Feature Detectors and Descriptors: Corners, Blobs, and SIFT

COS 429: Computer Vision

PRINCETON UNIVERSITY

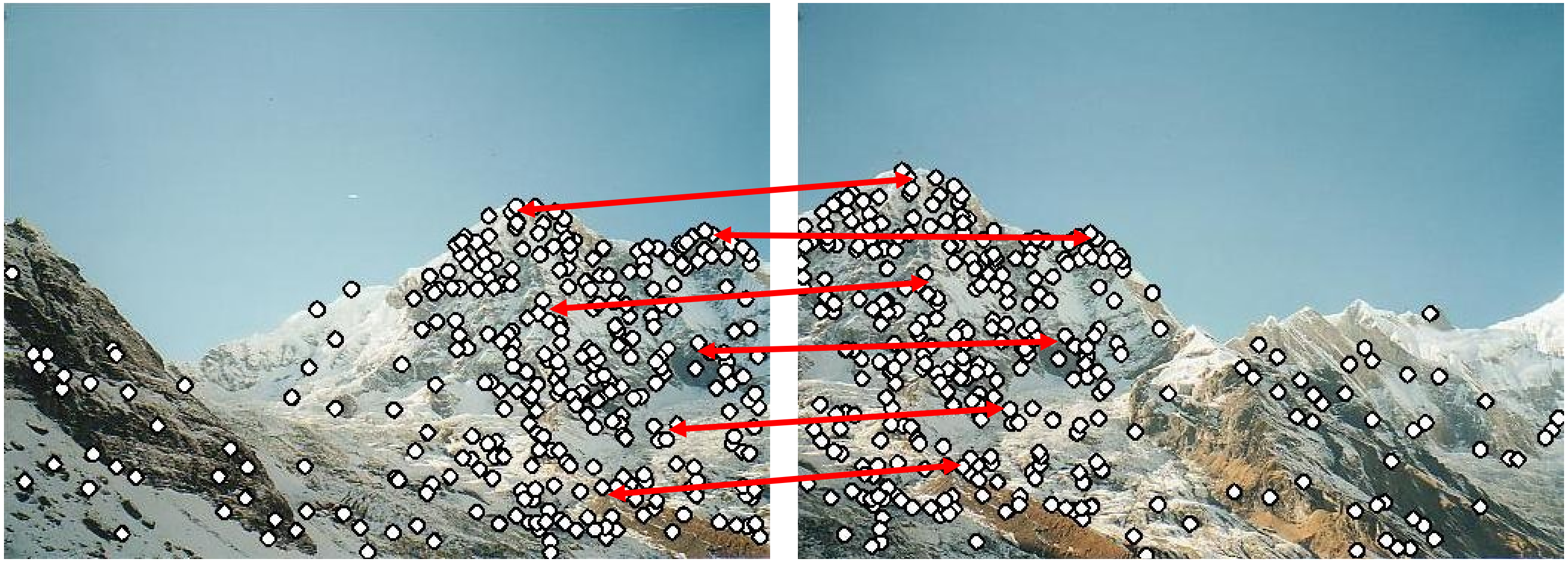
Figure credits: S. Lazebnik, S. Seitz

Why Extract Keypoints?

- Motivation: panorama stitching
  - We have two images – how do we combine them?

Why Extract Keypoints?

- Motivation: panorama stitching
  - We have two images – how do we combine them?



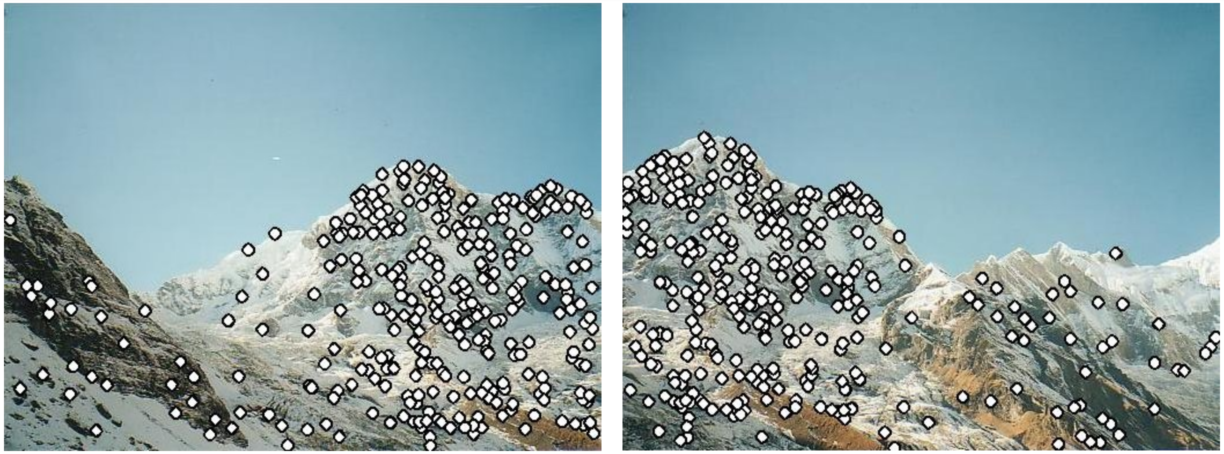
Step 1: extract keypoints
Step 2: match keypoint features

Why Extract Keypoints?

- Motivation: panorama stitching
  - We have two images – how do we combine them?

Step 1: extract keypoints
Step 2: match keypoint features
Step 3: align images

Characteristics of Good Keypoints



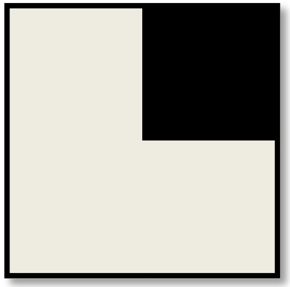
- Repeatability
  - Can be found despite geometric and photometric transformations
- Salience
  - Each keypoint is distinctive
- Compactness and efficiency
  - Many fewer keypoints than image pixels
- Locality
  - Occupies small area of the image; robust to clutter and occlusion

Applications

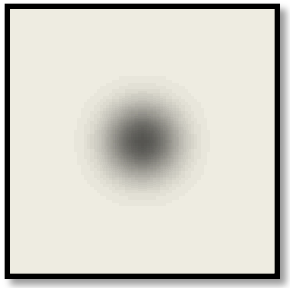
- Keypoints are used for:
  – Image alignment
  – 3D reconstruction
  – Motion tracking
  – Robot navigation
  – Indexing and database retrieval
  – Object recognition

