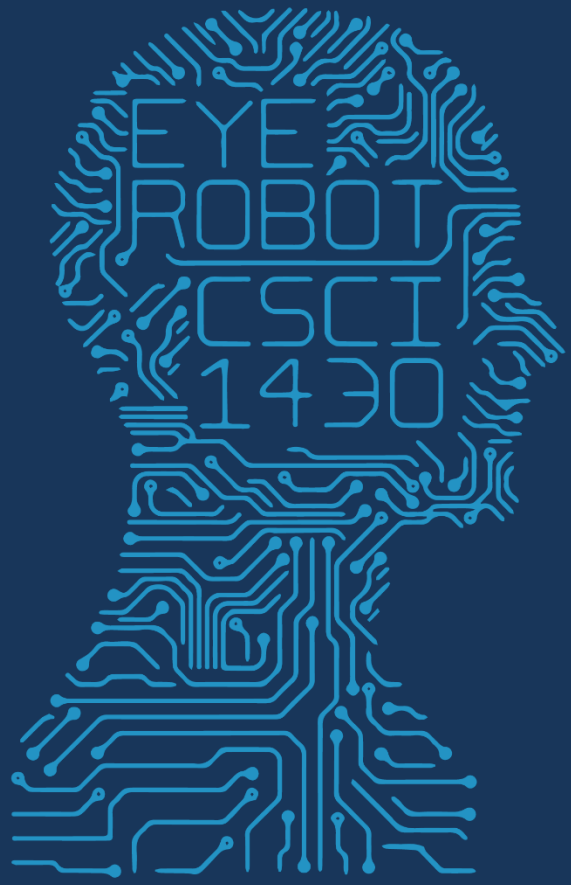
1950

Future Vision



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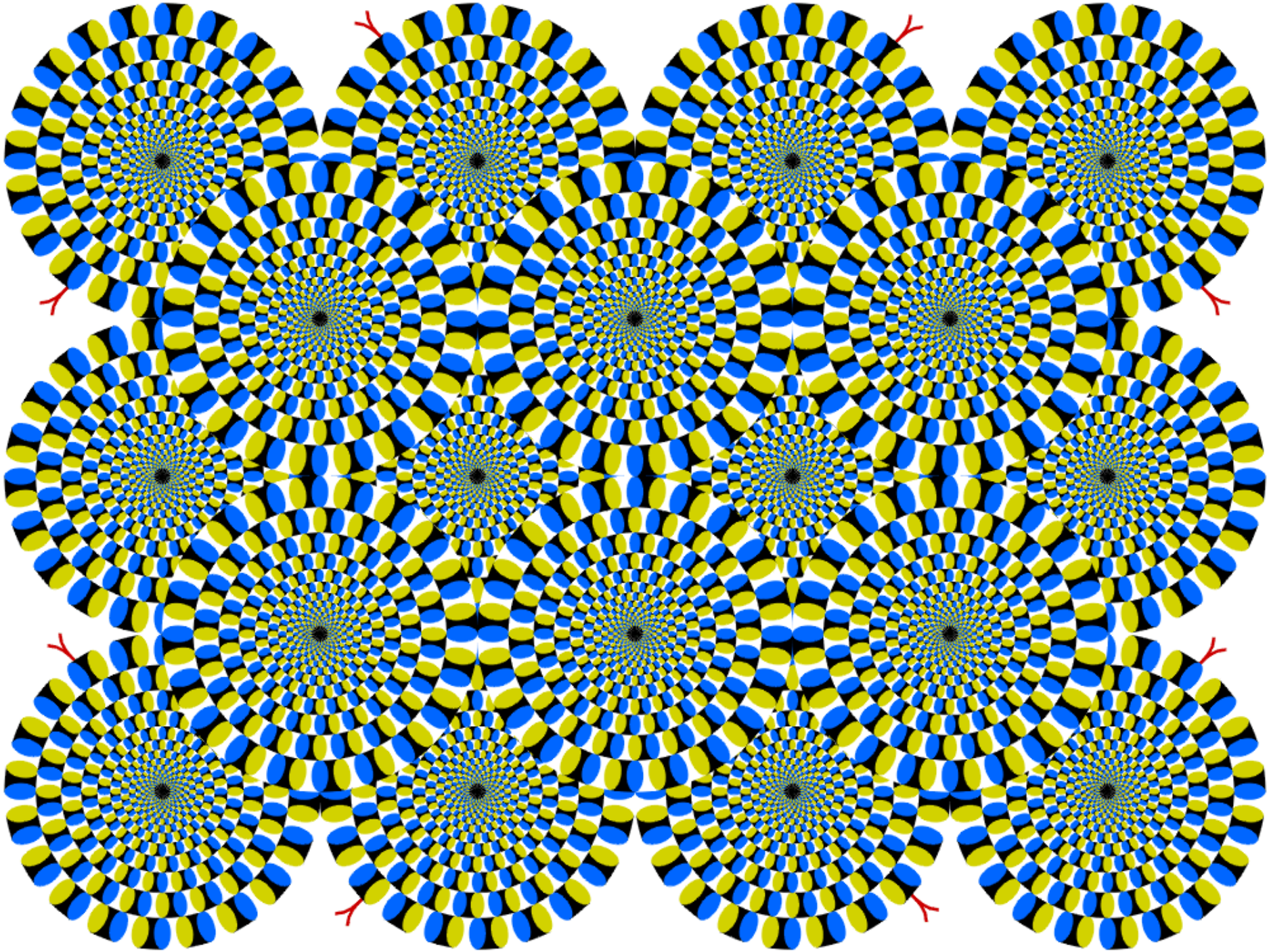
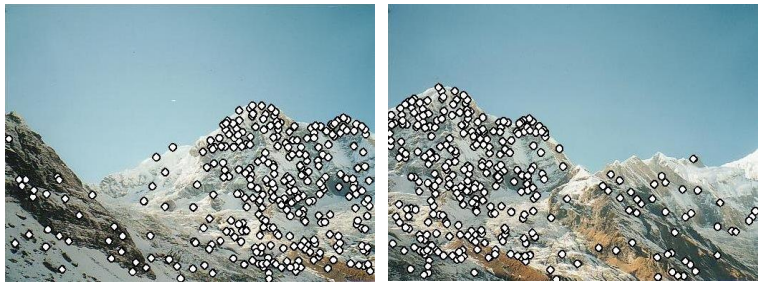
Computer Vision

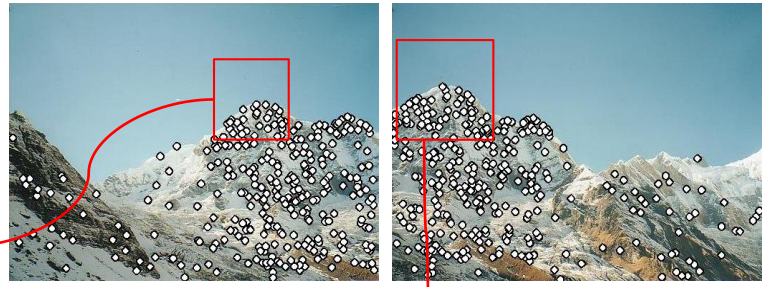


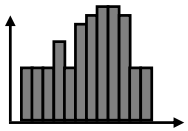
Local features: main components

1) Detection:
Find a set of distinctive key points.

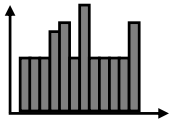


2) Description:
Extract feature descriptor around each interest point as vector.



x_1 

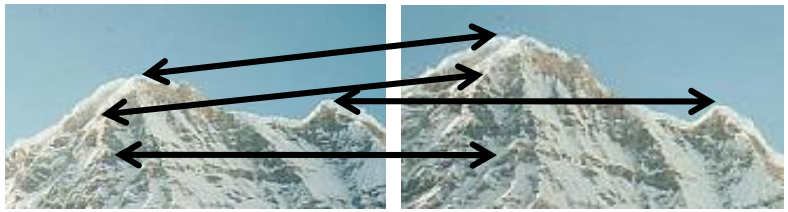
$$\mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}]$$

x_2 

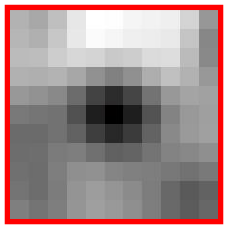
$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

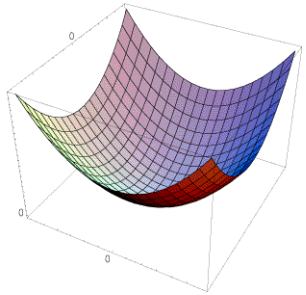
3) Matching:
Compute distance between feature vectors to find correspondence.

$$d(\mathrm{x}_1, \mathrm{x}_2) < T$$

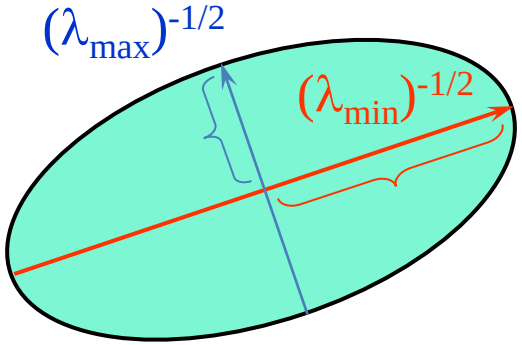


Review: Harris corner detector





- Approximate distinctiveness by local auto-correlation.
- Approximate local auto-correlation by second moment matrix **M**.
- Distinctiveness (or cornerness) relates to the eigenvalues of **M**.
- Instead of computing eigenvalues directly, we can use determinant and trace of **M**.



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

Trace / determinant and eigenvalues

- Given n x n matrix A with eigenvalues $\lambda_{1\ldots n}$

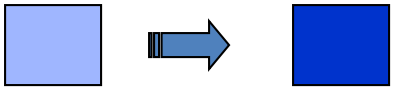
$$\operatorname{tr}(A) = \sum_{i=1}^{n} A_{ii} = \sum_{i=1}^{n} \lambda_i = \lambda_1 + \lambda_2 + \cdots + \lambda_n.$$

$$\det(A) = \prod_{i=1}^{n} \lambda_i = \lambda_1 \lambda_2 \cdots \lambda_n.$$

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

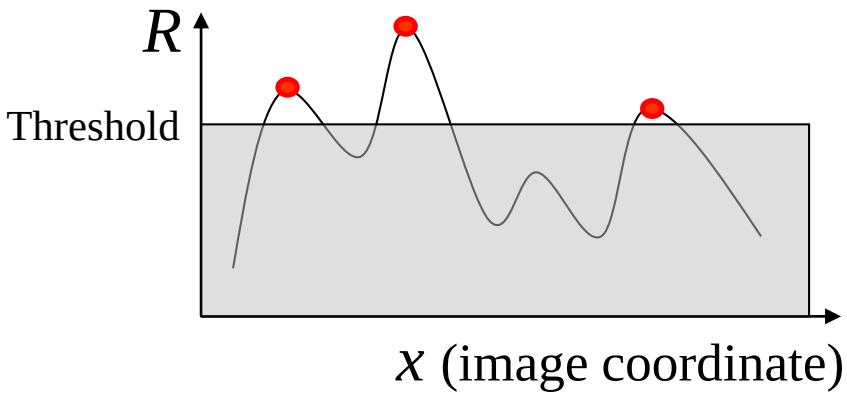
HOW INVARIANT ARE HARRIS CORNERS?

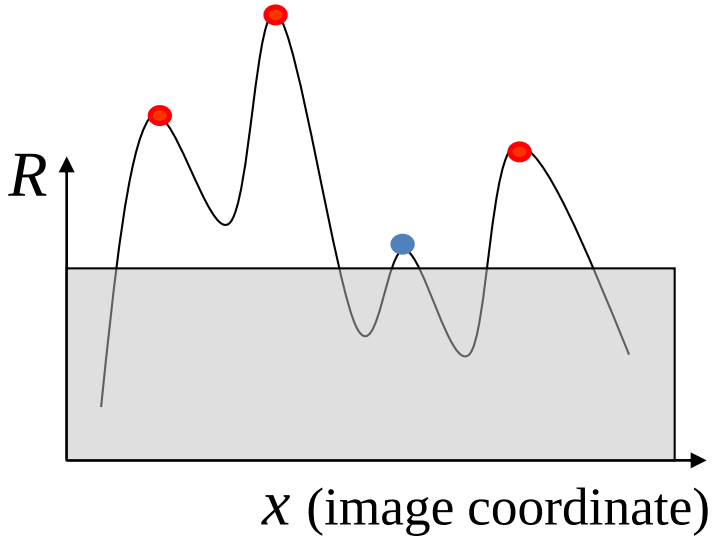
Affine intensity change



$$I \rightarrow a\,I + b$$

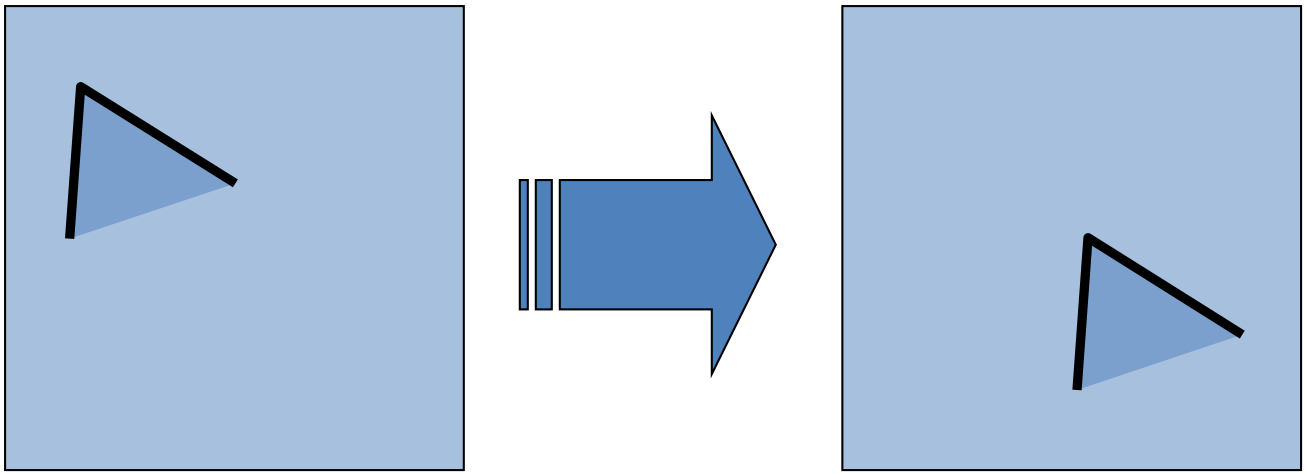
- Only derivatives are used => invariance to intensity shift $I \rightarrow I + b$
- Intensity scaling: $I \rightarrow a\,I$





Partially invariant to affine intensity change

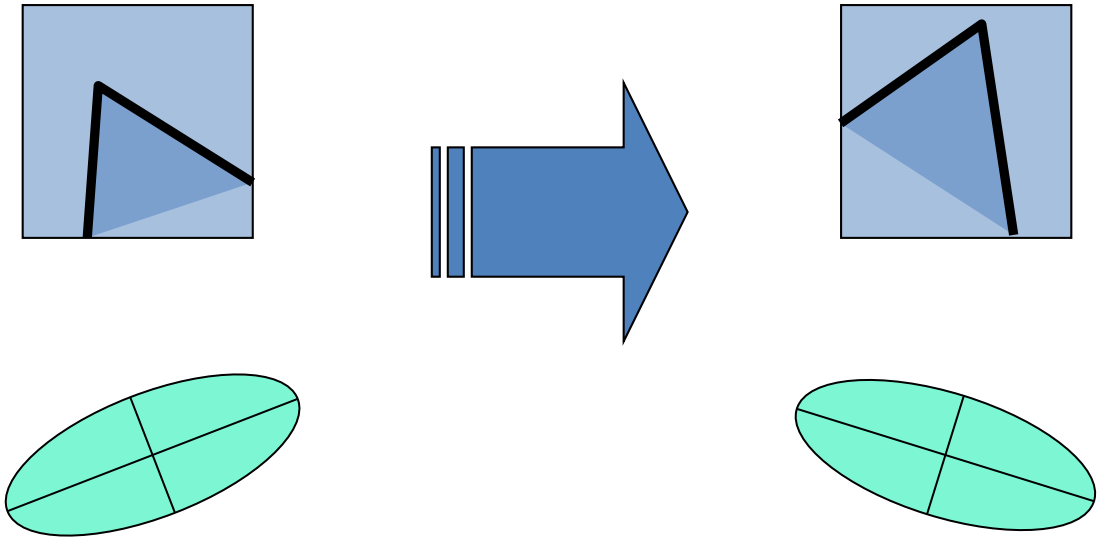
Image translation



- Derivatives and window function are shift-invariant.

