Computer Vision for HCI

Interest Points

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Topics of This Lecture

- Local Invariant Features
  - Motivation
  - Requirements, Invariances
- Keypoint Localization
  - Features from Accelerated Segment Test (FAST)
  - Harris
  - Shi-Tomasi
- Scale Invariant Region Selection
  - Automatic scale selection
  - Laplacian-of-Gaussian detector
  - Difference-of-Gaussians detector
- Local Descriptors
  - Orientation normalization
  - SIFT

Slides adapted from Brown, Efros, Frolova, Grauman, Jacobs, Lazebnik, Leibe, Lowe, Mikolajczyk, Seitz, Simakov, Szeliski, and Tuytelaars

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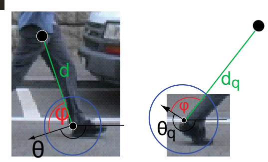
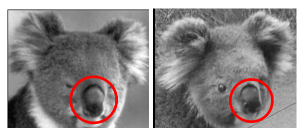
Global vs. Local Matching

- Global image representations can be easily corrupted (e.g., by even small occlusion)
- Instead, describe and match using multiple local regions
- Increased robustness to
  - Occlusions
  
  - Articulation
  

  - Within-category variations
  

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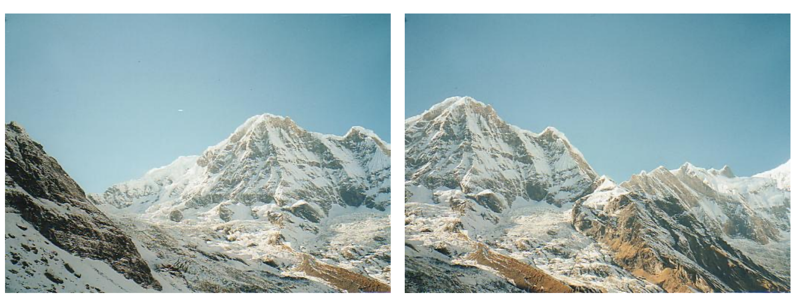
Application:

Image Stitching w/ Local Features



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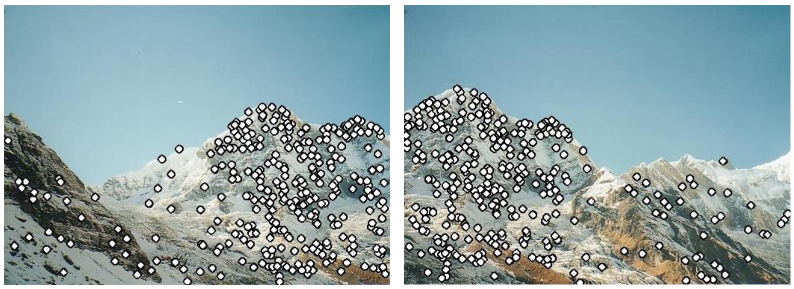
Application:
Image Stitching w/ Local Features

Find good locations



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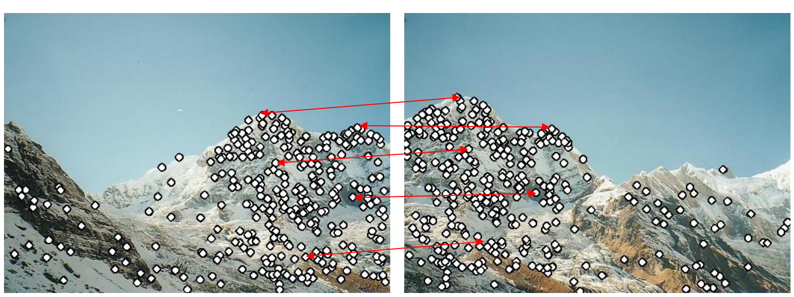
Application:
Image Stitching w/ Local Features

Match/Correspond them



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Application:
Image Stitching w/ Local Features

Transform images so points align

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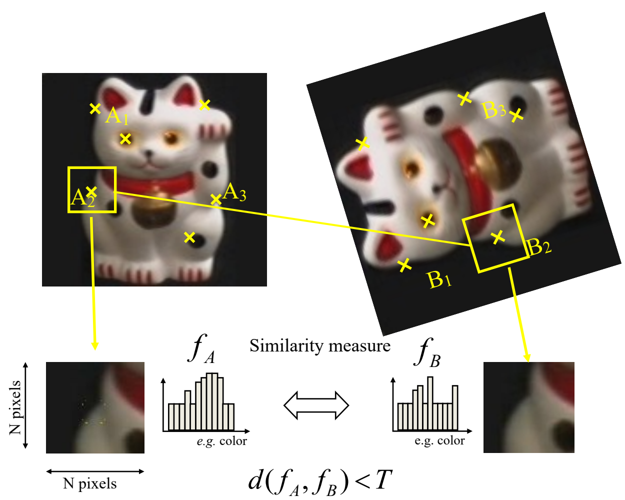
General Approach



1. Find a set of distinctive key-points
2. Define a region around each keypoint
3. Extract and *normalize* the region content
4. Compute a local descriptor from the normalized region
5. Match local descriptors

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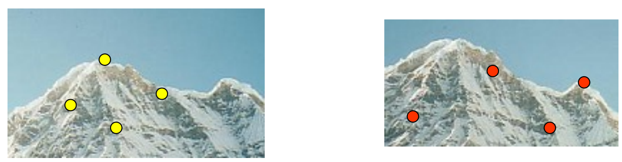
Common Requirements

- Problem 1:
  - Detect the <u>same</u> points *independently* in both images



No chance to match!

We need a <u>repeatable</u> detector!

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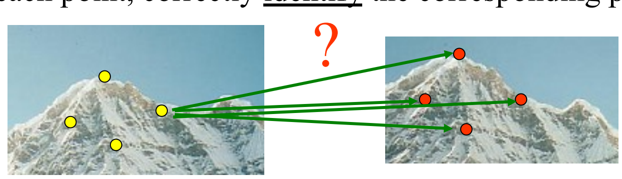
Common Requirements

- Problem 1:
  - Detect the same points *independently* in both images
- Problem 2:
  - For each point, correctly <u>identify</u> the corresponding point



We need a reliable and distinctive descriptor!

