

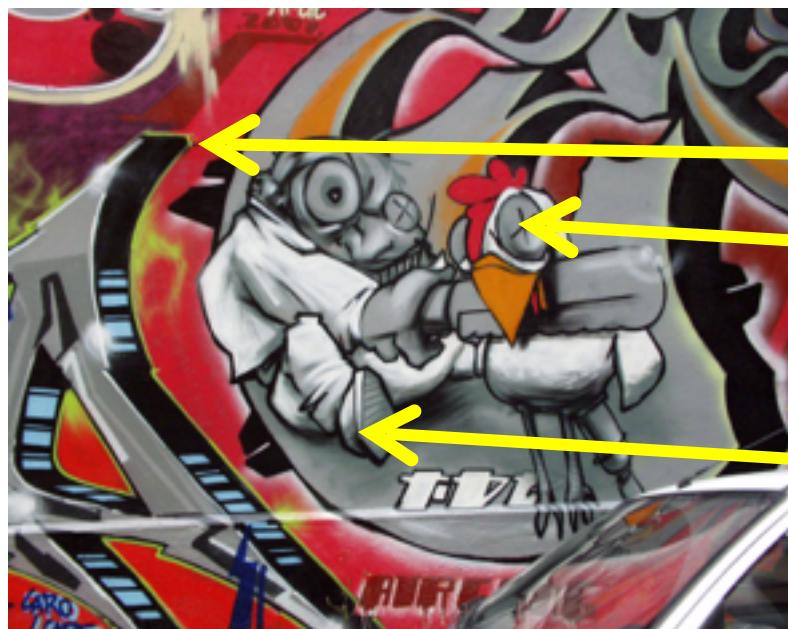
Descriptors

CSE 576

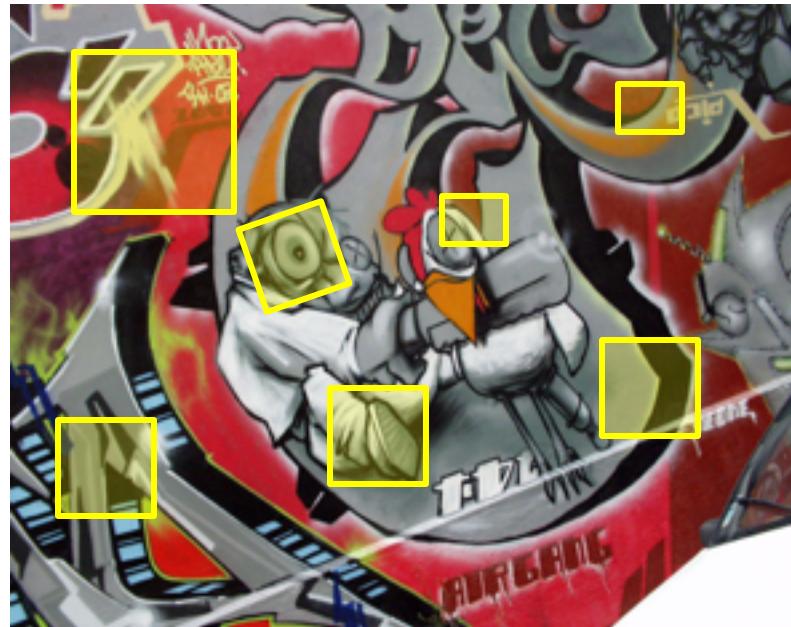
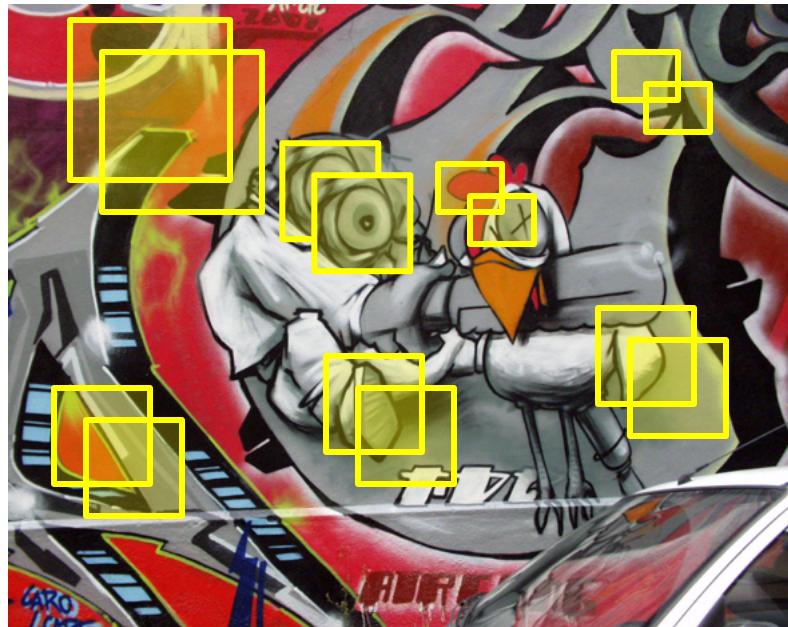
Ali Farhadi

Many slides from Larry Zitnick, Steve Seitz

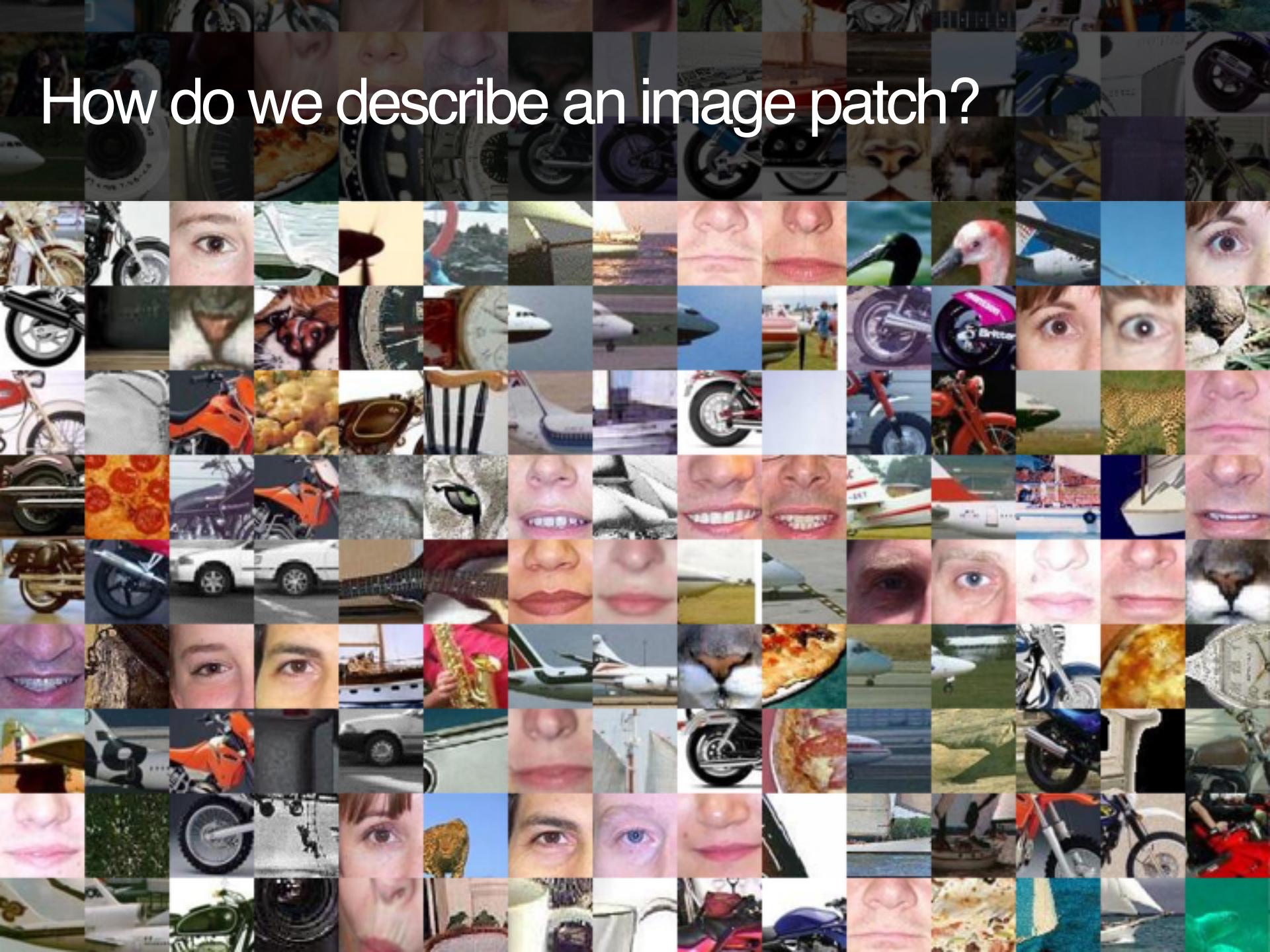
How can we find corresponding points?



