CAP 5415 Computer Vision
Fall 2012

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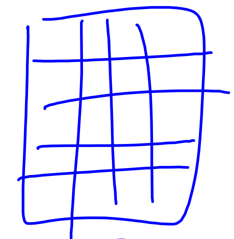
Lecture-5

SIFT: David Lowe, UBC

SIFT - Key Point Extraction

- Stands for scale invariant feature transform
- Patented by university of British Columbia
- Similar to the one used in primate visual system (human, ape, monkey, etc.)
- Transforms image data into scale-invariant coordinates

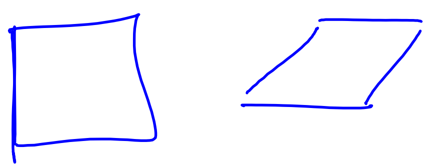


$$\begin{bmatrix} I_{xx} & I_{xy} \\ I_{yx} & I_{yy} \end{bmatrix}$$

D. Lowe. *Distinctive image features from scale-invariant key points.*, International Journal of Computer Vision 2004.

Goal

- Extracting distinctive invariant features
  - Correctly matched against a large database of features from many images
- Invariance to image scale and rotation
- Robustness to
  - Affine distortion,
  - Change in 3D viewpoint,
  - Addition of noise,
  - Change in illumination.



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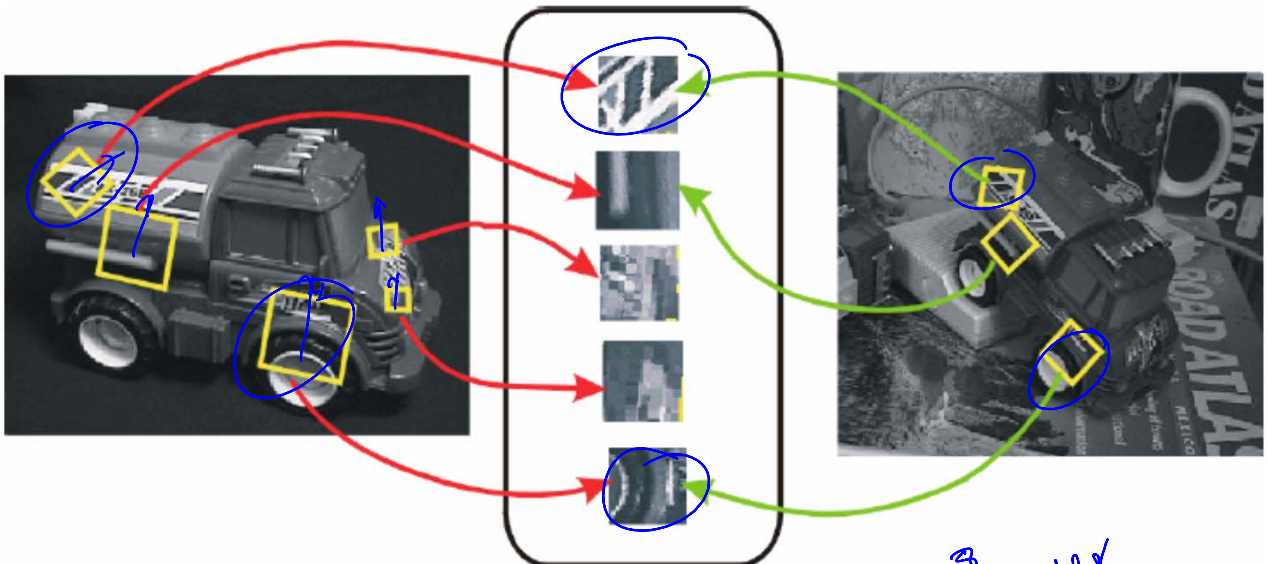
Advantages

- **Locality:** features are local, so robust to occlusion and clutter
- **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

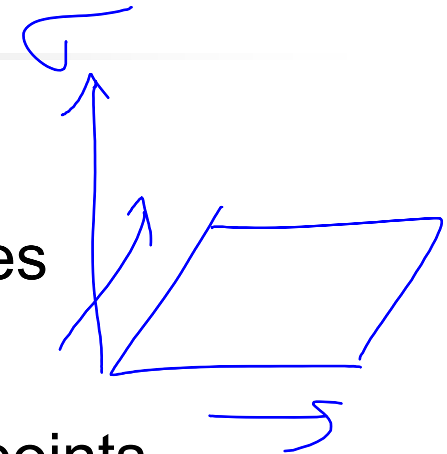
Invariant Local Features



SIFT Features

3 128

Steps for Extracting Key Points



- Scale space peak selection
  - Potential locations for finding features
- Key point localization
  - Accurately locating the feature key points
- Orientation Assignment
  - Assigning orientation to the key points
- Key point descriptor
  - Describing the key point as a high dimensional vector

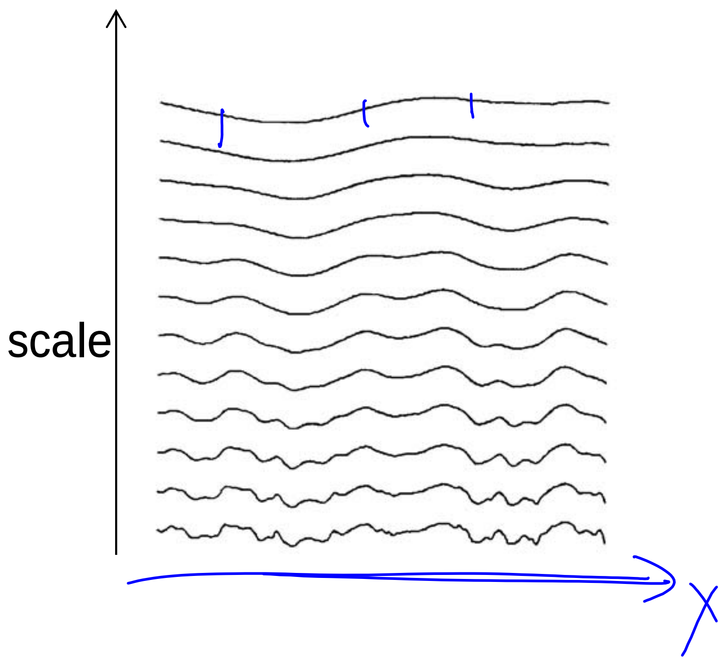
Scales

- What should be sigma value for Canny and LG edge detection?
- If use multiple sigma values (scales), how do you combine multiple edge maps?
- Marr-Hildreth:
  - *Spatial Coincidence* assumption:
    - Zerocrossings that coincide over several scales are physically significant.

