Computer Vision: Image Features

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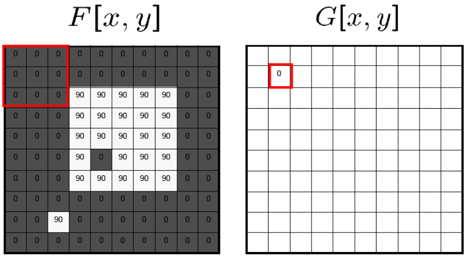
TTI Chicago

Jan 17, 2013

What did we see in class last week?

Last classes

- Image formation
- Filtering: convolution vs correlation



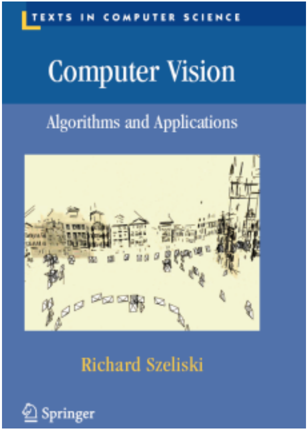
- Separable filters
- Computing edges
- Steerable filters
- Other transformations

Today's lecture ...

- **Local features**:
  - Interest point detection
  - Descriptors
  - Matching

Material

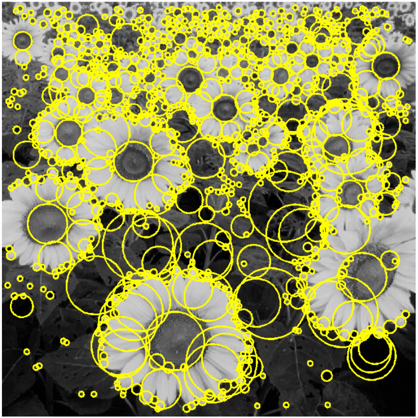
- Chapter 3 and 4 of Rich Szeliski book



- Available online here

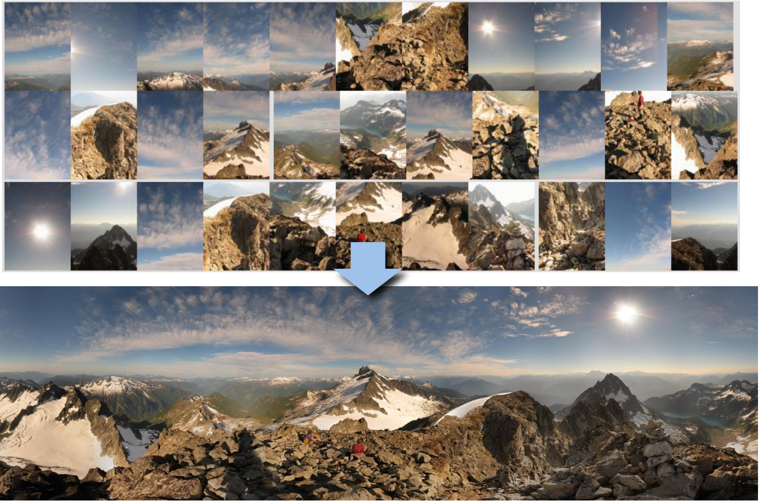
Local features

Feature extraction: Corners and blobs



[Source: N. Snavely]

Motivation: Automatic panoramas



Credit: Matt Brown

Motivation: Automatic panoramas

HD View
http://research.microsoft.com/en-us/um/redmond/groups/ivm/HDView/HDGigapixel.htm

Also see GigaPan:
http://gigapan.org/

Why extract features?

How to combine these two images to form a panorama?

Figure: Two images

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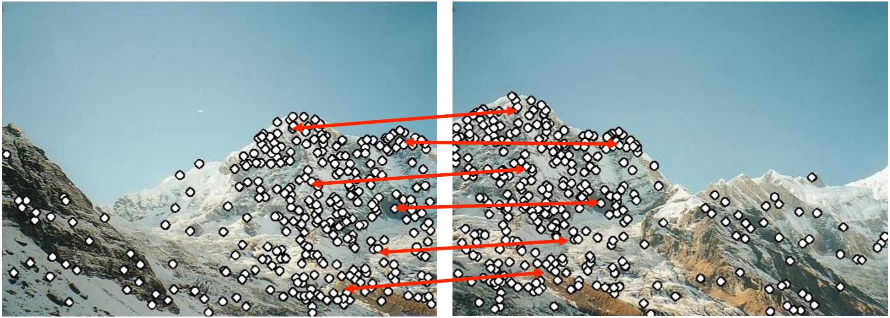


Figure: Feature extraction and matching

Why extract features?

How to combine these two images to form a panorama?

Figure: Image aligment

Image matching

by Diva Sian

by swashford

[Source: N. Snavely]

Harder Case

- Why is this harder?

by Diva Sian

by scgbt

[Source: N. Snavely]

Harder Still

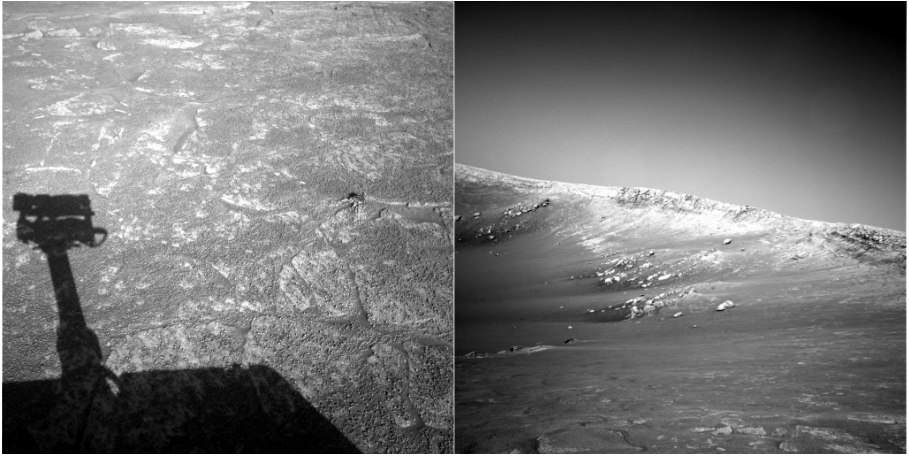


Figure: NASA Mars Rover images

[Source: N. Snavely]

Look for tiny squares ...

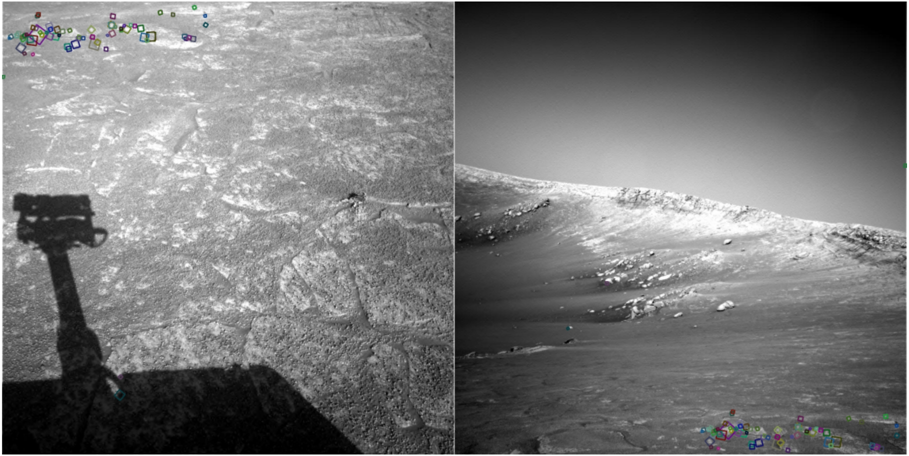
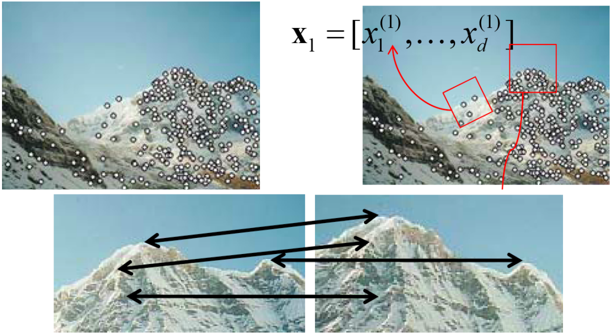


Figure: NASA Mars Rover images with SIFT feature matches

[Source: N. Snavely]

Local features

- **Detection**: Identify the interest points.
- **Description**: Extract vector feature descriptor around each interest point.
- **Matching**: Determine correspondence between descriptors in two views.



[Source: K. Grauman]

Two approaches to Find Features

- **Tracking**: searches in a small neighborhood around each detected feature.
  - When images are taken from nearby viewpoints
  - or in successive times (e.g., video sequence)
- **Matching**: Determine correspondence between descriptors in two views.
  - When a large motion can happen, e.g., panoramas, wide baseline stereo, object recognition.

Goal: interest operator repeatability

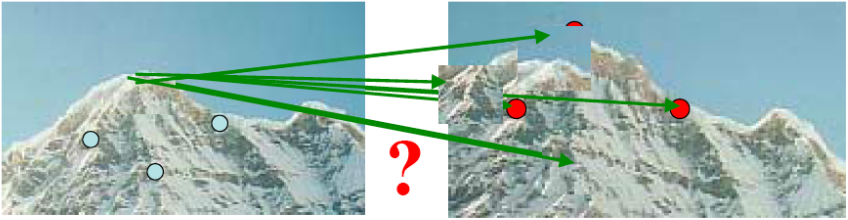
- We want to detect (at least some of) the **same points** in both images.
- We have to be able to run the detection procedure **independently per image**.