Kinds of Keypoints

- Corners

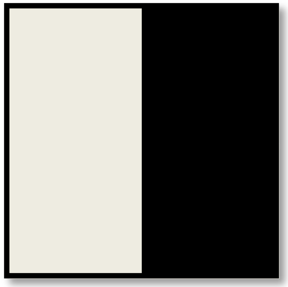


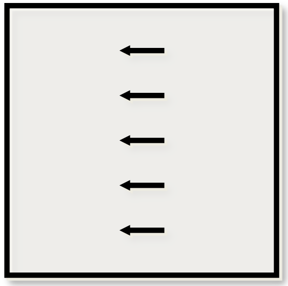
- Blobs



Edges vs. Corners

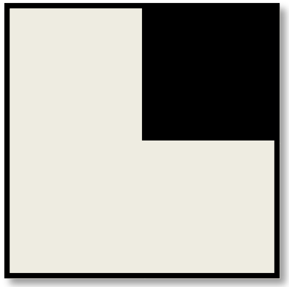
- Edges = maxima in intensity gradient

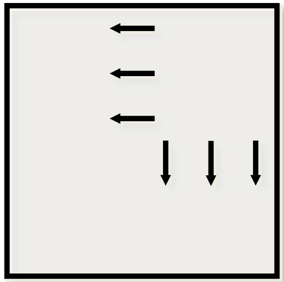




Edges vs. Corners

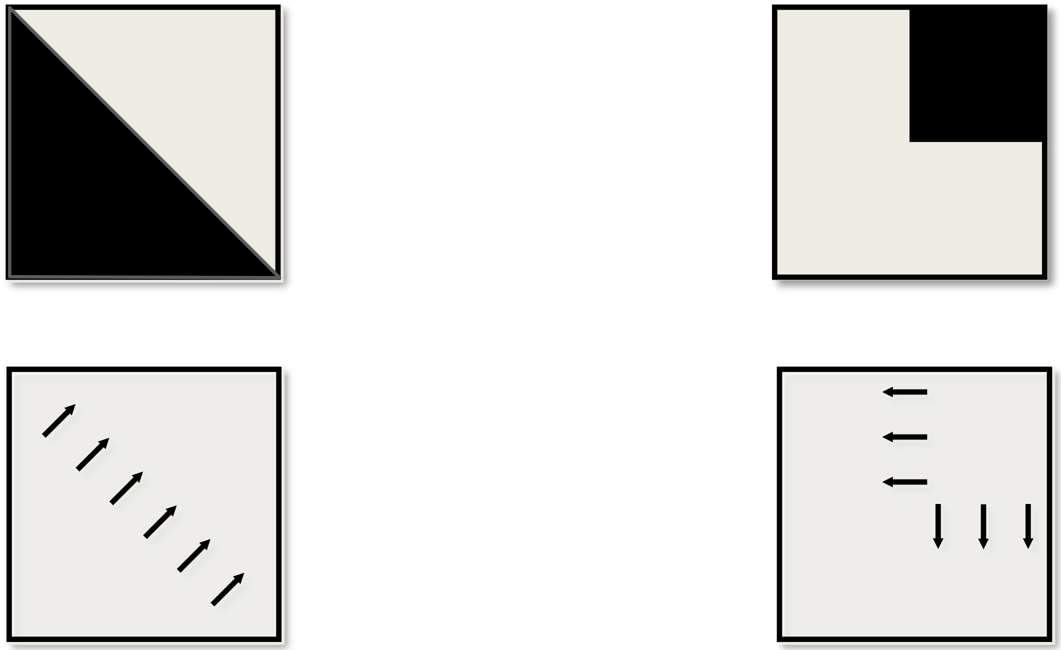
- Corners = lots of variation in direction of gradient in a small neighborhood





Detecting Corners

- How to detect this variation?
- Not enough to check average $\frac{\partial f}{\partial x}$ and $\frac{\partial f}{\partial y}$



Detecting Corners

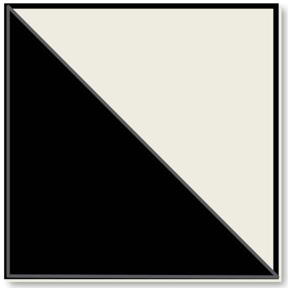
- Claim: the following "structure" matrix summarizes the second-order statistics of the gradient

$$C = \begin{bmatrix} \sum f_x^2 & \sum f_x f_y \\ \sum f_x f_y & \sum f_y^2 \end{bmatrix} \qquad f_x = \frac{\partial f}{\partial x}, \; f_y = \frac{\partial f}{\partial y}$$

- Summations over local neighborhoods
  - Can have spatially-varying weights (Gaussian, etc.)

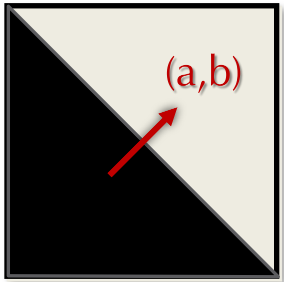
Detecting Corners

- Examine behavior of C by testing its effect in simple cases
- Case #1: Single edge in local neighborhood



Case#1: Single Edge

- Let (a,b) be gradient along edge
- Compute $C \cdot (a,b)$:



$$C \cdot \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \sum f_x^2 & \sum f_x f_y \\ \sum f_x f_y & \sum f_y^2 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix}$$

$$= \sum (\nabla f)(\nabla f)^{\mathrm{T}} \begin{bmatrix} a \\ b \end{bmatrix}$$

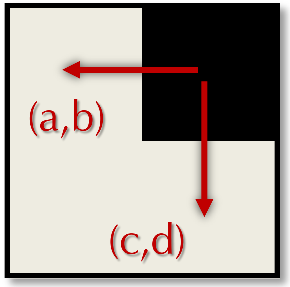
$$= \sum (\nabla f) \left(\nabla f \cdot \begin{bmatrix} a \\ b \end{bmatrix} \right)$$

Case #1: Single Edge

- However, in this simple case, the only nonzero terms are those where $\nabla f = (a,b)$
- So, $C \cdot (a,b)$ is just some multiple of (a,b)

Case #2: Corner

- Assume there is a corner, with perpendicular gradients (a,b) and (c,d)



Case #2: Corner

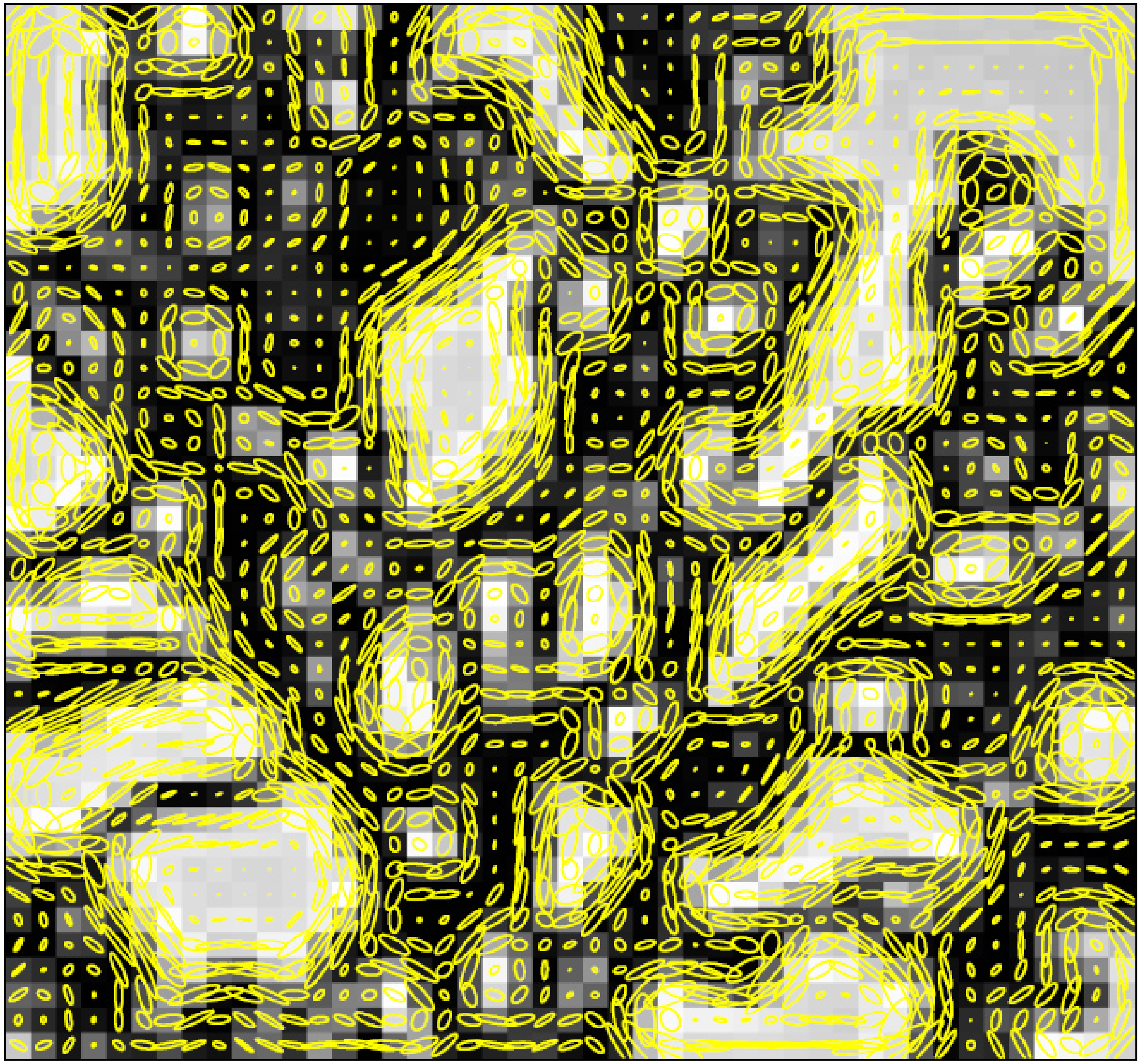
- What is $C \cdot (a,b)$?
  - Since $(a,b) \cdot (c,d) = 0$, the only nonzero terms are those where $\nabla f = (a,b)$
  - So, $C \cdot (a,b)$ is again just a multiple of (a,b)
- What is $C \cdot (c,d)$?
  - Since $(a,b) \cdot (c,d) = 0$, the only nonzero terms are those where $\nabla f = (c,d)$
  - So, $C \cdot (c,d)$ is a multiple of (c,d)