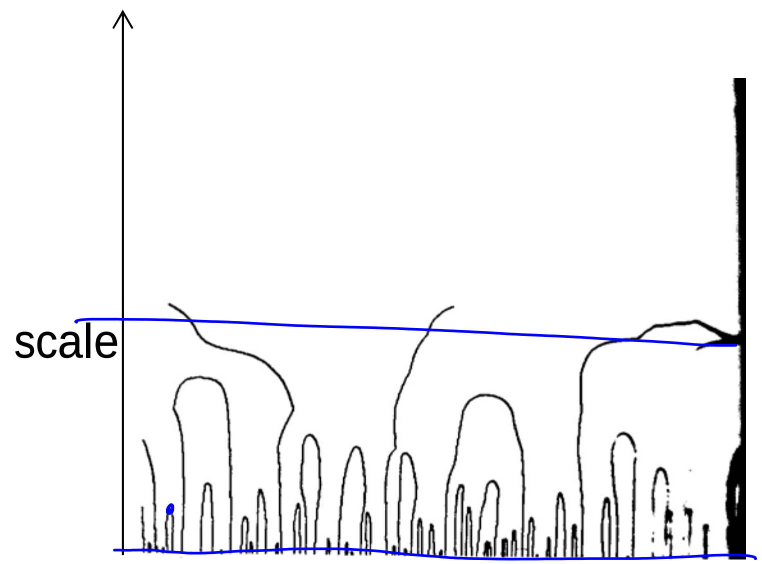
Scale Space (Witkin, IJCAI 1983)

- Apply whole spectrum of scales
- Plot zerocrossings vs scales in a scale-space

Scale Space

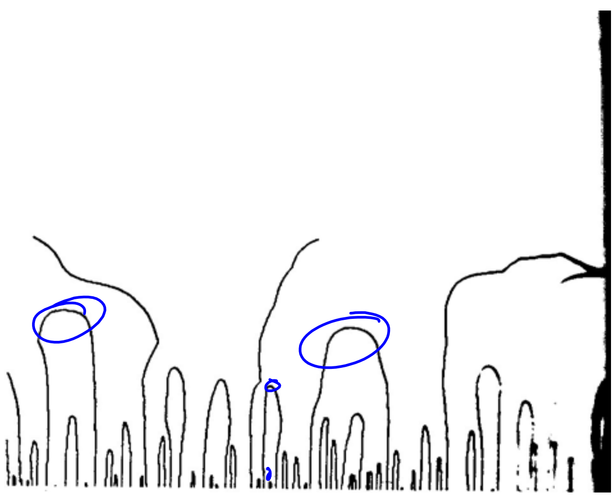


Multiple smooth versions of a signal

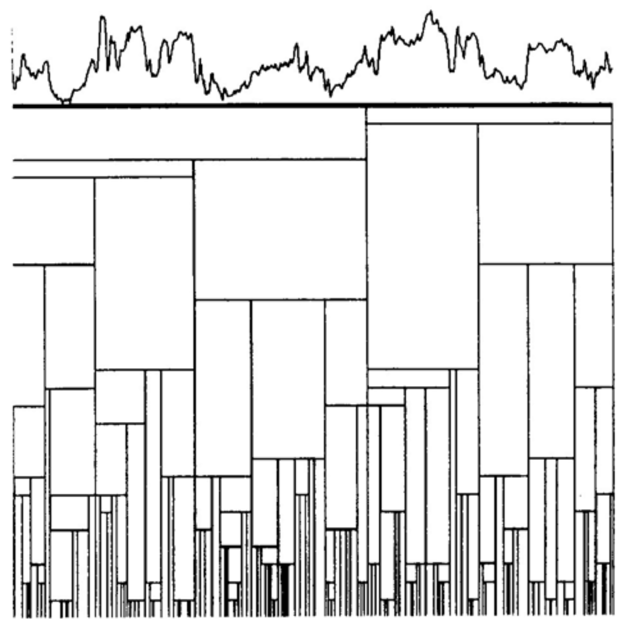


Zerocrossings at multiple scale

Scale Space



Scale Space



Interval Tree

Scale Space (Witkin, IJCAI 1983)

- Apply whole spectrum of scales
- Plot zerocrossings vs scales in a scale-space
- Interpret scale space contours
  - Contours are arches, open at the bottom, closed at the top
  - Interval tree
    - Each interval corresponds to a node in a tree, whose parent node represents larger interval, from which interval emerged, and whose off springs represent smaller intervals.
    - Stability of a node is a scale range over which the interval exits.

Scale Space

- Top level description
  - Iteratively remove nodes from the tree, splicing out nodes that are less stable than any of their parents and off springs

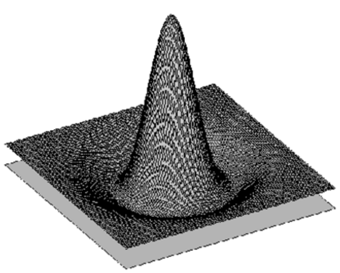
Scale Space

A top level description of several signals using stability criterion.

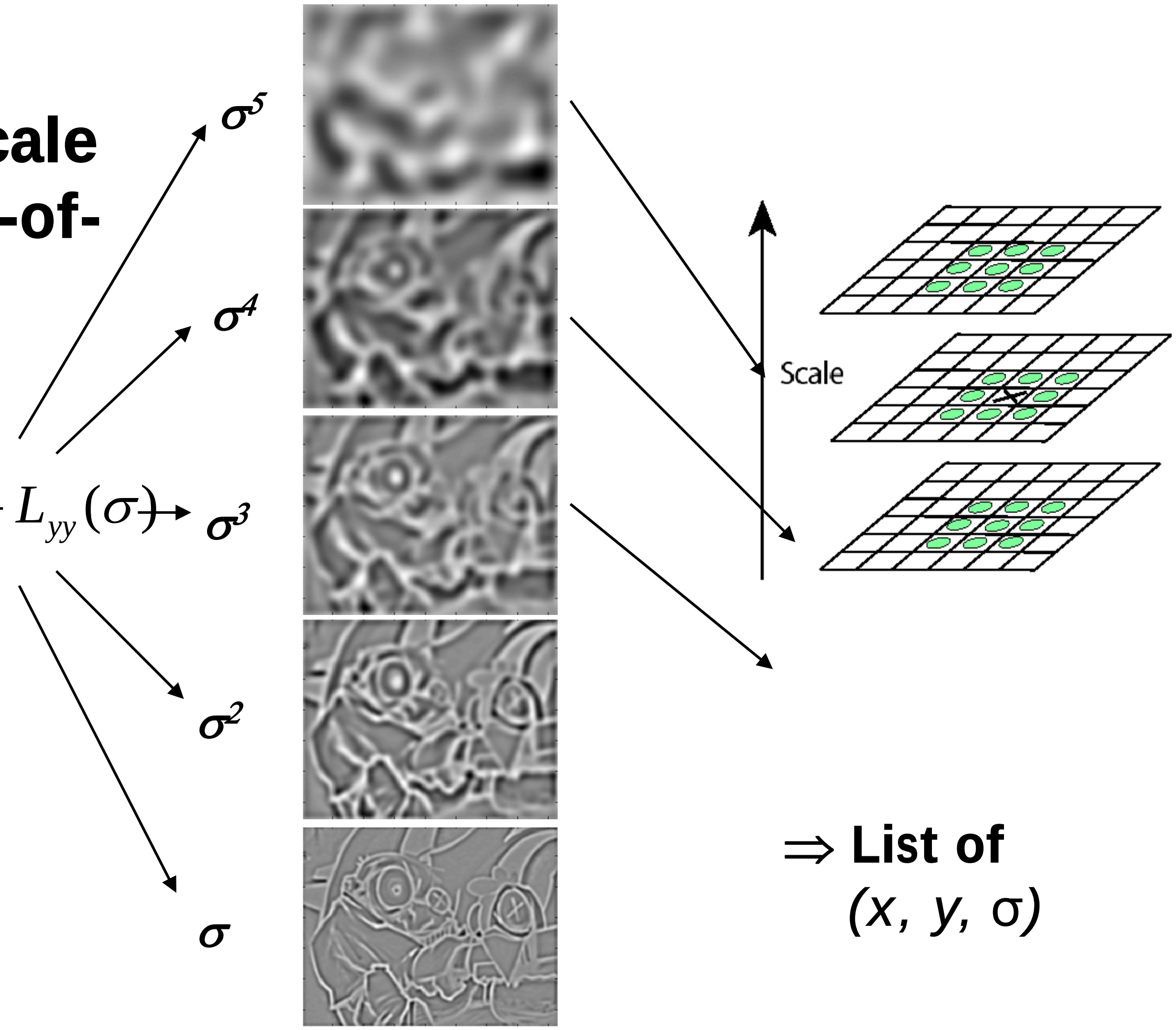
Laplacian-of-Gaussian (LoG)