Figure: No chance to find the true matches

[Source: K. Grauman]

Goal: descriptor distinctiveness

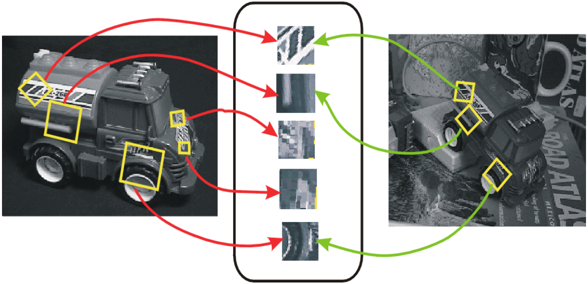
- We want to be able to **reliably match**, i.e., determine which point goes with which.
- Must provide some **invariance** to **geometric** and **photometric** differences between the two views.



[Source: K. Grauman]

Invariant local features

- **geometric invariance**: translation, rotation, scale
- **photometric invariance**: brightness, exposure,



Feature Descriptors

[Source: N. Snavely]

Advantages of local features

- **Locality:** features are local, so robust to occlusion and clutter
- **Quantity:** hundreds or thousands in a single image
- **Distinctiveness:** can differentiate a large database of objects
- **Efficiency:** real-time performance achievable

[Source: N. Snavely]

More motivation

Feature points are used for:

- Image alignment (e.g., mosaics)
- 3D reconstruction
- Motion tracking
- Object recognition
- Indexing and database retrieval
- Robot navigation
- ...

[Source: N. Snavely]

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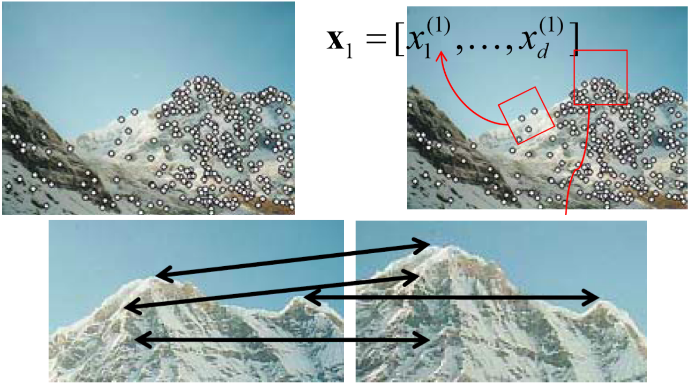

[Source: K. Grauman]

What points to choose?

[Source: K. Grauman]

Want uniqueness

- Look for image regions that are **unusual**: lead to unambiguous matches in other images
- How to define "unusual"?

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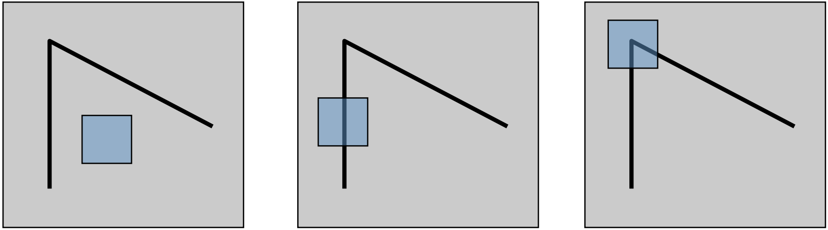
Local measure of uniqueness

Suppose we only consider a small window of pixels

- What defines whether a feature is a good or bad candidate?

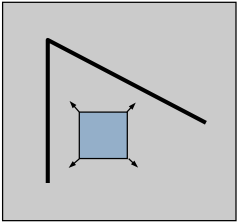


[Source: S. Seitz, D. Frolova, D. Simakov]

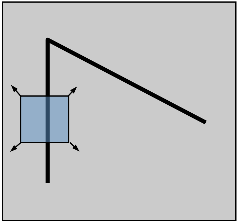
Local measure of feature uniqueness

Suppose we only consider a small window of pixels

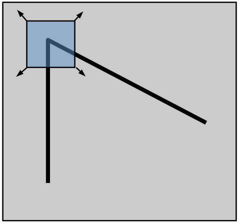
- How does the window change when you shift it?
- Shifting the window in any direction causes a big change



"flat" region:
no change in all directions



"edge":
no change along the edge direction



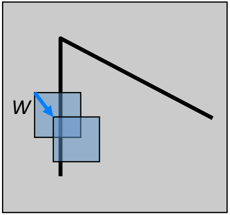
"corner":
significant change in all directions

Credit: S. Seitz, D. Frolova, D. Simakov

A Simple Matching Criteria

Consider shifting the window W by (u, v)

- how do the pixels in W change?
- compare each pixel before and after by **summing up the squared differences** (SSD)



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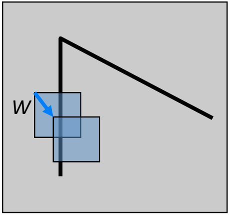

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A Simple Weighted Matching Criteria

- Compare two image patches using **(weighted) summed square difference**

$$E_{WSSD}(\mathbf{u}) = \sum_i w(\mathbf{p}_i)[I_1(\mathbf{p}_i + \mathbf{u}) - I_0(\mathbf{p}_i)]^2$$

  with I_0 and I_1 two images being compared, $\mathbf{u}(u_x, u_y)$ a displacement vector, $w(\mathbf{p})$ a spatially varying weighting function, and the summation i is over all the pixels in the patch.

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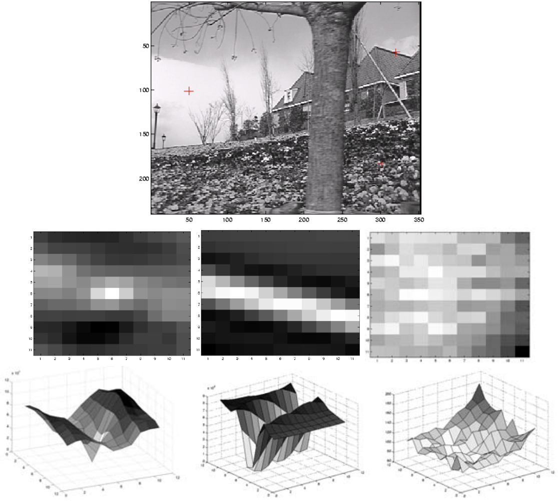
Which one is better?



[Source: R. Szeliski]

How to select and interest point?

- Small motion assumption
- Using a Taylor Series expansion $I_0(\mathbf{p}_i + \Delta\mathbf{u}) \approx I_0(\mathbf{p}_i) + \nabla I_0(\mathbf{p}_i)\Delta\mathbf{u}$ with

$$\nabla I_0(\mathbf{p}_i) = \left(\frac{\partial I_0}{\partial x}, \frac{\partial I_0}{\partial y}\right)(\mathbf{p}_i)$$

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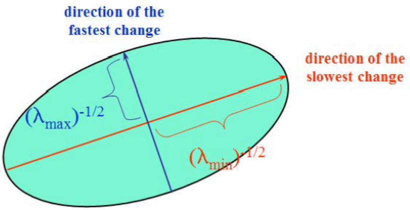
More on selection

- The autocorrelation is $E_{AC}(\Delta\mathbf{u}) = \Delta\mathbf{u}^T\mathbf{A}\Delta\mathbf{u}$, with

$$\mathbf{A} = \sum_u \sum_v w(u,v) \begin{bmatrix} I_x^2 & I_x I_y \\ I_y I_x & I_y^2 \end{bmatrix} = w * \begin{bmatrix} I_x^2 & I_x I_y \\ I_y I_x & I_y^2 \end{bmatrix}$$

  where we have replaced the weighted summations with discrete convolutions with the weighting kernel w.

