Local Features

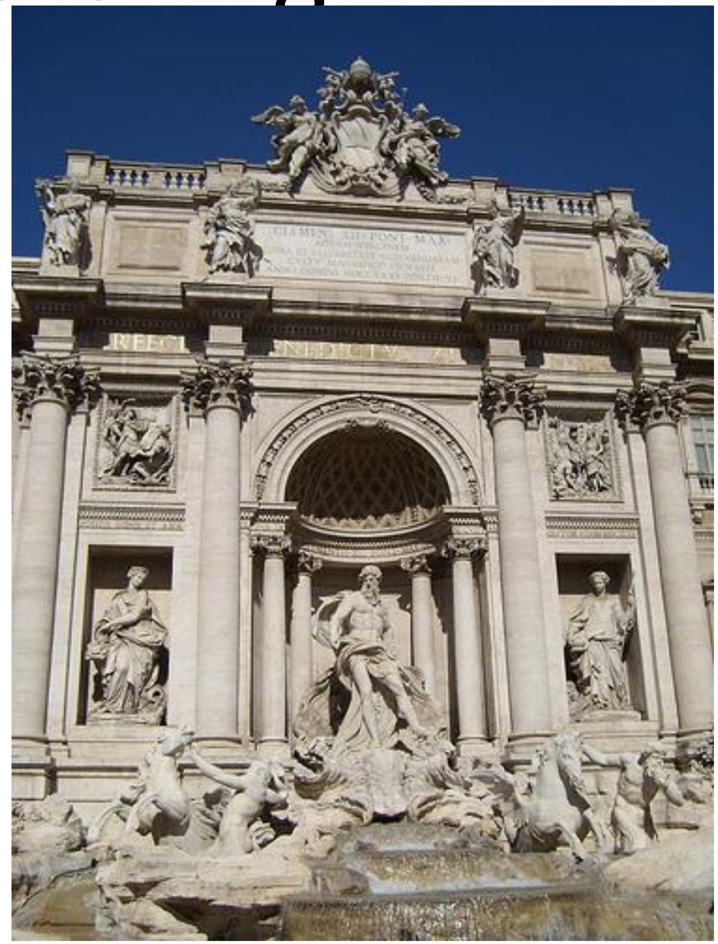
VBM686 - Bilgisayarlı Görü

Pinar Duygulu

Hacettepe University

Image matching

by [Diva Sian]



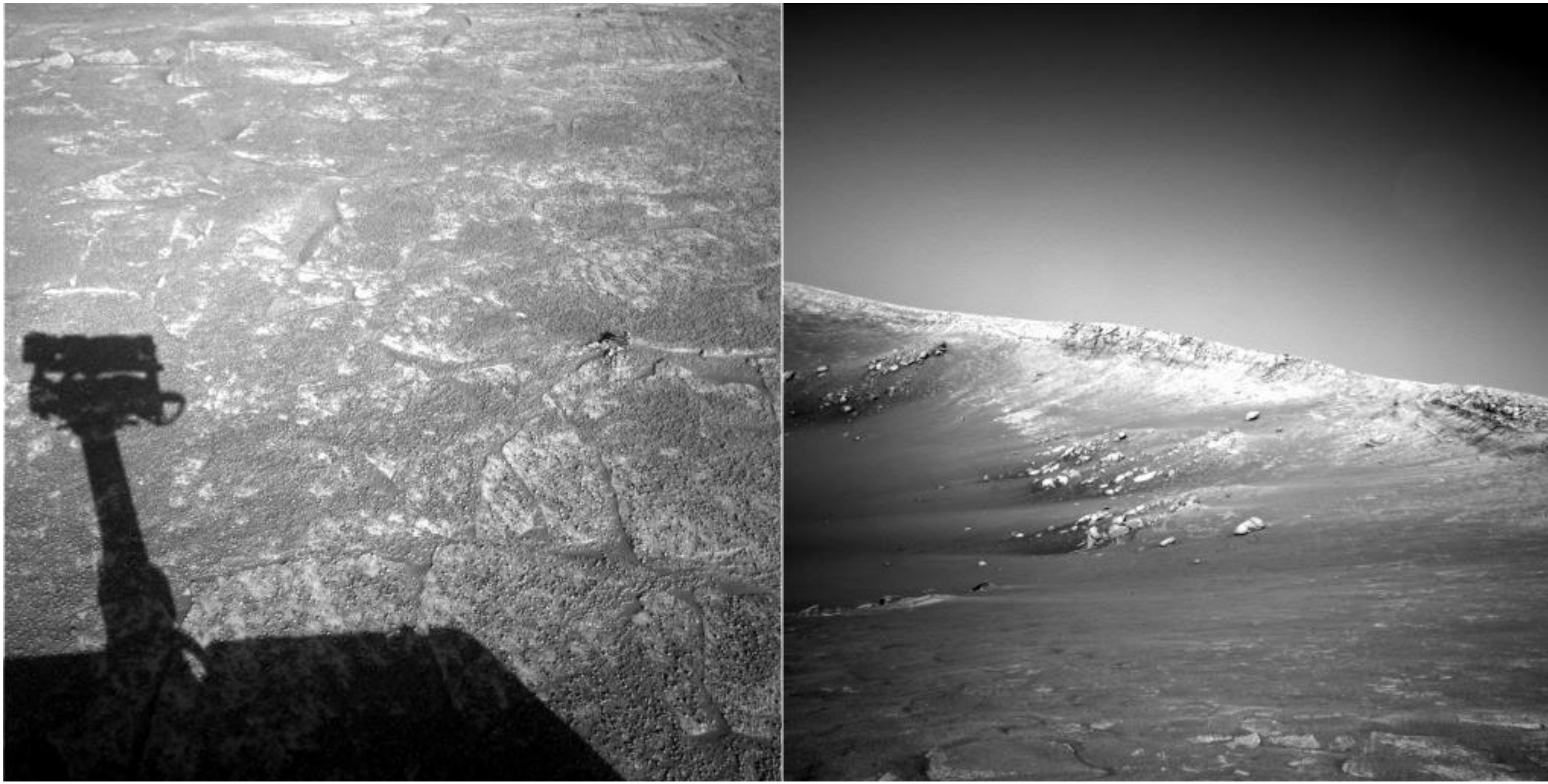
by [swashford]

Harder case

by [Diva Sian]

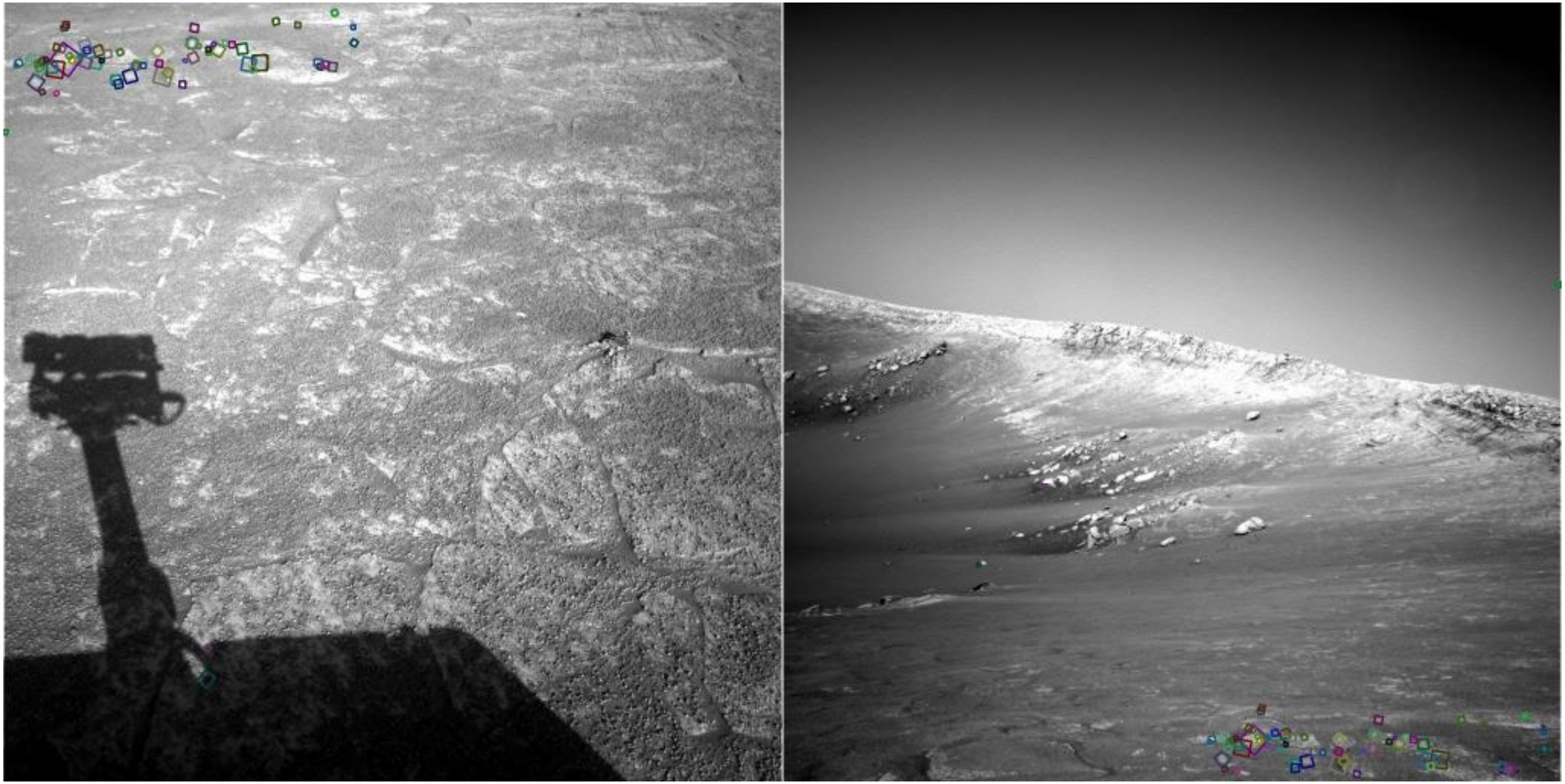
by [scgbt]

Harder still?



NASA Mars Rover images

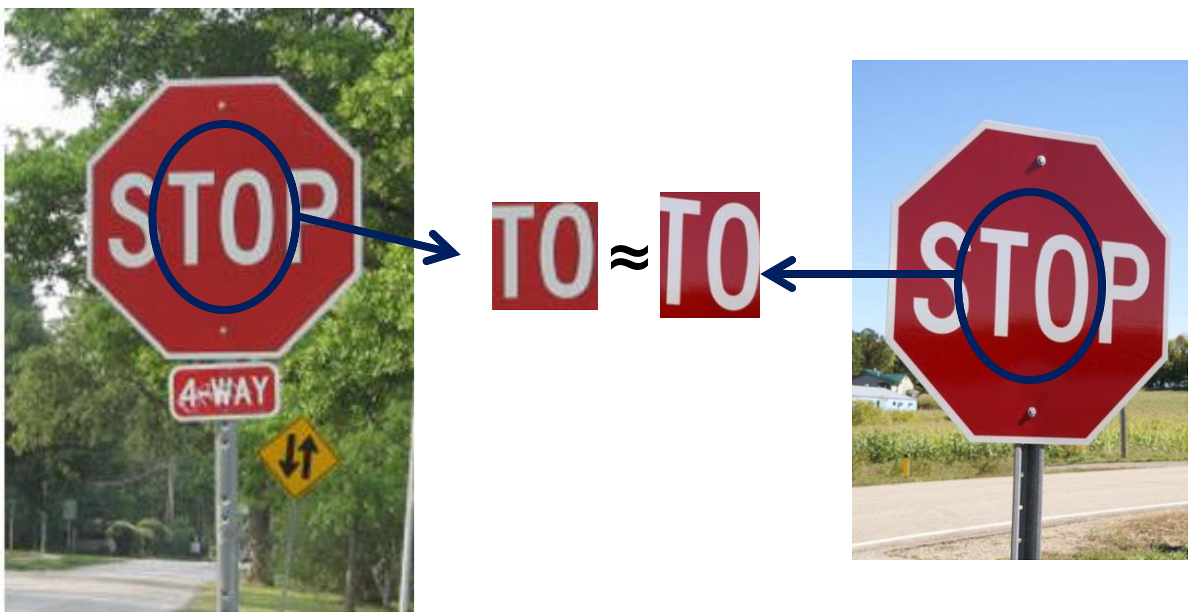
Answer below (look for tiny colored squares…)



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

This section: correspondence and alignment

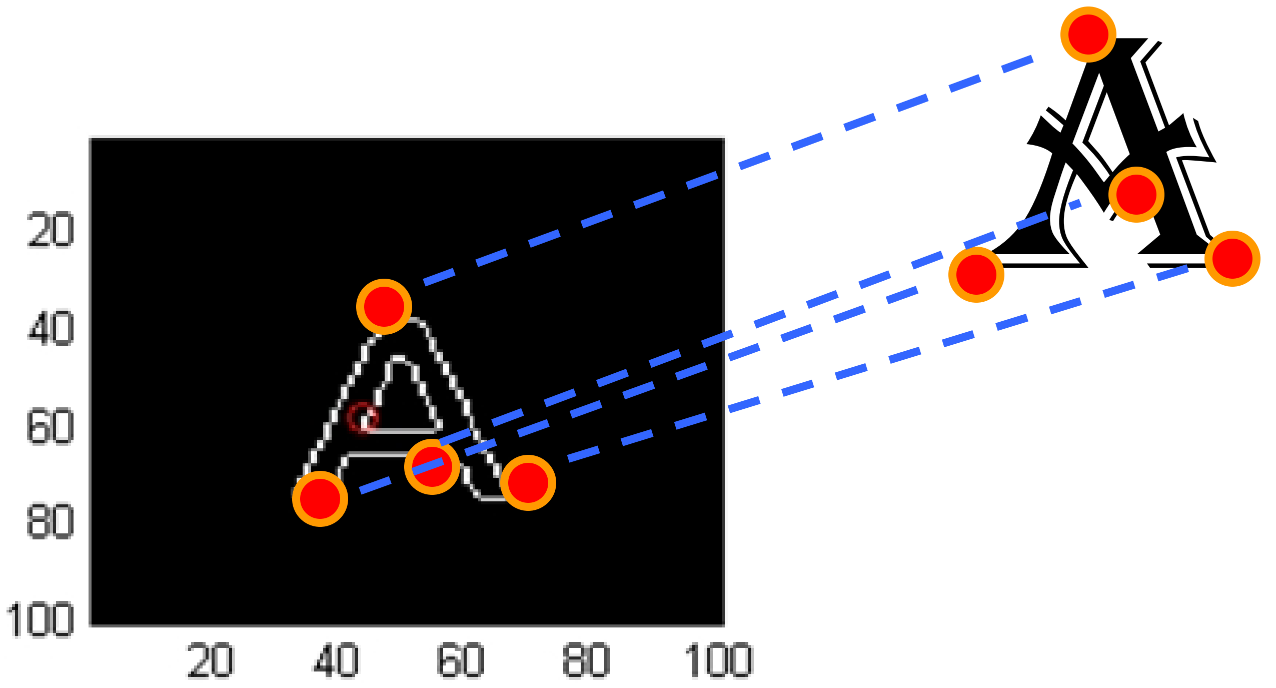
- Correspondence: matching points, patches, edges, or regions across images



This section: correspondence and alignment

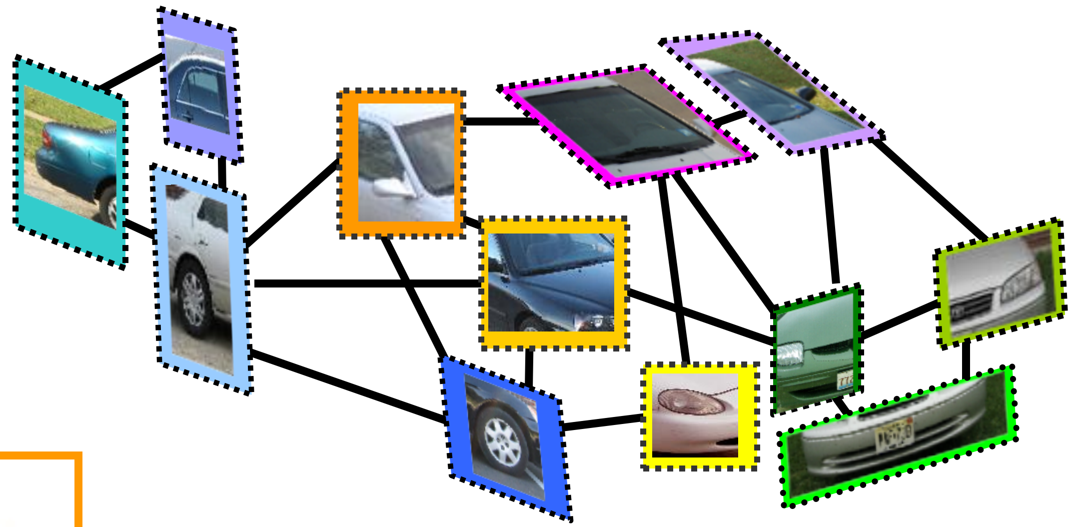
- Alignment: solving the transformation that makes two things match better

Example: fitting an 2D shape template



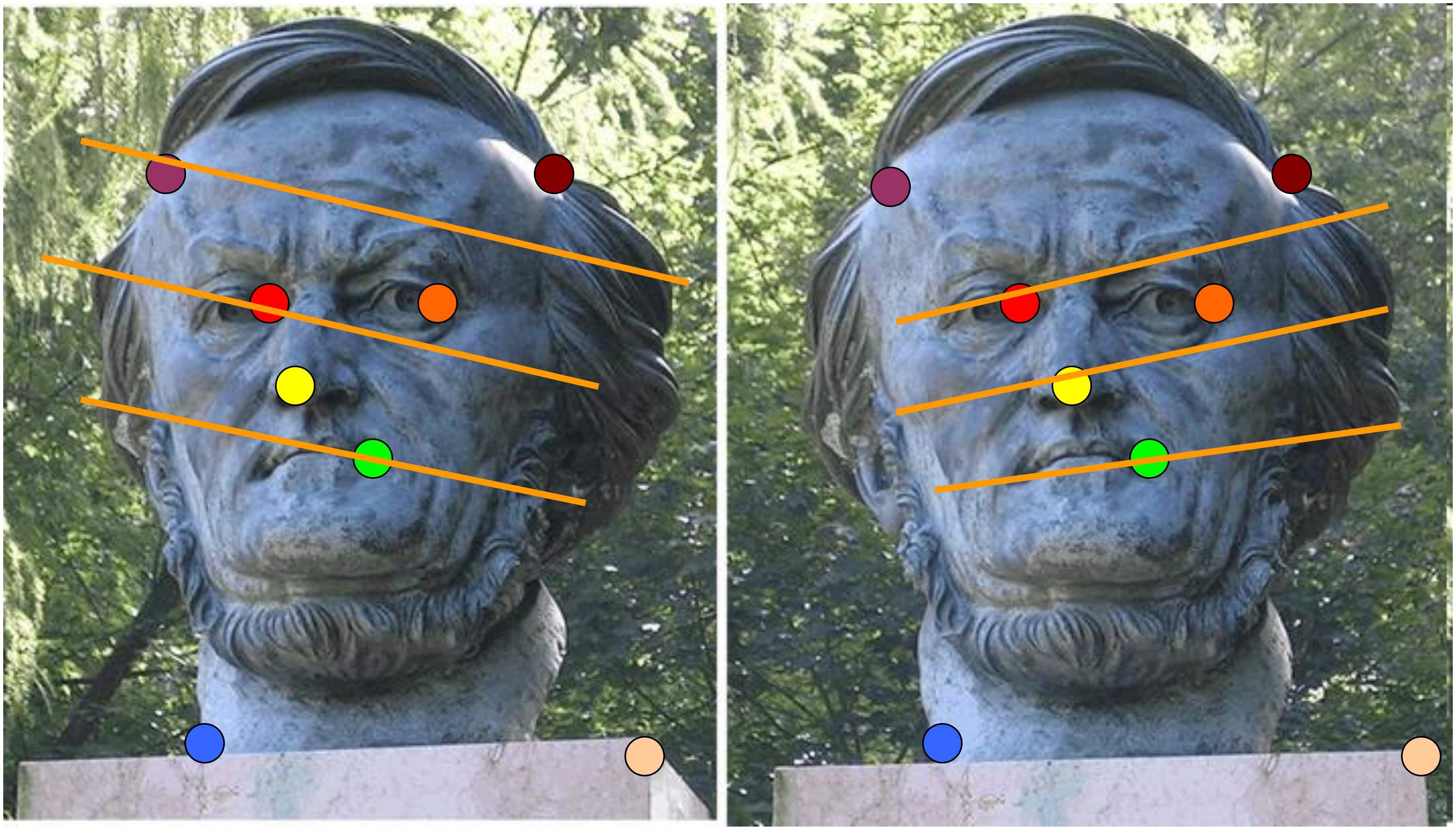
Slide from Silvio Savarese

Example: fitting a 3D object model



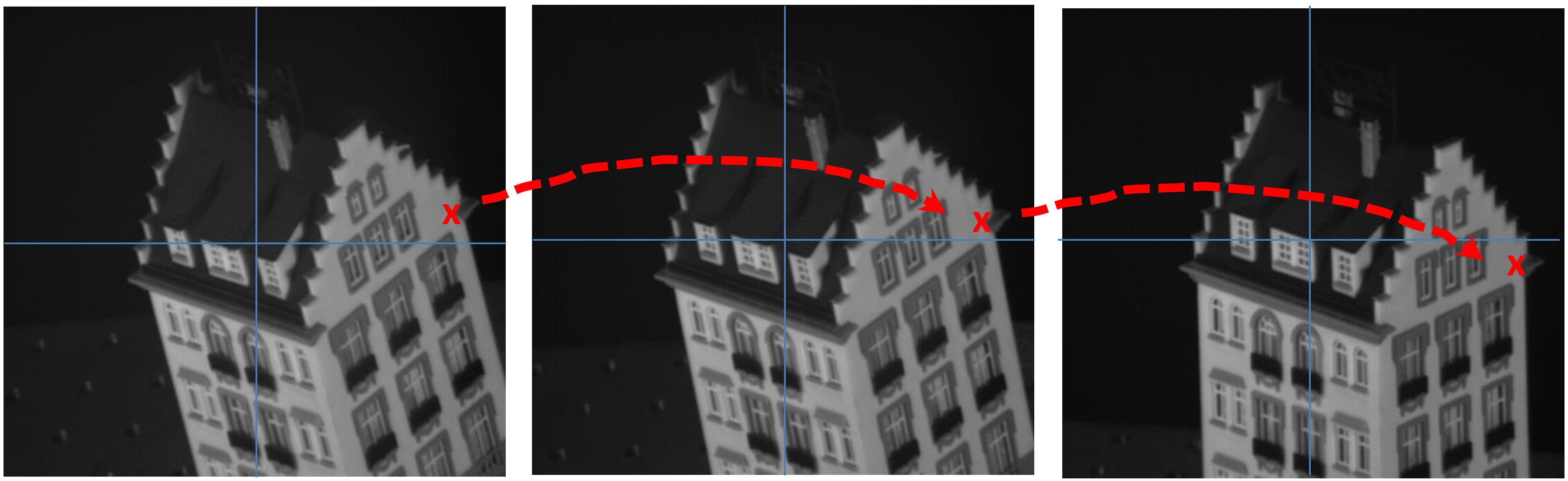
Slide from Silvio Savarese

Example: estimating "fundamental matrix" that corresponds two views



Slide from Silvio Savarese

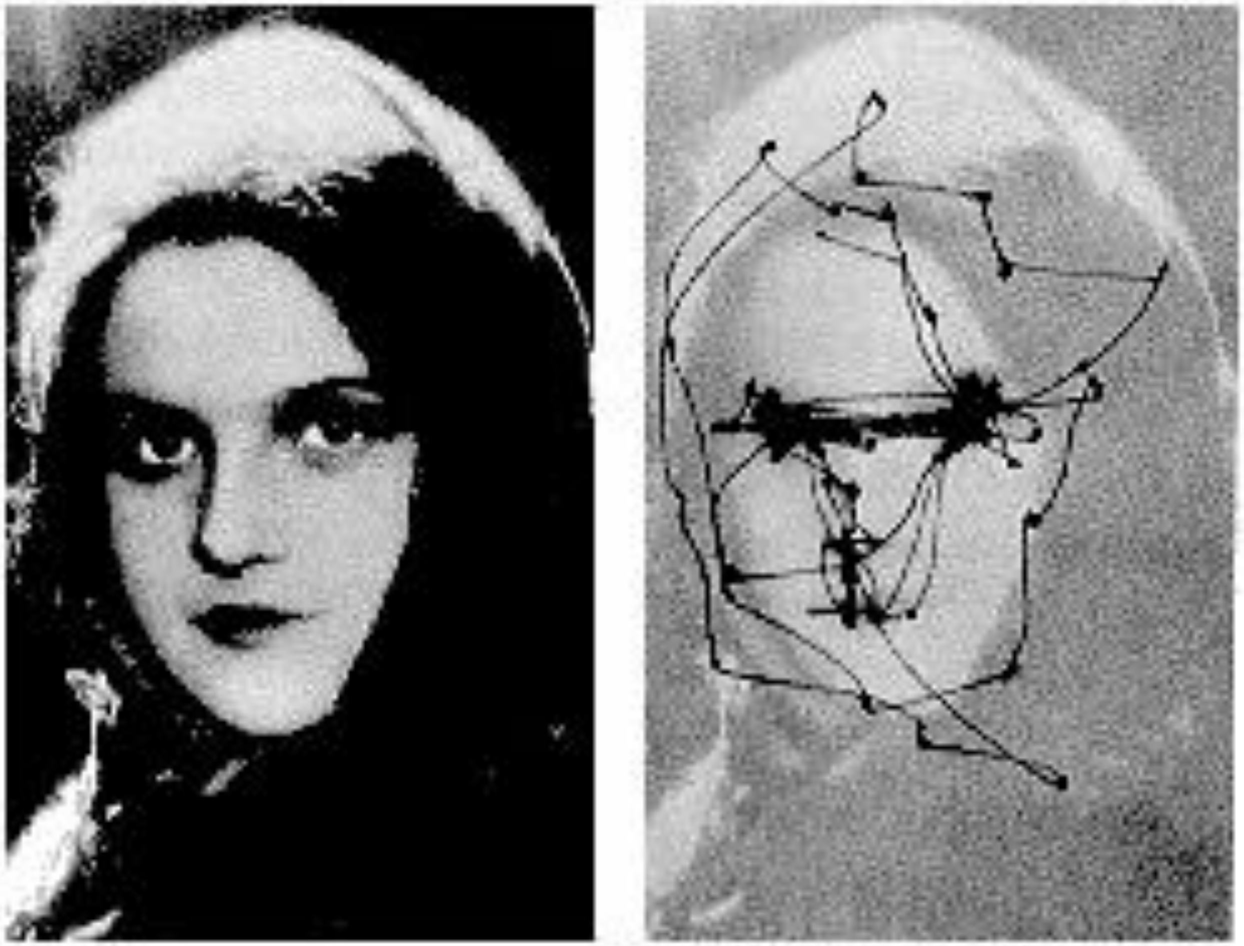
Example: tracking points



frame 0 frame 22 frame 49

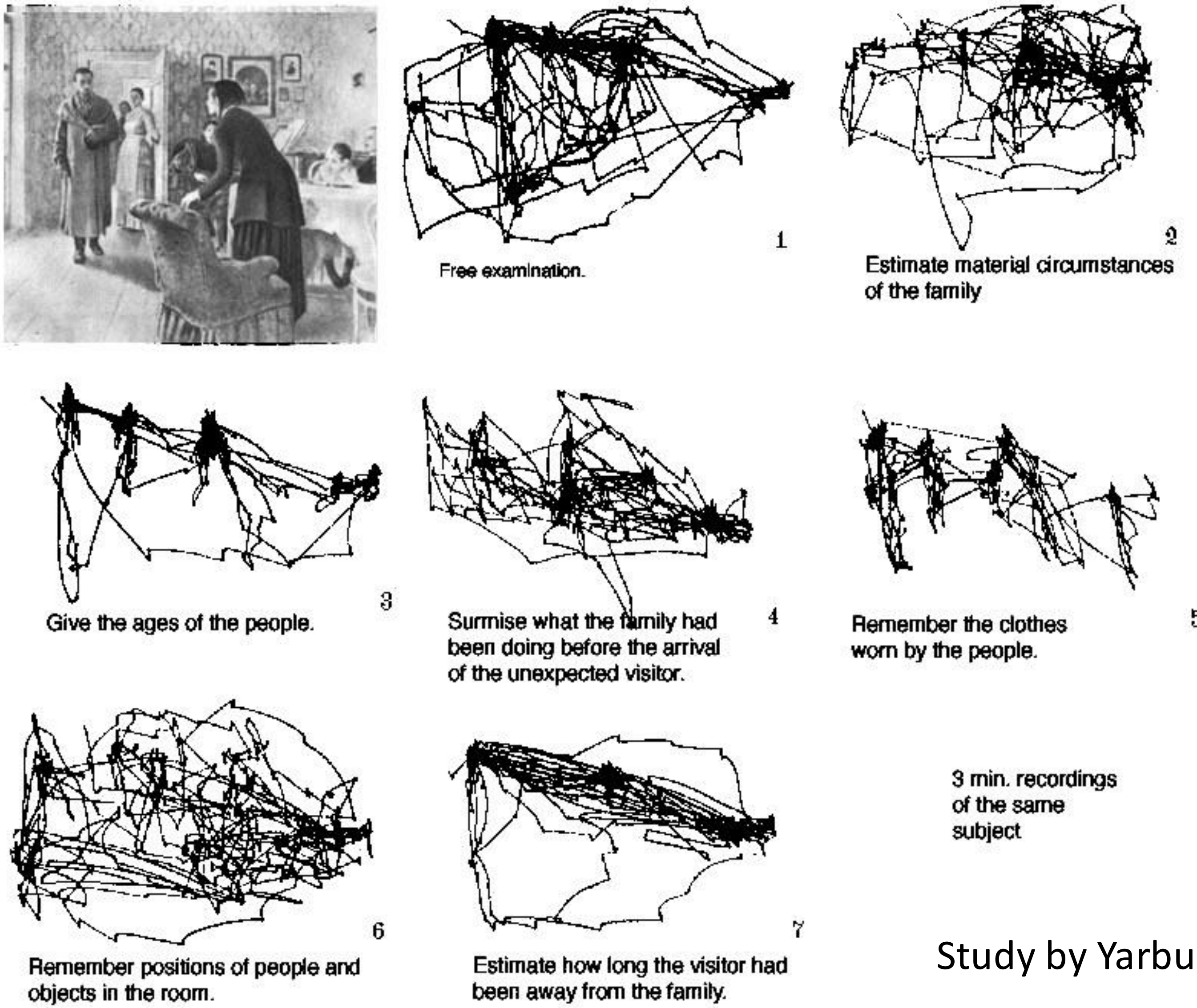
Your problem 1 for HW 2!

Human eye movements



Yarbus eye tracking

Human eye movements



Study by Yarbus

Change blindness: http://www.simonslab.com/videos.html

Local features and alignment

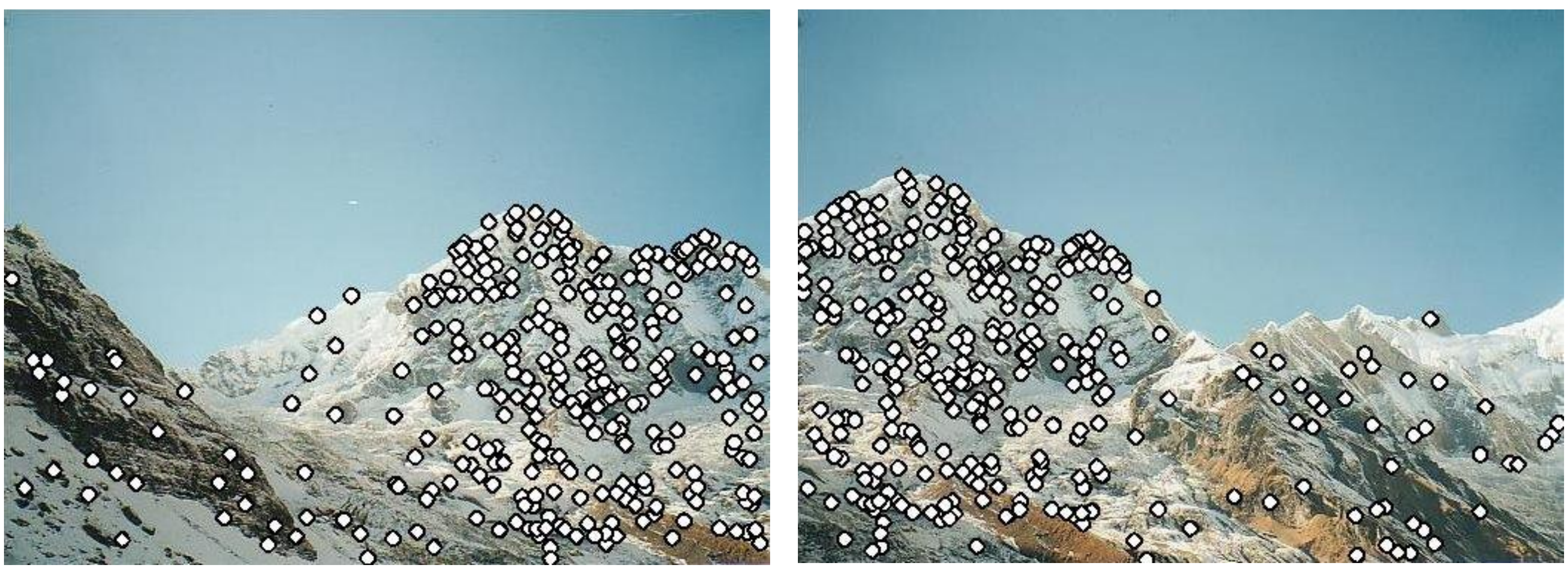
 

- We need to match (align) images
- Global methods sensitive to occlusion, lighting, parallax effects. So look for local features that match well.
- How would you do it by eye?