How can we find correspondences?

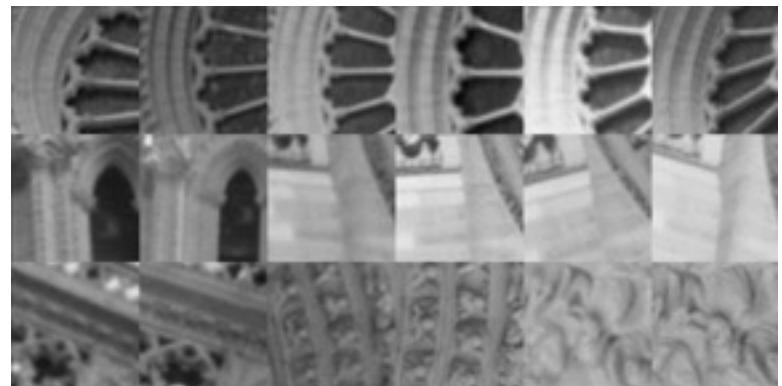


How do we describe an image patch?

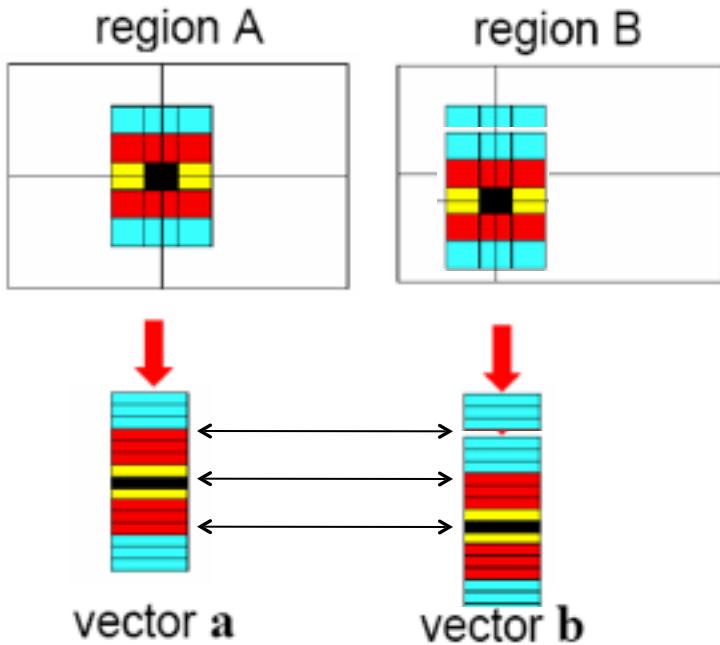


How do we describe an image patch?

Patches with similar content should have similar descriptors.



Raw patches as local descriptors

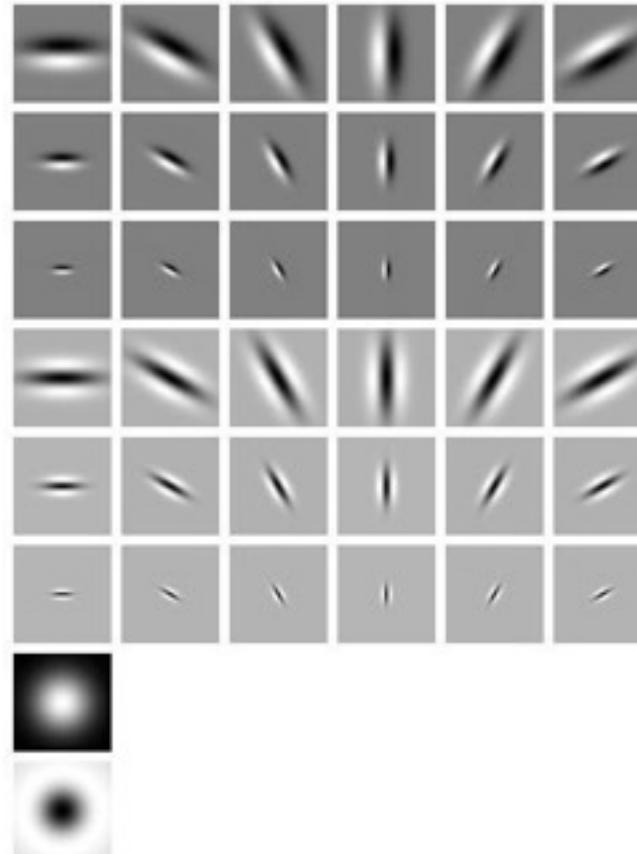


The simplest way to describe the neighborhood around an interest point is to write down the list of intensities to form a feature vector.

But this is very sensitive to even small shifts, rotations.

What do human use?

Gabor filters...