- $\mathbf{A}$ can be interpreted as a tensor where the outer products of the gradients are convolved with a weighting function.
- Eigenvalues a notion of uncertainty



[Source: R. Szeliski]

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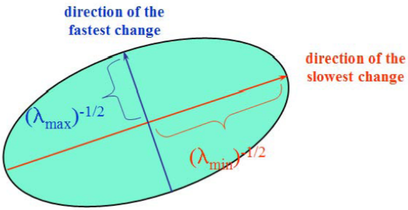

[Source: R. Szeliski]

Quick review on eigenvalue/eigenvector

- The **eigenvectors** of a matrix $\mathbf{A}$ are the vectors $\mathbf{x}$ that satisfy

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  with λ a scalar call the **eigenvalue**

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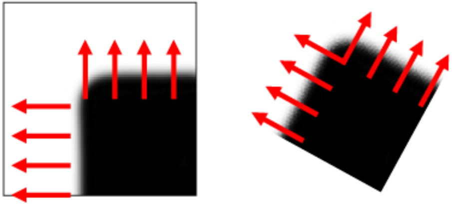
[Source: N. Snavely]

Eigenvalues a notion of uncertainty

- **A** is symmetric

$$\mathbf{A} = \mathbf{U} \begin{bmatrix} \lambda_0 & 0 \\ 0 & \lambda_1 \end{bmatrix} \mathbf{U}^T \quad \text{with} \quad \mathbf{A}\mathbf{u}_i = \lambda_i \mathbf{u}_i$$

- The eigenvalues of **A** reveal the amount of intensity change in the two principal orthogonal gradient directions in the window.
- How is this matrix for



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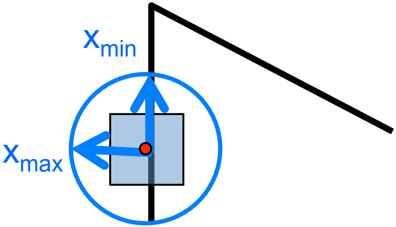
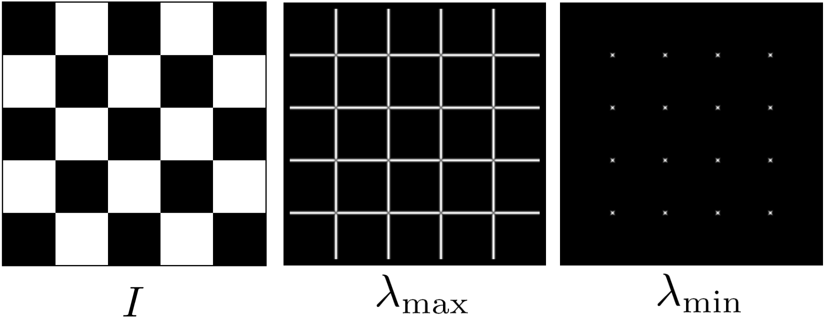


Eigenvalues and eigenvectors of $\mathbf{A}$

- $\mathbf{x}_{max}$ = direction of largest increase in E
- λ_{max} = amount of increase in direction $\mathbf{x}_{max}$
- $\mathbf{x}_{max}$ = direction of smallest increase in E
- λ_{min} = amount of increase in direction $\mathbf{x}_{min}$

[Source: N. Snavely]

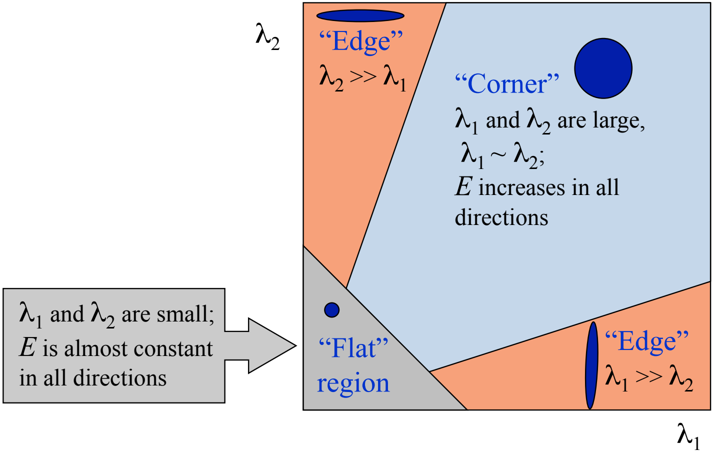
Example



[Source: N. Snavely]

Interpreting the eigenvalues

Classification of image points using eigenvalues of **A**:



[Source: N. Snavely]

Local Feature Selection Criteria

- Shi and Tomasi, 94 proposed the smallest eigenvalue of **A**, i.e., $\lambda_0^{-1/2}$, which is a rotationally invariant measure
- Harris and Stephens, 88 is rotationally invariant and downweights edge-like features where $\lambda_1 \gg \lambda_0$

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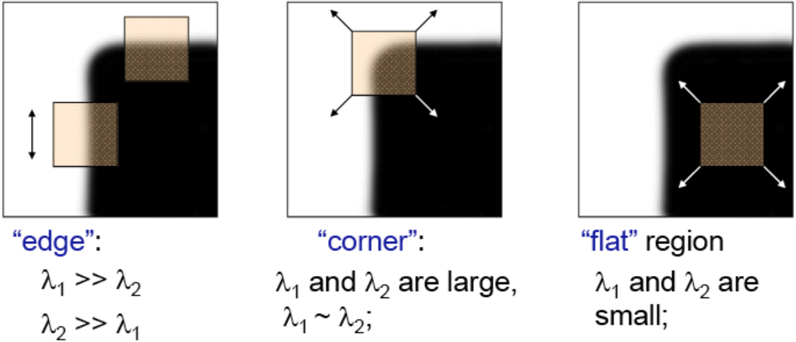


[Source: K. Grauman]

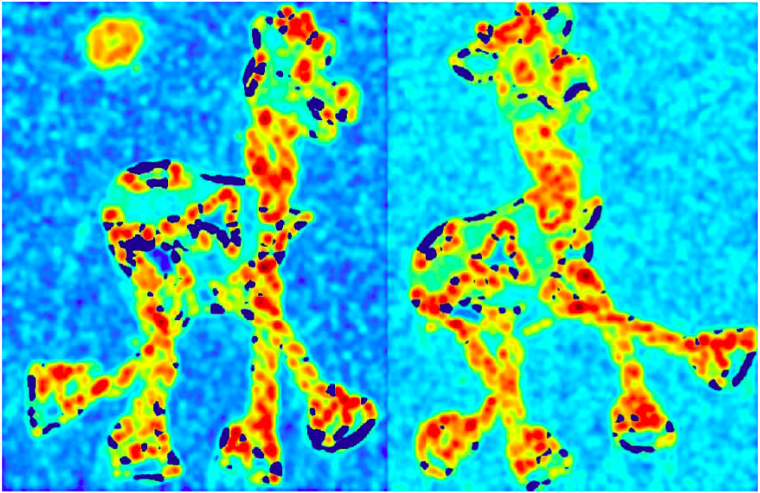
Harris Corner detector

1. Compute the gradients at each point in the image
2. Compute **A** for each image window to get its **cornerness** scores.
3. Compute the eigenvalues
4. Find points whose surrounding window gave large corner response ($f >$ threshold).
5. Take the points of local maxima, i.e., perform non-maximum suppression.

Example

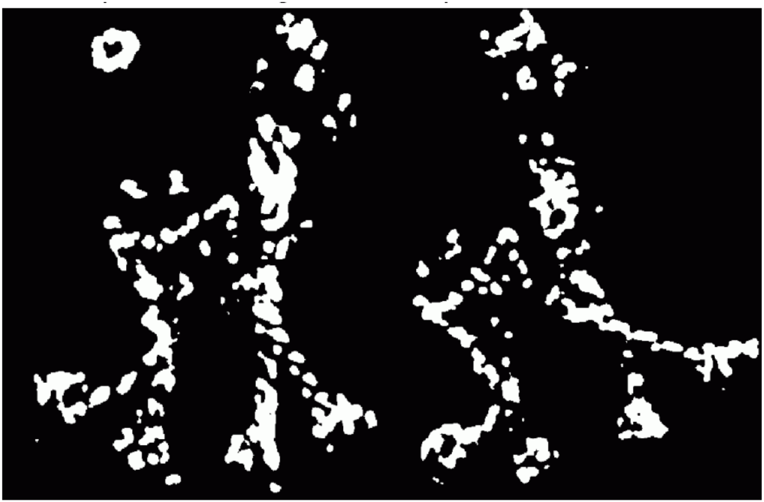
[Source: K. Grauman]

1) Compute Cornerness



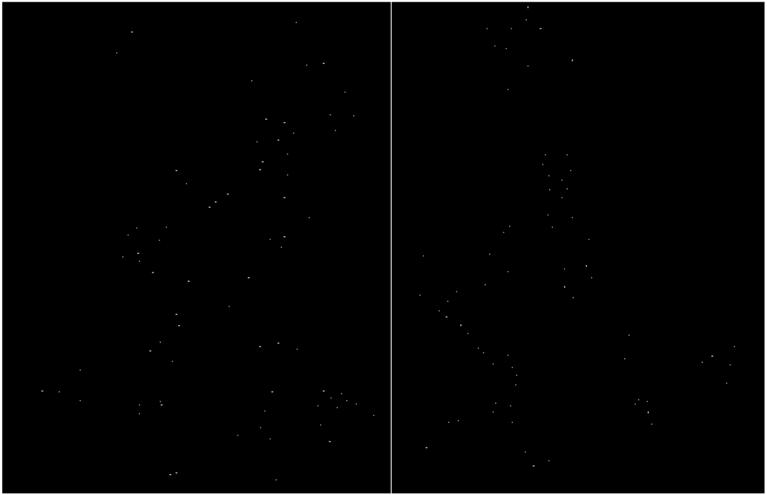
[Source: K. Grauman]

2) Find High Response



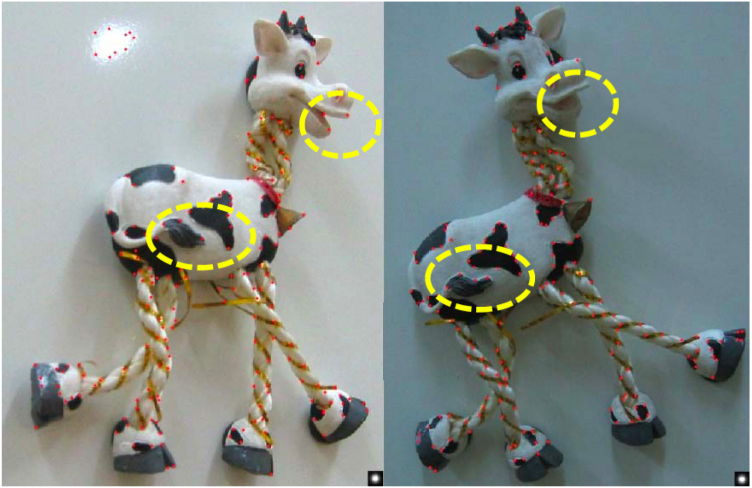
[Source: K. Grauman]

