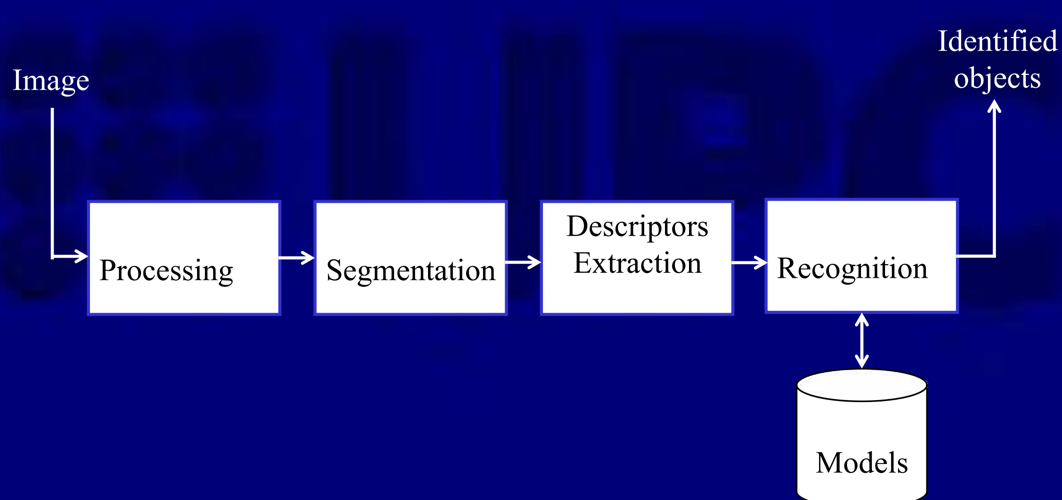
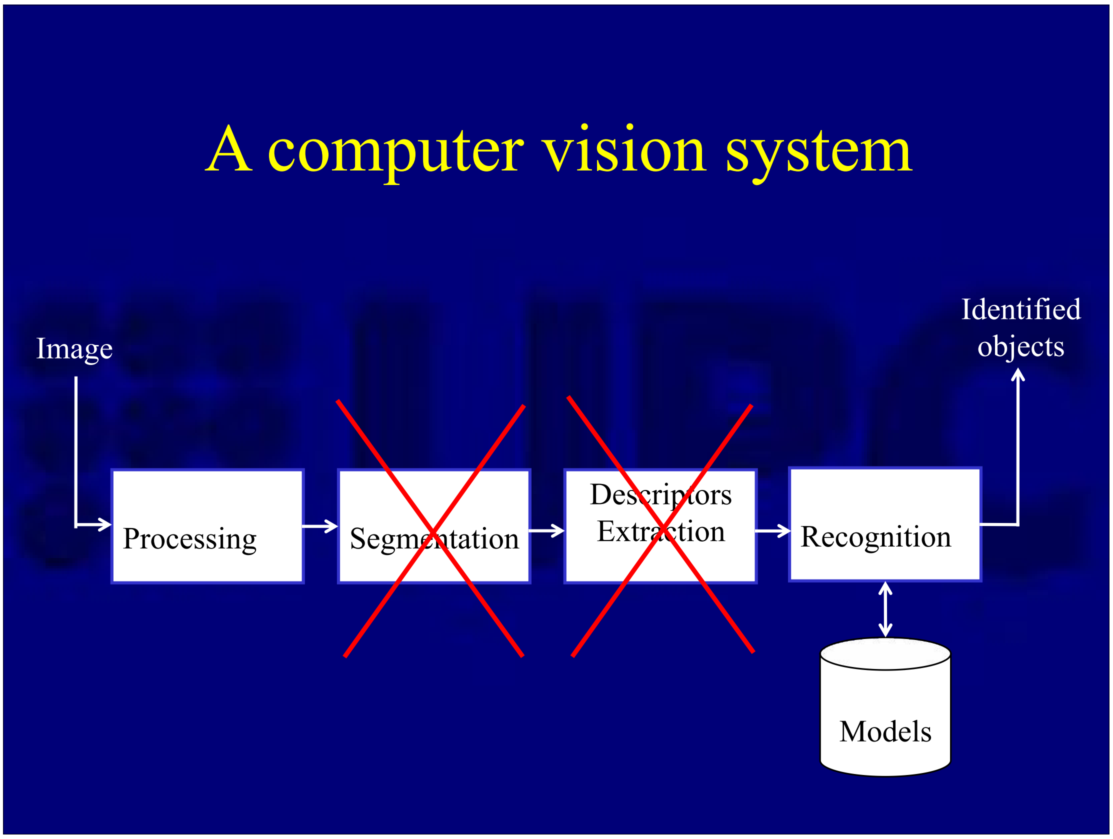
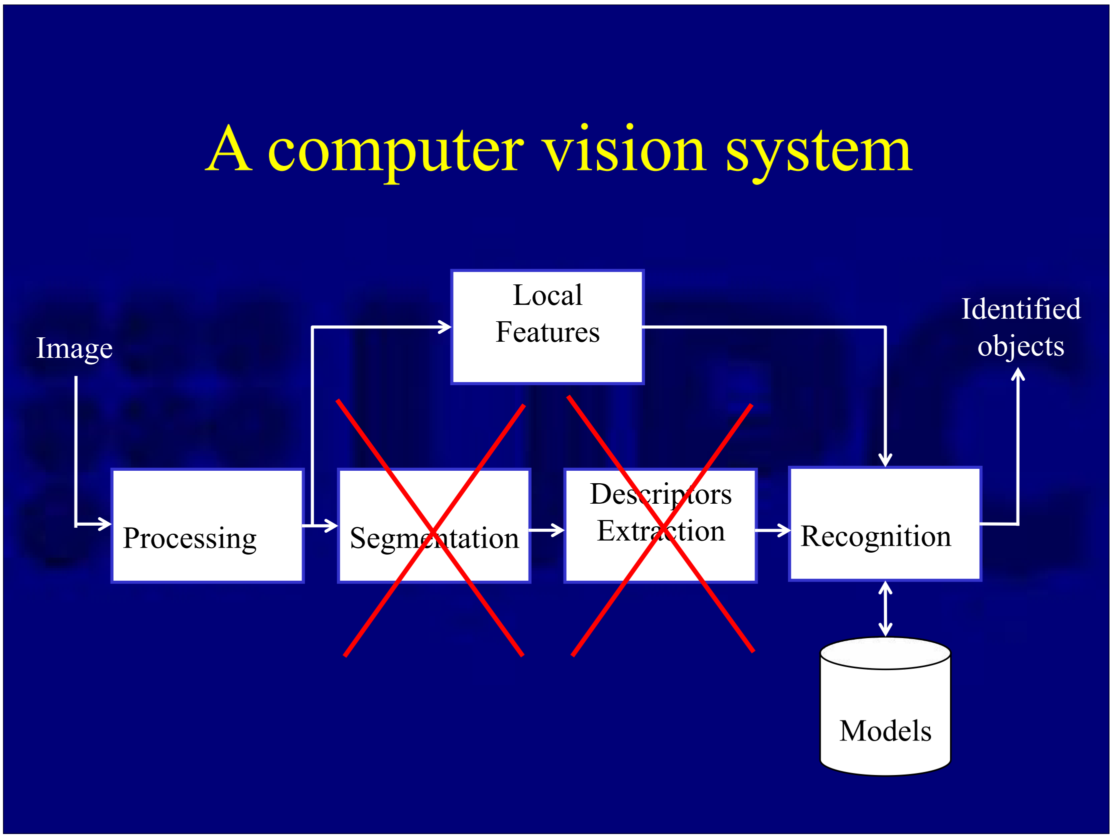
Local Features

