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# Scale Invariant Feature Transform (SIFT)

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# Aim

- 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

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

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**Distinctiveness:** individual features can be matched to a large database of objects

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**Quantity:** many features can be generated for even small objects

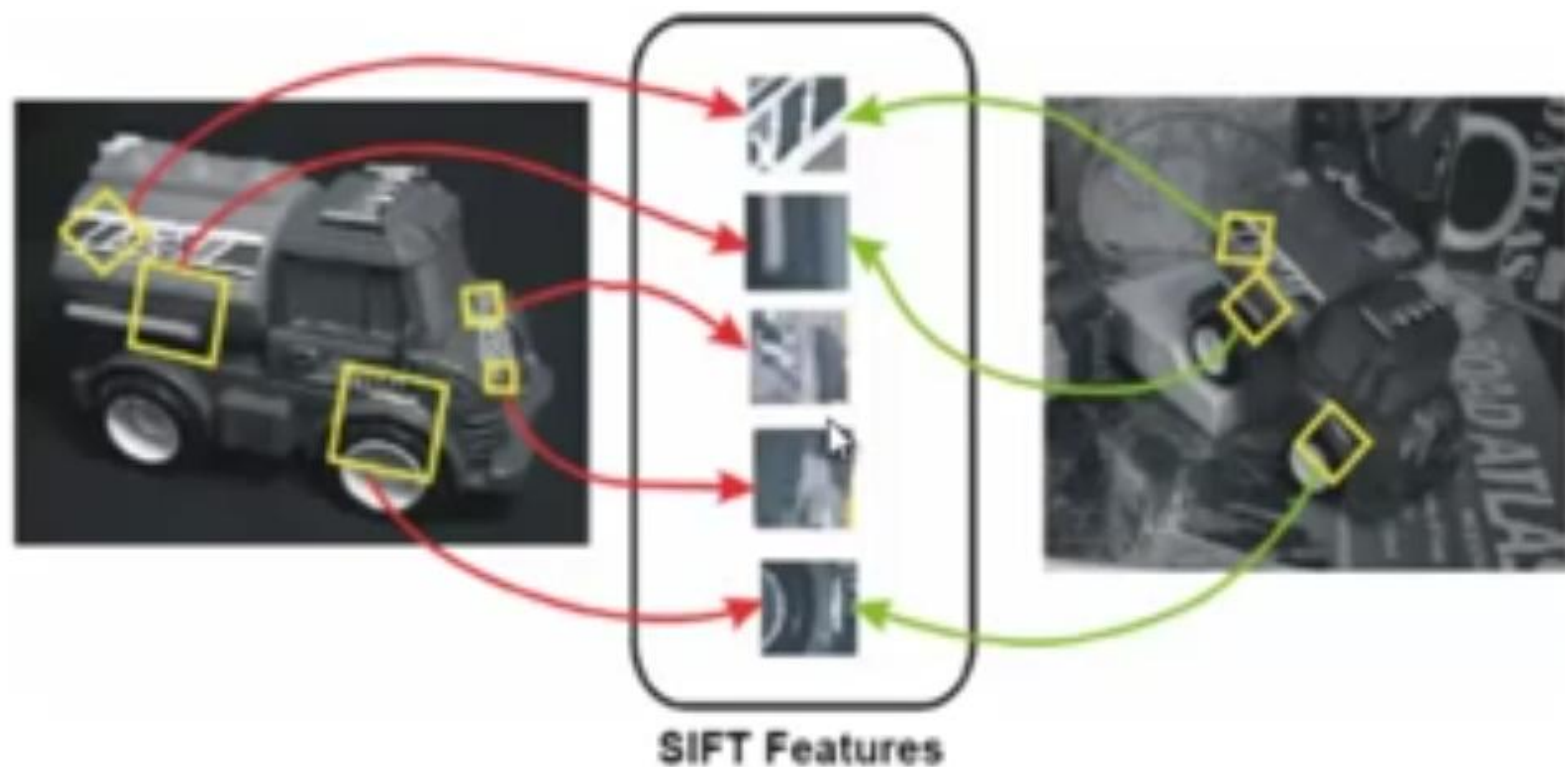
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**Efficiency:** close to real-time performance

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# Invariant Local features



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# Steps for Extracting Key Points

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**Scale space peak selection:** Potential locations for finding features

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**Key point localization:** Accurately locating the feature key points

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**Orientation Assignment:** Assigning orientation to the key points

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**Key point descriptor:** Describing the key point as a high dimensional vector

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# Scale

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What should be sigma value for Canny and LoG edge detection?

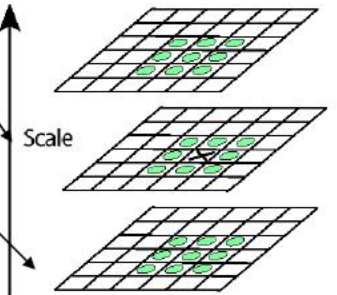
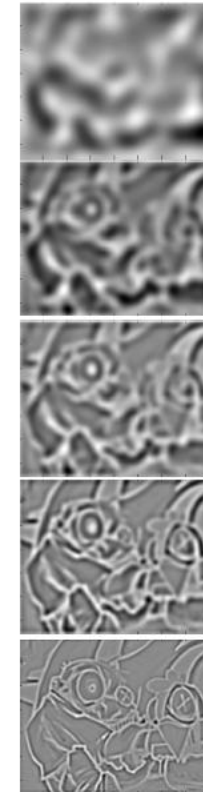
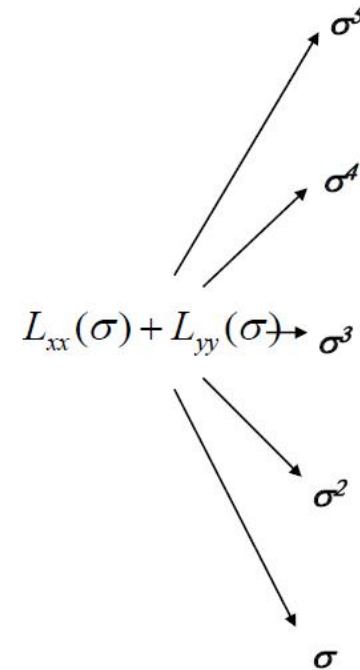
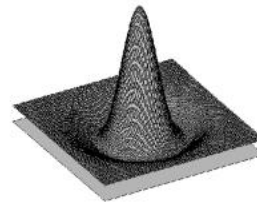
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If use multiple sigma values (scales), how do you combine multiple edge maps?