- **Interest points:**

  Local maxima in scale space of Laplacian-of-Gaussian



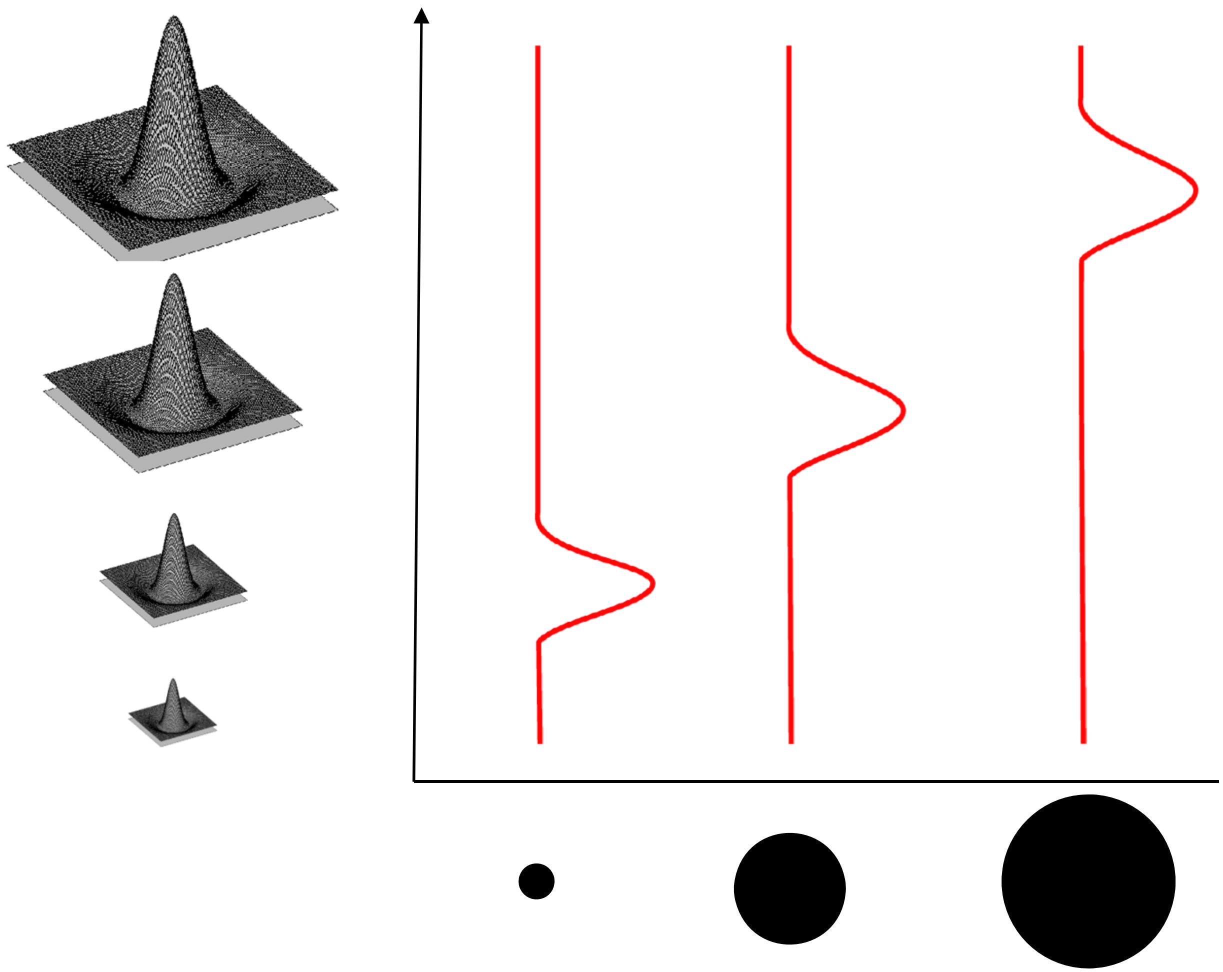
$$L_{xx}(\sigma) + L_{yy}(\sigma)$$



$\Rightarrow$ List of
(x, y, σ)

What Is A Useful Signature Function?