Corner Detection

- Matrix times vector = multiple of vector
- Eigenvectors and eigenvalues!
- In particular, if C has one large eigenvalue, there's an edge
- If C has two large eigenvalues, have corner
- "Harris" corner detector
  - Harris & Stephens 1988 look at trace and determinant of C; Shi & Tomasi 1994 directly look at minimum eigenvalue

Visualization of Structure Matrix

Visualization of Structure Matrix

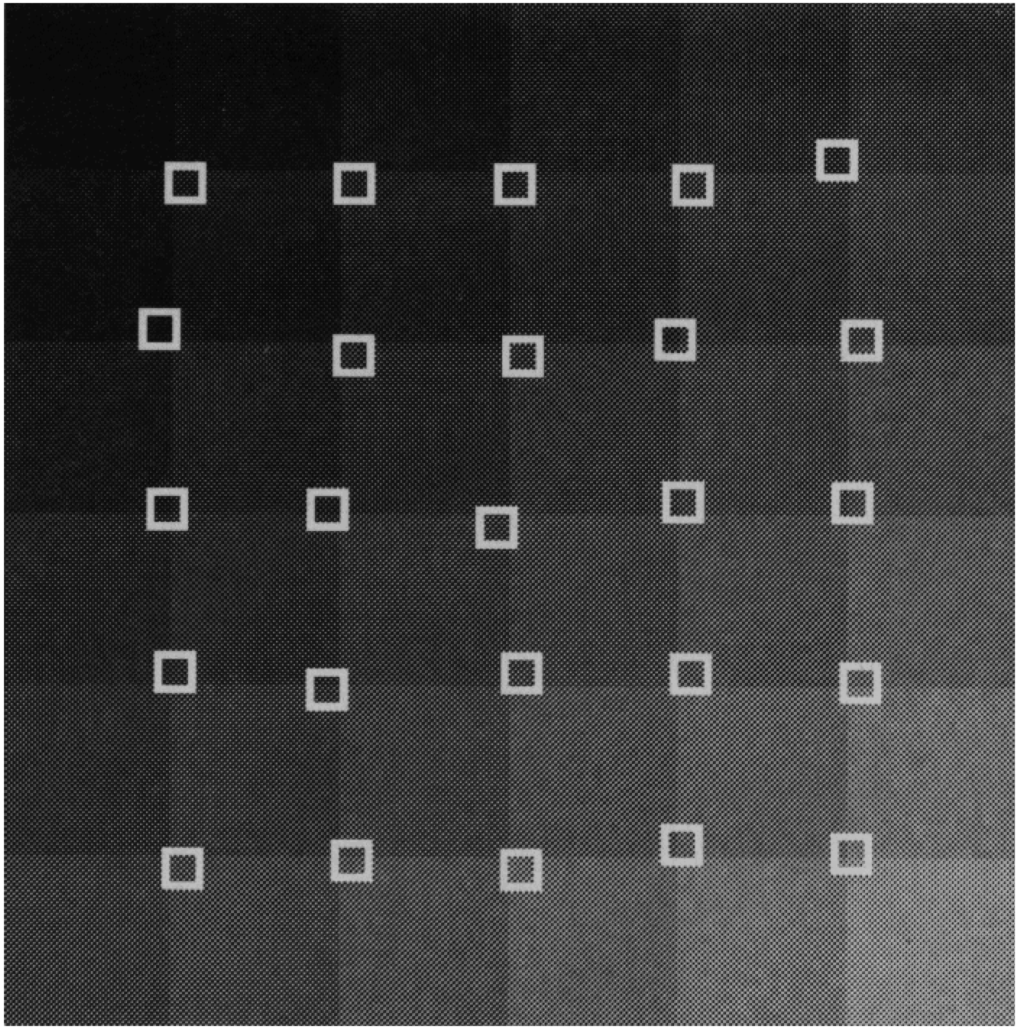


Corner Detection Implementation

1. Compute image gradient
2. For each $m \times m$ neighborhood, compute matrix C (optionally using weighted sum)
3. If smaller eigenvalue λ_2 is larger than threshold τ, record a corner
4. Nonmaximum suppression: only keep strongest corner in each $m \times m$ window