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# Laplacian of Gaussian (LoG)

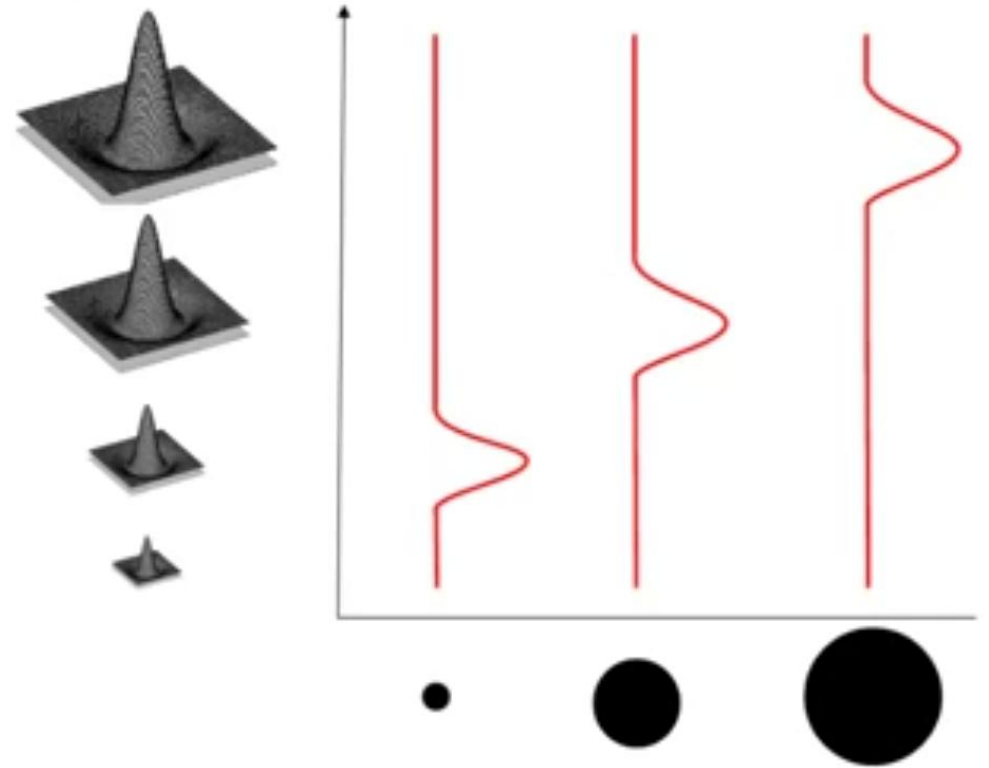
**Interest points:** Local maxima in scale space of Laplacian-of-Gaussian



$\Rightarrow$  List of  $(x, y, \sigma)$

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# Laplacian of Gaussian (LoG)





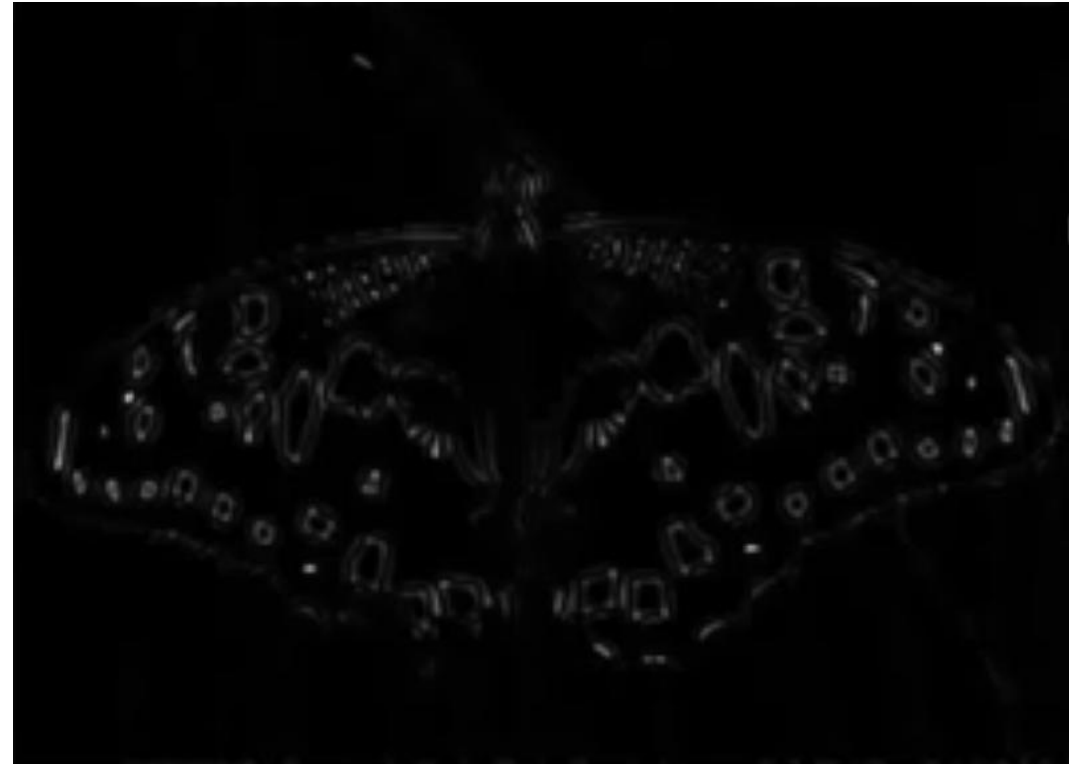
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# Scale Space