- **Laplacian-of-Gaussian = "blob" detector**



Scale-space blob detector: Example

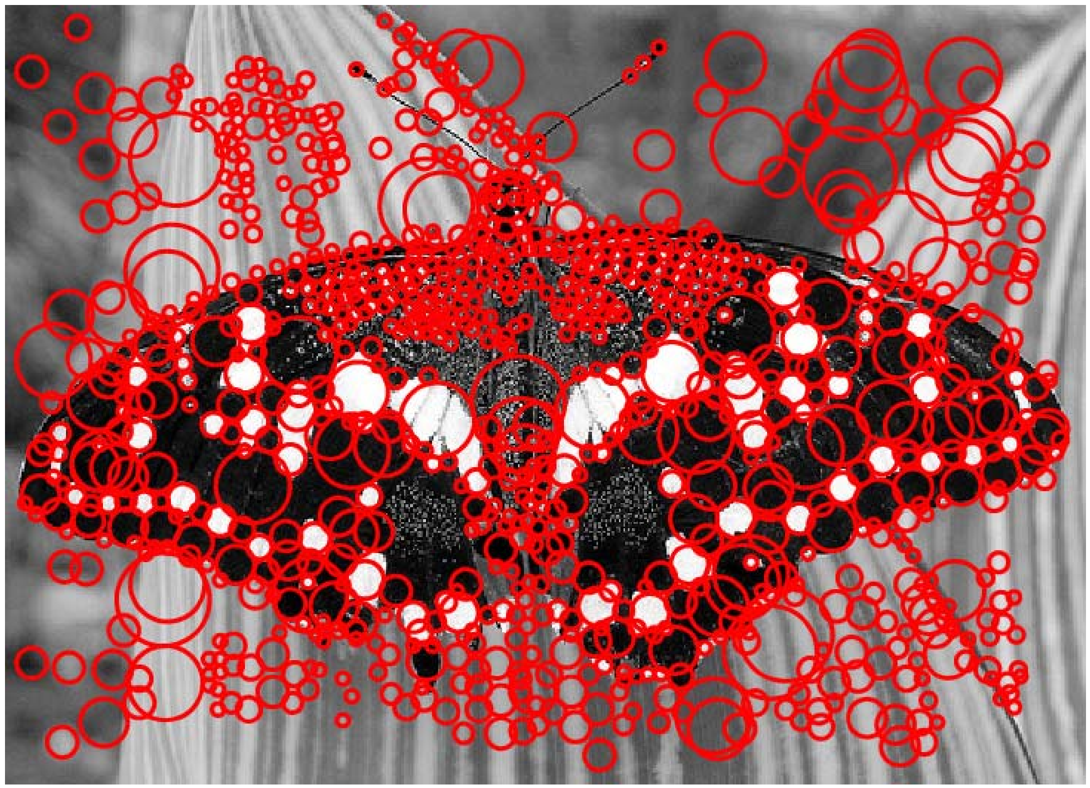
Source: Lana Lazebnik

Scale-space blob detector: Example

sigma = 11.9912

Source: Lana Lazebnik

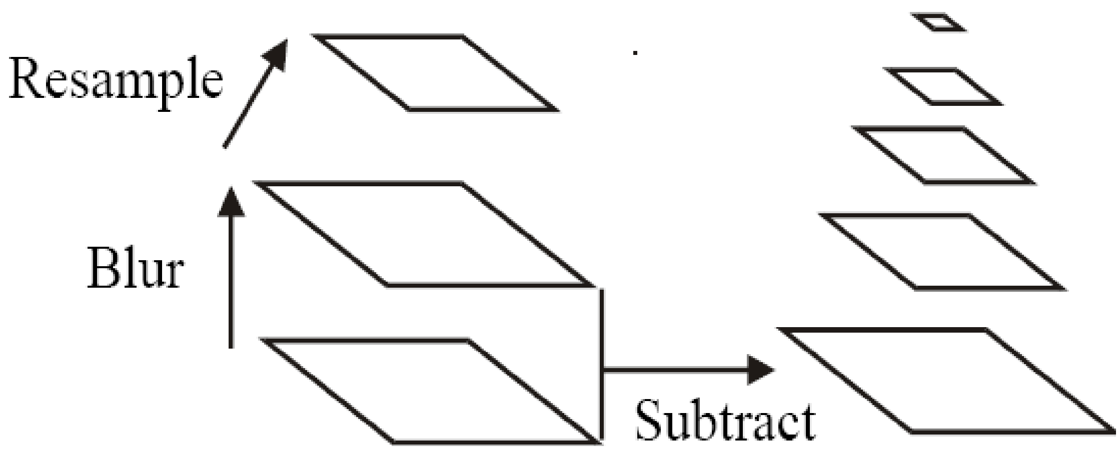
Scale-space blob detector: Example



Source: Lana Lazebnik

Building a Scale Space

- All scales must be examined to identify scale-invariant features
- An efficient function is to compute the Laplacian Pyramid (Difference of Gaussian) (Burt & Adelson, 1983)



Approximation of LoG by Difference of Gaussians

$$\frac{\partial G}{\partial \sigma} = \sigma \Delta^2 G$$

Heat Equation

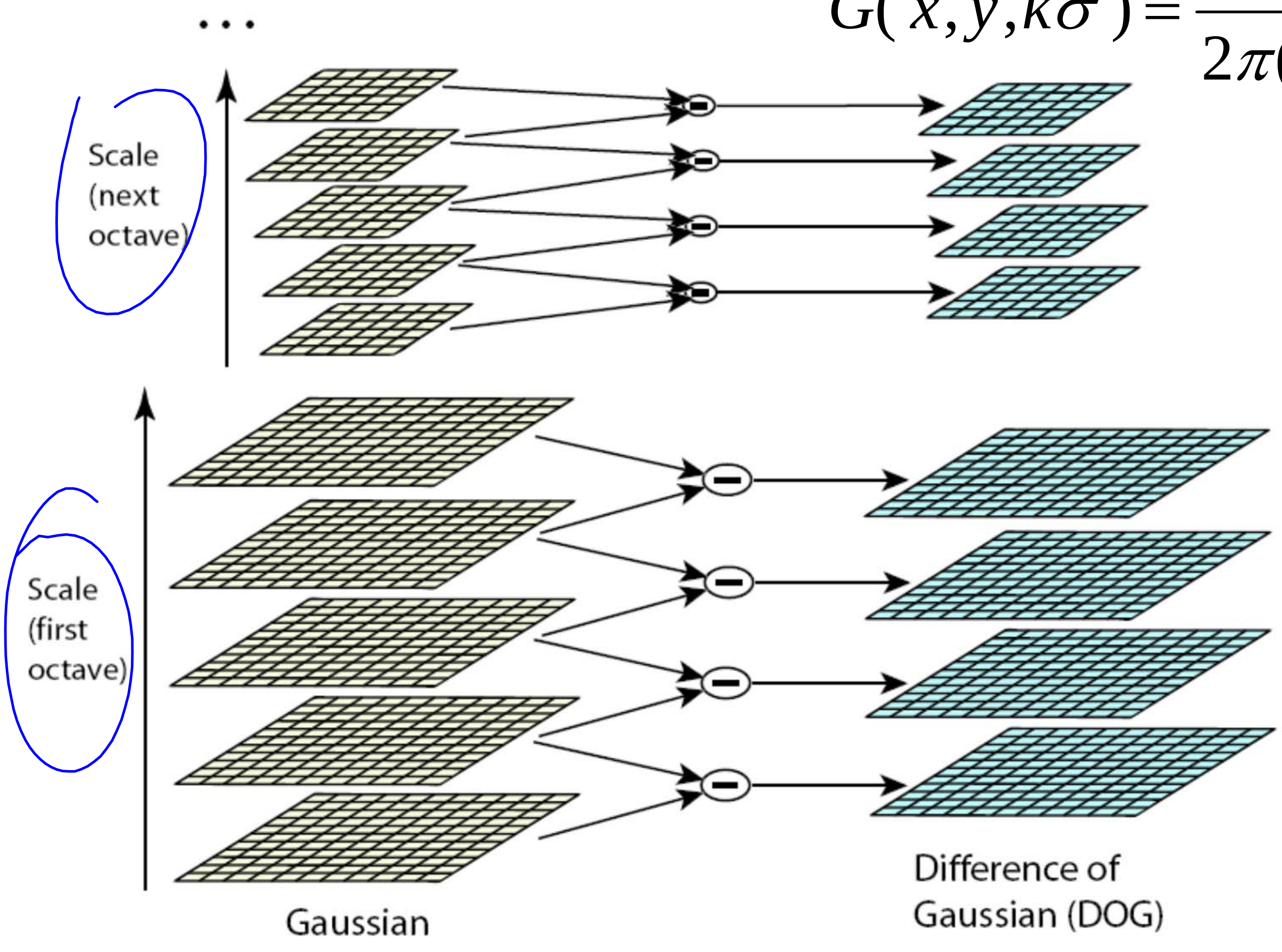
$$\sigma \Delta^2 G = \frac{\partial G}{\partial \sigma} = \frac{G(x, y, k\sigma) - G(x, y, \sigma)}{k\sigma - \sigma}$$

