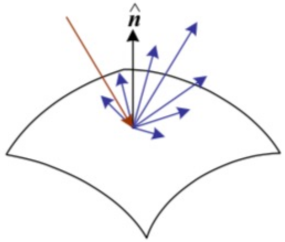


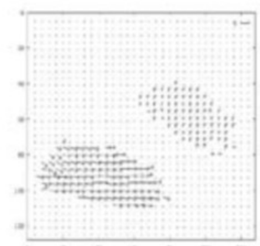
2. Image Formation

3. Image Processing

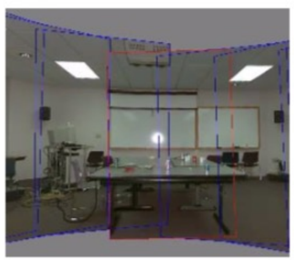
4. Features

5. Segmentation

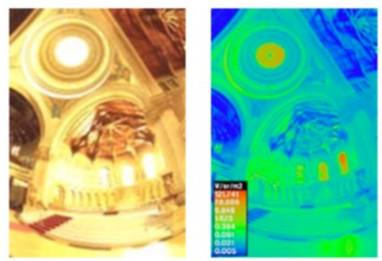
6-7. Structure from Motion



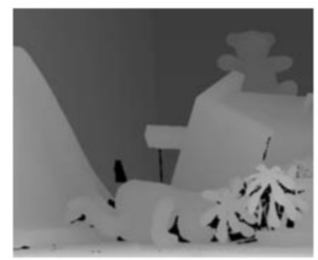
8. Motion



9. Stitching

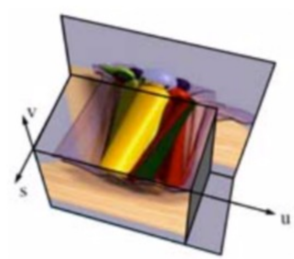


10. Computational Photography



11. Stereo

12. 3D Shape



13. Image-based Rendering

14. Recognition

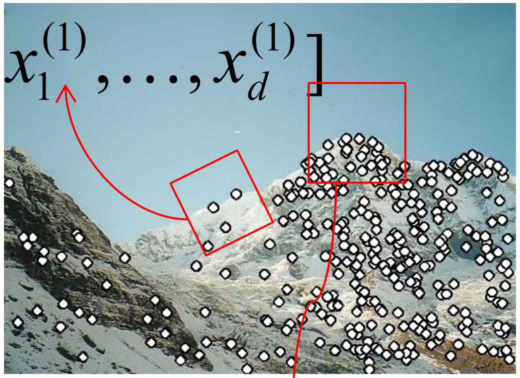
Descriptors

Local features: main components

1) Detection: Identify the interest points

2) **Description: Extract vector feature descriptor surrounding each interest point.**