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Scale Space:  
Sigma value 2



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Scale Space:  
Sigma value  
 $\sim 2.5$



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Scale Space:  
Sigma value  $\sim 3$



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Scale Space:  
Sigma value  $\sim 4$



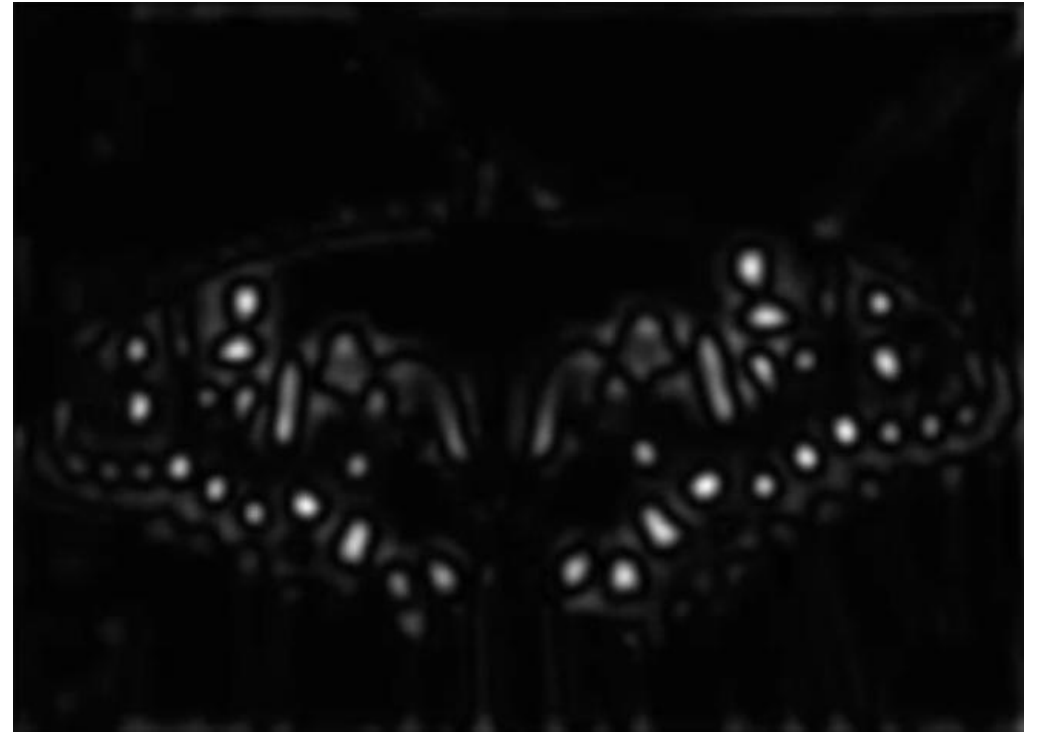
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Scale Space:  
Sigma value  $\sim 5$



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Scale Space:  
Sigma value  $\sim 6$



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Scale Space:  
Sigma value  
 $\sim 7.5$





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Scale Space:  
Sigma value  
 $\sim 9.5$



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Scale Space:  
Sigma value  $\sim 11$

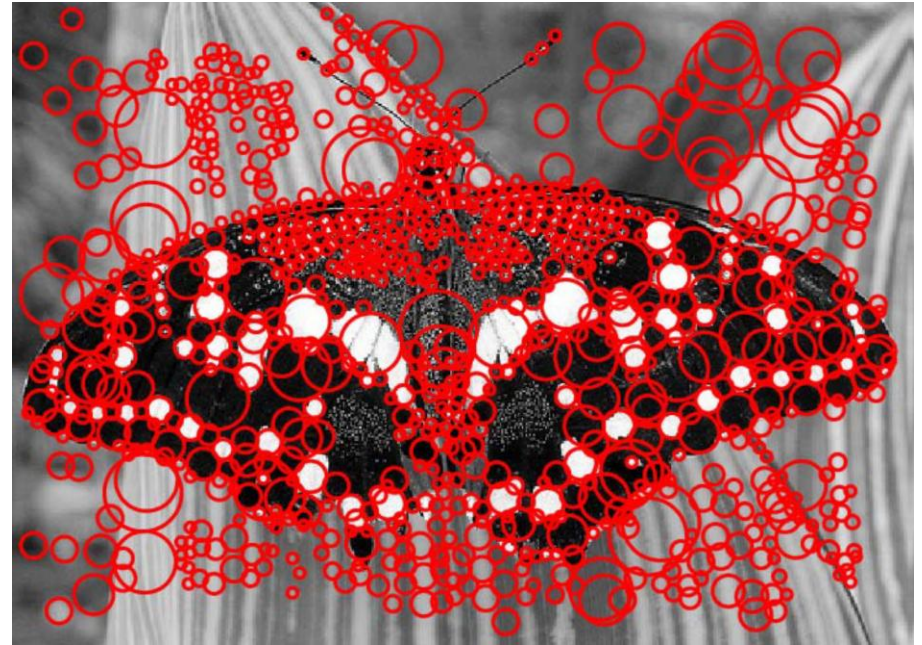




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# Scale Space

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# 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)