[Darya Frolova and Denis Simakov]

Local features and alignment

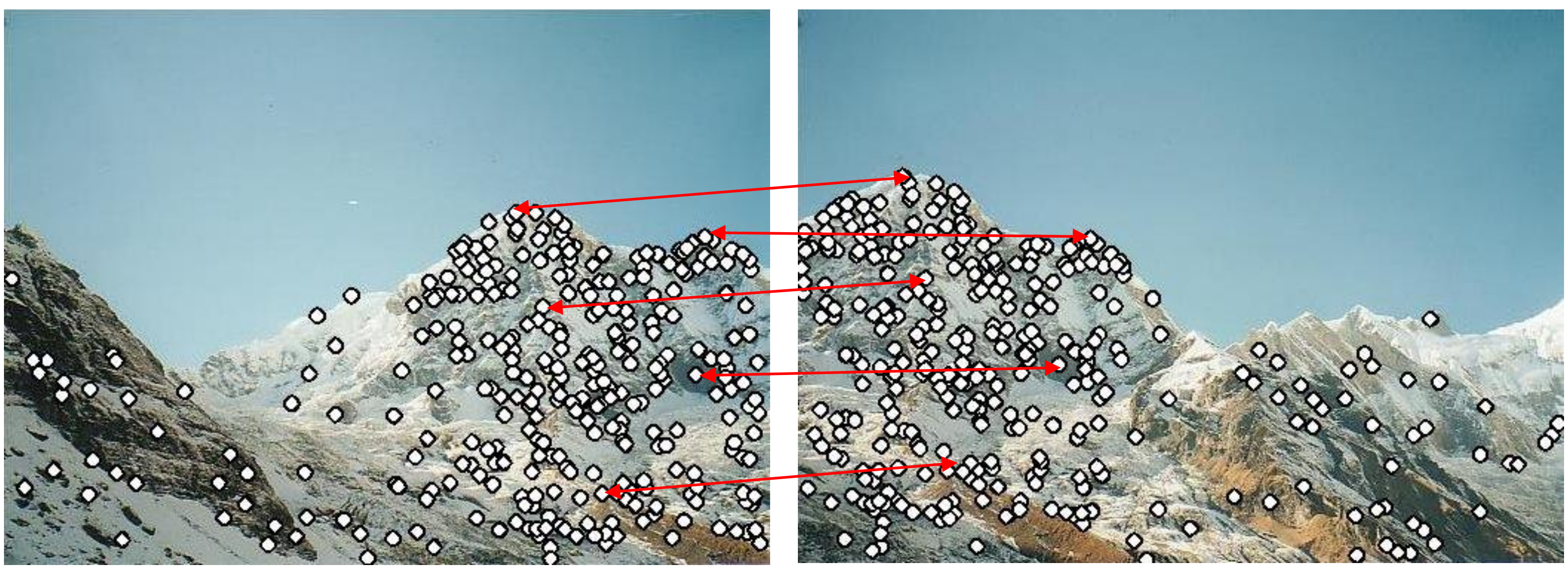
- Detect feature points in both images



[Darya Frolova and Denis Simakov]

Local features and alignment

- Detect feature points in both images
- Find corresponding pairs



[Darya Frolova and Denis Simakov]

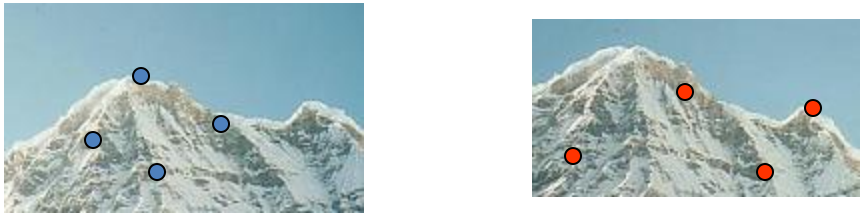
Local features and alignment

- Detect feature points in both images
- Find corresponding pairs
- Use these pairs to align images

[Darya Frolova and Denis Simakov]

Local features and alignment

- Problem 1:
  - Detect the *same* point *independently* in both images



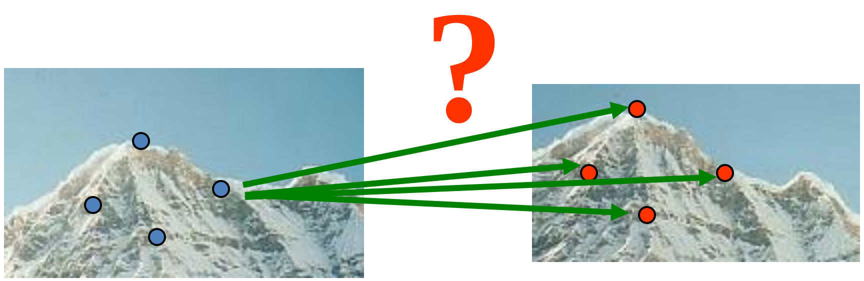
no chance to match!

We need a repeatable detector

[Darya Frolova and Denis Simakov]

Local features and alignment

- Problem 2:
  - For each point correctly recognize the corresponding one



We need a reliable and distinctive descriptor

[Darya Frolova and Denis Simakov]

Geometric transformations

Photometric transformations

Figure from T. Tuytelaars ECCV 2006 tutorial

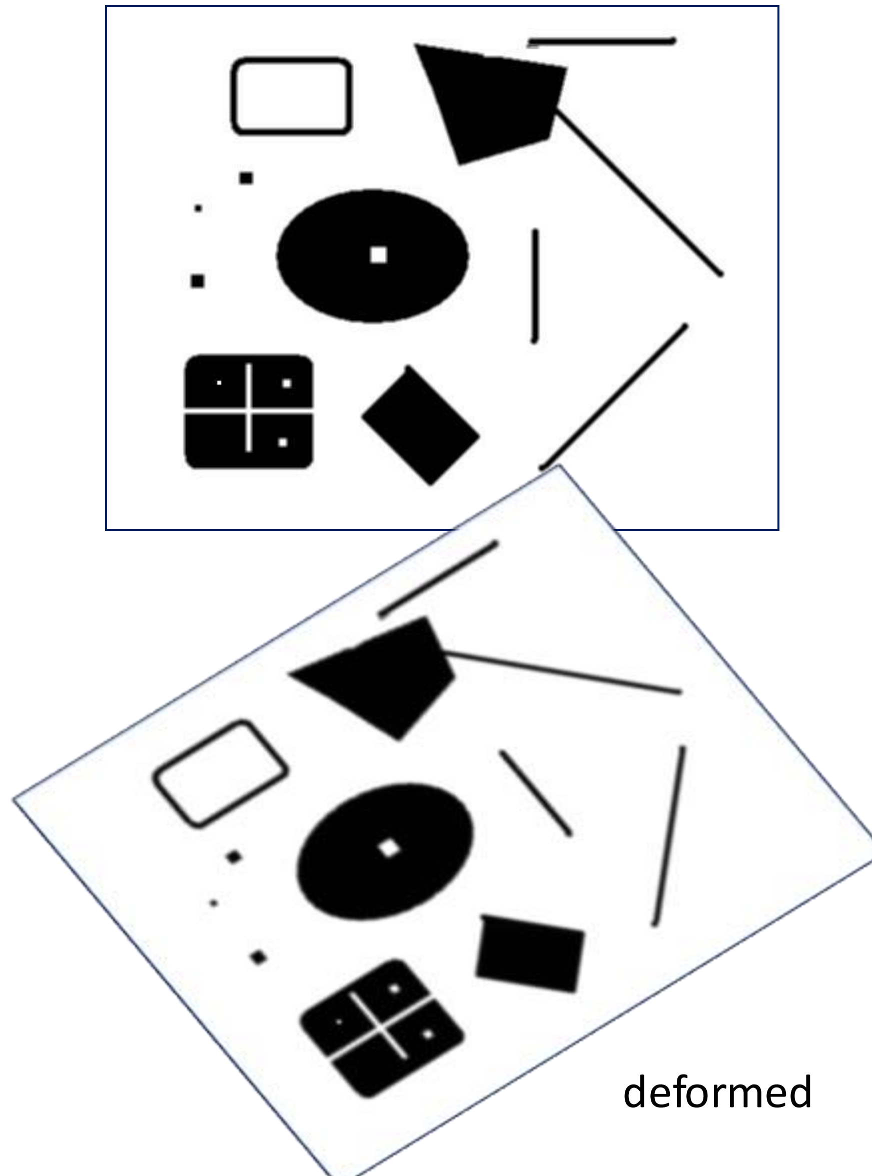
And other nuisances…

- Noise
- Blur
- Compression artifacts
- …

This class: interest points

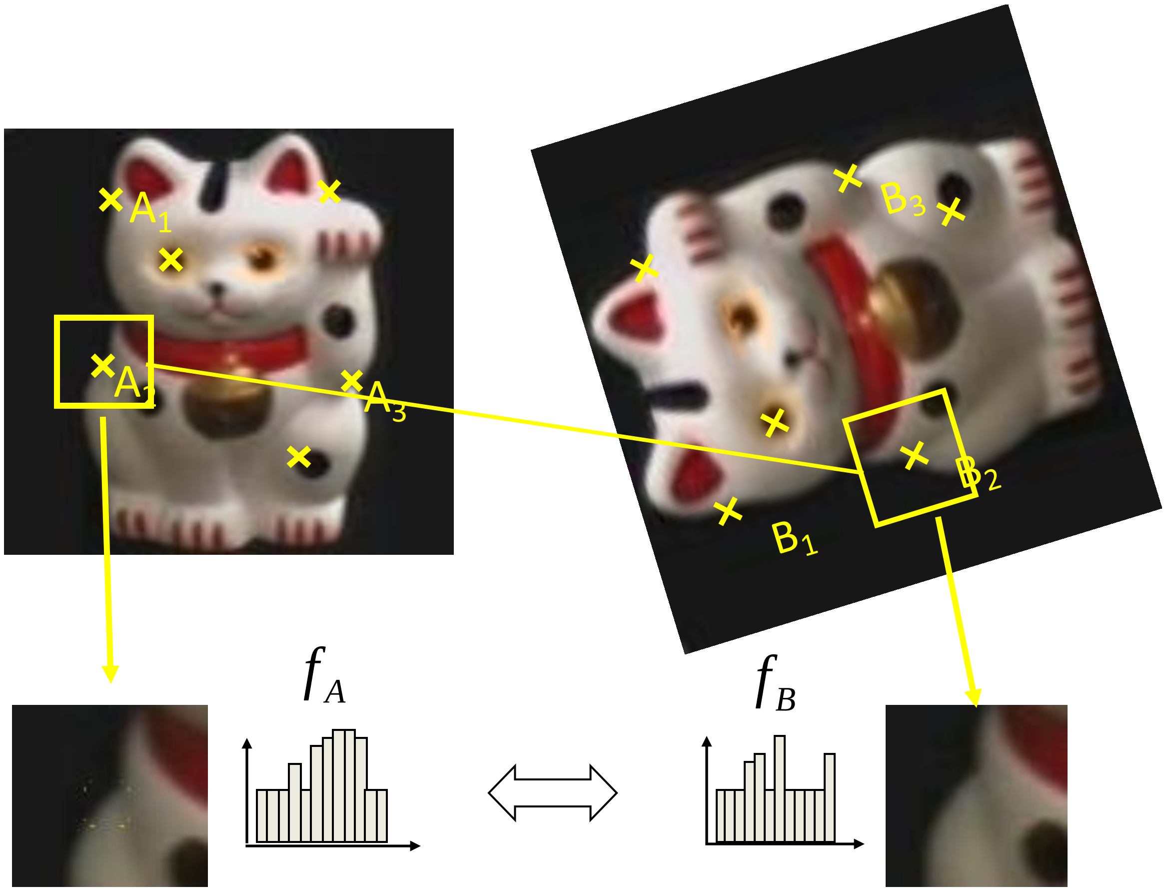
- Suppose you have to click on some point, go away and come back after I deform the image, and click on the same points again.
  - Which points would you choose?

original



deformed

Overview of Keypoint Matching



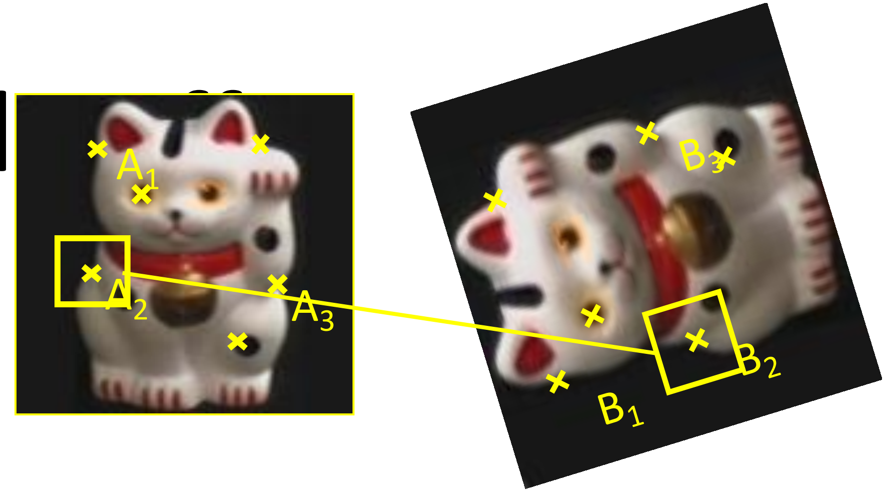
$$d(f_A, f_B) < T$$

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

Goals for Keypoints


Detect points that are *repeatable* and *distinctive*

Key trad



Detection

More Repeatable

Robust detection

Precise localization

More Points

Robust to occlusion

Works with less texture

Description

More Distinctive

Minimize wrong matches

More Flexible

Robust to expected variations

Maximize correct matches

Choosing interest points

Where would you tell your friend to meet you?

Choosing interest points

Where would you tell your friend to meet you?

Many Existing Detectors Available

Hessian & Harris	[Beaudet '78], [Harris '88]
Laplacian, DoG	[Lindeberg '98], [Lowe 1999]
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…	

Invariant local features

Subset of local feature types designed to be invariant to common geometric and photometric transformations.

Basic steps:

1) Detect distinctive interest points

2) Extract invariant descriptors

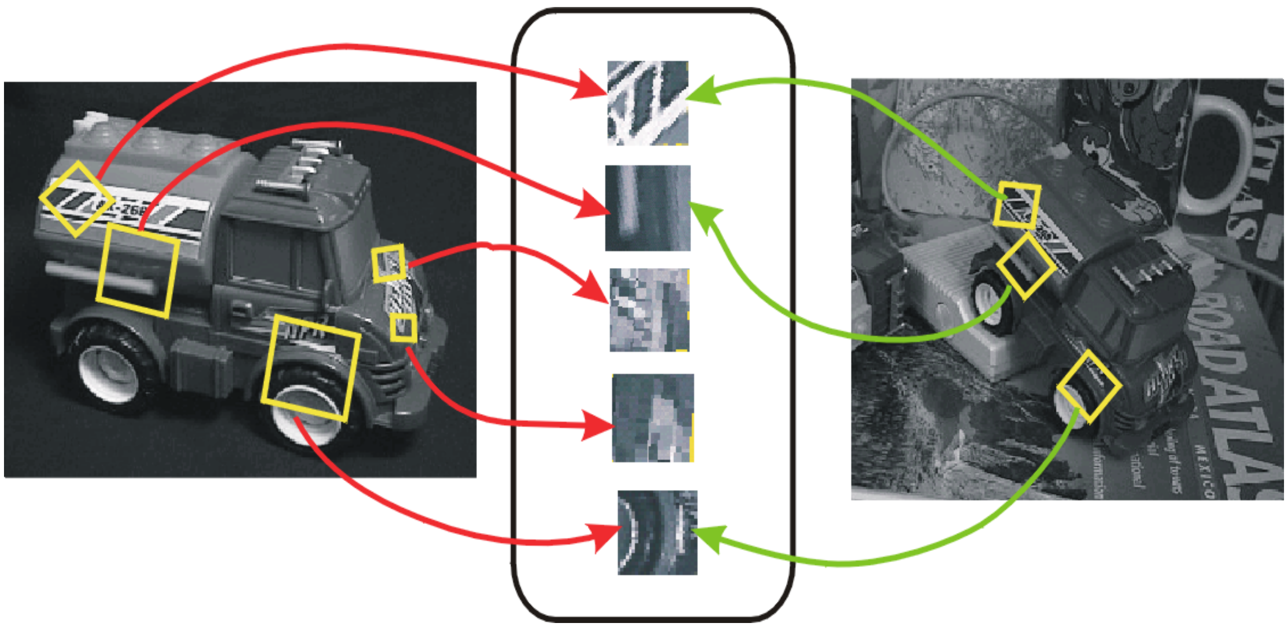


Figure: David Lowe

Main questions

- Where will the interest points come from?
  - What are salient features that we'll *detect* in multiple views?
- How to *describe* a local region?
- How to establish *correspondences*, i.e., compute matches?

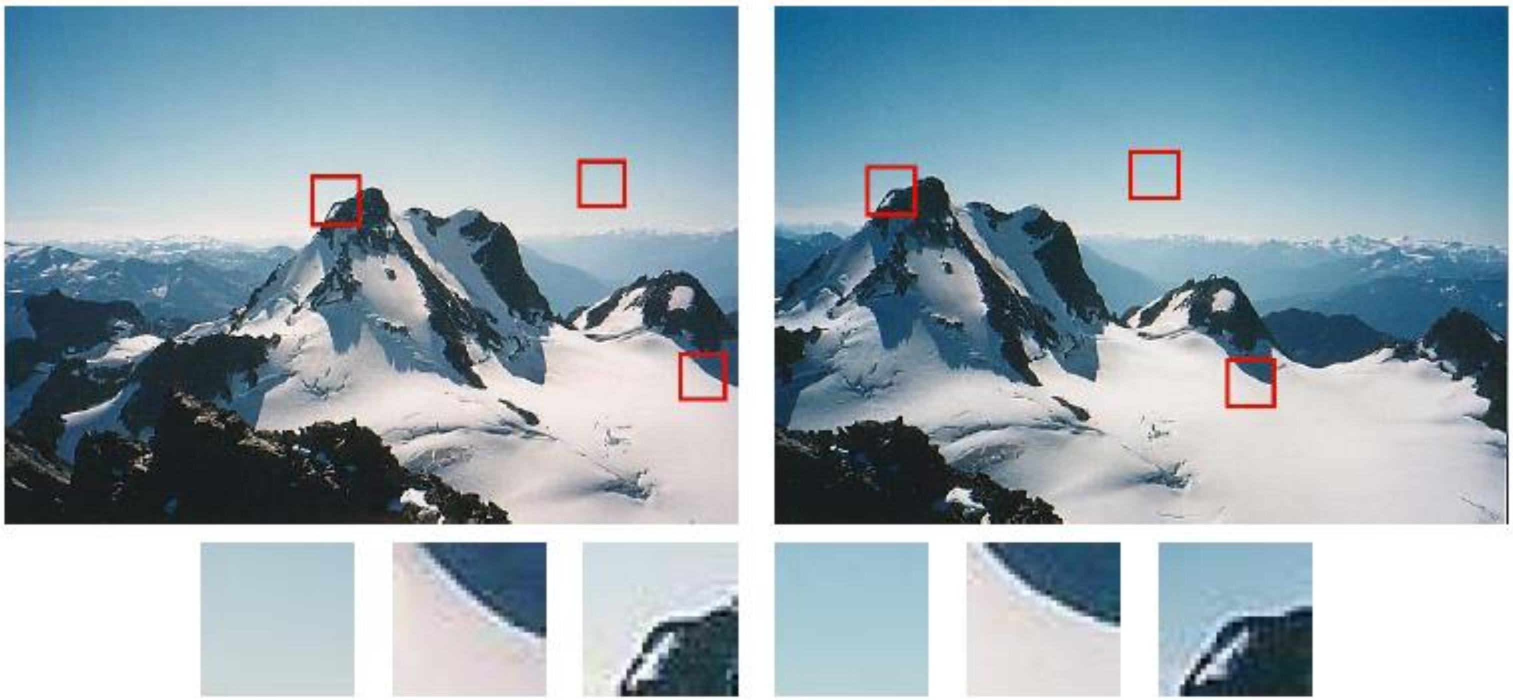
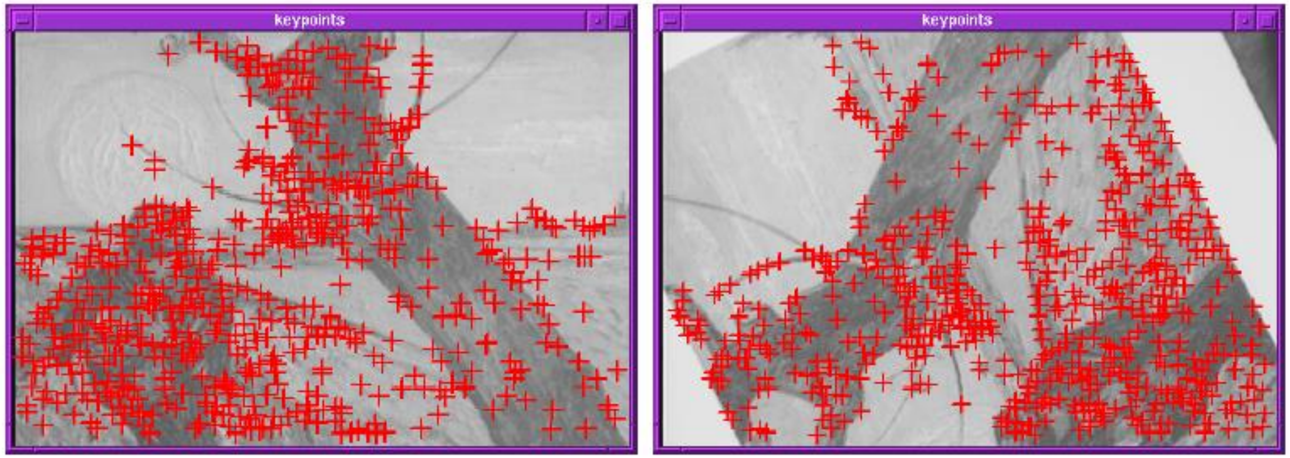


Figure 4.3: *Image pairs with extracted patches below. Notice how some patches can be localized or matched with higher accuracy than others.*

Finding Corners



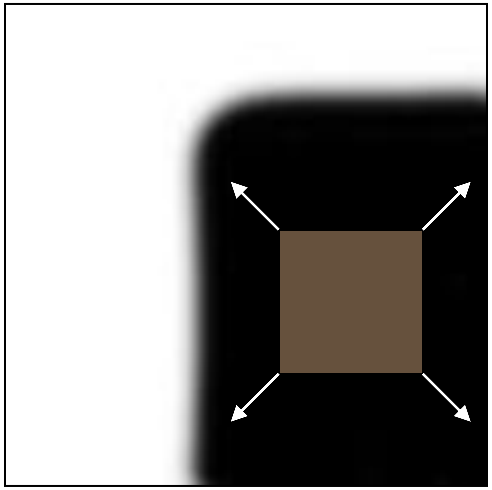
- Key property: in the region around a corner, image gradient has two or more dominant directions
- Corners are repeatable and **distinctive**

C.Harris and M.Stephens. ["A Combined Corner and Edge Detector."](#)
Proceedings of the 4th Alvey Vision Conference: pages 147--151.

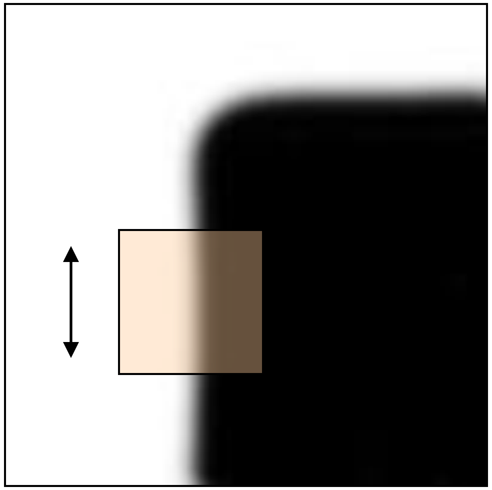
Source: Lana Lazebnik

Corners as distinctive interest points

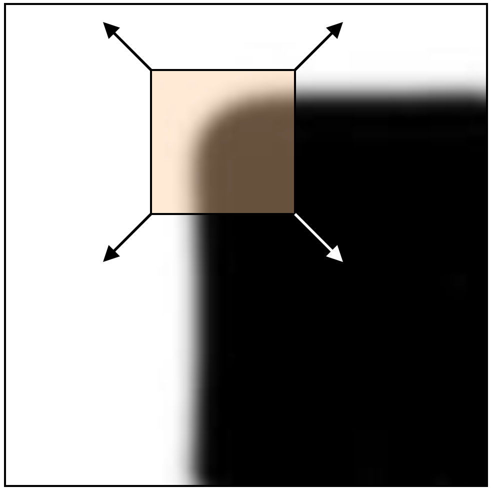
- We should easily recognize the point by looking through a small window
- Shifting a window in *any direction* should give *a large change* in intensity



"flat" region:
no change in
all directions



"edge":
no change
along the edge
direction



"corner":
significant
change in all
directions

Source: A. Efros

Harris Detector formulation

Change of intensity for the shift [u,v]:

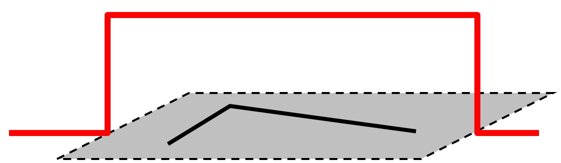
$$E(u,v) = \sum_{x,y} w(x,y)\left[I(x+u, y+v) - I(x,y)\right]^2$$

Window function

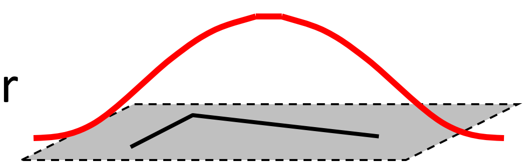
Shifted intensity

Intensity

Window function $w(x,y)$ =



or

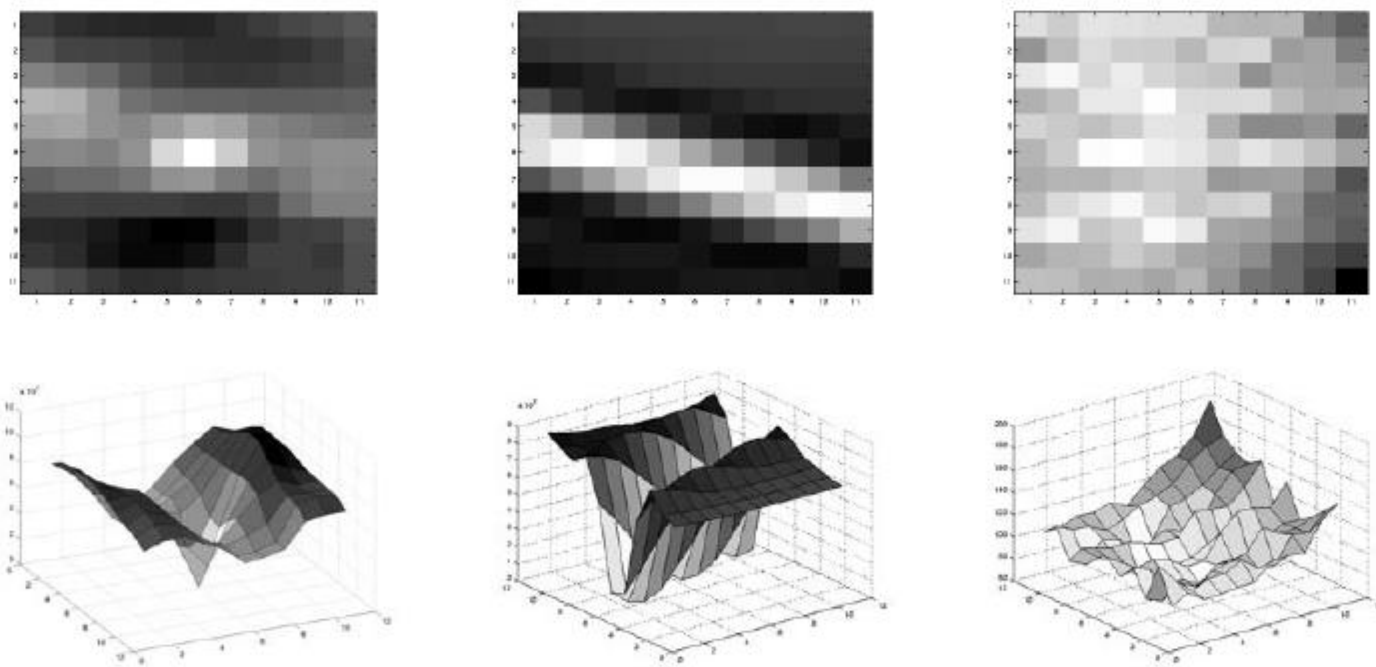


1 in window, 0 outside

Gaussian

Source: R. Szeliski

(a)



Harris Detector formulation

This measure of change can be approximated by:

$$E(u,v) \approx [u \ \ v] \ M \begin{bmatrix} u \\ v \end{bmatrix}$$

where *M* is a 2×2 matrix computed from image derivatives:

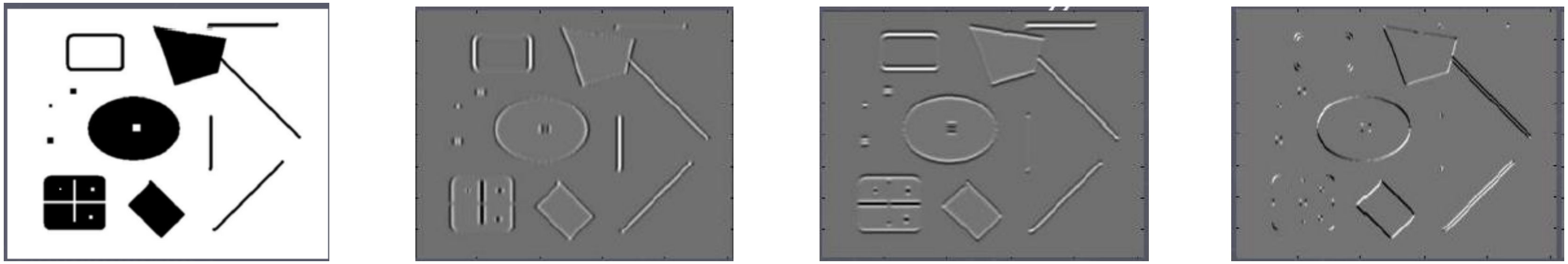
$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

Gradient with respect to x, times gradient with respect to y

Sum over image region – area we are checking for corner

$$M = \begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix} = \sum \begin{bmatrix} I_x \\ I_y \end{bmatrix} [I_x \ \ I_y]$$

Harris Detector formulation



where M is a 2×2 matrix computed from image derivatives:

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

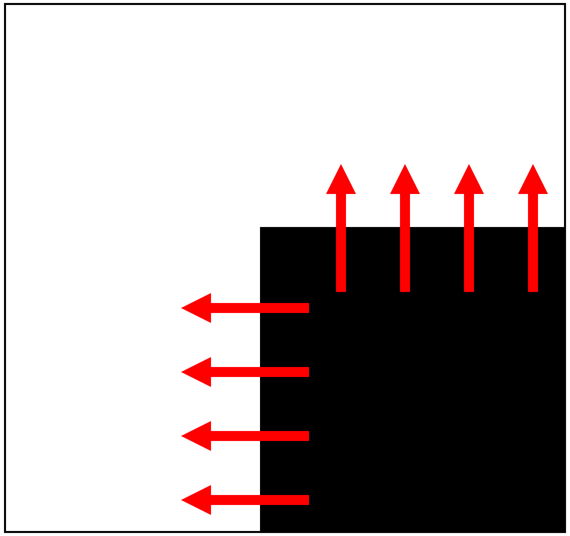
Gradient with respect to x, times gradient with respect to y

Sum over image region – area we are checking for corner

$$M = \begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix} = \sum \begin{bmatrix} I_x \\ I_y \end{bmatrix} [I_x \; I_y]$$

What does this matrix reveal?

First, consider an axis-aligned corner:



What does this matrix reveal?

First, consider an axis-aligned corner:

$$M = \begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

This means dominant gradient directions align with x or y axis

If either λ is close to 0, then this is **not** a corner, so look for locations where both are large.