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Invariance: Geometric Transformations

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Invariance: Photometric Transformations

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Requirements

- **Repeatable**: region extraction needs to be
  - Invariant to translation, rotation, scale changes, and other simple (affine) transformations
  - Robust to lighting variations, noise, blur, quantization
- **Local**: to be more robust to occlusion and clutter
- **Large Quantity**: need a sufficient number of regions to cover the object
- **Highly Distinctive**: regions should contain "interesting" structure
- **Efficient**: close to real-time performance

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Many Existing Detectors Available

- Hessian & Harris [Beaudet '78], [Harris '88]
- Laplacian, DoG [Lindeberg '98], [Lowe '99]
- Harris-/Hessian-Laplace [Mikolajczyk & Schmid '01]
- Harris-/Hessian-Affine [Mikolajczyk & Schmid '04]
- EBR and IBR [Tuytelaars & Van Gool '04]
- MSER [Matas '02]
- Salient Regions [Kadir & Brady '01]
- Others…

Detectors are a basic building block for many applications in Computer Vision

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FAST Detector

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Features from Accelerated Segment Test (**FAST**)

- Compare local neighborhood around each pixel to determine if the pixel is a good feature point
- For each pixel x
  - Look at the pixels on the border of a circle of radius r around x
  - Let n be the number of **contiguous pixels** (check for wrap-around!!) whose intensities are either
    1) **all** $> (I(x) + T)$ ***or*** 2) **all** $< (I(x) - T)$
    - $I(x)$ is the intensity at pixel x and T is a threshold
  - If $n \geq n^*$ then the pixel is considered a feature
    - Original paper (Rosten 2006) suggests using $r = 3$ (yields 16 pixels on border) and $n^* = 12$
    - Later results suggest using $r = 3$ (yields 16 pixels on border) and $n^* = 9$ provides best detector

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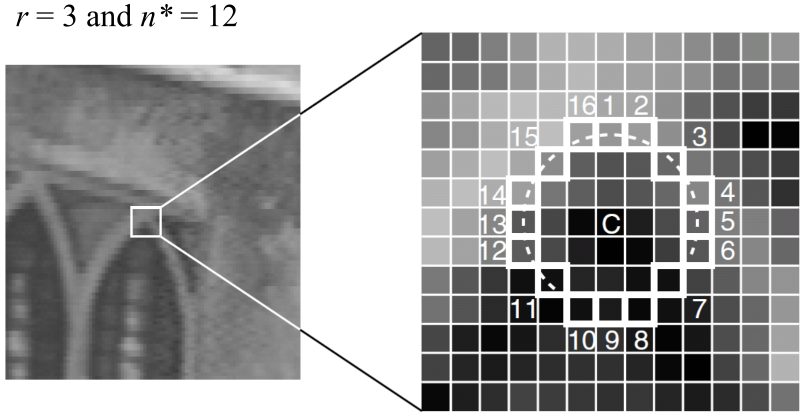
FAST Example

- $r = 3$ and $n^* = 12$



- Techniques can be employed to decrease computation time

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Example

- Use FAST corner detector to determine if pixel X with intensity value of 100 is a corner point
  - Intensity threshold T = 20
    - Thus “Above” > 120 and “Below” < 80 (else “Within”)
  - Contiguous pixel count $n \geq n^* = 9$

Values of the pixels on the border of the circle (of radius 3) centered at X:

70	125	130	125	140	135	75	70	65	140	145	140	100	105	65	60
B	A	A	A	A	A	B	B	B	A	A	A	W	W	B	B
			5				3			3				3	

5 < 9 so **NO** (the pixel X is <u>not</u> a corner point)!

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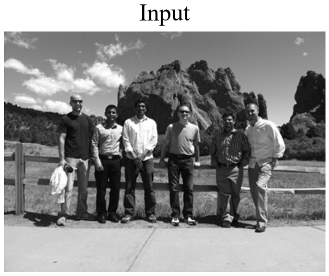
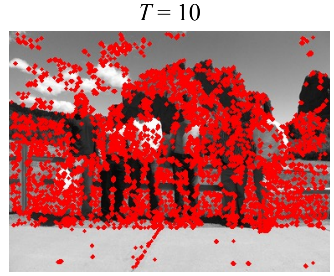
FAST Example ($r = 3$, $n^* = 12$)

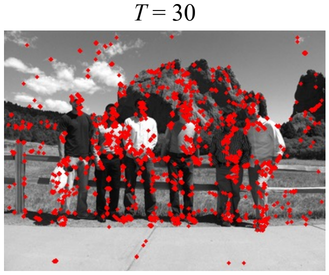
Input



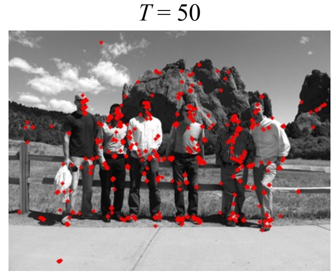
$T = 10$



$T = 30$



$T = 50$



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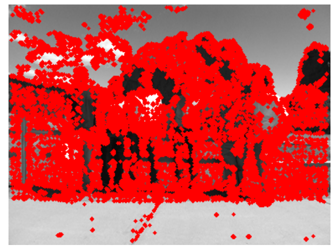
FAST Example ($r = 3$, $n^* = 9$)

Input

$T = 10$



$T = 30$

$T = 50$

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Harris Detector

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Harris Detector

- Based on the matrix M, which is a 2x2 correlation matrix from image derivatives around a pixel (recall from Optic Flow and KLT!):

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

Sum over image region – the area we are checking for corner

Window/Weighting function

Gradients with respect to x and y

To evaluate the "cornerness" of a particular pixel location from its local region

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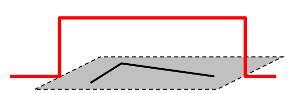
Window/Weighting Function $w(x,y)$

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

- Option 1: uniform window
  - Sum over square window

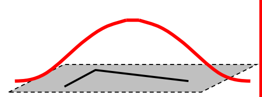
$$M = \sum_{x,y} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$



1 in window, 0 outside

- Option 2: Gaussian window
  - Gaussian performs weighted sum
  - Also is rotation invariant

$$M = g(\sigma) * \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$



Gaussian

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Gradients

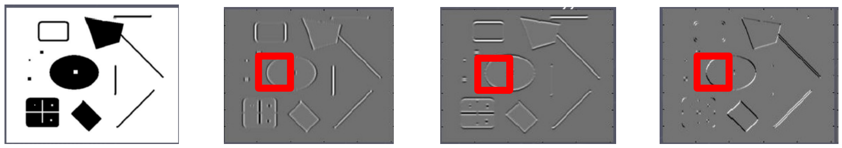

Image I | I_x | I_y | I_xI_y

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

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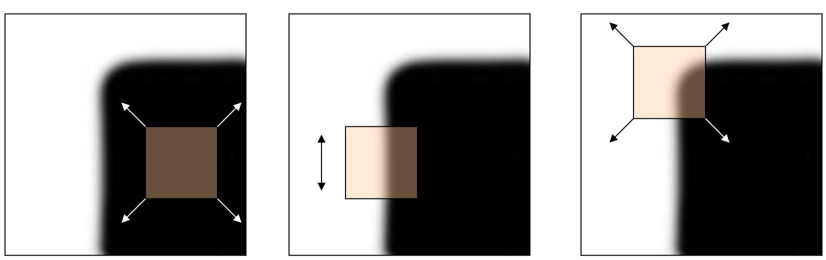
Flat vs. Edge vs. Corner



"flat" region: no change in all directions

"edge": no change along the edge direction

"corner": significant change in all directions

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Eigenvalues of M

Let $\lambda_1 \geq \lambda_2$ be the Eigenvalues of M

$\lambda_1 < e$: intensity is nearly constant over patch

$\lambda_1 \gg \lambda_2$: edge was found

$\lambda_2 > T$: corner or textured patch found

(Recall KLT "Good Features" to track!)