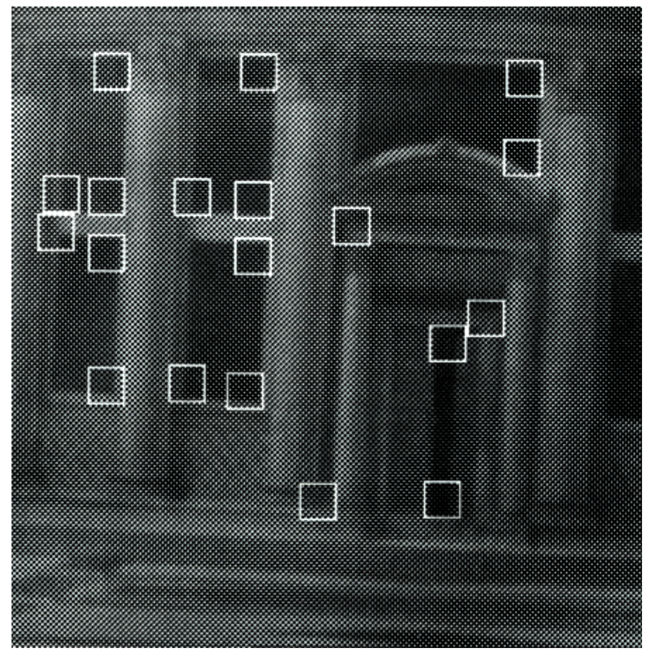
Corner Detection Results

- Checkerboard with noise

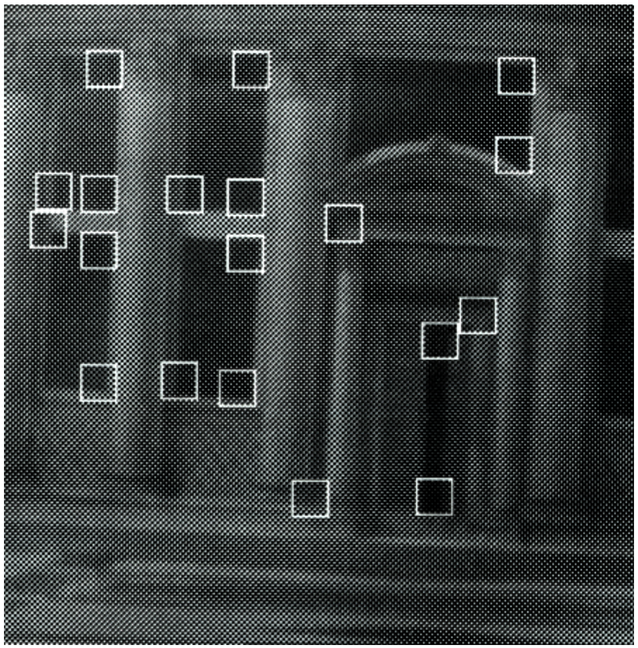


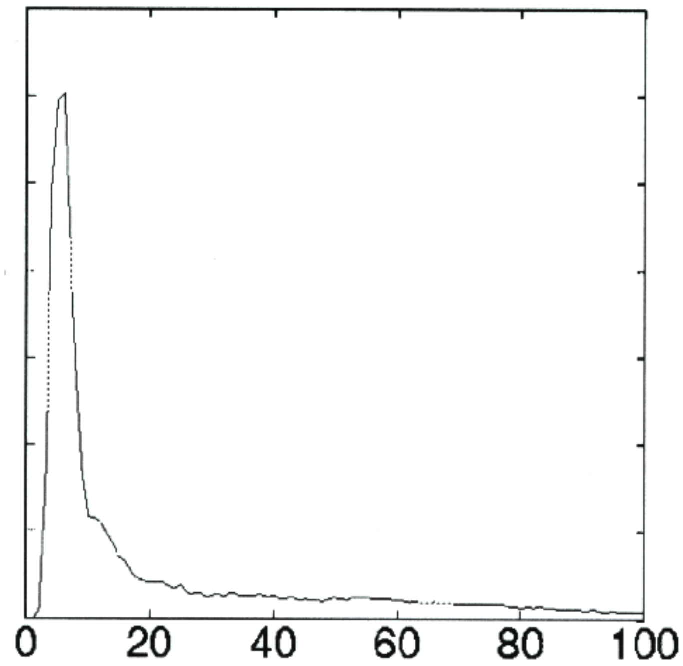
Trucco & Verri

Corner Detection Results



Corner Detection Results





Histogram of λ_2 (smaller eigenvalue)

Corner Detection

- Application: good features for tracking, correspondence, etc.
  - Why are corners better than edges for tracking?
- Other corner detectors
  - Look for maxima of curvature in edge detector output
  - Perform color segmentation on image, look for places where 3 segments meet
  - …

Invariance

- Suppose you rotate the image by some angle
  - Will you still find the same corners?
- What if you change the brightness?
- Scale?

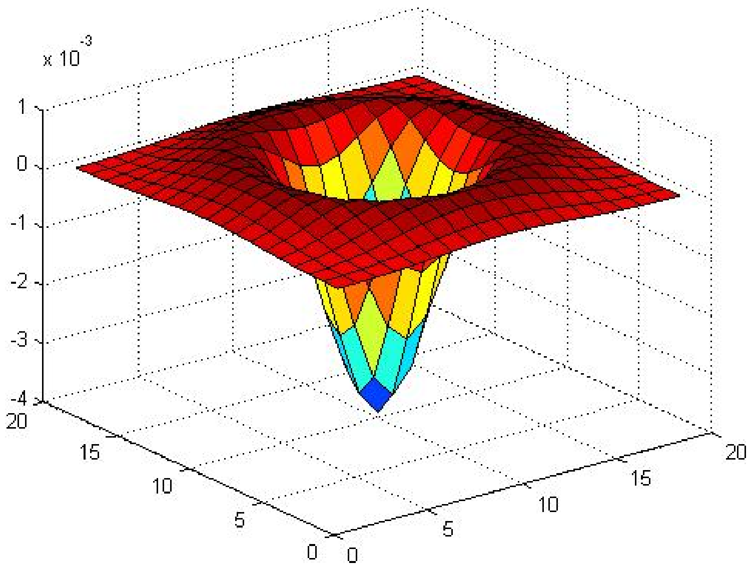
[Seitz]

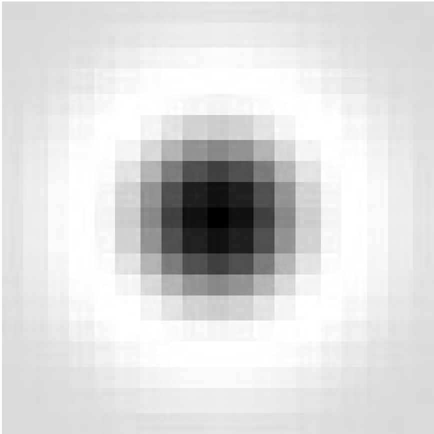
Scale-Invariant Feature Detection

- Key idea: compute some function *f* over different scales, find extremum
  - Common definition of *f*: convolution with LoG or DoG
  - Find local minima or maxima over position and scale

Blob Filter

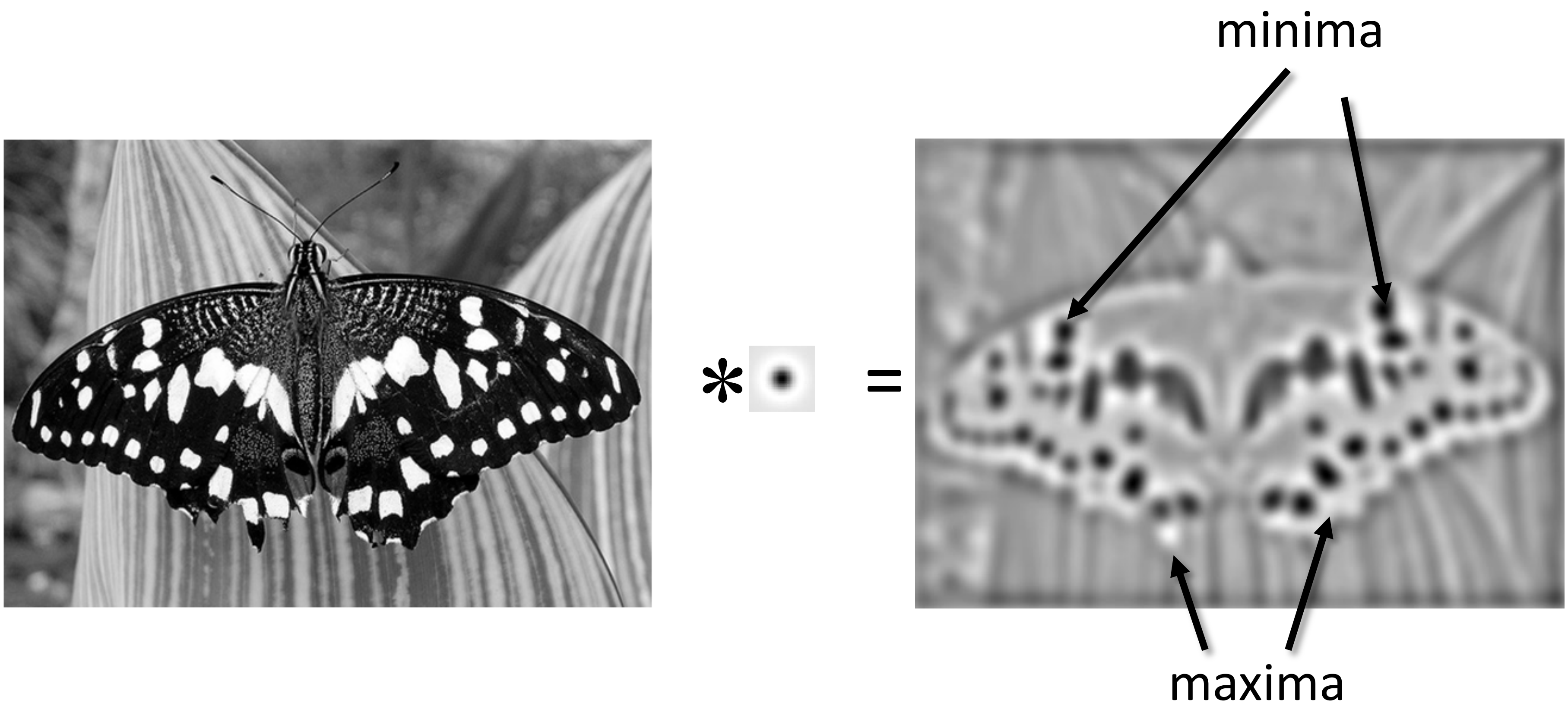
- Recall: Laplacian of Gaussian
  - Circularly symmetric operator for blob detection