$$G(x, y, k\sigma) - G(x, y, \sigma) \approx (k-1)\sigma^2 \Delta^2 G$$

$$\text{Typical values}: \sigma = 1.6;\ k = \sqrt{2}$$

Building a Scale Space

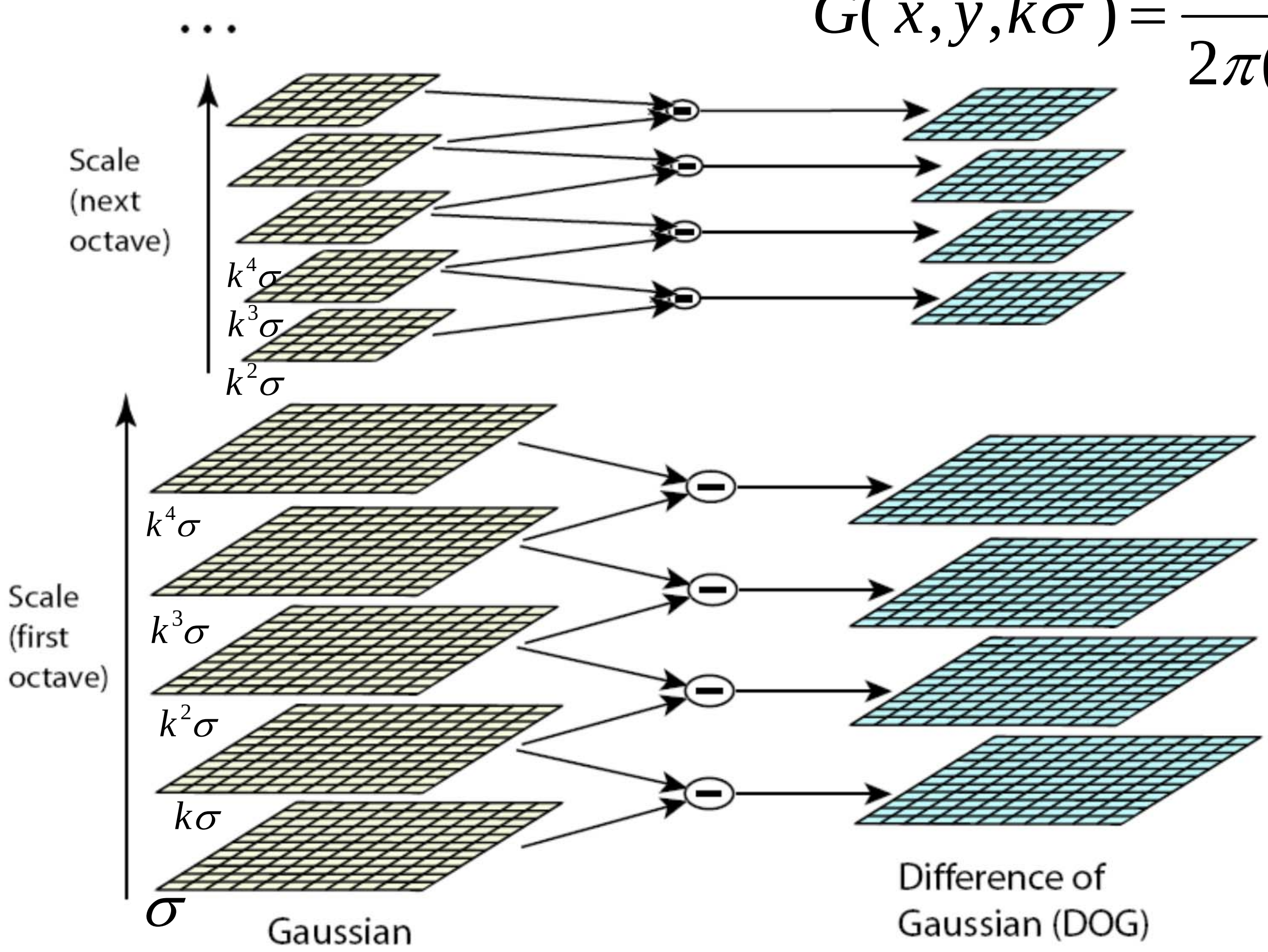
$$G(x,y,k\sigma)=\frac{1}{2\pi(k\sigma)^2}e^{-(x^2+y^2)/2k^2\sigma^2}$$