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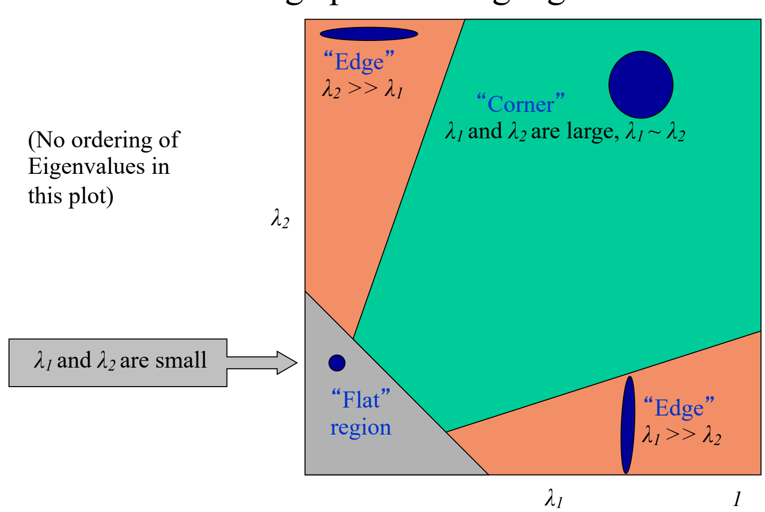
Interpreting the Eigenvalues

- Classification of image points using eigenvalues of M



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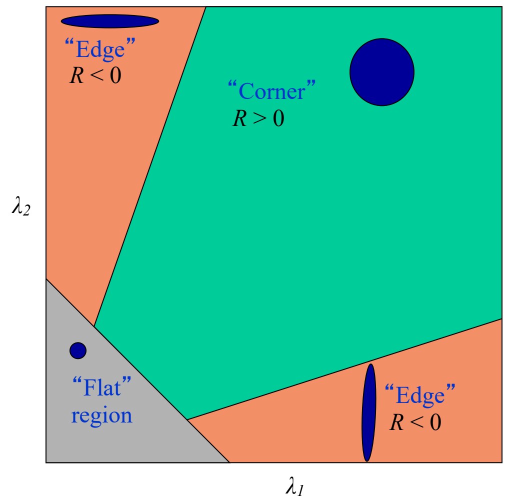
"Harris" Corner Response Function

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

Know the det() and trace() relationship to eigenvalues!

- Fast approximation
  - Avoids computing Eigenvalues
  - α: constant (0.04 to 0.06)



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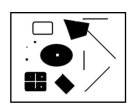
Summary: Harris Detector

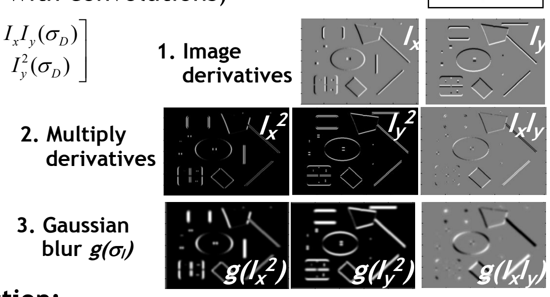


Compute *M* (can easily do with convolutions)

$$M(\sigma_I,\sigma_D) = g(\sigma_I) * \begin{bmatrix} I_x^2(\sigma_D) & I_xI_y(\sigma_D) \\ I_xI_y(\sigma_D) & I_y^2(\sigma_D) \end{bmatrix}$$

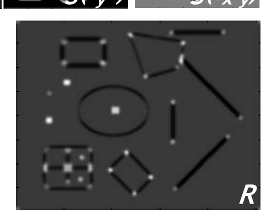
Gaussian **window** sigma

Gaussian **derivative** sigma



Compute Cornerness function:

$$R = \det[M(\sigma_I,\sigma_D)] - \alpha[\mathrm{trace}(M(\sigma_I,\sigma_D))]^2$$
$$= g(I_x^2)g(I_y^2) - [g(I_xI_y)]^2 - \alpha[g(I_x^2)+g(I_y^2)]^2$$



Remove small values in *R*, and then perform non-maximum suppression (keeping only peaks)

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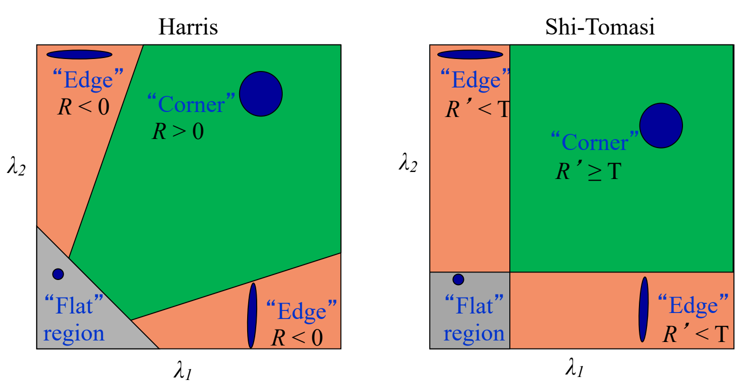
Harris Detector – Responses

Shi-Tomasi Corner Detector

- Similar to Harris corner points

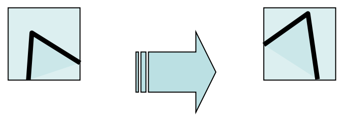
Harris $R = \det(M) - \alpha\, \mathrm{trace}(M)^2 = \lambda_1 \lambda_2 - \alpha(\lambda_1 + \lambda_2)^2$

Shi-Tomasi $R' = \min(\lambda_1, \lambda_2)$ (recall KLT good features!)



Harris and Shi-Tomasi Detector: Properties

- Rotation invariance?



Eigenvalues remains the same

Corner response R is invariant to image rotation

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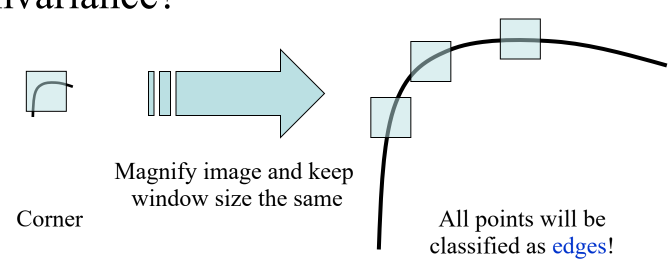
Harris and Shi-Tomasi Detector: Properties

- Rotation invariance
- Scale invariance?



Not invariant to image scale!

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From Points to Regions…

- Harris and Shi-Tomasi operators define interest points

- How can we detect scale invariant "interest *regions*"?
  - In order to **compare** points (e.g., for image matching or stitching), we need to compute a descriptor over a region
  - How can we define such a region in a **scale invariant** manner?