A computer vision system




A computer vision system
Image
Identified objects
Processing
Segmentation
Descriptors Extraction
Recognition
Models


A computer vision system
Local Features
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Local Features

- Histograms
- Hough transform
- Corners
- Scale Invariant Feature transform (SIFT)
- Haar Features (face detection)

Point Features

Corners

Want uniqueness

Look for image regions that are unusual

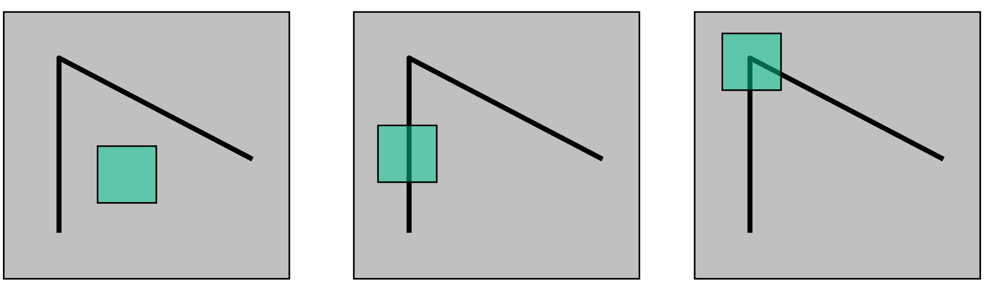
- Lead to unambiguous matches in other images

How to define "unusual"?

Local measures of uniqueness

Suppose we only consider a small window of pixels

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

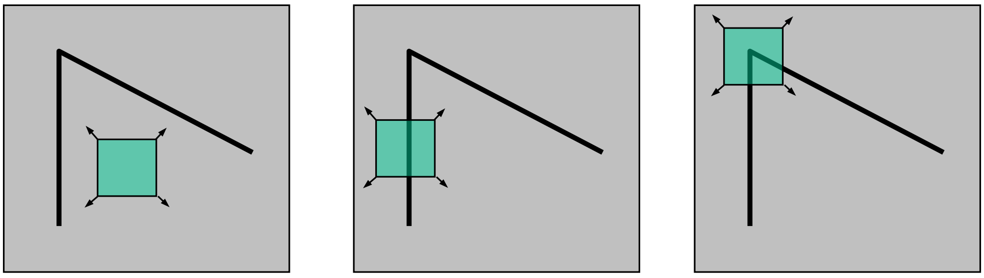


Slide adapted from Darya Frolova, Denis Simakov, Weizmann Institute.