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# LoG and DoG

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

Heat Equation

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

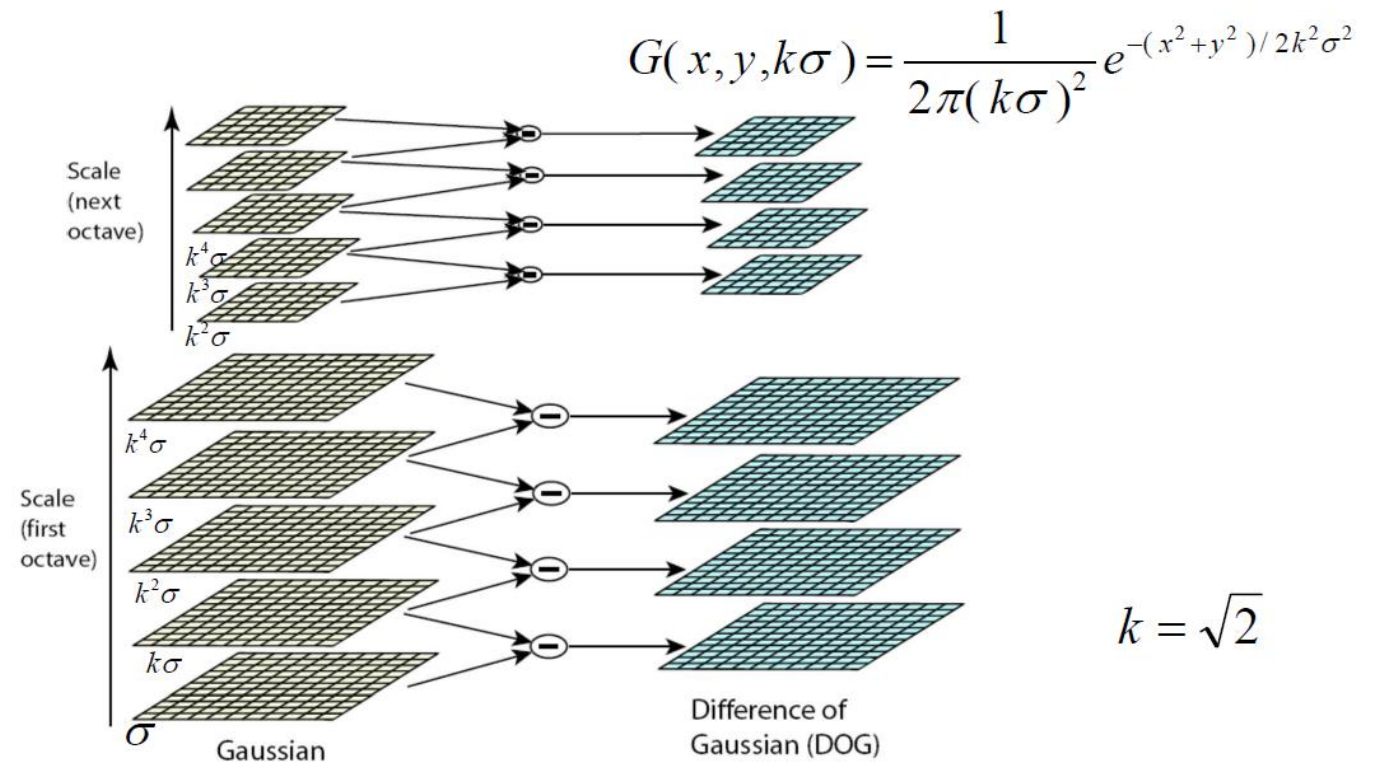
$$G(x, y, k\sigma) - G(x, y, \sigma) \approx (k - 1)\sigma^2 \Delta^2 G$$