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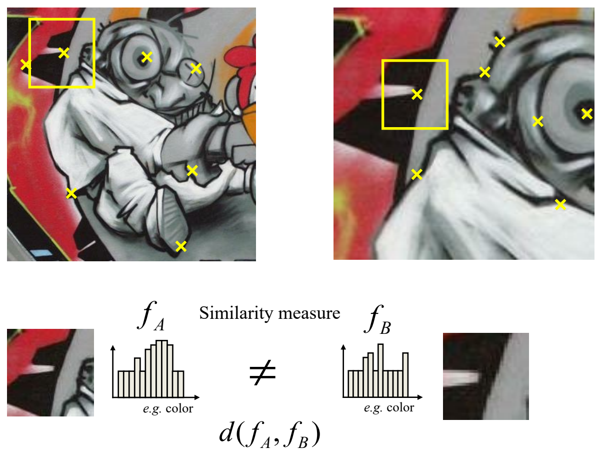
Naïve Approach: Exhaustive Search

- Multi-scale procedure
  - Compare descriptors while varying the patch size in the other image



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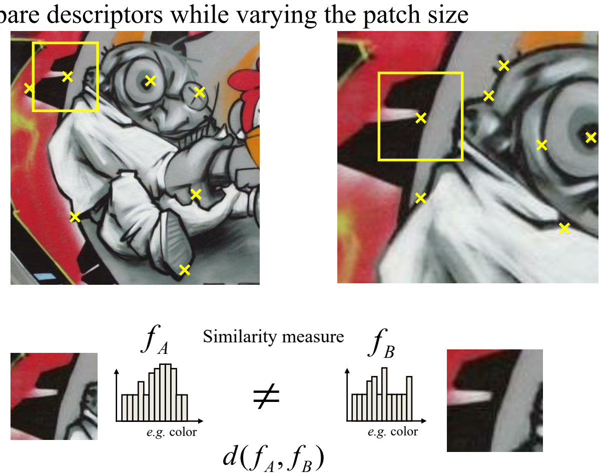
Naïve Approach: Exhaustive Search

- Multi-scale procedure
  - Compare descriptors while varying the patch size



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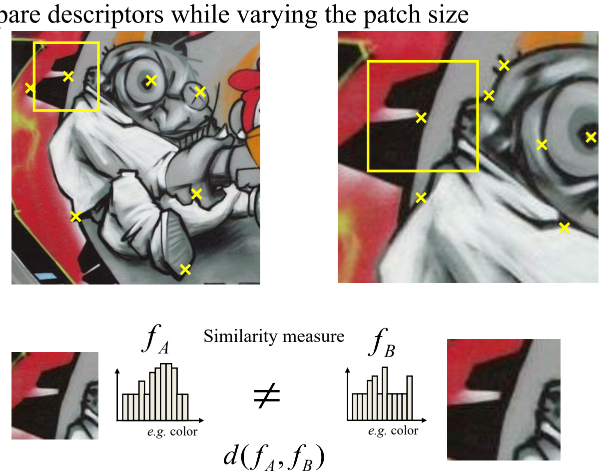
Naïve Approach: Exhaustive Search

- Multi-scale procedure
  - Compare descriptors while varying the patch size



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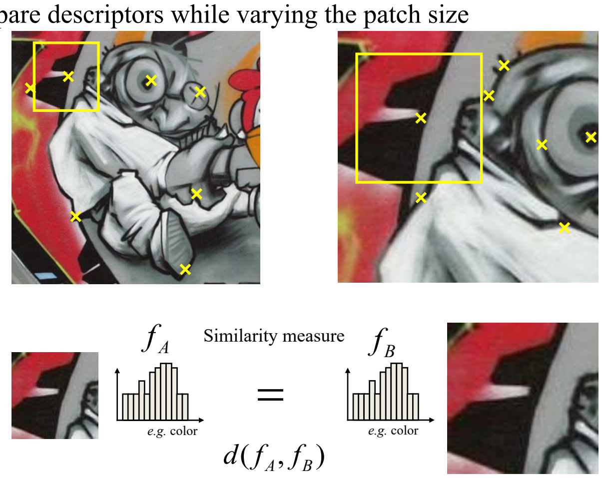
Naïve Approach: Exhaustive Search

- Multi-scale procedure
  - Compare descriptors while varying the patch size



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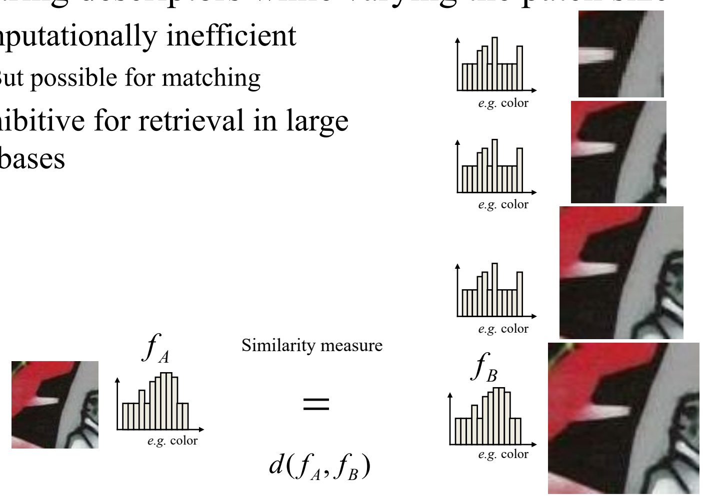
Naïve Approach: Exhaustive Search

- Comparing descriptors while varying the patch size
  - Computationally inefficient
    - But possible for matching
  - Prohibitive for retrieval in large databases



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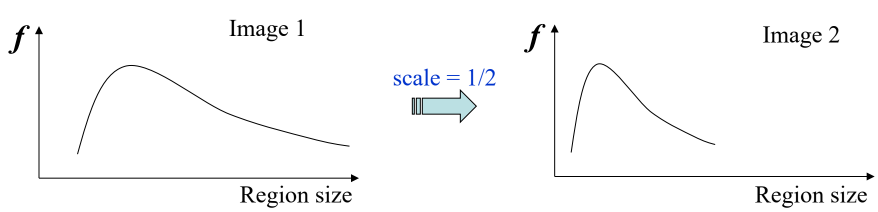
Automatic Scale Selection

- Solution:
  - Design a "magic" function ***f*** that is maximal at the correct region size for a given location (indicates the best region size)



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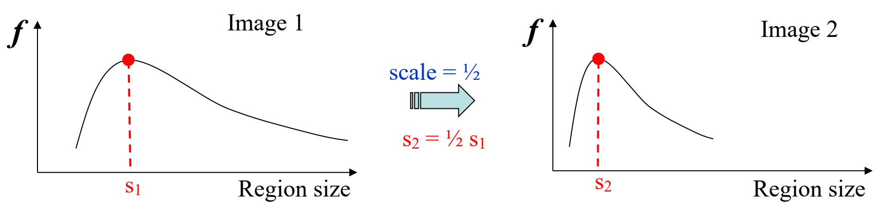
Automatic Scale Selection

- Choose the region size that is "best"

Important: this scale invariant region size (for a point) is found in each image **independently**!