Corner location is covariant w.r.t. translation

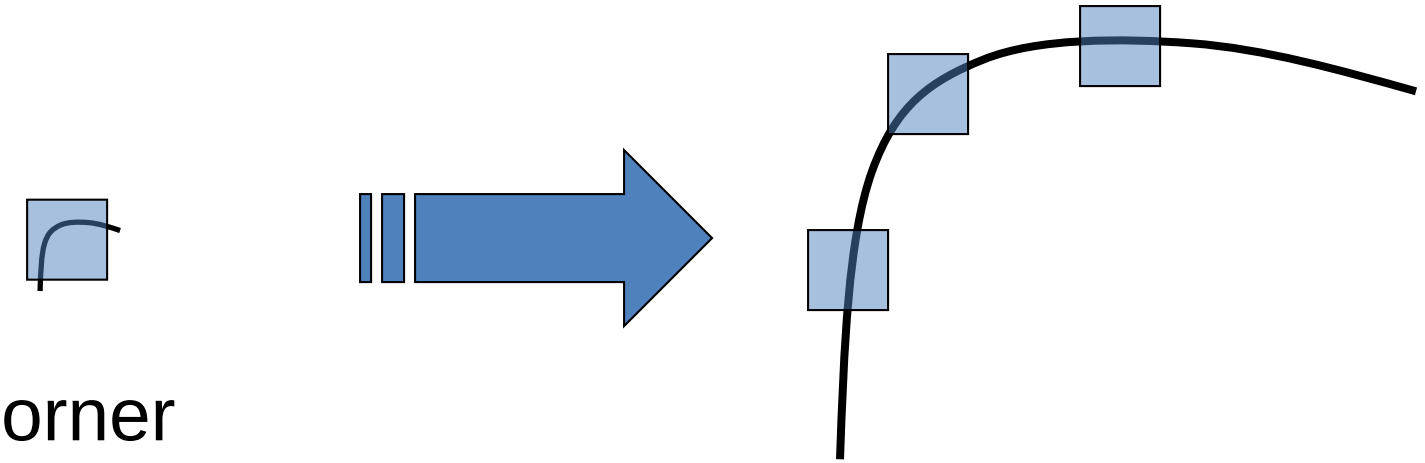
Image rotation



Second moment ellipse rotates but its shape (i.e., eigenvalues) remains the same.

Corner location is covariant w.r.t. rotation

Scaling



Corner

All points will be classified as edges

Corner location is not covariant to scaling!

WHAT IS THE ‘SCALE’ OF A FEATURE POINT?

Automatic Scale Selection

$$f(I_{i_1 \ldots i_m}(x,\sigma)) \;=\; f(I_{i_1 \ldots i_m}(x',\sigma'))$$

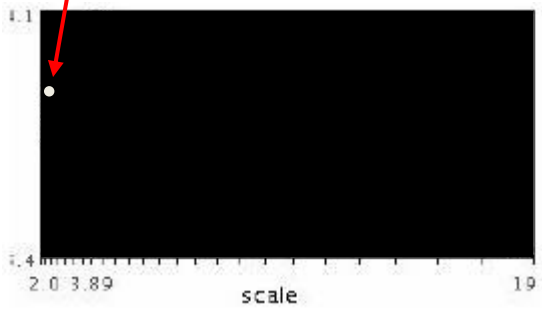
How to find patch sizes at which *f* response is equal?

What is a good *f* ?

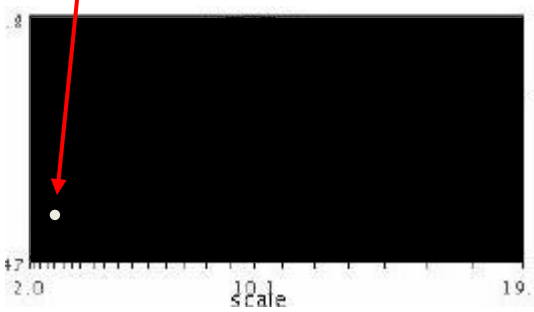
Automatic Scale Selection

- Function responses for increasing scale (scale signature)

Response of some function *f*



$f(I_{i_1 \ldots i_m}(x,\sigma))$

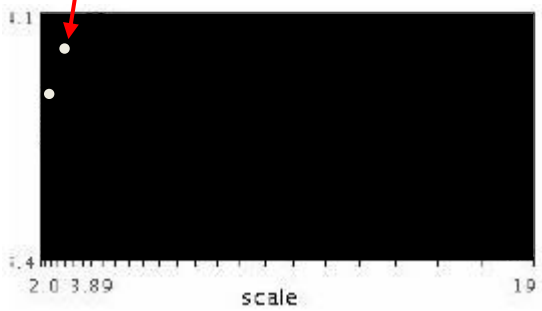


$f(I_{i_1 \ldots i_m}(x',\sigma'))$

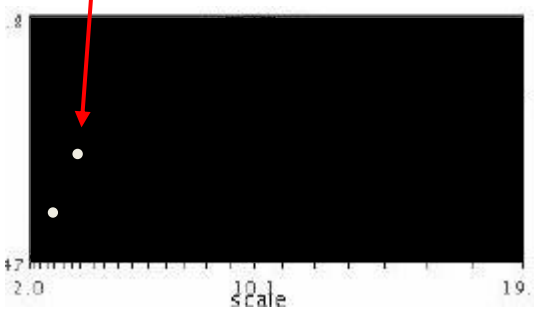
Automatic Scale Selection

- Function responses for increasing scale (scale signature)

Response of some function *f*



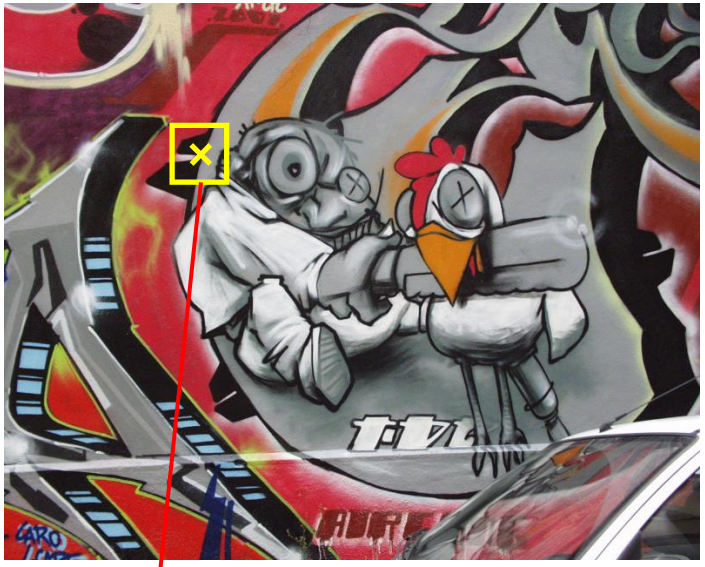
$f(I_{i_1 \ldots i_m}(x,\sigma))$



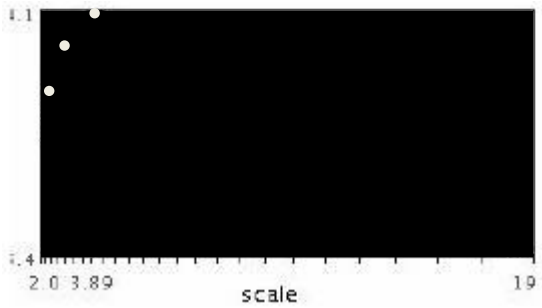
$f(I_{i_1 \ldots i_m}(x',\sigma'))$

Automatic Scale Selection

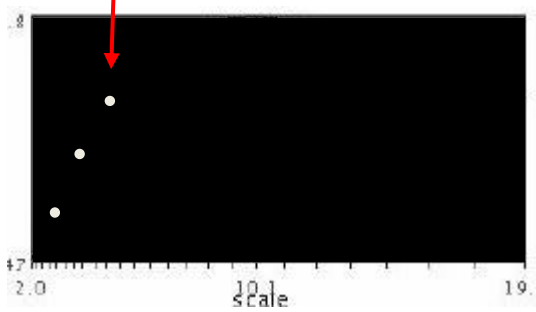
- Function responses for increasing scale (scale signature)



Response of some function *f*



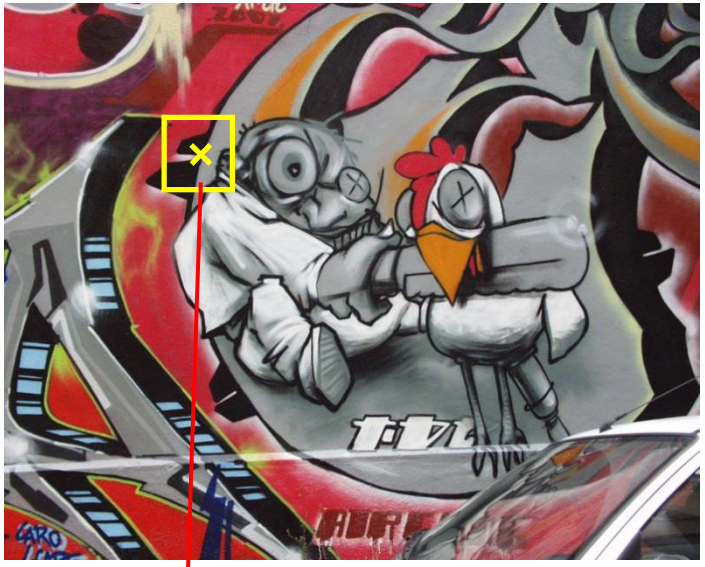
$f(I_{i_1 \ldots i_m}(x,\sigma))$



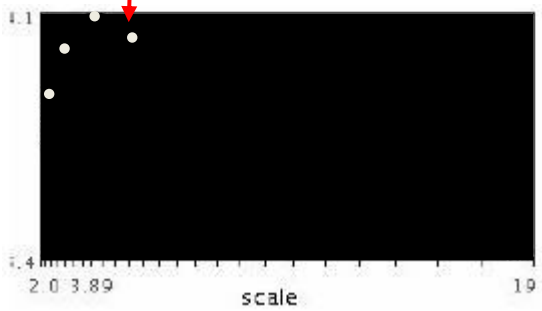
$f(I_{i_1 \ldots i_m}(x',\sigma'))$

Automatic Scale Selection

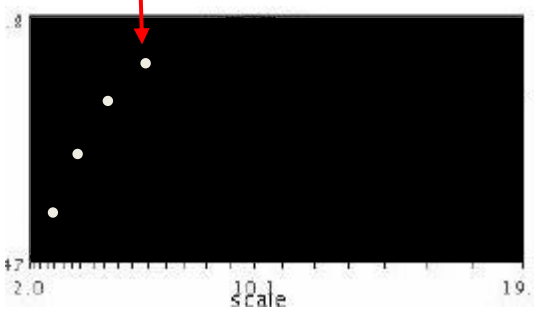
- Function responses for increasing scale (scale signature)



Response of some function *f*



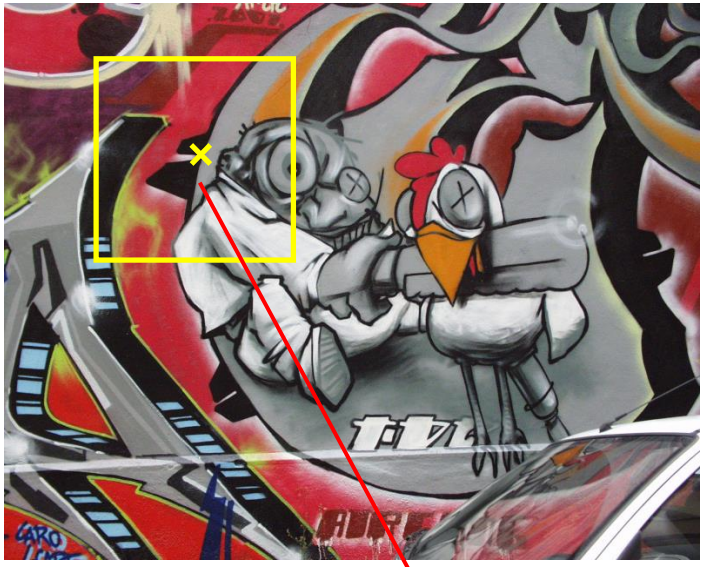
$f(I_{i_1 \ldots i_m}(x,\sigma))$

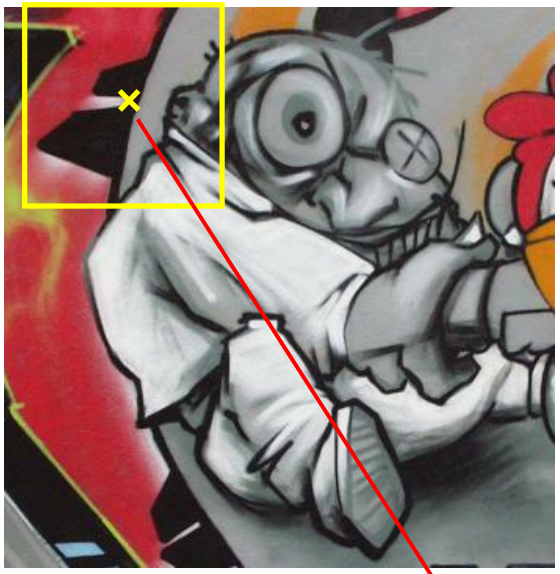


$f(I_{i_1 \ldots i_m}(x',\sigma'))$

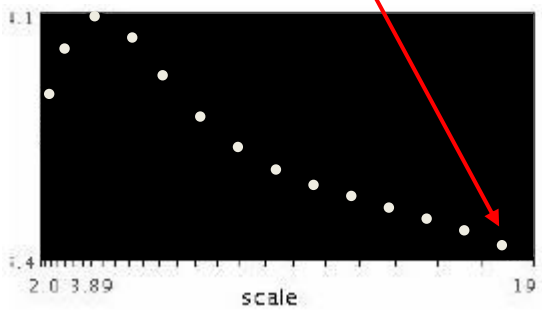
Automatic Scale Selection

- Function responses for increasing scale (scale signature)

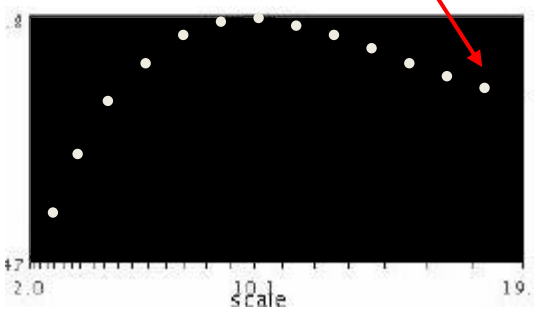




Response of some function *f*



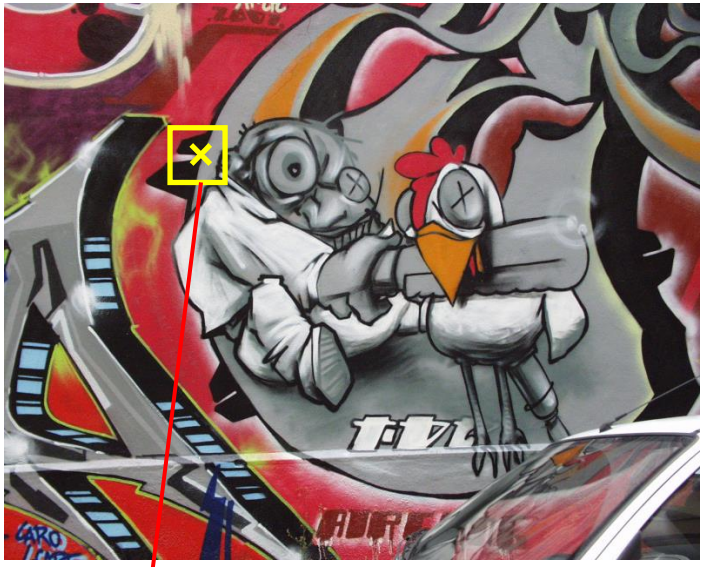
$f(I_{i_1 \ldots i_m}(x,\sigma))$



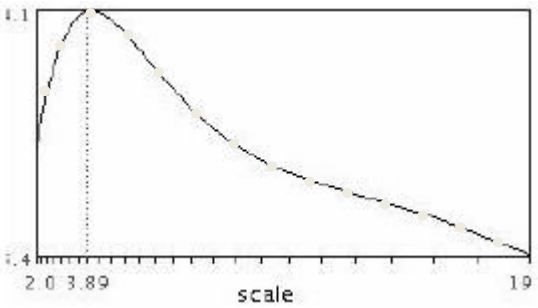
$f(I_{i_1 \ldots i_m}(x',\sigma'))$

Automatic Scale Selection

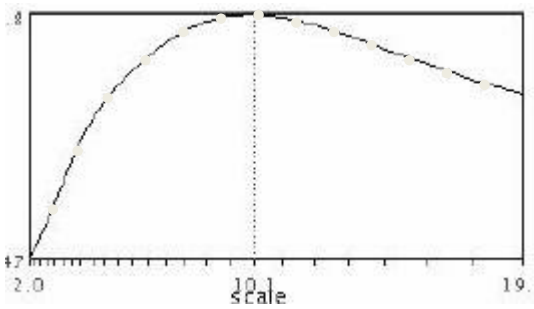
- Function responses for increasing scale (scale signature)