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

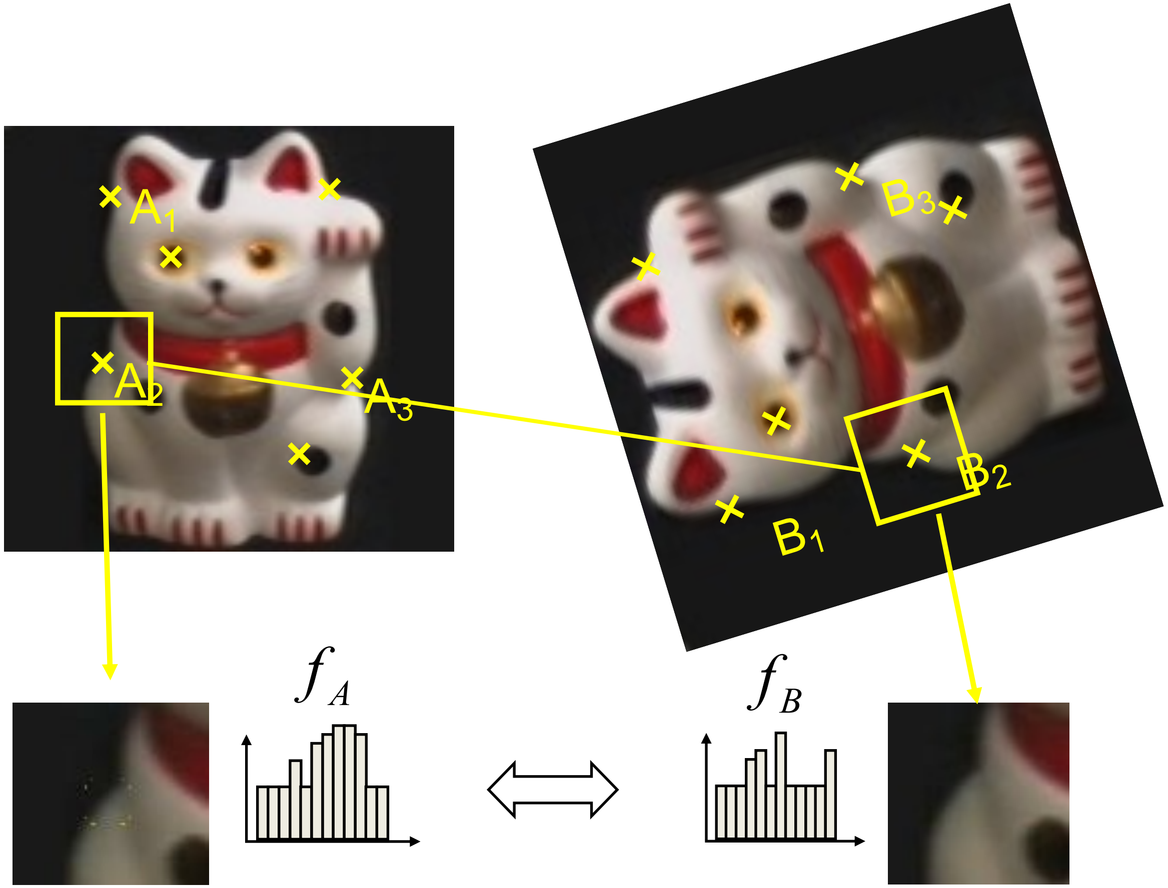


$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

3) Matching: Determine correspondence between descriptors in two views

Kristen Grauman

Overview of Keypoint Matching



$$d(f_A, f_B) < T$$

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

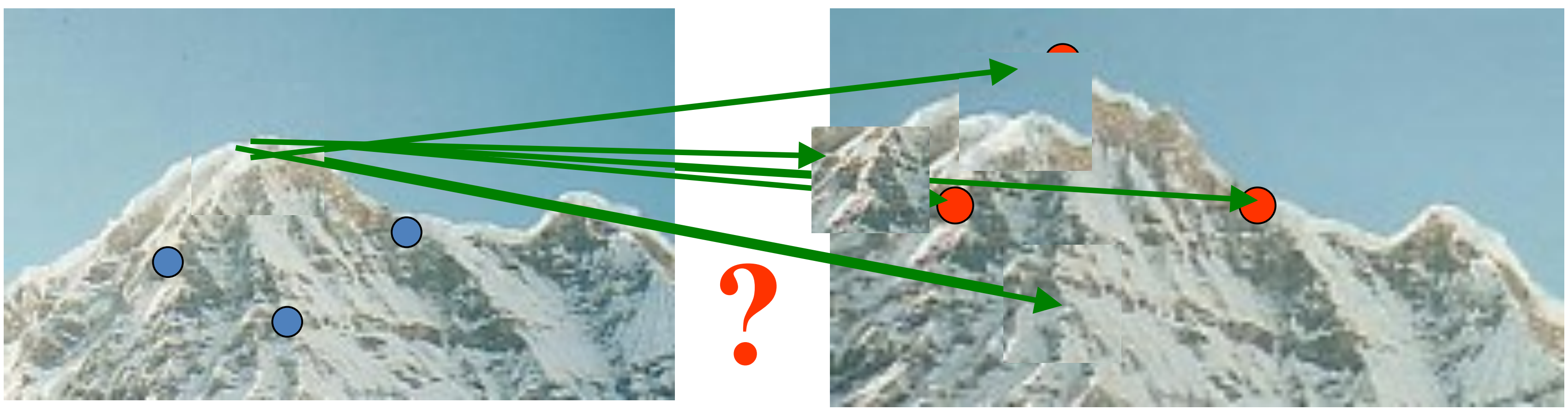
K. Grauman, B. Leibe

Goals for interest points


Detect points that are *repeatable* and *distinctive*

Goal for descriptors: distinctiveness

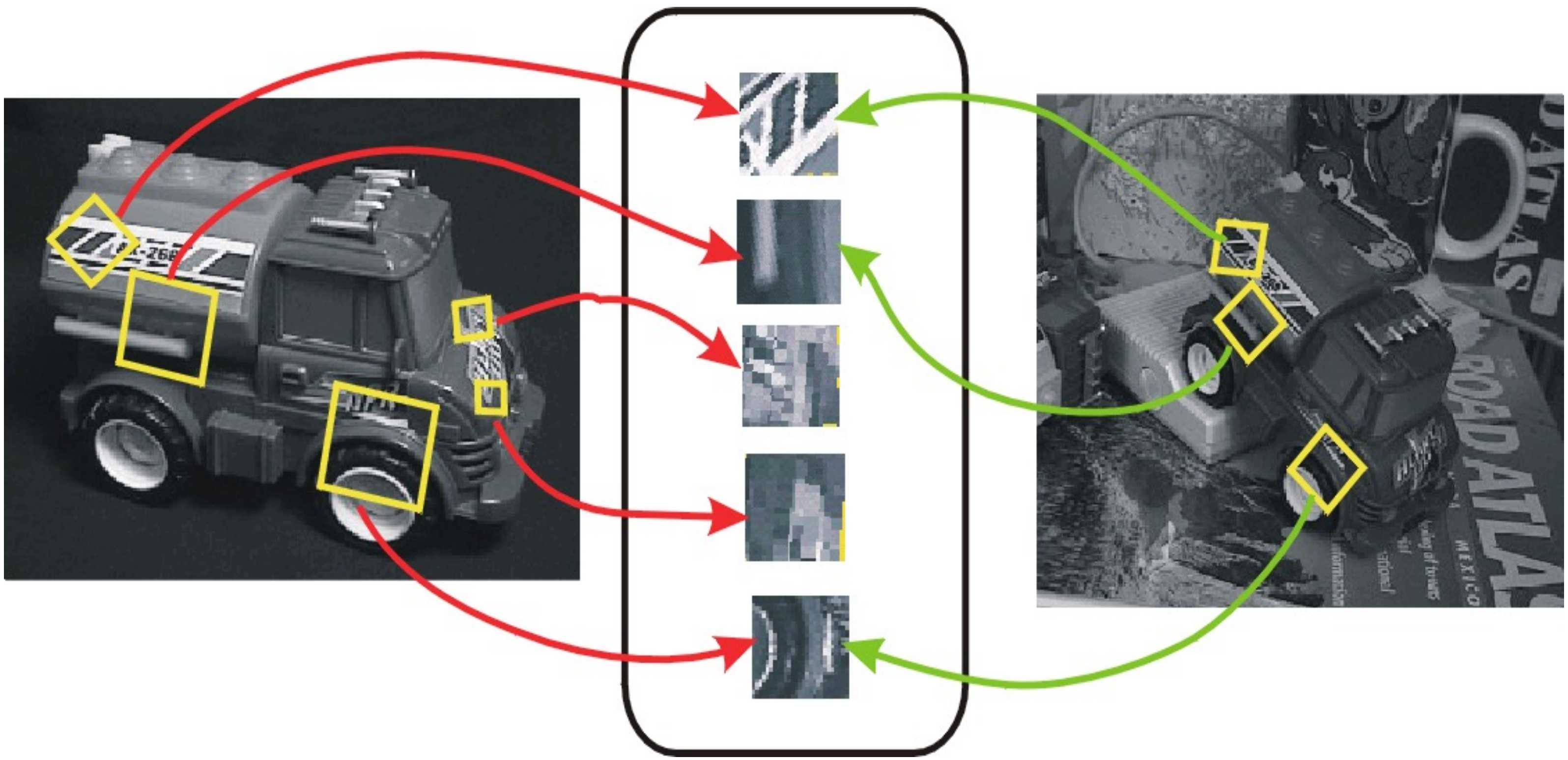
- We want to be able to reliably determine which point goes with which.



- Must provide some invariance to geometric and photometric differences between the two views.

Invariant Local Features

- Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters



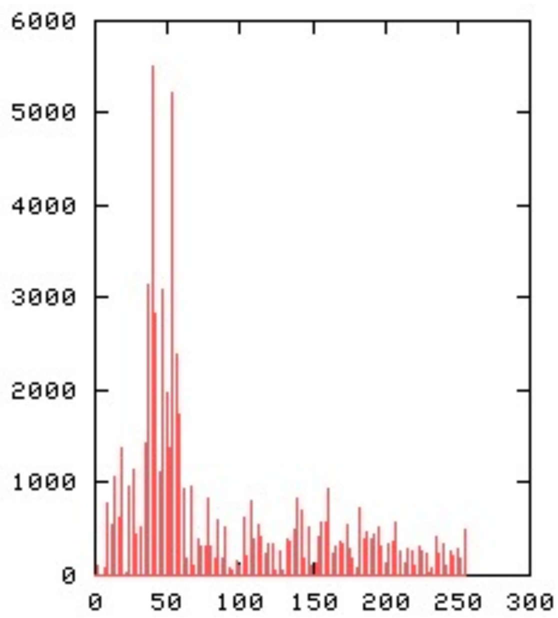
Feature Descriptors

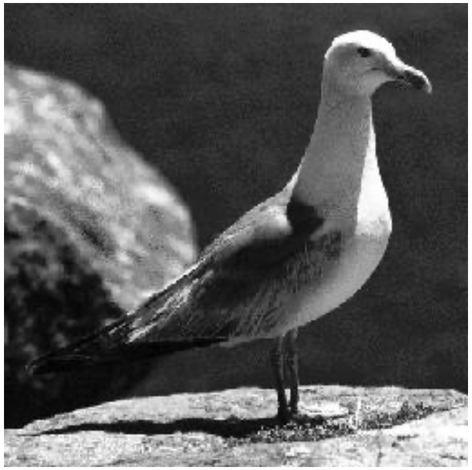
Image representations

- Templates
  - Intensity, gradients, etc.

- Histograms
  - Color, texture, SIFT descriptors, etc.

Image Representations: Histograms





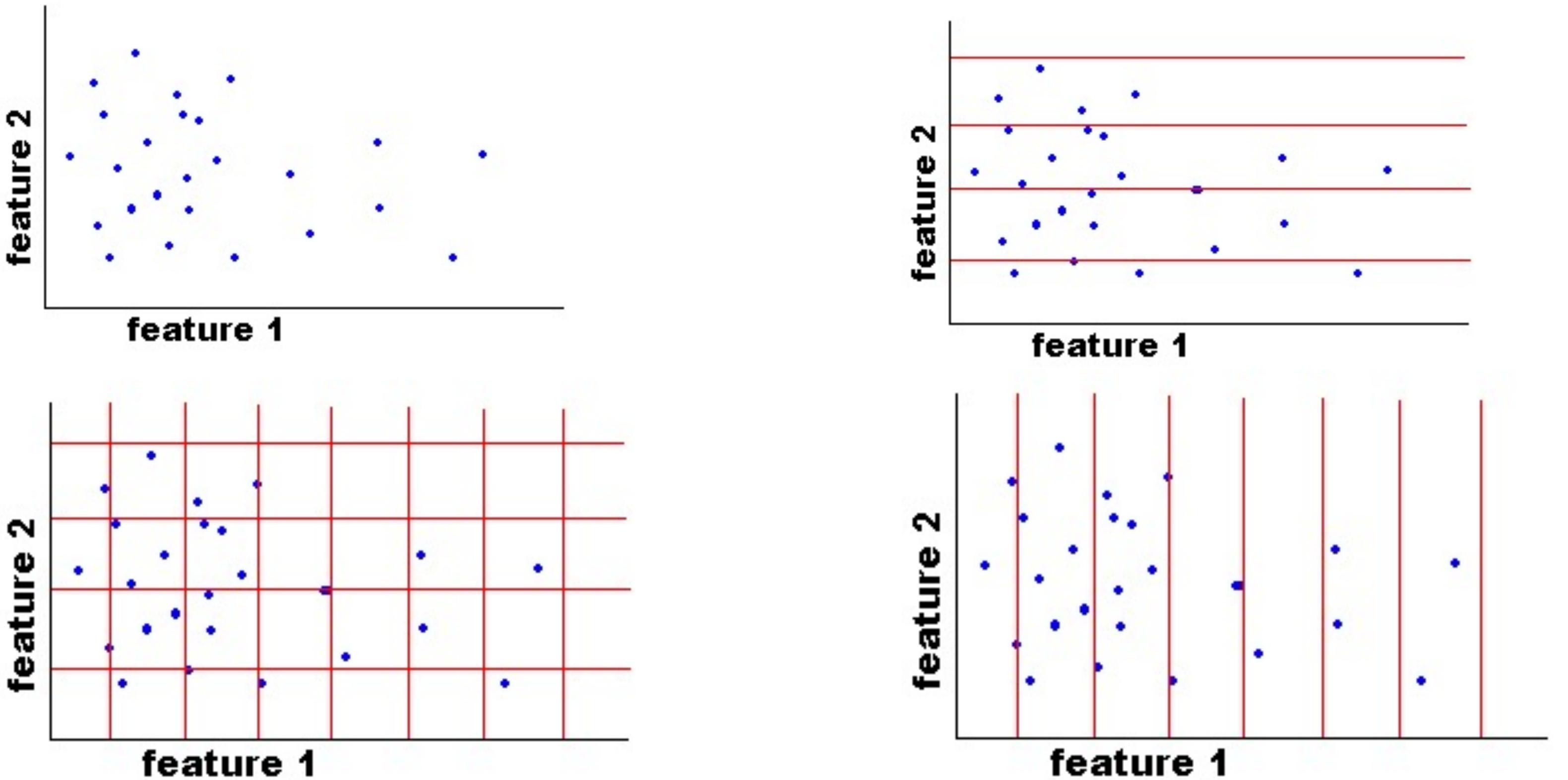
Global histogram

- Represent distribution of features
  - Color, texture, depth, …

Images from Dave Kauchak

Image Representations: Histograms

Histogram: Probability or count of data in each bin



- Joint histogram
  - Requires lots of data
  - Loss of resolution to avoid empty bins