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

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# Building a Scale Space



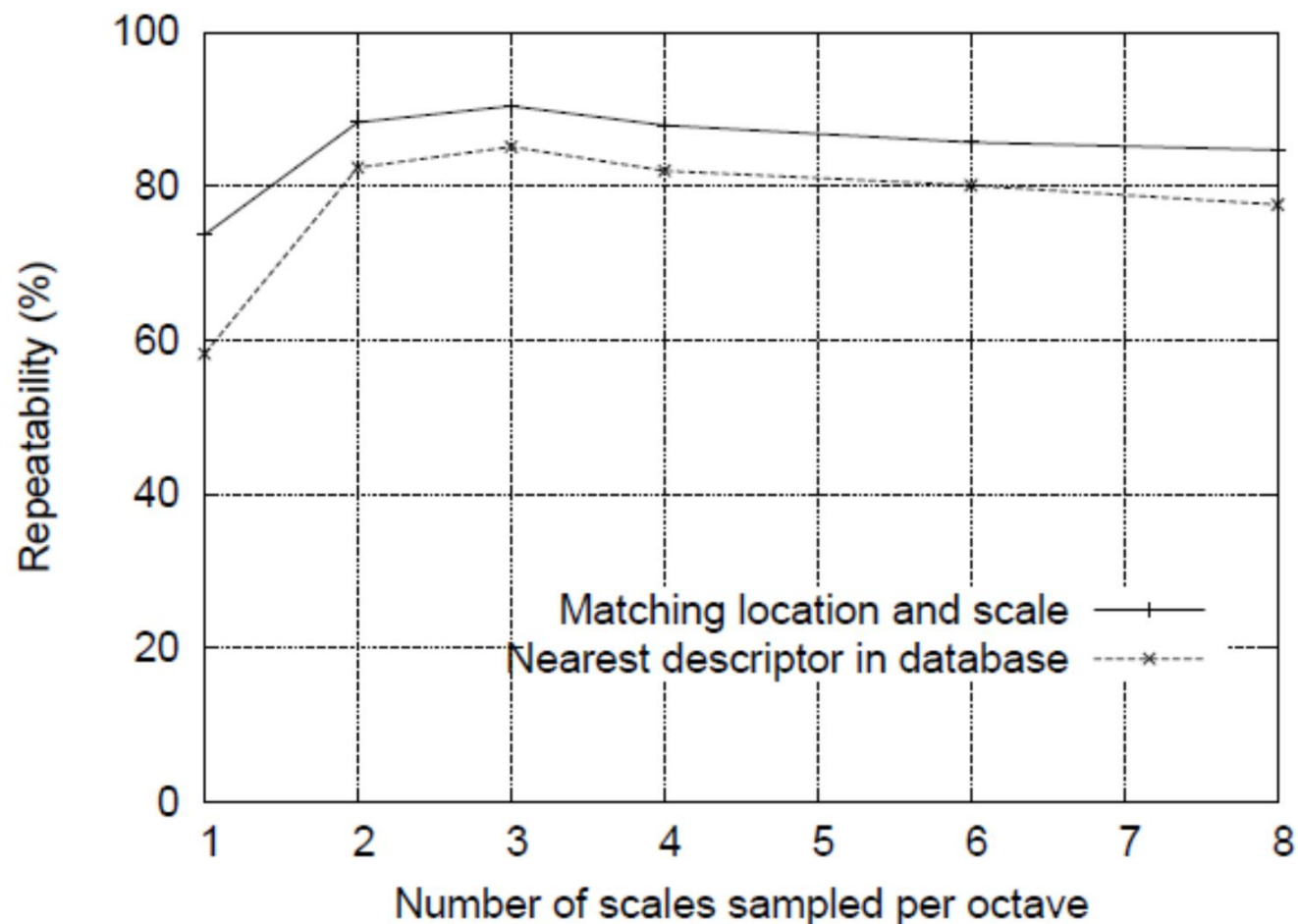
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# Scale & Octave

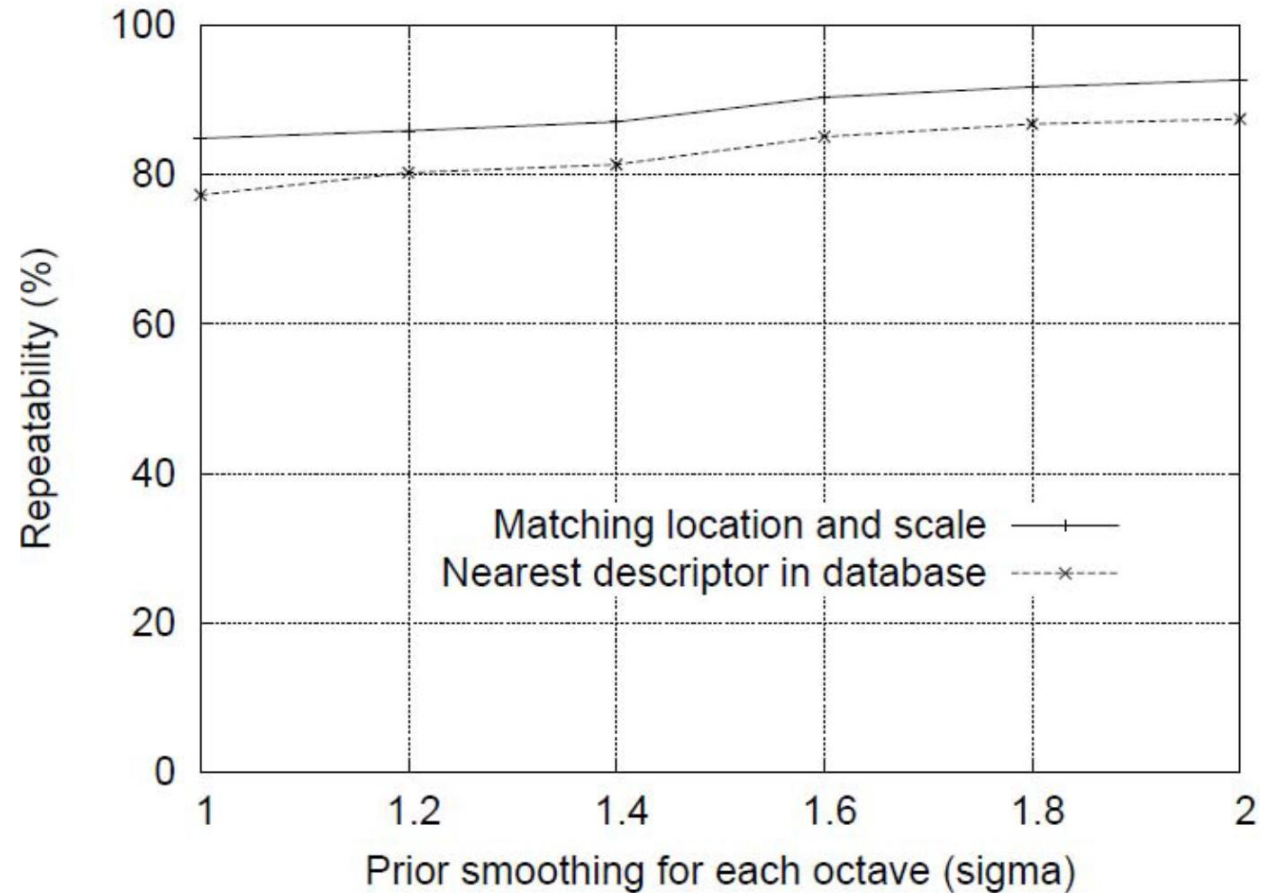
	scale 				
octave	0.707107	1.000000	1.414214	2.000000	2.828427
	1.414214	2.000000	2.828427	4.000000	5.656854
	2.828427	4.000000	5.656854	8.000000	11.313708
	5.656854	8.000000	11.313708	16.000000	22.627417