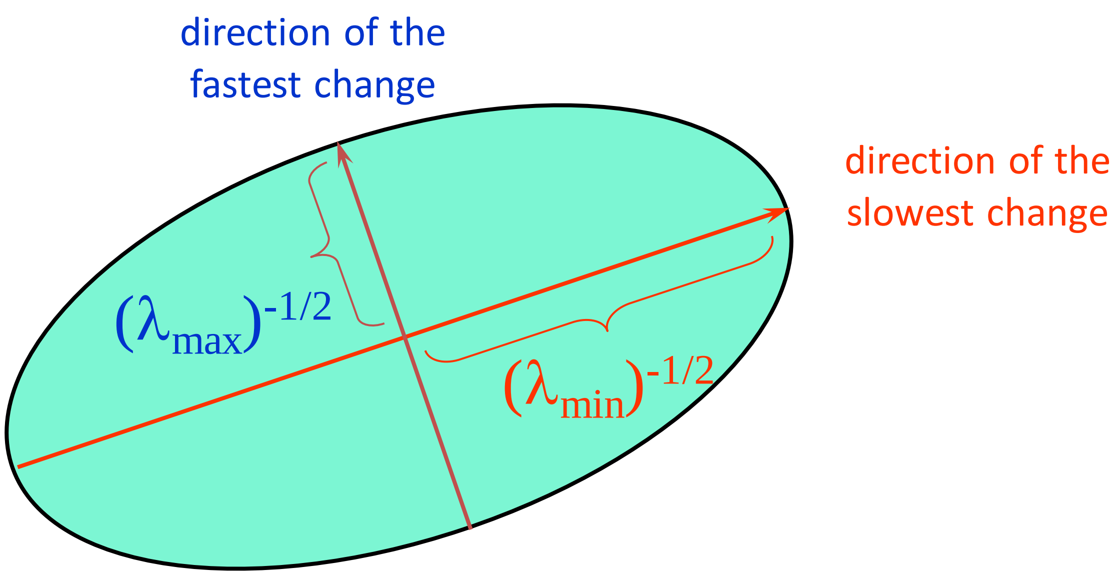
What if we have a corner that is not aligned with the image axes?

Slide credit: David Jacobs

General Case

Since M is symmetric, we have $M = R^{-1}\begin{bmatrix}\lambda_1 & 0 \\ 0 & \lambda_2\end{bmatrix}R$

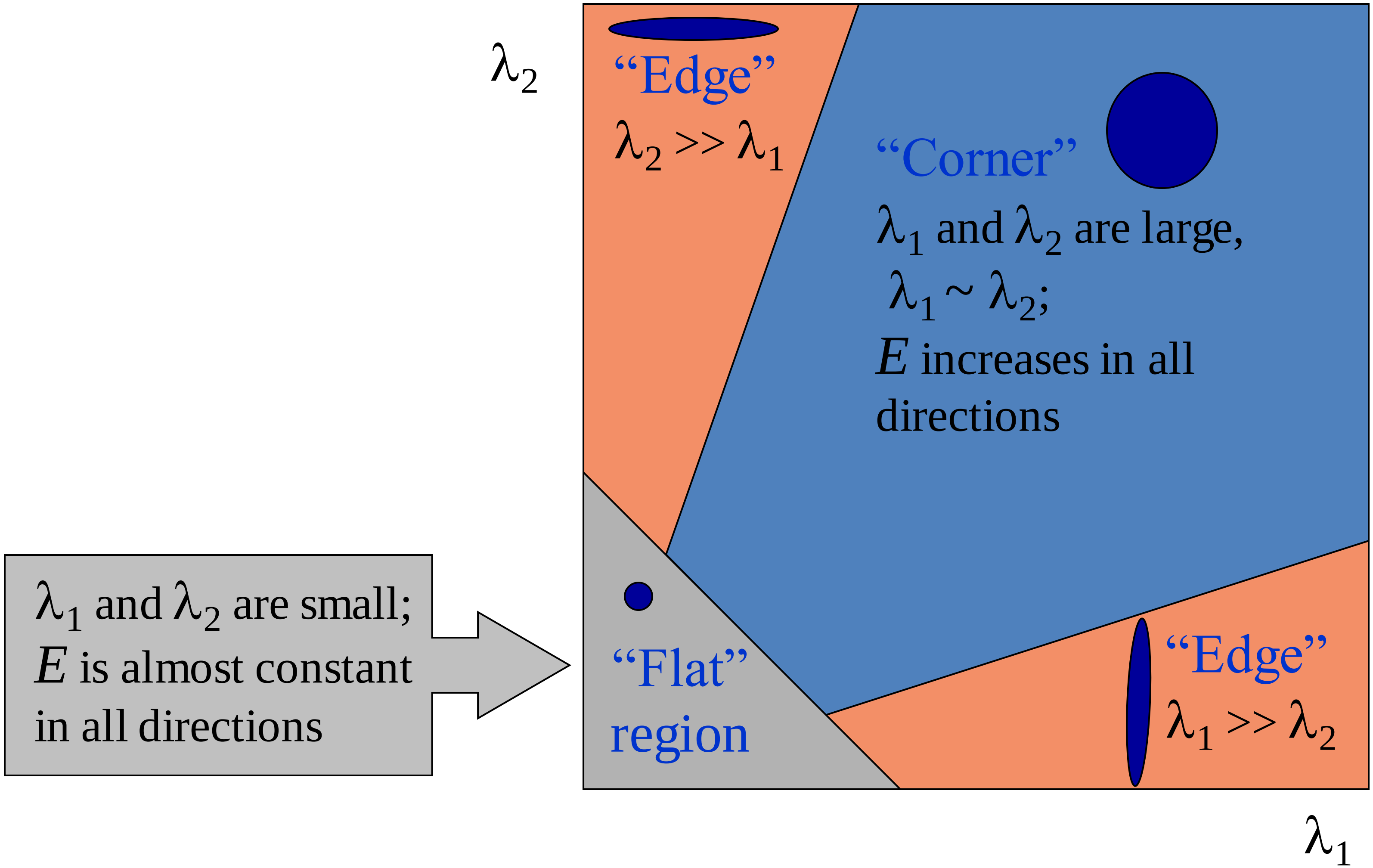
We can visualize *M* as an ellipse with axis lengths determined by the eigenvalues and orientation determined by *R*



Slide adapted form Darya Frolova, Denis Simakov.

Interpreting the eigenvalues

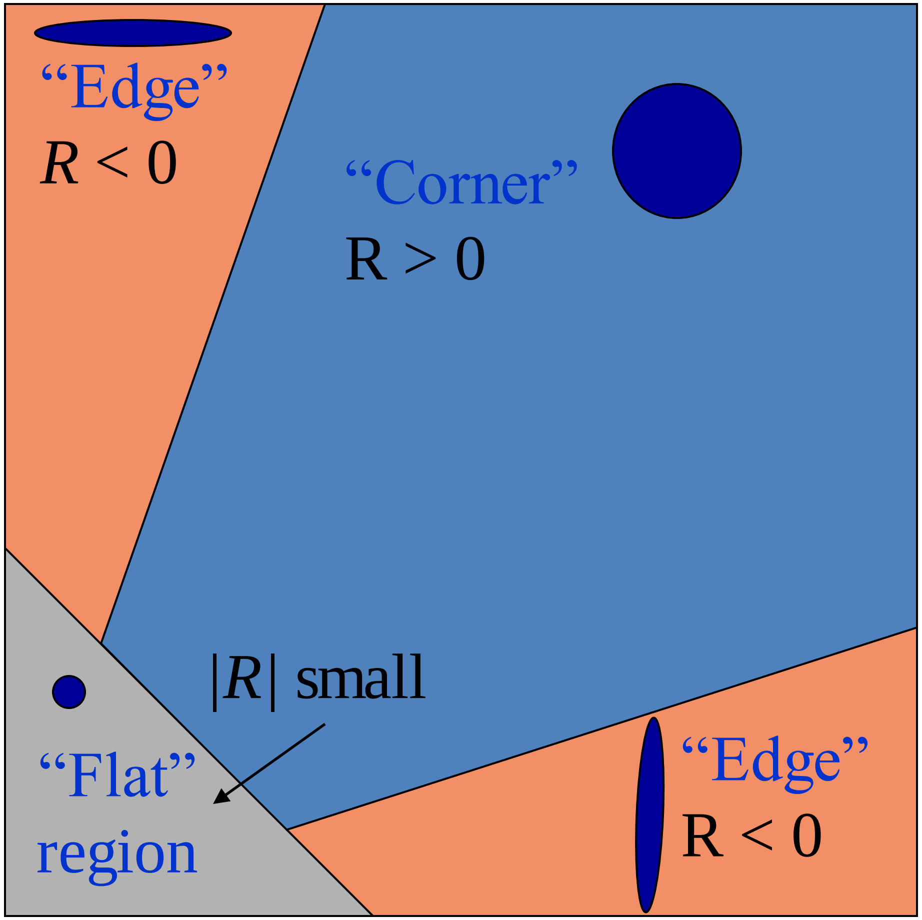
Classification of image points using eigenvalues of *M*:



Corner response function

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

α: constant (0.04 to 0.06)



Harris Corner Detector

- Algorithm steps:
  - Compute M matrix within all image windows to get their R scores
  - Find points with large corner response

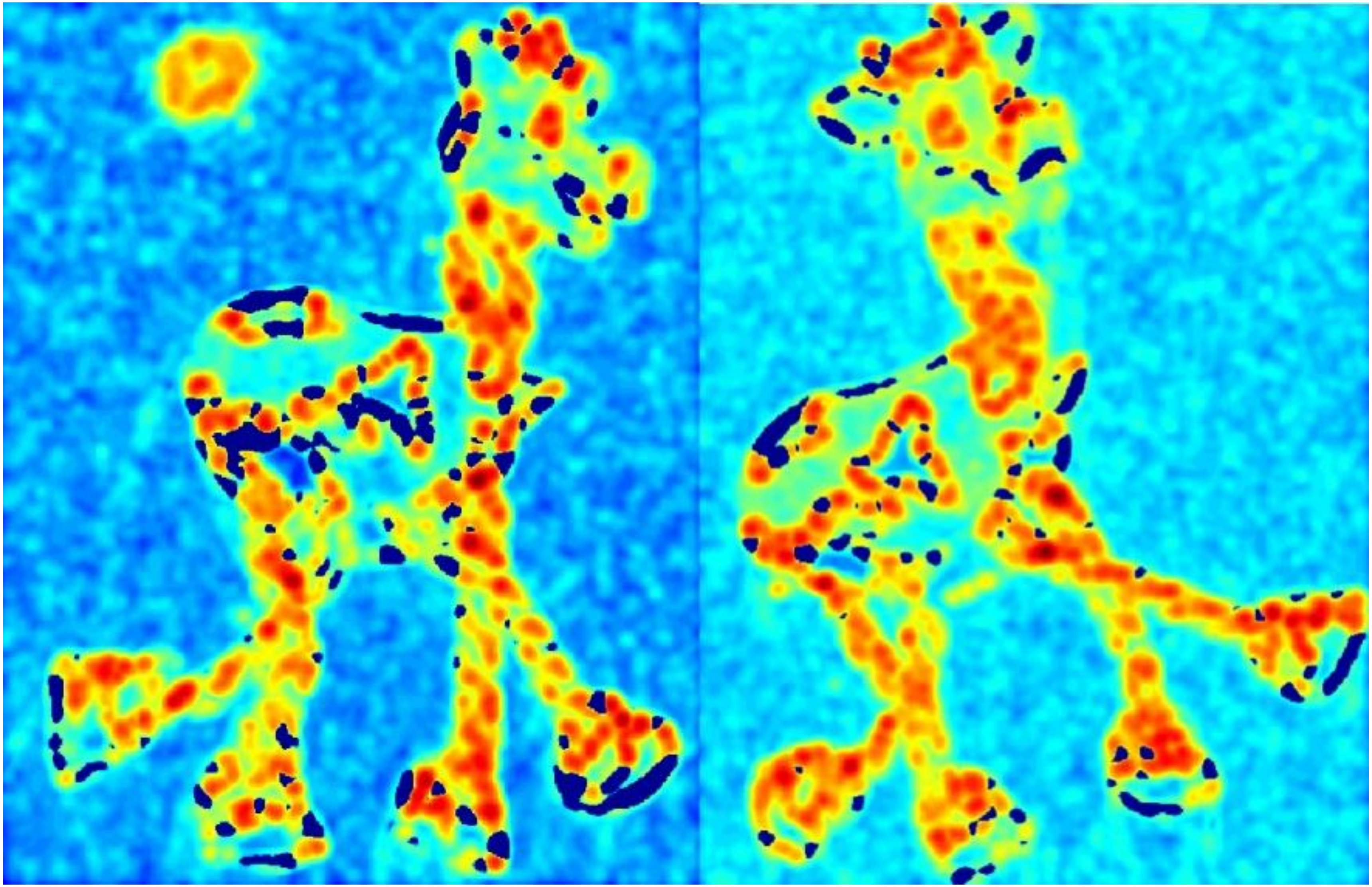
    (R > threshold)
  - Take the points of local maxima of R

Harris Detector: Workflow

Slide adapted form Darya Frolova, Denis Simakov, Weizmann Institute.

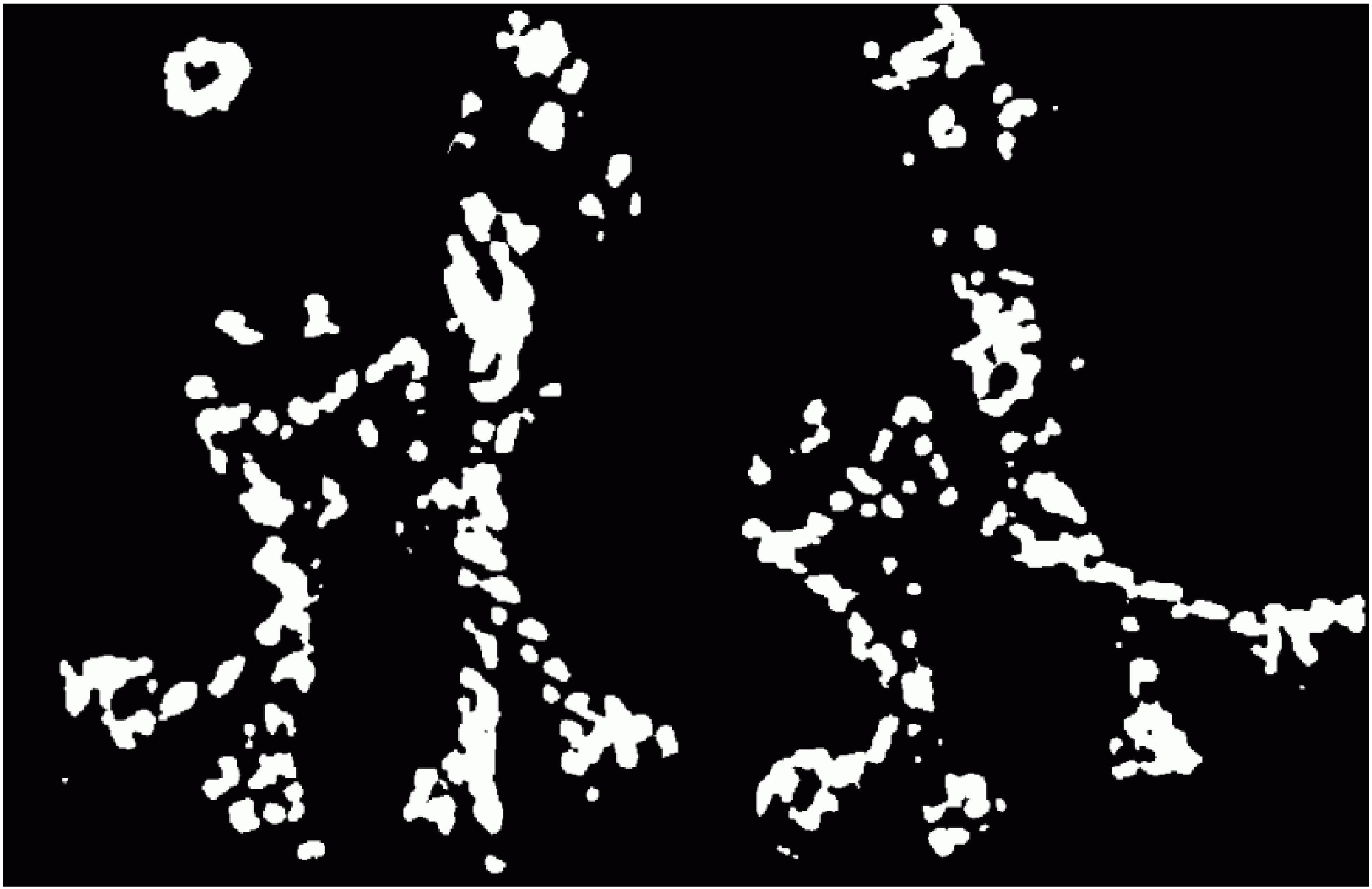
Harris Detector: Workflow

Compute corner response R



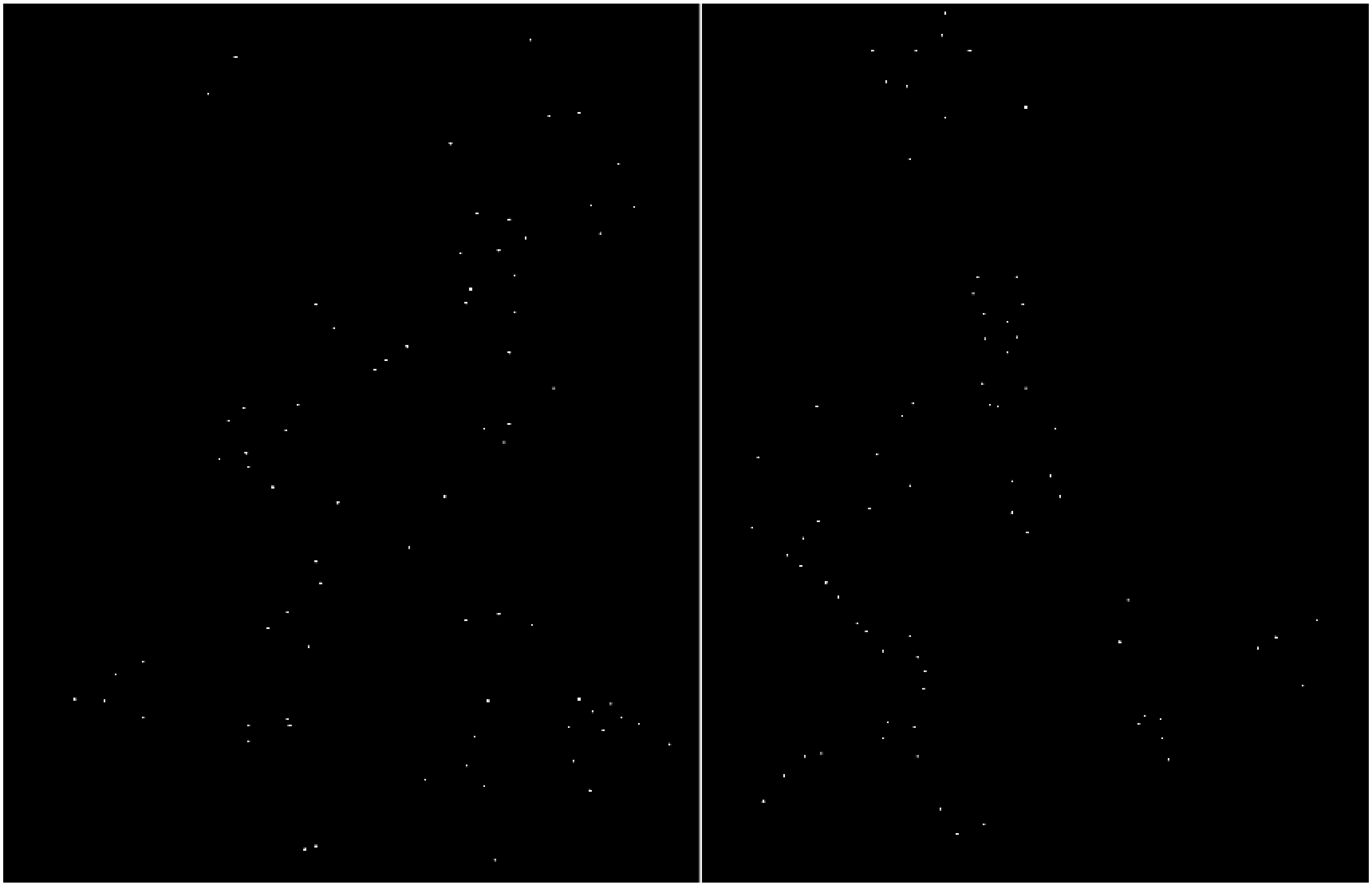
Harris Detector: Workflow

Find points with large corner response: R>threshold



Harris Detector: Workflow

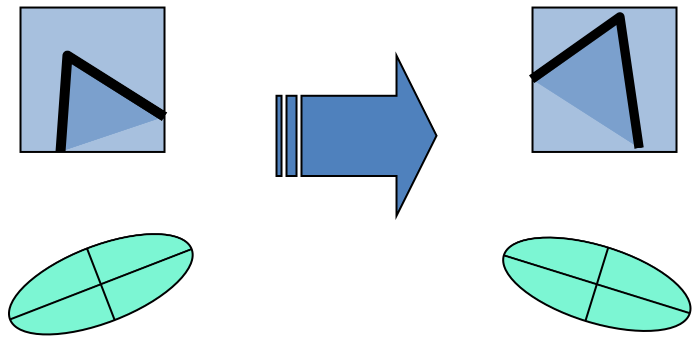
Take only the points of local maxima of R



Harris Detector: Workflow

Harris Detector: Properties

- Rotation invariance

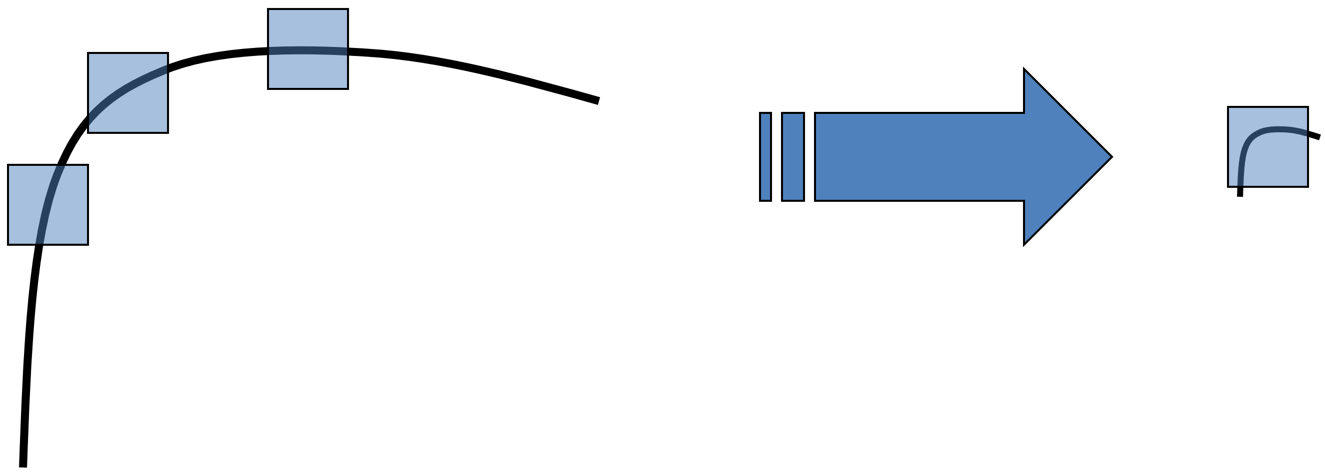


Ellipse rotates but its shape (i.e. eigenvalues) remains the same

Corner response R is invariant to image rotation

Harris Detector: Properties

- Not invariant to image scale



All points will be classified as edges

Corner !

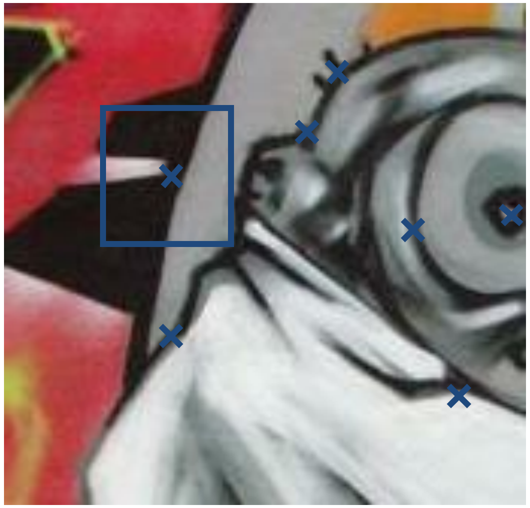
- How can we detect **scale invariant** interest points?

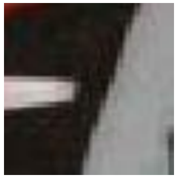
How to cope with transformations?

- Exhaustive search
- Invariance
- Robustness

Exhaustive search

- Multi-scale approach

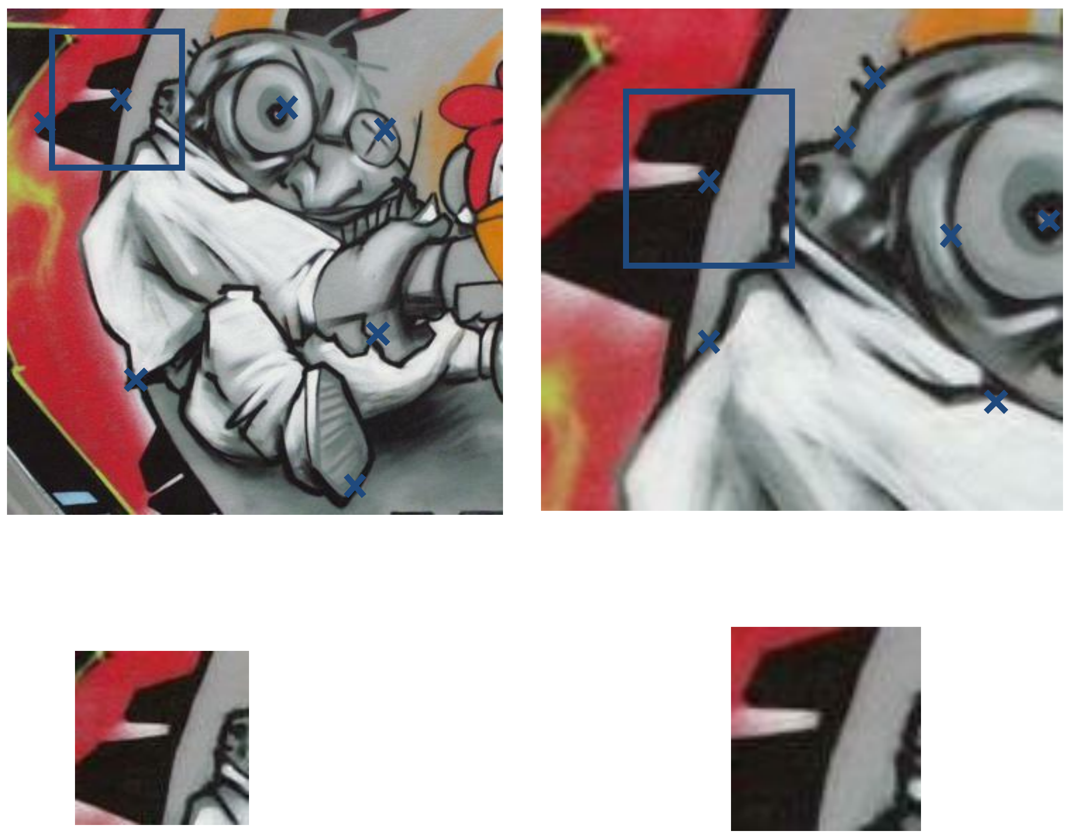



Slide from T. Tuytelaars ECCV 2006 tutorial

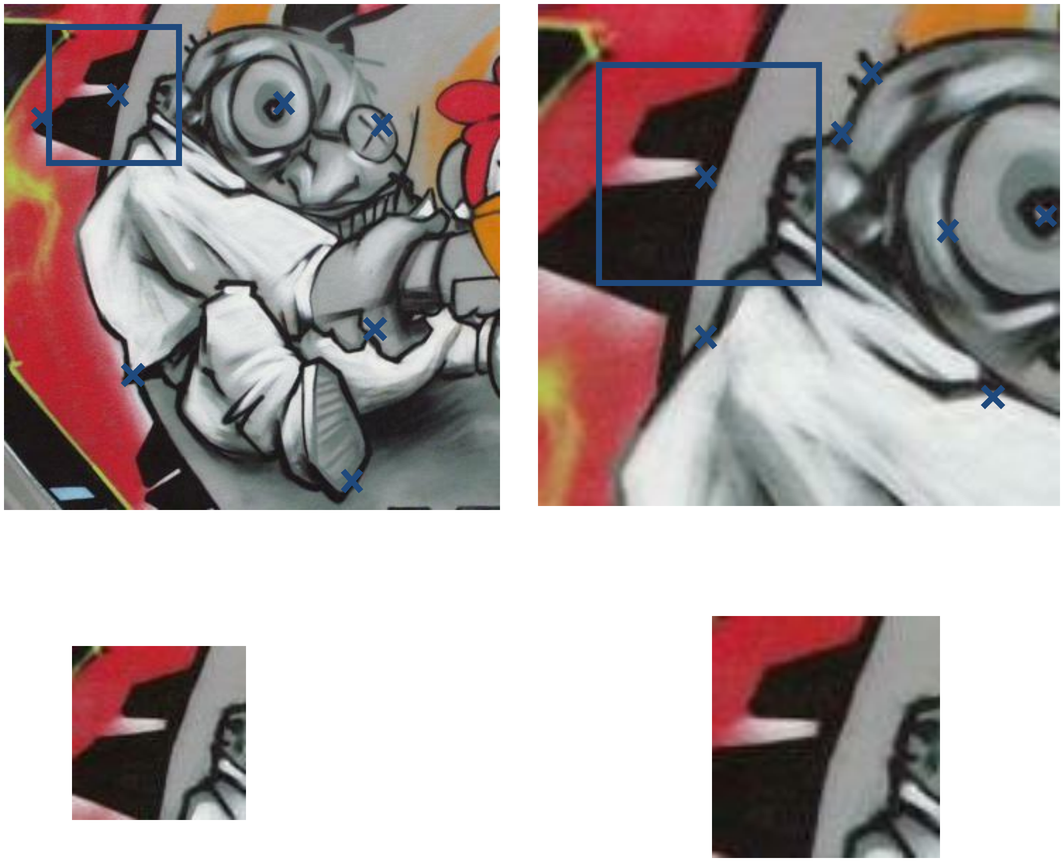
Exhaustive search

- Multi-scale approach



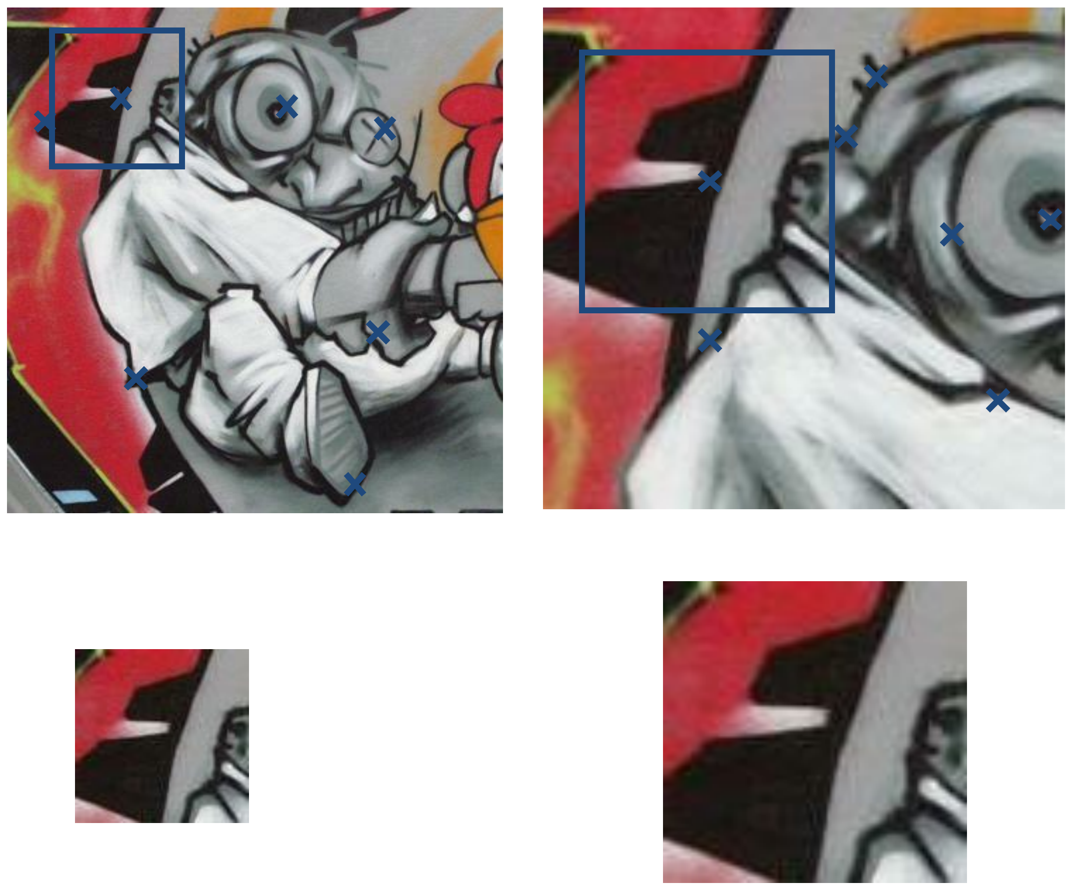
Exhaustive search

- Multi-scale approach



Exhaustive search

- Multi-scale approach



Invariance

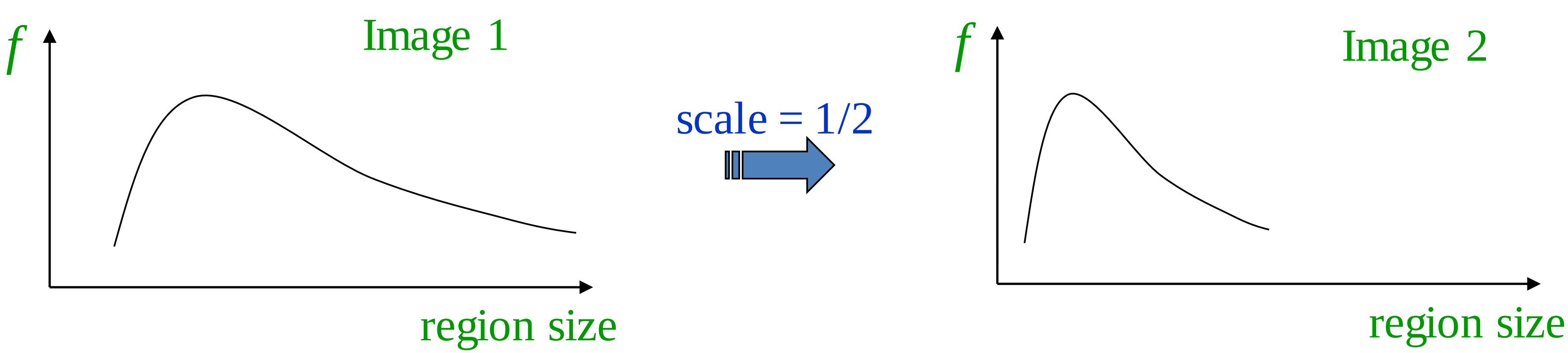
- Extract patch from each image individually

Automatic scale selection

- Solution:
  - Design a function on the region, which is “scale invariant” (*the same for corresponding regions, even if they are at different scales*)

    Example: average intensity. For corresponding regions (even of different sizes) it will be the same.