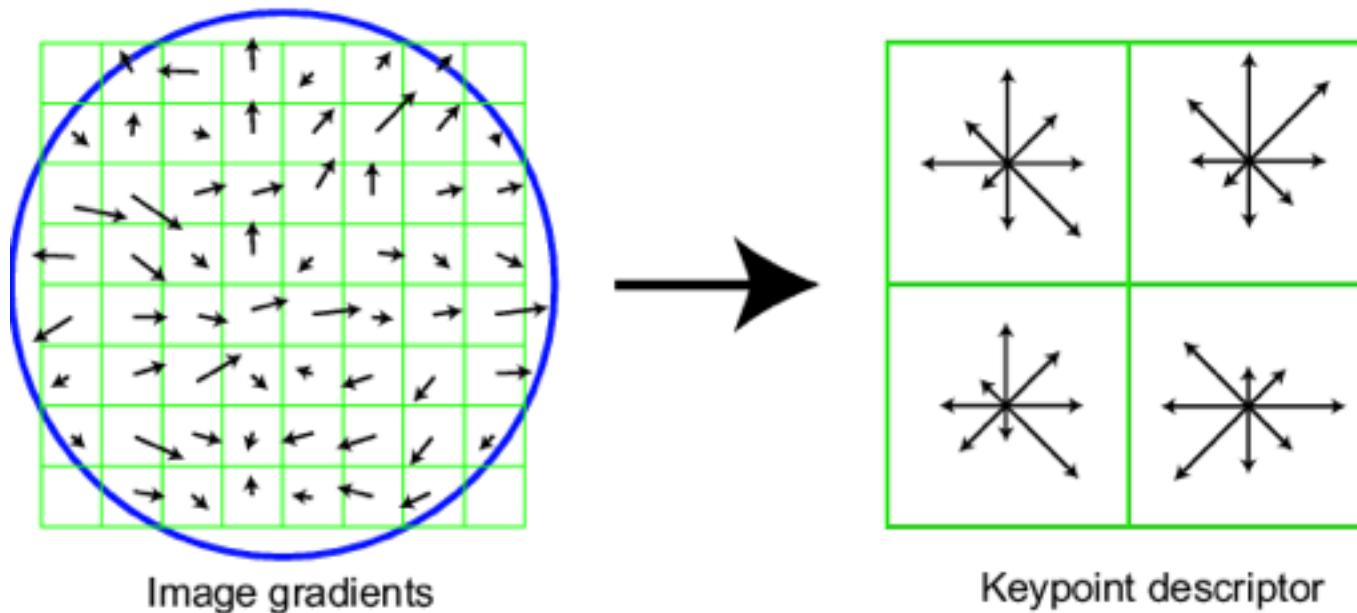


... and many other things.

SIFT descriptor

Full version

- Divide the 16x16 window into a 4x4 grid of cells (2x2 case shown below)
- Compute an orientation histogram for each cell
- 16 cells * 8 orientations = 128 dimensional descriptor



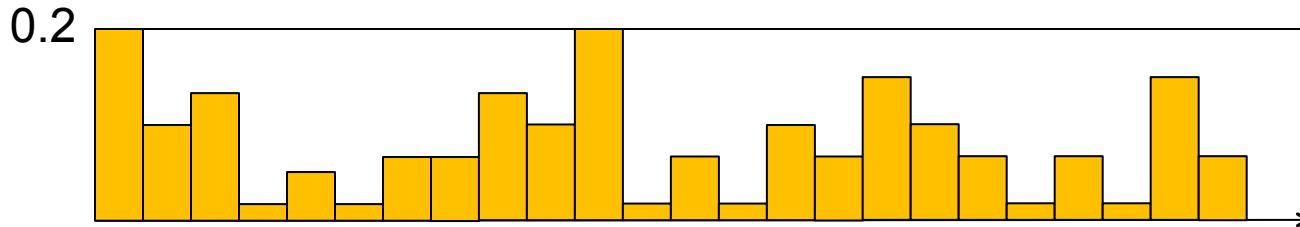
Adapted from slide by David Lowe

SIFT descriptor

Full version

- Divide the 16x16 window into a 4x4 grid of cells (2x2 case shown below)
- Compute an orientation histogram for each cell
- 16 cells * 8 orientations = 128 dimensional descriptor
- Threshold normalize the descriptor:

$$\sum_i d_i^2 = 1 \quad \text{such that: } d_i < 0.2$$



Adapted from slide by David Lowe

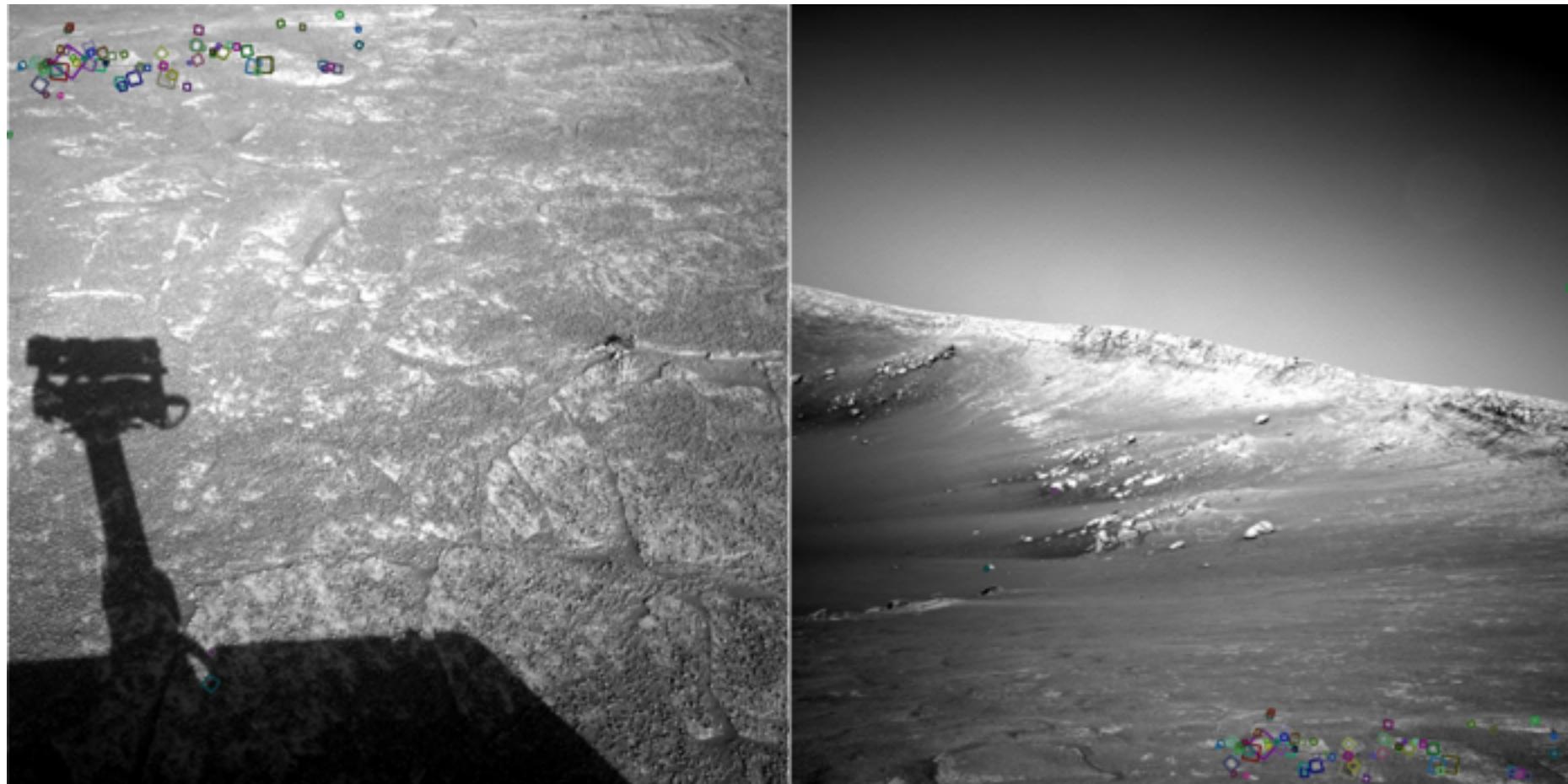
Properties of SIFT

Extraordinarily robust matching technique

- Can handle changes in viewpoint
 - Up to about 30 degree out of plane rotation
- Can handle significant changes in illumination
 - Sometimes even day vs. night (below)
- Fast and efficient—can run in real time
- Lots of code available
 - http://people.csail.mit.edu/albert/ladypack/wiki/index.php/Known_implementations_of_SIFT