3) Non-maxima Suppresion



[Source: K. Grauman]

Results

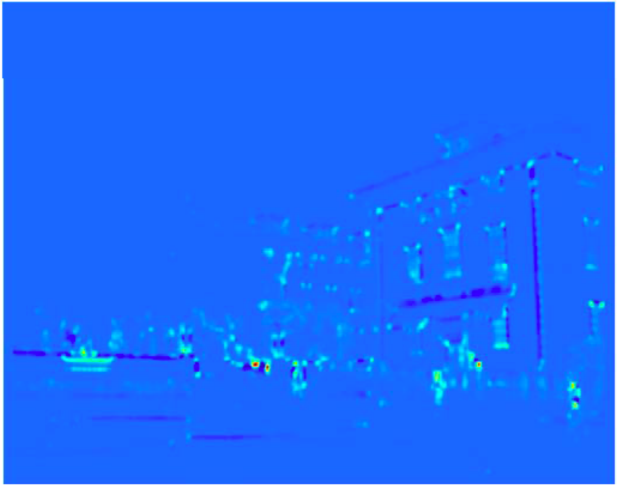


[Source: K. Grauman]

Another Example

[Source: K. Grauman]

Cornerness



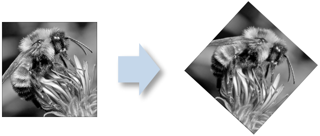
[Source: K. Grauman]

Interest Points

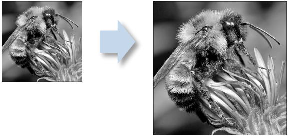
[Source: K. Grauman]

Image Transformations

Geometric:

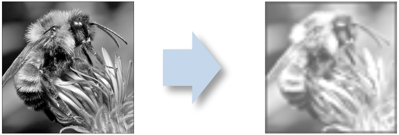


Rotation



Scale

Photometric:



Intensity change

[Source: N. Snavely]

Properties of Harris Corner Detector

- Rotation invariant?

$$\mathbf{A} = w * \begin{bmatrix} I_x^2 & I_x I_y \\ I_y I_x & I_y^2 \end{bmatrix} = \mathbf{U} \begin{bmatrix} \lambda_0 & 0 \\ 0 & \lambda_1 \end{bmatrix} \mathbf{U}^T \quad \text{with} \quad \mathbf{A}\mathbf{u}_i = \lambda_i \mathbf{u}_i$$

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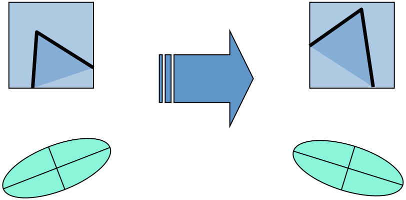
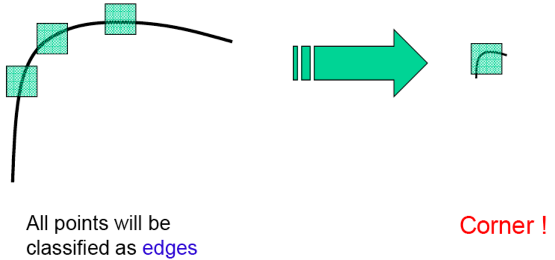


Ellipse rotates but its shape (i.e. eigenvalues) remains the same

[Source: N. Snavely]

Properties of Harris Corner Detector

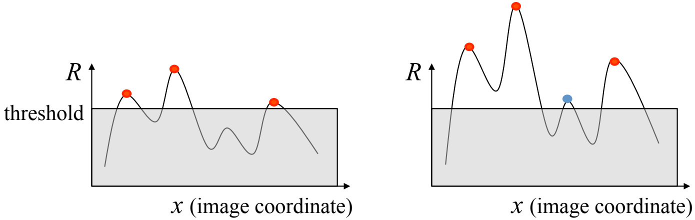
- Scale Invariant?



[Source: K. Grauman]

Properties of Harris Corner Detector

- Affine intensity change $I \rightarrow aI + b$?
- Only derivatives are used, so it's invariant to shift $I \rightarrow I + b$
- What about intensity scale?



Partially invariant to affine intensity change

[Source: K. Grauman]

Scale invariant interest points

How can we independently select interest points in each image, such that the detections are repeatable across different scales?

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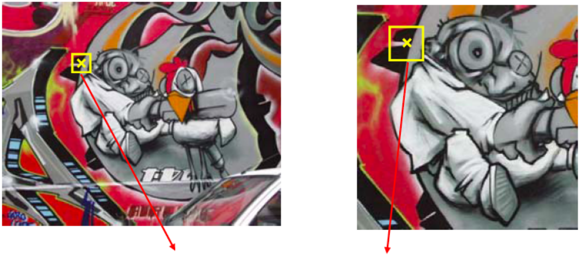

$$f(I_{i_1 \dots i_m}(x, \sigma)) = f(I_{i_1 \dots i_m}(x', \sigma'))$$

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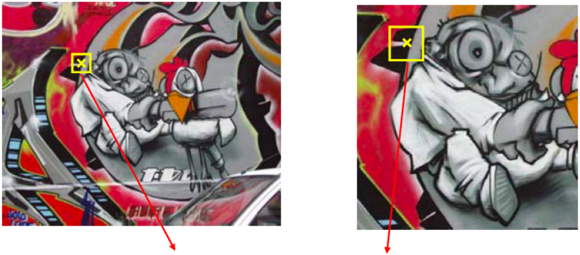

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Function responses for increasing scale (scale signature).

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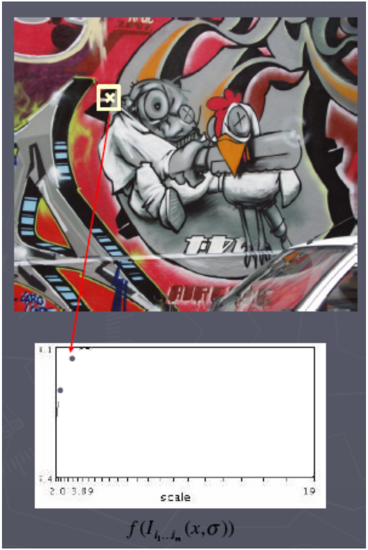

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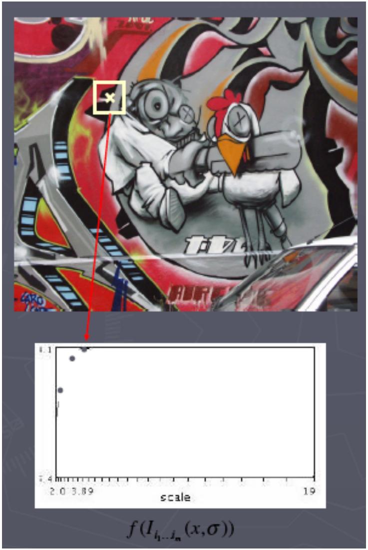

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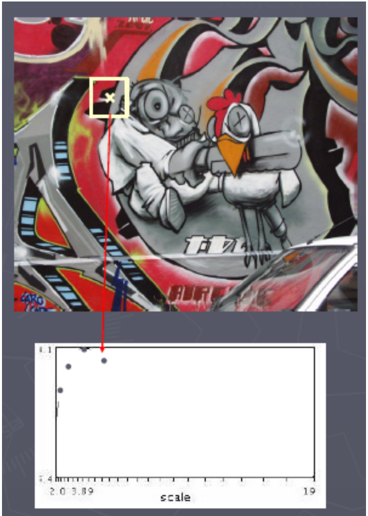

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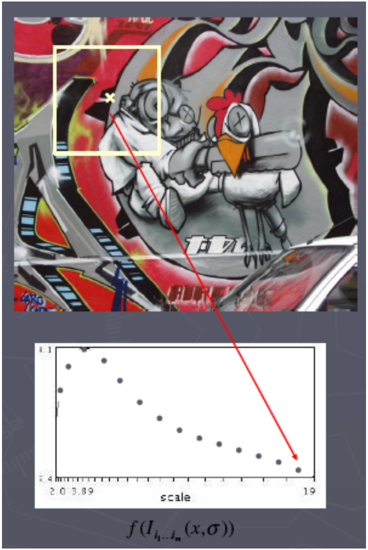

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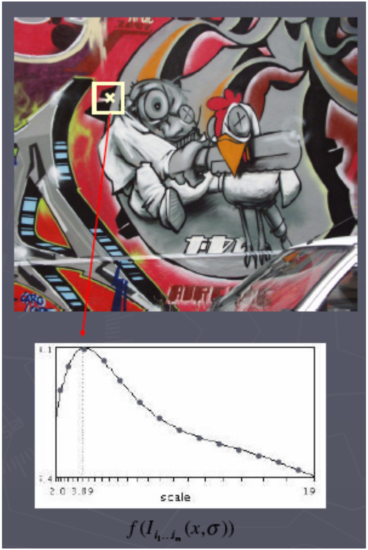