Response of some function *f*

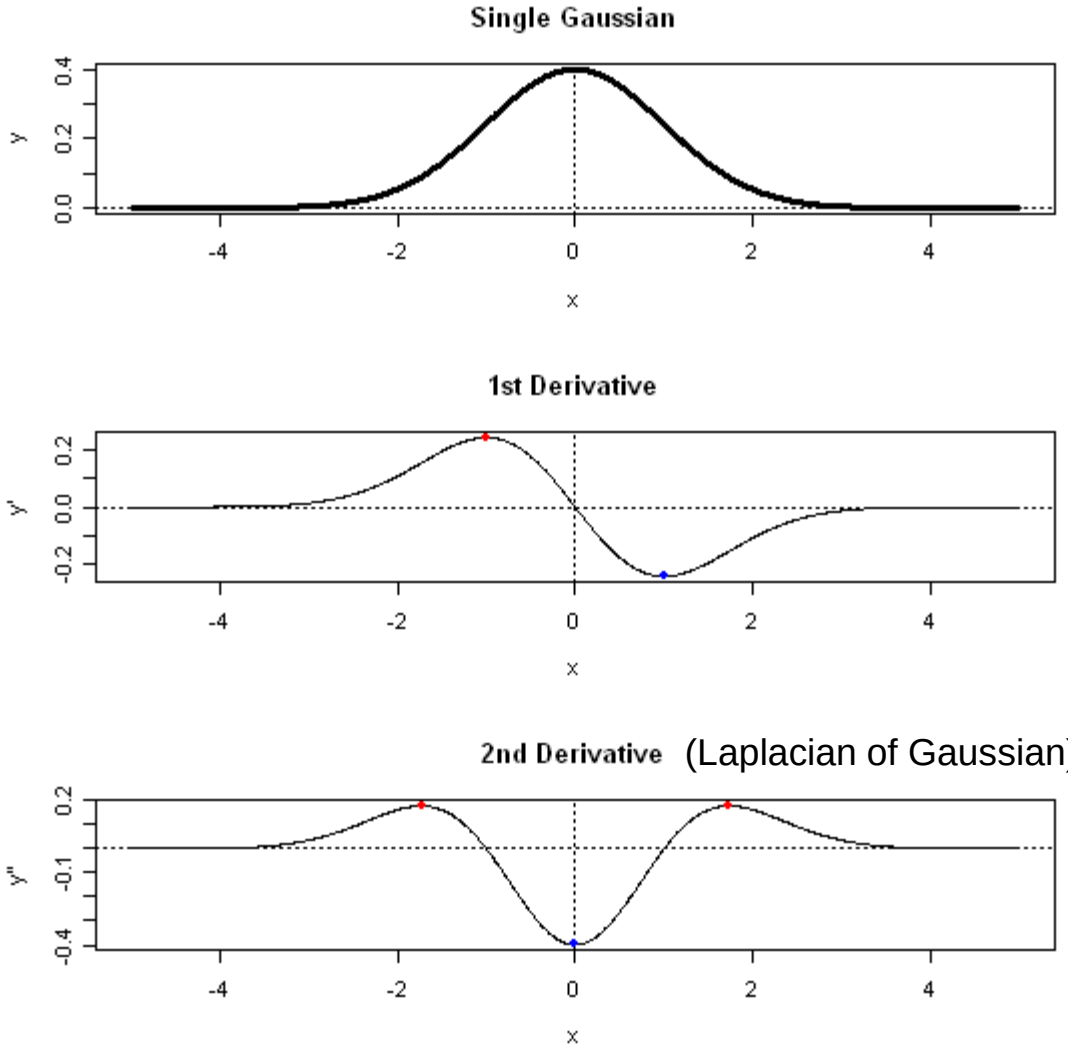


$f(I_{i_1 \ldots i_m}(x,\sigma))$



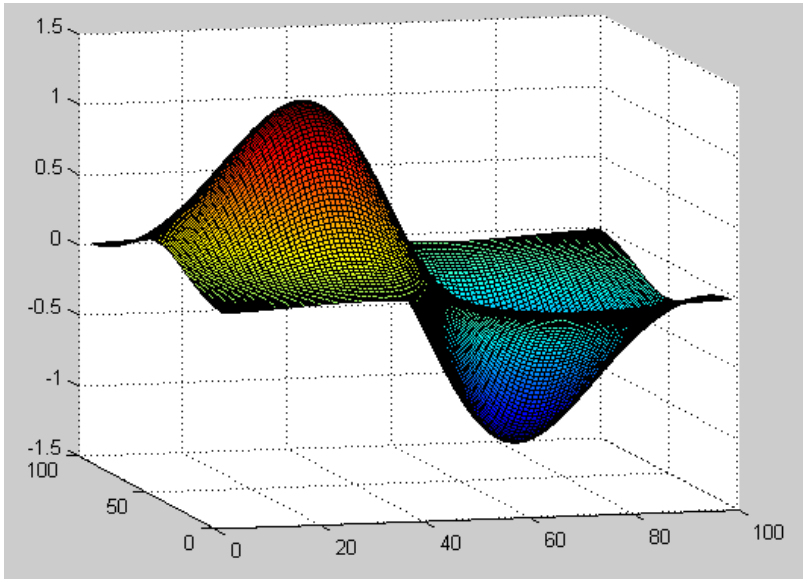
$f(I_{i_1 \ldots i_m}(x',\sigma'))$

What Is A Useful Signature Function *f* ?



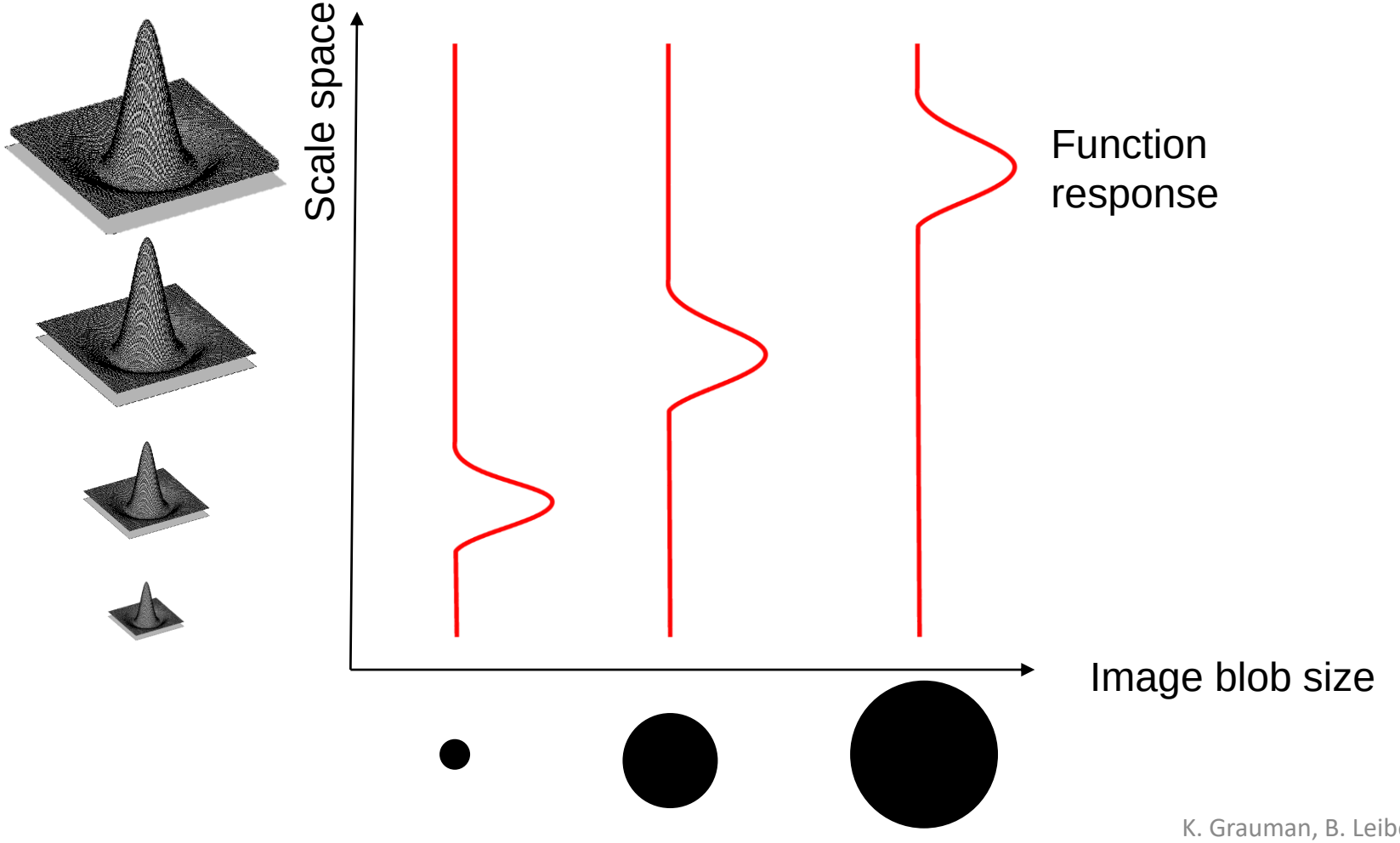
(Laplacian of Gaussian)

1st Derivative of Gaussian



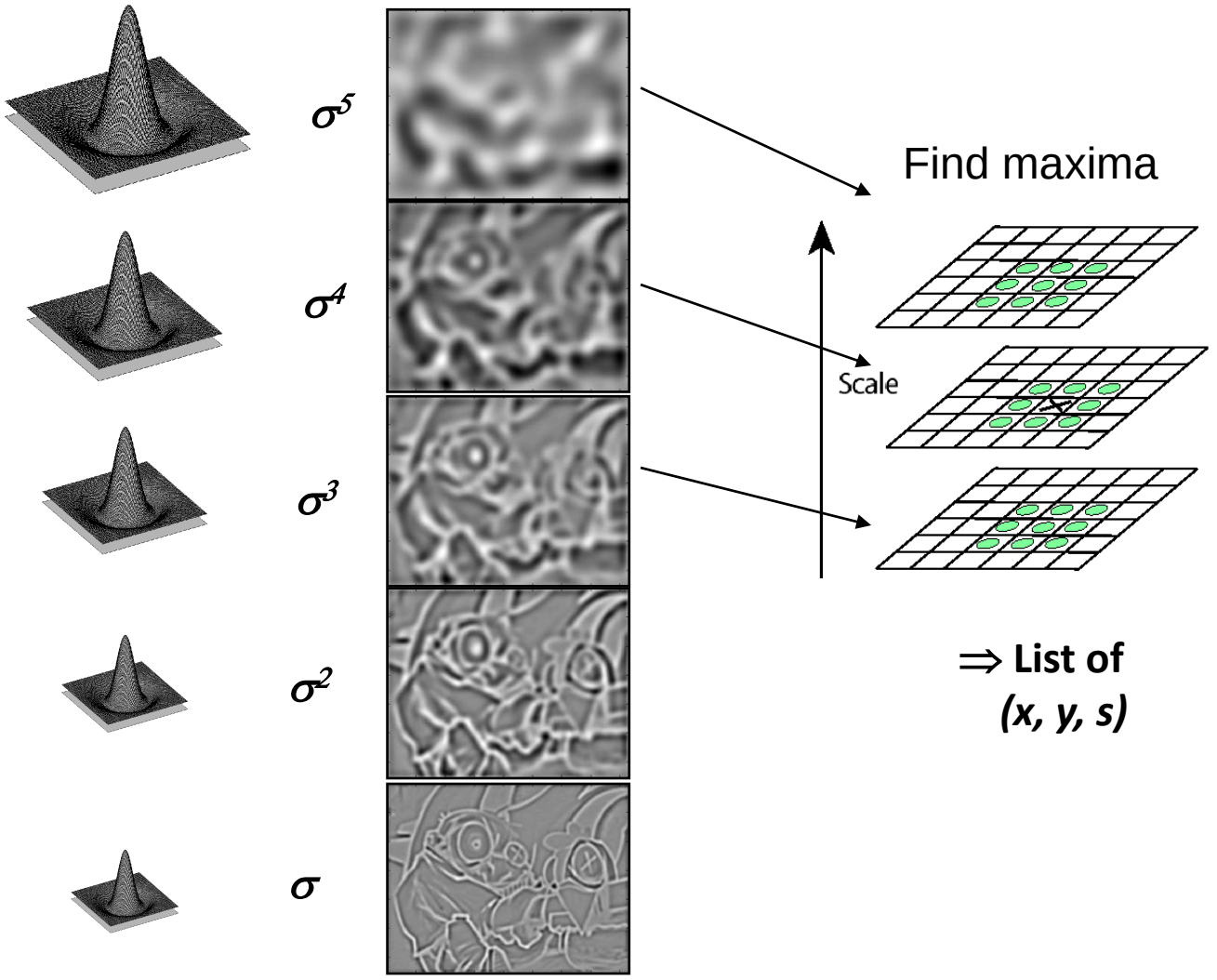
What Is A Useful Signature Function *f* ?

- "Blob" detector is common for corners
  - - Laplacian (2nd derivative) of Gaussian (LoG)



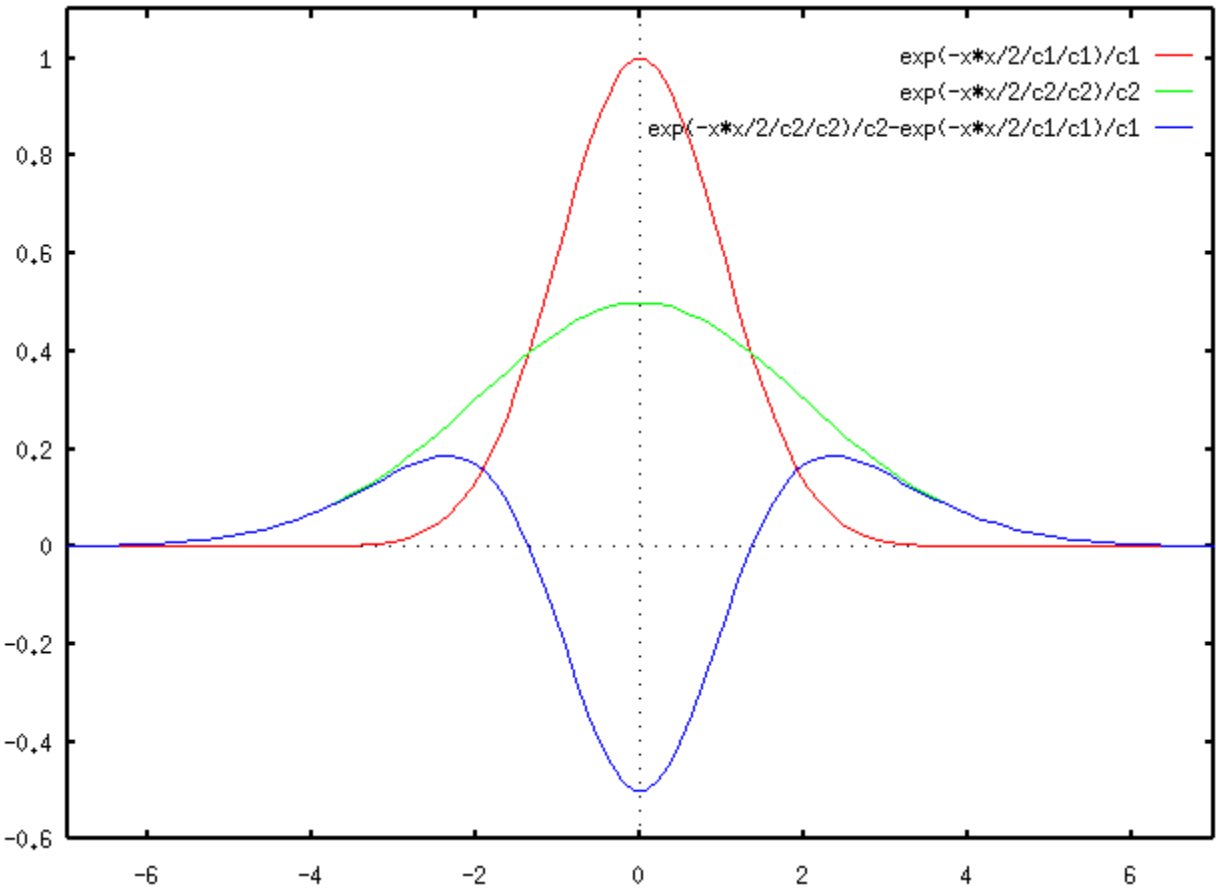
K. Grauman, B. Leibe

Find local maxima in position-scale space



Alternative approach

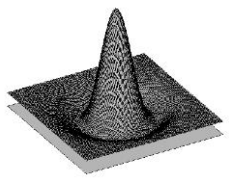
Approximate LoG with Difference-of-Gaussian (DoG).



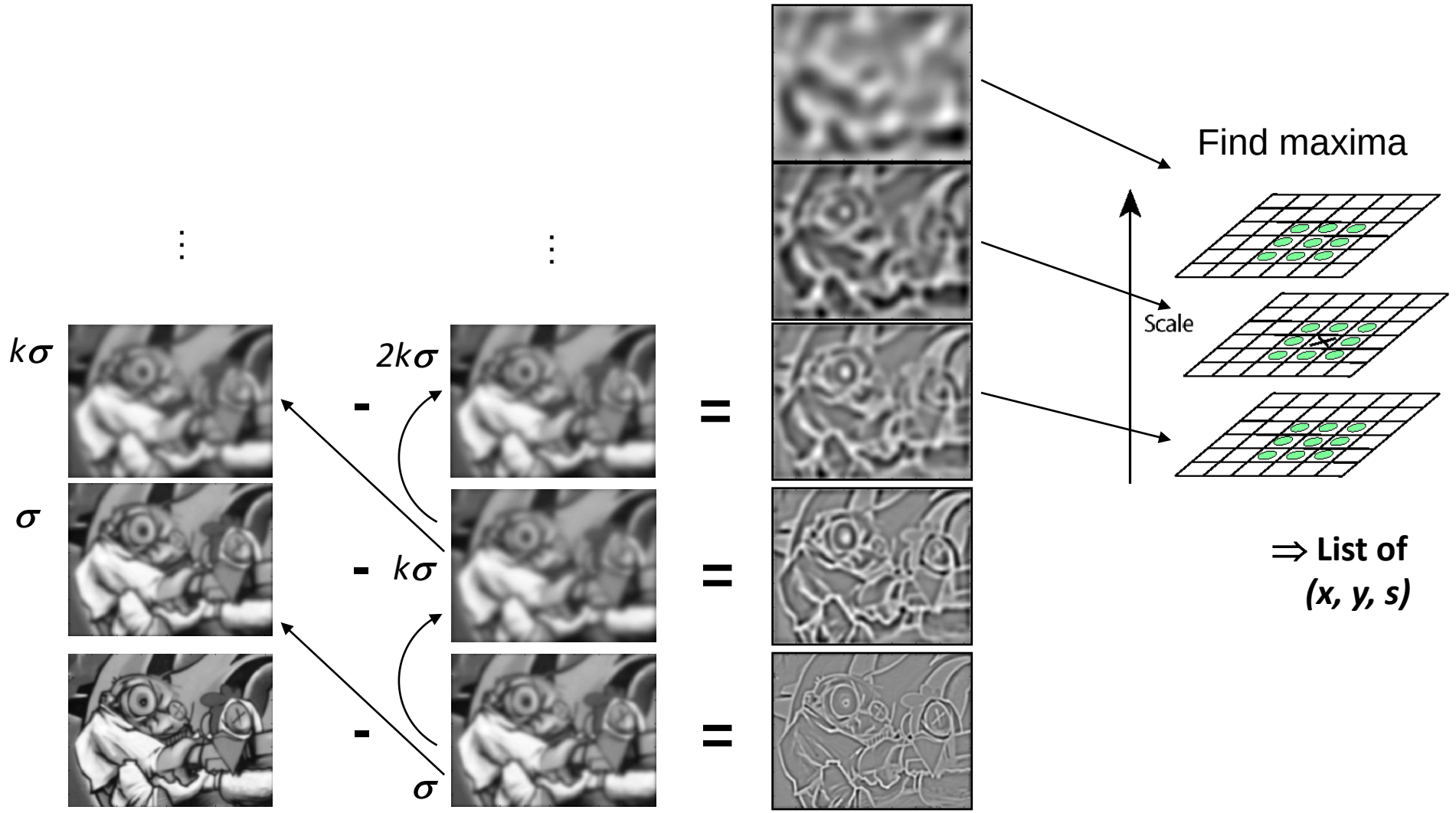
Alternative approach

Approximate LoG with Difference-of-Gaussian (DoG).