# How many Scale per Octave?



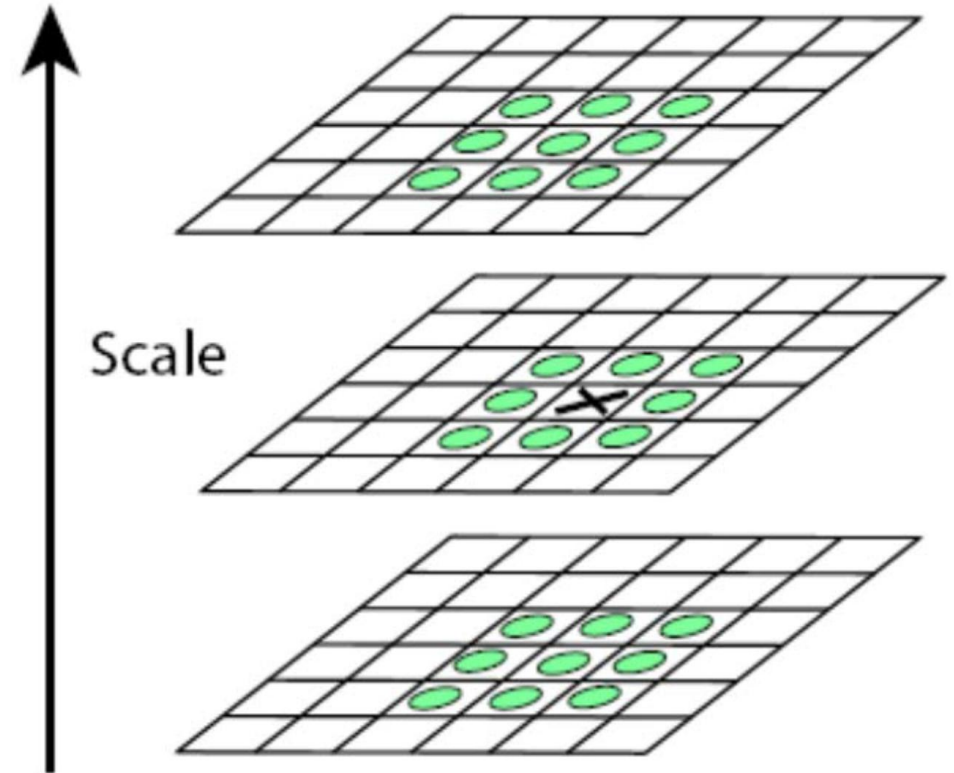
# Initial value of Sigma?



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# 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



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# Initial Outlier Rejection

Low contrast candidates

Poorly localized candidates along an edge

Taylor series expansion of DoG, **D**

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

Extrema is located at

$$\hat{\mathbf{x}} = -\frac{\partial^2 D}{\partial \mathbf{x}^2}^{-1} \frac{\partial D}{\partial \mathbf{x}}$$

Value of  $D(\mathbf{x})$  at extrema must be large,  $|D(\mathbf{x})| > Th$

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# Initial Outlier Rejection

832 interest points to 729 interest points

Th = 0.03



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# Further Outlier Rejection

DoG has strong response along edge

Assume DoG as a surface

- Compute principle curvature (PC)
  - Along the edge, one of the PC is very low, across the edge high
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# Further Outlier Rejection

Compute Hessian of D

$$\mathbf{H} = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix} \quad \begin{aligned} \text{Tr}(\mathbf{H}) &= D_{xx} + D_{yy} = \lambda_1 + \lambda_2 \\ \text{Det}(\mathbf{H}) &= D_{xx}D_{yy} - (D_{xy})^2 = \lambda_1\lambda_2 \end{aligned}$$

Remove outliers by evaluating

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

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# Further Outlier Rejection

Eliminate interest point if  $r > 10$

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

# Further Outlier Rejection

729 interest points to 536 interest points



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# Orientation Assignment

To achieve rotation invariance

Compute central derivatives, gradient magnitude and direction of  $L$  at the scale of interest point  $(x,y)$

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

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

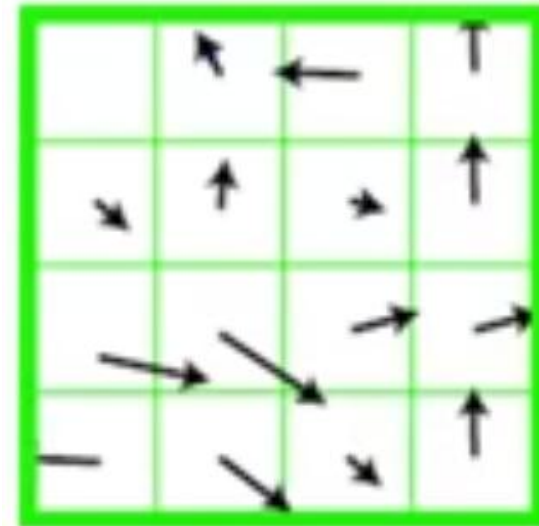
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# Orientation Assignment