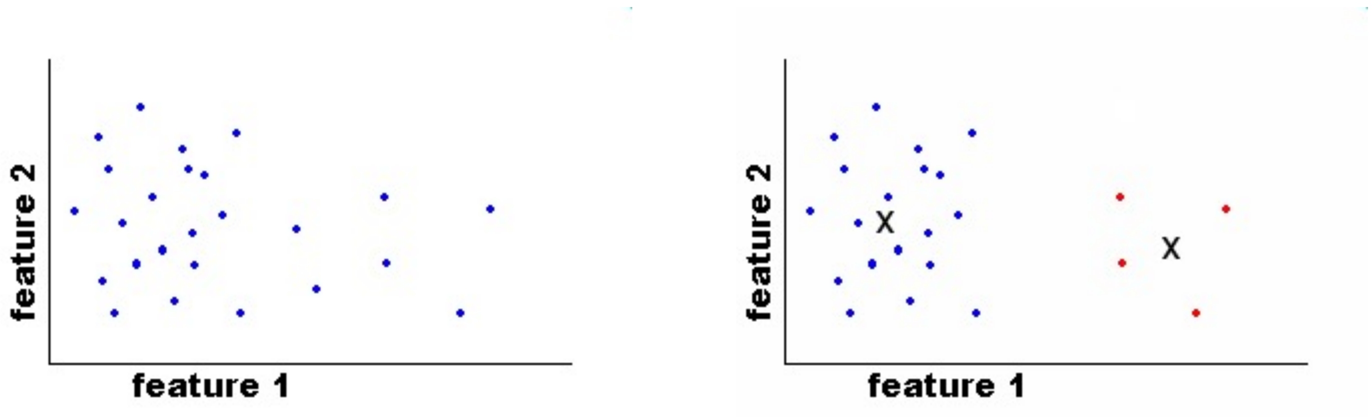
Marginal histogram

- Requires independent features
- More data/bin than joint histogram

Images from Dave Kauchak

Image Representations: Histograms

Clustering

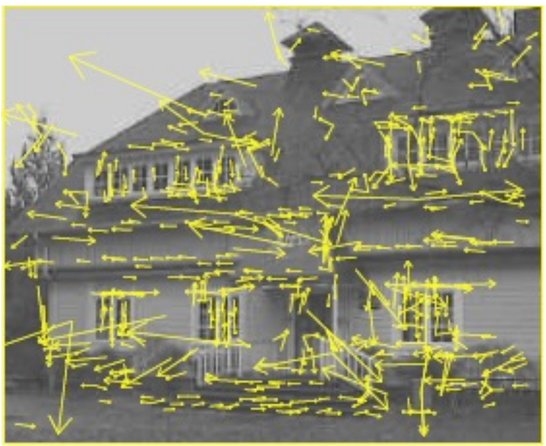


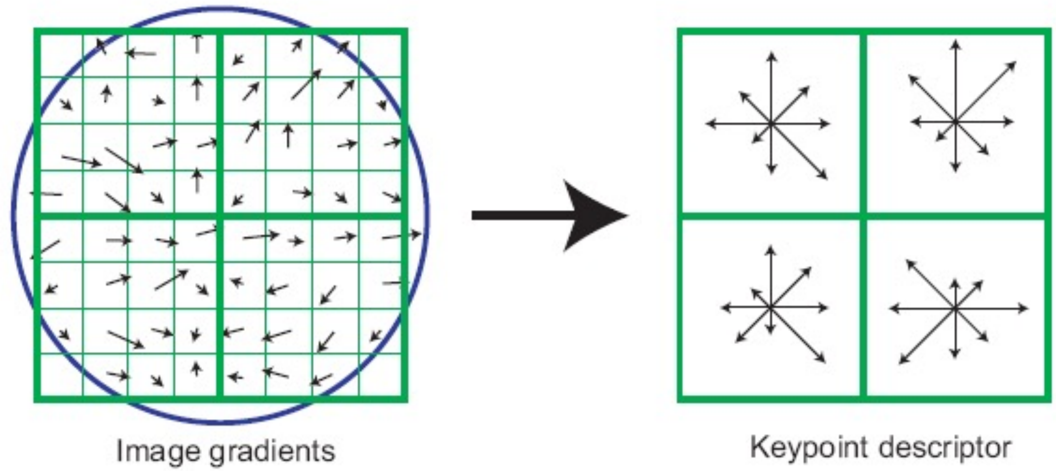
Use the same cluster centers for all images

Images from Dave Kauchak

What kind of things do we compute histograms of?

- Histograms of oriented gradients





SIFT – Lowe IJCV 2004

SIFT vector formation

- Computed on rotated and scaled version of window according to computed orientation & scale
  - resample the window
- Based on gradients weighted by a Gaussian of variance half the window (for smooth falloff)

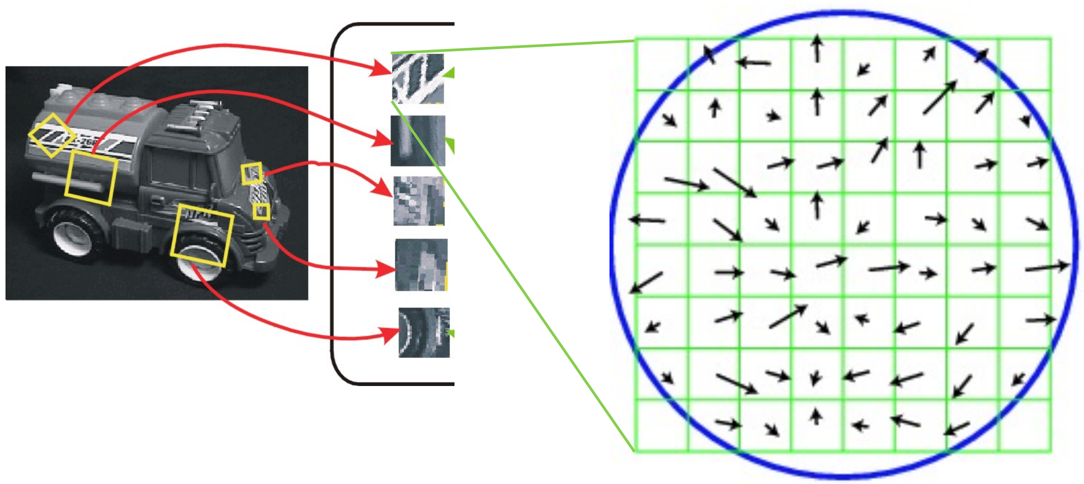


Image gradients

SIFT vector formation

- 4x4 array of gradient orientation histogram weighted by magnitude
- 8 orientations x 4x4 array = 128 dimensions
- Motivation: some sensitivity to spatial layout, but not too much.