  - For a point in one image, we can consider it as a function of region size (patch width)



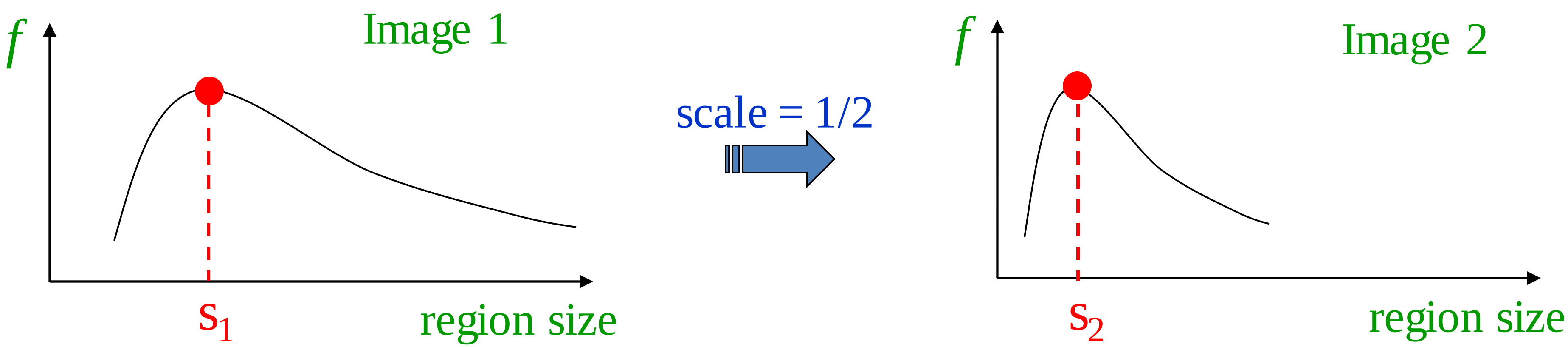
Automatic scale selection

- Common approach:

Take a local maximum of this function

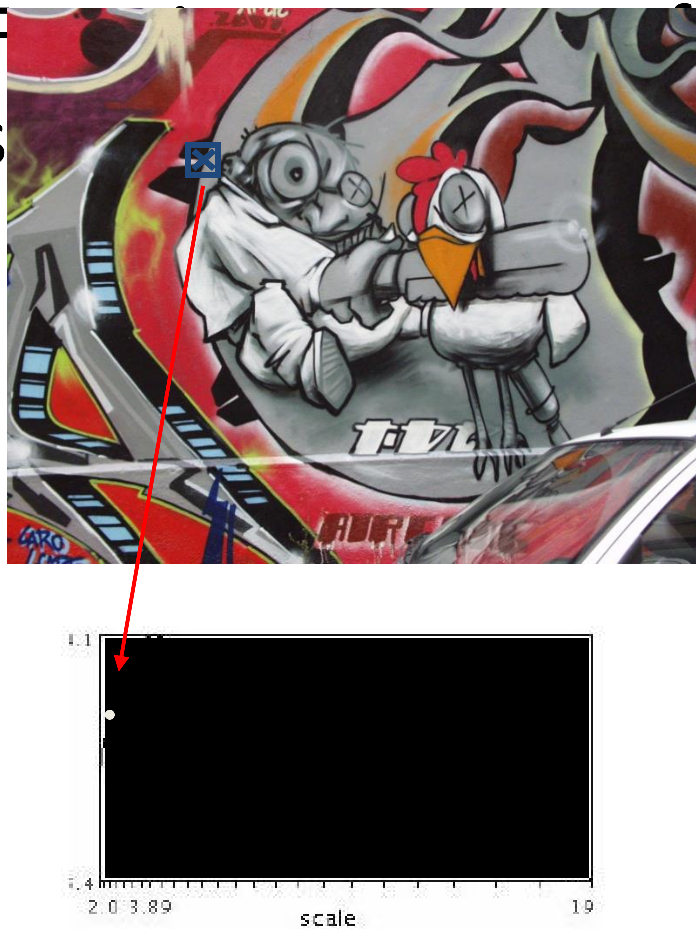
Observation: region size, for which the maximum is achieved, should be *invariant* to image scale.

Important: this scale invariant region size is found in each image independently!



Automatic Scale Selection

- F … or inc … ale
  s



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

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

K. Grauman, B. Leibe

Automatic Scale Selection

- F or inc ale s

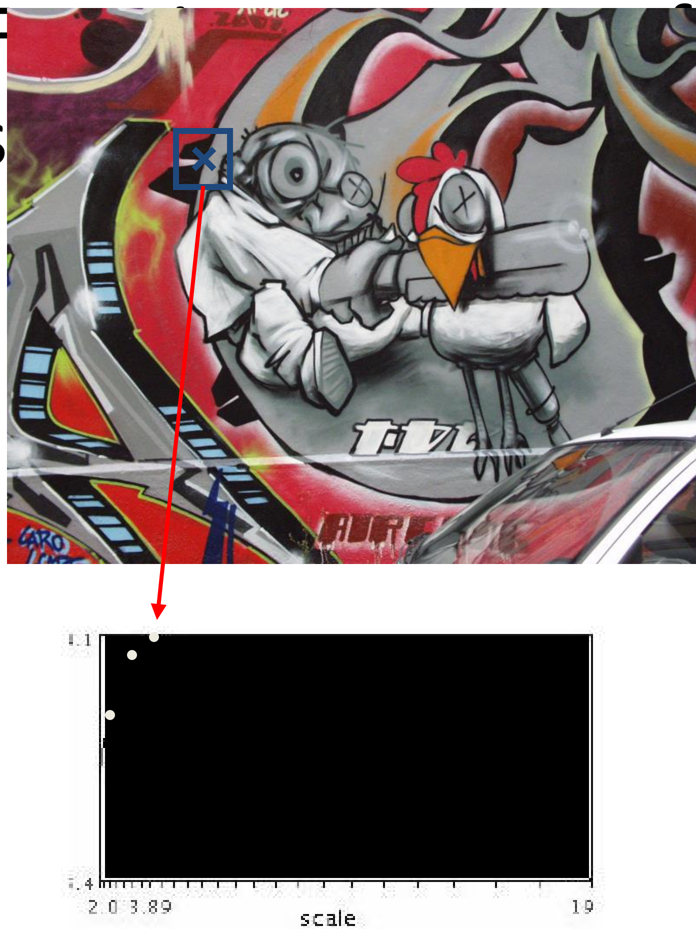
$f(I_{i_1 \ldots i_m}(x, \sigma))$

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

K. Grauman, B. Leibe

Automatic Scale Selection

• F for inc ale
s



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

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

K. Grauman, B. Leibe

Automatic Scale Selection

• F … or inc … ale s

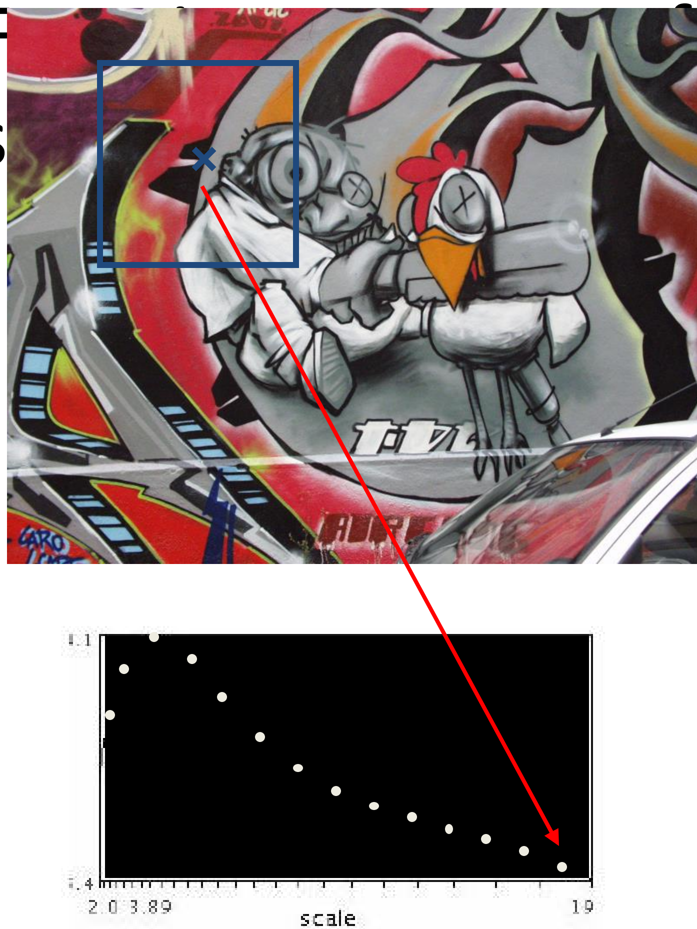
$$f(I_{i_1 \ldots i_m}(x,\sigma))$$

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

K. Grauman, B. Leibe

Automatic Scale Selection

- F or inc ale
  s



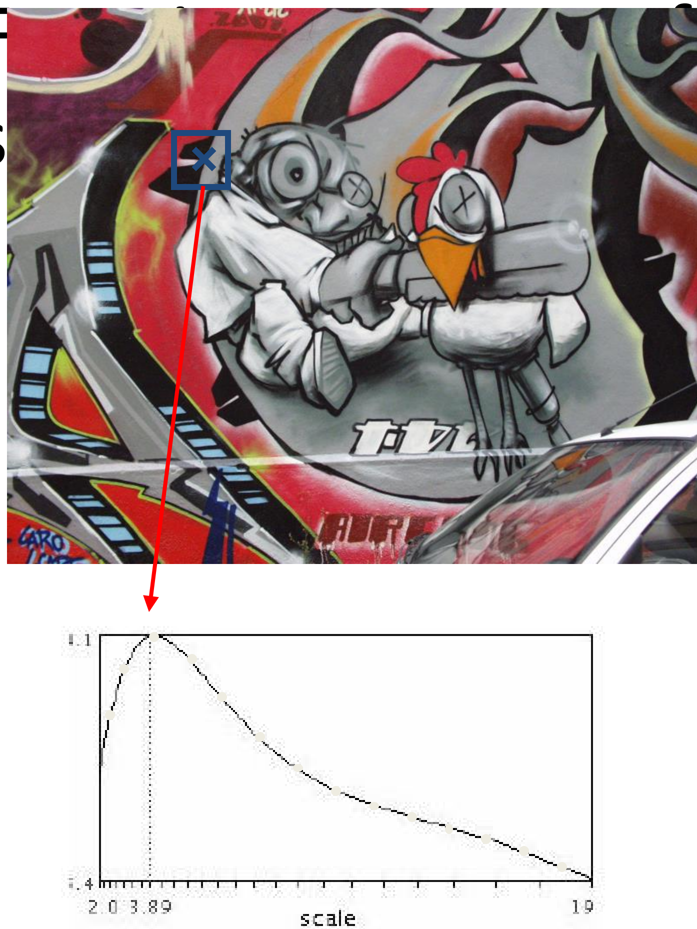
$f(I_{i_1 \ldots i_m}(x, \sigma))$

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

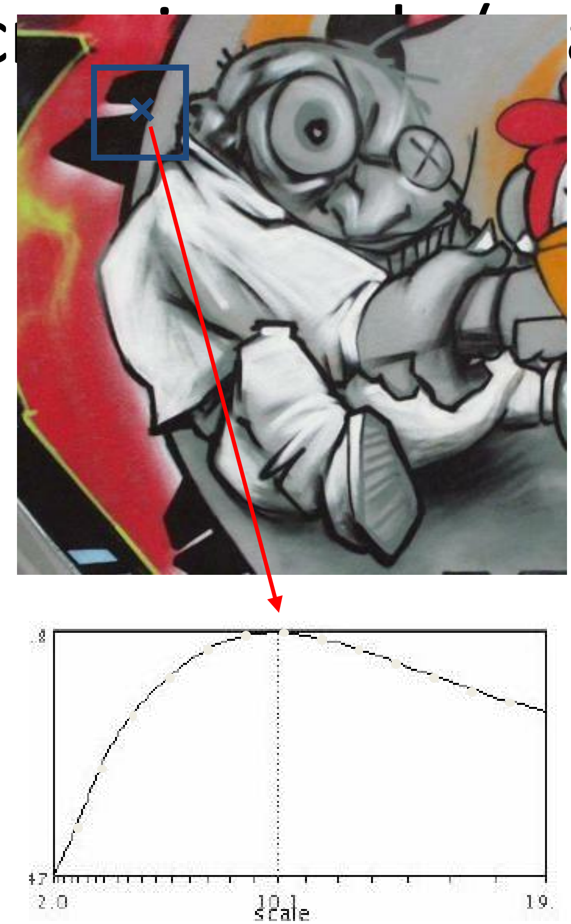
K. Grauman, B. Leibe
K. Grauman, B. Leibe

Automatic Scale Selection

- F … or inc … ale
  s …



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

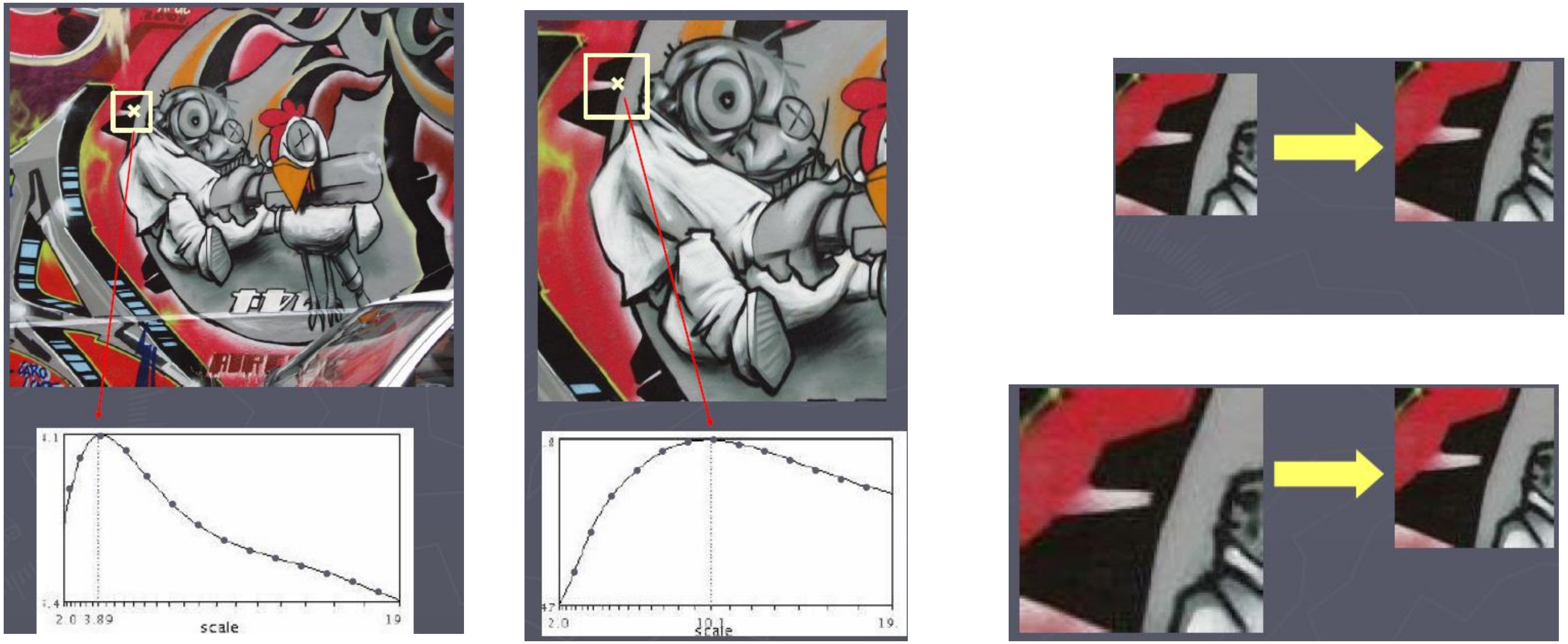


$f(I_{i_1 \ldots i_m}(x', \sigma'))$

K. Grauman, B. Leibe

Scale selection

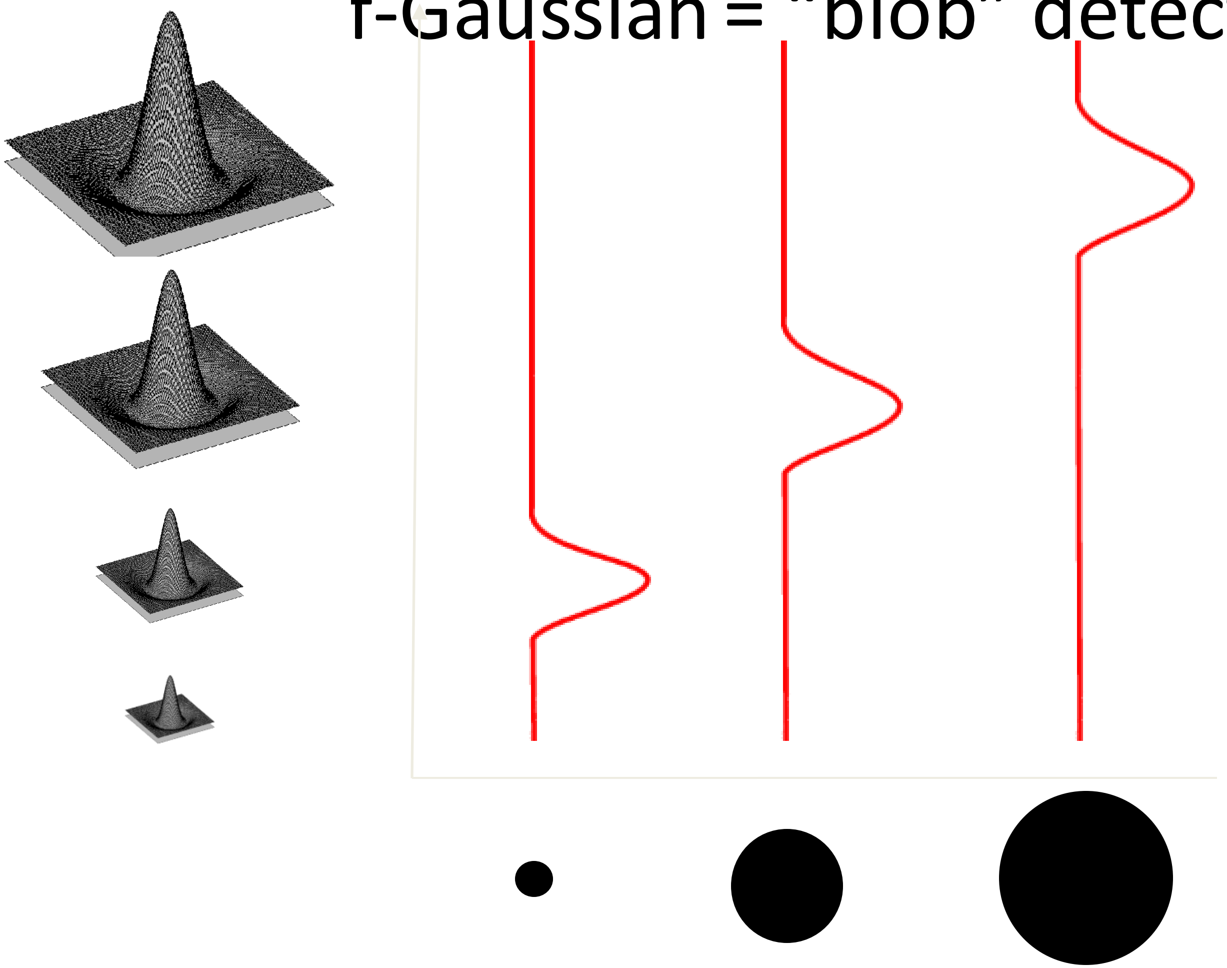
- Use the scale determined by detector to compute descriptor in a normalized frame



[Images from T. Tuytelaars]

What Is A Useful Signature Function?

- La f-Gaussian = "blob" detector



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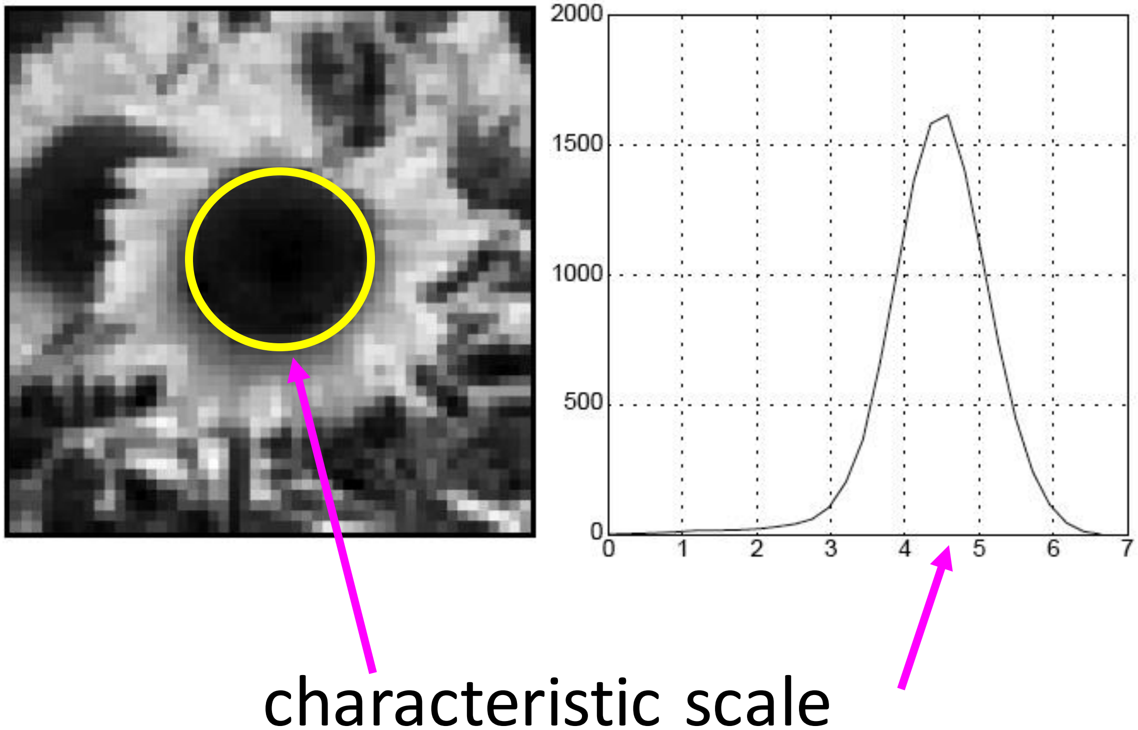
Characteristic scale

- We define the *characteristic scale* as the scale that produces peak of Laplacian response



T. Lindeberg (1998). "Feature detection with automatic scale selection." *International Journal of Computer Vision* **30** (2): pp 77--116.

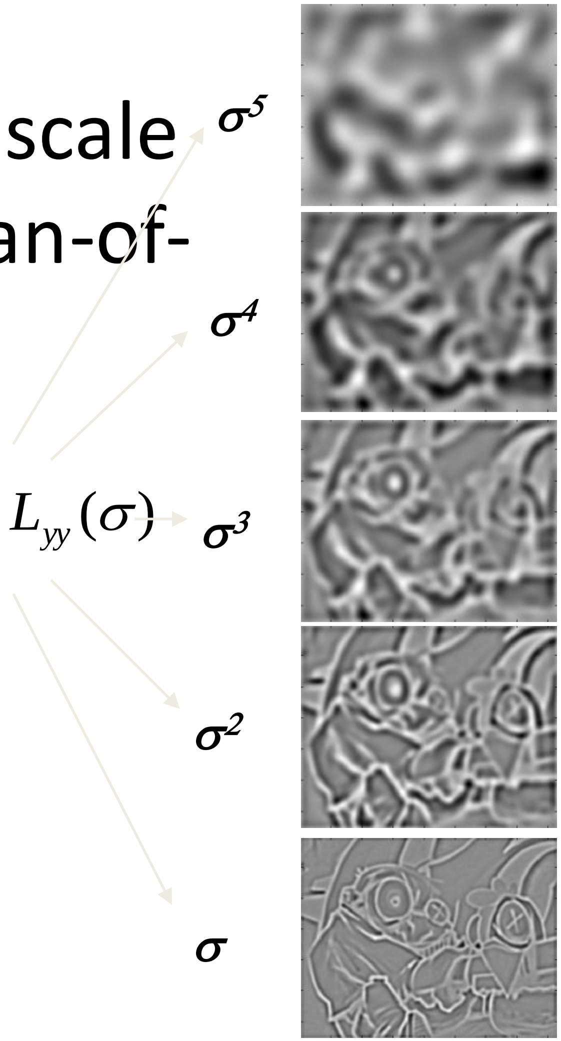
Source: Lana Lazebnik

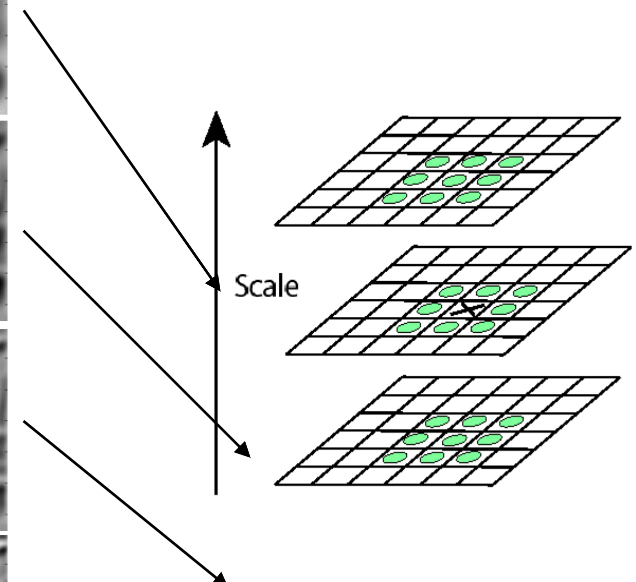
Laplacian-of-Gaussian (LoG)

- Interest points:

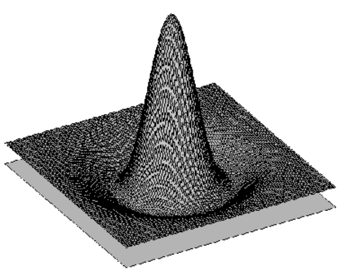
  Local maxima in scale space of Laplacian-of-Gaussian

$$L_{xx}(\sigma) + L_{yy}(\sigma)$$





$\Rightarrow$ **List of *(x, y, σ)***



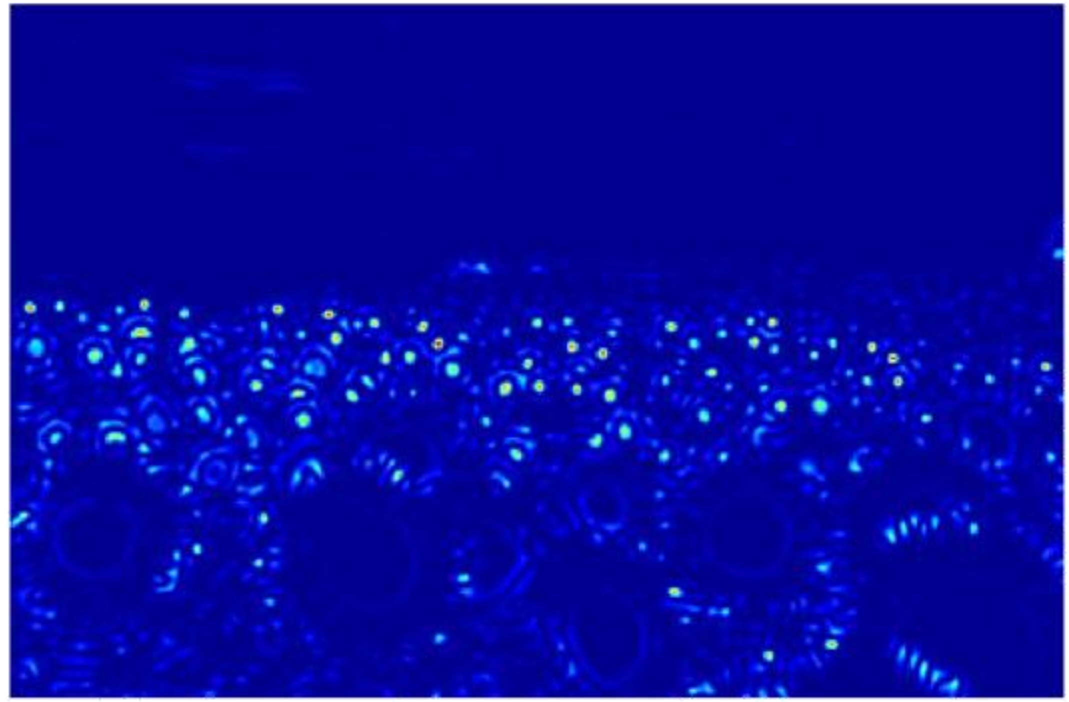
K. Grauman, B. Leibe

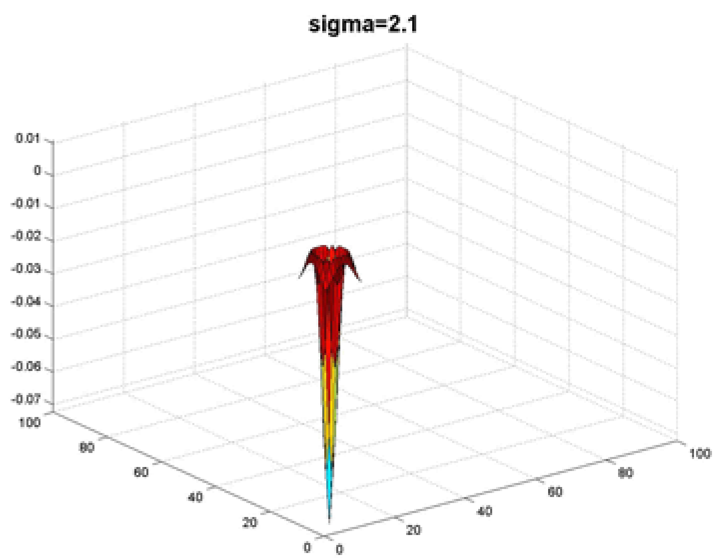
Exa

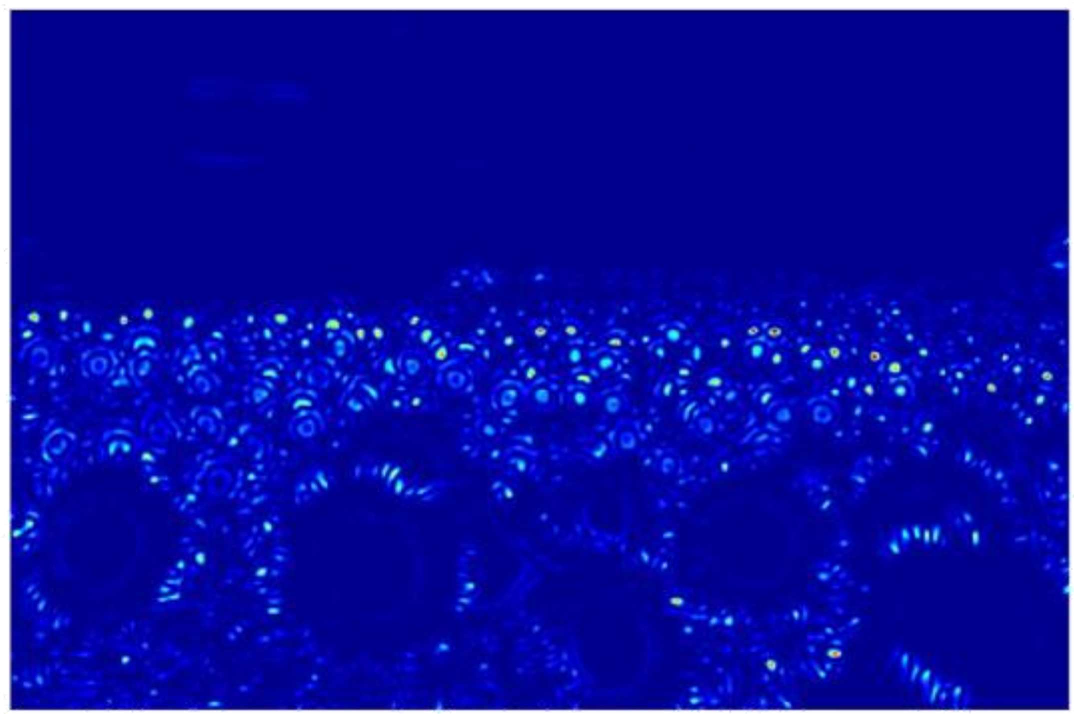
Original image at
¾ the size

Kristen Grauman

Original image at
¾ the size







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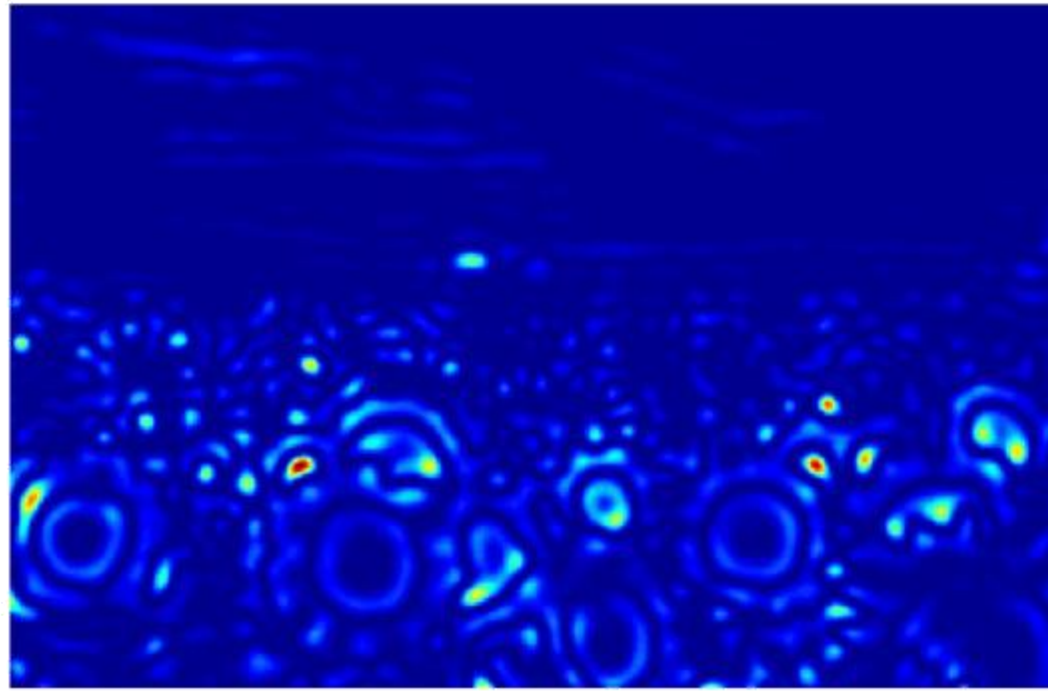