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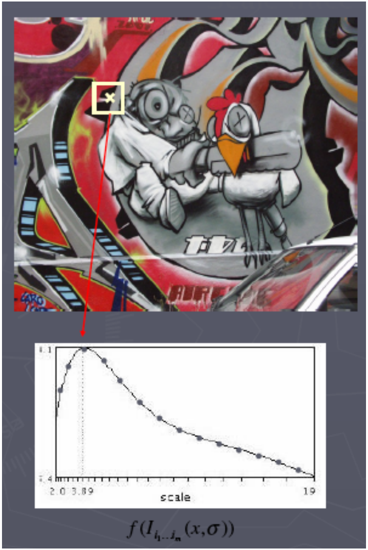

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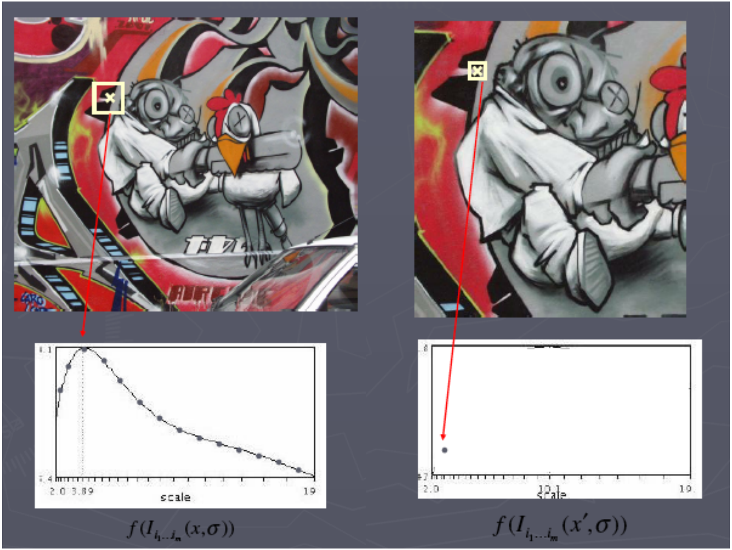

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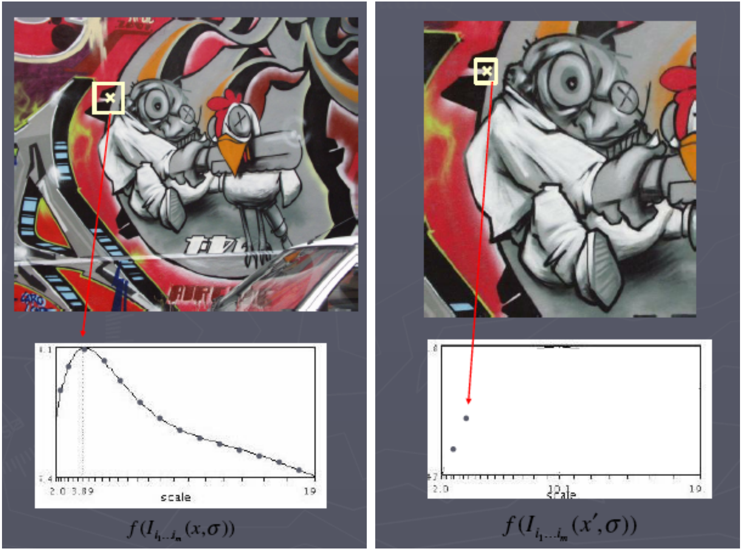

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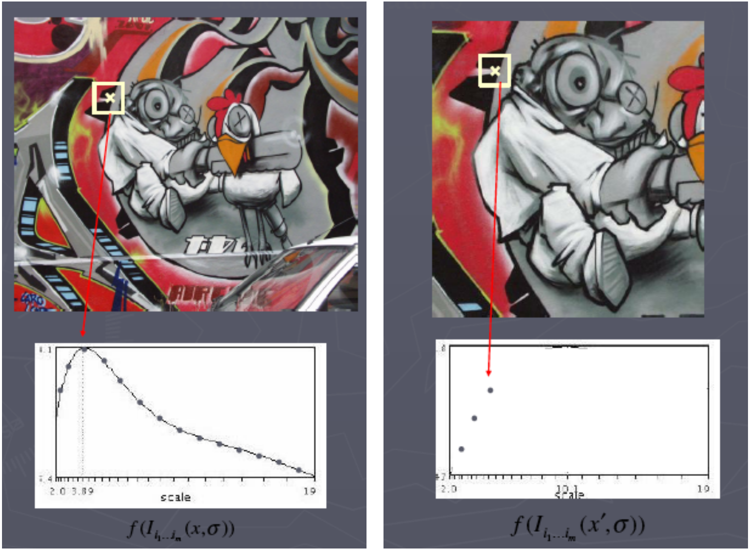

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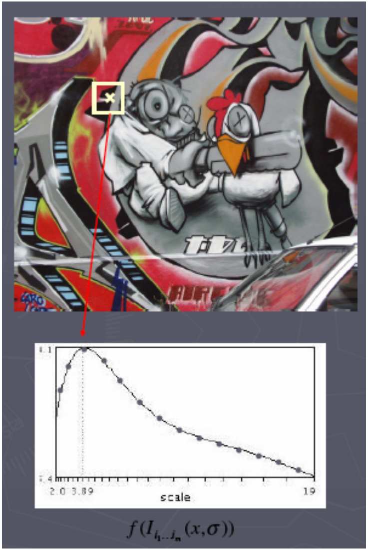

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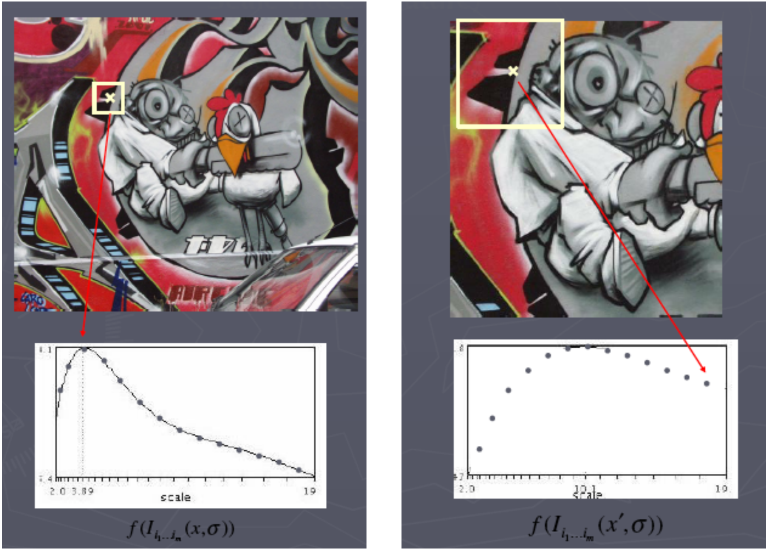

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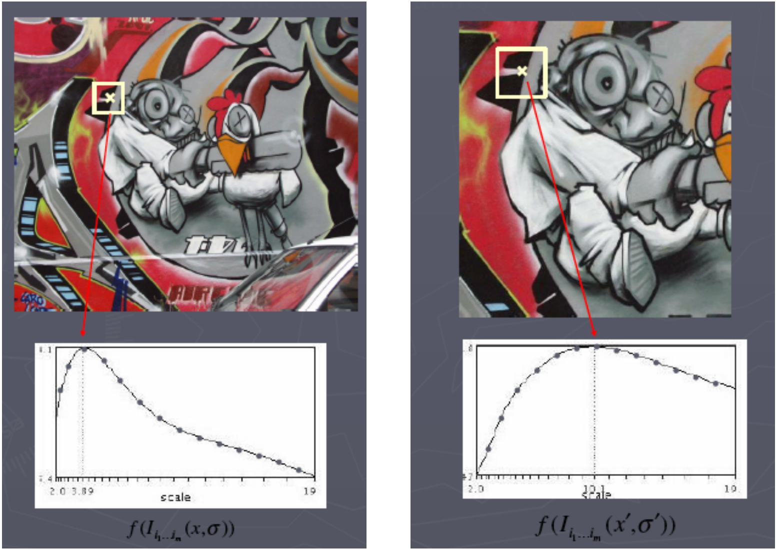
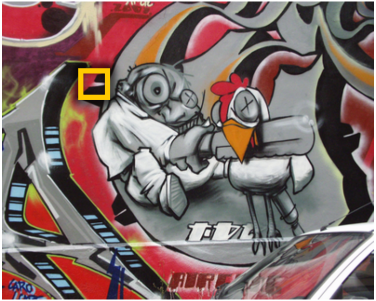


- Instead of computing f for larger and larger windows, we can implement using a fixed window size with a Gaussian pyramid

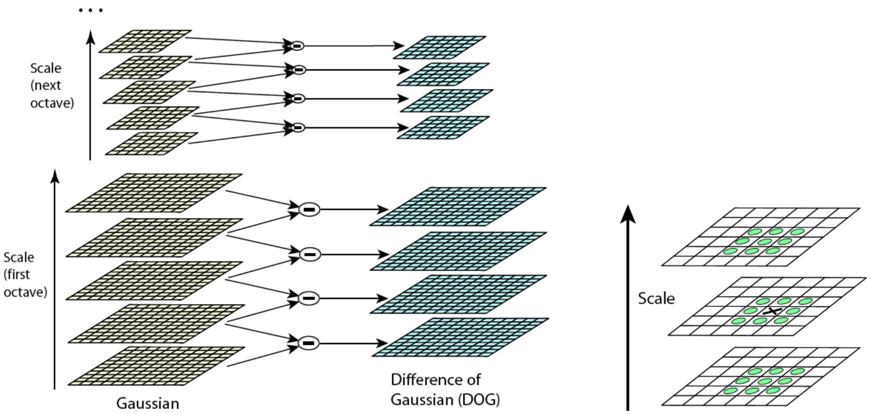


(sometimes need to create in-between levels, e.g. a ¾-size image)

[Source: N. Snavely]

What can the signature function be?