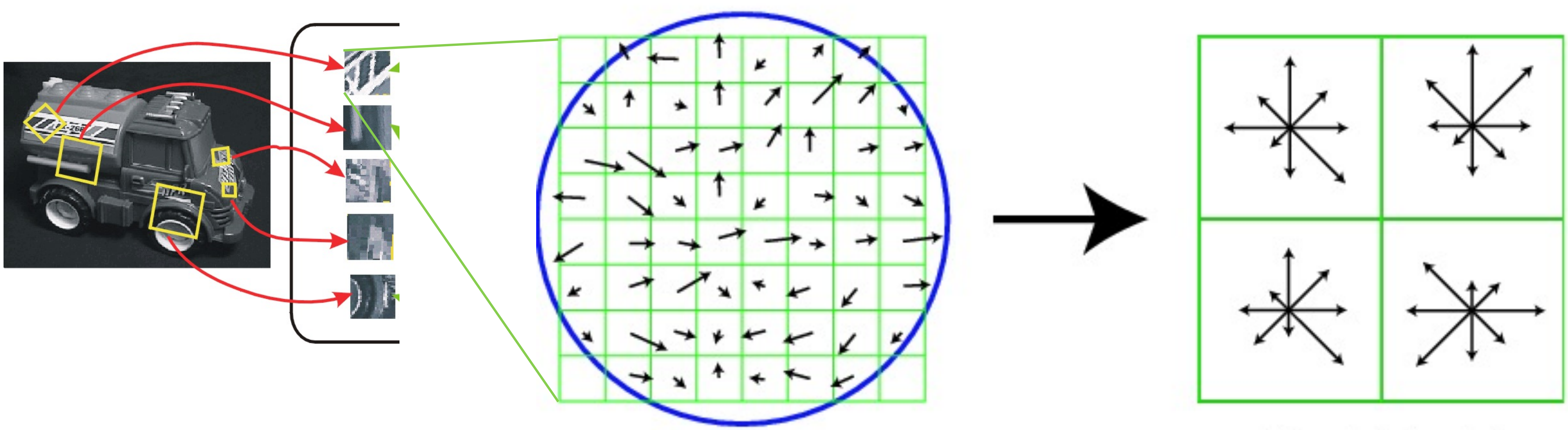


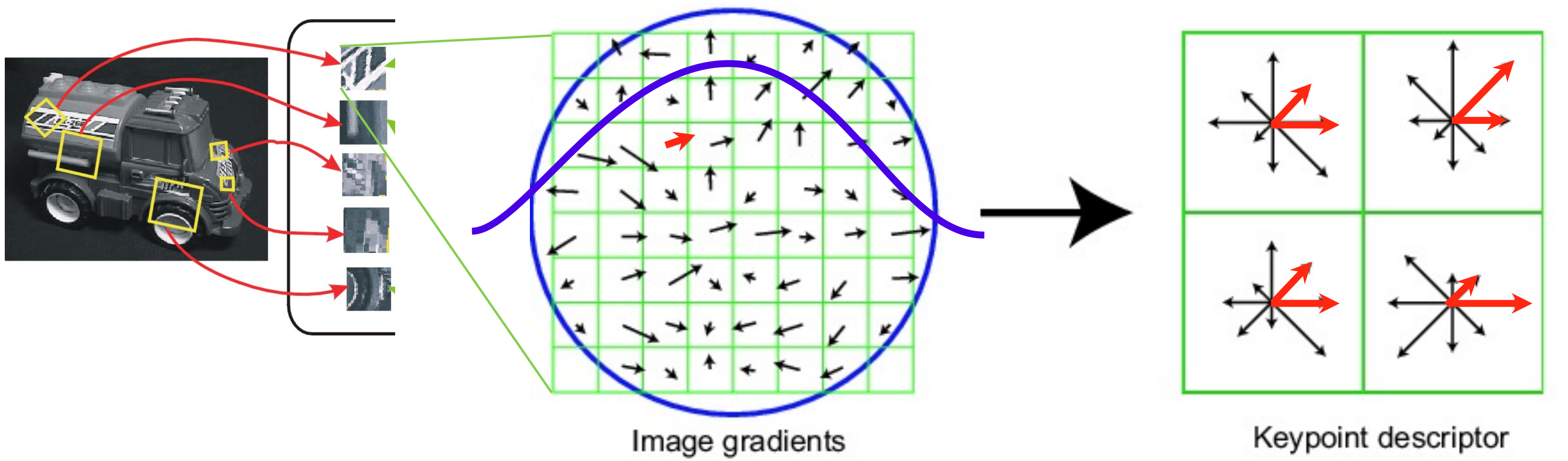
Image gradients

Keypoint descriptor

showing only 2x2 here but is 4x4

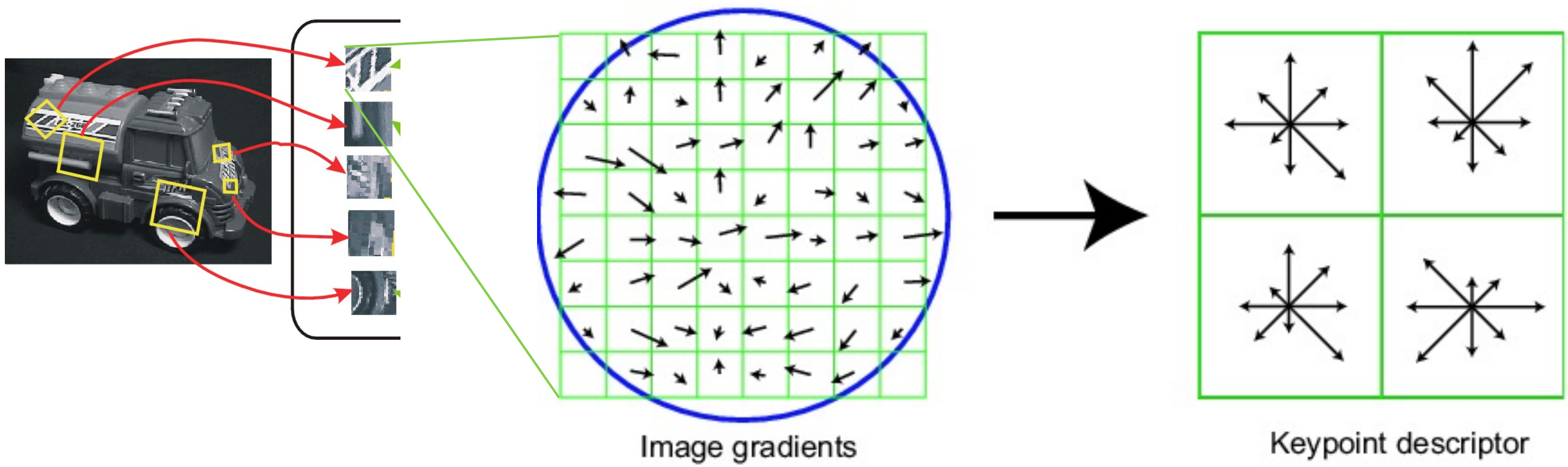
Ensure smoothness

- Gaussian weight
- Interpolation
  – a given gradient contributes to 8 bins: 4 in space times 2 in orientation

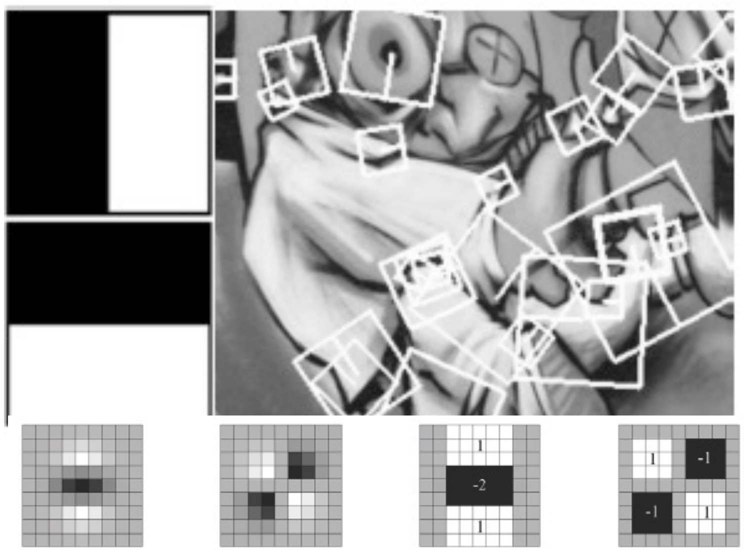


Reduce effect of illumination

- 128-dim vector normalized to 1
- Threshold gradient magnitudes to avoid excessive influence of high gradients
  - after normalization, clamp gradients >0.2
  - renormalize



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**

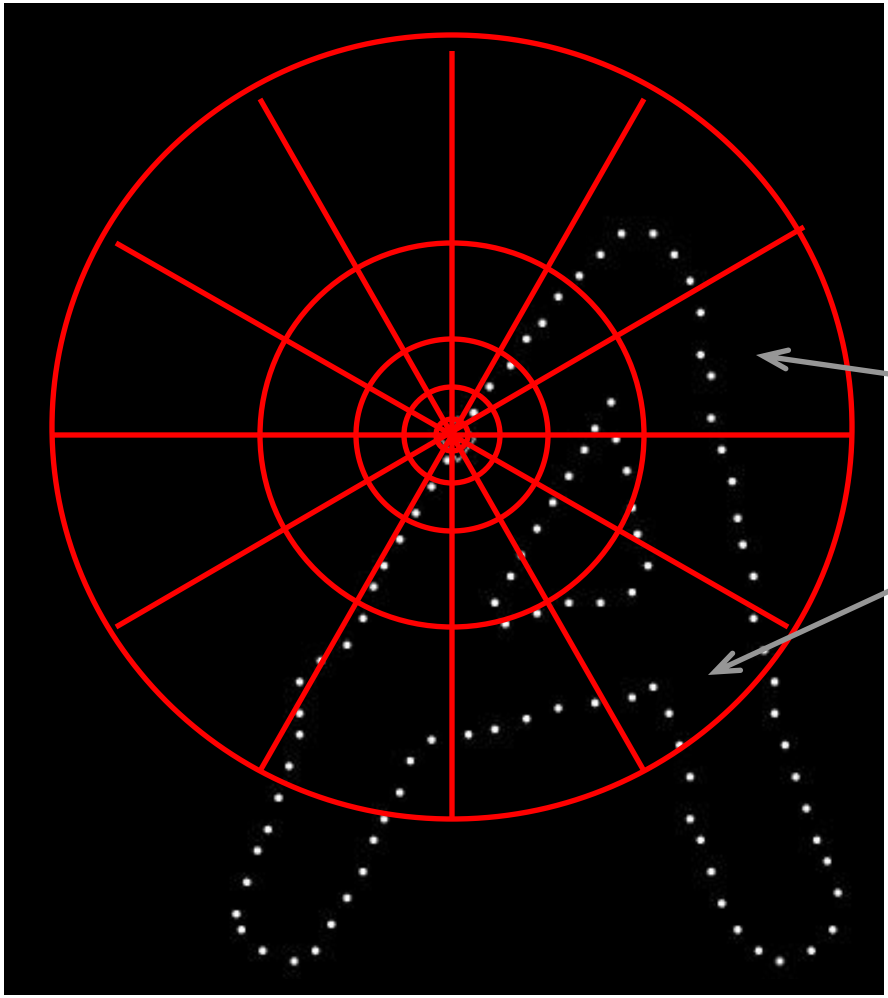
GPU implementation available

- **Feature extraction @ 200Hz (detector + descriptor, 640×480 img)**
- http://www.vision.ee.ethz.ch/~surf