$$k=\sqrt{2}$$

Building a Scale Space

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



$$k=\sqrt{2}$$

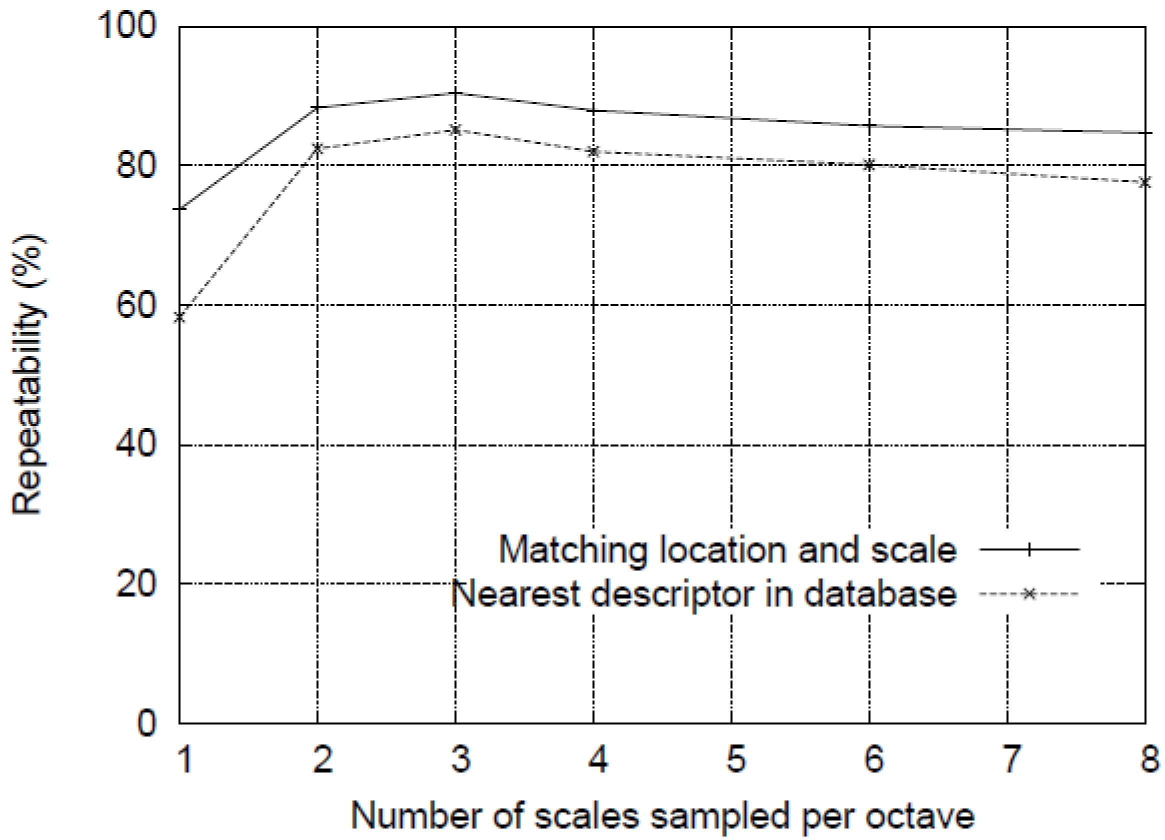
scale $\rightarrow$

octave

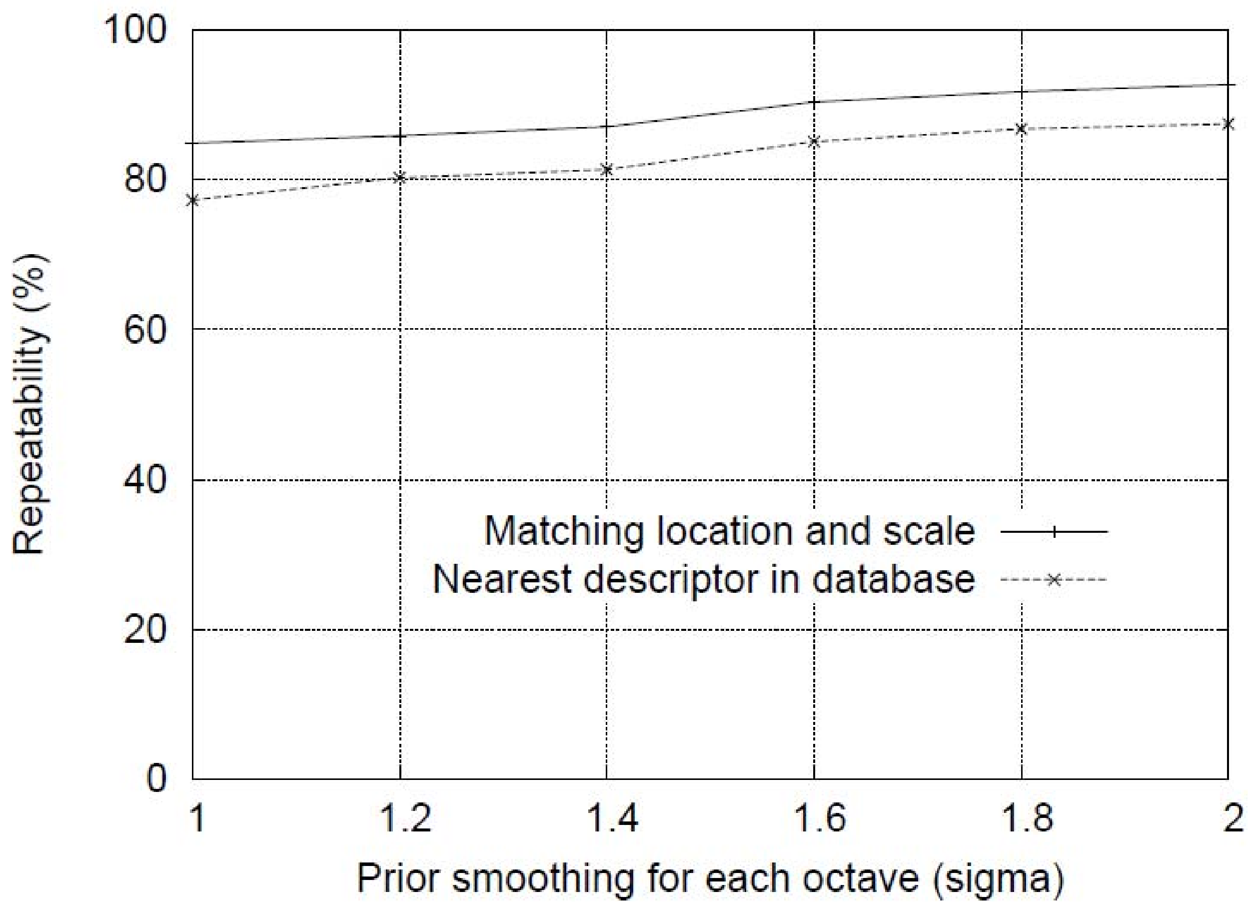
0.707107	1.000000	1.414214	2.000000	2.828427
1.414214	2.000000	2.828427	4.000000	5.656854
2.828427	4.000000	5.656854	8.000000	11.313708
5.656854	8.000000	11.313708	16.000000	22.627417

$$\sigma = .707187.6; \; k = \sqrt{2}$$

How many scales per octave?

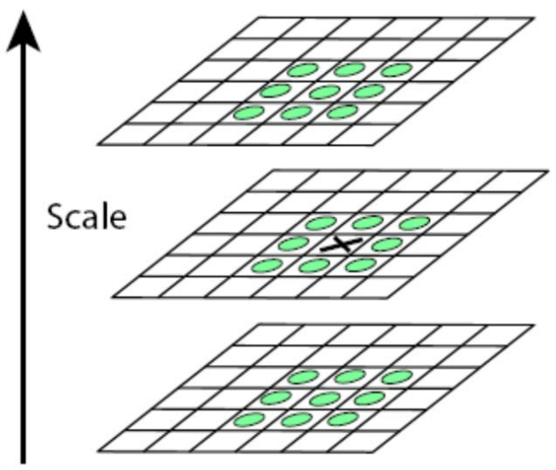


Initial value of sigma



Scale Space Peak Detection

- Compare a pixel (**X**) with 26 pixels in current and adjacent scales (Green Circles)
- Select a pixel (**X**) if larger/smaller than all 26 pixels
- Large number of extrema, computationally expensive
  - Detect the most stable subset with a coarse sampling of scales



Key Point Localization

- Candidates are chosen from extrema detection

original image

extrema locations

Initial Outlier Rejection

1. Low contrast candidates
2. Poorly localized candidates along an edge

- Taylor series expansion of DOG, $\mathbf{D}$.

$$\boxed{D(\mathbf{x}) = D + \frac{\partial D}{\partial \mathbf{x}}^T \mathbf{x} + \frac{1}{2}\mathbf{x}^T \frac{\partial^2 D}{\partial \mathbf{x}^2}\mathbf{x}} \qquad \mathbf{x} = (x, y, \sigma)^T$$

Homework

- Minima or maxima is located at $\hat{\mathbf{x}} = -\frac{\partial^2 D}{\partial \mathbf{x}^2}^{-1} \frac{\partial D}{\partial \mathbf{x}}$
- Value of $D(x)$ at minima/maxima must be large, $|D(x)|>th$.

Initial Outlier Rejection

from 832 key points to 729 key points, th=0.03.

Further Outlier Rejection

- DOG has strong response along edge
- Assume DOG as a surface
  - Compute principal curvatures (PC)
  - Along the edge one of the PC is very low, across the edge is high

Further Outlier Rejection

- Analogous to Harris corner detector
- Compute Hessian of D

$$\mathbf{H} = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}$$

$$Tr(H) = D_{xx} + D_{yy} = \lambda_1 + \lambda_2$$

$$Det(H) = D_{xx} D_{yy} - (D_{xy})^2 = \lambda_1 \lambda_2$$

- Remove outliers by evaluating

$$\frac{Tr(H)^2}{Det(H)} = \frac{(r+1)^2}{r} \qquad r = \frac{\lambda_1}{\lambda_2}$$

Further Outlier Rejection

- Following quantity is minimum when *r*=1
- It increases with *r*

$$r = \frac{\lambda_1}{\lambda_2}$$

$$\frac{Tr(H)^2}{Det(H)} = \frac{(r+1)^2}{r}$$

- Eliminate key points if $r > 10$

Further Outlier Rejection

from 729 key points to 536 key points.