- Lindeberg (1998): extrema in the **Laplacian of Gaussians** (LoG).
- Lowe (2004) proposed computing a set of sub-octave **Difference of Gaussian filters** looking for 3D (space+scale) maxima in the resulting structure.

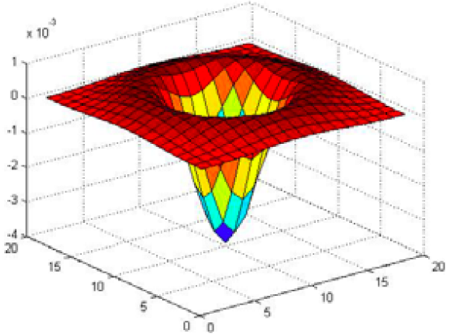


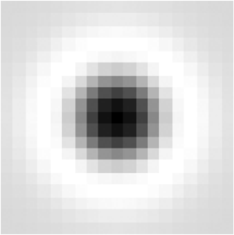
[Source: R. Szeliski]

Blob detection

- **Laplacian of Gaussian**: Circularly symmetric operator for blob detection in 2D

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

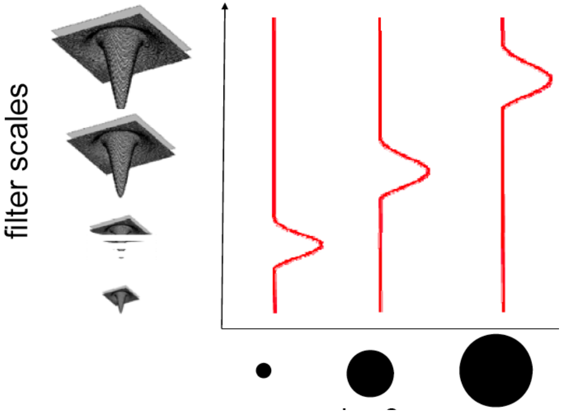




[Source: K. Grauman]

Blob detection in 2D: scale selection

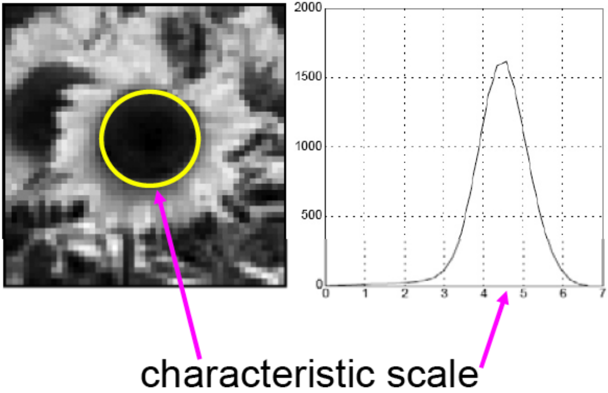
Laplacian-of-Gaussian = blob detector



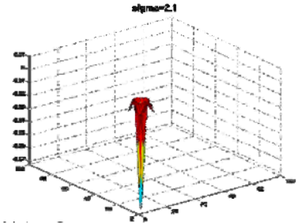
[Source: B. Leibe]

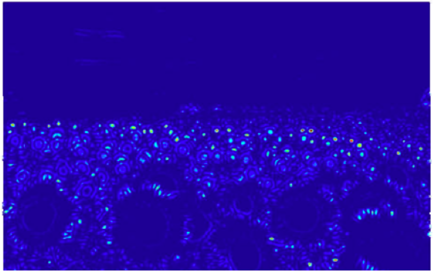
Characteristic Scale

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



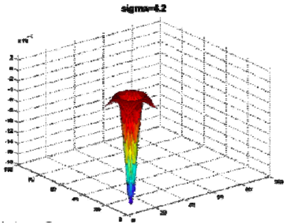
[Source: S. Lazebnik]

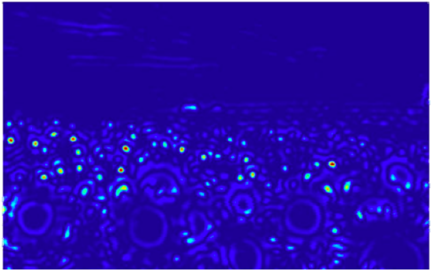




[Source: K. Grauman]

Example





[Source: K. Grauman]

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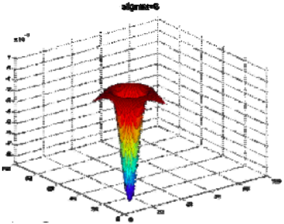

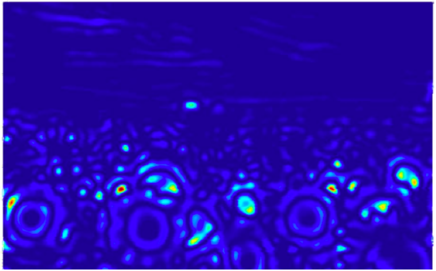

[Source: K. Grauman]

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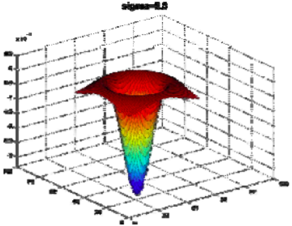

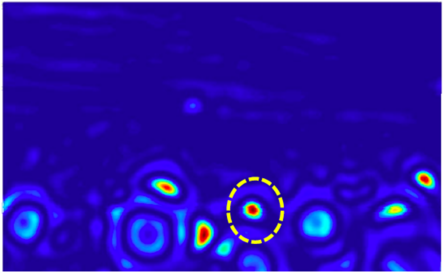

[Source: K. Grauman]

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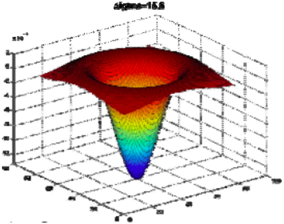

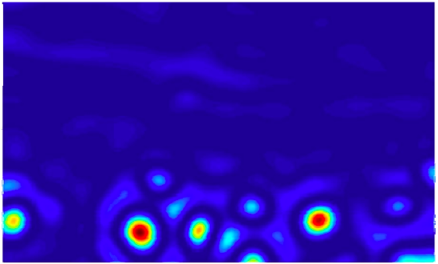

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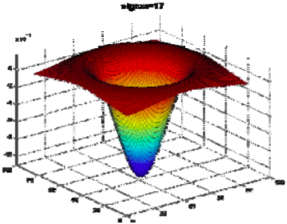
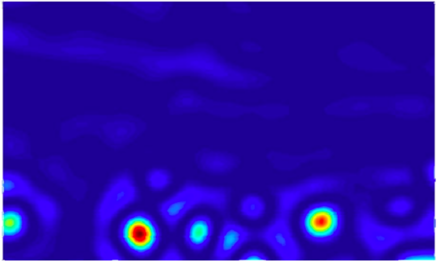
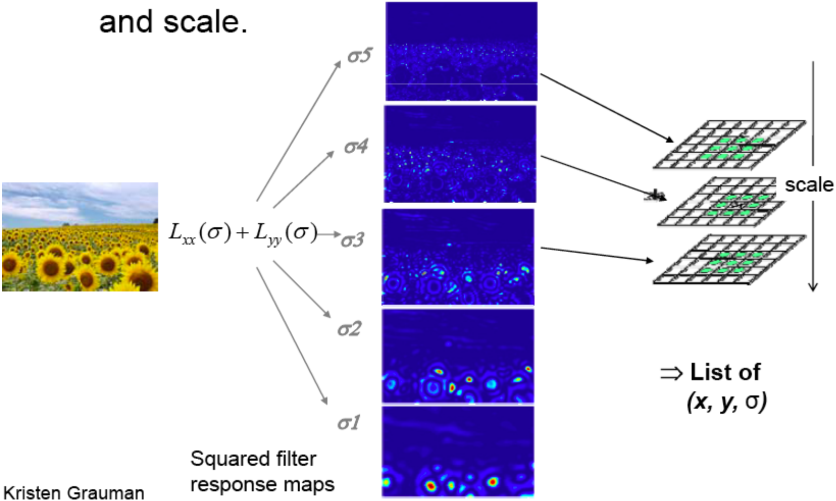




[Source: K. Grauman]

Scale invariant interest points

Interest points are local maxima in both position and scale.