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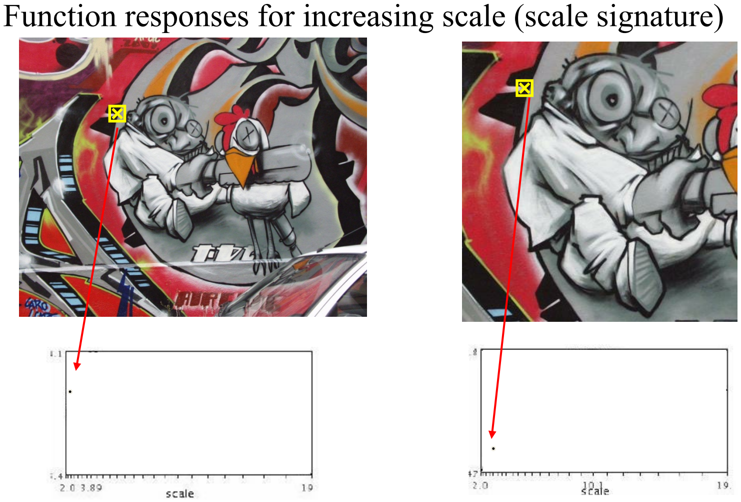
Automatic Scale Selection

- Function responses for increasing scale (scale signature)



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

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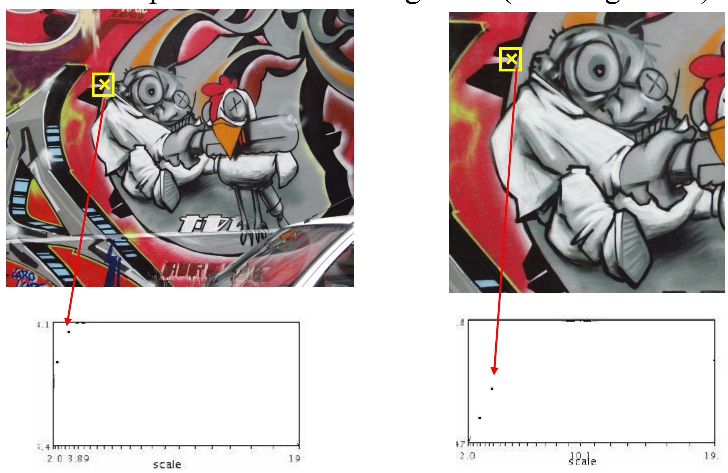
Automatic Scale Selection

- Function responses for increasing scale (scale signature)



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

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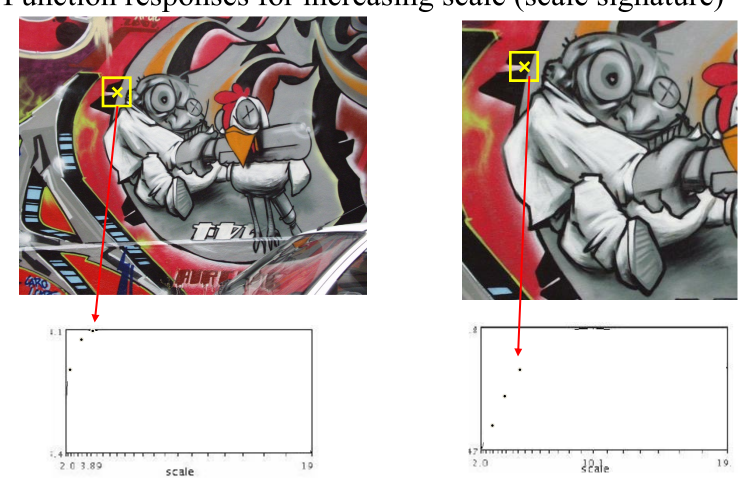
Automatic Scale Selection

- Function responses for increasing scale (scale signature)



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

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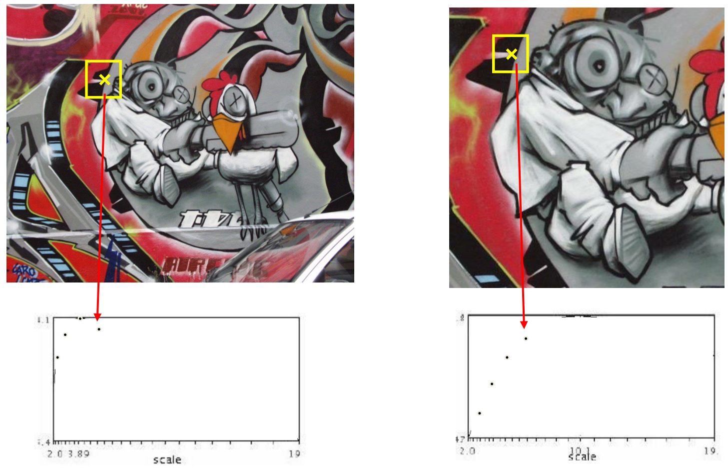
Automatic Scale Selection

- Function responses for increasing scale (scale signature)



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

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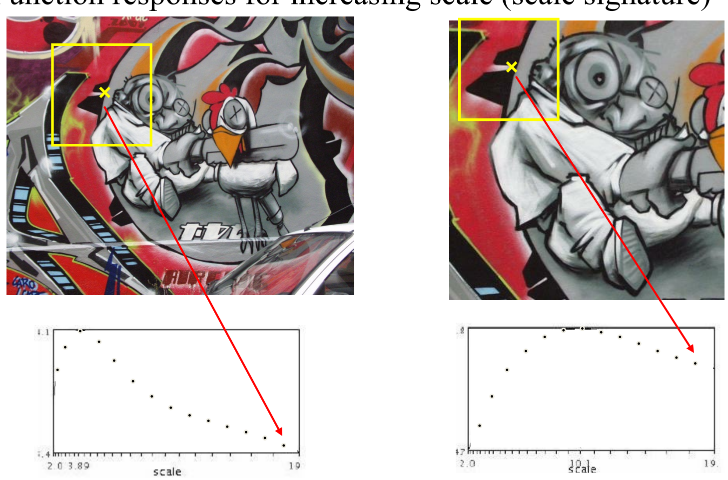
Automatic Scale Selection

- Function responses for increasing scale (scale signature)



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

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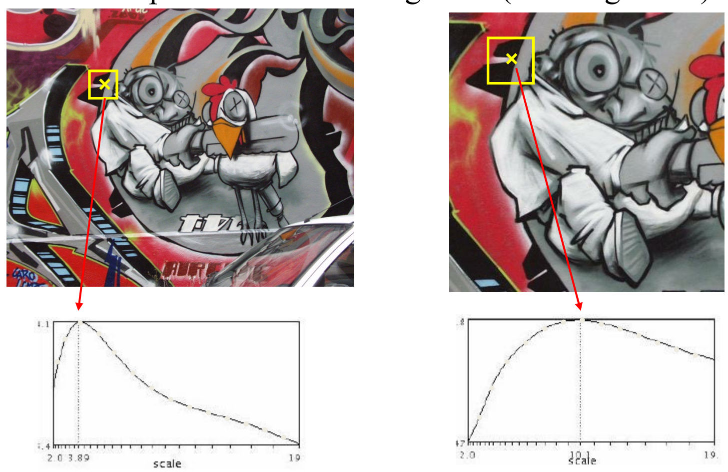
Automatic Scale Selection

- Function responses for increasing scale (scale signature)



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

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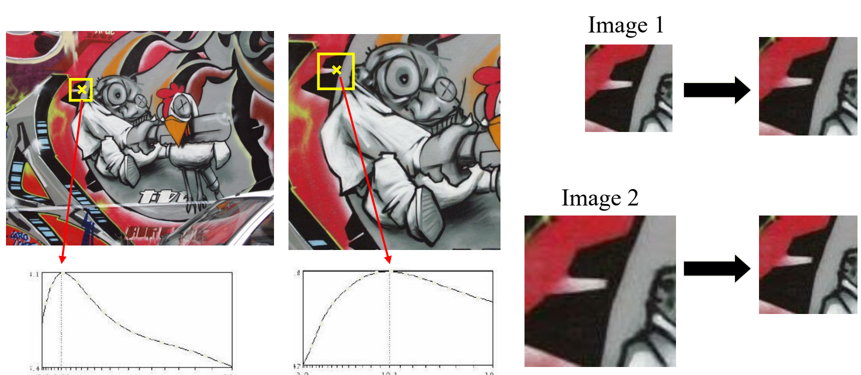
Automatic Scale Selection

- Normalize: Rescale best region size to fixed size



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

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So what could be a possible "magic function" for ***f*** ???

