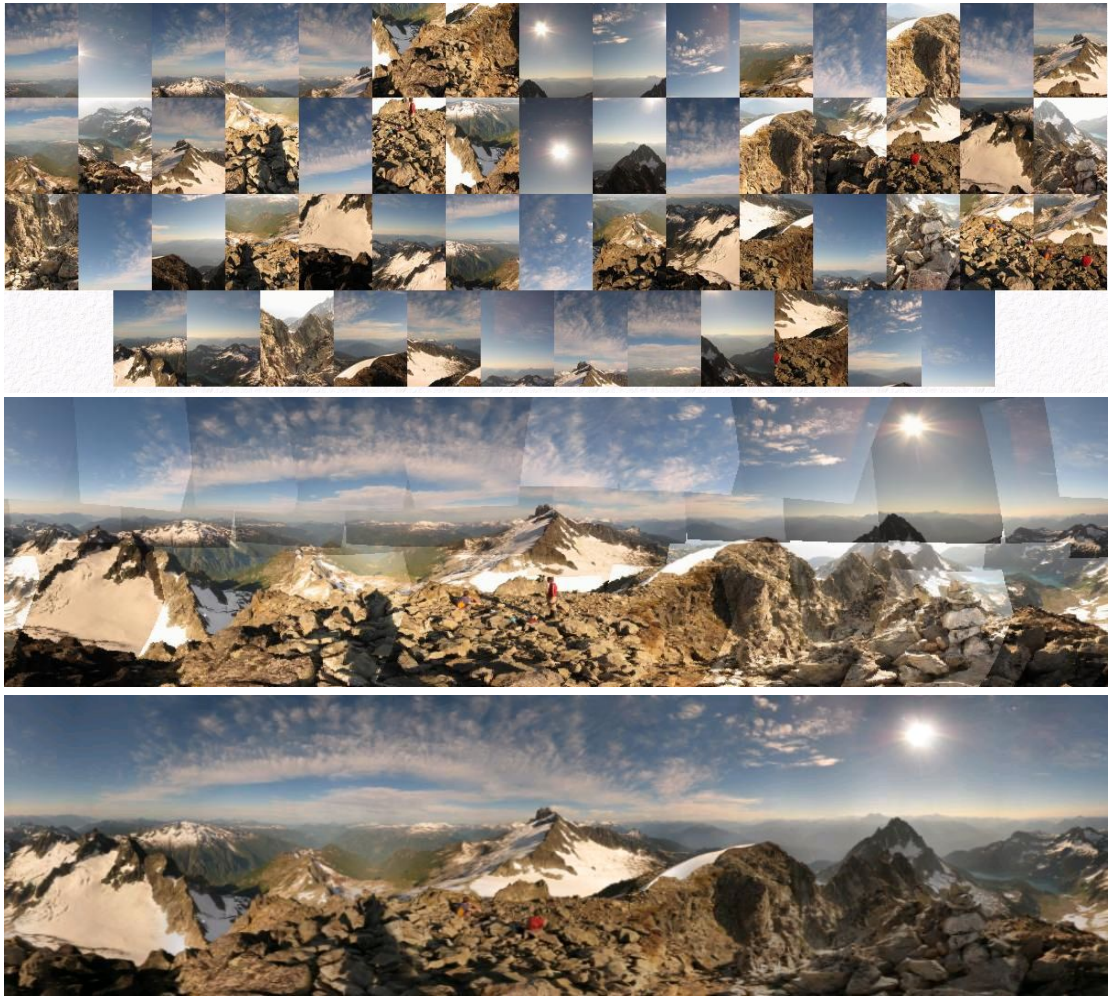
Automatic mosaicing



http://www.cs.ubc.ca/~mbrown/autostitch/autostitch.html

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Wide baseline stereo

[Image from T. Tuytelaars ECCV 2006 tutorial]

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Recognition of specific objects, scenes

Schmid and Mohr 1997

Sivic and Zisserman, 2003

Rothganger et al. 2003

Lowe 2002

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Applications of local invariant features

- Wide baseline stereo
- Motion tracking
- **Panoramas**
- Mobile robot navigation
- 3D reconstruction
- Recognition
- …

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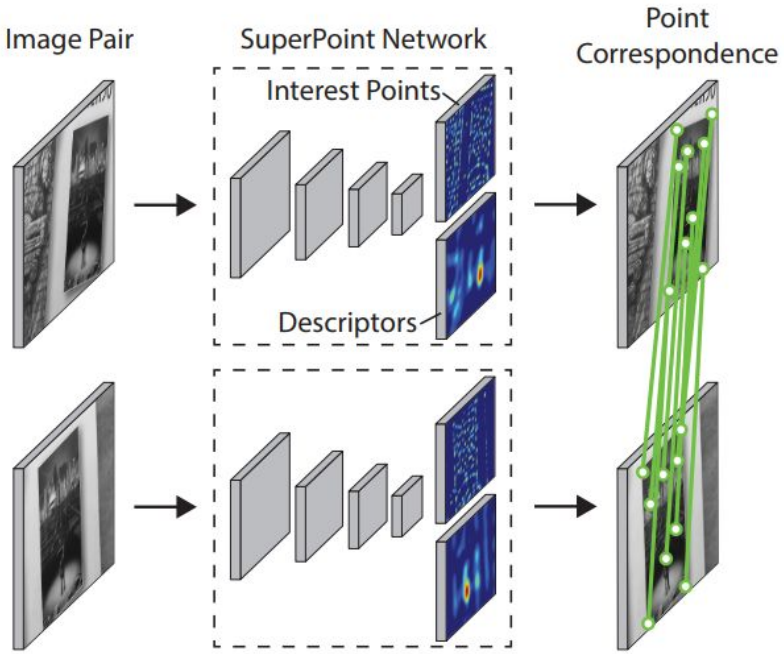
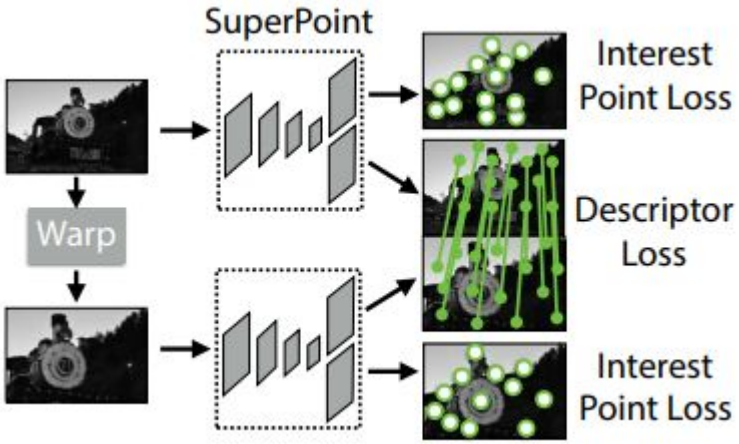
Deep learning based interest point detection & description





SuperPoint: Self-Supervised Interest Point Detection and Description (CVPRW'18)

Adapted from slides by Juan Carlos Niebles, and Ranjay Krishna

What we have learned

- Scale invariant region selection
  - Automatic scale selection
  - Difference-of-Gaussian (DoG) detector
- SIFT: an image region descriptor

Required reading:

- https://en.m.wikipedia.org/wiki/Scale-invariant_feature_transform

Some background reading: R. Szeliski, Ch 4.1.1; David Lowe, IJCV 2004

Adapted from slides by Juan Carlos Niebles, and Ranjay Krishna