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

K. Grauman, B. Leibe

Local Descriptors: Shape Context



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

Count = 4

⋮

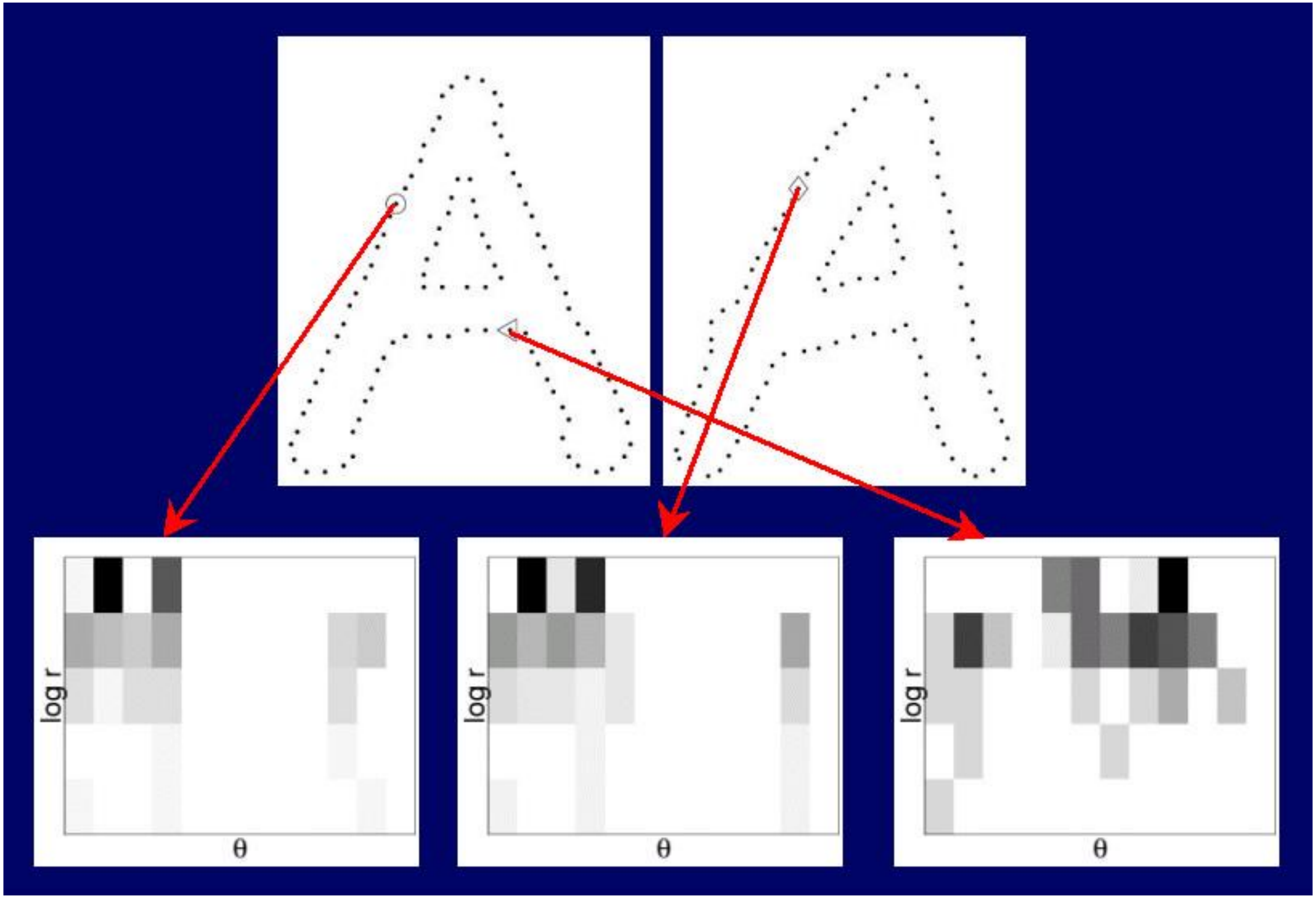
Count = 10

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

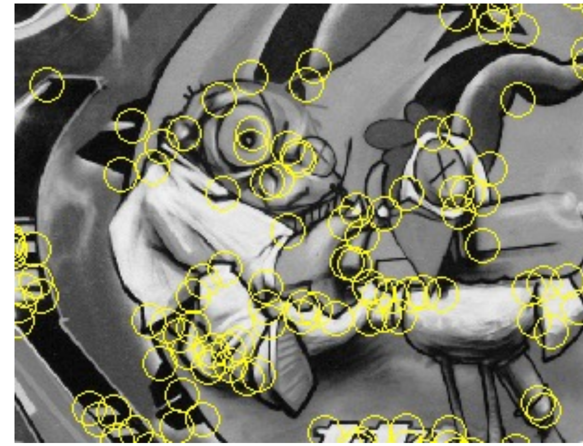
Belongie & Malik, ICCV 2001

K. Grauman, B. Leibe

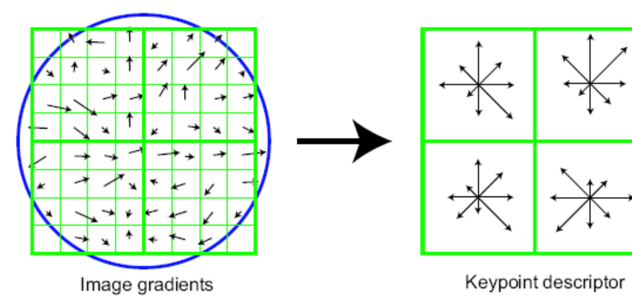
Shape Context Descriptor



Things to remember



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



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

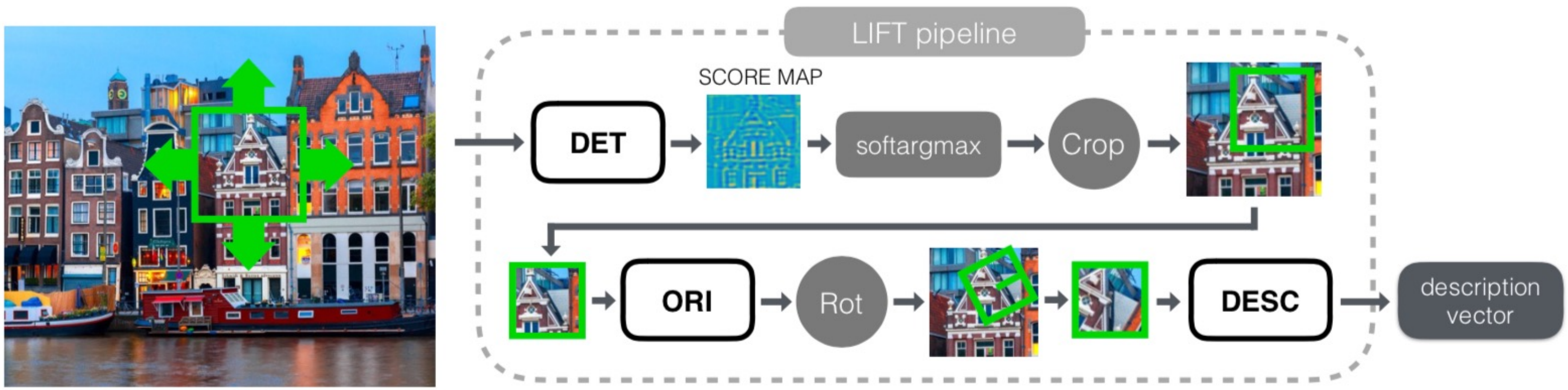
Deep Descriptors

LIFT: Learned Invariant Feature Transform

ECCV 2016

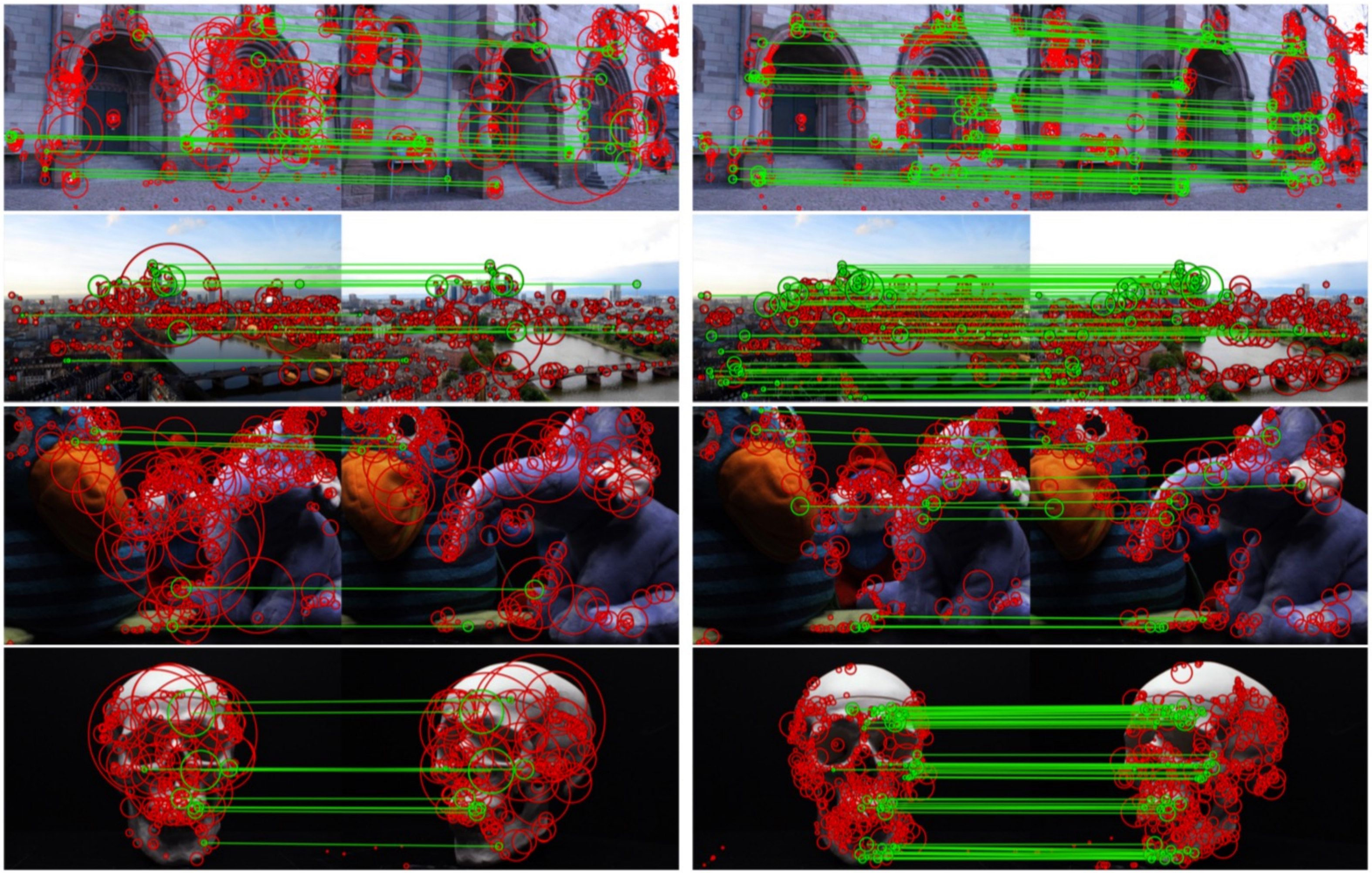
Kwang Moo Yi[*,1], Eduard Trulls[*,1], Vincent Lepetit[2], Pascal Fua[1]

[1]Computer Vision Laboratory, Ecole Polytechnique Fédérale de Lausanne (EPFL)
[2]Institute for Computer Graphics and Vision, Graz University of Technology



- Three networks: detection, orientation, description
- detection+orientation -> STN -> descriptor
- Trained separately :-(