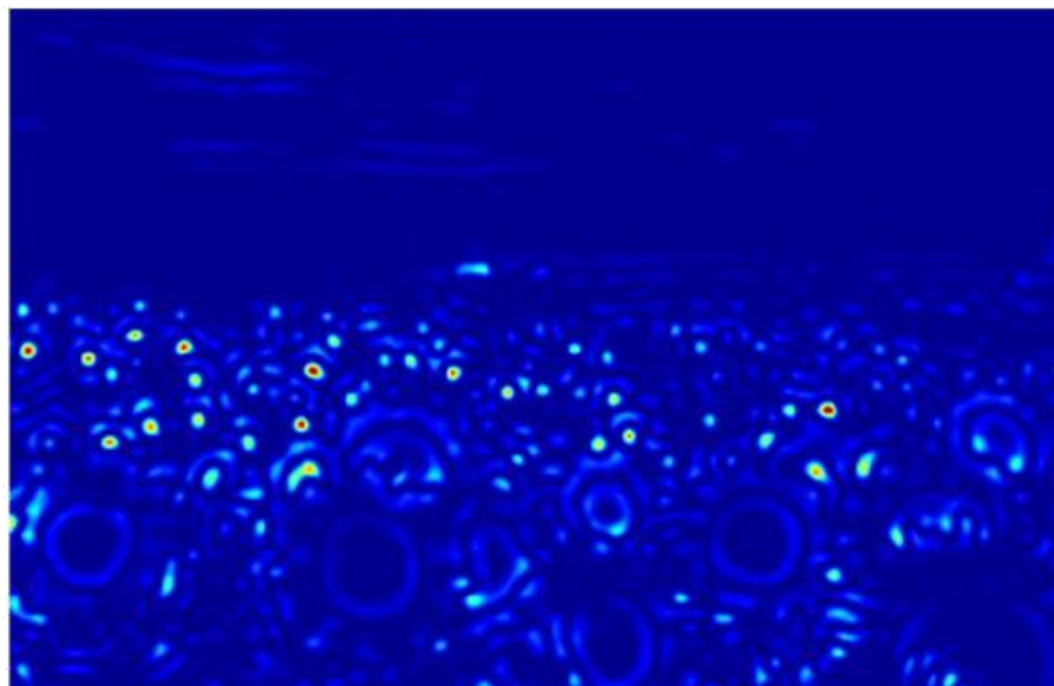

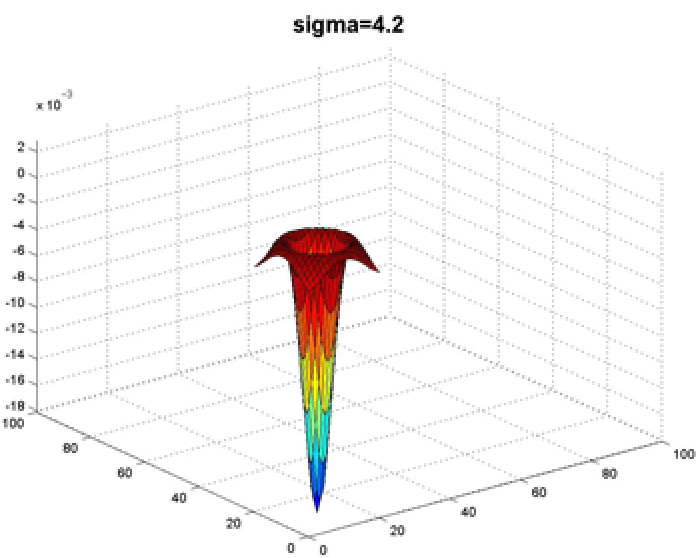

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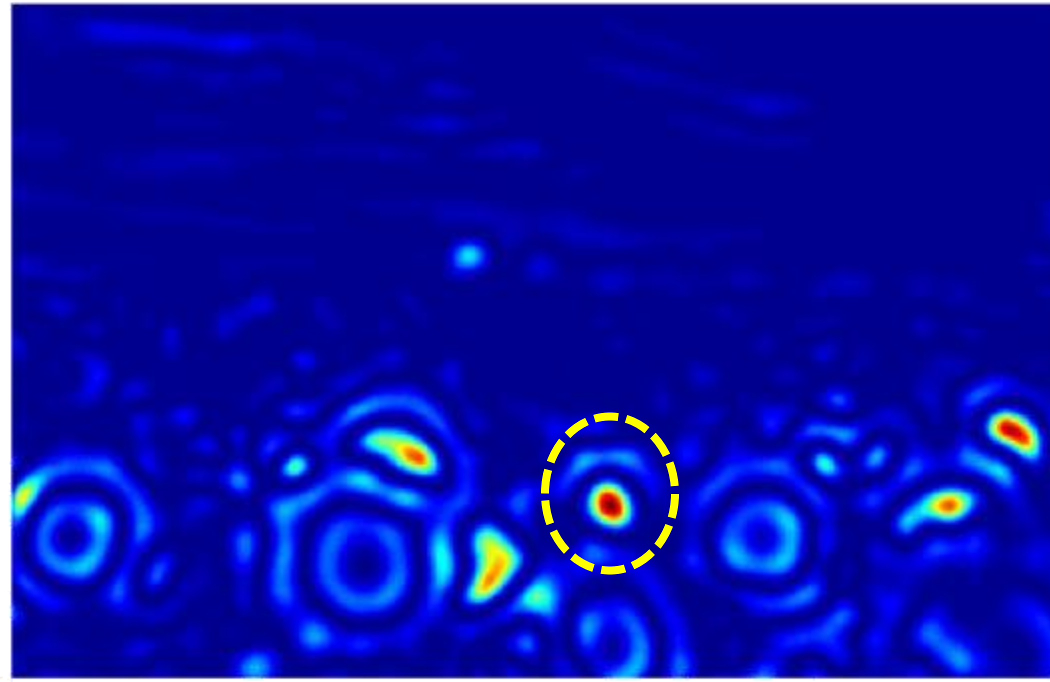
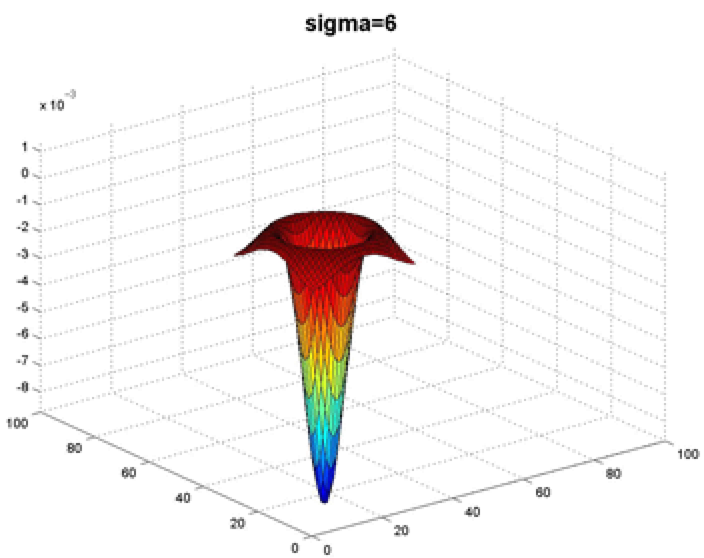
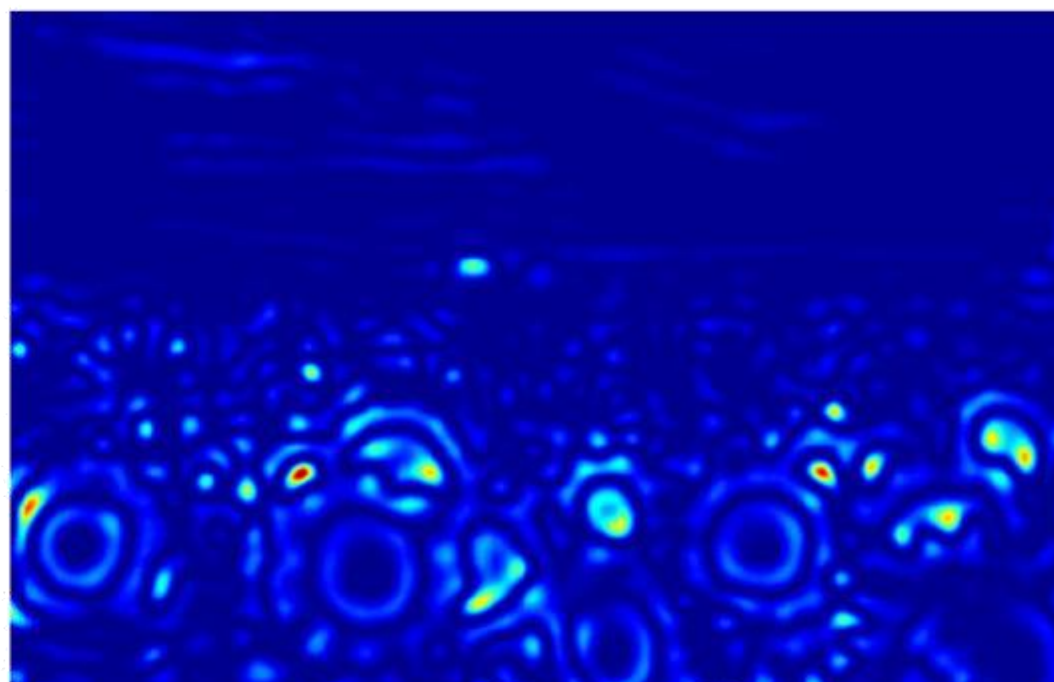
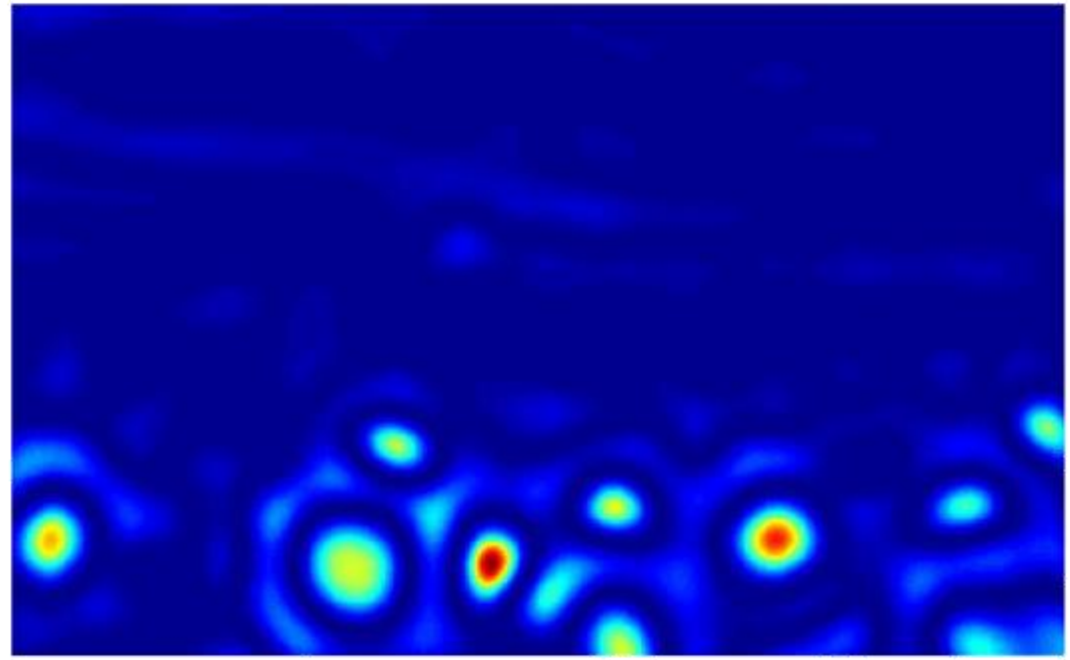
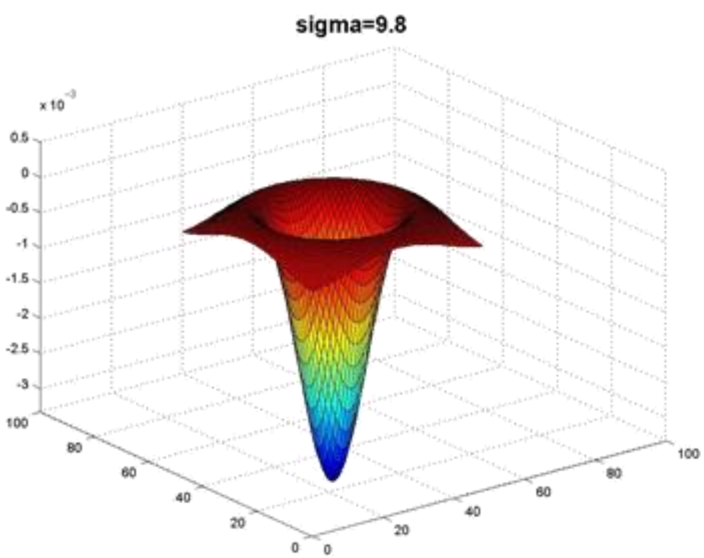


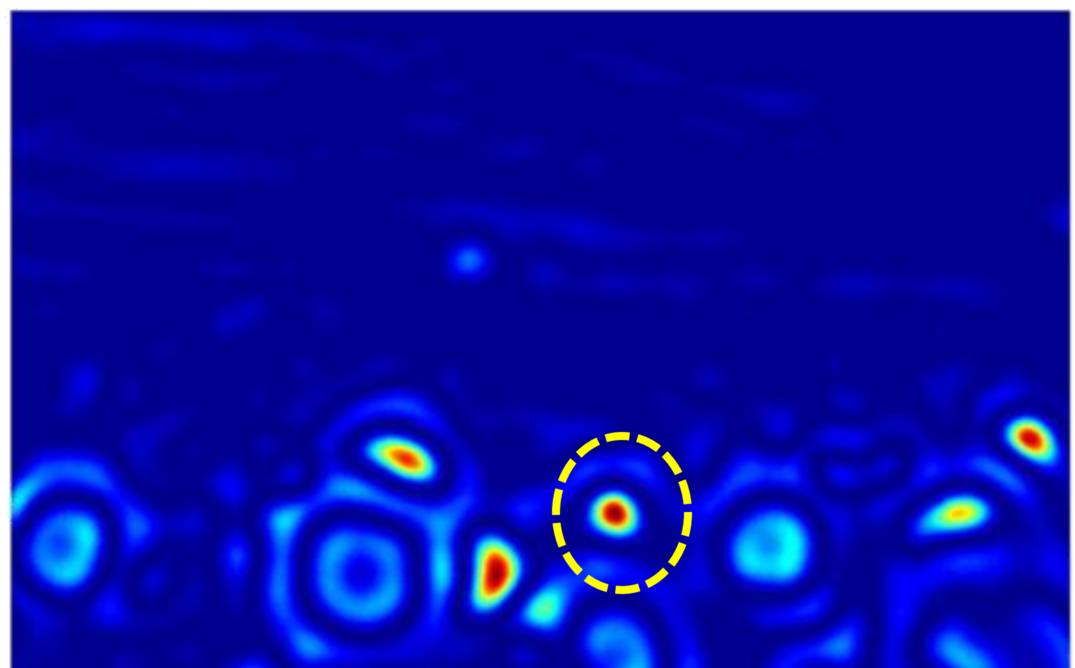




Kristen Grauman







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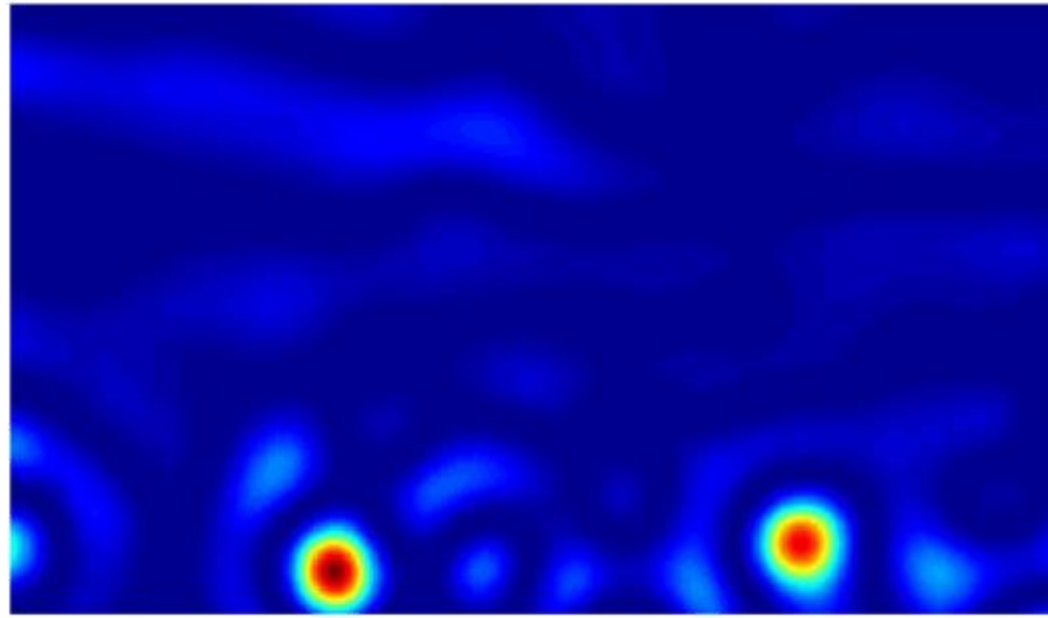

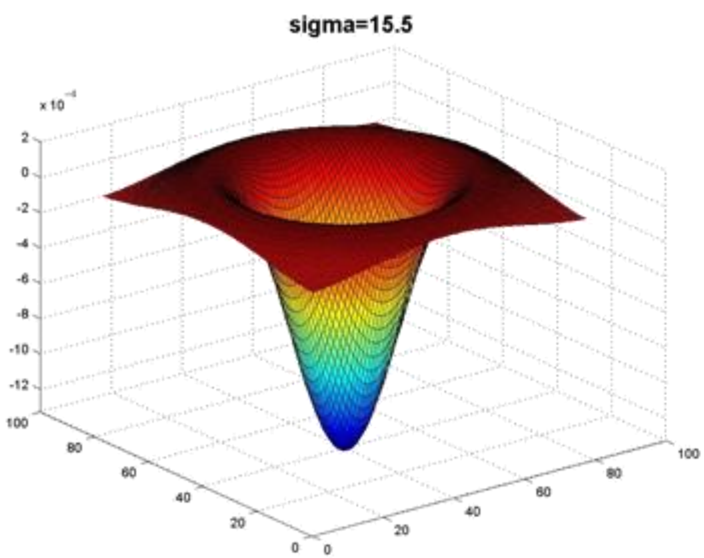

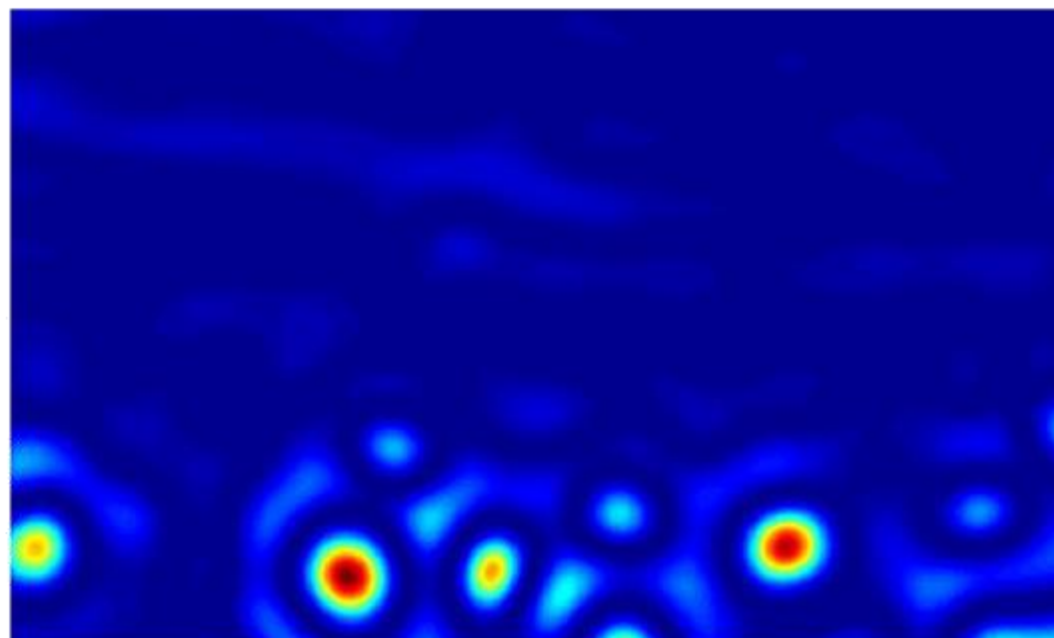

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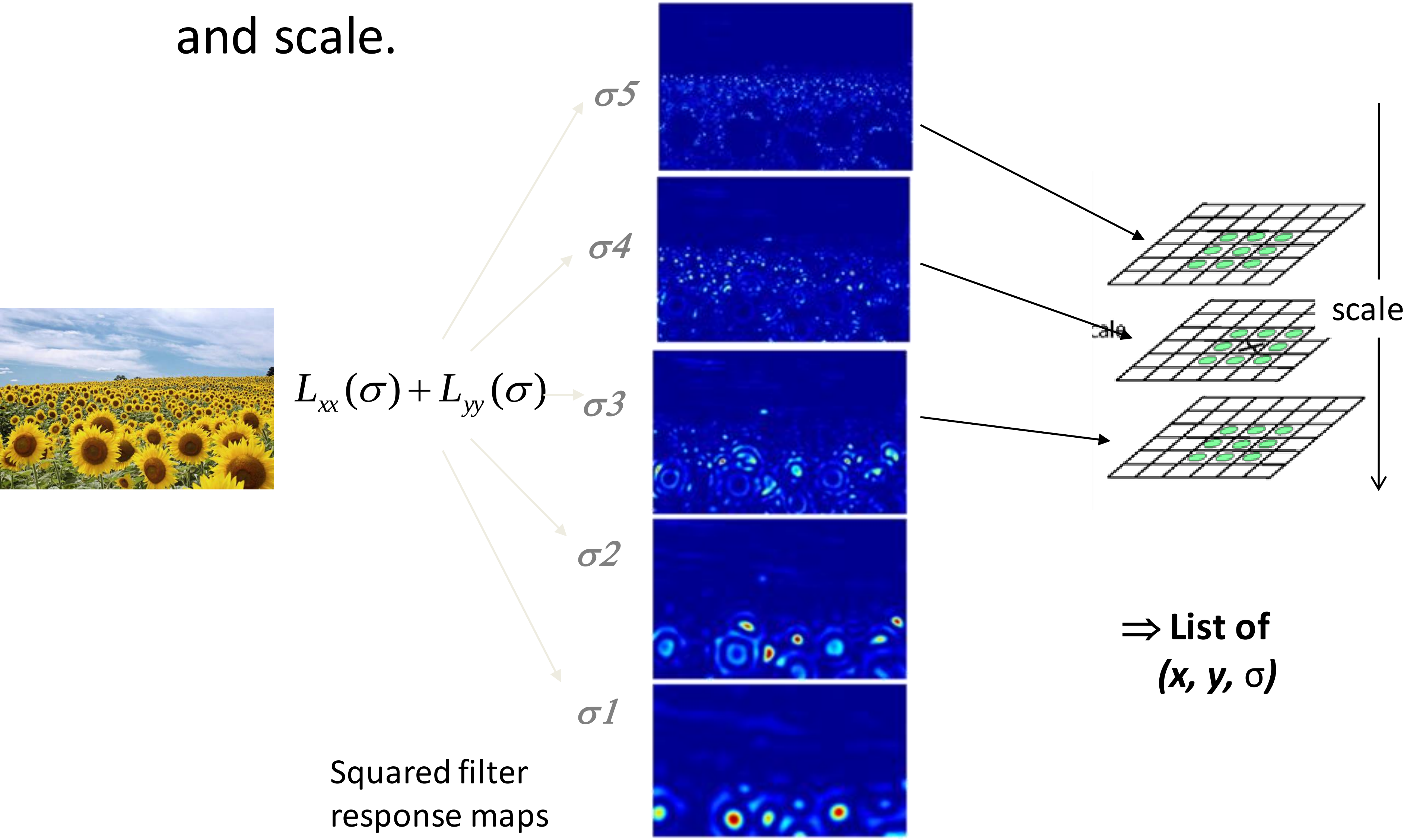
Scale invariant interest points

Interest points are local maxima in both position and scale.



Scale-space blob detector: Example

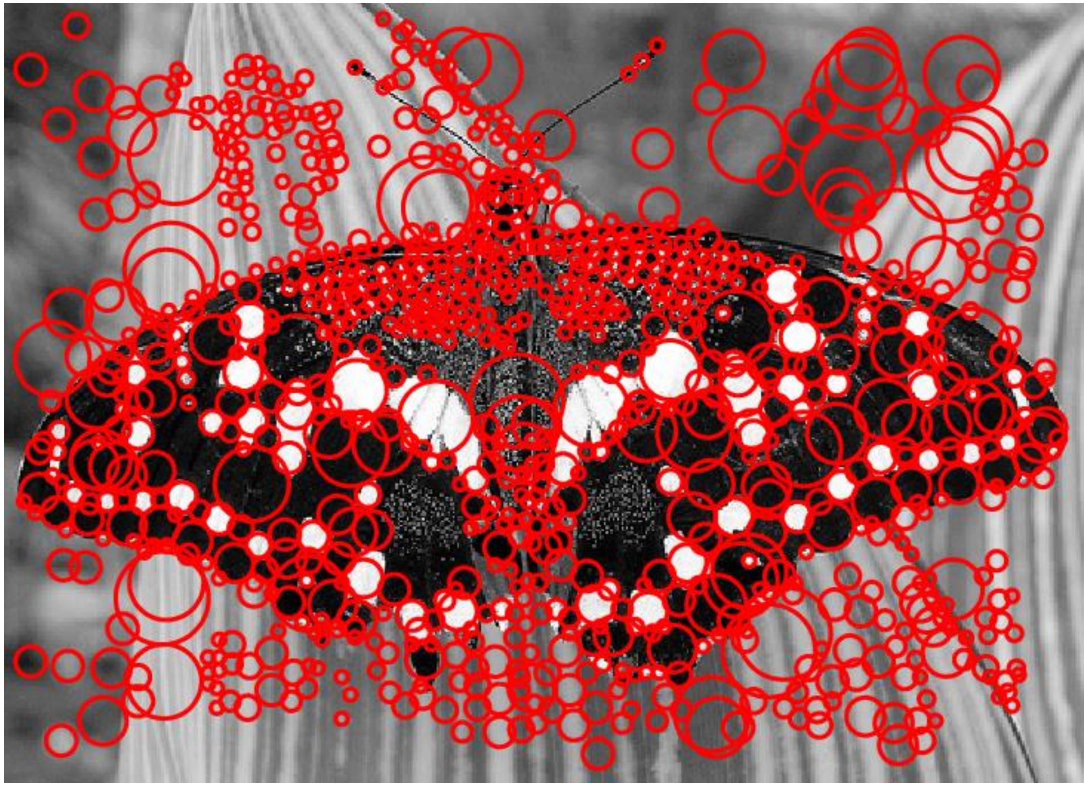
Source: Lana Lazebnik

Scale-space blob detector: Example

sigma = 11.9912

Source: Lana Lazebnik

Scale-space blob detector: Example



Source: Lana Lazebnik

Scale-space blob detector: Example

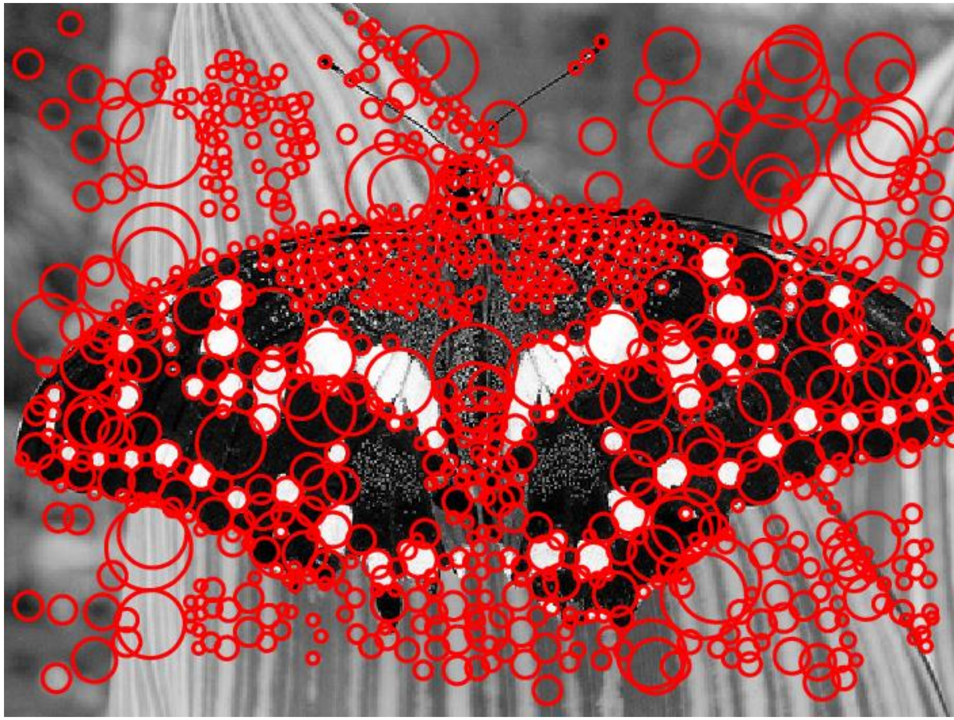


Image credit: Lana Lazebnik

Technical detail

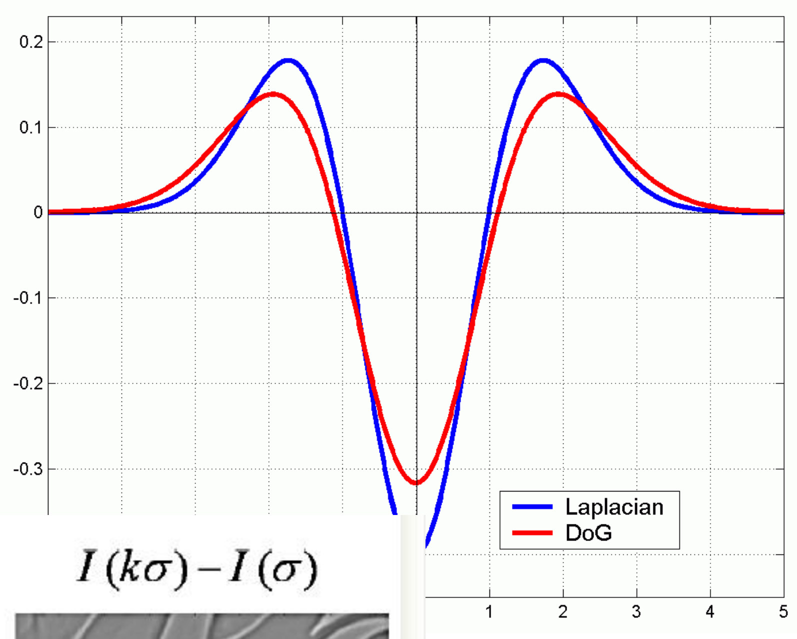
- We can approximate the Laplacian with a difference of Gaussians; more efficient to implement.