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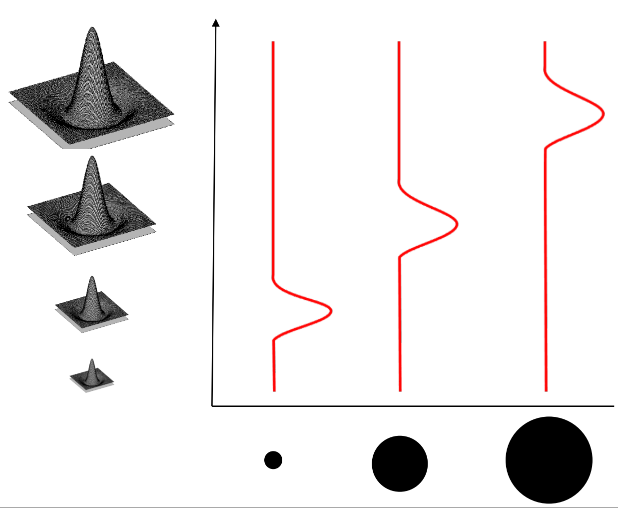
A Useful Function

- "Scale-normalized" Laplacian-of-Gaussian = *blob/spot* detector



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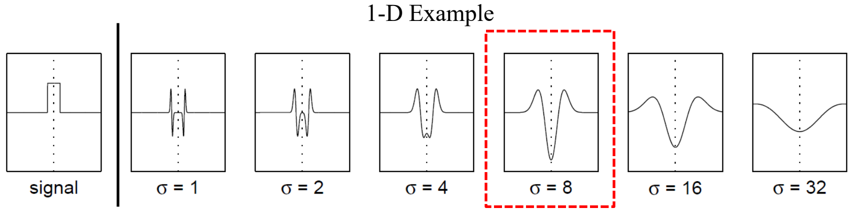
Scale-Normalized Laplacian-of-Gaussian

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

1-D Example



Scale-normalized Laplacian shows the strongest response at the *characteristic scale* of the original signal ($\sigma = 8$, $x = 0$)

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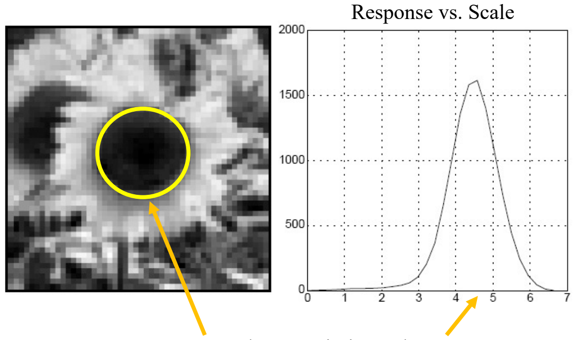
Characteristic Scale

2-D Example

Response vs. Scale



Characteristic scale

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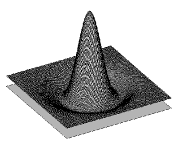
Laplacian-of-Gaussian (LoG)

- Interest points:
  - Local <u>maxima</u> in scale space (above/below/around) of scale-normalized Laplacian-of-Gaussian



$$\sigma^2\left(G_{xx}(\sigma)+G_{yy}(\sigma)\right)$$

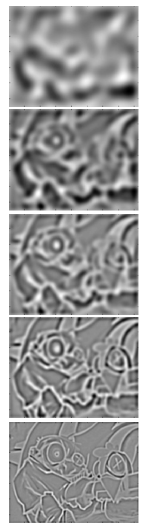
$\sigma = \sigma_0^5$

$\sigma = \sigma_0^4$

$\sigma = \sigma_0^3$

$\sigma = \sigma_0^2$

$\sigma = \sigma_0$



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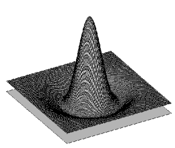

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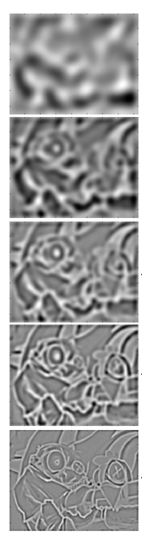

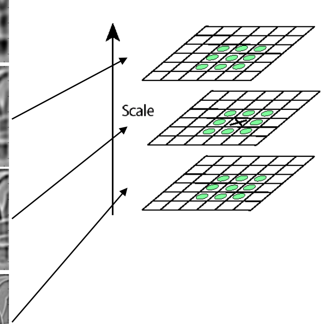

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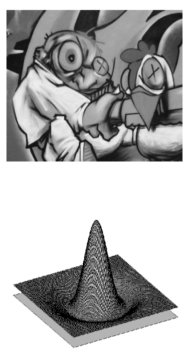

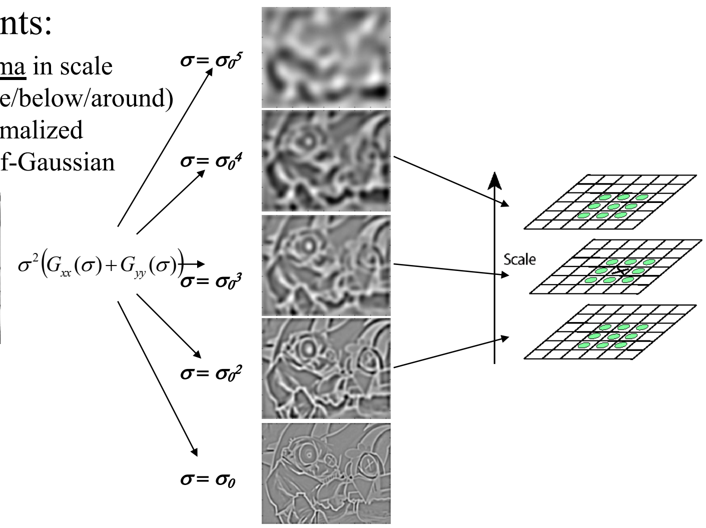

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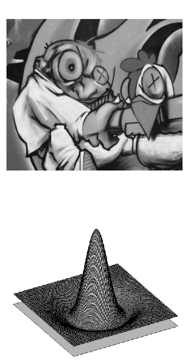