1. Blur image with σ Gaussian kernel
2. Blur image with $k\sigma$ Gaussian kernel
3. Subtract 2. from 1.

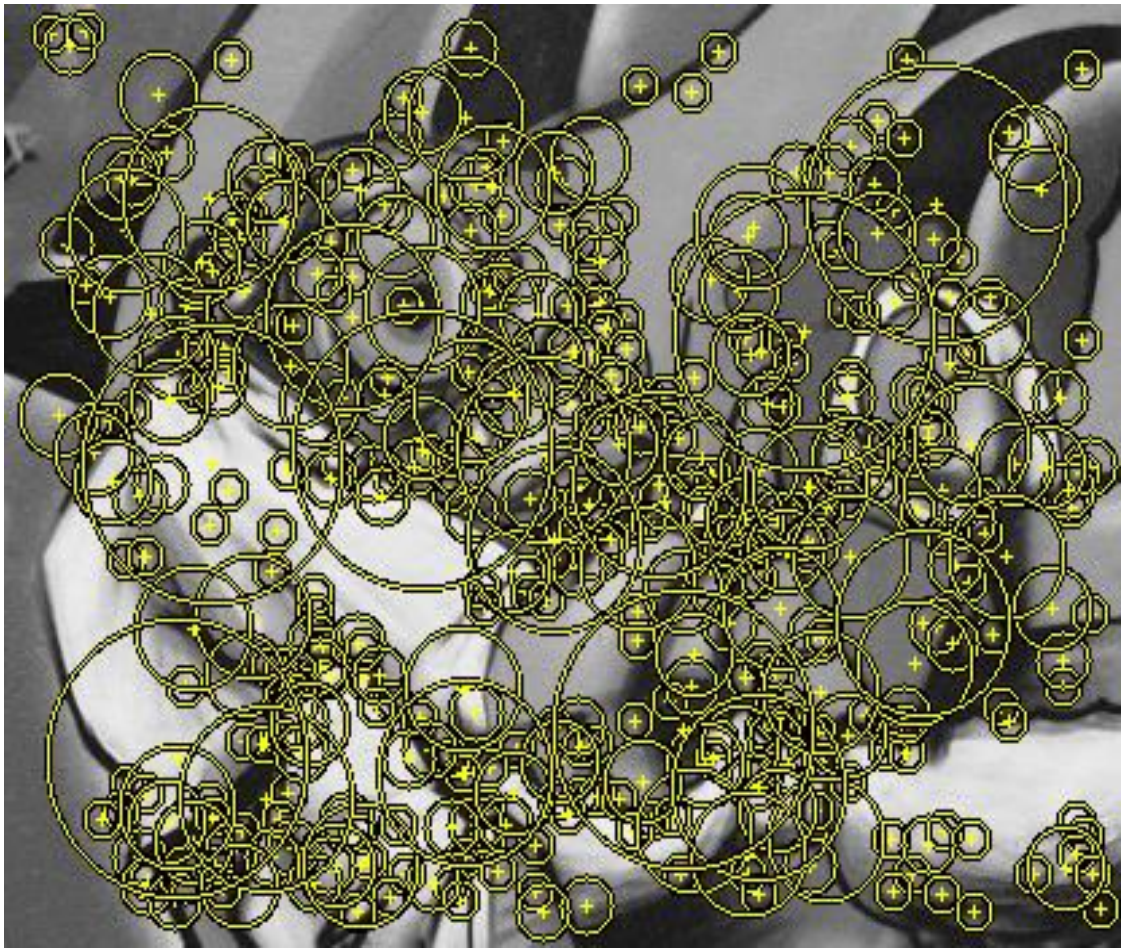


Find local maxima in position-scale space of DoG



Results: Difference-of-Gaussian

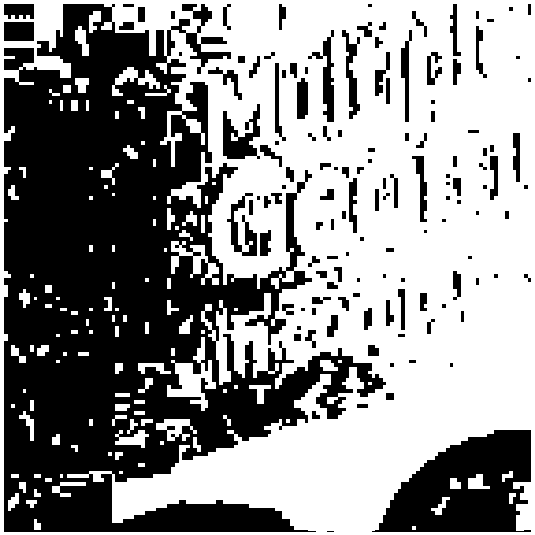
- Larger circles = larger scale
- Descriptors with maximal scale response



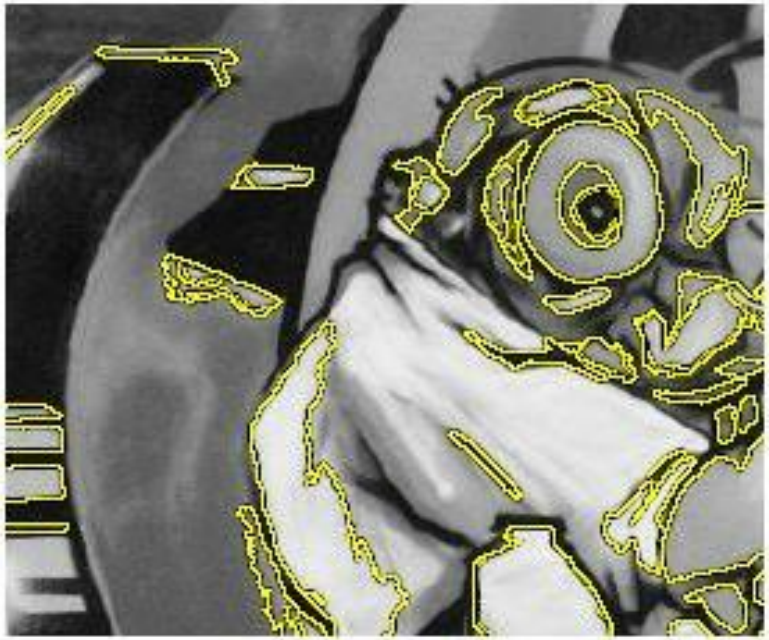
K. Grauman, B. Leibe

Maximally Stable Extremal Regions [Matas '02]

- Based on Watershed segmentation algorithm
- Select regions that stay stable over a large parameter range

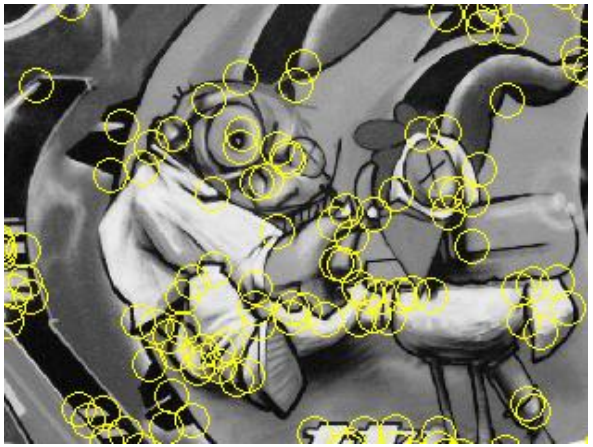


Example Results: MSER



Review: Interest points

- Keypoint detection: repeatable and distinctive
  - Corners, blobs, stable regions
  - Harris, DoG, MSER



(a) Gray scale input image (b) Detected MSERs

Review: Choosing an interest point detector

- Why choose?
  - Collect more points with more detectors, for more possible matches

- What do you want it for?
  - Precise localization in x-y: Harris
  - Good localization in scale: Difference of Gaussian
  - Flexible region shape: MSER

- Best choice often application dependent
  - Harris-/Hessian-Laplace/DoG work well for many natural categories
  - MSER works well for buildings and printed things

- There have been extensive evaluations/comparisons
  - [Mikolajczyk et al., IJCV'05, PAMI'05]
  - All detectors/descriptors shown here work well

Comparison of Keypoint Detectors

Table 7.1 Overview of feature detectors.

Feature Detector	Corner	Blob	Region	Rotation invariant	Scale invariant	Affine invariant	Repeatability	Localization accuracy	Robustness	Efficiency
Harris	√			√			+++	+++	+++	++
Hessian		√		√			++	++	++	+
SUSAN	√			√			++	++	++	+++
Harris-Laplace	√	(√)		√	√		+++	+++	++	+
Hessian-Laplace	(√)	√		√	√		+++	+++	+++	+
DoG	(√)	√		√	√		++	++	++	++
SURF	(√)	√		√	√		++	++	++	+++
Harris-Affine	√	(√)		√	√	√	+++	+++	++	++
Hessian-Affine	(√)	√		√	√	√	+++	+++	+++	++
Salient Regions	(√)	√		√	√	(√)	+	+	++	+
Edge-based	√			√	√	√	+++	+++	+	+
MSER			√	√	√	√	+++	+++	++	+++
Intensity-based			√	√	√	√	++	++	++	++
Superpixels			√	√	(√)	(√)	+	+	+	+

Tuytelaars Mikolajczyk 2008

Local Image Descriptors

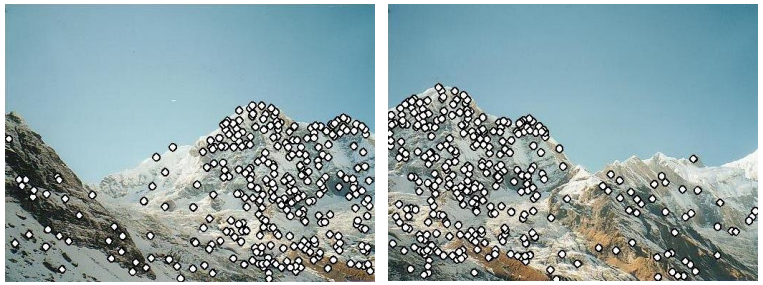
Read Szeliski 4.1

Acknowledgment: Many slides from James Hays, Derek Hoiem and Grauman & Leibe 2008 AAAI Tutorial

Local features: main components

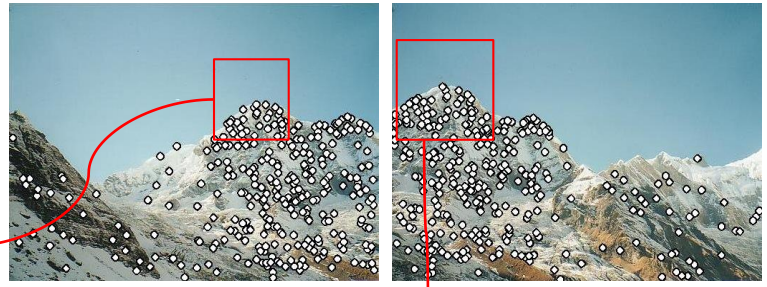
1) Detection:

Find a set of distinctive key points.



2) Description:

Extract feature descriptor around each interest point as vector.

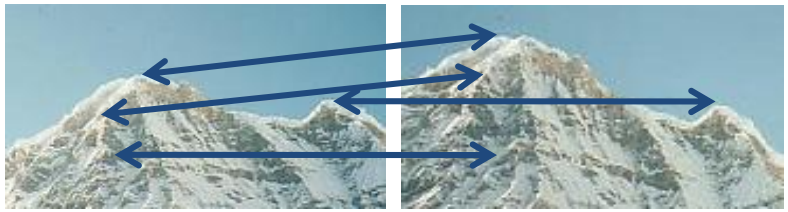


$$\mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}]$$

$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

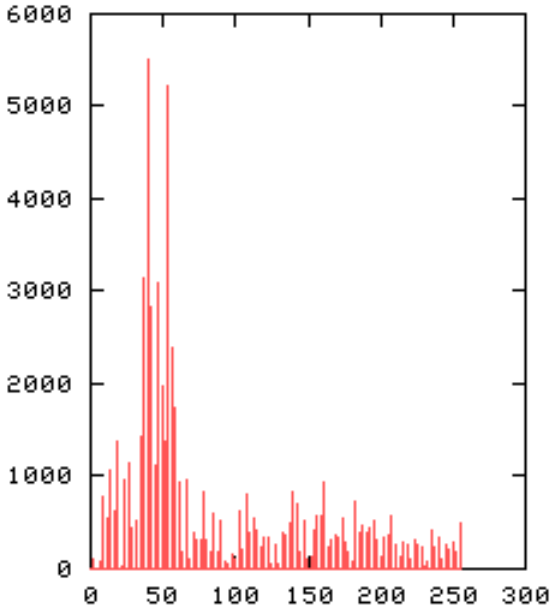
3) Matching:

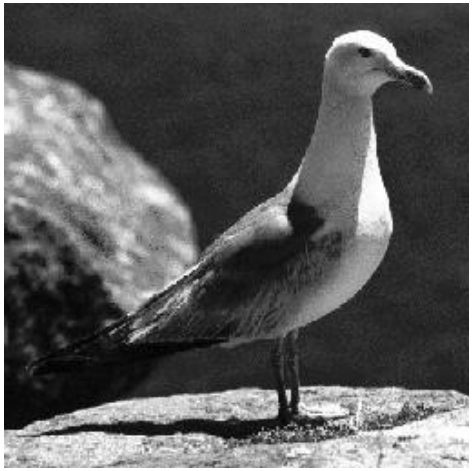
Compute distance between feature vectors to find correspondence.



$$d(\mathbf{x}_1, \mathbf{x}_2) < T$$

Image Representations: Histograms





Global histogram to represent distribution of features

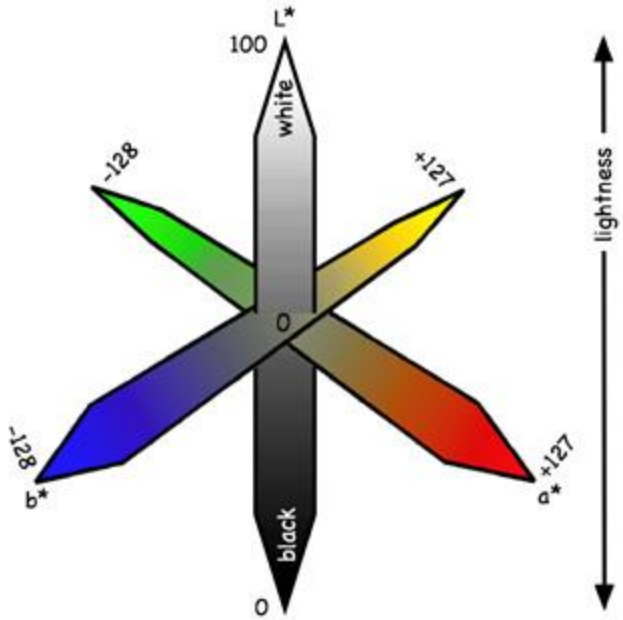
- Color, texture, depth, …

Local histogram per detected point

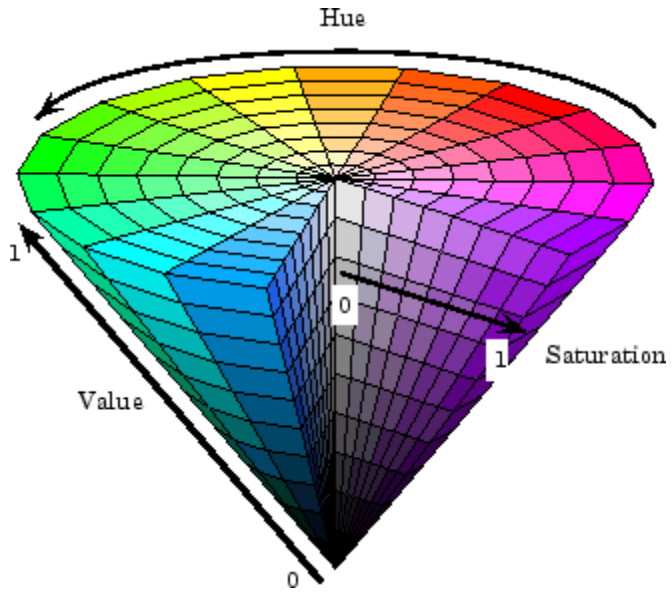
Images from Dave Kauchak

For what things do we compute histograms?