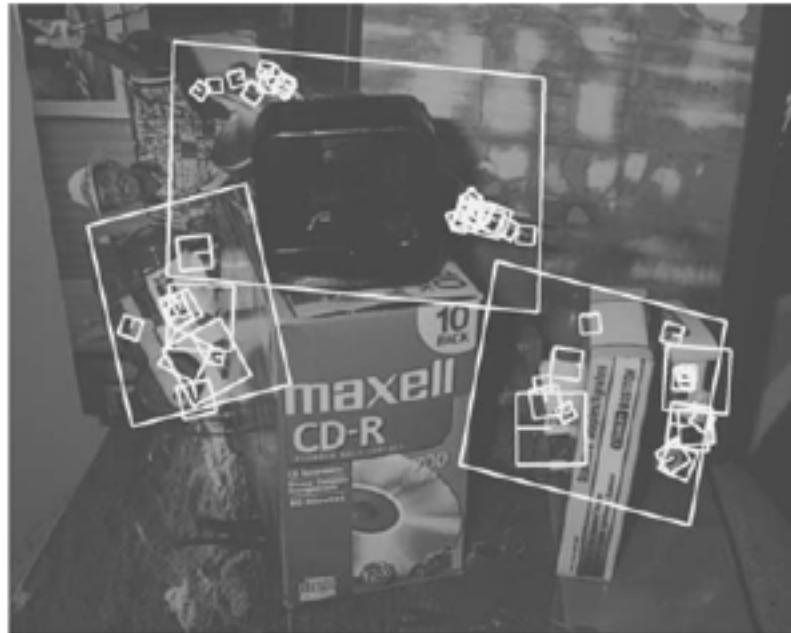


Example



NASA Mars Rover images
with SIFT feature matches
Figure by Noah Snavely

Example: Object Recognition



SIFT is extremely powerful for object instance recognition, especially for well-textured objects

Example: Google Goggle

Google Goggles in Action

Click the icons below to see the different ways Google Goggles can be used.



Landmark



Book



Contact Info.



Artwork



Places



Wine



Logo



The screenshot shows a smartphone displaying search results. At the top, there is a header bar with the text "Google goggles labs". Below the header, there is a section labeled "Wine" featuring a thumbnail image of the same wine bottle from the previous image. To the right of the image, the text "Bodegas Terrazas De Los Andes Malbec Reserva 2004" is displayed. Further down, under the heading "Web Results", there is a list of years from 2009 to 1984, followed by a link to the website "http://www.terrazasdelosandes.com/". At the bottom of the screen, there is a summary line: "Bodegas Terrazas de los Andes Winery (Perdriel, Luján de Cuyo , AR ... Popular wines by Bodegas Terrazas de los Andes."

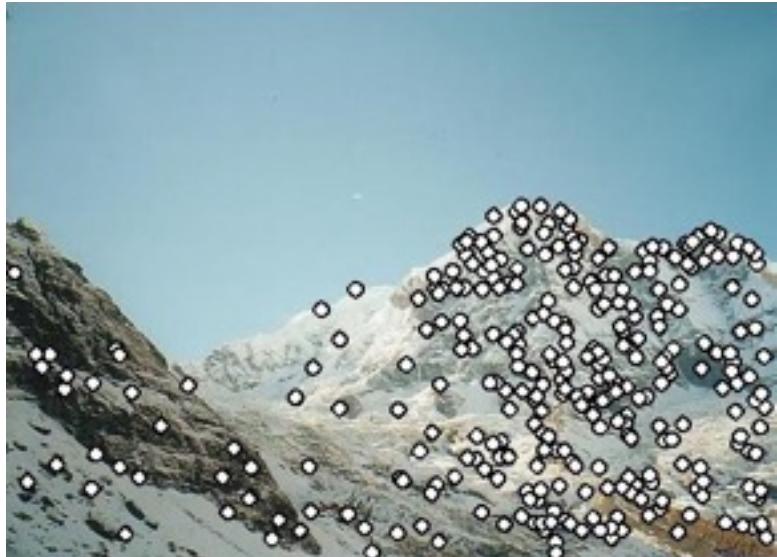
panorama?