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

(Laplacian)

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

(Difference of Gaussians)



$I(k\sigma)$

-

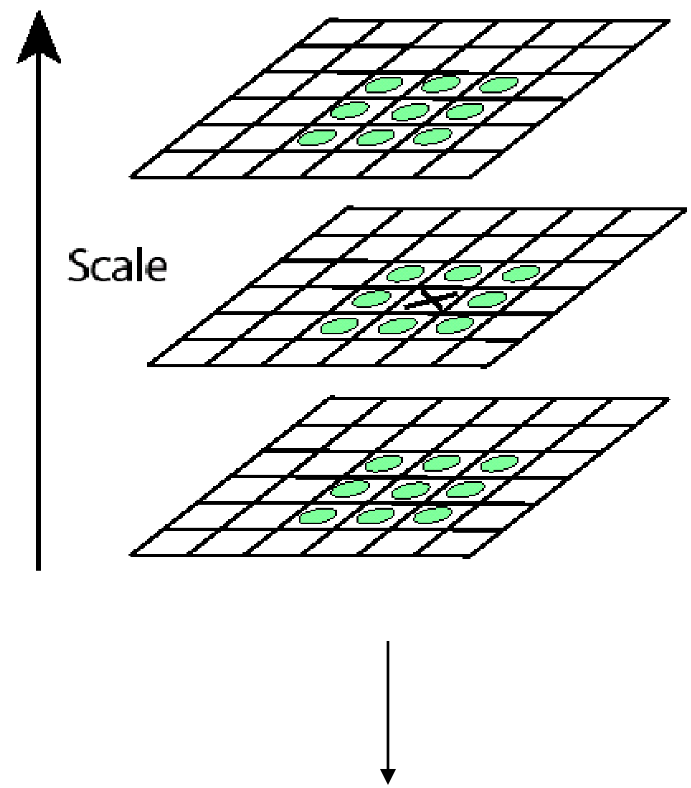
$I(\sigma)$

=

$I(k\sigma) - I(\sigma)$

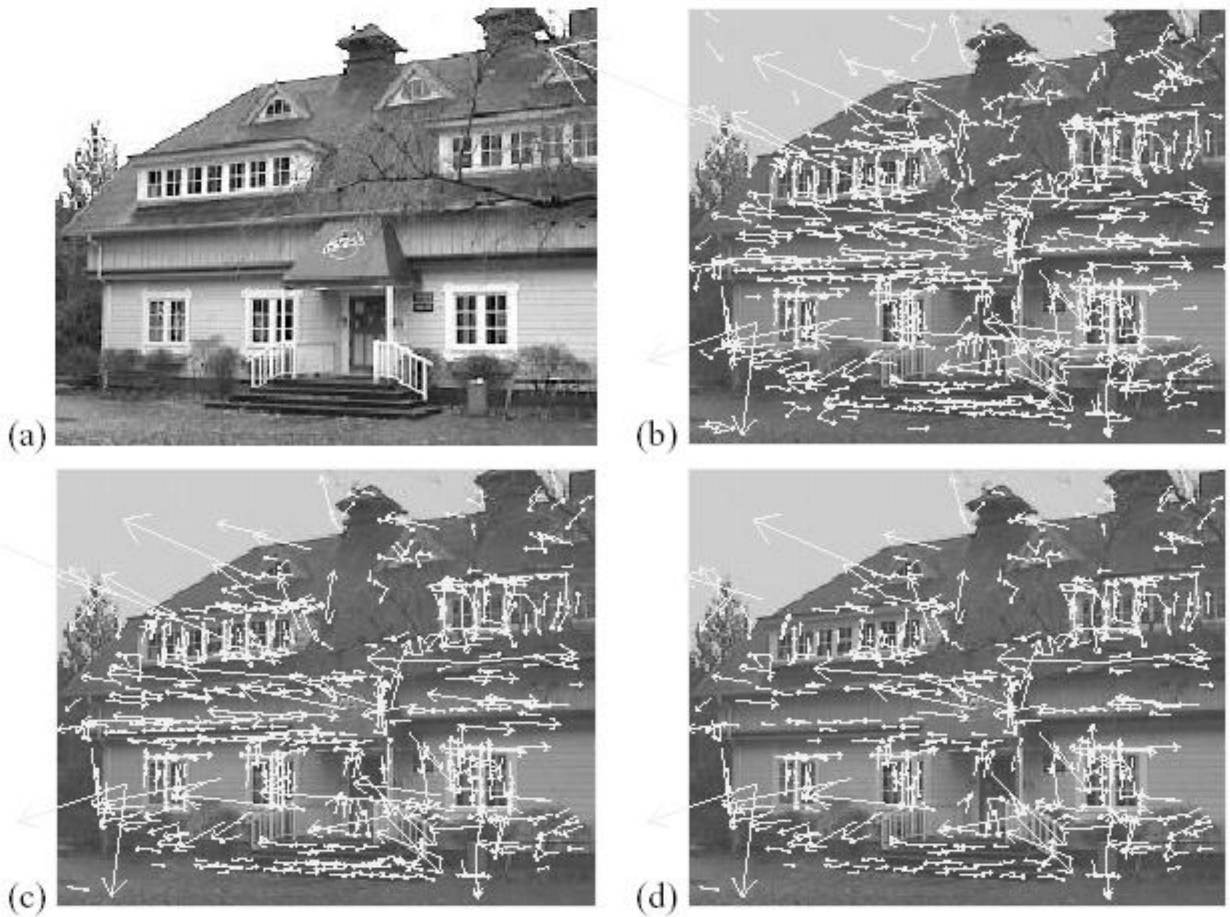
Key point localization with DoG

- Detect maxima of difference-of-Gaussian (DoG) in scale space
- Then reject points with low contrast (threshold)
- Eliminate edge responses



Candidate keypoints: list of (x,y,σ)

Example of keypoint detection



(a) 233x189 image
(b) 832 DOG extrema
(c) 729 left after peak value threshold
(d) 536 left after testing ratio of principle curvatures (removing edge responses)

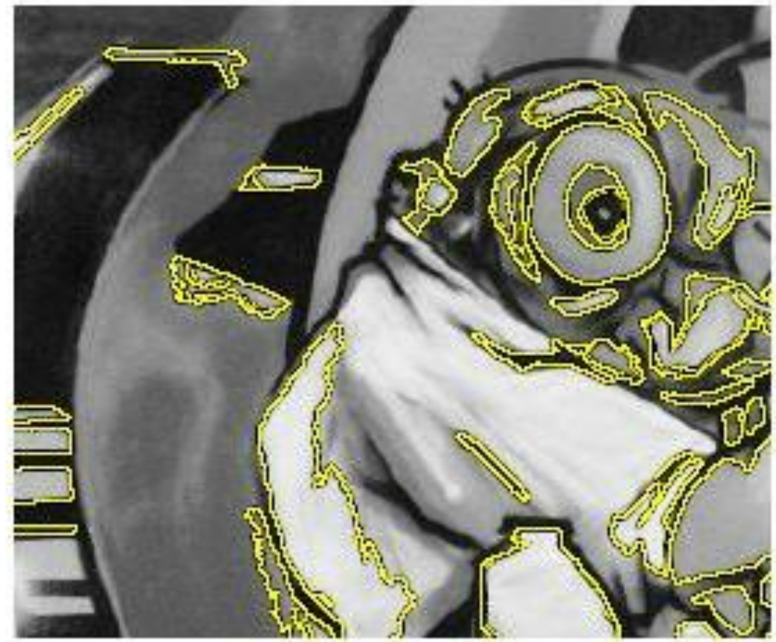
Scale Invariant Detection: Summary

- Given: two images of the same scene with a large *scale difference* between them
- Goal: find *the same* interest points *independently* in each image
- Solution: search for *maxima* of suitable functions in *scale* and in *space* (over the image)

Maximally Stable Extremal Regions [Matas '02]

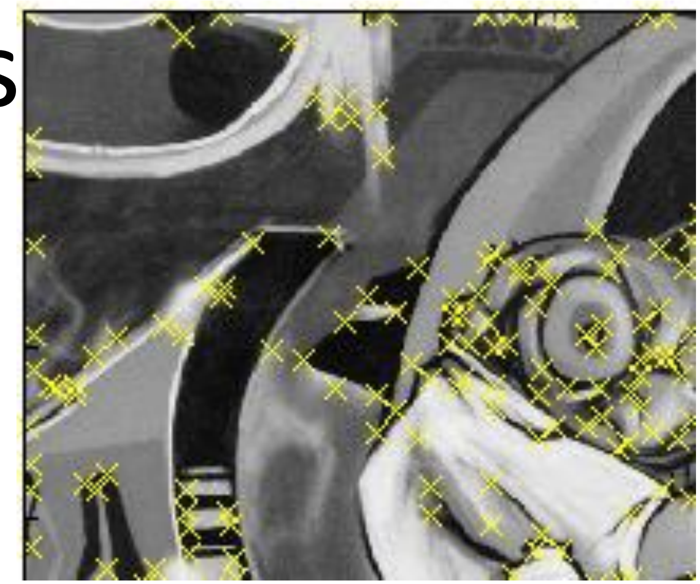
- Based on Watershed segmentation algorithm
- Select regions that stay stable over a large para

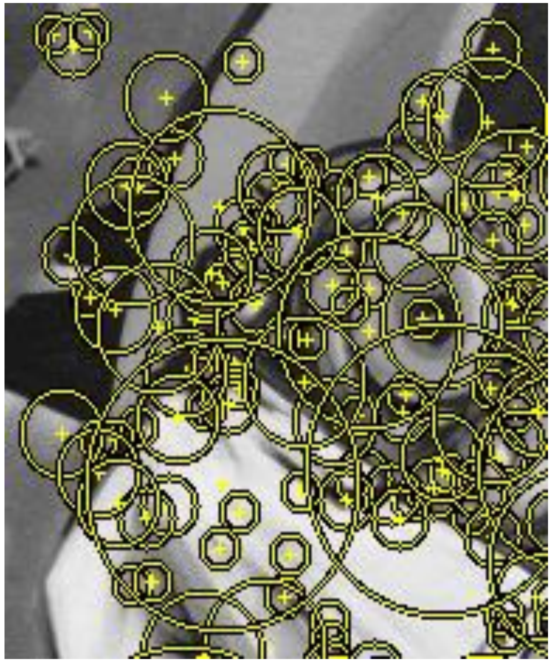
Example Results: MSER



Comparis

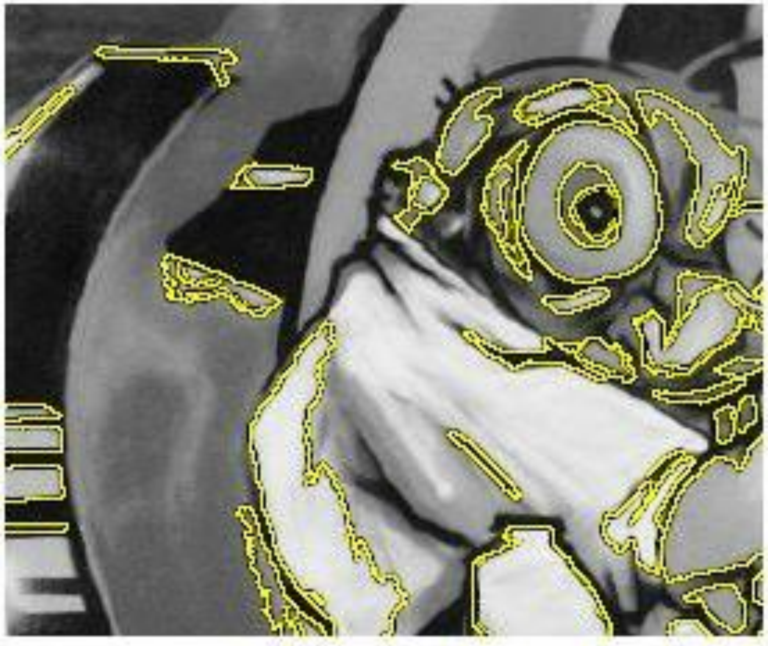
Harris



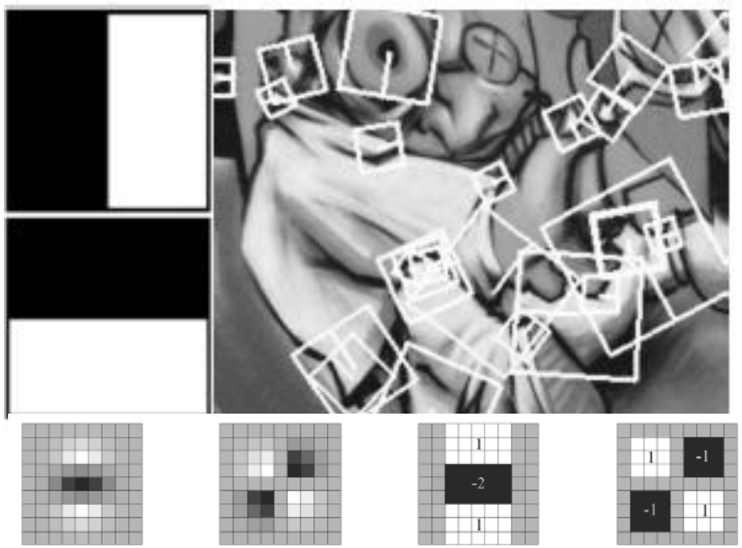


LoG

MSER



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

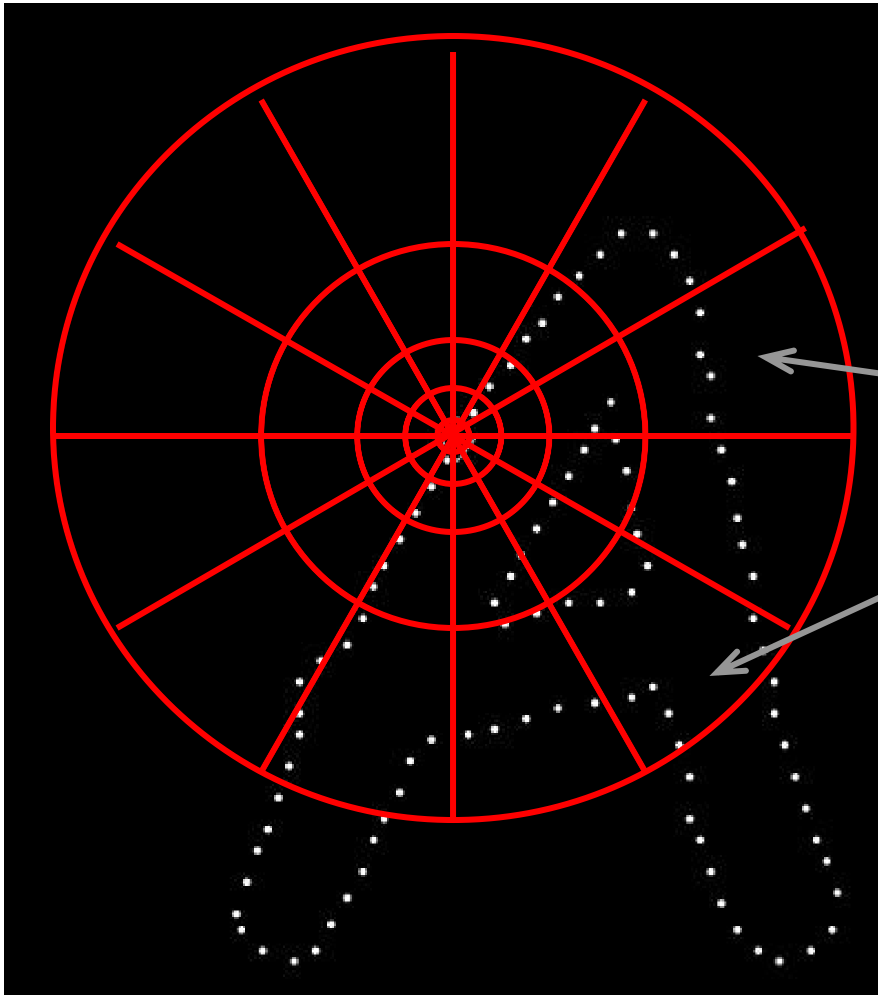
- **Feature extraction @ 200Hz (detector + descriptor, 640×480 img)**
- http://www.vision.ee.ethz.ch/~surf

Many other efficient descriptors are also available

[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

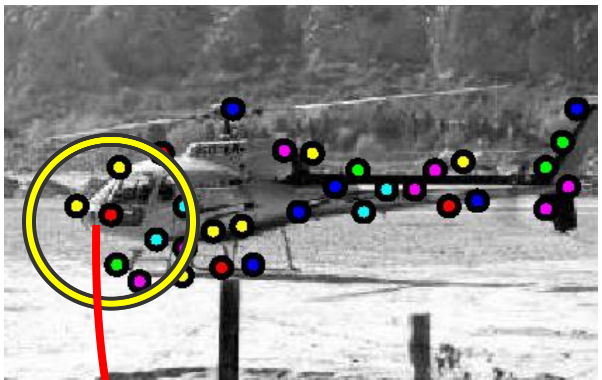
⋮

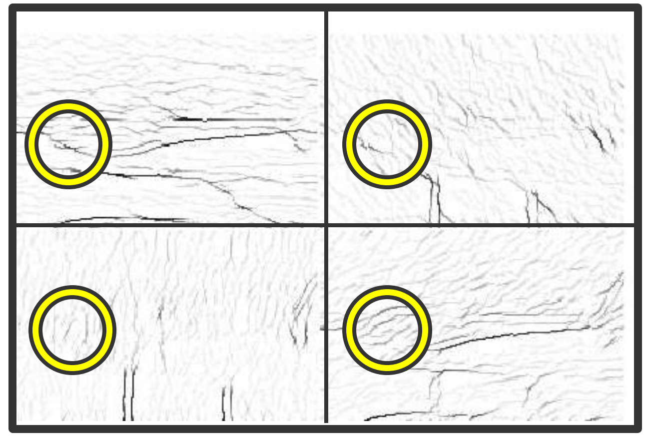
Count = 10

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

Belongie & Malik, ICCV 2001

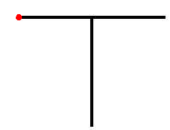
Local Descriptors: Geometric Blur





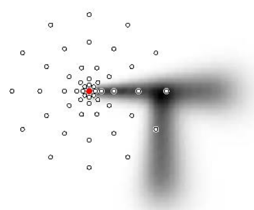
Compute edges at four orientations

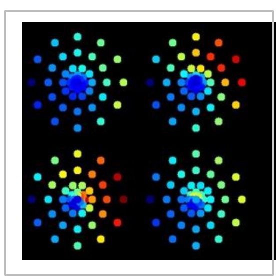
Extract a patch in each channel



Apply spatially varying blur and sub-sample

(Idealized signal)





Example descriptor

Berg & Malik, CVPR 2001

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

Choosing a detector

- 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
- Why choose?
  - Get more points with more detectors
- There have been extensive evaluations/comparisons
  - [Mikolajczyk et al., IJCV'05, PAMI'05]
  - All detectors/descriptors shown here work well

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

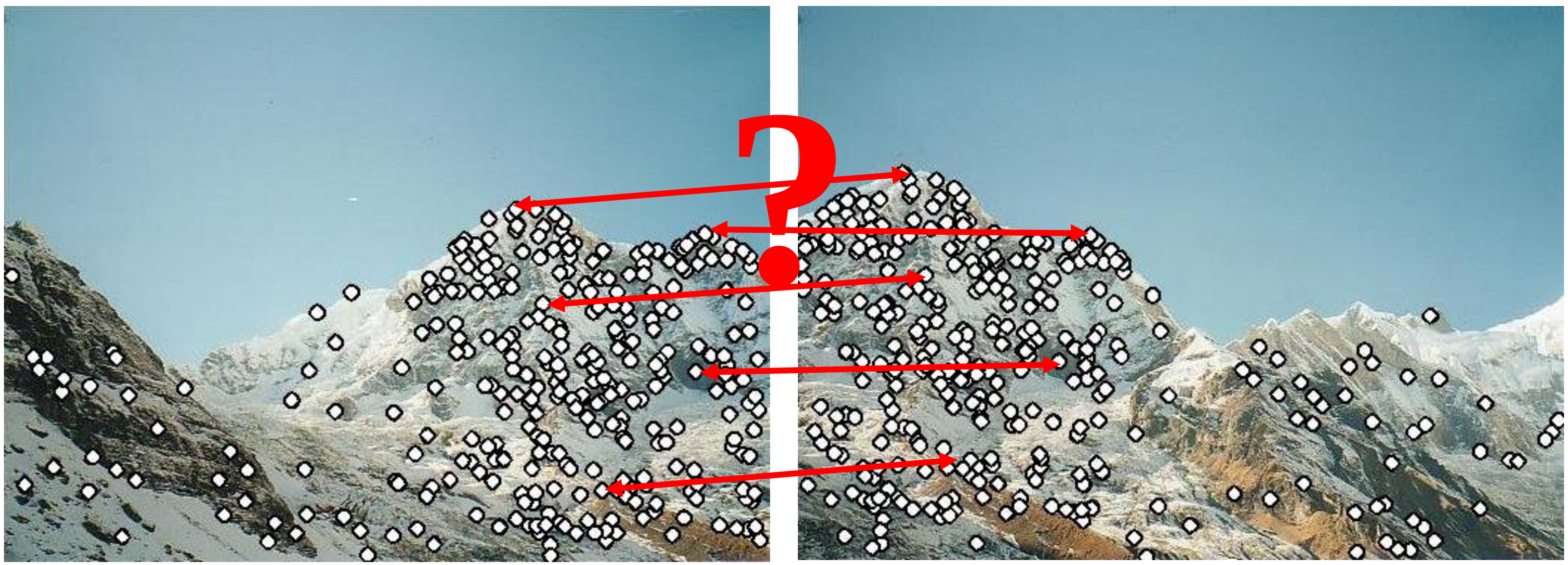
Main questions

- Where will the interest points come from?
  - What are salient features that we'll *detect* in multiple views?
- How to *describe* a local region?
- How to establish *correspondences*, i.e., compute matches?

Local descriptors

- We know how to detect points
- Next question:

How to *describe* them for matching?



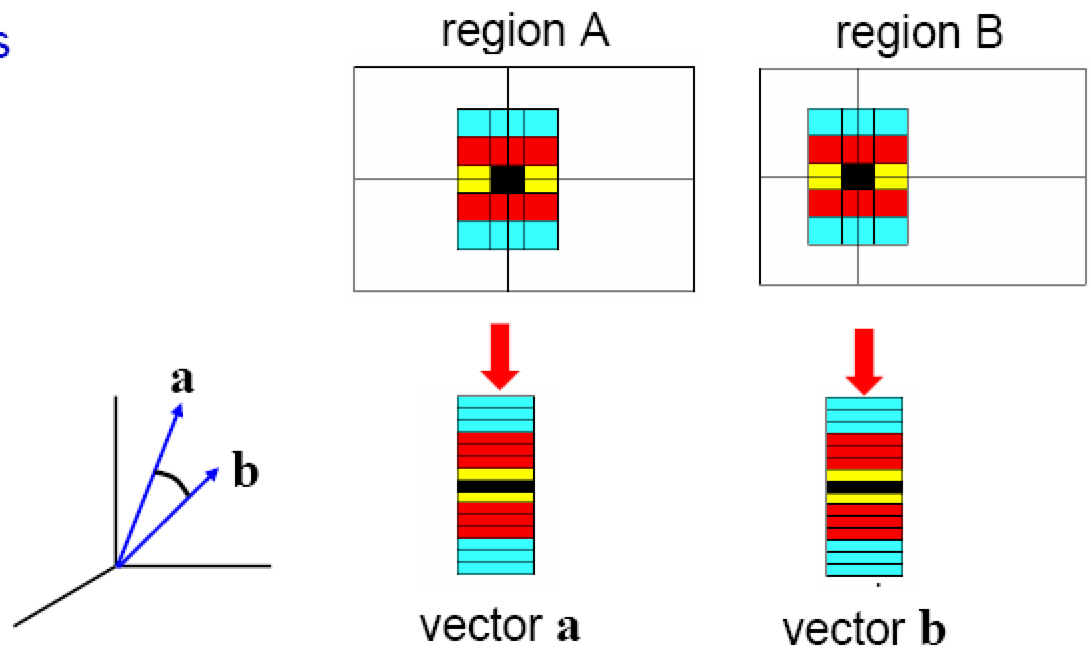
Point descriptor should be:
1. Invariant
2. Distinctive

Local descriptors

- Simplest descriptor: list of intensities within a patch.
- What is this going to be invariant to?

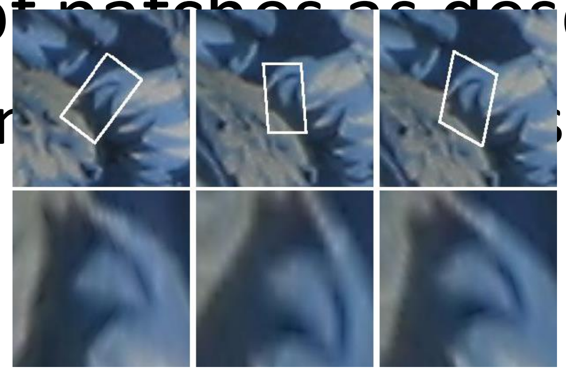
Write regions as vectors

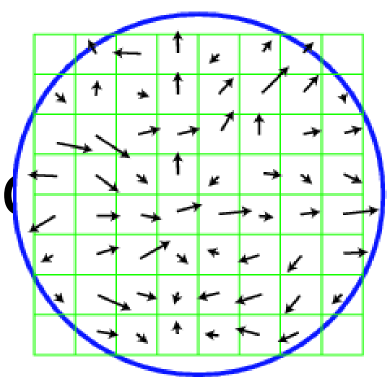
$$A \to \mathbf{a}, \;\; B \to \mathbf{b}$$



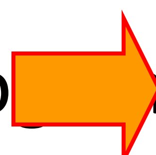
Feature descriptors

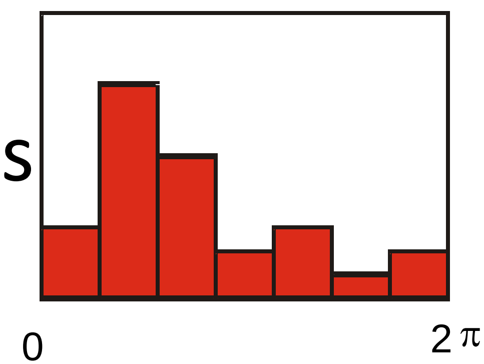
- Disadvantage of patches as descriptors:
  - Small shifts car … score a lot

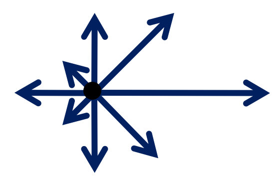




- Sc … o … ns



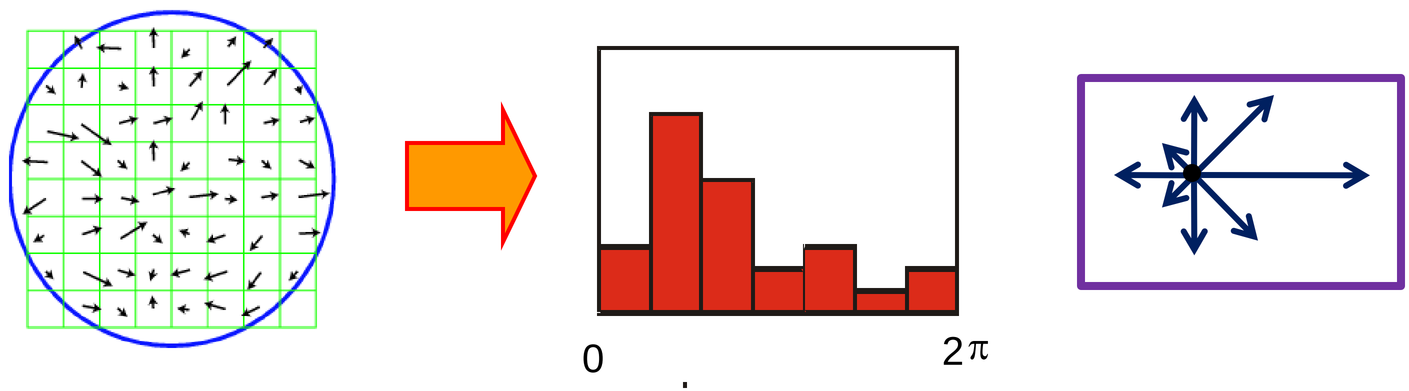


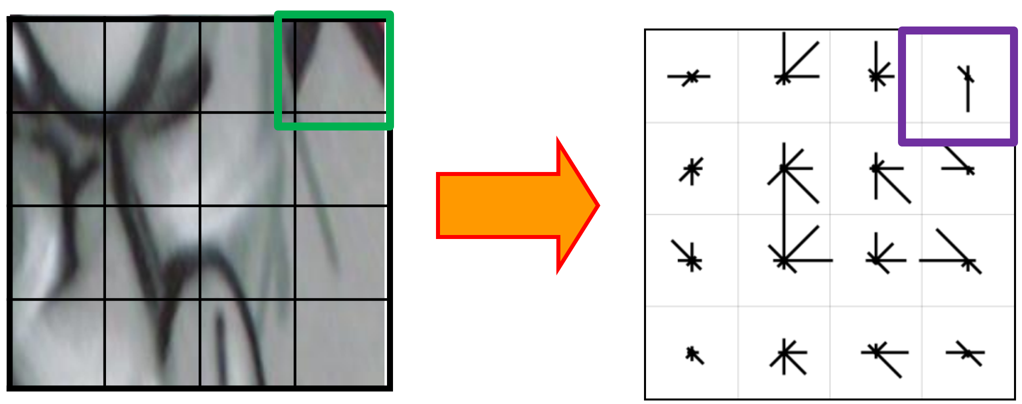


Source: Lana Lazebnik

SIFT descriptor [Lowe 2004]

- Use histograms to bin pixels within sub-patches according to their orientation.



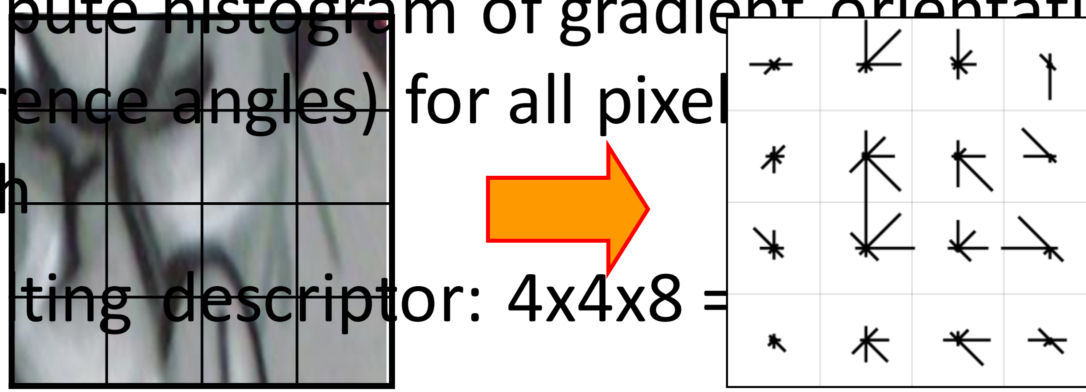


Why subpatches?

Why does SIFT have some illumination invariance?

Feature descriptors: SIFT

- **S**cale **I**nvariant **F**eature **T**ransform
- Descriptor computation:
  - Divide patch into 4x4 sub-patches: 16 cells
  - Compute histogram of gradient orientations (8 reference angles) for all pixel[illegible]h sub-patch
  - Resulting descriptor: 4x4x8 =[illegible]ions



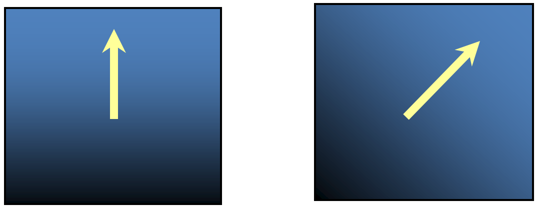
David G. Lowe. "Distinctive image features from scale-invariant keypoints." *IJCV* 60 (2), pp. 91-110, 2004.

Source: Lana Lazebnik

Rotation Invariant Descriptors

- Find local orientation

  Dominant direction of gradient for the image patch



- Rotate patch according to this angle

  This puts the patches into a canonical orientation.