Feature detection

Local measure of feature uniqueness

- 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

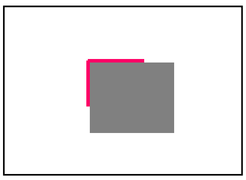
Slide adapted from Darya Frolova, Denis Simakov, Weizmann Institute.

Corner Features

- Places where TWO strong edges meet.
- They can be used for:
  - Object tracking
  - 3D triangulation (stereo)
  - Object recognition
  - Mosaic images

Detection of Corner Features

- Need two strong edges:
- Example:

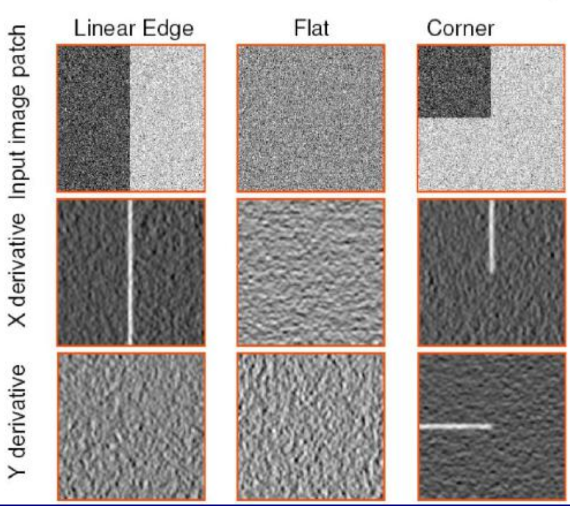


Create the following matrix:

$$C = \begin{bmatrix} \sum I_x^{\,2} & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^{\,2} \end{bmatrix}$$

Both I_x or I_y are large in a neighborhood of corner

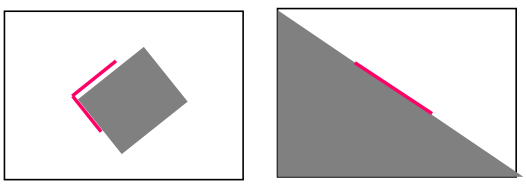
Corner Detector : Intuitive Example



Treat gradient vectors as a set of (dx, dy) points with center of mass at (0,0)

Detection of Corner Features

- What happens if the corner is not aligned with the image coordinate system?



$$C = \begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix}$$

Both, I_x or I_y are large in neighborhood of the corner

But this is also true for a slanted edge!

Detection of Corner Features

- Solution: "rotate" the corner to align it with the image coordinate system!

$$C = \begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix}$$

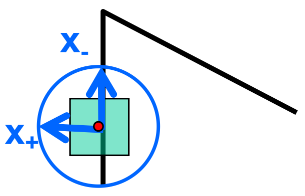
$$C = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

Detection of Corner Features

- How do we do this rotation?
  - Since C is symmetric, it can be diagonalized;
  - the diagonalization is done by the rotation we need!

Feature detection: the math

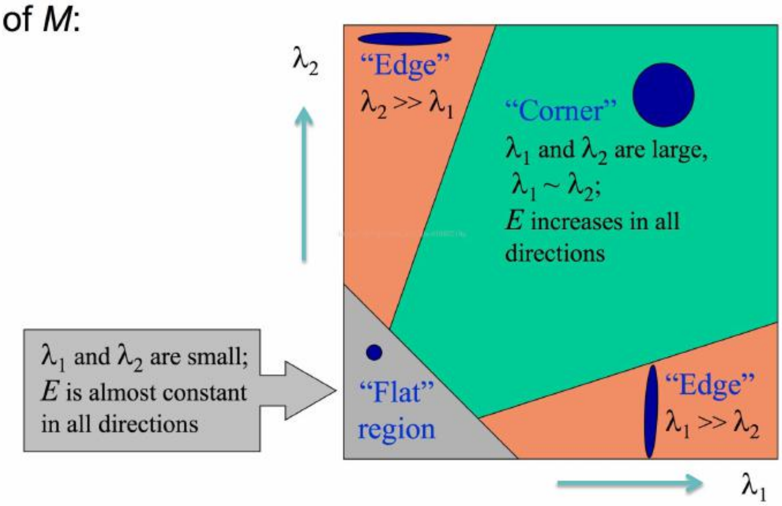
$$C = \begin{bmatrix} \sum I_x{}^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y{}^2 \end{bmatrix}$$



Eigenvalues and eigenvectors of C

- Define shifts with the smallest and largest change (E value)
- x_+ = direction of **largest** increase.
- λ_+ = amount of increase in direction x_+
- x_- = direction of **smallest** increase.
- λ_- = amount of increase in direction x_+

Classification of image points using eigenvalues of M:



Harris Corner Detector: Cornerness Measure

Measure of corner response:

$$R = \det M - k\left(\operatorname{trace} M\right)^2$$

$$\det M = \lambda_1 \lambda_2$$
$$\operatorname{trace} M = \lambda_1 + \lambda_2$$