SIFT vs. LIFT



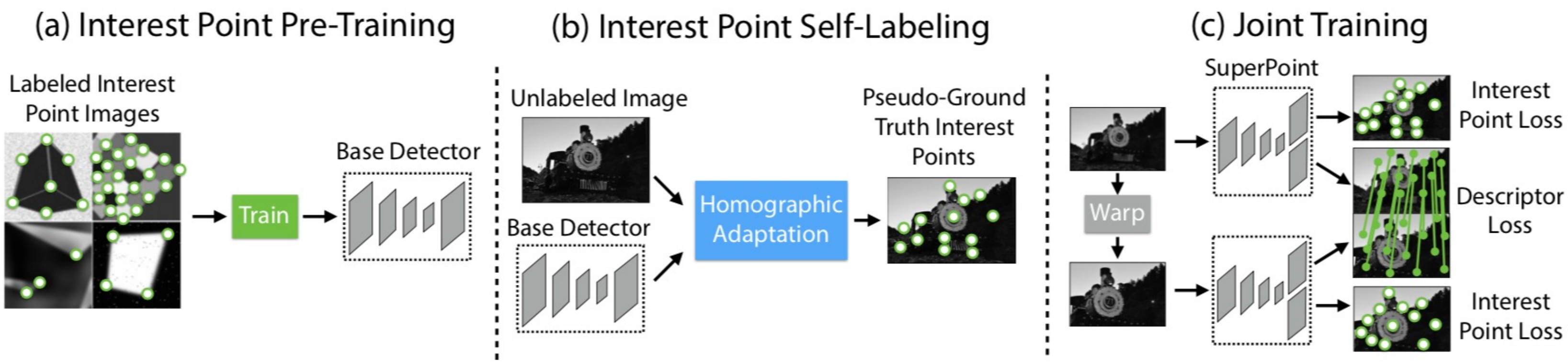
SuperPoint: Self-Supervised Interest Point Detection and Description

2018 CVPR Workshop

Daniel DeTone
Magic Leap
Sunnyvale, CA

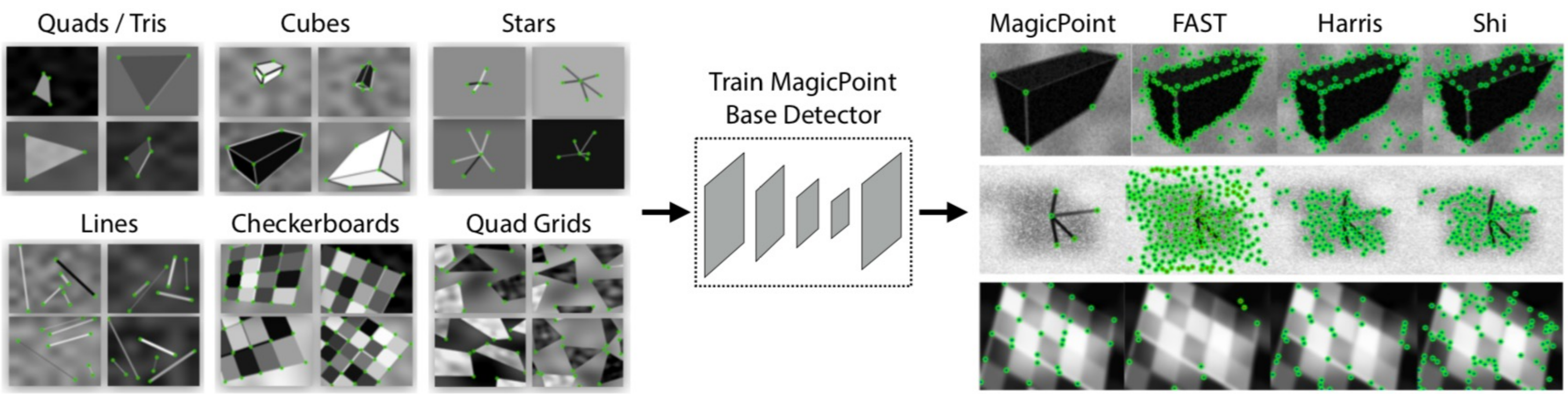
Tomasz Malisiewicz
Magic Leap
Sunnyvale, CA

Andrew Rabinovich
Magic Leap
Sunnyvale, CA



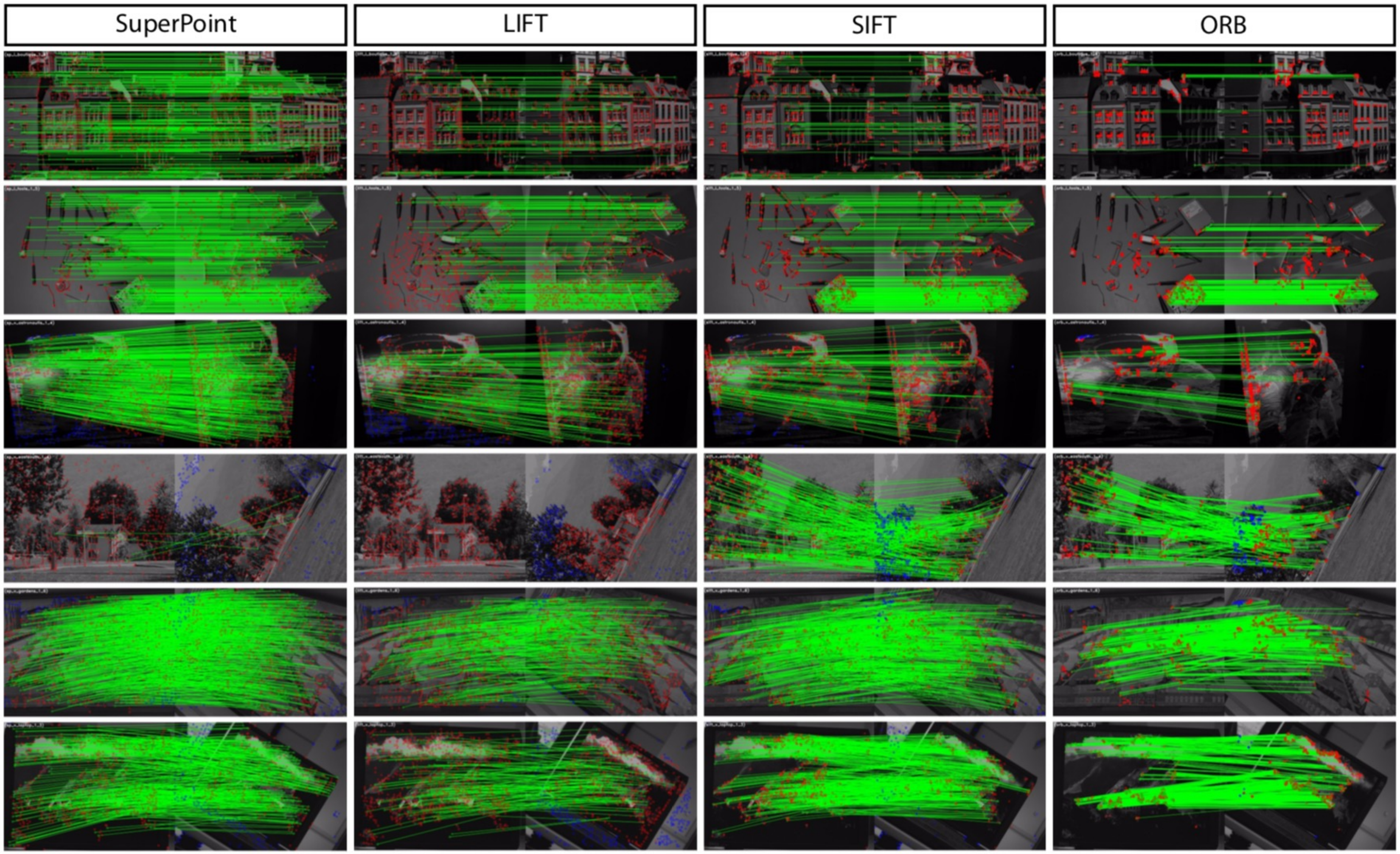
- Interest point = ill-defined -> self-supervised
- MagicPoint -> SuperPoint

MagicPoint



Quads / Tris
Cubes
Stars
Lines
Checkerboards
Quad Grids
Train MagicPoint
Base Detector
MagicPoint
FAST
Harris
Shi

SuperPoint Results

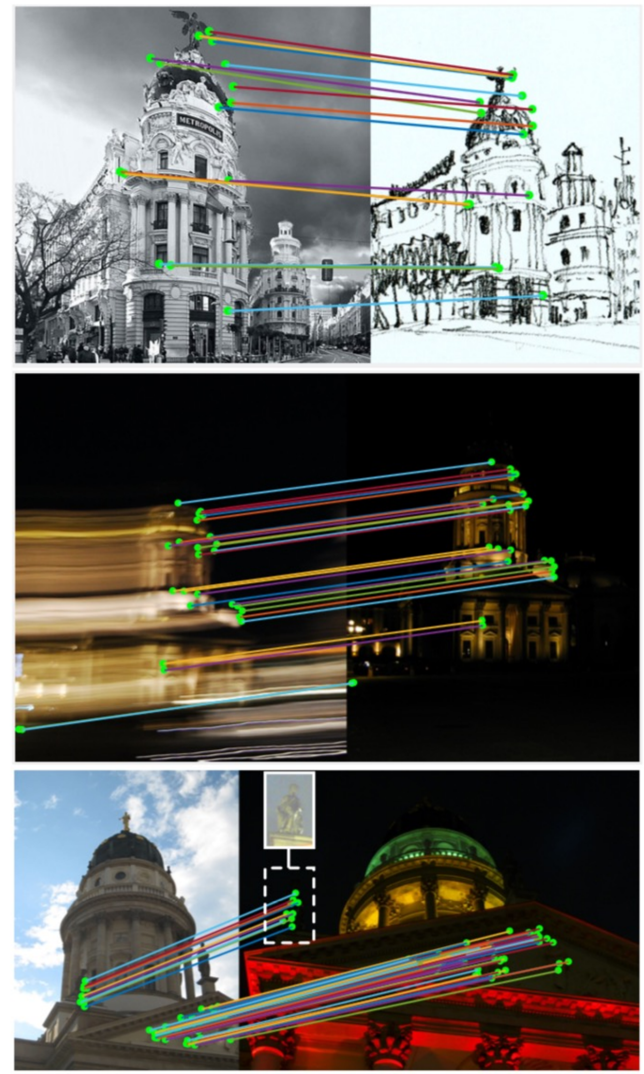


D2-Net: A Trainable CNN for *Joint Description and Detection* of Local Features

CVPR 2019

Mihai Dusmanu[1,2,3] Ignacio Rocco[1,2] Tomas Pajdla[4] Marc Pollefeys[3,5]
Josef Sivic[1,2,4] Akihiko Torii[6] Torsten Sattler[7]