Rotation Invariant Descriptors

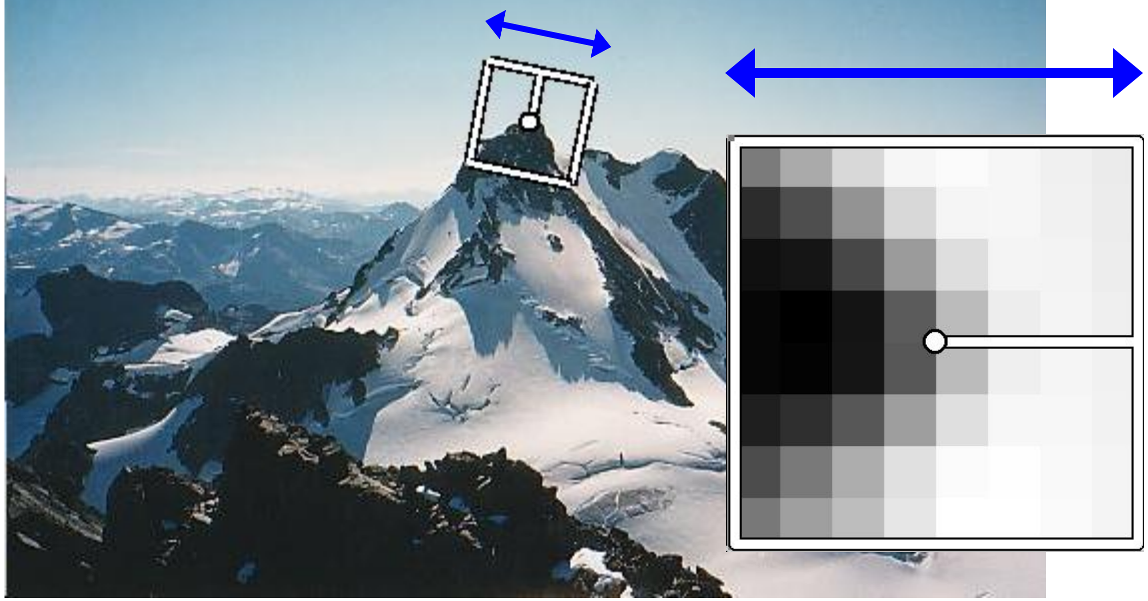
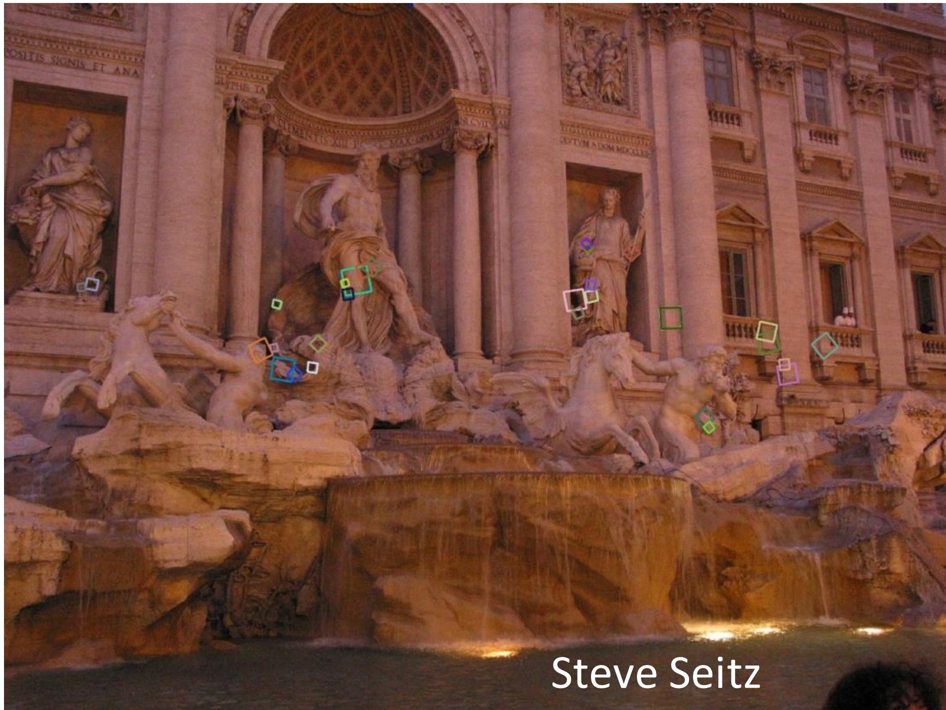


Image from Matthew Brown

Feature descriptors: SIFT

- Extraordinarily robust matching technique
  - Can handle changes in viewpoint
    - Up to about 60 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



Working with SIFT descriptors

- One image yields:
  - n 128-dimensional descriptors: each one is a histogram 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 2d points giving positions of the patches
    - [n x 2 matrix]

More on feature detection/description

Address http://www.robots.ox.ac.uk/~vgg/research/affine/

Google mikolajczyk Search Web

Affine Covariant Regions

Publications

Region detectors

- *Harris-Affine & Hessian Affine*: K. Mikolajczyk and C. Schmid, Scale and Affine invariant interest point detectors. In IJCV 1(60):63-86, 2004. PDF
- *MSER*: J.Matas, O. Chum, M. Urban, and T. Pajdla, Robust wide baseline stereo from maximally stable extremal regions. In BMVC p. 384-393, 2002. PDF
- *IBR & EBR*: T.Tuytelaars and L. Van Gool, Matching widely separated views based onaffine invariant regions. In IJCV 1 (59):61-85, 2004. PDF
- *Salient regions*: T. Kadir, A. Zisserman, and M. Brady, An affine invariant salient region detector. In ECCV p. 404-416, 2004. PDF

Region descriptors

- *SIFT*: D. Lowe, Distinctive image features from scale invariant keypoints. In IJCV 2(60):91-110, 2004. PDF

Performance evaluation

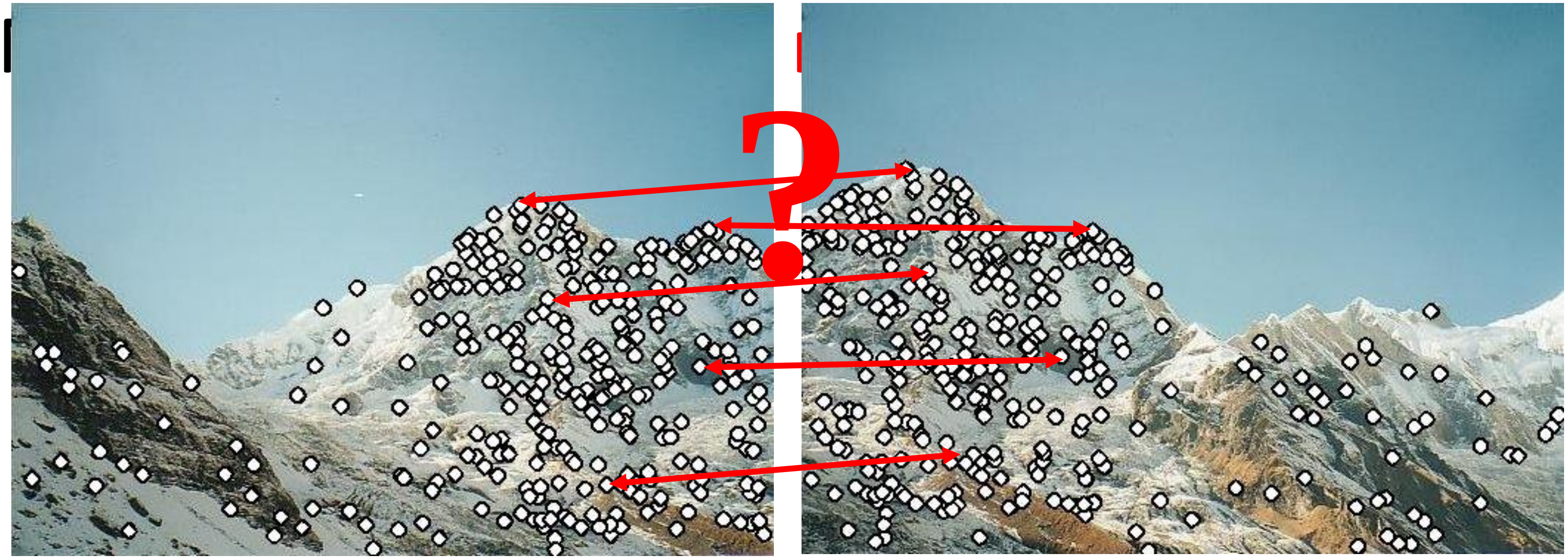
- K. Mikolajczyk, T. Tuytelaars, C. Schmid, A. Zisserman, J. Matas, F. Schaffalitzky, T. Kadir and L. Van Gool, A comparison of affine region detectors. Technical Report, accepted to IJCV. PDF
- K. Mikolajczyk, C. Schmid, A performance evaluation of local descriptors. Technical Report, accepted to PAMI. PDF

Main questions

- Where will the interest points come from?
  - What are salient features that we'll *detect* in multiple views?
- How to *describe* a local region?
- How to establish *correspondences*, i.e., compute matches?

Feature descriptors

We know how to detect **and describe** good points



Feature matching

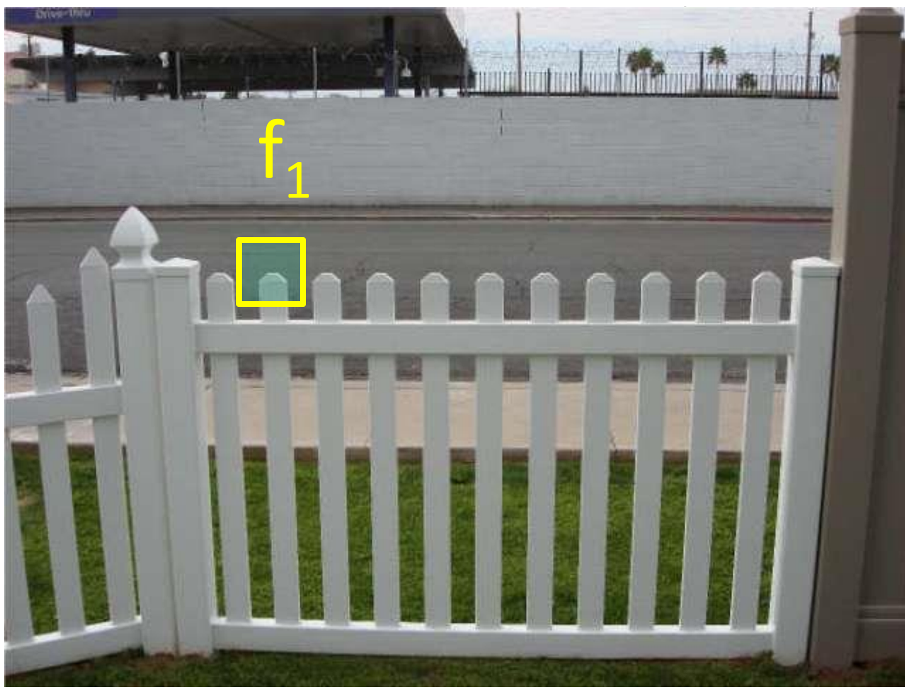
Given a feature in I_1, how to find the best match in I_2?

1. Define distance function that compares two descriptors
2. Test all the features in I_2, find the one with min distance

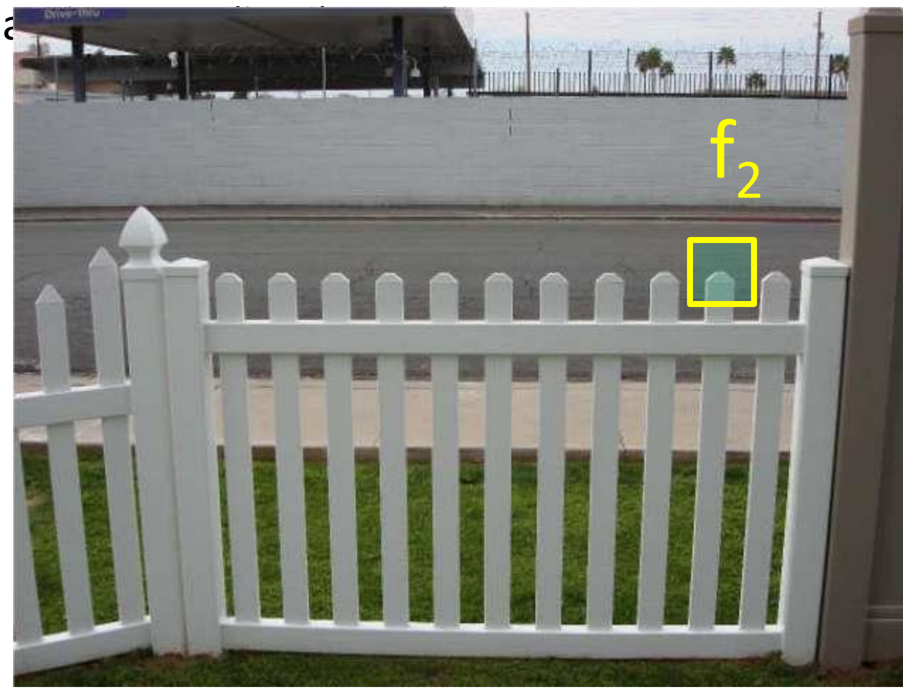
Feature distance

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

- Simple approach is $SSD(f_1, f_2)$
  - sum of square differences between entries of the two descriptors
  - ery a



I_1



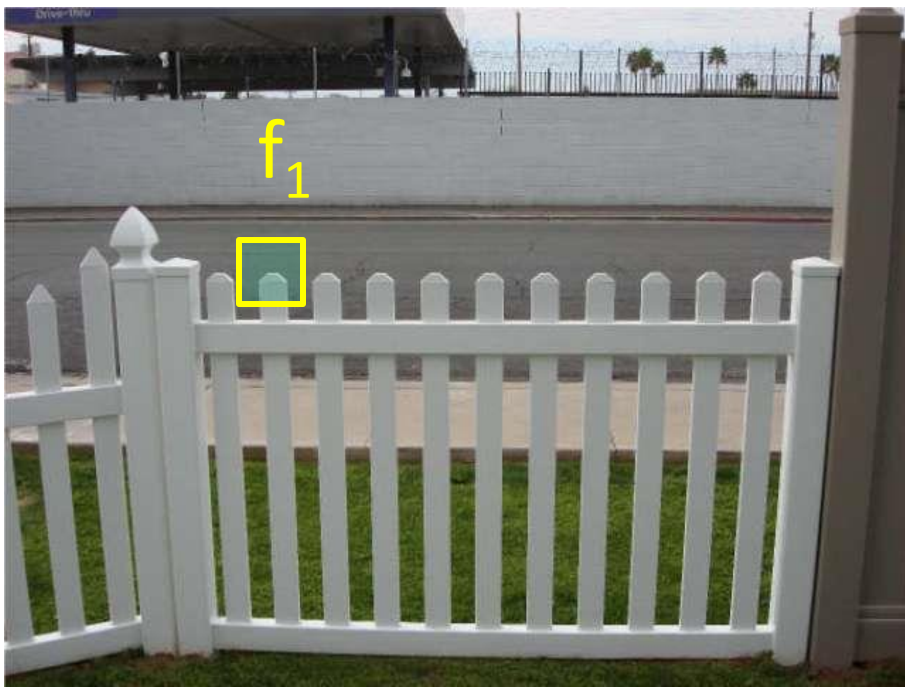
I_2

Feature distance

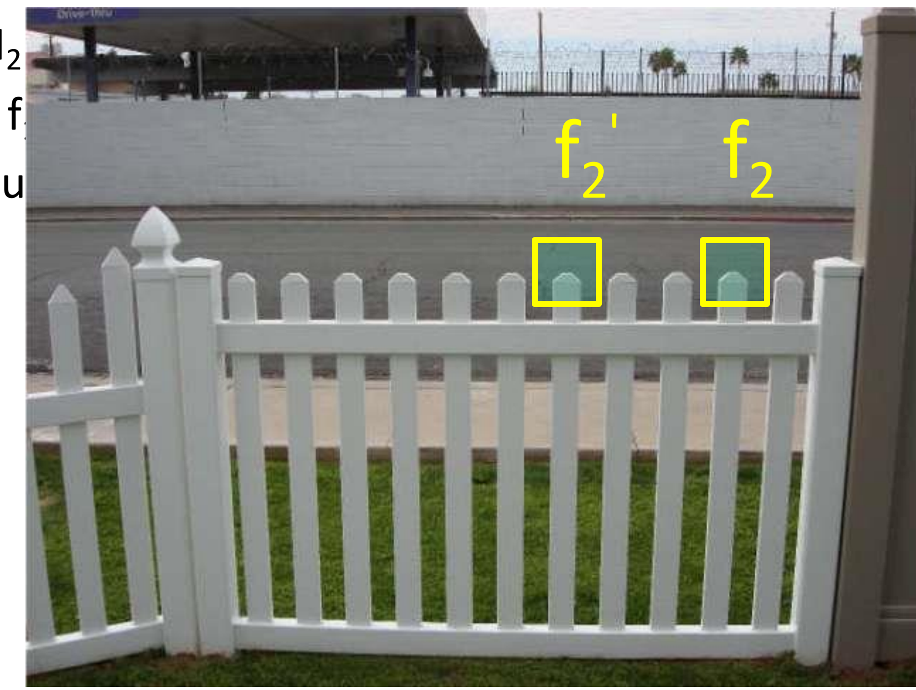
How to define the difference between two features f_1, f_2?

- Better approach: ratio distance = $SSD(f_1, f_2)$ / $SSD(f_1, f_2')$

in I_2
to f
bigu



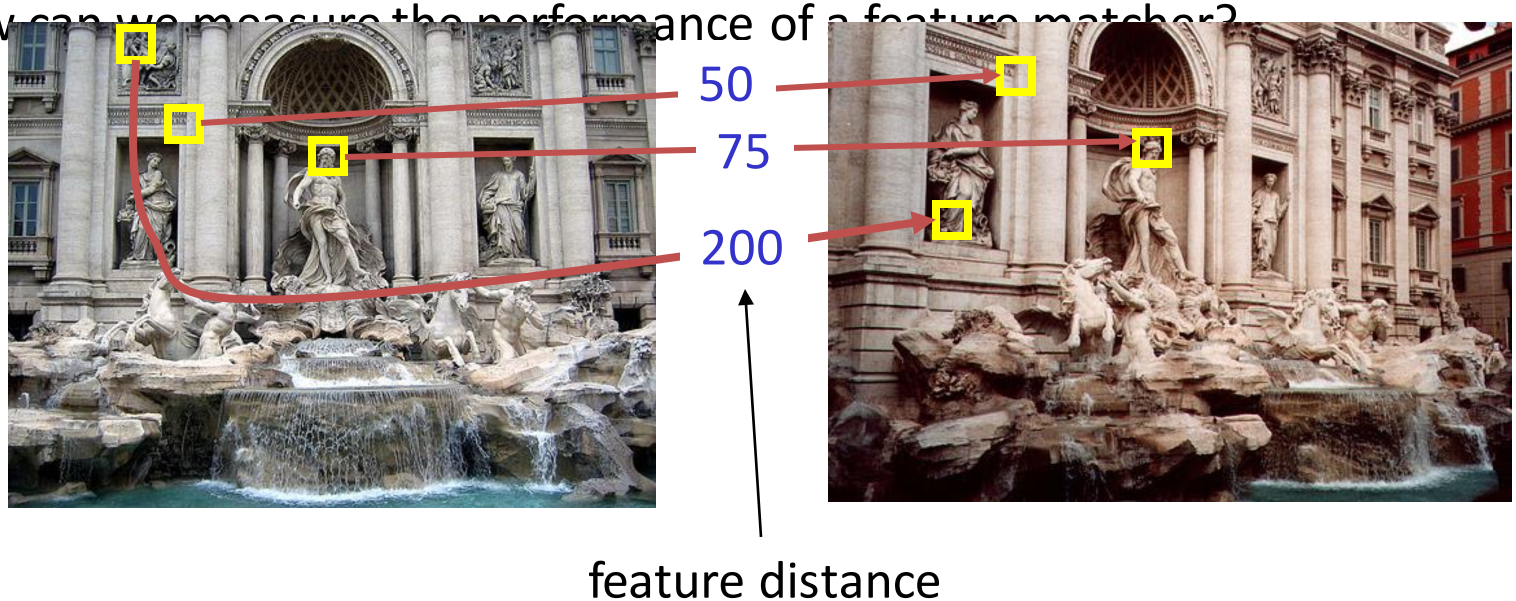
I_1



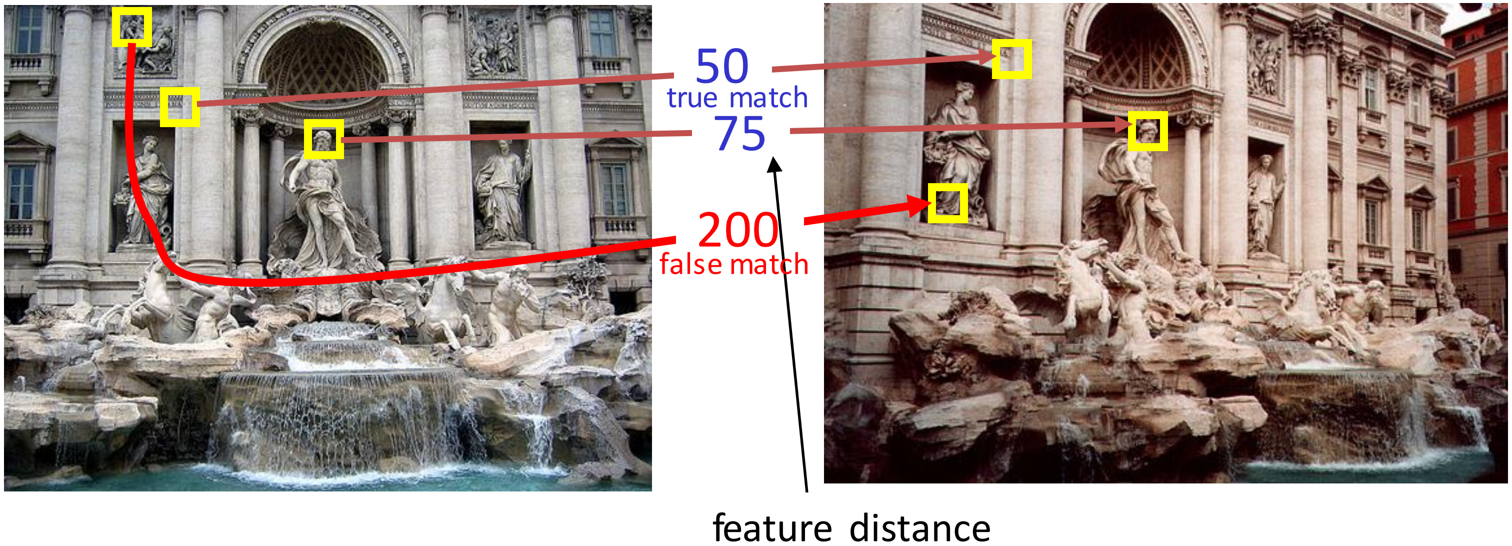
I_2

Evaluating the results

How can we measure the performance of a feature matcher?



True/false positives



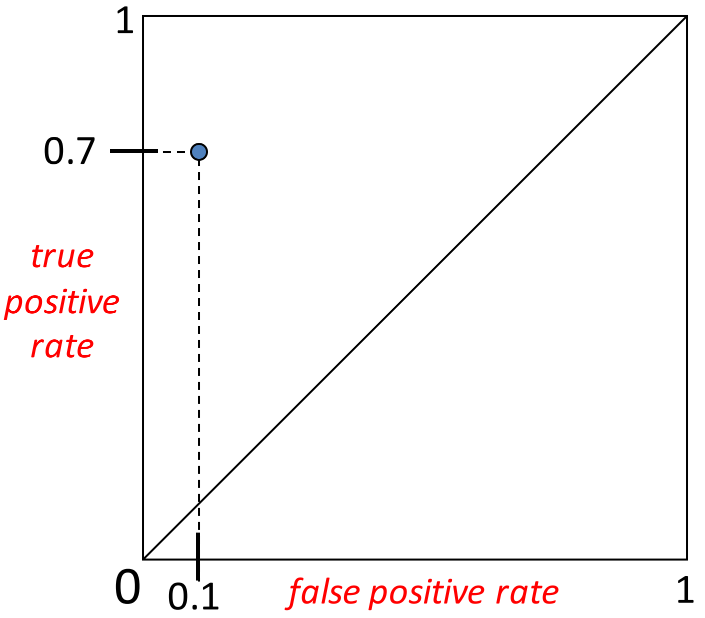
The distance threshold affects performance

- 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?

Evaluating the results

How can we measure the performance of a feature matcher?

$$\text{true positive rate} = \frac{\#\ \text{true positives}}{\#\ \text{matching features (positives)}}$$



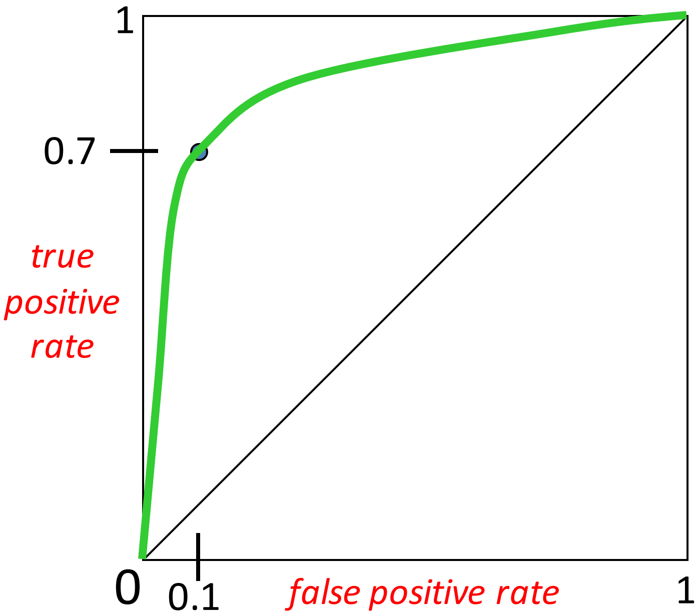
$$\text{false positive rate} = \frac{\#\ \text{false positives}}{\#\ \text{unmatched features (negatives)}}$$

Evaluating the results

How can we measure the performance of a feature matcher?

ROC curve **("Receiver Operator Characteristic")**

$$\frac{\#\text{ true positives}}{\#\text{ matching features (positives)}}$$



$$\frac{\#\text{ false positives}}{\#\text{ unmatched features (negatives)}}$$

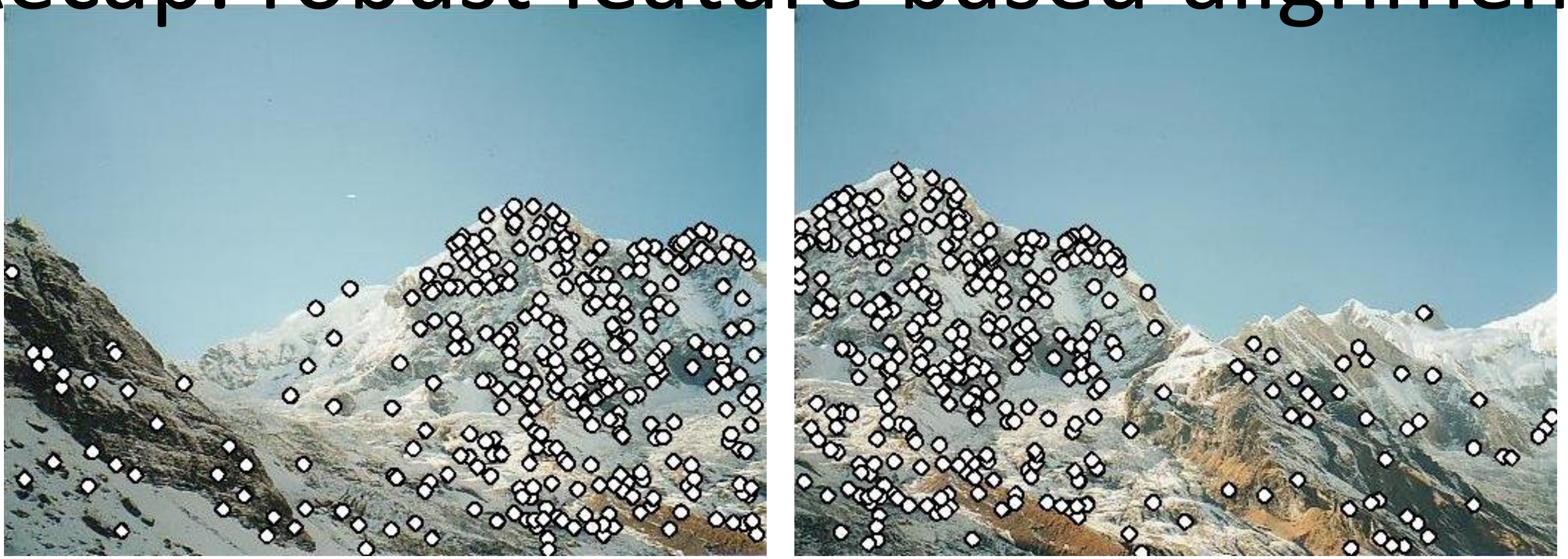
ROC Curves

- Generated by counting # current/incorrect matches, for different threholds
- Want to maximize area under the curve (AUC)
- Useful for comparing different feature matching methods
- For more info: http://en.wikipedia.org/wiki/Receiver_operating_characteristic

Recap: robust feature-based alignment

Source: L. Lazebnik

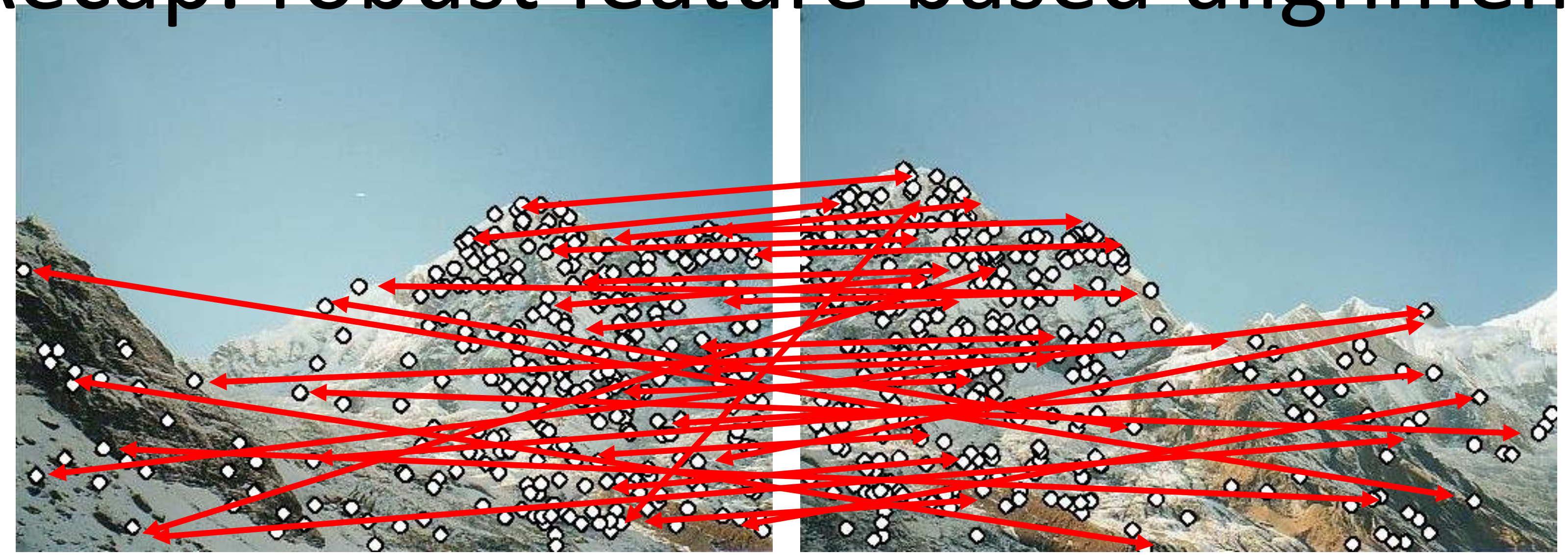
Recap: robust feature-based alignment



- Extract features

Source: L. Lazebnik

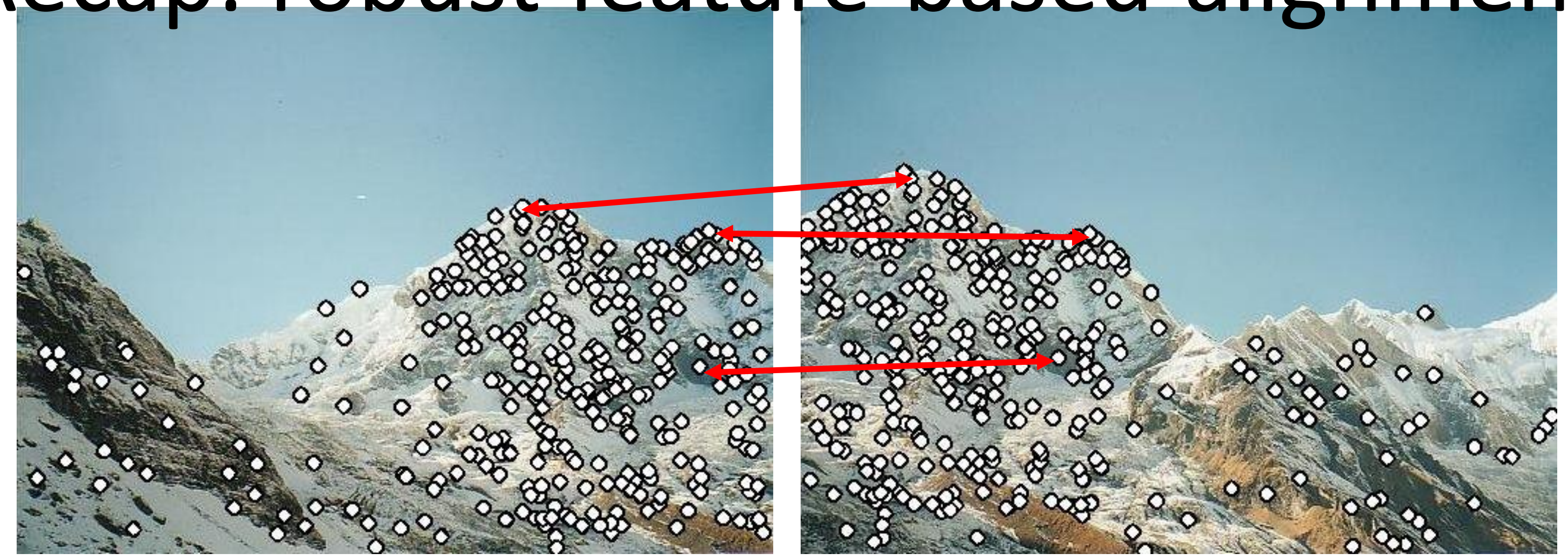
Recap: robust feature-based alignment



- Extract features
- Compute *putative matches*

Source: L. Lazebnik

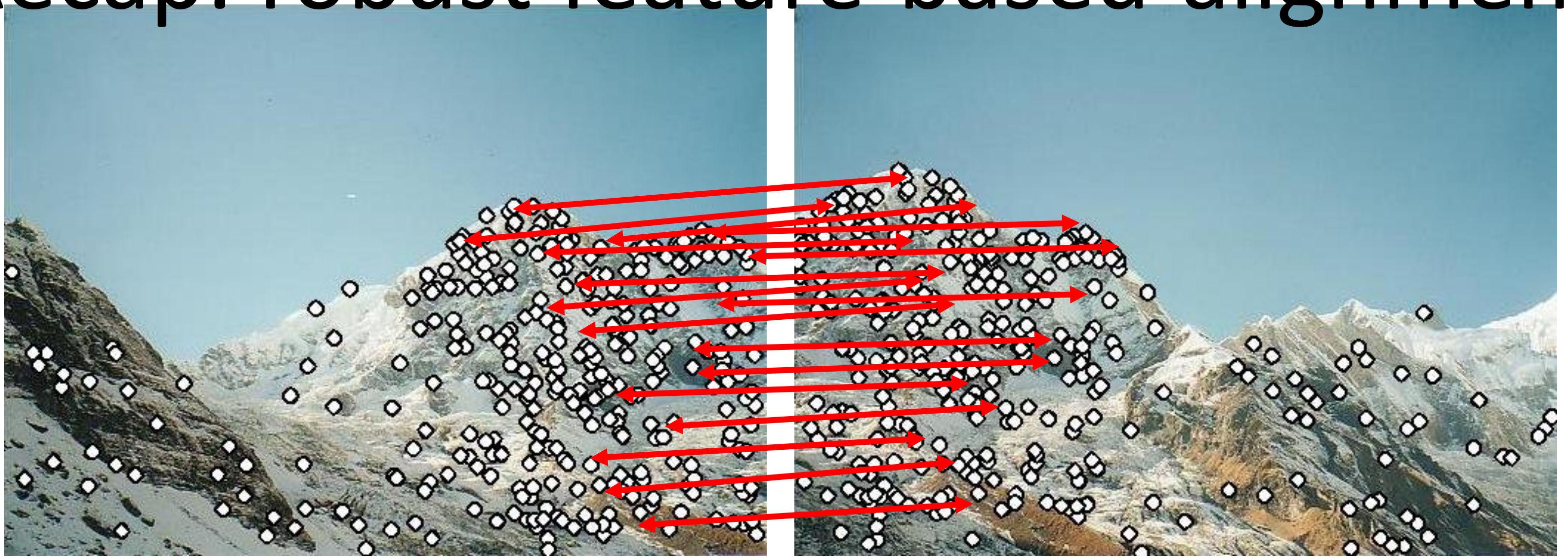
Recap: robust feature-based alignment



- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation *T* (small group of putative matches that are related by *T*)