- Color



L*a*b* color space

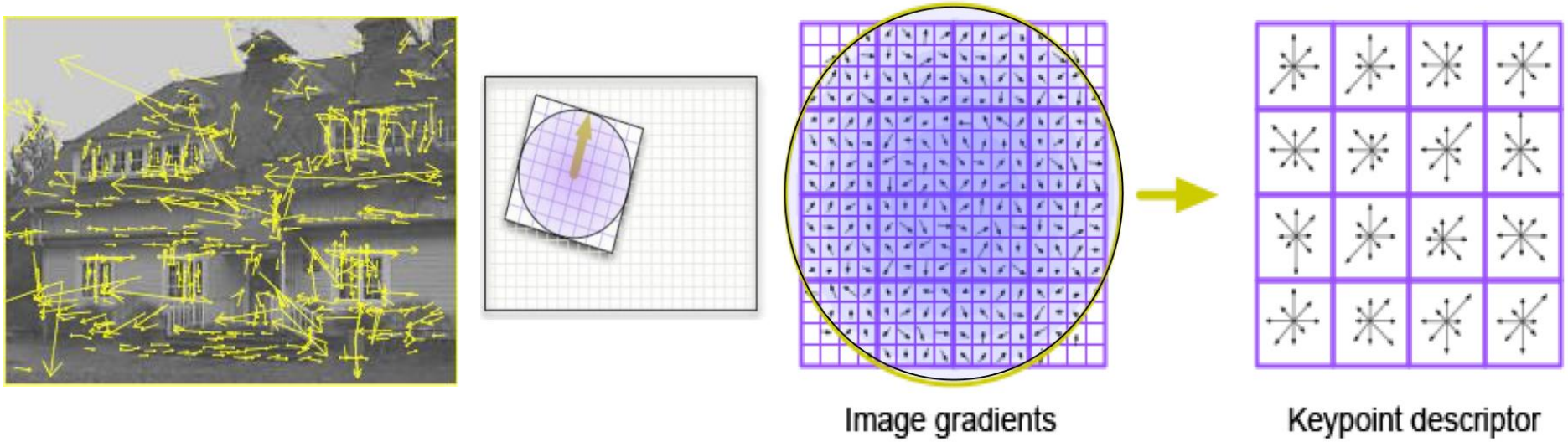


HSV color space

- Model local appearance

For what things do we compute histograms?

- Texture
- Local histograms of oriented gradients
- SIFT: Scale Invariant Feature Transform
  - Extremely popular (40k citations)



SIFT – Lowe IJCV 2004

SIFT

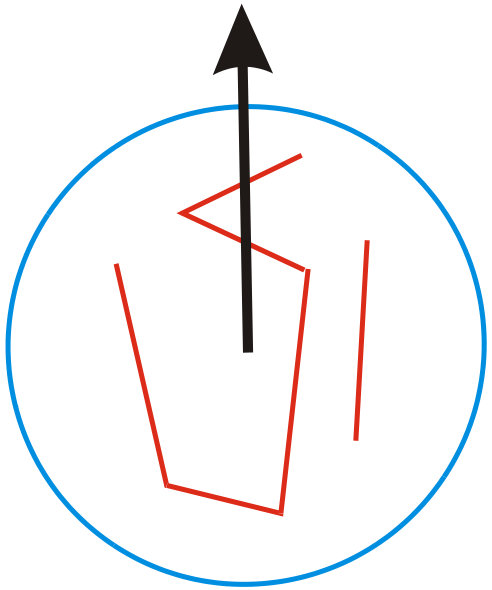
- Find Difference of Gaussian scale-space extrema
- Post-processing
  - Position interpolation
  - Discard low-contrast points
  - Eliminate points along edges

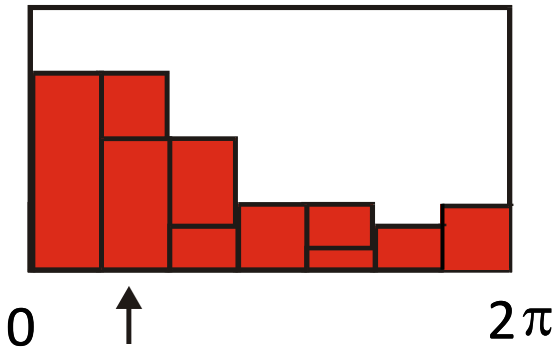
SIFT

- Find Difference of Gaussian scale-space extrema
- Post-processing
  - Position interpolation
  - Discard low-contrast points
  - Eliminate points along edges
- Orientation estimation

SIFT Orientation Normalization

- Compute orientation histogram
- Select dominant orientation θ
- Normalize: rotate to fixed orientation





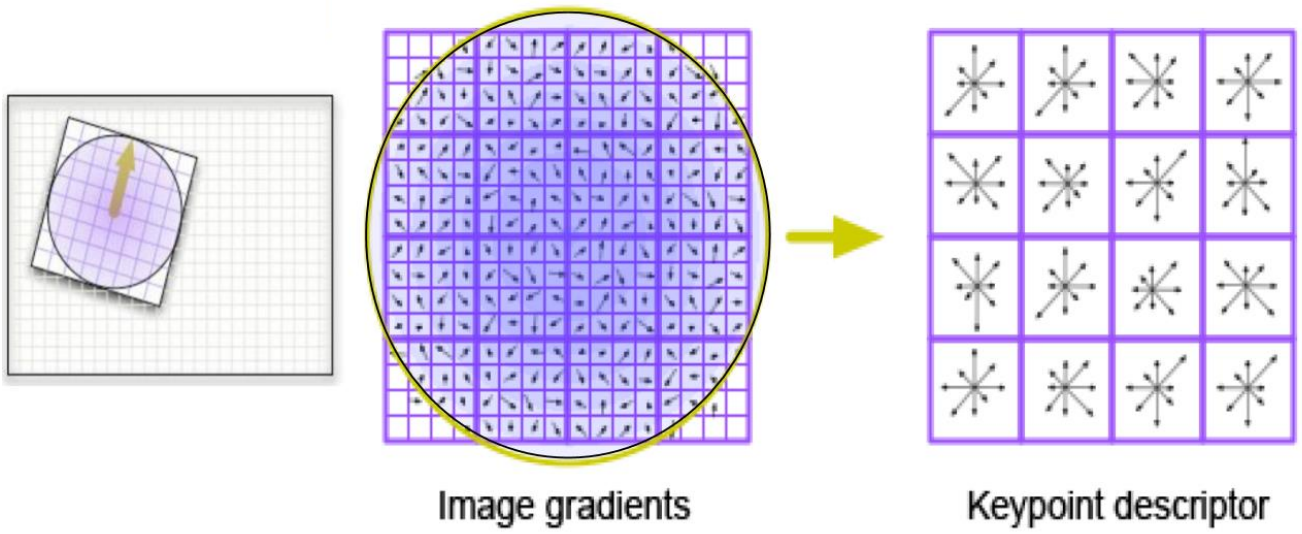
[Lowe, SIFT, 1999]

SIFT

- Find Difference of Gaussian scale-space extrema
- Post-processing
  - Position interpolation
  - Discard low-contrast points
  - Eliminate points along edges
- Orientation estimation
- Descriptor extraction
  - Motivation: We want some sensitivity to spatial layout, but not too much, so blocks of histograms give us that.

SIFT Descriptor Extraction

- Given a keypoint with scale and orientation:
  - Pick scale-space image which most closely matches estimated scale
  - Resample image to match orientation OR
  - Subtract detector orientation from vector to give invariance to general image rotation.



SIFT Orientation Normalization

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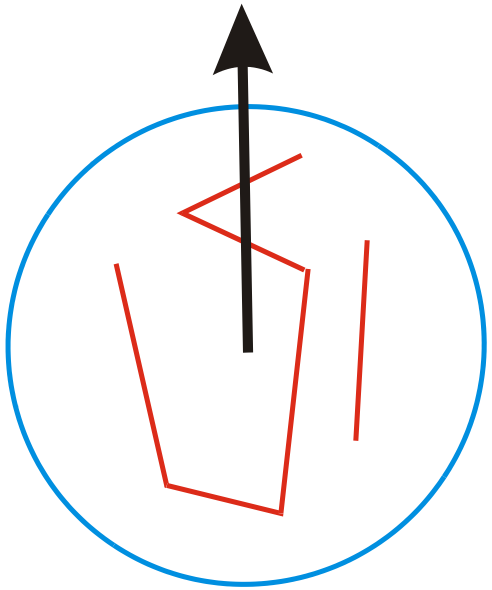
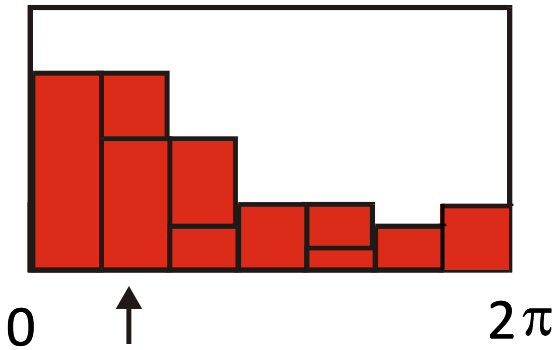
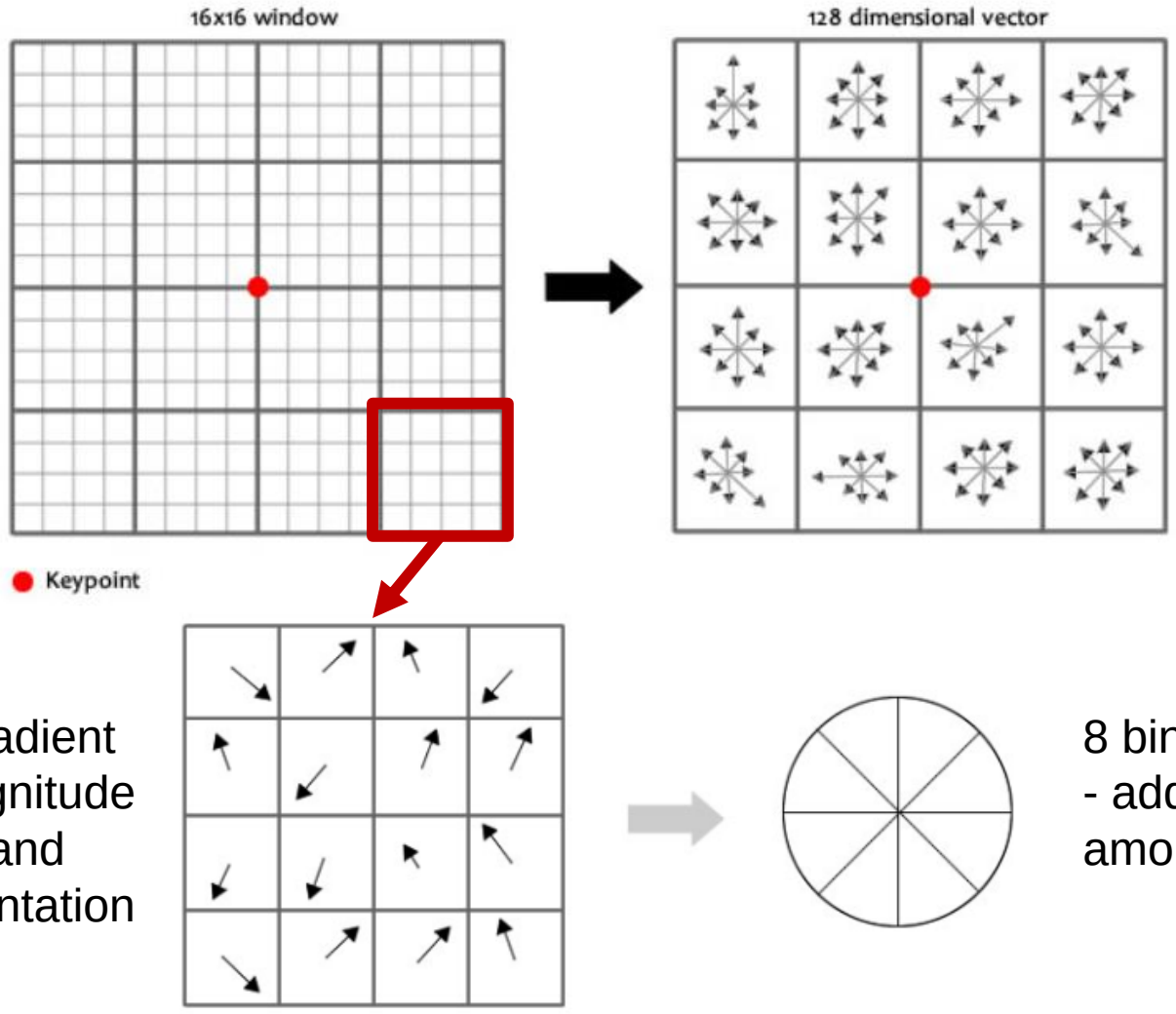




[Lowe, SIFT, 1999]

SIFT Descriptor Extraction

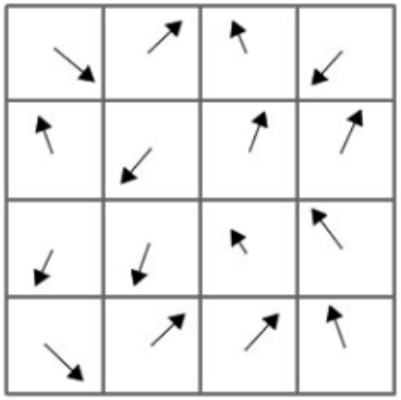
- Given a keypoint with scale and orientation

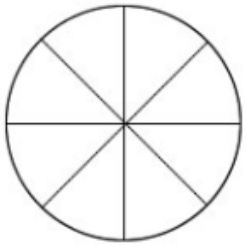


SIFT Descriptor Extraction

- Within each 4x4 window

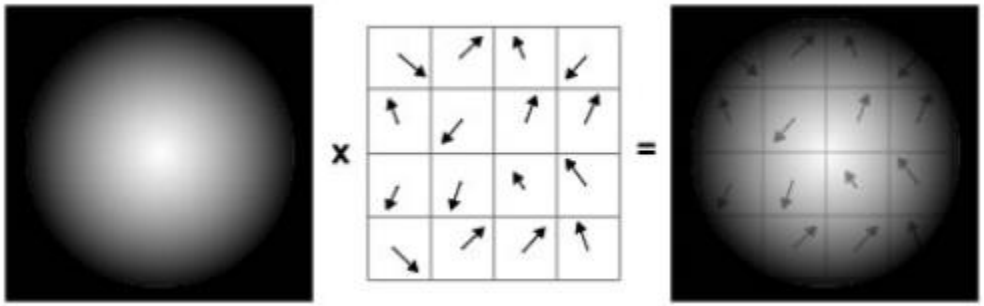
Gradient magnitude and orientation





8 bin ‘histogram’ - add magnitude amounts!

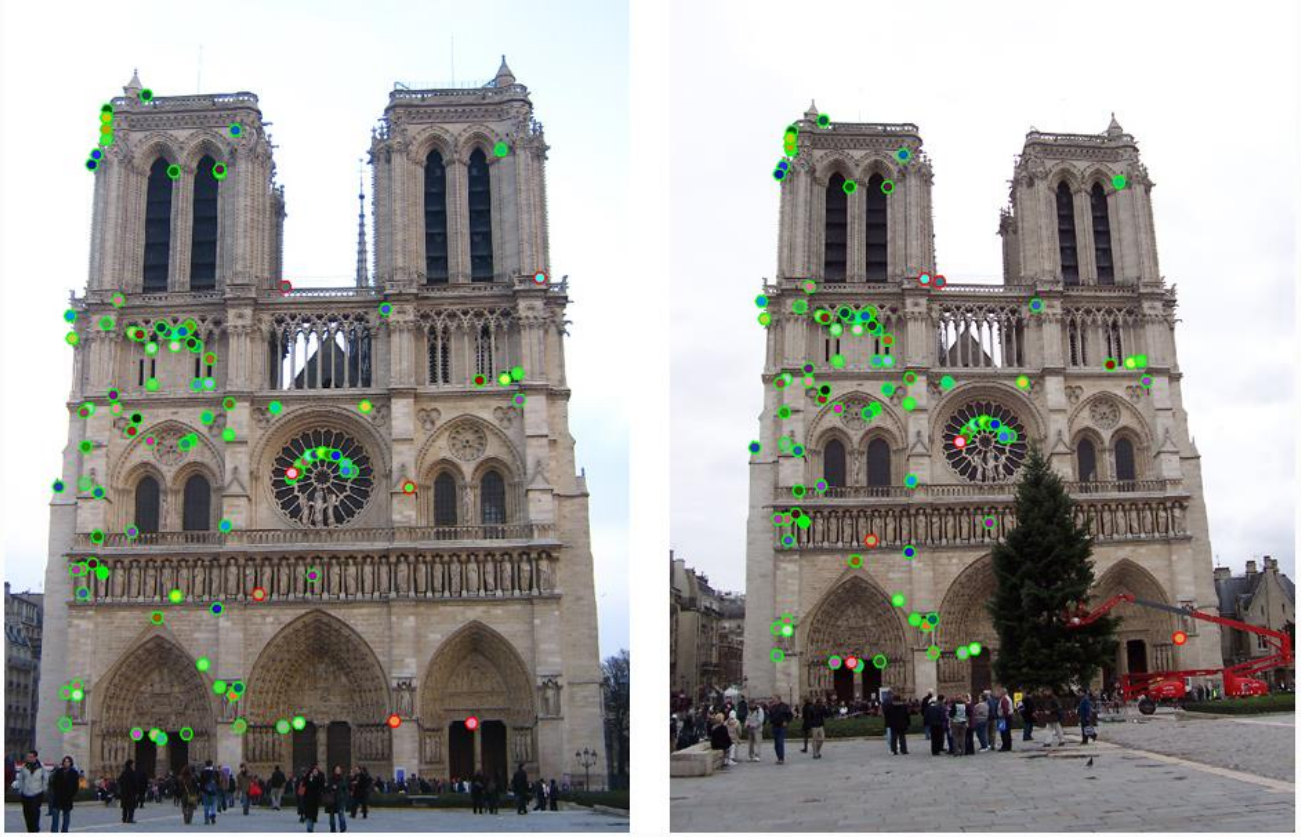
Weight magnitude that is added to ‘histogram’ by Gaussian



SIFT Descriptor Extraction

- Extract 8 x 16 values into 128-dim vector
- Illumination invariance:
  - Working in gradient space, so robust to $I = I + b$
  - Normalize vector to [0…1]
    - Robust to $I = \alpha I$ brightness changes
  - Clamp all vector values > 0.2 to 0.2.
    - Robust to “non-linear illumination effects”
    - Image value saturation / specular highlights
  - Renormalize

Specular highlights move between image pairs!