- Tensor viewed as descriptors and detector maps
- VGG16-based, loss encourages distinctiveness and repeatability
- Results beat the star of the art in day-night and indoor localization, but not in more traditional settings (Superpoint shines for HPatches, **GeoDesc** for SFM)



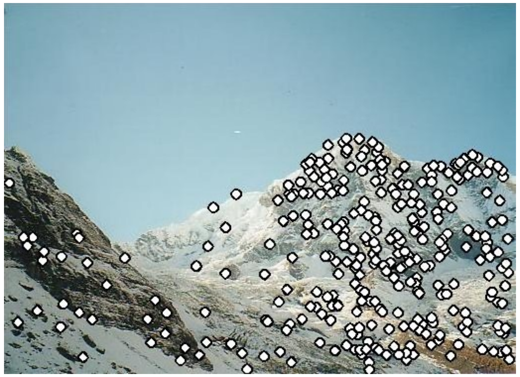
Matching

Local features: main components

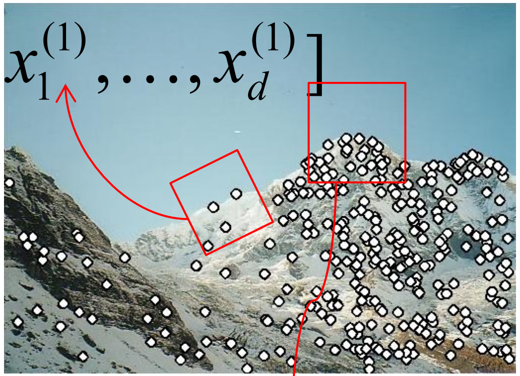
1) **Detection:** Identify the interest points

2) **Description:** Extract vector feature descriptor surrounding each interest point.

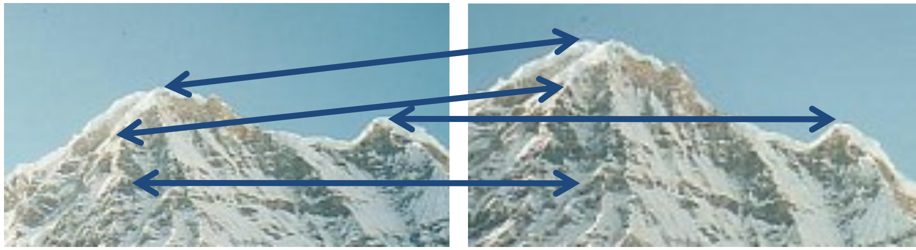
3) **Matching: Determine correspondence between descriptors in two views**



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



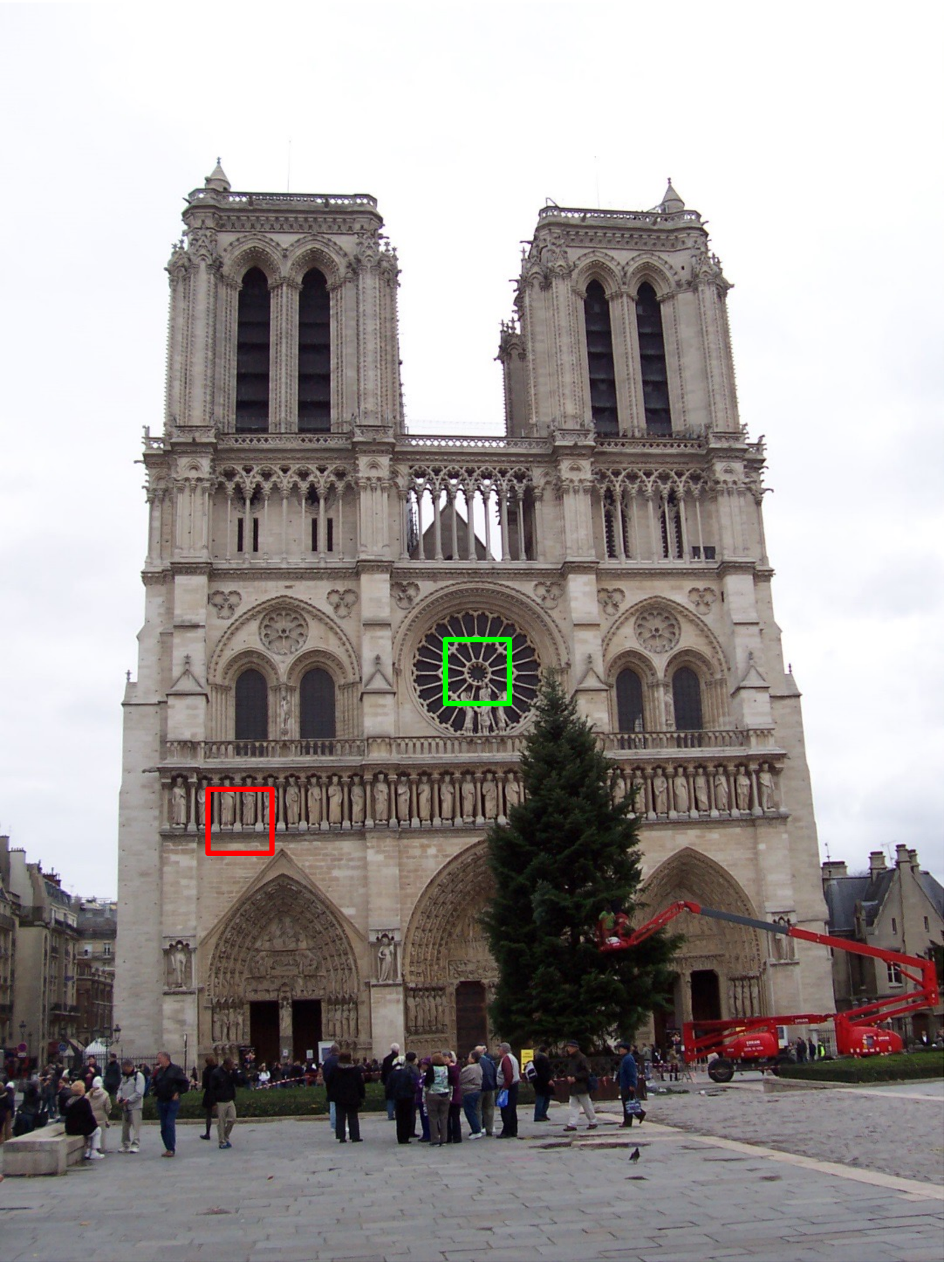
$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