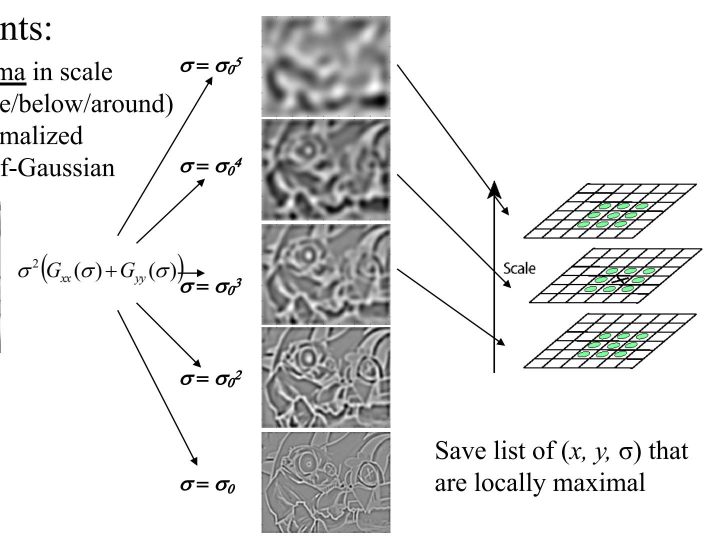

Save list of (x, y, σ) that are locally maximal

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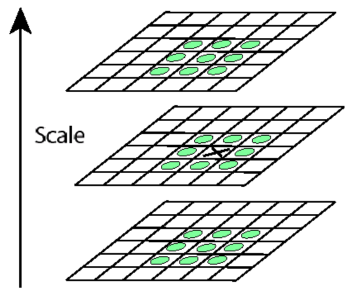
Keypoint Localization

- Detect maxima in scale space
- Then reject points with low image contrast (threshold)
- Eliminate edge responses



Candidate keypoints:
list of (x,y,σ)

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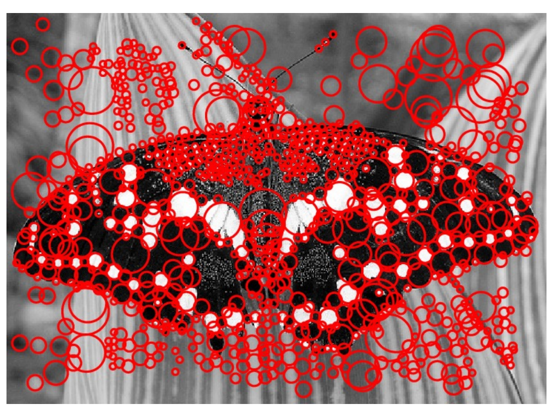
LoG Detector



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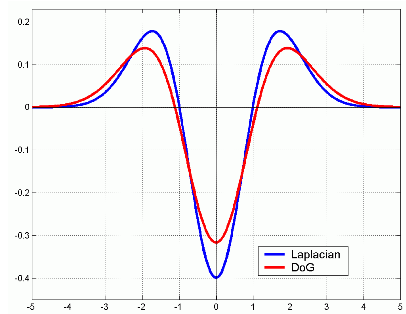
Technical Detail

- We can efficiently approximate the <u>scale-normalized</u> Laplacian with a “difference of Gaussians” (DoG):

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

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



(Since it is an approximation, DoG is generally slightly inferior to LoG)

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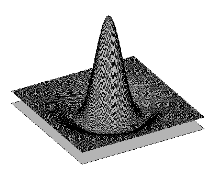
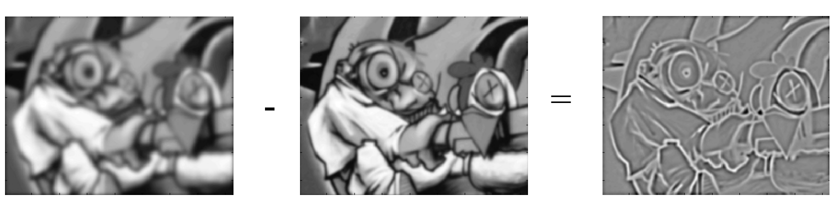
Difference-of-Gaussians (DoG)

- Difference-of-Gaussians as approximation of the scale-normalized LoG
- Advantage
  - No need to compute 2^{nd} derivatives





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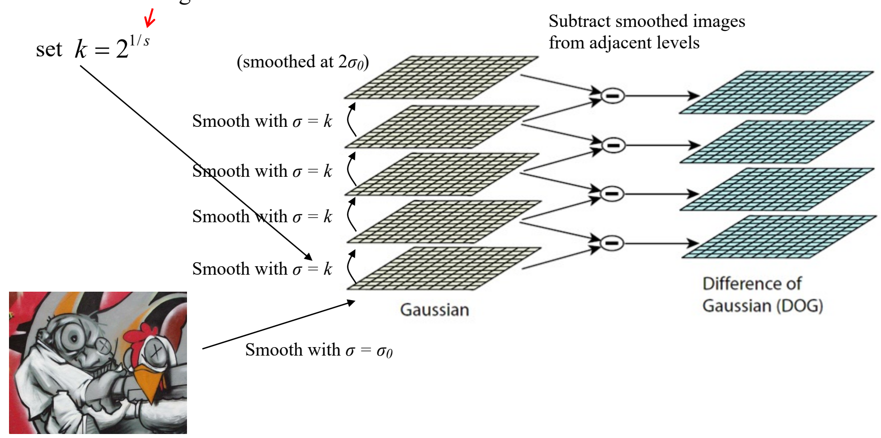
DoG "Octave"

Octave = "set of images for which smoothing σ is **doubled**"

s = desired # of images in DoG "octave"

set $k = 2^{1/s}$



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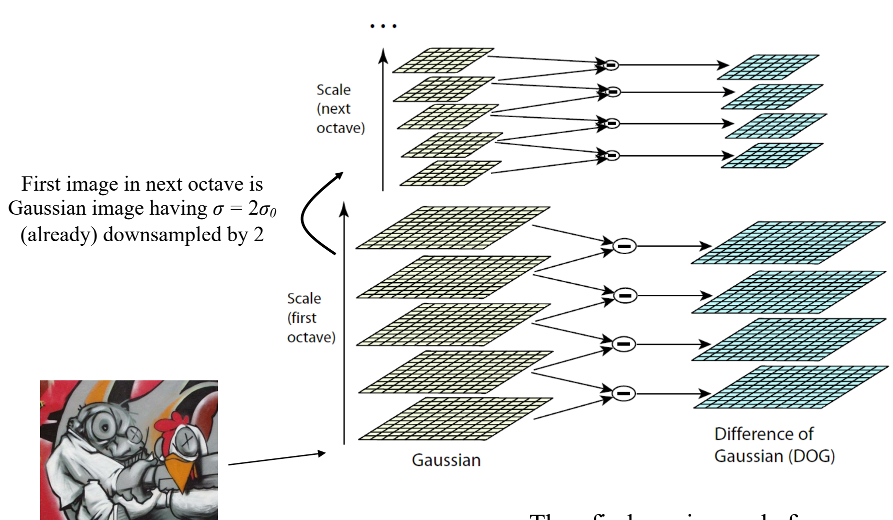
DoG Octave Pyramid



Then find maxima as before

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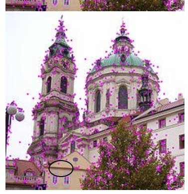
Example of Keypoint Detection