- We need to match (align) images



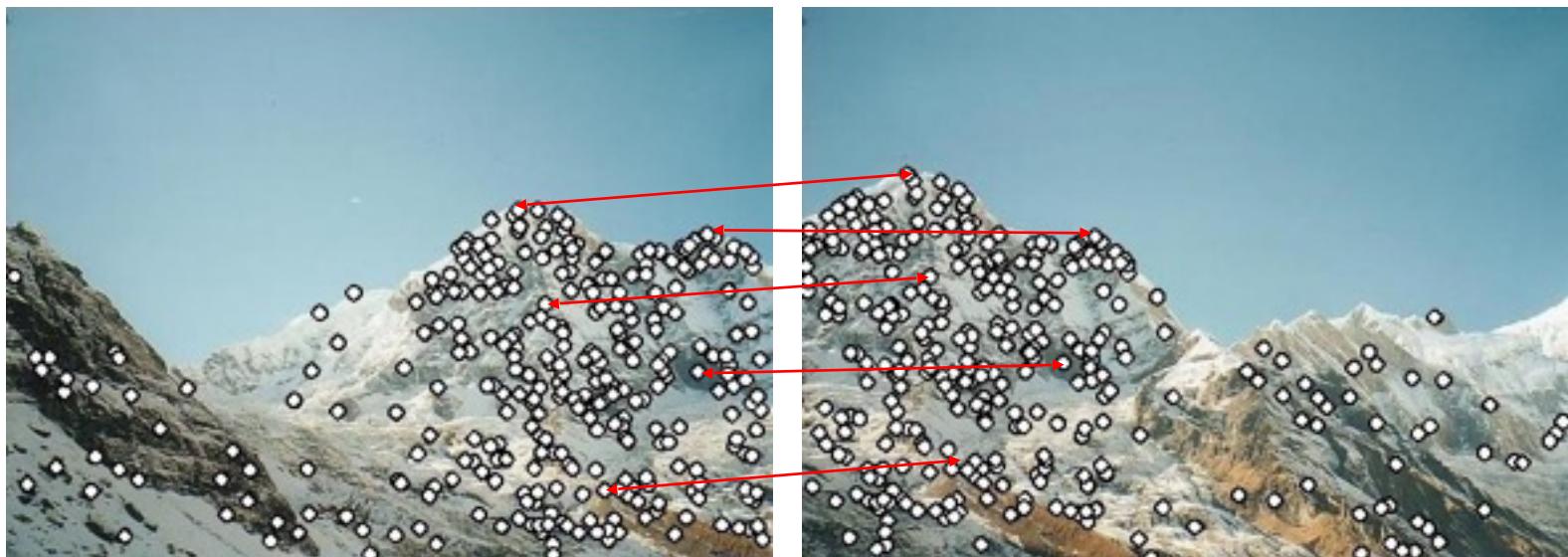
Matching with Features

- Detect feature points in both images



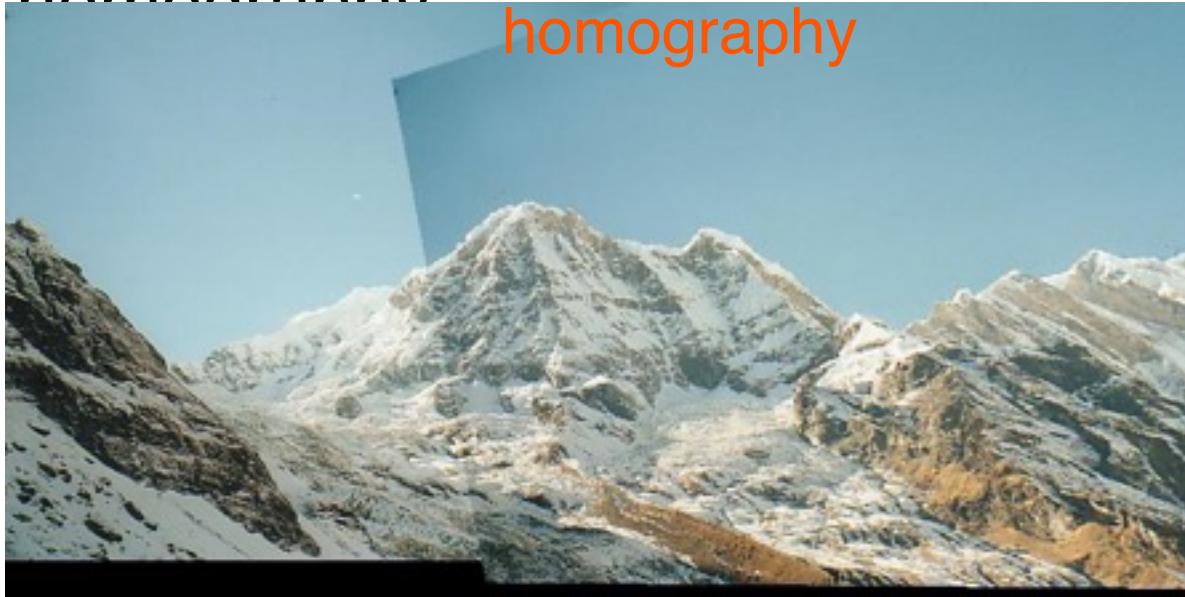
Matching with Features

- Detect feature points in both images
- Find corresponding pairs

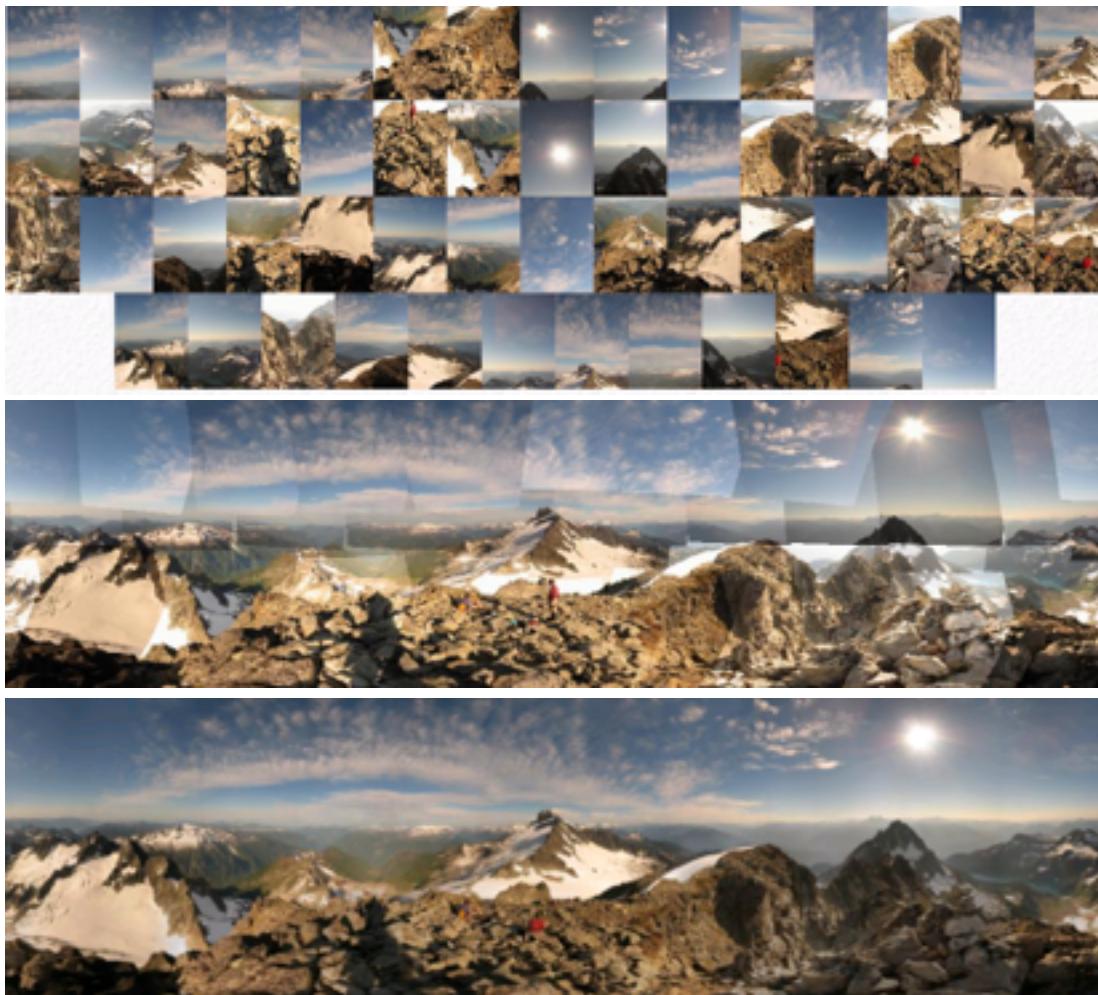


Matching with Features

- Detect feature points in both images
- Find corresponding pairs
- Use these matching pairs to align images -
the required mapping is called a
homography



Automatic mosaicing



<http://www.cs.ubc.ca/~mbrown/autostitch/autostitch.html>

Recognition of specific objects, scenes



Schmid and Mohr 1997



Sivic and Zisserman, 2003



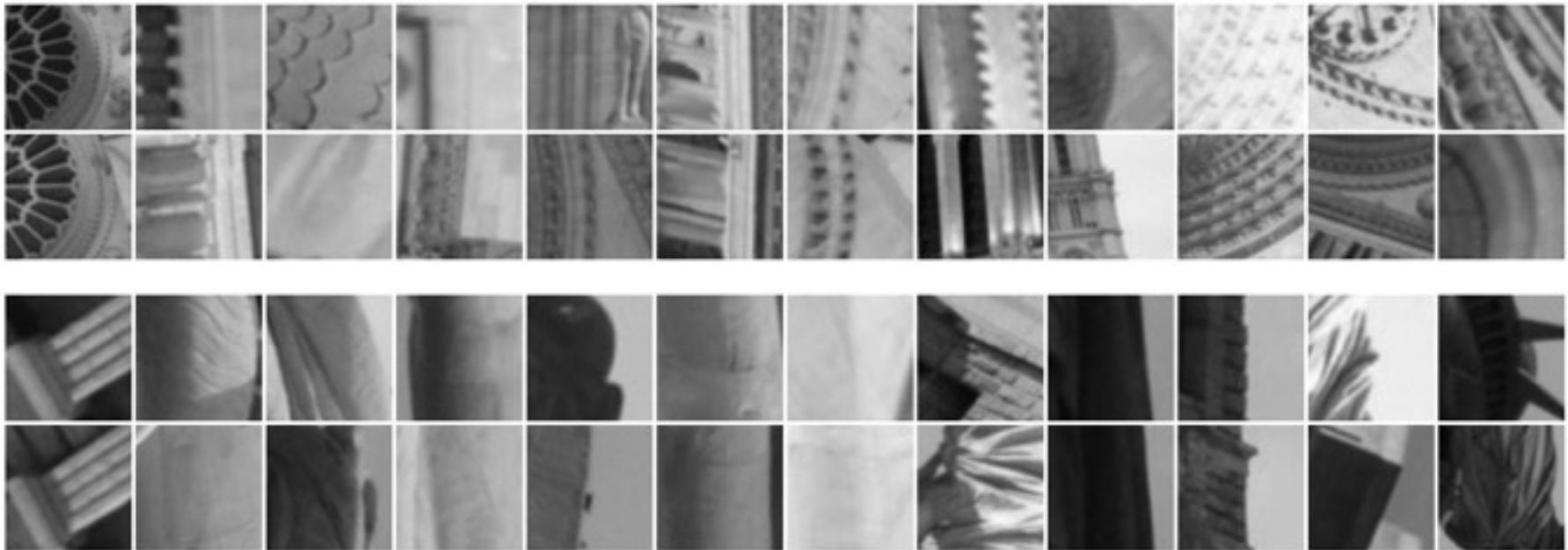
Rothganger et al. 2003



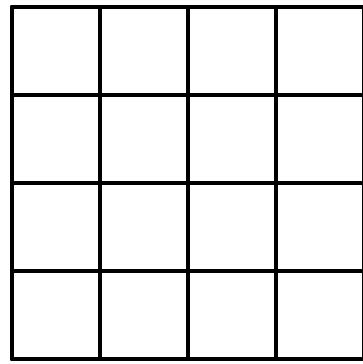
Lowe 2002

When does SIFT fail?