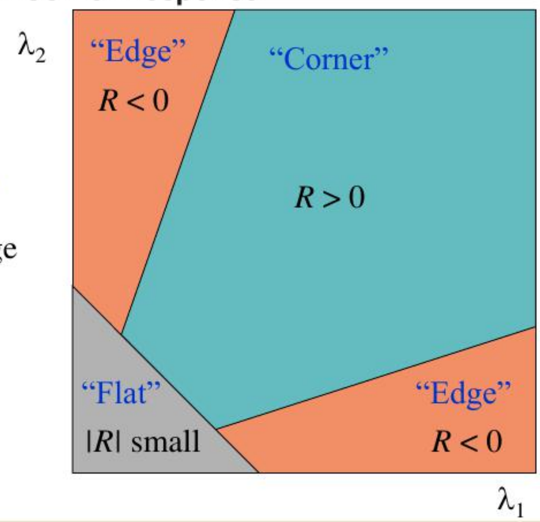
(k – empirical constant, k = 0.04-0.06)

The computation of the eigenvalues is computationally expensive. Harris proves that:

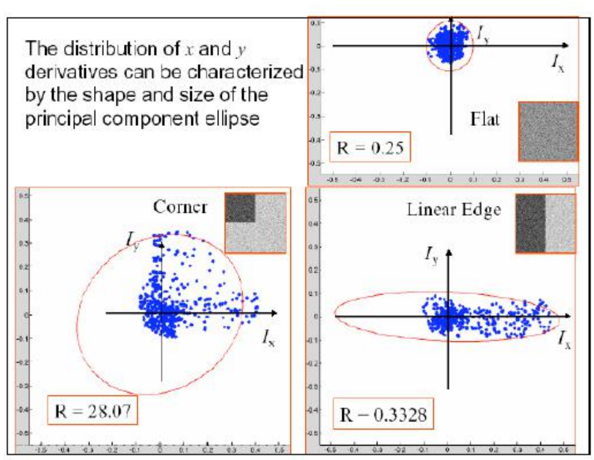
$$R=\left(\sum I_x^2 \cdot \sum I_y^2 - \left(\sum I_x \cdot I_y\right)^2\right) - k\cdot\left(\sum I_x^2 + \sum I_y^2\right)^2$$

Harris Corner Detector: Corner Response

- R depends only on eigenvalues of M
- R is large for a corner
- R is negative with large magnitude for an edge
- $|R|$ is small for a flat region