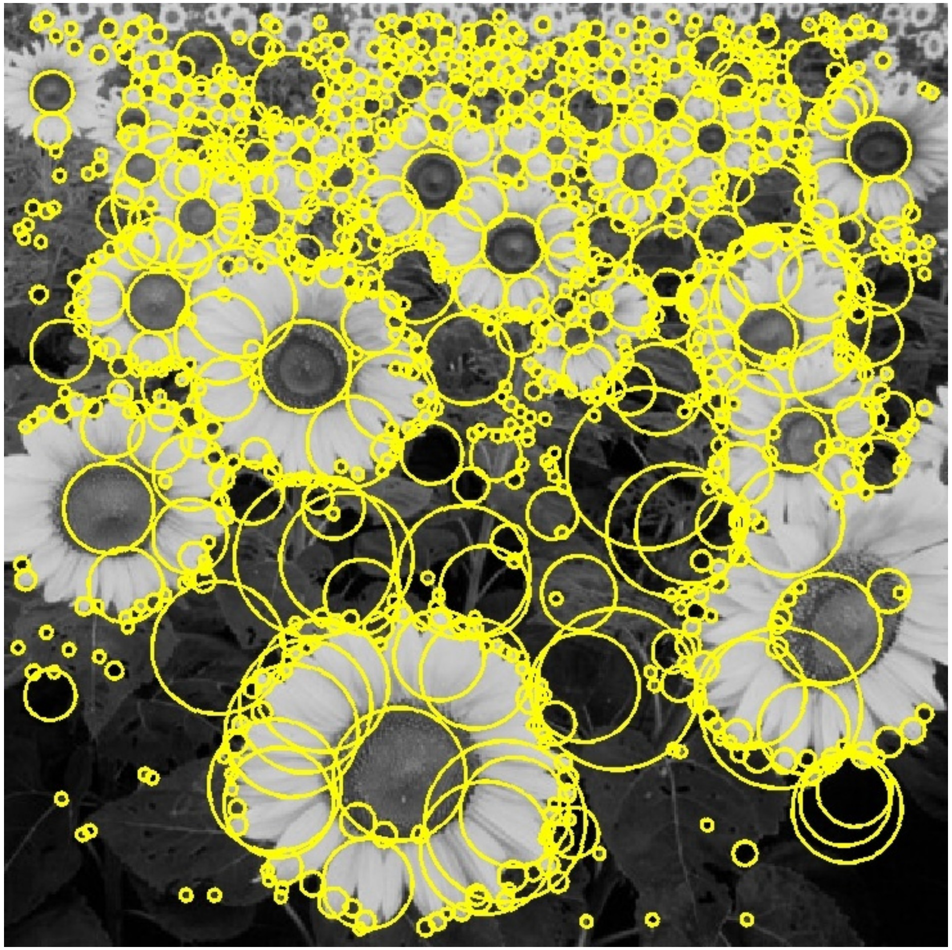
$$\nabla^2 g = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2}$$

Blob Detection – Single Scale



Source: N. Snavely

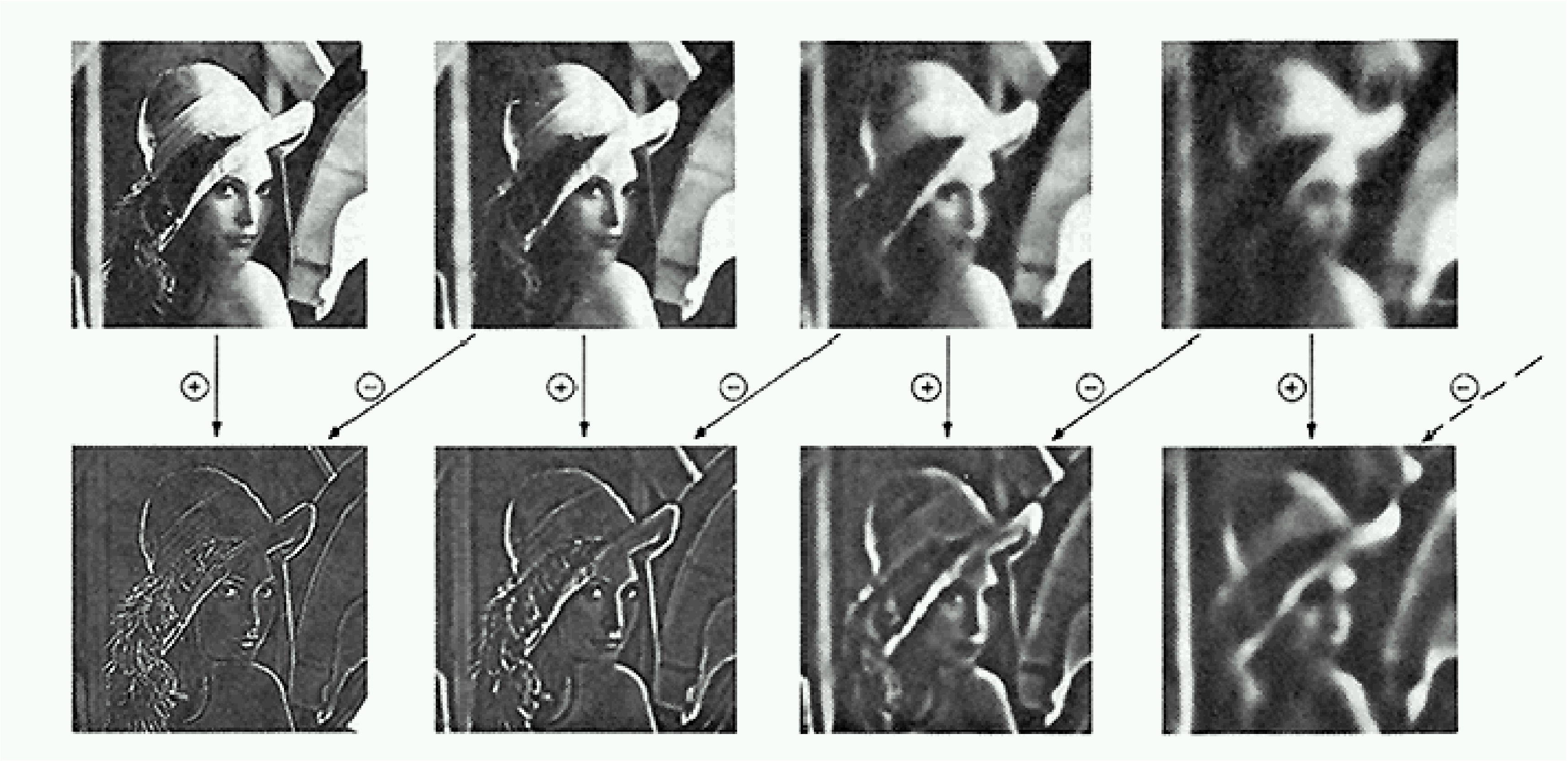
Blob Detection – Over Multiple Scales



T. Lindeberg. Feature detection with automatic scale selection. *IJCV* 30(2), pp 77-116, 1998.

Multiscale Difference of Gaussians

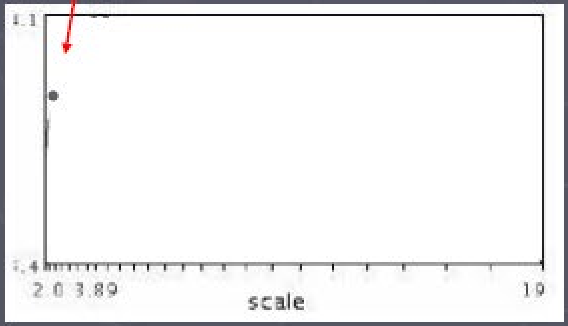
Gaussian-filtered images with increasing σ