Patches SIFT thought were the same but aren't:



Other methods: Daisy

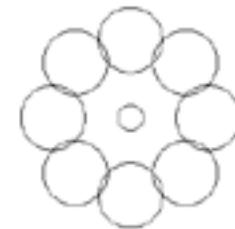


SIFT

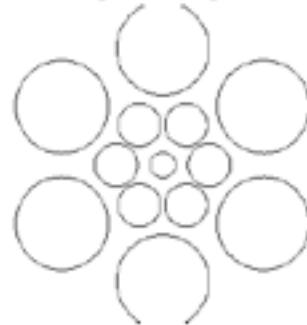
Circular gradient binning



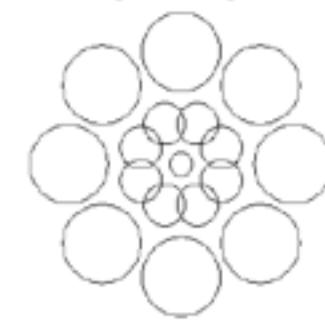
1 Ring 6 Segments



1 Ring 8 Segments



2 Rings 6 Segments



2 Rings 8 Segments

Daisy

Other methods: SURF

For computational efficiency only compute gradient histogram with 4 bins:



Fig. 3. The descriptor entries of a sub-region represent the nature of the underlying intensity pattern. Left: In case of a homogeneous region, all values are relatively low. Middle: In presence of frequencies in x direction, the value of $\sum |d_x|$ is high, but all others remain low. If the intensity is gradually increasing in x direction, both values $\sum d_x$ and $\sum |d_x|$ are high.

Other methods: BRIEF

Randomly sample pair of pixels a and b.
1 if $a > b$, else 0. Store binary vector.

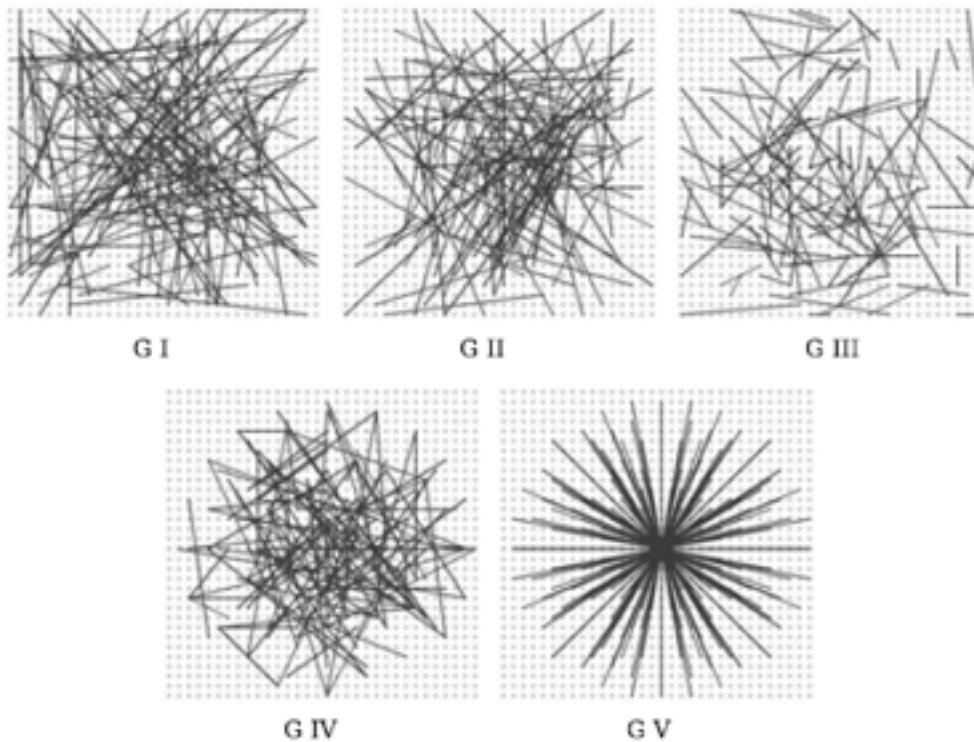


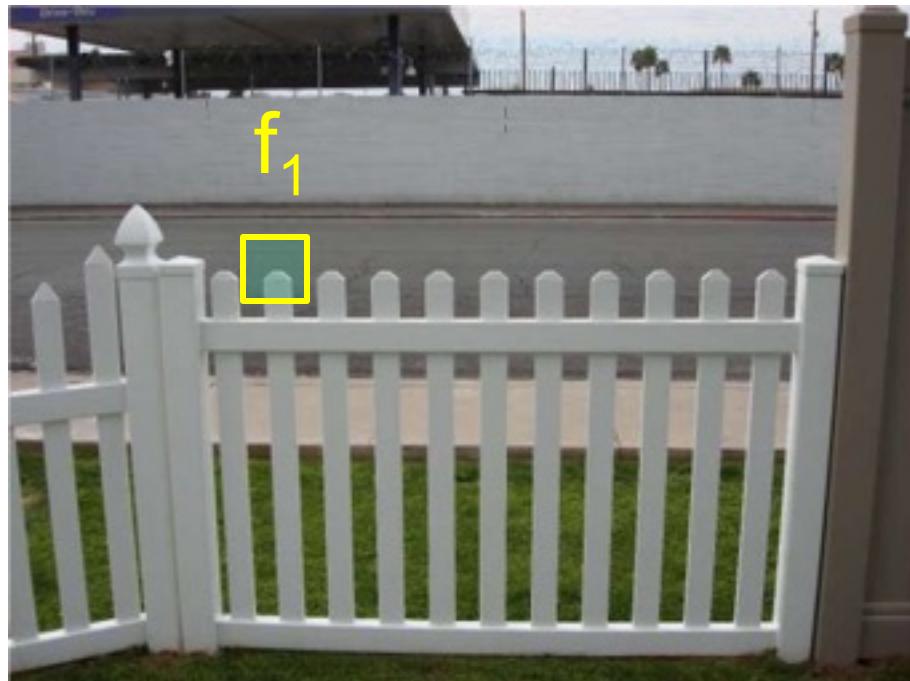
Fig. 2. Different approaches to choosing the test locations. All except the rightmost one are selected by random sampling. Showing 128 tests in every image.