Source: L. Lazebnik

Recap: robust feature-based alignment



- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation T (small group of putative matches that are related by T)
  - *Verify* transformation (search for other matches consistent with T)

Source: L. Lazebnik

Recap: robust feature-based alignment

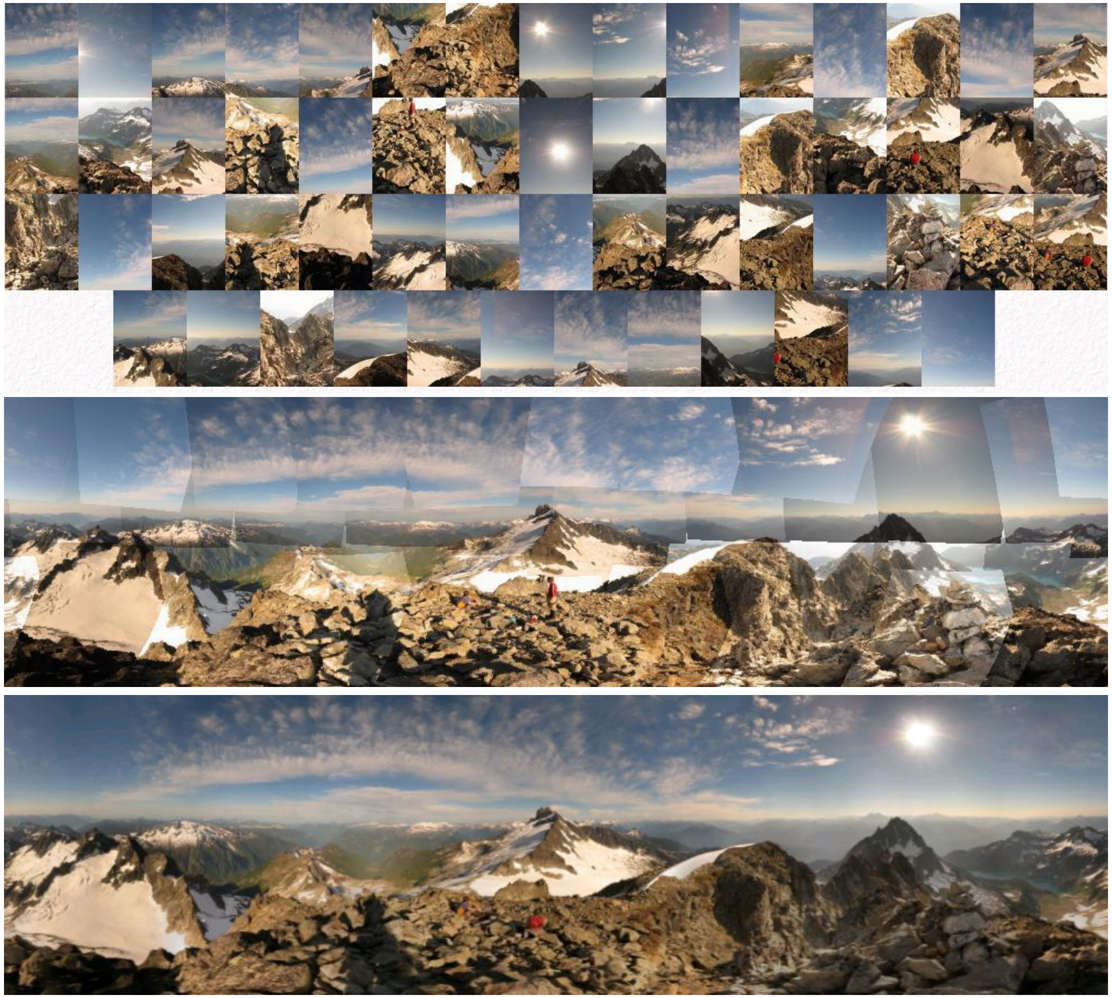
- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation T (small group of putative matches that are related by T)
  - *Verify* transformation (search for other matches consistent with T)

Source: L. Lazebnik

Applications of local invariant features

- Wide baseline stereo
- Motion tracking
- Panoramas
- Mobile robot navigation
- 3D reconstruction
- Recognition
- …

Automatic mosaicing

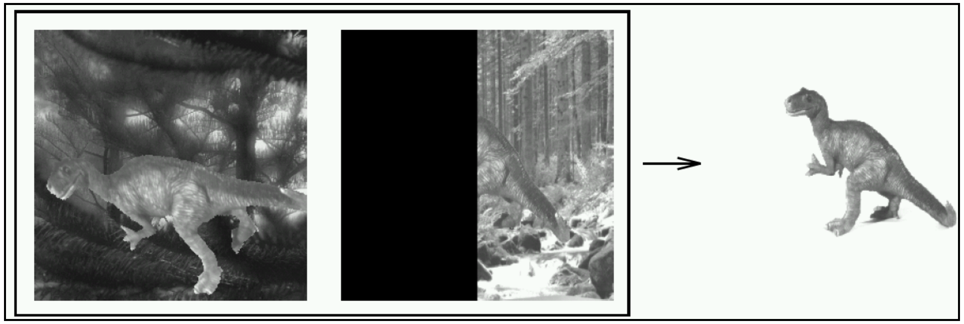


http://www.cs.ubc.ca/~mbrown/autostitch/autostitch.html

Wide baseline stereo

[Image from T. Tuytelaars ECCV 2006 tutorial]

Recognition of specific objects, scenes



Schmid and Mohr 1997

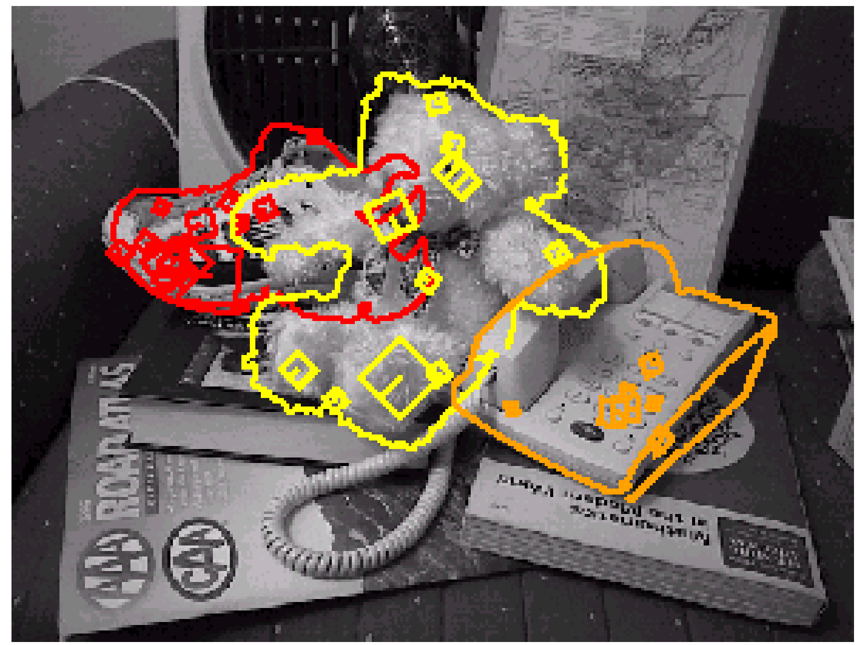
Sivic and Zisserman, 2003

Rothganger et al. 2003

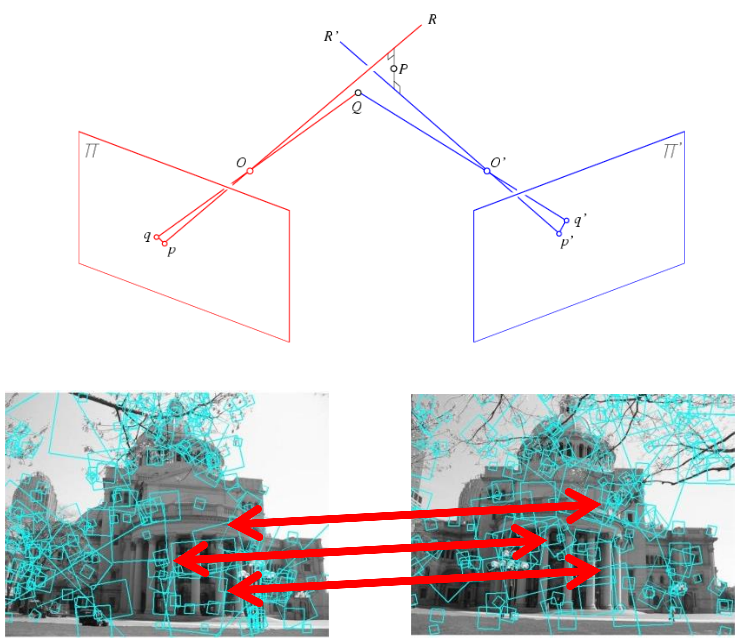
Lowe 2002

Kristen Grauman

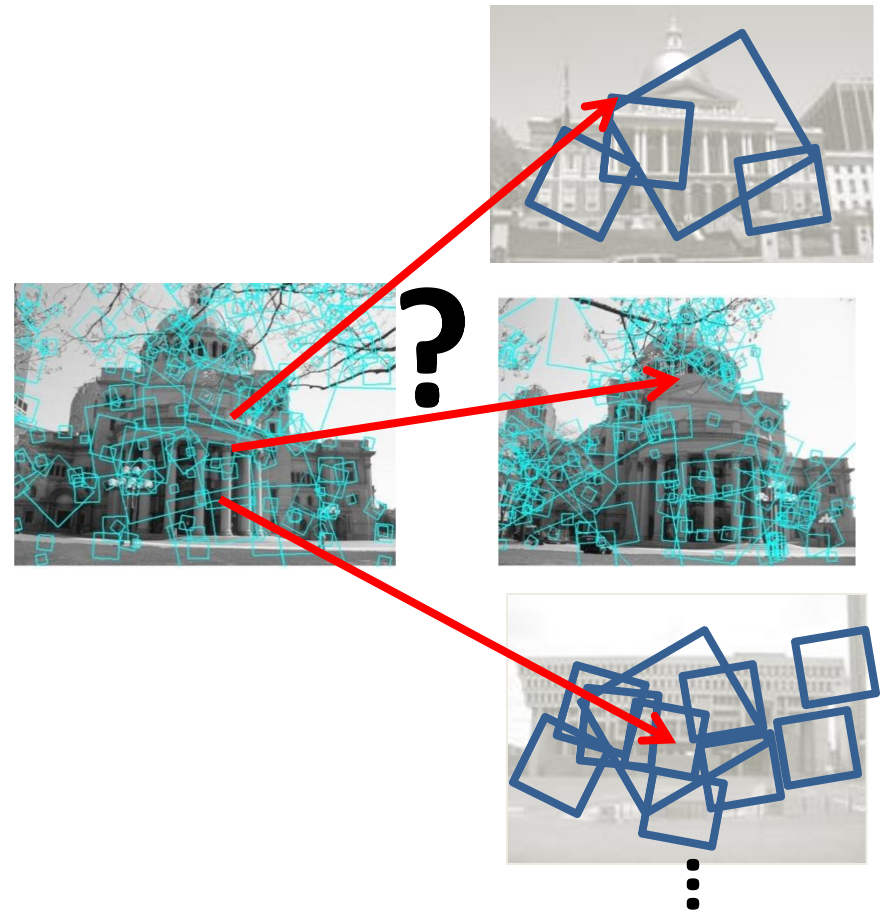
Object recognition (David Lowe)



Multi-view matching



vs

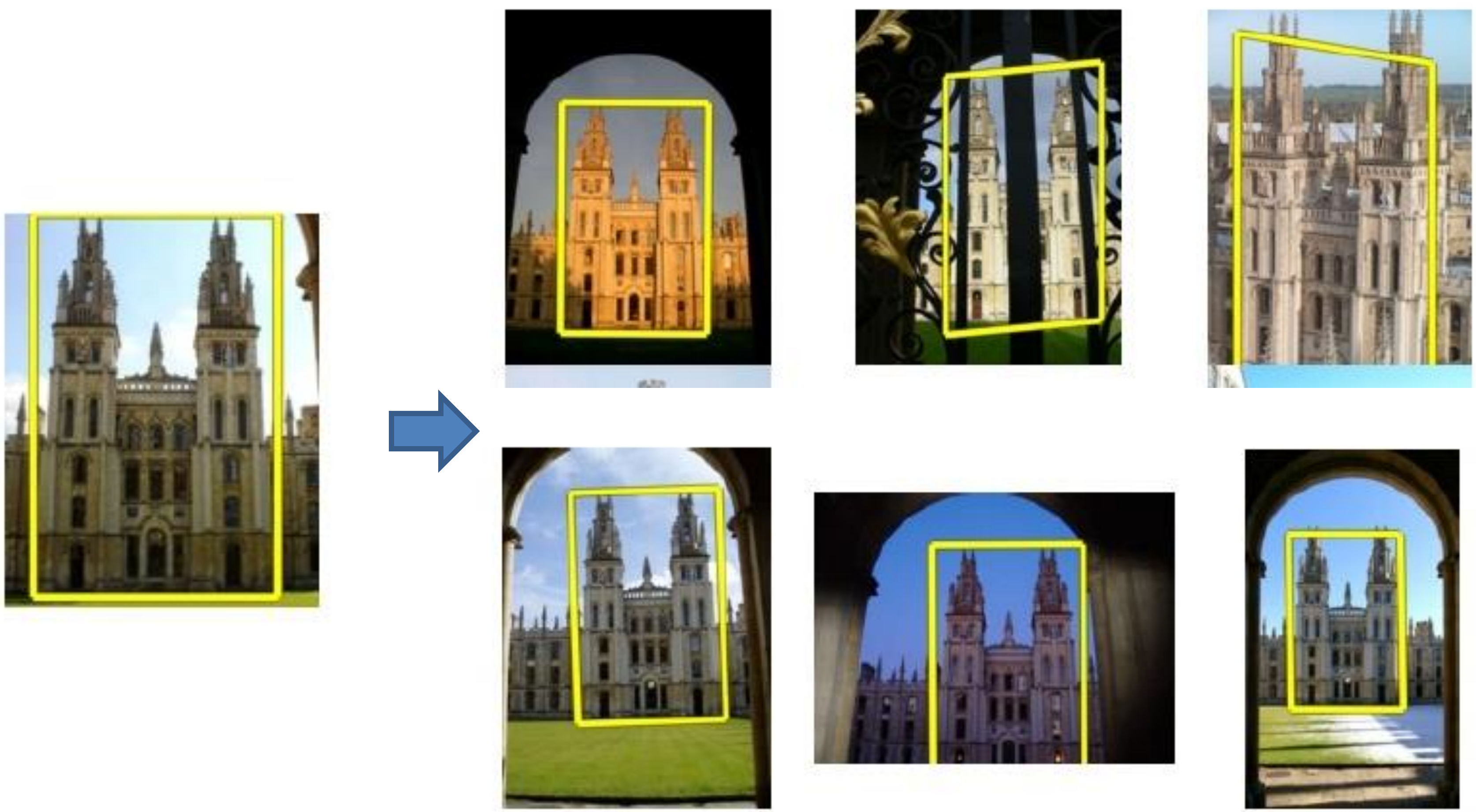


Matching two given views for depth

Search for a matching view for recognition

Kristen Grauman

How to quickly find images in a large database that match a given image region?

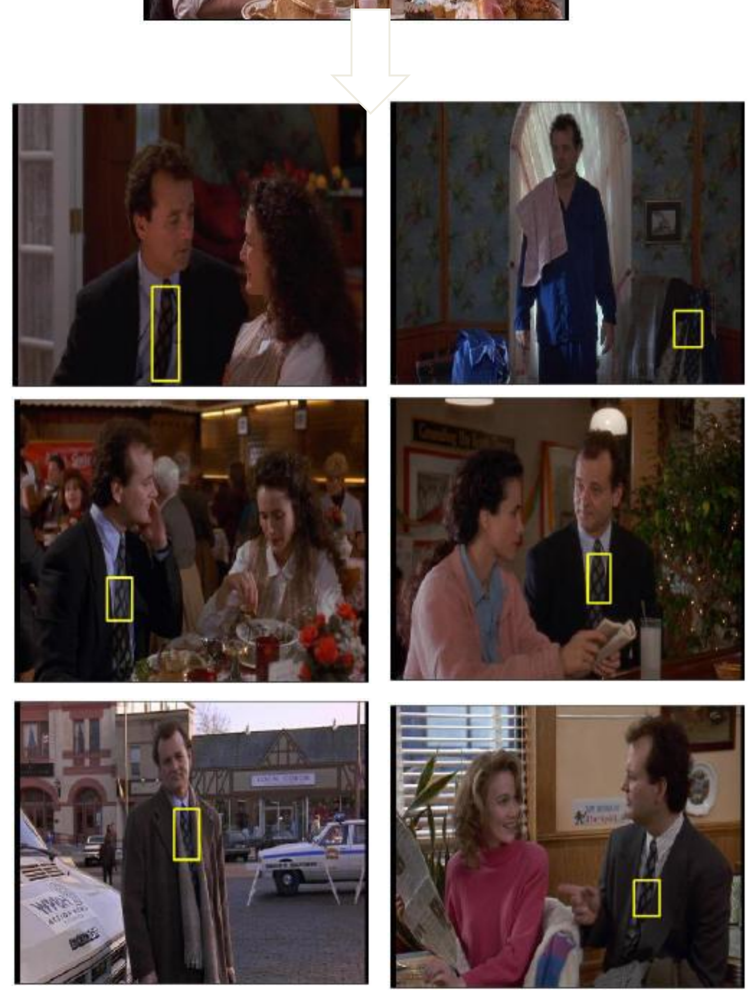


Video Google Sy

1. Collect all words within query region
2. Inverted file index to find relevant frames
3. Compare word counts
4. Spatial verification

Sivic & Zisserman, ICCV 2003

- Demo online at :
  http://www.robots.ox.ac.uk/~vgg/research/vgoogle/index.html



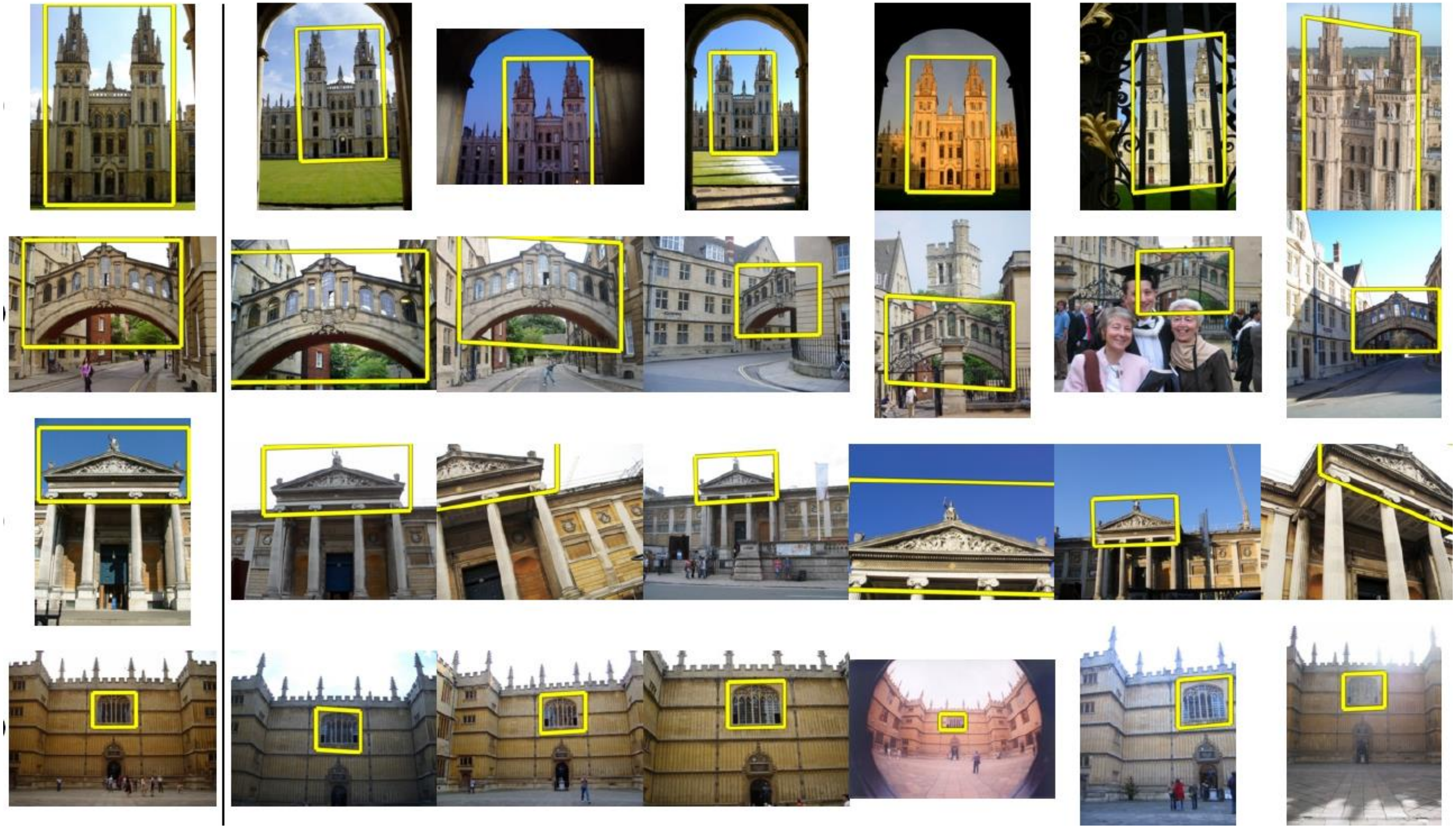
Kristen Grauman

Example Applications

Mobile tourist guide
- **Self-localization**
- **Object/building recognition**
- **Photo/video augmentation**

[Quack, Leibe, Van Gool, CIVR'08]

Application: Large-Scale Retrieval



Query Results from 5k Flickr images (demo available for 100k set)

[Philbin CVPR'07]

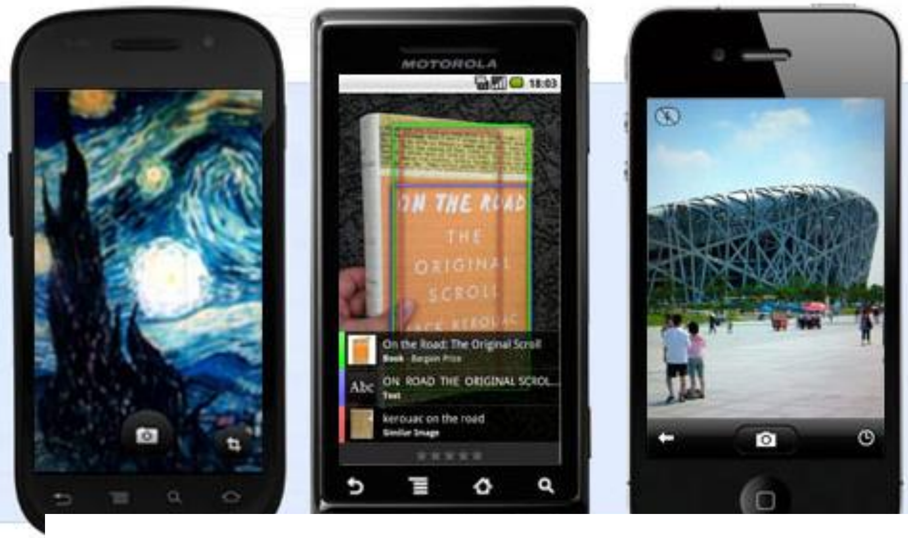
Application: Image Auto-Annotation

Left: Wikipedia image
Right: closest match from Flickr

[Quack CIVR'08]

Google Goggles

Use pictures to search the web. Watch a video



Get Google Goggles

Android (1.6+ required)

Download from Android Market.

Send Goggles to Android phone

New! **iPhone (iOS 4.0 required)**

Download from the App Store.

Send Goggles to iPhone

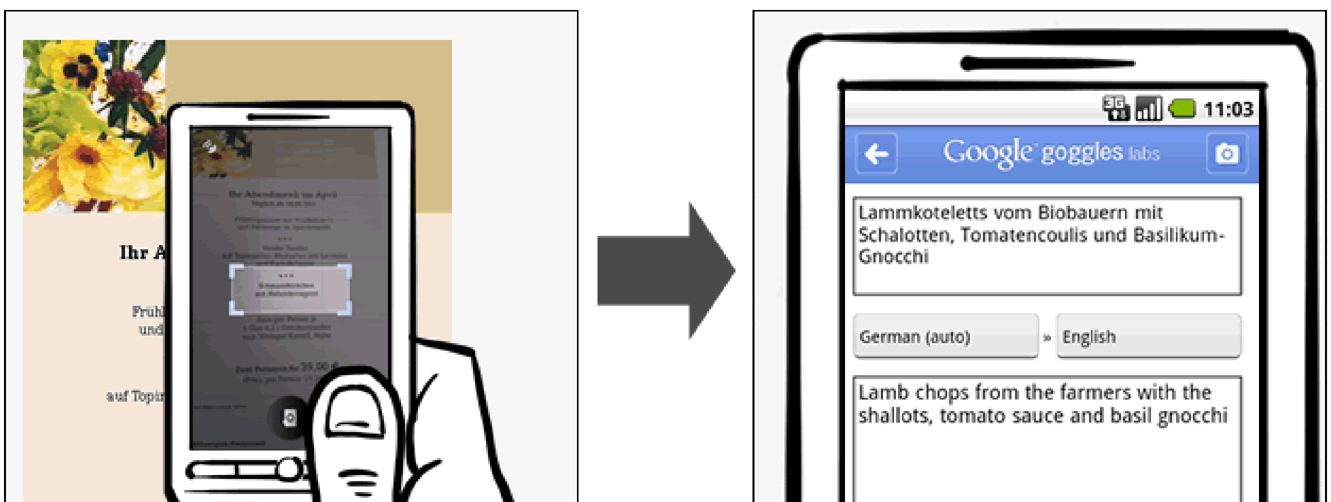
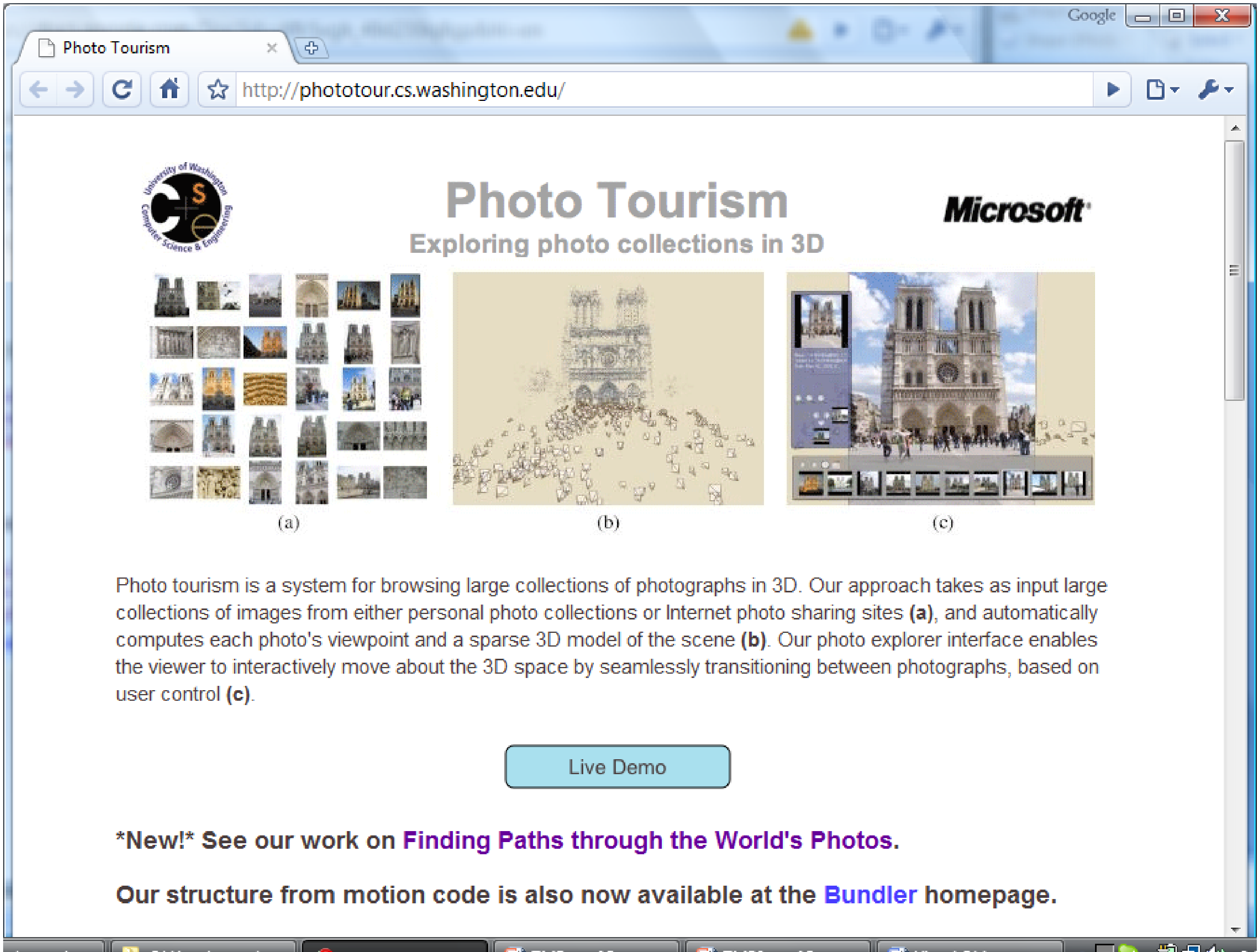


Photo Tourism



Slide Credits

- Trevor Darrell
- Bill Freeman
- Kristen Grauman
- Steve Seitz
- Ivan Laptev
- Tinne Tuytelaars
- James Hays
- Svetlana Lazebnik
- Derek Hoiem