Difference-of-Gaussians Images

Automatic scale selection

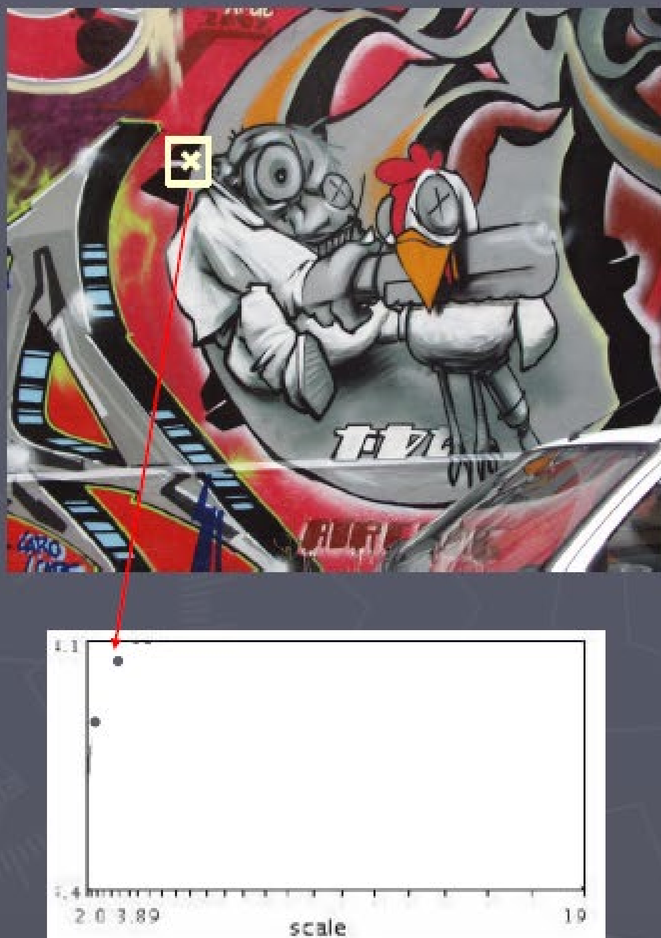
Lindeberg et al., 1996



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

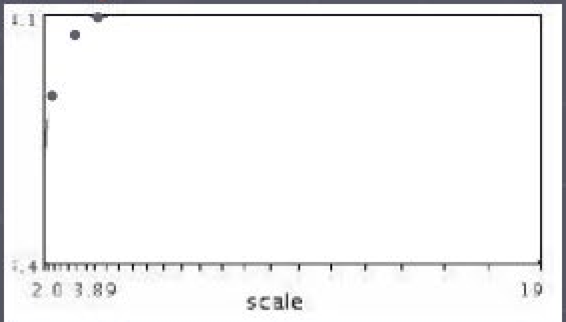
Slide from Tinne Tuytelaars

Automatic scale selection



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

Automatic scale selection

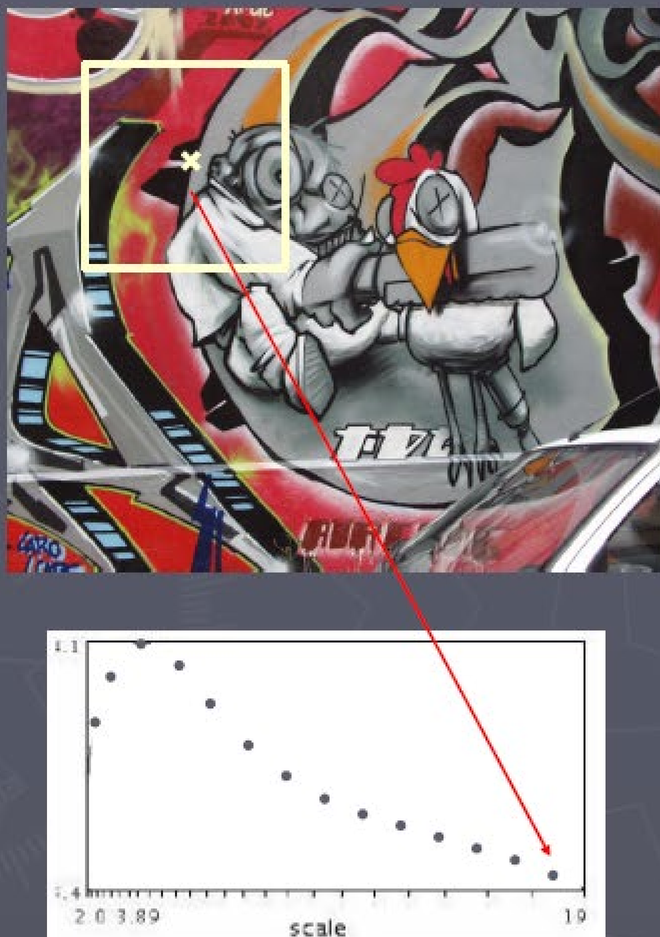


$f(I_{i_1 \ldots i_m}(x, \sigma))$

Automatic scale selection

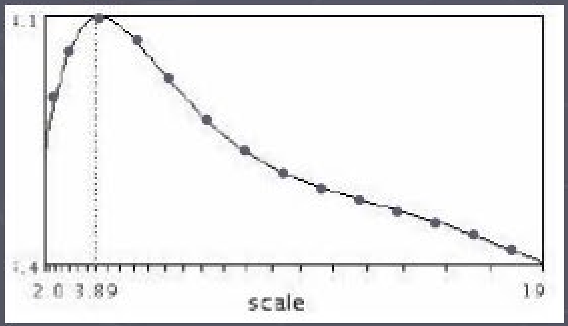
$$f(I_{i_1 \ldots i_m}(x,\sigma))$$

Automatic scale selection



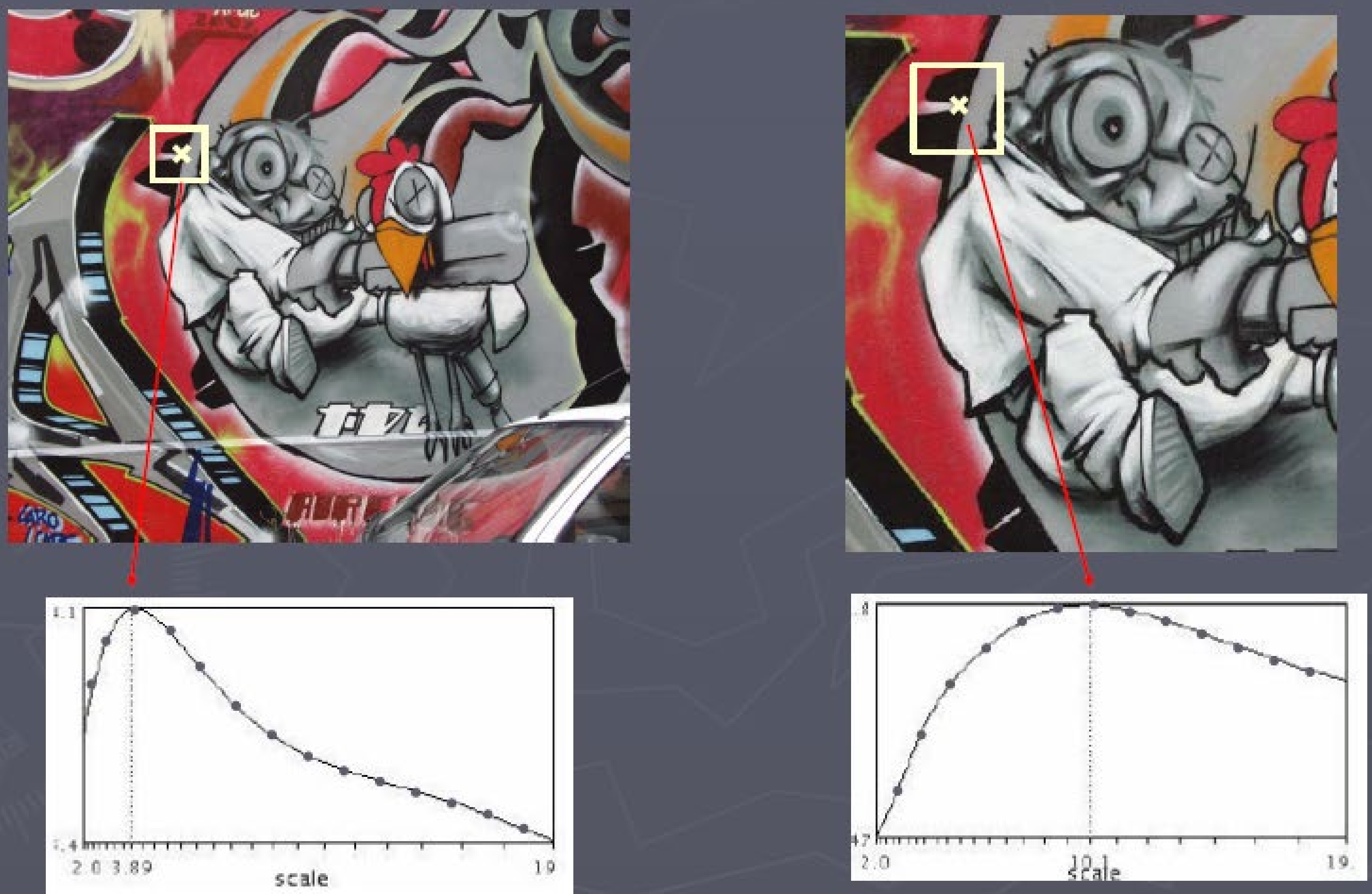