DoG extrema

Points remaining after contrast threshold



Points remaining after removing edge responses

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Topics of This Lecture

- Local Invariant Features
  - Motivation
  - Requirements, Invariances
- Keypoint Localization
  - Features from Accelerated Segment Test (FAST)
  - Harris
  - Shi-Tomasi
- Scale Invariant Region Selection
  - Automatic scale selection
  - Laplacian-of-Gaussian detector
  - Difference-of-Gaussians detector
- Local Descriptors
  - Orientation normalization
  - SIFT

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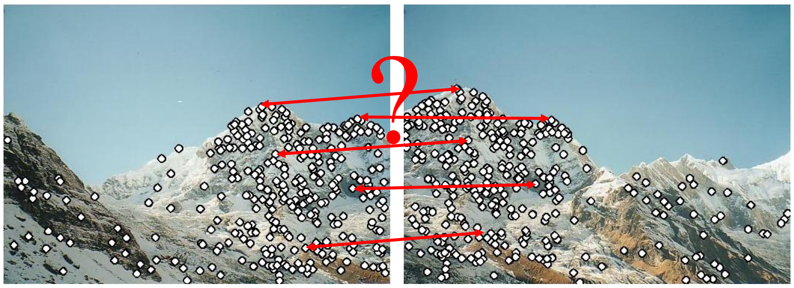
Local Descriptors

- We now know how to detect points and appropriate scales
- Next question:

How to *describe* them for matching?



Point descriptor should be:
1. Invariant
2. Distinctive

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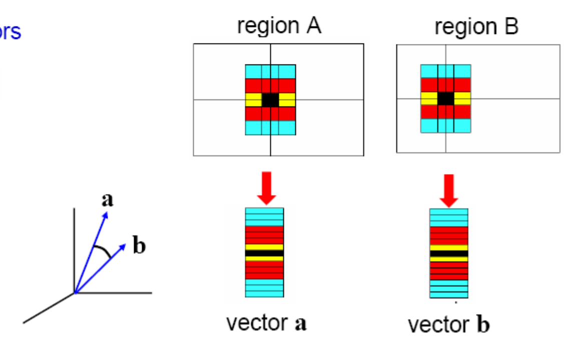
Local Descriptors

- Simplest descriptor: rasterized list of intensities within a patch
- To what is this going to be invariant (for normalized patch sizes)?
  - Translation and scale only (not rotation!)

Write regions as vectors

$$\mathtt{A} \rightarrow \mathbf{a}, \ \mathtt{B} \rightarrow \mathbf{b}$$



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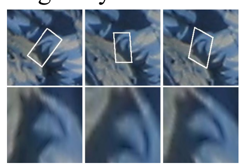
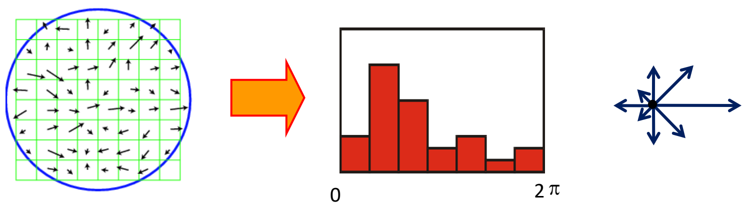
Feature Descriptors

- Disadvantage of patches as descriptors:
  - Small deformations can greatly affect matching score



- Solution: "**histogram of gradient directions**"



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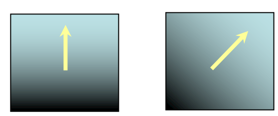
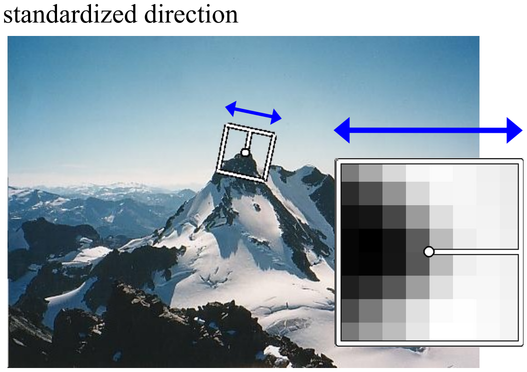
Rotation Invariant Descriptors

- Find local gradient directions in patch
- Find <u>dominant</u> direction of overall gradient for the patch



- Rotate patch according to this angle
  - This puts the patches into a standardized direction



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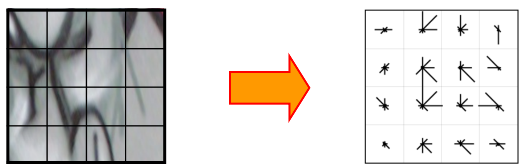
Feature Descriptors: **SIFT**

- Scale Invariant Feature Transform
- Descriptor computation:
  - Divide patch (for keypoint at chosen scale) **after** standardized direction alignment into 4x4 sub-patches: 16 cells
  - Compute Gaussian weighted histogram of gradient directions (8 reference angles) for all pixels inside each sub-patch
  - Resulting descriptor: 4x4x8 = 128 dimensions
  - Rasterize and normalize to unit vector (enhances invariance to affine changes in illumination)
    - Clip high values and renormalize vector to reduce effects of non-linear illumination



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Working with SIFT Descriptors

- One image with *n* feature points yields:
  - *n* 128-dimensional descriptors: each one is a collection of histograms of the gradient orientations within a patch
    - [n x 128 matrix]
  - *n* scale parameters specifying the size of each patch
    - [n x 1 vector]
  - *n* orientation parameters specifying the angle of the patch
    - [n x 1 vector]
  - *n* 2-D points giving positions of the patches
    - [n x 2 matrix]

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Matching Sift Descriptors

- Given two images…
- Match each keypoint independently (and greedily)
  - Employ 128-D descriptors
  - Best candidate match is “closest Euclidean neighbor”
  - **Can discard matches using ratio of closest (“best”) and second closest (“2nd best”) neighbors**
    - Simple measure of how <u>unique</u> is the match
- Can employ more costly (better) approaches to match complete <u>sets</u> of points (e.g., Hungarian algorithm)

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Advantages of SIFT

- Fairly robust matching technique
  - Can handle significant changes in viewpoint
  - Can handle significant changes in illumination
    - Sometimes even day vs. night
  - Fast and efficient—can run in real time
    - Lots of code available

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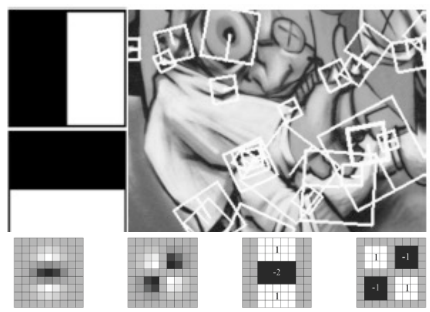
Variations and Implementations

- SURF: Fast approximation of SIFT (multiple times faster)
  - Efficient computation by 2-D box filters and integral images
  - Essentially equivalent quality for object identification
- GPU implementations of SIFT and SURF exist



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Summary

- Corners
  - Image gradient has two dominant directions
  - FAST, Harris, Shi-Tomasi
  - Corner detectors are rotation invariant but not scale invariant
- Automatic scale selection
  - Select patch size yielding maximum value of scale invariant function
  - LoG and DoG detectors
- Need descriptors to match keypoints
  - Use histograms for rotation invariance
  - SIFT, SURF

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