Orientation Assignment

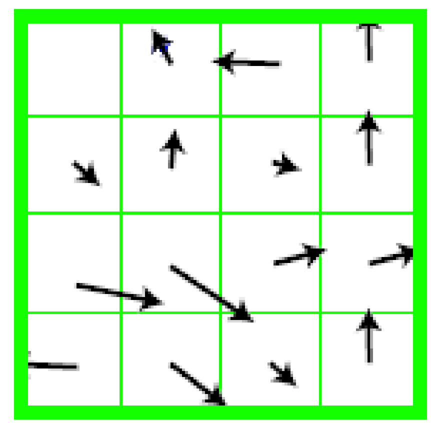
- To achieve rotation invariance
- Compute central derivatives, gradient magnitude and direction of *L (*smooth image) at the scale of key point (x,y)

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2}$$

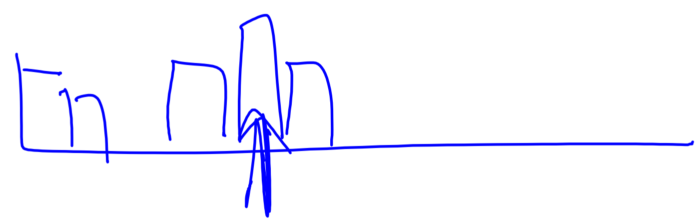
$$\theta(x,y) = \tan^{-1}((L(x,y+1) - L(x,y-1))/(L(x+1,y) - L(x-1,y)))$$

Orientation Assignment

- Create a weighted direction histogram in a neighborhood of a key point (36 bins)

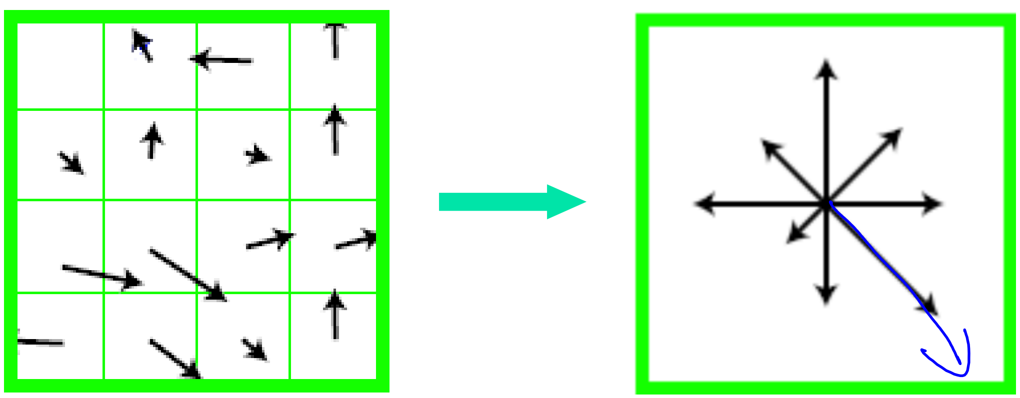


- Weights are
  - Gradient magnitudes
  - Spatial gaussian filter with σ=1.5 x <scale of key point>



Orientation Assignment

- Select the peak as direction of the key point
- Introduce additional key points (same location) at local peaks (within 80% of max peak) of the histogram with different directions



Local Image Descriptors at Key Points

- Possible descriptor
  - Store intensity samples in the neighborhood
  - Sensitive to lighting changes, 3D object transformation
- Use of gradient orientation histograms
  - Robust representation

Similarity to IT cortex

- Complex neurons respond to a gradient at a particular orientation.
- Location of the feature can shift over a small receptive field.
- Edelman, Intrator, and Poggio (1997)
  - The function of the cells allow for matching and recognition of 3D objects from a range of view points.
- Experiments show better recognition accuracy for 3D objects rotated in depth by up to 20 degrees

Extraction of Local Image Descriptors at Key Points

- Compute relative orientation and magnitude in a 16x16 neighborhood at key point
- Form weighted histogram (8 bin) for 4x4 regions
  - Weight by magnitude and spatial Gaussian
  - Concatenate 16 histograms in one long vector of 128 dimensions
- Example for 8x8 to 2x2 descriptors

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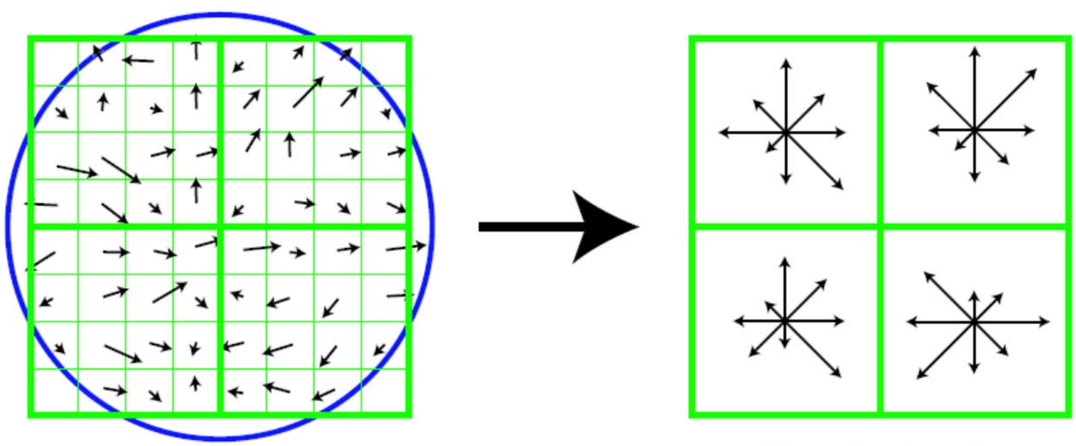
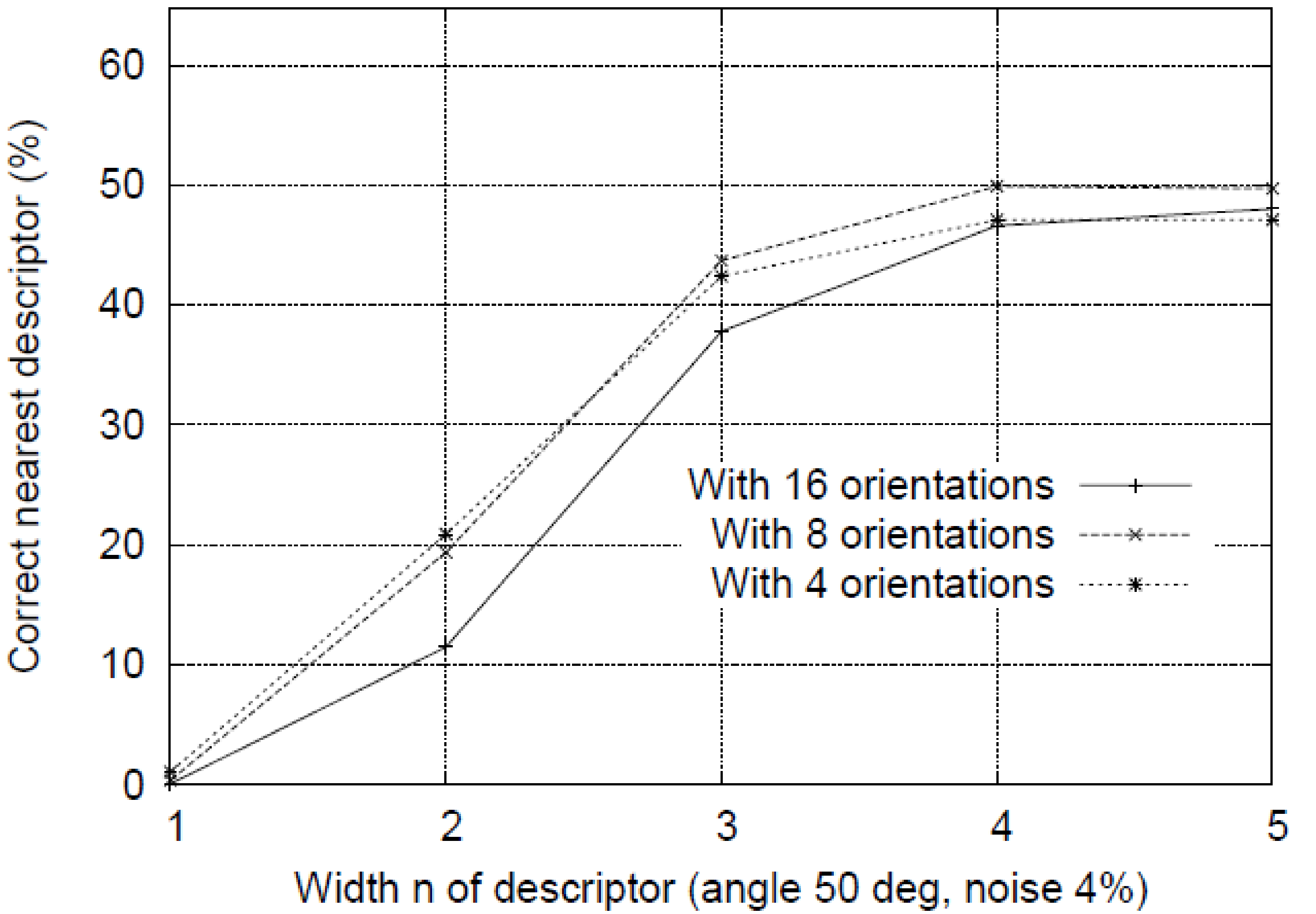