BRIEF: binary robust independent elementary features, Calonder,
V Lepetit, C Strecha, ECCV 2010

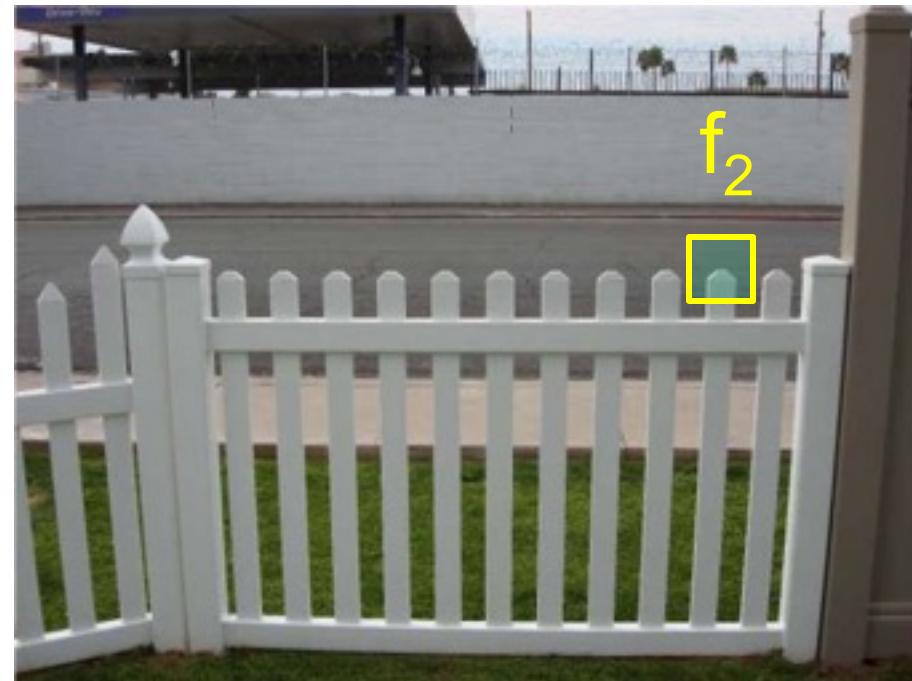
Feature distance

How to define the difference between two features f_1 , f_2 ?

- Simple approach is $\text{SSD}(f_1, f_2)$
 - sum of square differences between entries of the two descriptors
 - can give good scores to very ambiguous (bad) matches



I_1

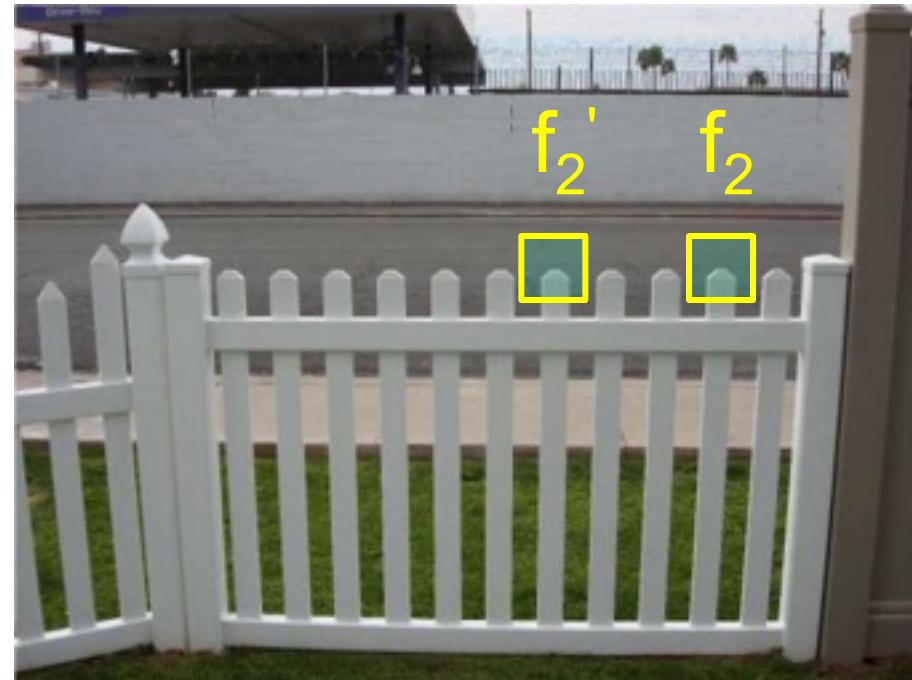
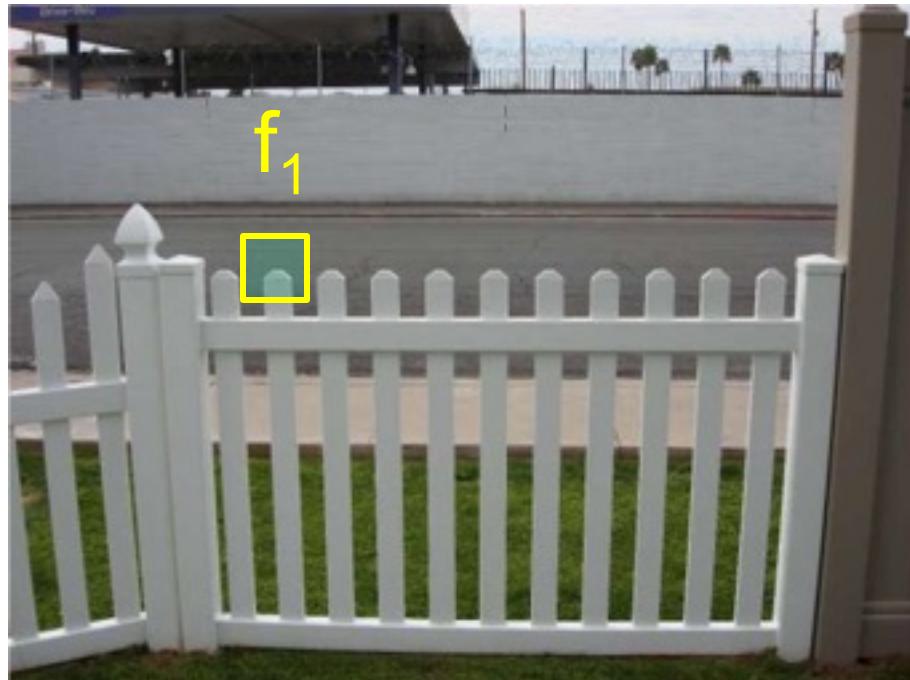


I_2

Feature distance

How to define the difference between two features f_1 , f_2 ?