Plotting Derivatives as 2D Points for PCA

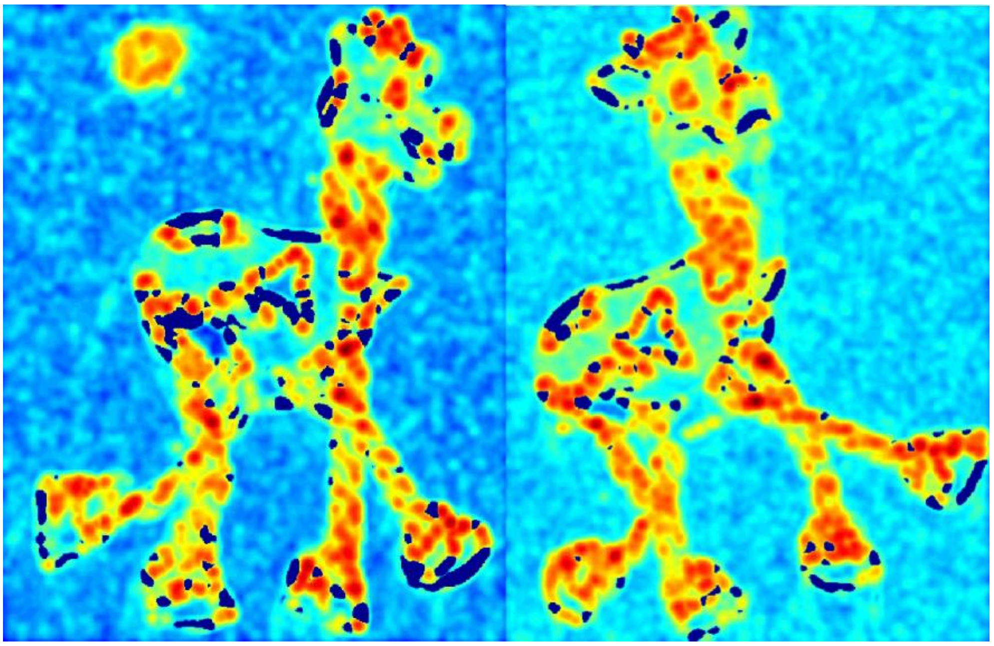


Algorithm : Harris Corner Detector

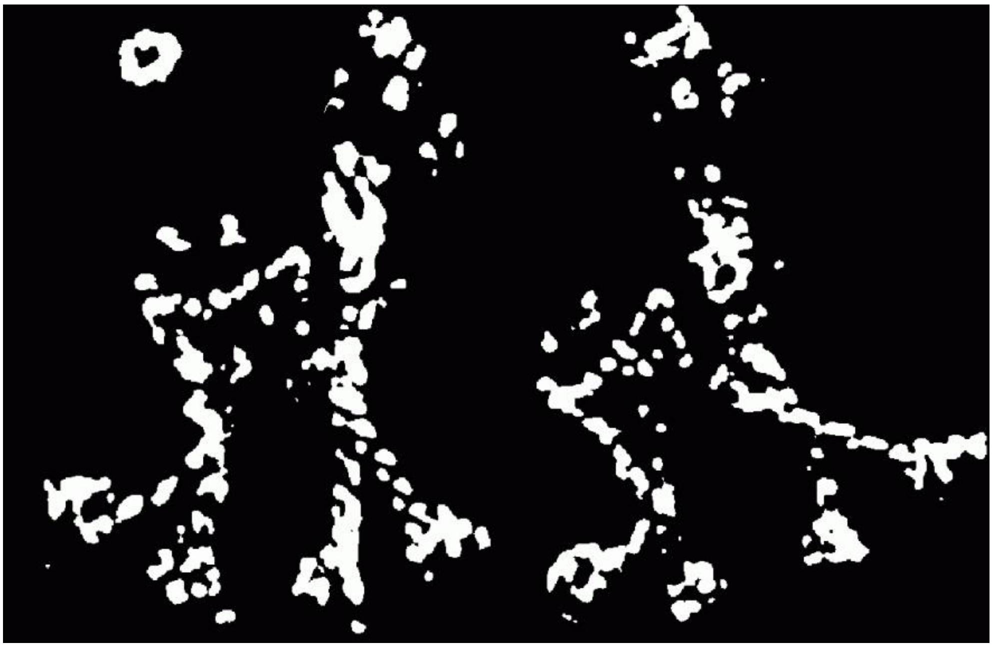
1. Computer x and y derivatives I_x and I_y of the input image
2. Computer products of derivatives $I_x I_x$, $I_x I_y$ and $I_y I_y$
3. For each pixel, compute the matrix M in a local neighborhood
4. Compute the corner response R at each pixel
5. Threshold the value of R to select corners
6. Perform non-maximum suppression

Harris detector example

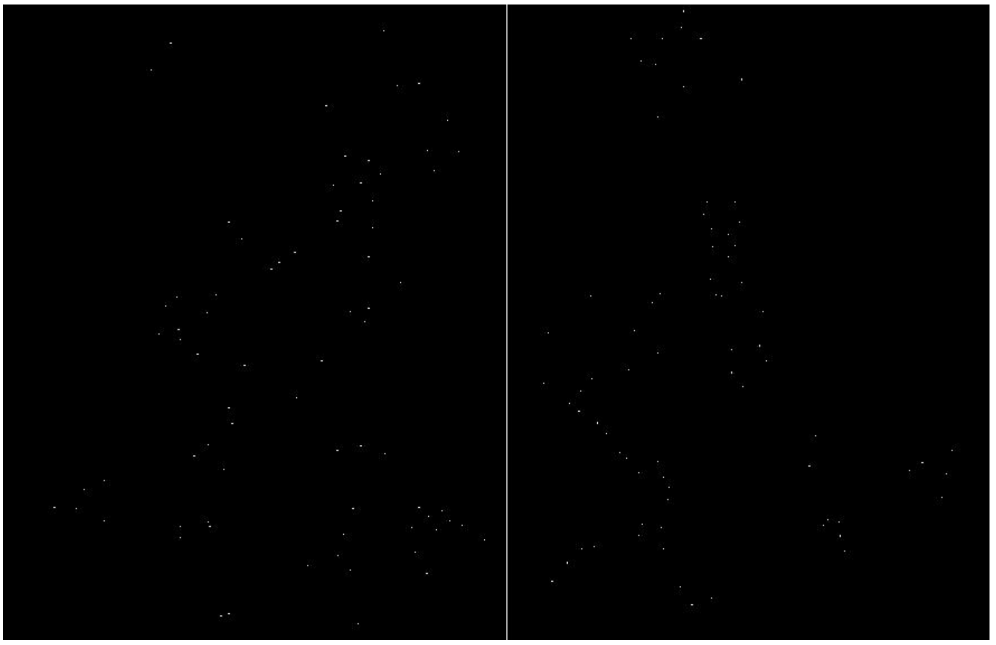
R value (red high, blue low)



Threshold (R > value)



Find local maxima of R



Harris features (in red)

Invariance

Suppose you **rotate** the image by some angle

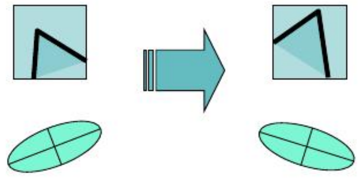
- Will you still pick up the same features?

What if you change the brightness?

Scale?

Properties of Harris Corners

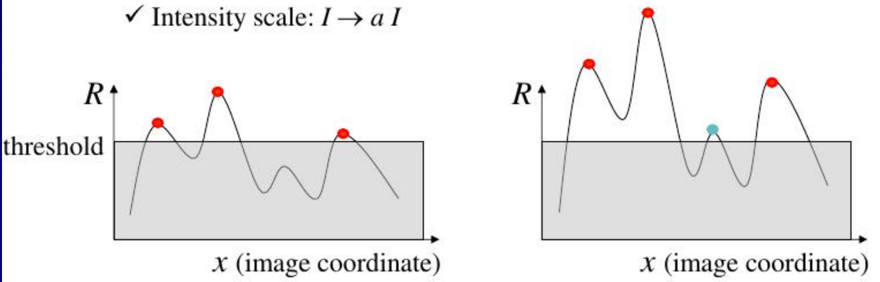
- Rotation Invariance



- Ellipse rotates but the shape (i.e. eigenvalues) remain the same
- Corner response R is invariant to image rotation.