The top 100 most confident local feature matches from a baseline implementation of project 2. In this case, 93 were correct (highlighted in green) and 7 were incorrect (highlighted in red).

Project 2: Local Feature Matching
CSCI 1430: Introduction to Computer Vision

Logistics

- Files: proj2.zip (6.9 MB).
- Part 1: Questions
  - Questions + template: Now in the zip: questions/
  - Hand-in process: Gradescope as PDF. Submit anonymous materials please!
  - Due: Friday 29th Sept. 2017, 9pm.
- Part 2: Code
  - Writeup template: In the zip: writeup/
  - Required files: code/, writeup/writeup.pdf
  - Hand-in process: Gradescope as ZIP file. Submit anonymous materials please!

SIFT-like descriptor in Project 2

- SIFT is hand designed based on intuition
- You implement your own SIFT-like descriptor
  - Ignore scale/orientation to start.

- Parameters: stick with defaults + minor tweaks
- Feel free to look at papers / resources for inspiration

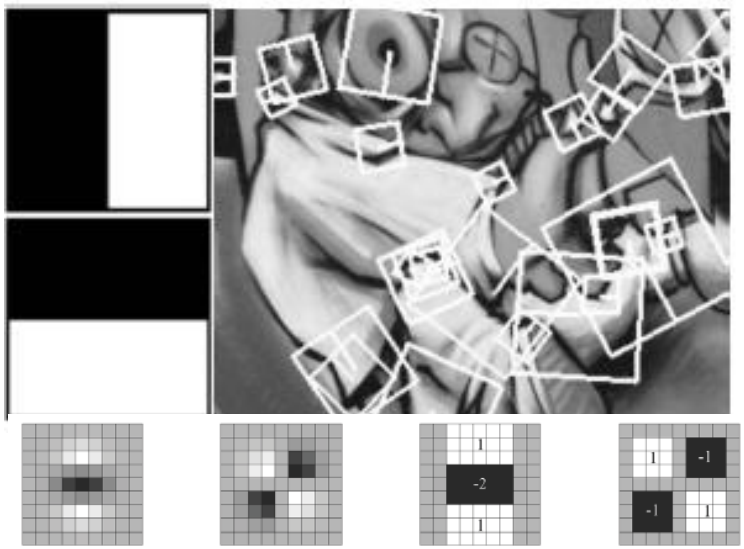
2017 Spring TA Martin Zhu recommends this tutorial:
http://aishack.in/tutorials/sift-scale-invariant-feature-transform-features/

Lowe's original paper: http://www.cs.ubc.ca/~lowe/papers/ijcv04.pdf

Efficient Implementation

- Filter using oriented kernels based on directions of histogram bins.
- Called ‘steerable filters’

Local Descriptors: SURF



Fast approximation of SIFT idea

Efficient computation by 2D box filters & integral images

⇒ 6 times faster than SIFT

Equivalent quality for object identification

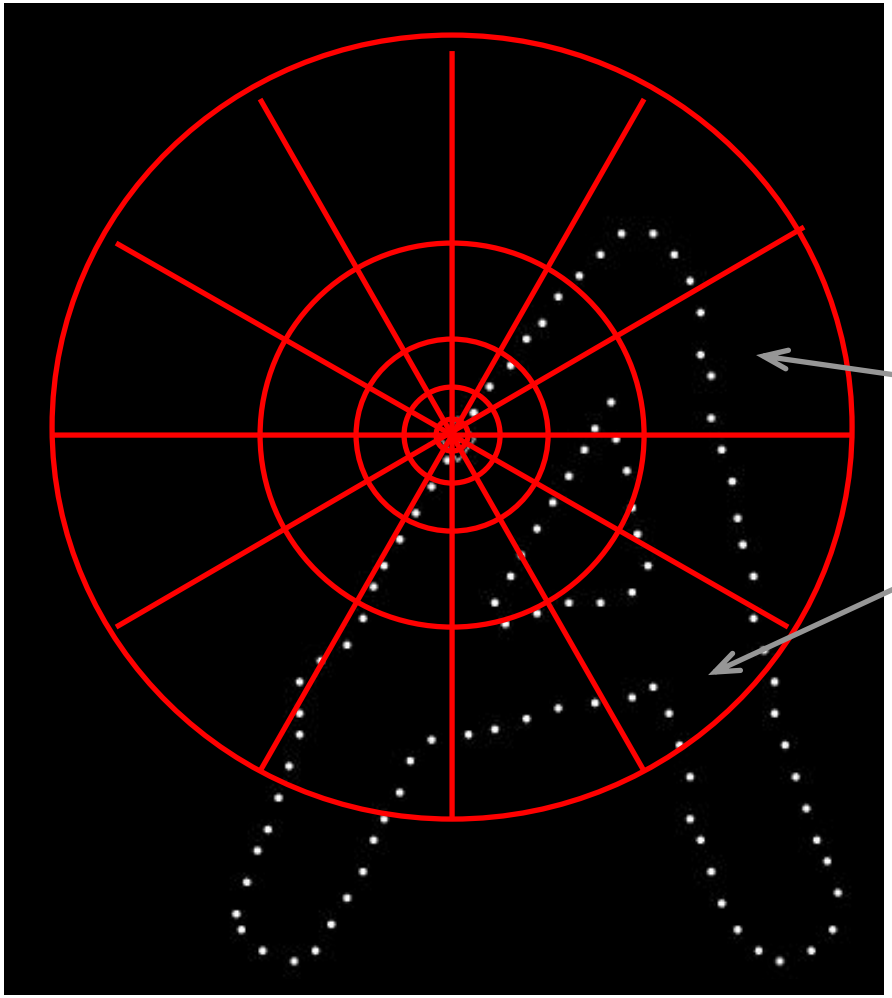
GPU implementation available

Feature extraction @ 200Hz (detector + descriptor, 640×480 img)

http://www.vision.ee.ethz.ch/~surf

[Bay, ECCV'06], [Cornelis, CVGPU'08]

Local Descriptors: Shape Context



Count the number of points inside each bin, e.g.:

Count = 4

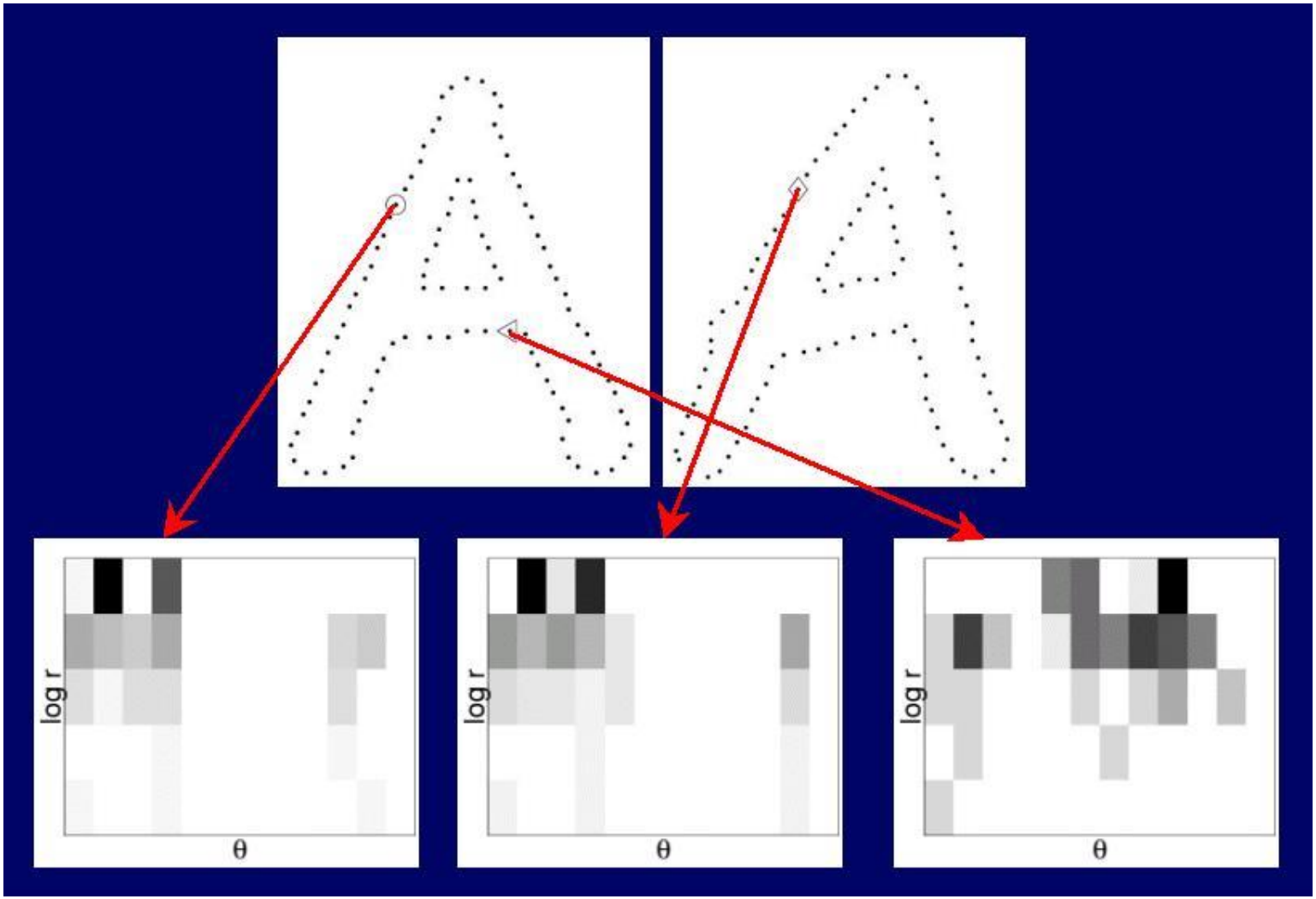
⋮

Count = 10

Log-polar binning:
More precision for nearby points, more flexibility for farther points.

Belongie & Malik, ICCV 2001

Shape Context Descriptor

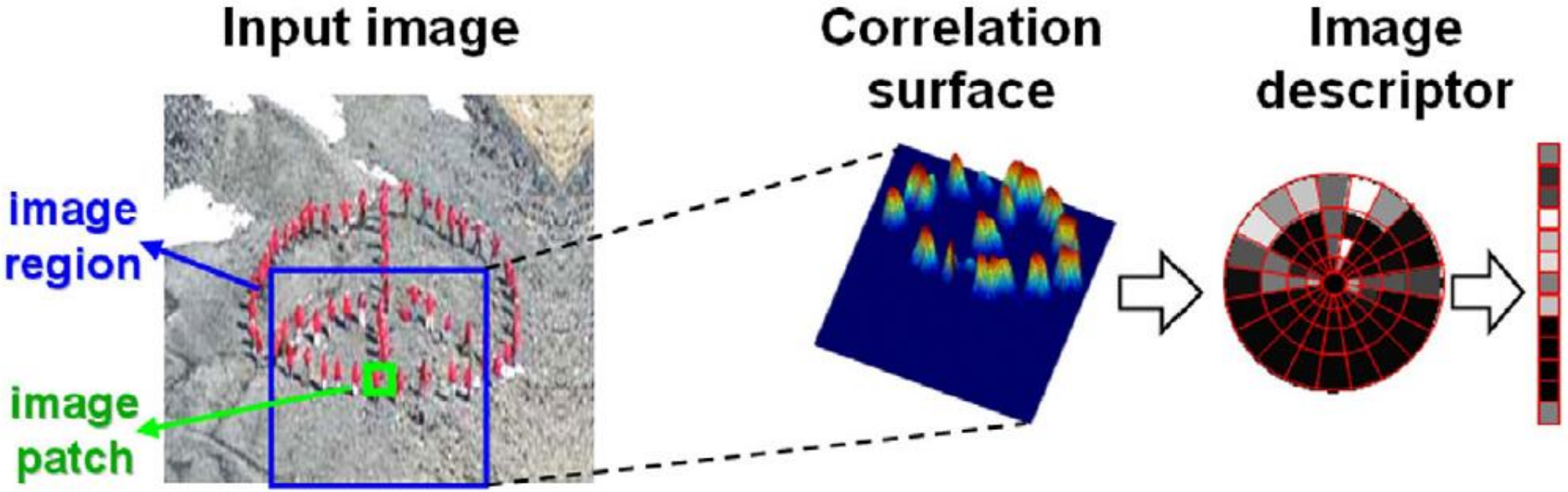


Self-similarity Descriptor

Figure 1. *These images of the same object (a heart) do NOT share common image properties (colors, textures, edges), but DO share a similar geometric layout of local internal self-similarities.*

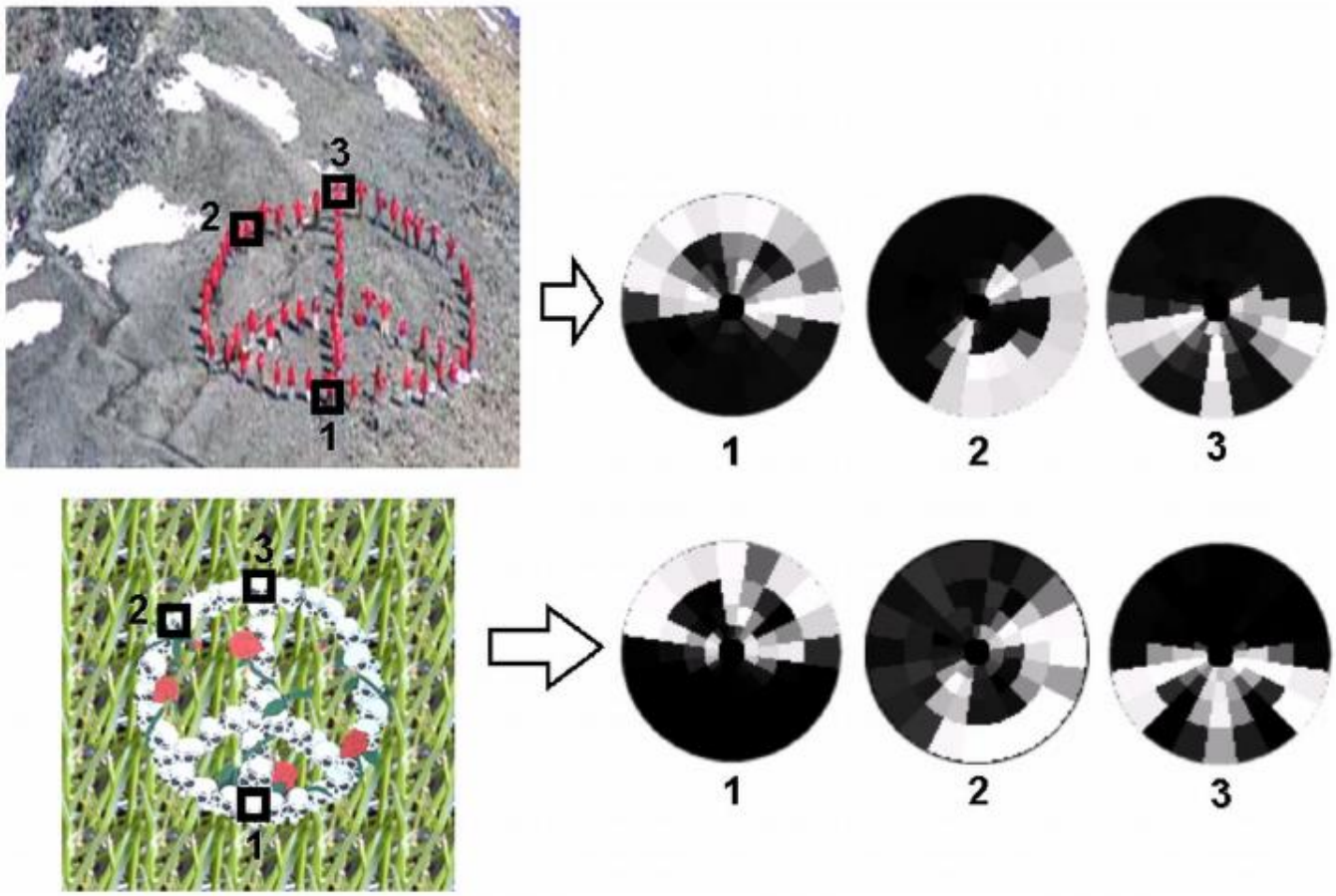
Matching Local Self-Similarities across Images and Videos, Shechtman and Irani, 2007