Create a weighted direction histogram in a neighbourhood of an interest point

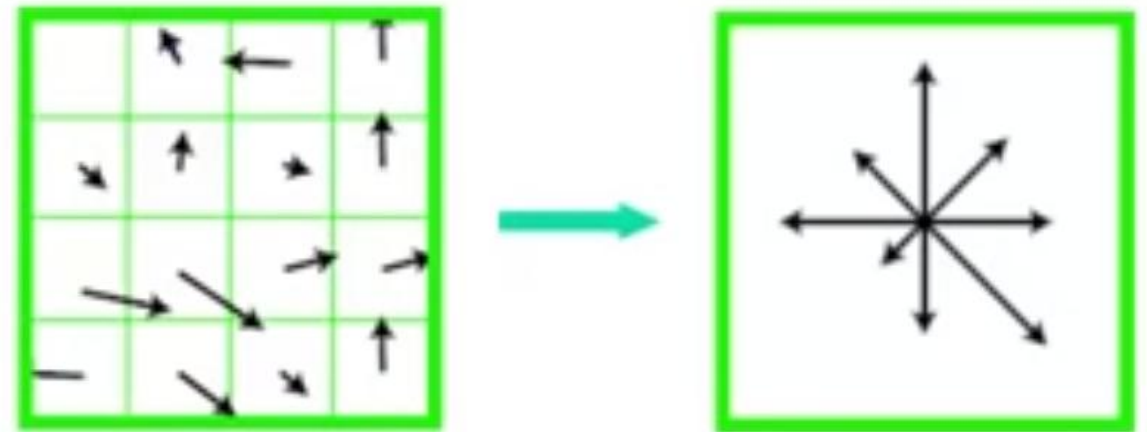
Weights are Gradient magnitude and spatial Gaussian



# Orientation Assignment

Select the peak as direction of the interest point

Introduce additional interest points (same location) at local peaks (within 80% of the max peak) of the histogram with different directions



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# SIFT Descriptor

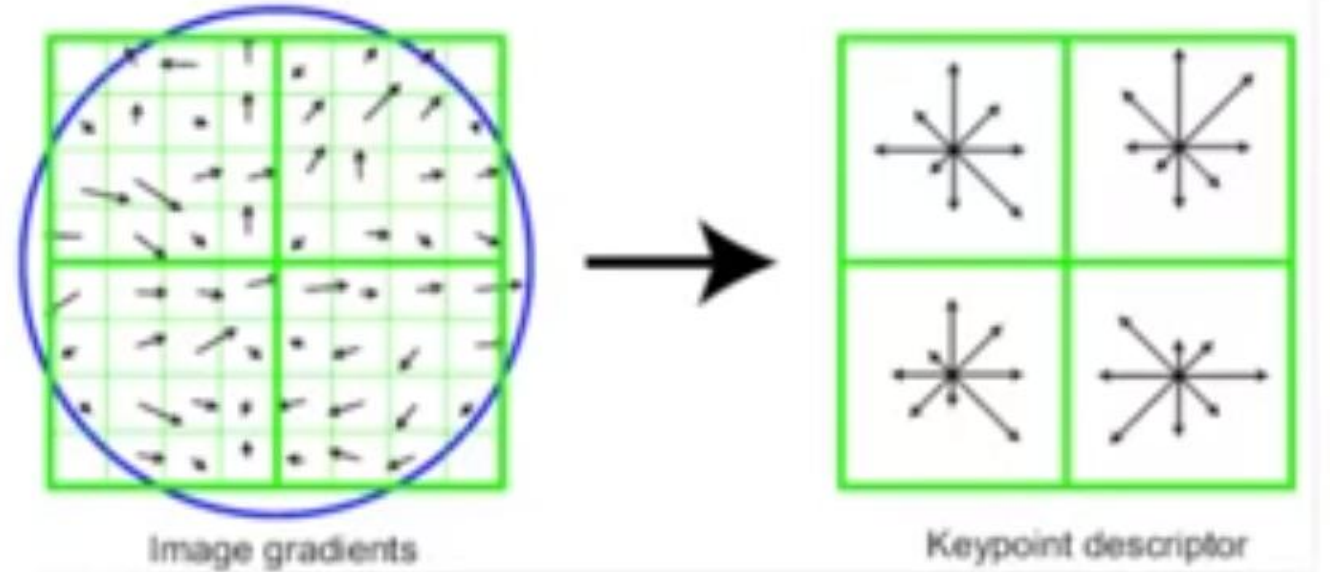
Possible descriptor

- Store intensity sample in the neighbourhood
- Sensitive to lighting changes, 3D transformations

Gradient Orientation histogram

- Robust representation
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# SIFT Descriptor