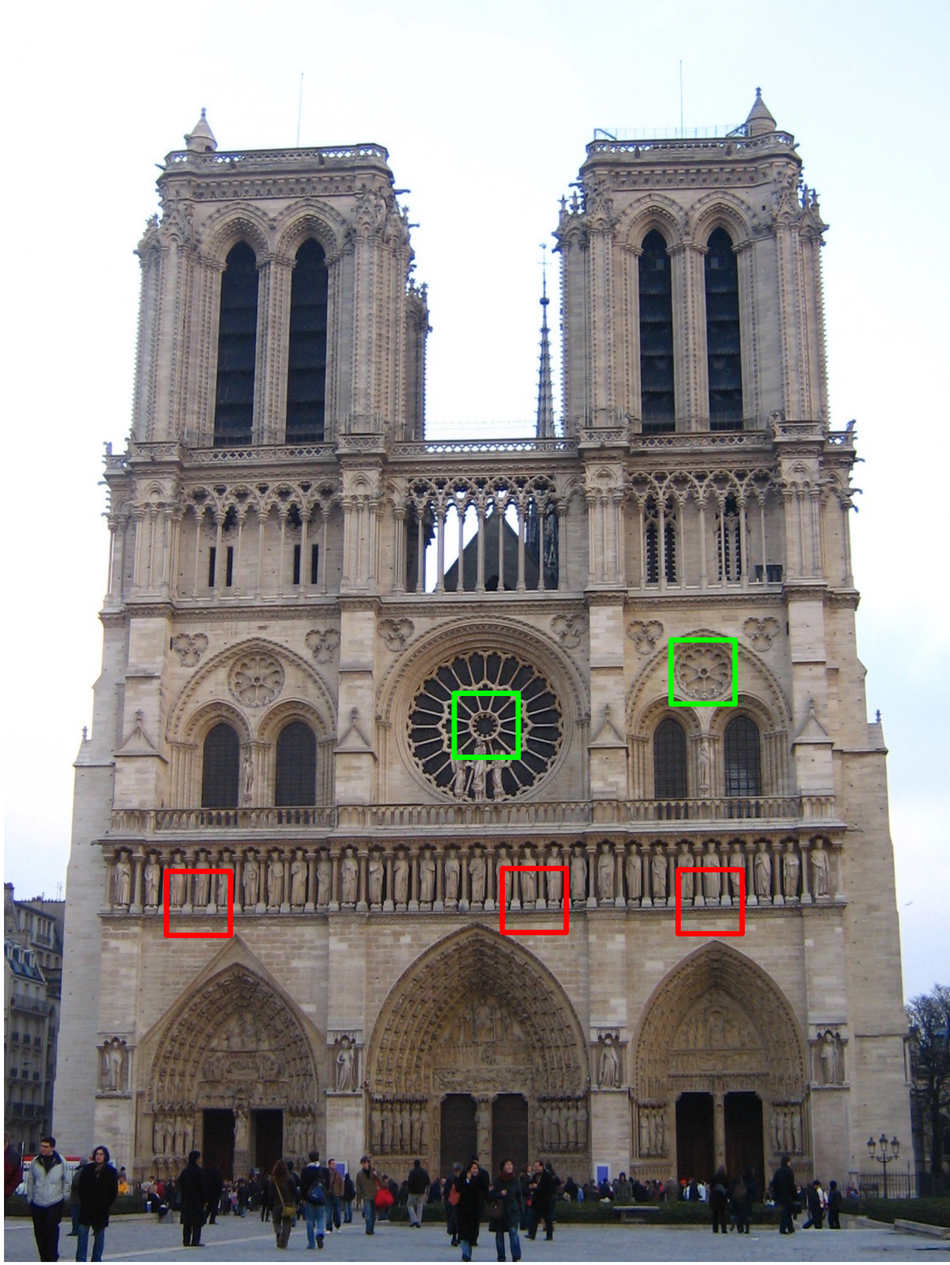


Kristen Grauman

Matching

- Simplest approach: Pick the nearest neighbor. Threshold on absolute distance
- Problem: Lots of self similarity in many photos





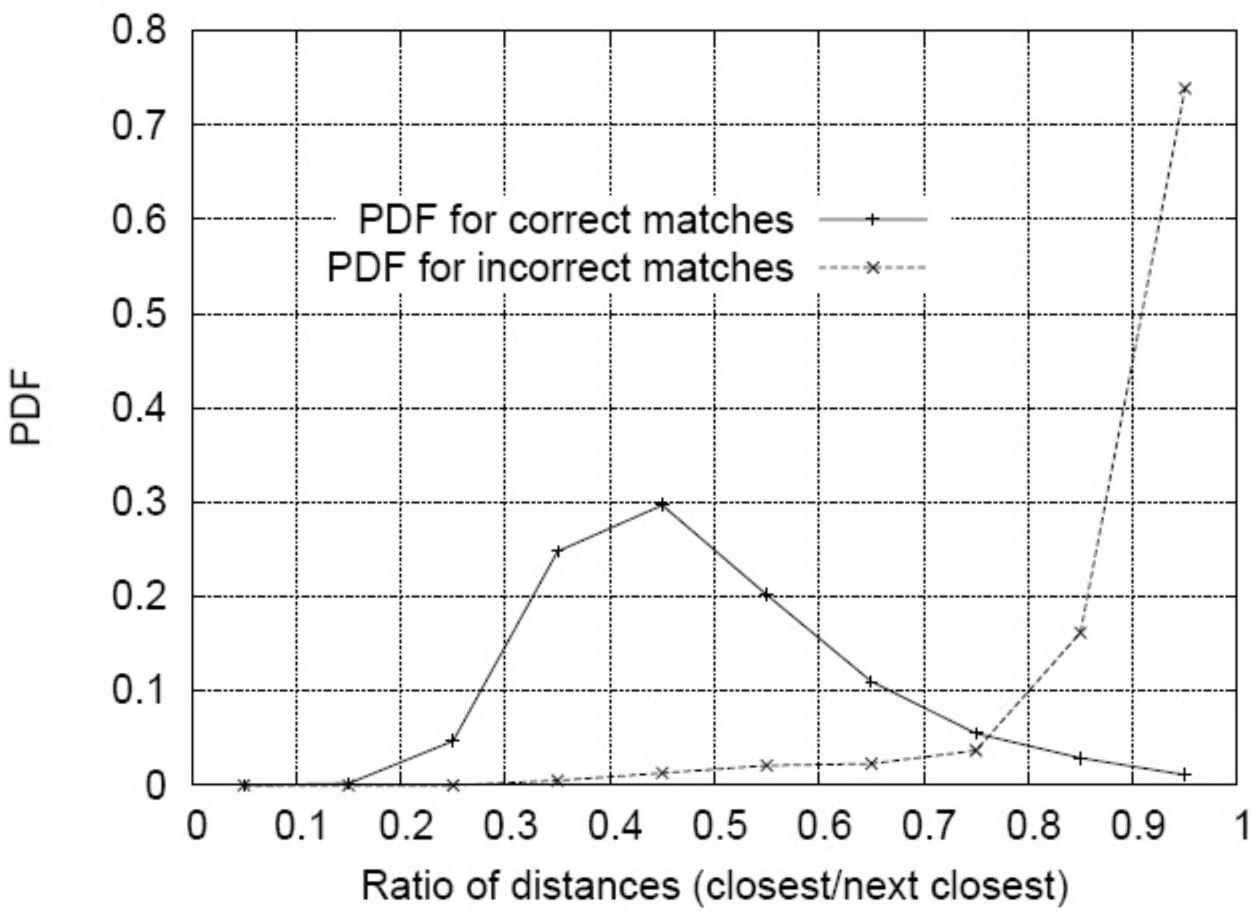
Distance: 0.34, 0.30, 0.40 Distance: 0.61
Distance: 1.22

Nearest Neighbor Distance Ratio

- $\frac{NN1}{NN2}$ where NN1 is the distance to the first nearest neighbor and NN2 is the distance to the second nearest neighbor.
- Sorting by this ratio puts matches in order of confidence.

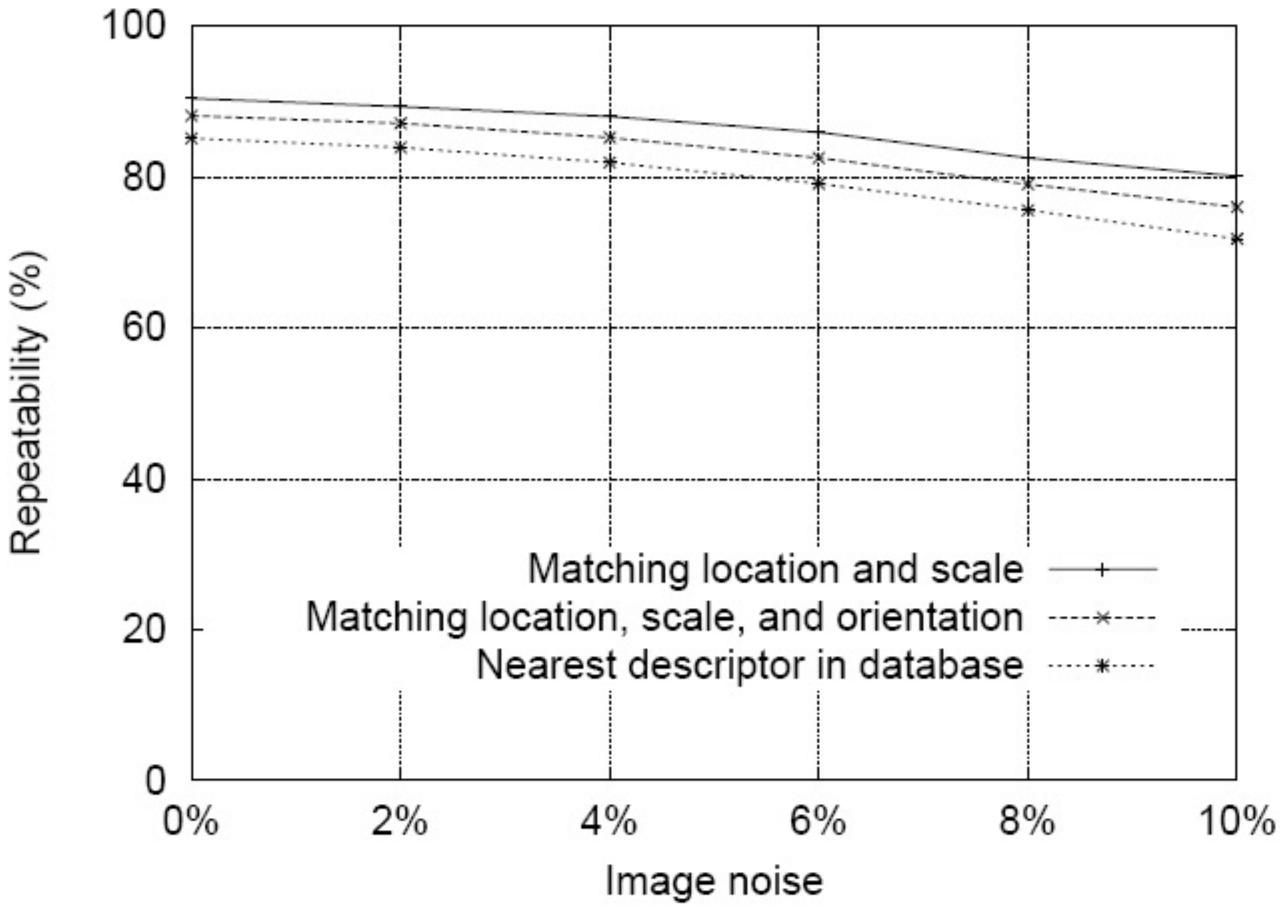
Matching Local Features

- Nearest neighbor (Euclidean distance)
- Threshold ratio of nearest to 2nd nearest descriptor



Lowe IJCV 2004

SIFT Repeatability



Lowe IJCV 2004

SIFT Repeatability