Squared filter response maps

Kristen Grauman

Example

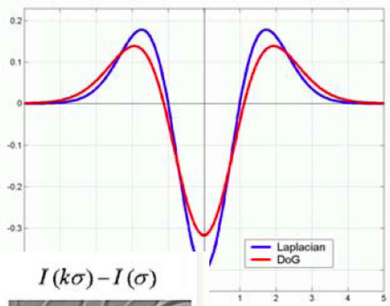
[Source: S. Lazebnik]

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

(Laplacian)

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

(Difference of Gaussians)



[Source: K. Grauman]

Lowe's DoG

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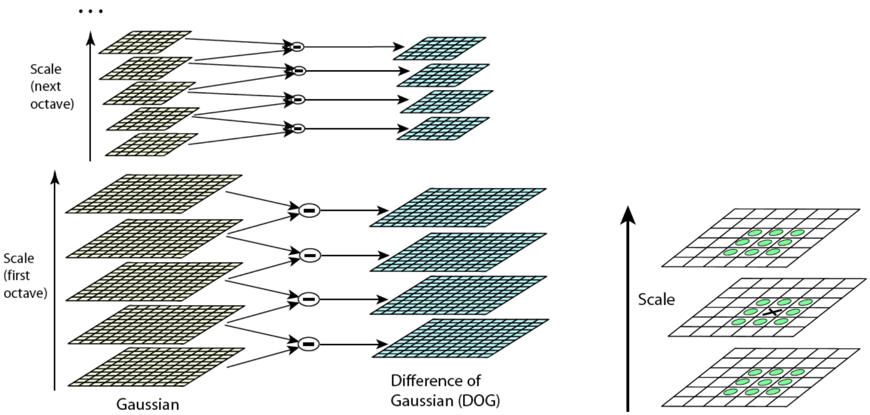

[Source: R. Szeliski]

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- **Quantity**: many features can be generated for even small objects.

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Properties of the ideal feature

- **Local**: features are local, so robust to occlusion and clutter (no prior segmentation).
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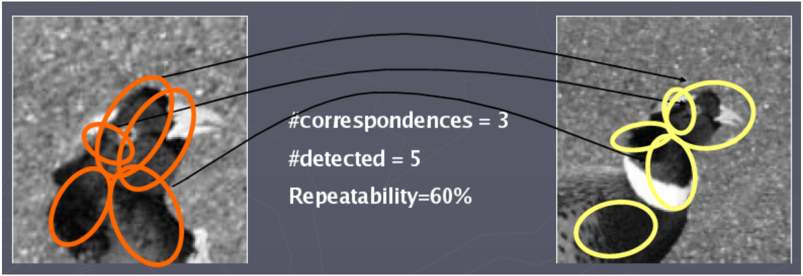
A lot of other interest point detectors

- Hessian
- Lowe: DoG
- Lindeberg: scale selection
- Miikolajczyk & Schmid: Hessian/Harris-Laplacian/Affine
- Tuyttelaars & Van Gool: EBR and IBR
- Matas: MSER
- Kadir & Brrady: Salient Regions
- Speeded–Up Robust Features (SURF) of Bay et al.
- ...

Evaluation criteria: repeatability

- **Repeatability rate**: percentage of detected features that have correct corresponding points
- What's the problem of this?



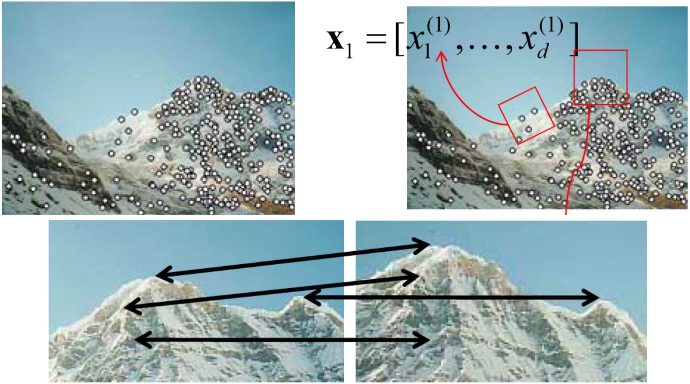
[Source: T. Tuytelaars]

Evaluation criteria: repeatability

- Two points are in correspondence if the intersection over union is bigger than a certain threshold.
- Look for affine invariant features!

[Source: T. Tuytelaars]

- **Detection**: Identify the interest points.
- **Description**: Extract vector feature descriptor around each interest point.
- **Matching**: Determine correspondence between descriptors in two views.



[Source: K. Grauman]

The ideal feature descriptor

- Repeatable (invariant/robust)
- Distinctive
- Compact
- Efficient

How to achieve invariance?

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[Source: N. Snavely]

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[Source: N. Snavely]

Invariances

[Source: T. Tuytelaars]

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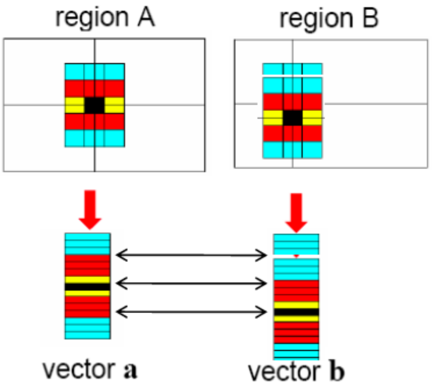
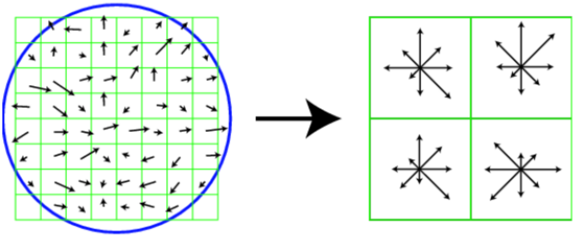
Raw Pixels as Local Descriptrs

- The simplest way is to write down the list of intensities to form a feature vector, and normalize them (i.e., mean 0, variance 1).
- Why normalization?
- But this is very sensitive to even small shifts, rotations and any affine transformation.



SIFT descriptor [Lowe 2004]

- Compute the gradient at each pixel in a 16×16 window around the detected keypoint, using the appropriate level of the Gaussian pyramid at which the keypoint was detected.
- Downweight gradients by a Gaussian fall-off function (blue circle) to reduce the influence of gradients far from the center.
- In each 4×4 quadrant, compute a gradient orientation histogram using 8 orientation histogram bins.



(a) image gradients (b) keypoint descriptor

[Source: R. Szeliski]

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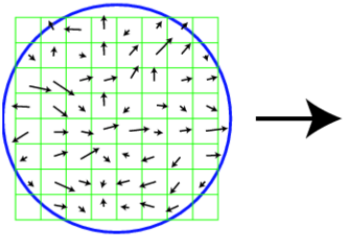
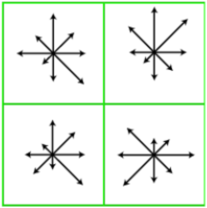


(a) image gradients



(b) keypoint descriptor

[Source: R. Szeliski]

SIFT descriptor [Lowe 2004]

- The resulting 128 non-negative values form a raw version of the SIFT descriptor vector.
- To reduce the **effects of contrast or gain** (additive variations are already removed by the gradient), the 128-D vector is normalized to unit length.

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SIFT descriptor [Lowe 2004]

Extraordinarily robust matching technique

- Changes in viewpoint: up to about 60 degree out of plane rotation
- Changes in illumination: sometimes even day vs. night
- Fast and efficient – can run in real time
- Lots of code available

[Source: S. Seitz]

Example

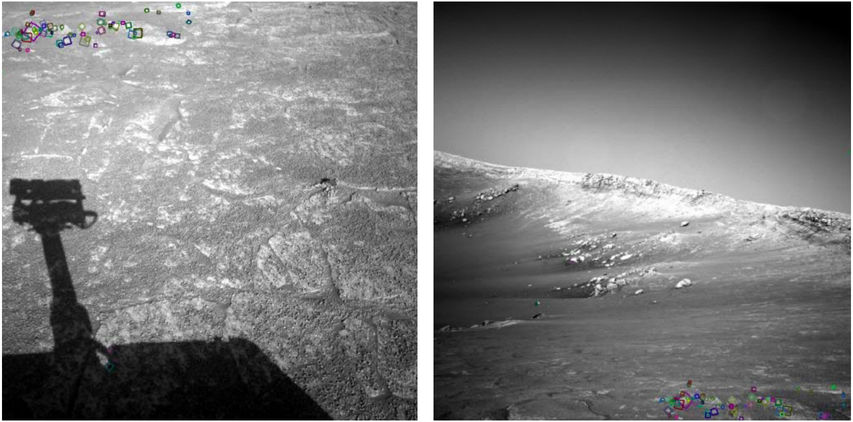


Figure: NASA Mars Rover images with SIFT feature matches

[Source: N. Snavely]

PCA-SIFT

- The dimensionality of SIFT is very high, i.e., 128D for each keypoint
- Reduce the dimensionality using linear dimensionality reduction
- In this case, principal component analysis (PCA)
- Use 10D or so descriptor

SIFT properties

Invariant to

- Scale
- Rotation

Partially invariant to

- Illumination changes
- Camera viewpoint
- Occlusion, clutter

Making descriptor rotation invariant (MOPS)

- Rotate patch according to its dominant gradient orientation
- This puts the patches into a canonical orientation
- Multiscale Oriented PatcheS descriptor