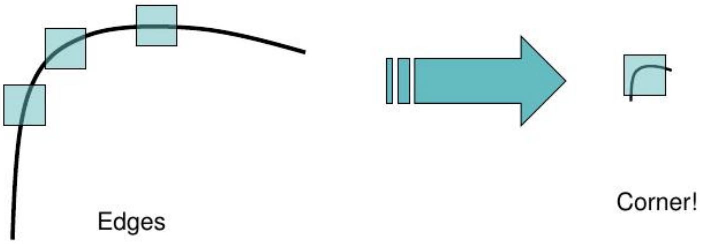
Properties of Harris Corners

- Partial invariance to affine intensity change
  - ✓ Only derivatives are used => invariance to intensity shift $I \rightarrow I + b$
  - ✓ Intensity scale: $I \rightarrow a\,I$

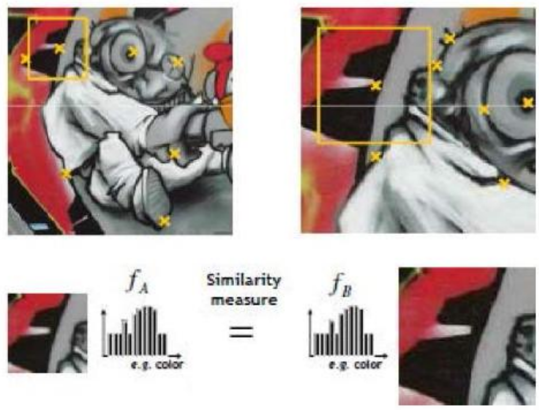


Properties of Harris Corners

- NOT invariant to image scale
- Corner at one scale may not be a corner at another
- Scale is user specified parameter