Self-similarity Descriptor



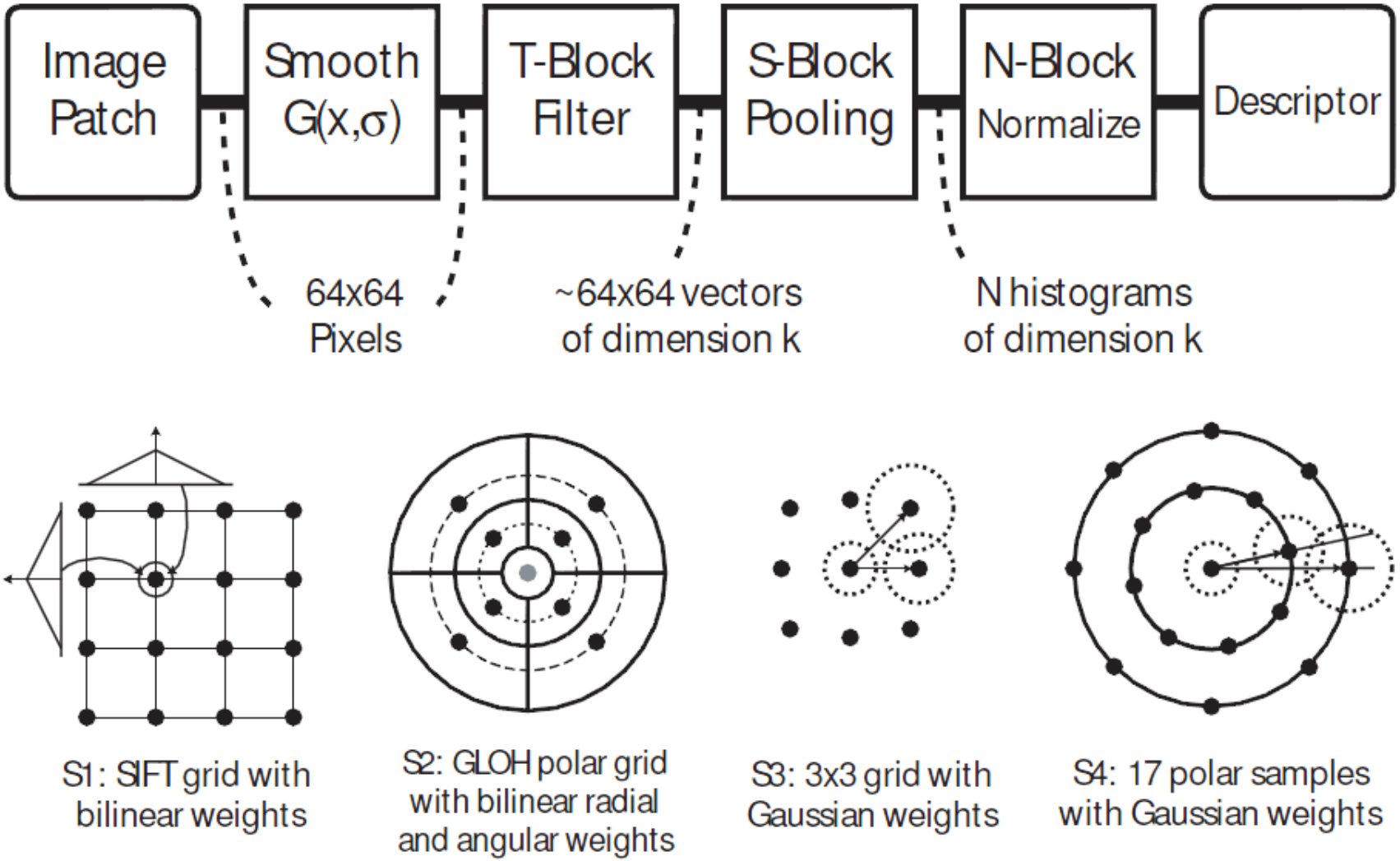
Matching Local Self-Similarities across Images and Videos, Shechtman and Irani, 2007

Self-similarity Descriptor



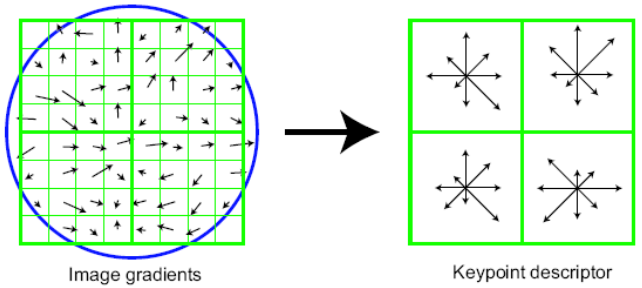
Matching Local Self-Similarities across Images and Videos, Shechtman and Irani, 2007

Learning Local Image Descriptors
Winder and Brown, 2007



Review: Local Descriptors

- Most features can be thought of as templates, histograms (counts), or combinations
- The ideal descriptor should be
  - Robust and Distinctive
  - Compact and Efficient
- Most available descriptors focus on edge/gradient information
  - Capture texture information
  - Color rarely used



Available at a web site near you…

- Many local feature detectors have executables available online:
  - http://www.robots.ox.ac.uk/~vgg/research/affine
  - http://www.cs.ubc.ca/~lowe/keypoints/
  - http://www.vision.ee.ethz.ch/~surf

Feature Matching

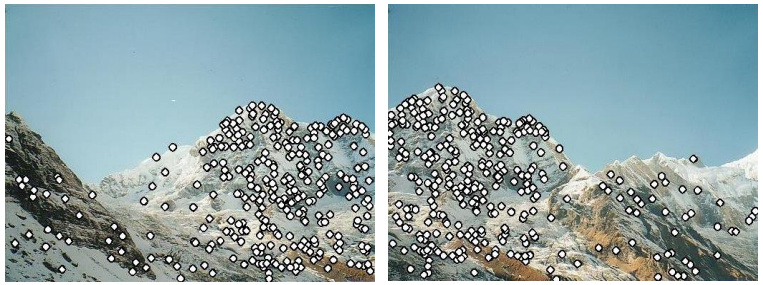
Read Szeliski 4.1

Many slides from James Hays, Derek Hoiem, and Grauman&Leibe 2008 AAAI Tutorial

Local features: main components

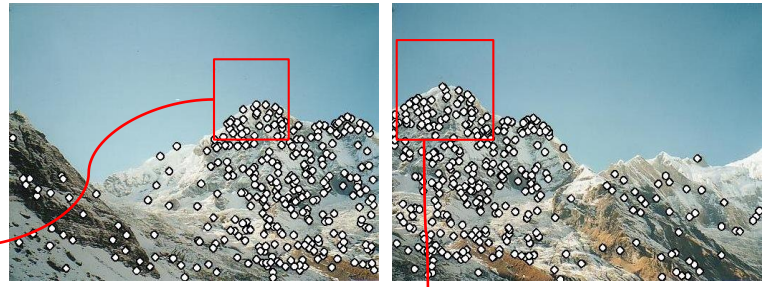
1) Detection:

Find a set of distinctive key points.



2) Description:

Extract feature descriptor around each interest point as vector.

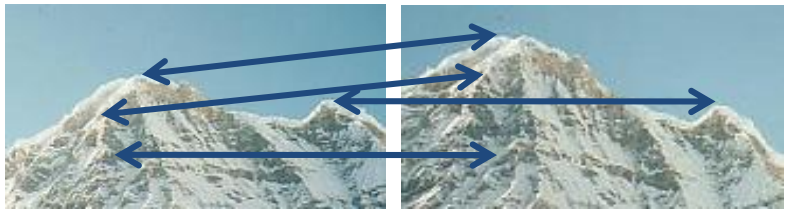


$$\mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}]$$

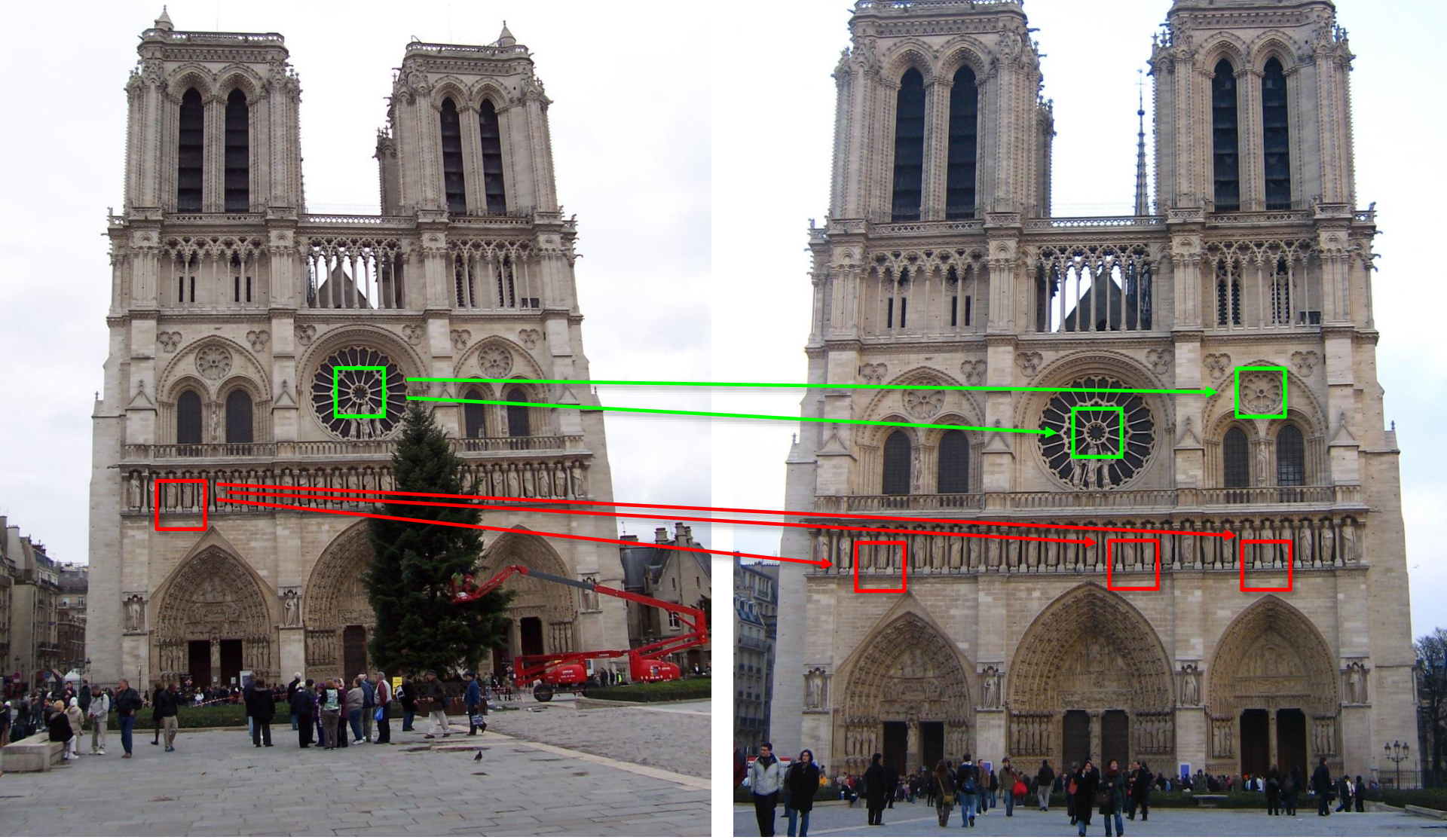
$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

3) Matching:

Compute distance between feature vectors to find correspondence.



How do we decide which features match?

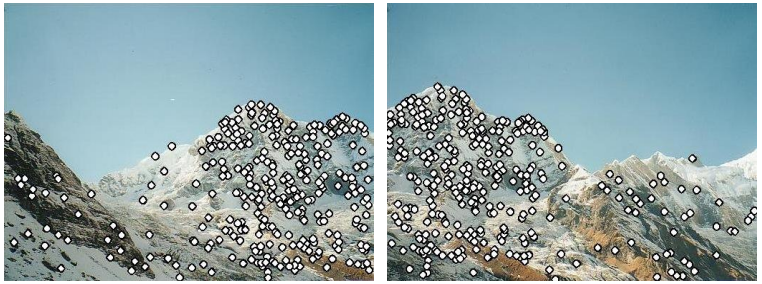


Distance: 0.34, 0.30, 0.40

Distance: 0.61, 1.22

Think-Pair-Share

- *Design a feature point matching scheme.*
- Two images, I_1 and I_2



- Two sets X_1 and X_2 of feature points
  - Each feature point $\mathbf{x_1}$ has a descriptor $\mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}]$

- Distance, bijective/injective/surjective, noise, confidence, computational complexity, generality…

Euclidean distance vs. Cosine Similarity

- Euclidean distance:

$$\mathrm{d}(\mathbf{p}, \mathbf{q}) = \mathrm{d}(\mathbf{q}, \mathbf{p}) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \cdots + (q_n - p_n)^2}$$

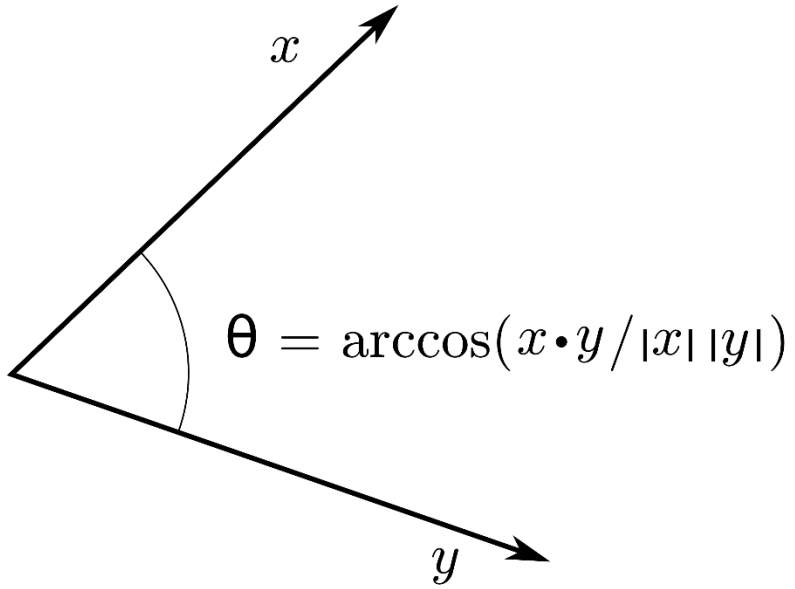
$$= \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2}.$$

$$\|\mathbf{q} - \mathbf{p}\| = \sqrt{(\mathbf{q} - \mathbf{p}) \cdot (\mathbf{q} - \mathbf{p})}.$$

- Cosine similarity:

$$\mathbf{a} \cdot \mathbf{b} = \|\mathbf{a}\|_2 \|\mathbf{b}\|_2 \cos\theta$$

$$\mathbf{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|_2 \|\mathbf{B}\|_2}$$



Wikipedia

Feature Matching

- Criteria 1:
  - Compute distance in feature space, e.g., Euclidean distance between 128-dim SIFT descriptors
  - Match point to lowest distance (nearest neighbor)

- Problems:
  - Does everything have a match?

Feature Matching

- Criteria 2:
  - Compute distance in feature space, e.g., Euclidean distance between 128-dim SIFT descriptors
  - Match point to lowest distance (nearest neighbor)
  - Ignore anything higher than threshold (no match!)

- Problems:
  - Threshold is hard to pick
  - Non-distinctive features could have lots of close matches, only one of which is correct

Nearest Neighbor Distance Ratio

Compare distance of closest (NN1) and second-closest (NN2) feature vector neighbor.

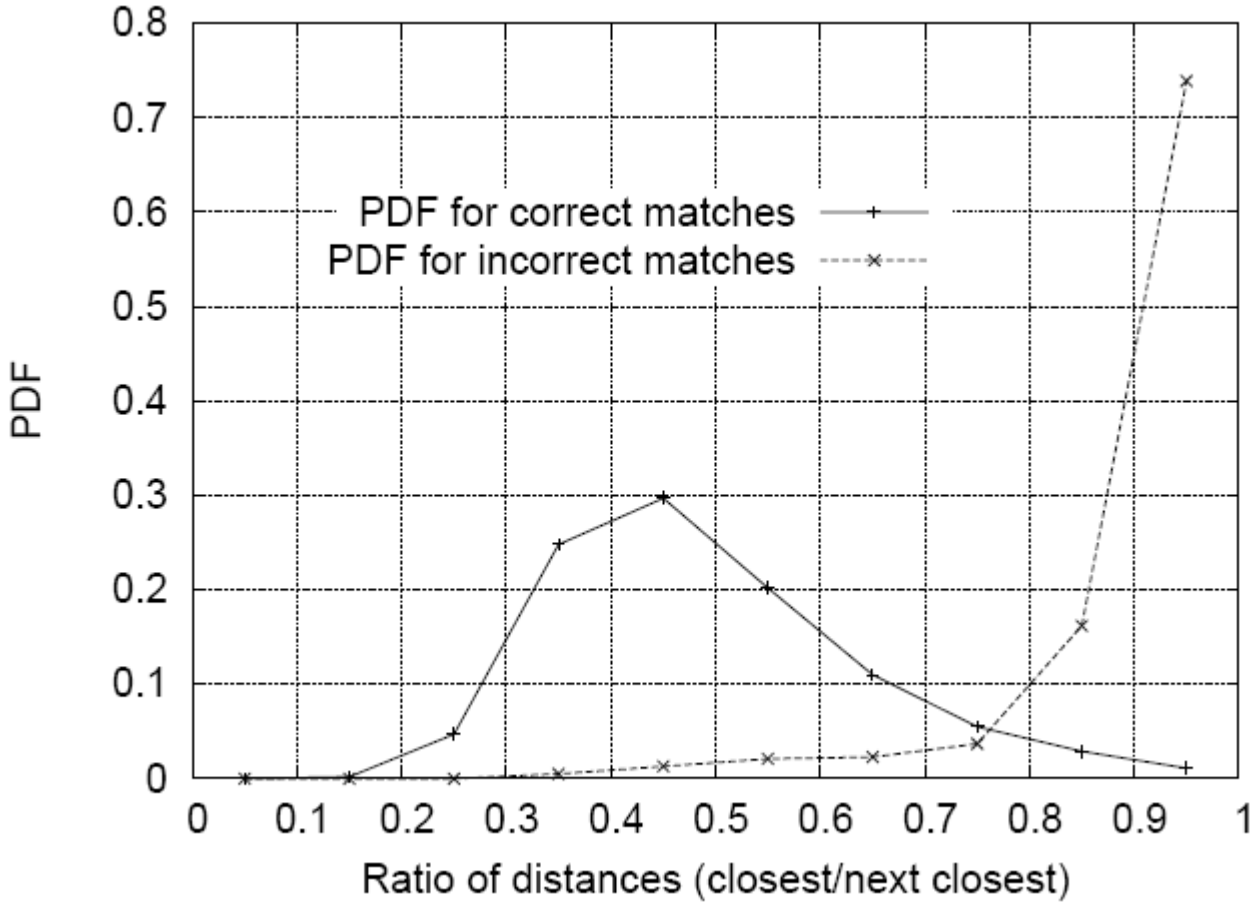
- If NN1 ≈ NN2, ratio $\frac{NN1}{NN2}$ will be ≈ 1 -> matches too close.
- As NN1 << NN2, ratio $\frac{NN1}{NN2}$ tends to 0.