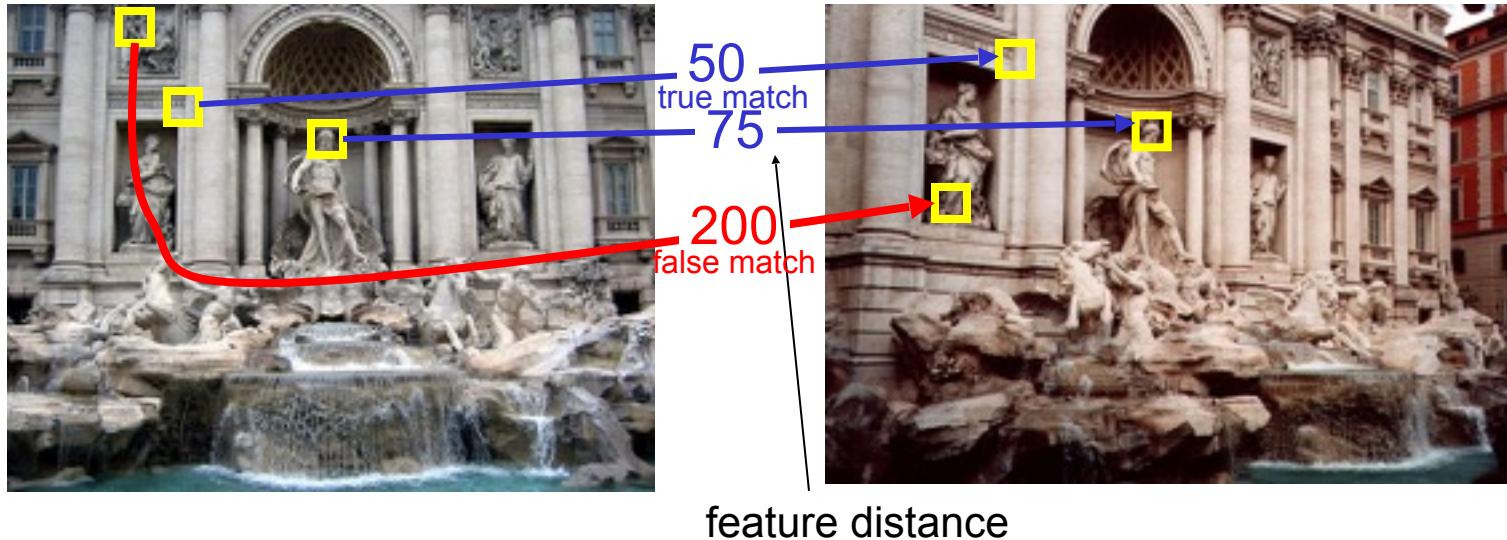
- Better approach: $\text{ratio distance} = \text{SSD}(f_1, f_2) / \text{SSD}(f_1, f_2')$
 - f_2 is best SSD match to f_1 in I_2
 - f_2' is 2nd best SSD match to f_1 in I_2
 - gives large values (~1) for ambiguous matches



I_1

I_2

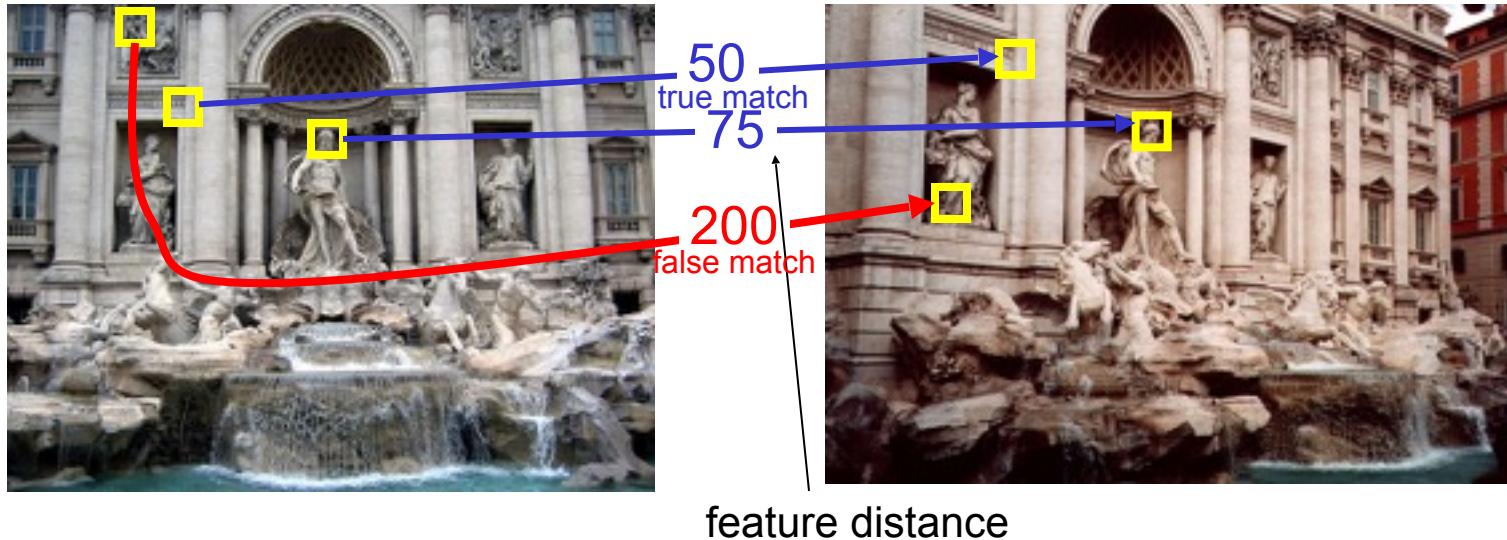
Eliminating bad matches



Throw out features with distance > threshold

- How to choose the threshold?

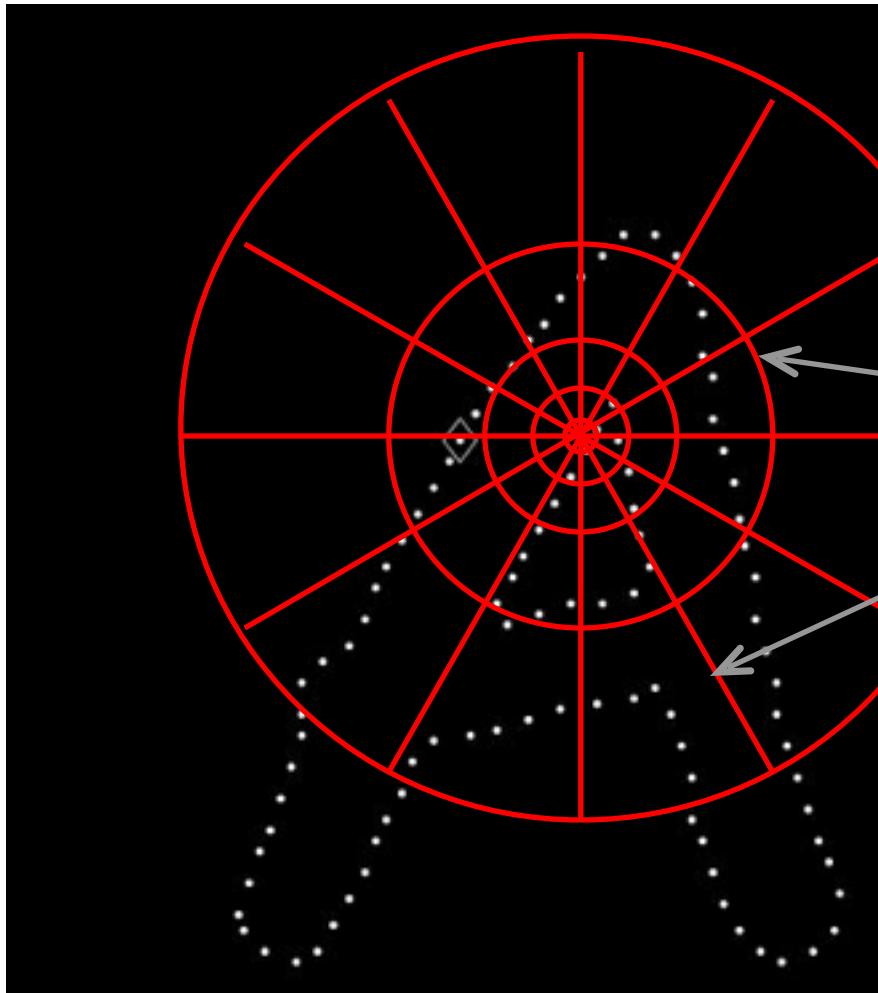
True/false positives



The distance threshold affects performance

- True positives = # of detected matches that are correct
 - Suppose we want to maximize these—how to choose threshold?
- False positives = # of detected matches that are incorrect
 - Suppose we want to minimize these—how to choose threshold?

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.