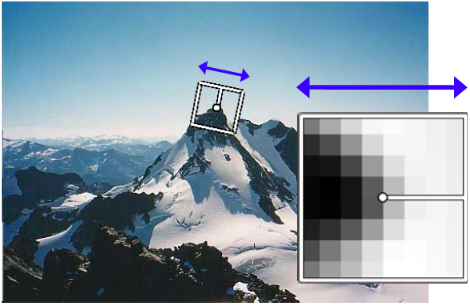
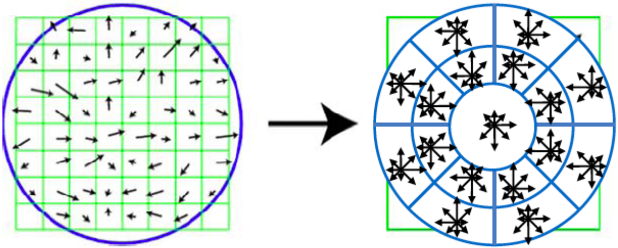


Figure: Figure from M. Brown

[Source: K. Grauman]

Gradient location-orientation histogram (GLOH)

- Developed by Mikolajczyk and Schmid (2005): variant on SIFT that uses a log-polar binning structure instead of the four quadrants.
- The spatial bins are 11, and 15, with eight angular bins (except for the central region), for a total of 17 spatial bins and 16 orientation bins.
- The 272D histogram is then projected onto a 128D descriptor using PCA trained on a large database.



(a) image gradients (b) keypoint descriptor

[Source: R. Szeliski]

Other Descriptors

- Steerable filters
- moment invariants,
- complex filters
- shape context,
- PCA-SIFT,
- HOG,
- SURF
- DAISY
- $\cdots$

Local features

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- **Description**: Extract vector feature descriptor around each interest point.
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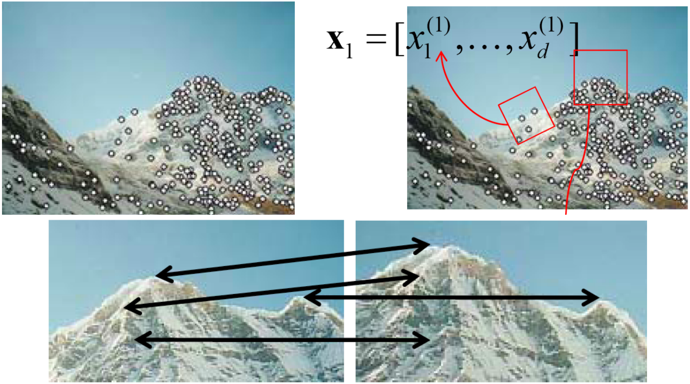


[Source: K. Grauman]

Matching local features

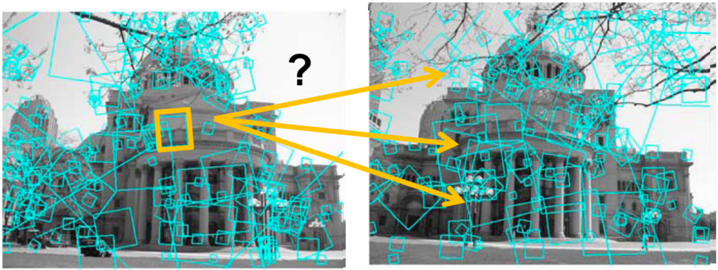
Once we have extracted features and their descriptors, we need to match the features between these images.

- **Matching strategy:** which correspondences are passed on to the next stage
- Devise **efficient data structures and algorithms** to perform this matching

Figure: Images from K. Grauman

Matching local features

- To **generate candidate matches**, find patches that have the most similar appearance (e.g., lowest SSD)
- Simplest approach: **compare them all**, take the closest (or closest k, or within a thresholded distance)



[Source: K. Grauman]

Ambiguous matches

- At what SSD value do we have a good match?
- To add robustness, consider ratio of distance to best match to distance to second best match
  - If low, first match looks good.
  - If high, could be ambiguous match.

[Source: K. Grauman]

Matching SIFT Descriptors

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

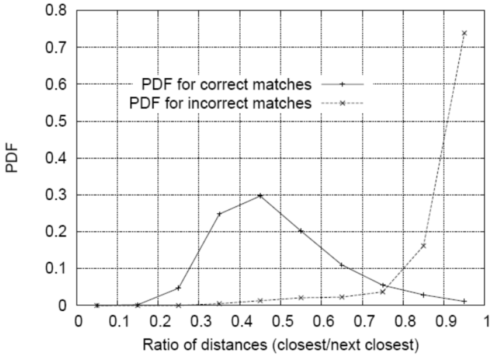


Figure: Images from D. Lowe

[Source: K. Grauman]

Which threshold to use?

- Setting the threshold too high results in too many false positives, i.e., incorrect matches being returned.
- Setting the threshold too low results in too many false negatives, i.e., too many correct matches being missed

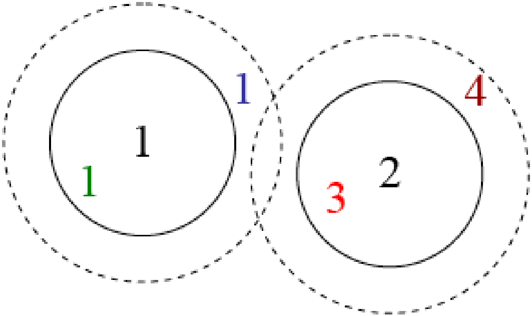
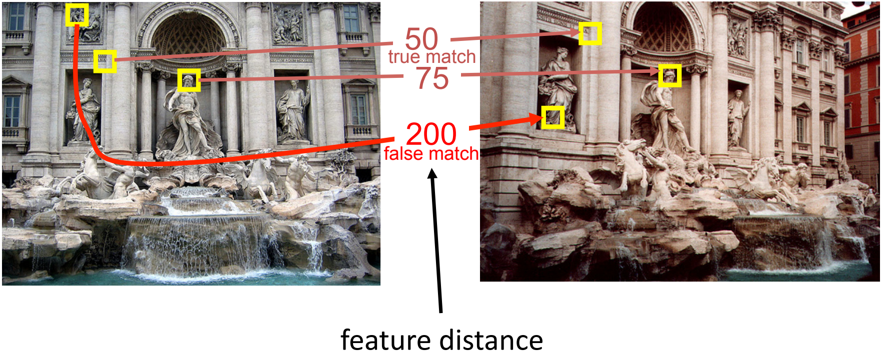


Figure: Images from R. Szeliski

How to measure performance

- How can we measure the performance of a feature matcher?



[Source: N. Snavely]

How to quantize how good is our matching?

- **TP: true positives**, i.e., number of correct matches
- **FN: false negatives**, matches that were not correctly detected
- **FP: false positives**, proposed matches that are incorrect
- **TN: true negatives**, non-matches that were correctly rejected.

True positive rate (recall) $$TPR = \frac{TP}{TP + FN} = \frac{TP}{P}$$

False positive rate $$FPR = \frac{FP}{FP + TN} = \frac{FP}{N}$$

positive predictive value (precision) $$PPV = \frac{TP}{TP + FP} = \frac{TP}{P'}$$

accuracy $$ACC = \frac{TP + TN}{P + N}$$

Measuring performance

- Any particular matching strategy (at a particular threshold or parameter setting) can be rated by the TPR and FPR numbers
- We want TPR=1 (recall) and FPR=0
- As we vary the matching threshold, we obtain a family of such points, i.e., **receiver operating characteristic (ROC curve)**
- The closer this curve lies to the upper left corner, the better its performance

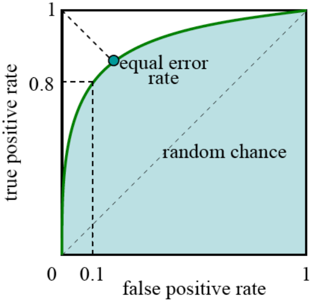


Figure: Images from R. Szeliski

Measuring performance

- **Area under the curve (AUC)** is a way to summarize ROC with 1 number.
- **Mean average precision**, which is the average precision (PPV) as you vary the threshold, i.e., area under the curve in the precision-recall curve.
- The **equal error rate** is sometimes used as well.

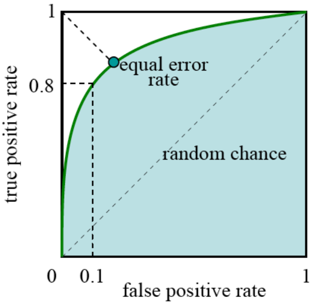


Figure: Images from R. Szeliski

Applications of local invariant features

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

[Source: K. Grauman]

Wide Baseline Stereo

[Source: T. Tuytelaars]

Recognizing the Same Object

Schmid and Mohr 1997

Sivic and Zisserman, 2003

Rothganger et al. 2003

Lowe 2002

[Source: K. Grauman]

Motion Tracking

Figure: Images from J. Pilet

Summary

Interest point detection

- Harris corner detector
- Laplacian of Gaussian, automatic scale selection
- Difference of Gaussians

Invariant descriptors

- Rotation according to dominant gradient direction
- Histograms for robustness to small shifts and translations (SIFT descriptor)
- Polar coordinate descriptors GLOH.

Next class ... more sophisticated matching