Sorting by this ratio puts matches in order of confidence.

Threshold ratio – but how to choose?

Nearest Neighbor Distance Ratio

- Lowe computed a probability distribution functions of ratios
- 40,000 keypoints with hand-labeled ground truth



Ratio threshold depends on your application's view on the trade-off between the number of false positives and true positives!

Lowe IJCV 2004

Efficient compute cost

- Naïve looping: Expensive

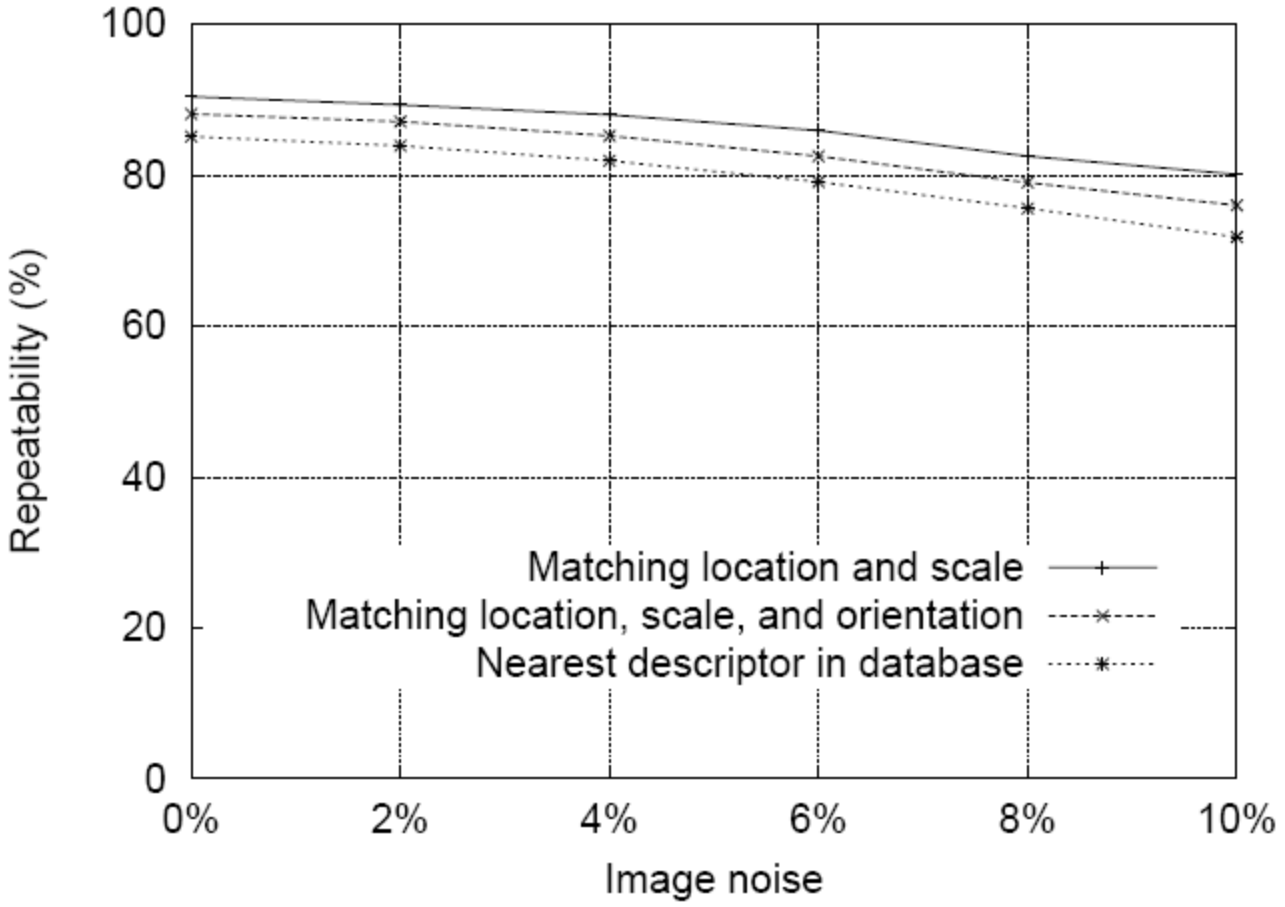
- Operate on matrices of descriptors
- E.g., for row vectors,

  $\texttt{features\_image1} * \texttt{features\_image2}^{T}$

  produces matrix of dot product results for all pairs of features

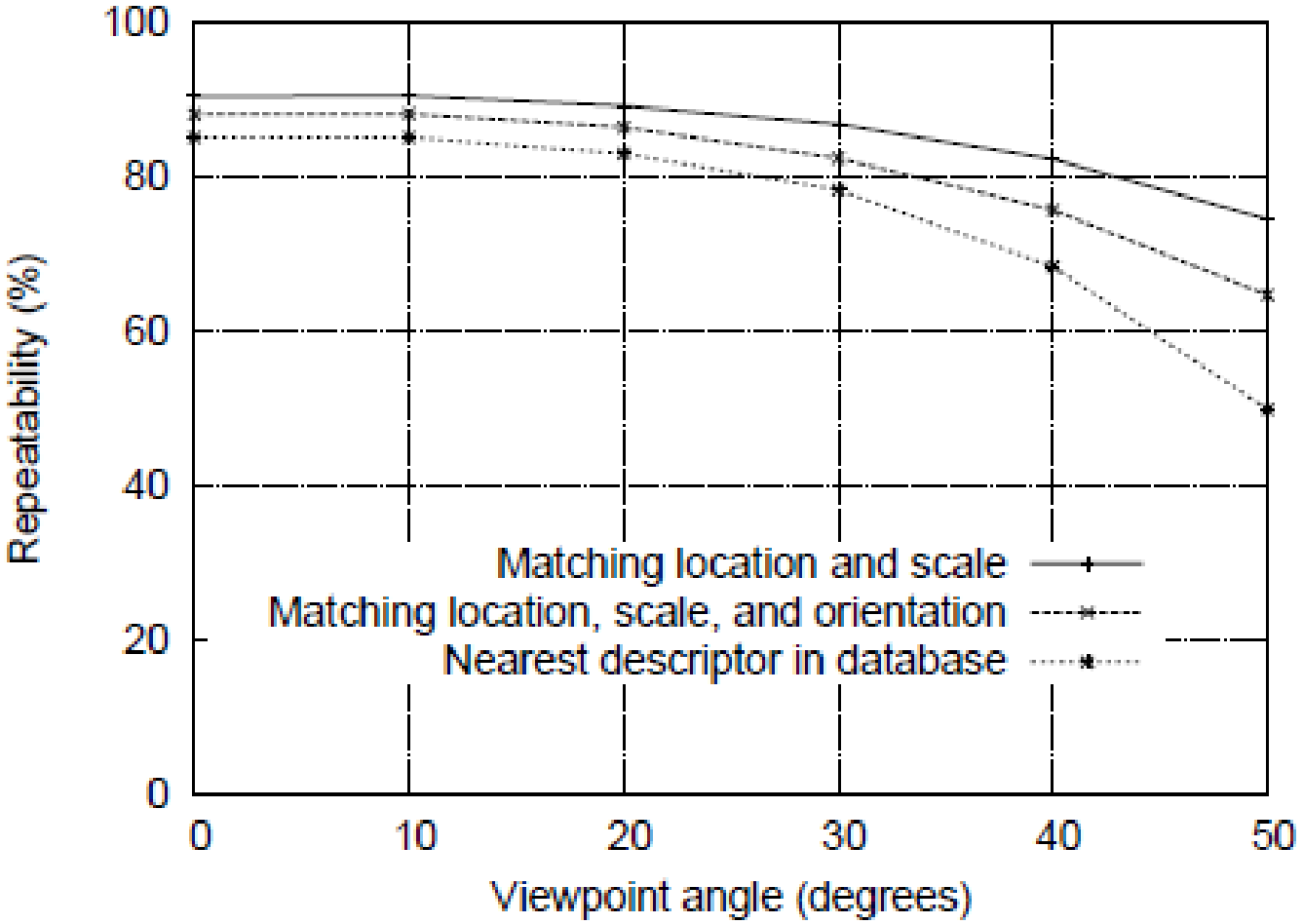
HOW GOOD IS SIFT?

SIFT Repeatability



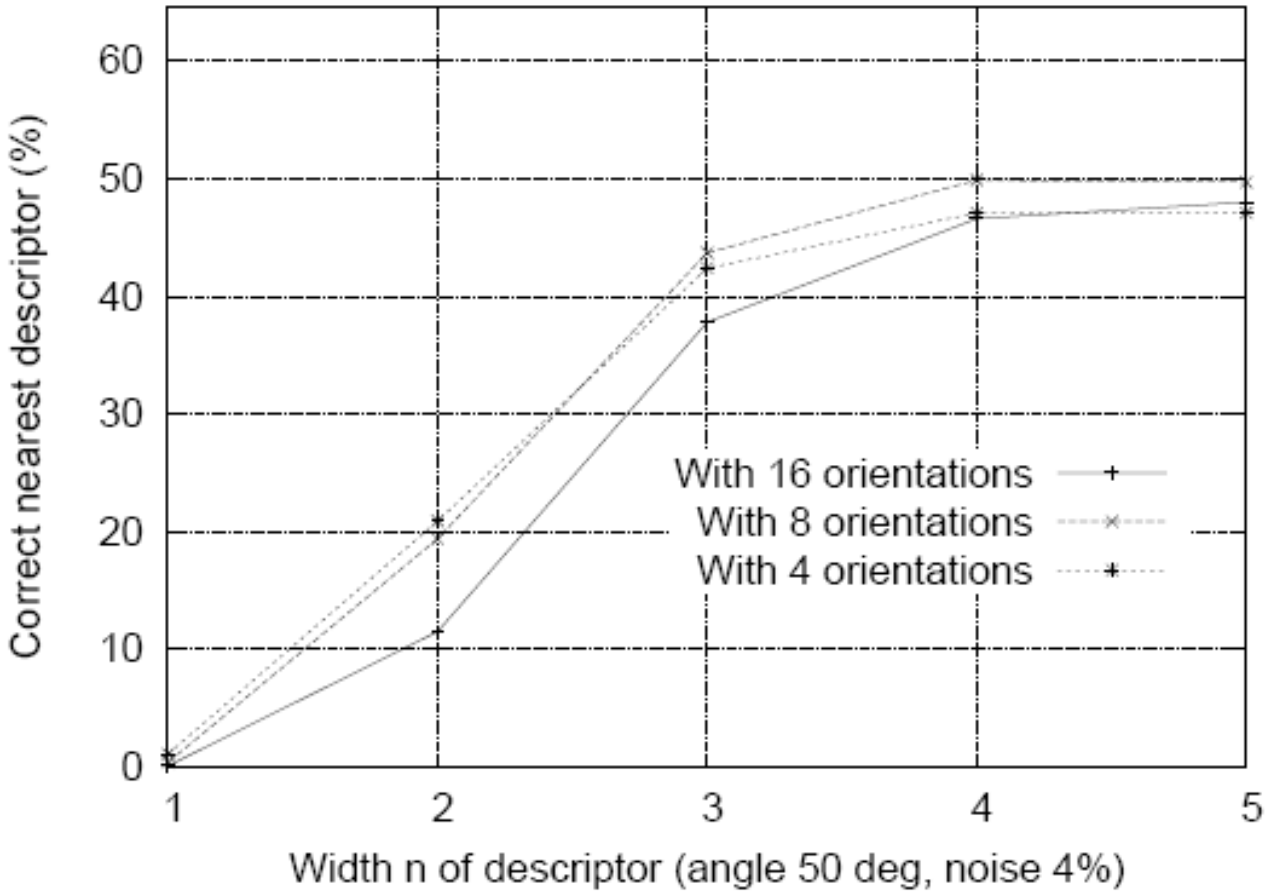
Lowe IJCV 2004

SIFT Repeatability



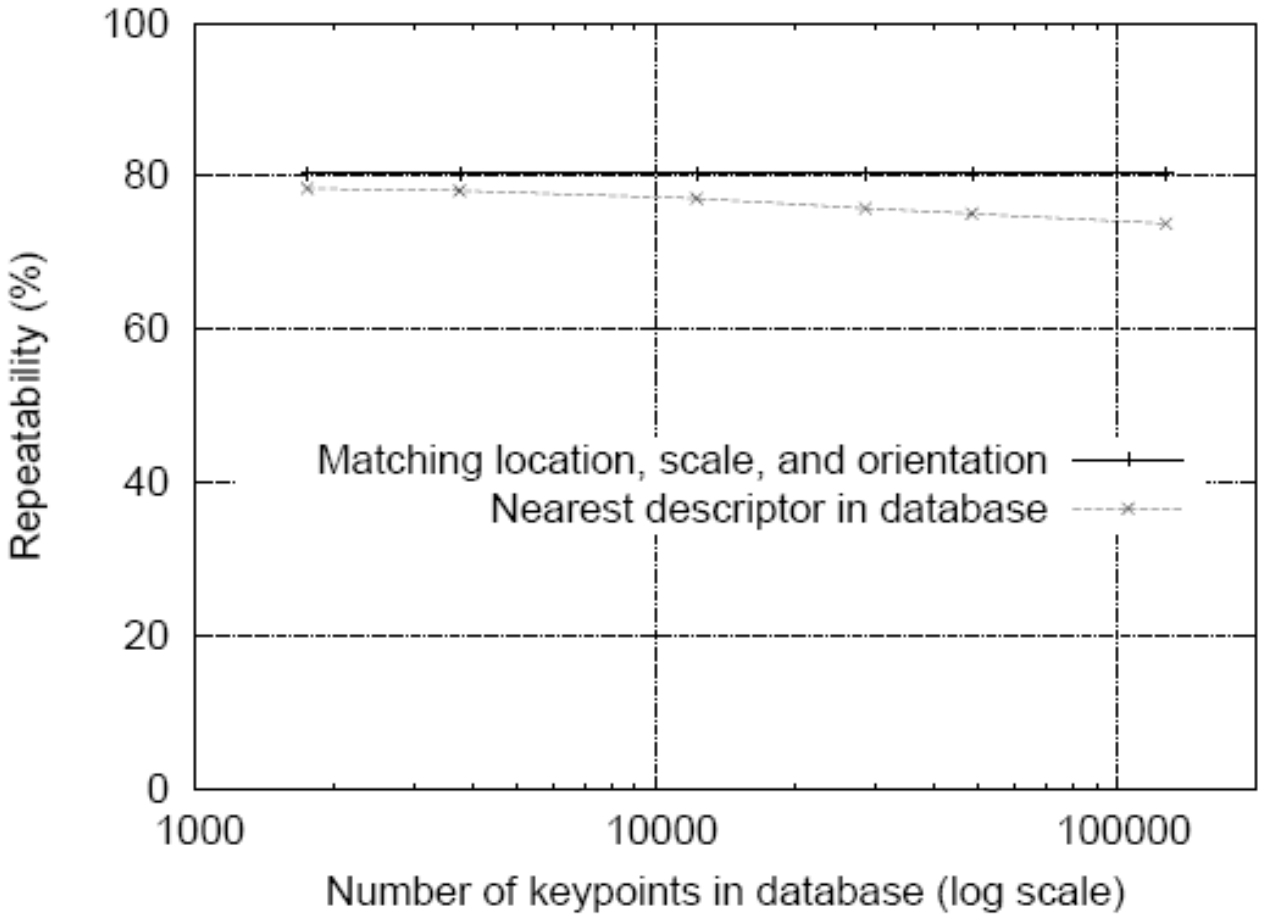
Lowe IJCV 2004

SIFT Repeatability



Lowe IJCV 2004

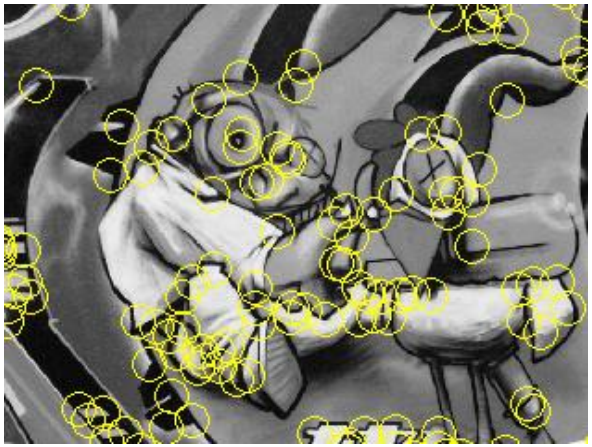
SIFT Repeatability



Lowe IJCV 2004

Review: Interest points

- Keypoint detection: repeatable and distinctive
  - Corners, blobs, stable regions
  - Harris, DoG



- Descriptors: robust and selective
  - Spatial histograms of orientation
  - SIFT