Try Different Window Sizes



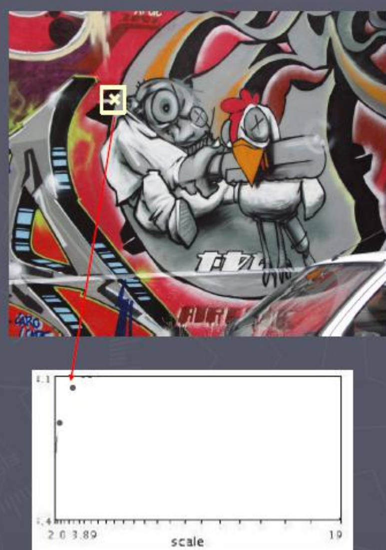
Automatic scale selection

Lindeberg et al., 1996

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

Slide from Tinne Tuytelaars

Automatic scale selection

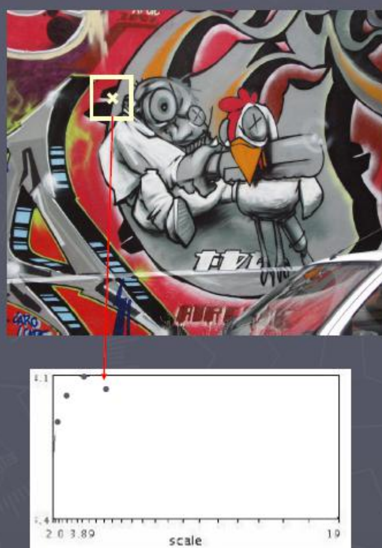


$f(I_{i_1\ldots i_m}(x,\sigma))$

Automatic scale selection

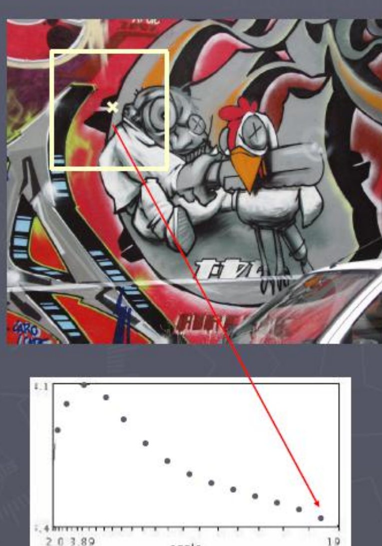
$f(I_{i_1\ldots i_m}(x,\sigma))$

Automatic scale selection



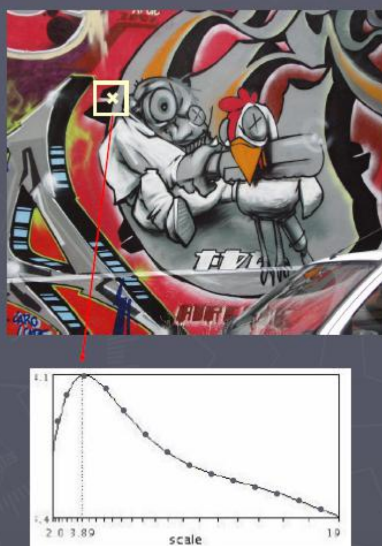
$f(I_{i_1 \ldots i_m}(x,\sigma))$

Automatic scale selection



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

Automatic scale selection



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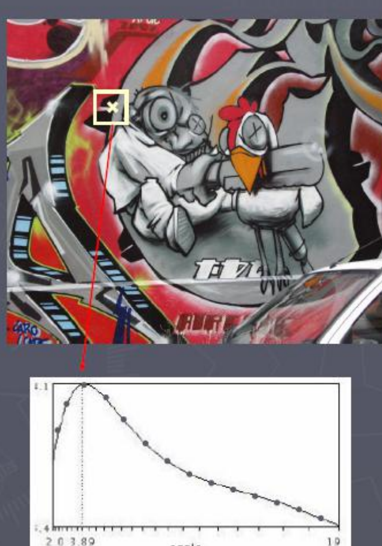
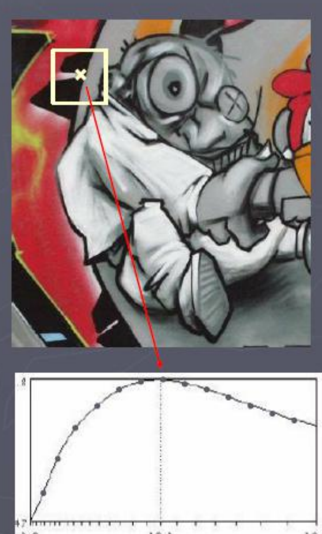
Automatic scale selection