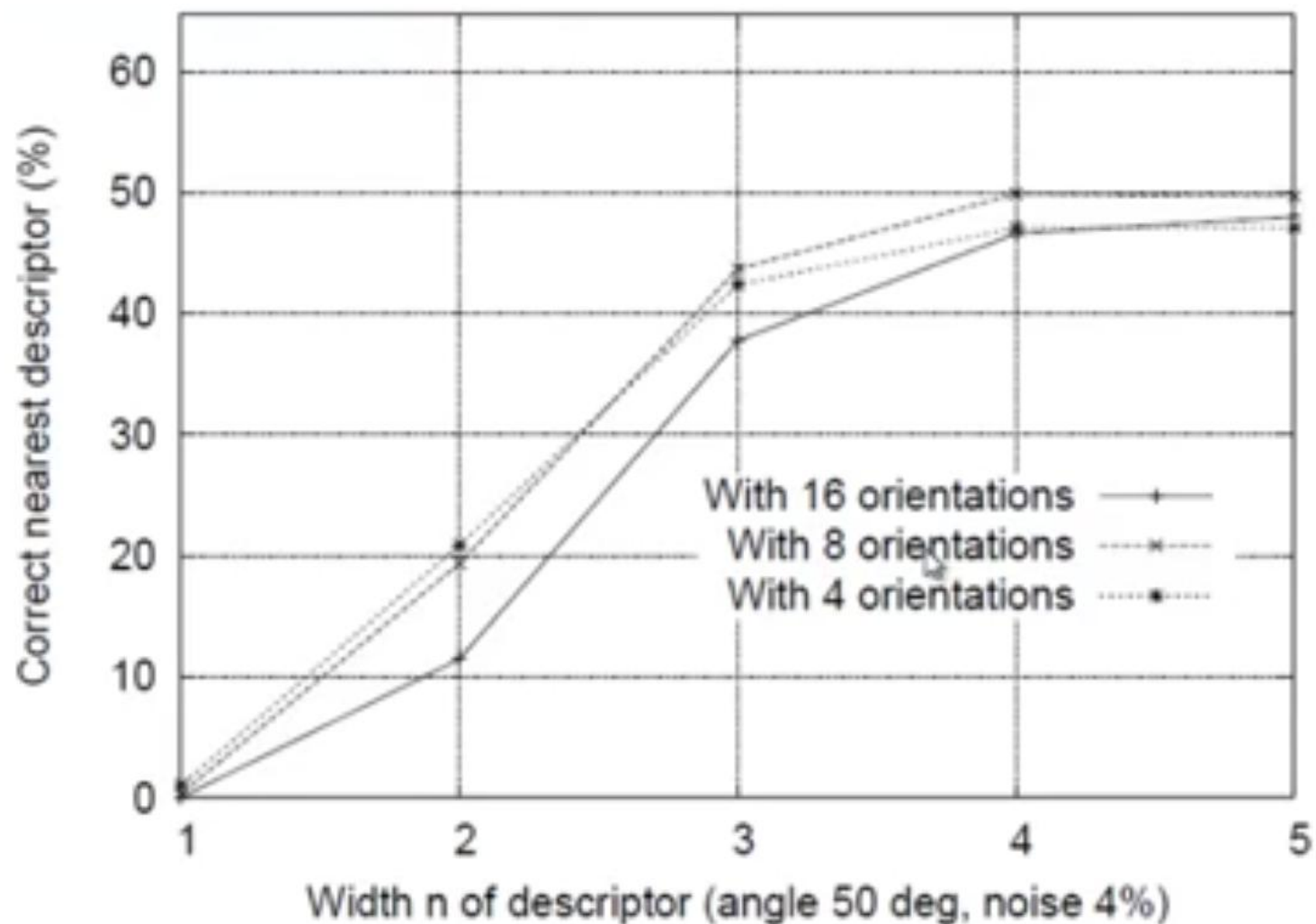


Compute relative orientation and magnitude in a  $16 \times 16$  neighbourhood at interest point

Form weighted histogram (8 bin) for  $4 \times 4$  regions

- Weight by magnitude and spatial Gaussian
- Concatenate 16 histograms in one long vector of 128 dimensions

# SIFT Descriptor regions





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# SIFT Descriptor

Store numbers in a vector

Normalize to unit vector

Bound unit vector items to maximum 0.2 and renormalize to unit vector

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# Matching

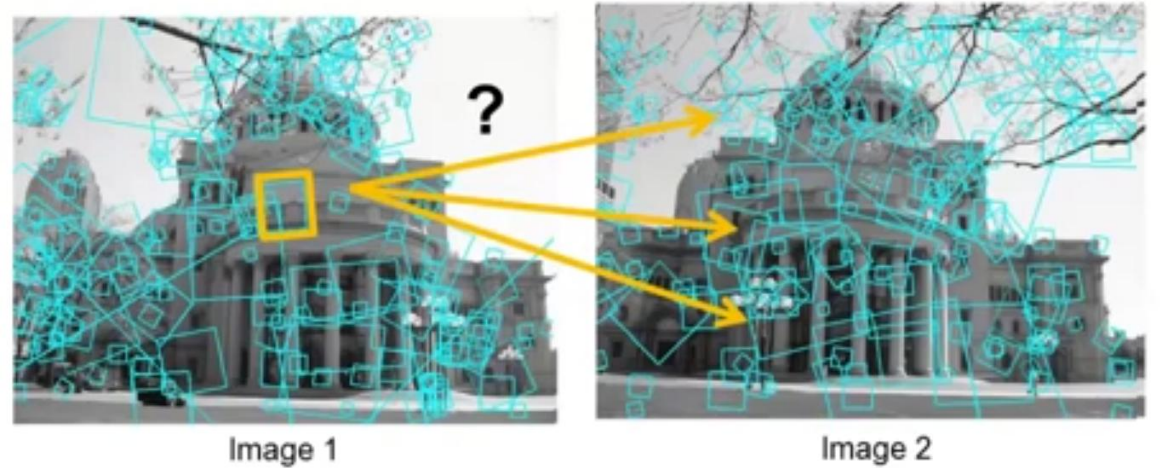
Find nearest neighbour i.e. an interest point with minimum Euclidean distance

Look at ratio of distance between best and 2<sup>nd</sup> best match (0.8)

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# Matching

Candidate match using SIFT descriptor  
Compare them all and pick closest (or  
closest k, or within a threshold distance)



# Matching

For robustness consider ratio of distance to best match and second-best match

If ratio is low, then select first match  
otherwise ambiguous match



Image 1



Image 2

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Ratio of distance  
to best match and  
second-best  
match