$f(I_{i_1 \ldots i_m}(x, \sigma))$

Automatic scale selection



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

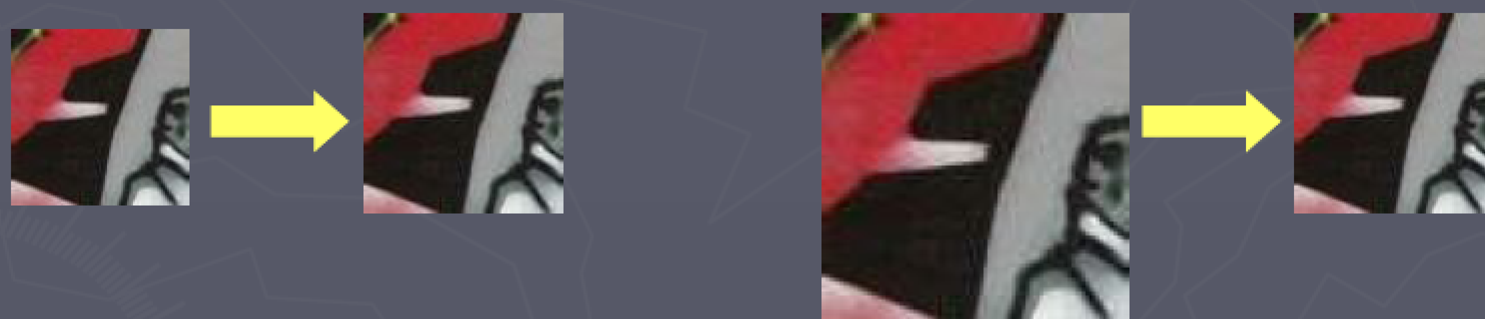
Automatic scale selection



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

Automatic scale selection

Normalize: rescale to fixed size



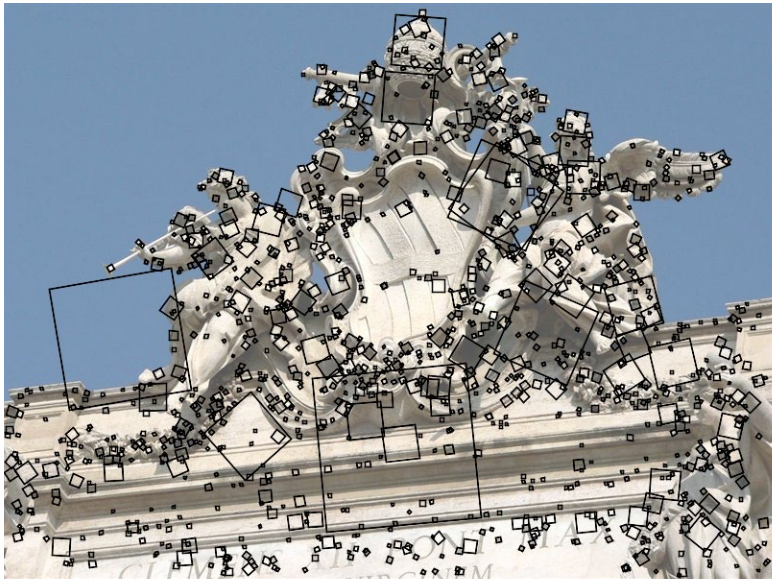
Rotation Normalization

- Rotate window according to dominant orientation
  - Eigenvector of C corresponding to maximum eigenvalue

[Matthew Brown]

Detected Features

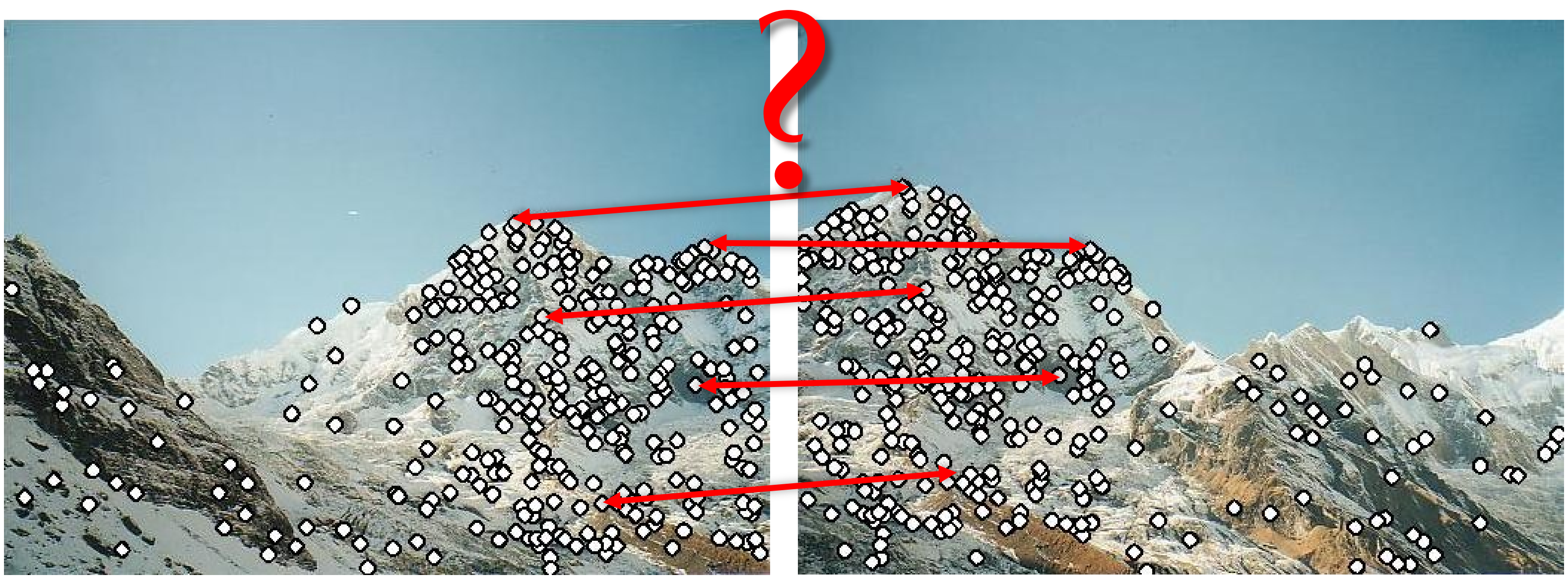
- Detected features with characteristic scales and orientations:



David G. Lowe. **"Distinctive image features from scale-invariant keypoints."**
IJCV 60 (2), pp. 91-110, 2004.

Feature Descriptors

- Once we have *detected* distinctive and repeatable features, still have to *match* them across images
  - Image alignment (e.g., mosaics), 3D reconstruction, motion tracking, object recognition, indexing and retrieval, robot navigation, etc.



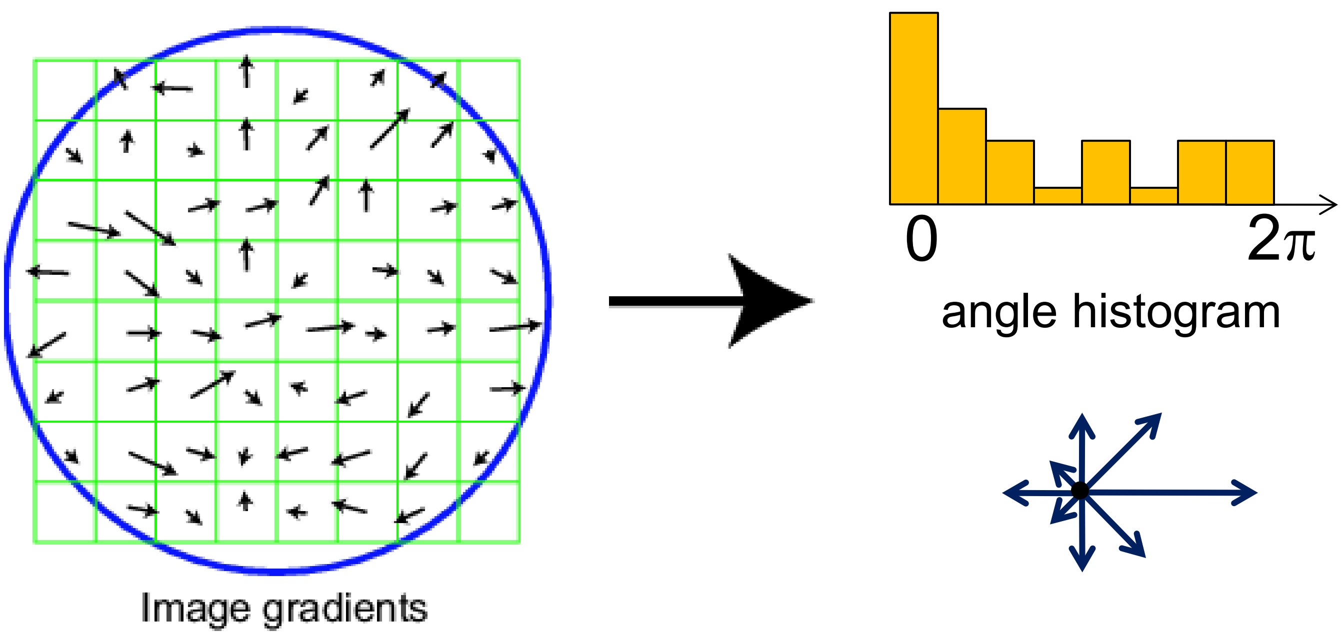
[Seitz]

Properties of Feature Descriptors

- Easily compared (compact, fixed-dimensional)
- Easily computed
- Invariant
  - Translation
  - Rotation
  - Scale
  - Change in image brightness
  - Change in perspective?

Scale Invariant Feature Transform

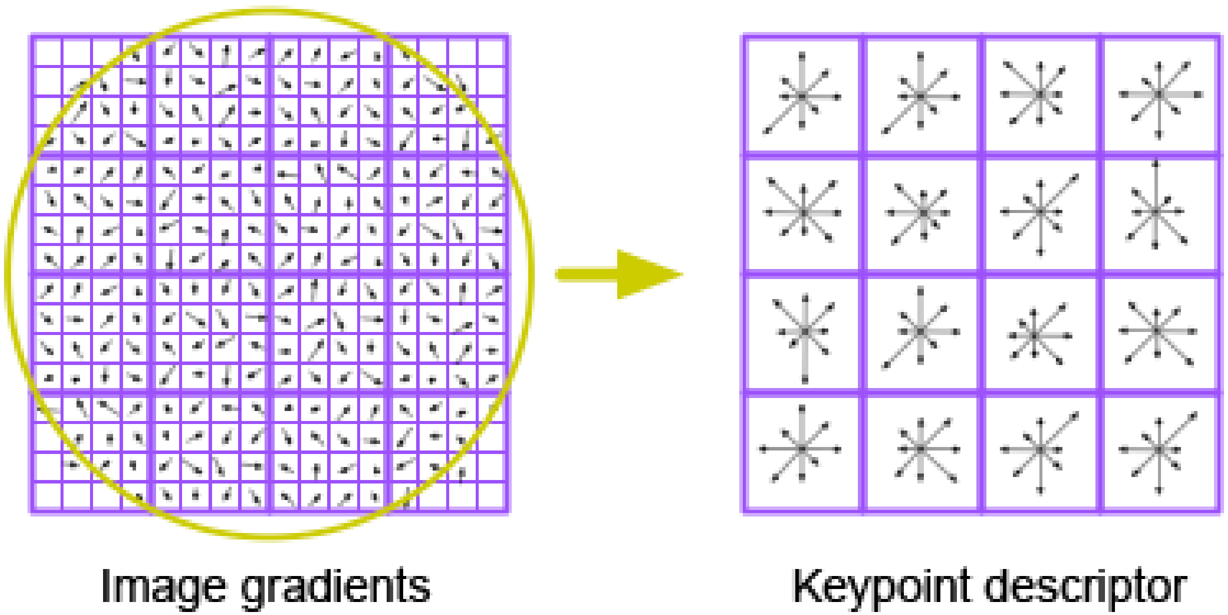
- Simple version:
  - Take 16×16 normalized window around detected feature
  - Create histogram of quantized gradient directions
  - Invariant to changes in brightness



[Seitz / Lowe]

Full SIFT Descriptor

- Divide 16×16 window into 4×4 grid of cells
- Compute an orientation histogram for each cell
  - 16 cells * 8 orientations = 128-dimensional descriptor



David G. Lowe. ["Distinctive image features from scale-invariant keypoints."](#) *IJCV* 60 (2), pp. 91-110, 2004.

Properties of SIFT

- Fast (real-time) and robust descriptor for matching
  - Handles changes in viewpoint (~60° out of plane rotation)
  - Handles significant changes in illumination
  - Lots of code available