Image gradients — Keypoint descriptor

Descriptor Regions (n by n)



Extraction of Local Image Descriptors at Key Points

- Store numbers in a vector
- Normalize to unit vector (**UN**)
  - Illumination invariance (affine changes)
- For non-linear intensity transforms
  - Bound **Unit Vector** items to maximum 0.2 (remove larger gradients)
  - Renormalize to unit vector

Key point matching

- Match the key points against a database of that obtained from training images.
- Find the nearest neighbor i.e. a key point with minimum Euclidean distance.
  - Efficient Nearest Neighbor matching
    - Looks at ratio of distance between best and 2nd best match (.8)

Matching local features

Kristen Grauman

Matching local features

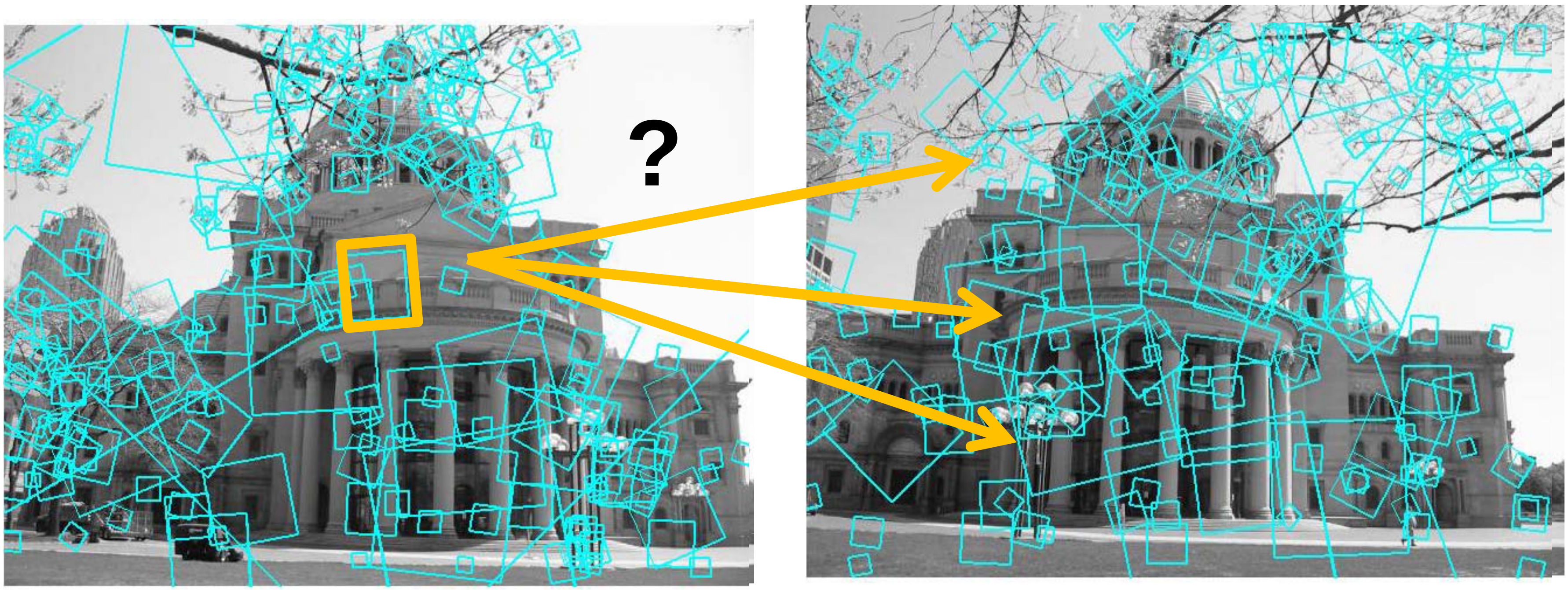


Image 1 Image 2

- To generate **candidate matches**, find patches that have the most similar appearance or SIFT descriptor
- Simplest approach: compare them all, take the closest (or closest k, or within a thresholded distance)

Kristen Grauman

Ambiguous matches

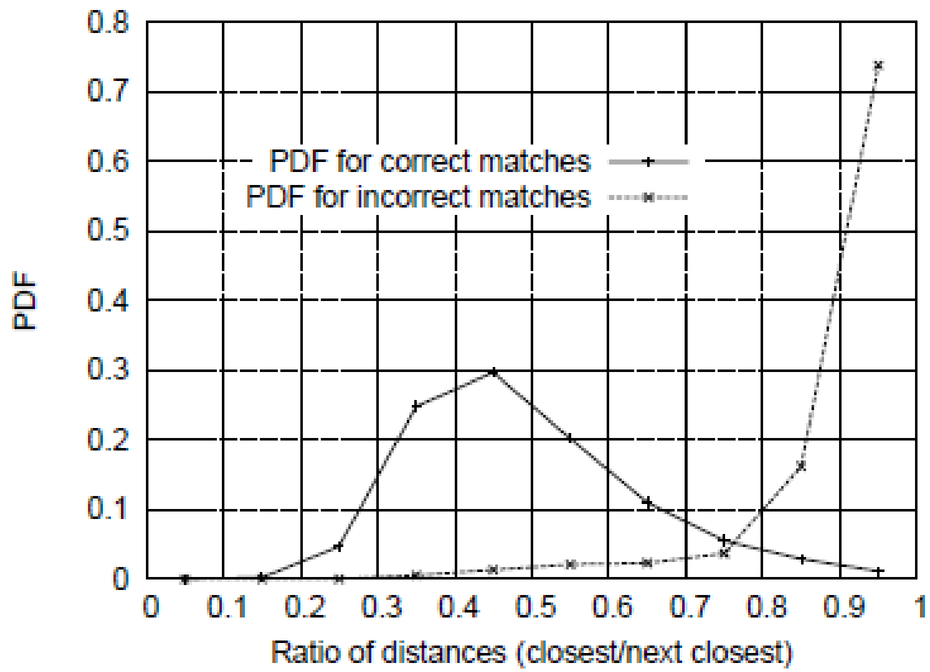
Image 1

Image 2

- At what distance do we have a good match?
- To add robustness to matching, can consider **ratio** : distance to best match / distance to second best match
- If low, first match looks good.
- If high, could be ambiguous match.

Kristen Grauman

The ratio of distance from the closest to the distance of the second closest



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