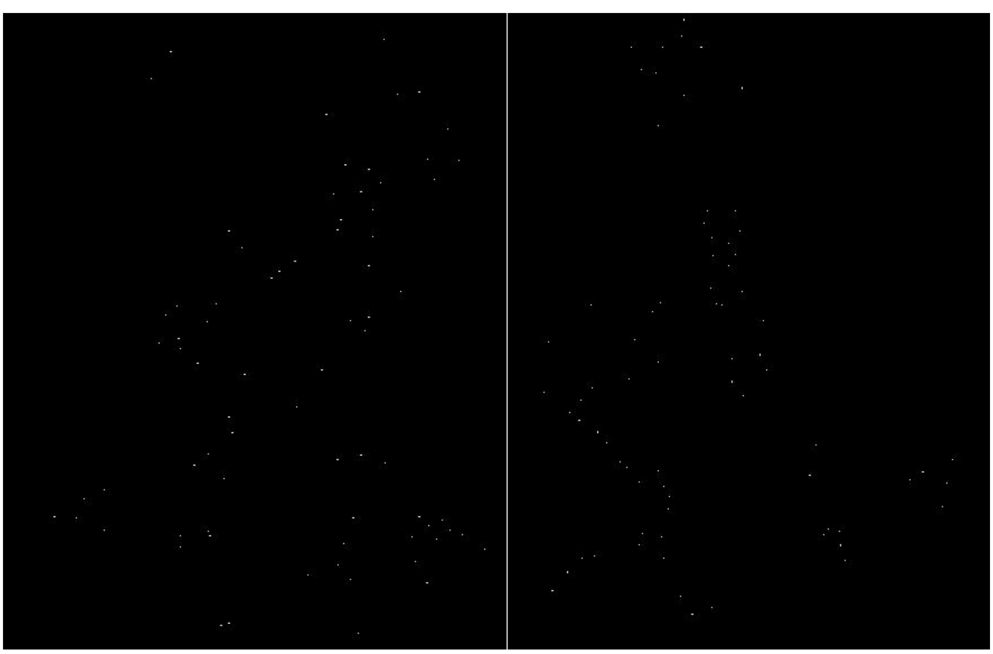
$f(I_{i_1 \ldots i_m}(x,\sigma))$



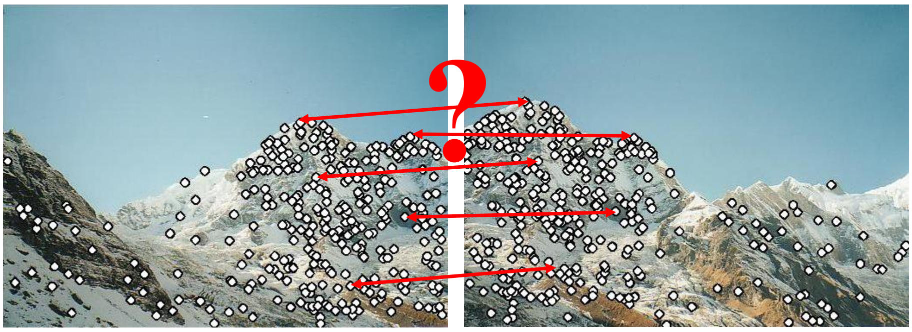
$f(I_{i_1 \ldots i_m}(x',\sigma'))$

We know how to detect good points
Next question: **How to match them?**

We know how to detect good points
Next question: **How to match them?**

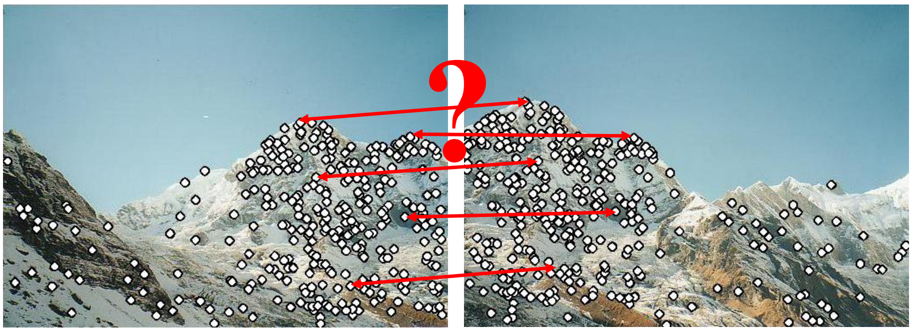


Feature descriptors



Feature descriptors

How to match them?



Lots of possibilities (this is a popular research area)

- Simple option: match square windows around the point
- State of the art approach: SIFT
  - David Lowe, UBC http://www.cs.ubc.ca/~lowe/keypoints/

Invariance

Suppose we are comparing two images $\mathbf{I}_1$ and $\mathbf{I}_2$

- I_2 may be a transformed version of I_1
- What kinds of transformations are we likely to encounter in practice?

We'd like to find the same features regardless of the transformation

- This is called transformational ***invariance***
- Most feature methods are designed to be invariant to
  - Translation, 2D rotation, scale
- They can usually also handle
  - Limited 3D rotations (SIFT works up to about 60 degrees)
  - Limited affine transformations (some are fully affine invariant)
  - Limited illumination/contrast changes

How to achieve invariance

Need both of the following:

1. Make sure your detector is invariant
   - Harris is invariant to translation and rotation
   - Scale is trickier
     - common approach is to detect features at many scales using a Gaussian pyramid (e.g., MOPS)
     - More sophisticated methods find "the best scale" to represent each feature (e.g., SIFT)
2. Design an invariant feature *descriptor*
   - A descriptor captures the information in a region around the detected feature point
   - The simplest descriptor: a square window of pixels
     - What's this invariant to?
   - Let's look at some better approaches…

Rotation invariance for feature descriptors

Find dominant orientation of the image patch

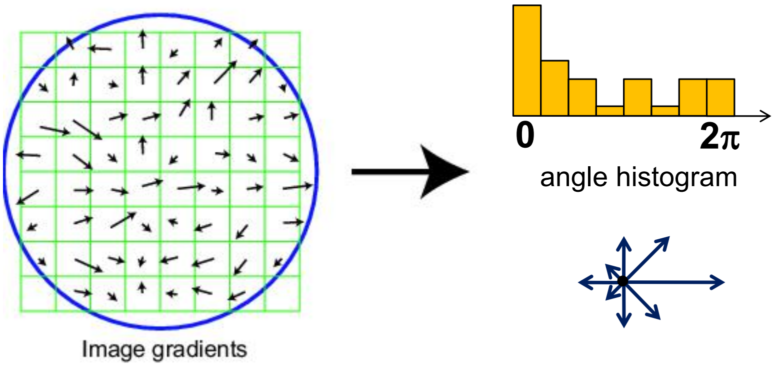
- Rotate the patch according to this angle

Figure by Matthew Brown

Scale Invariant Feature Transform

Basic idea:

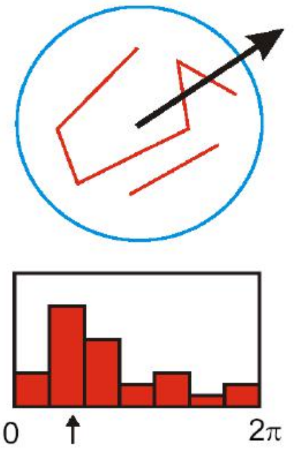
- Take 16x16 square window around detected feature
- Compute edge orientation (angle of the gradient - 90°) for each pixel
- Throw out weak edges (threshold gradient magnitude)
- Create histogram of surviving edge orientations



Adapted from slide by David Lowe

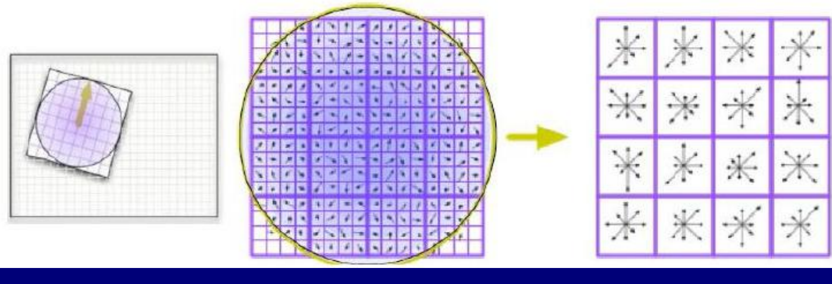
Orientation Assignment : Concept

- Create histogram of local gradient directions at the selected scale
- Assign canonical orientation at the peak of the smoothed histogram
- If two major orientations, use both



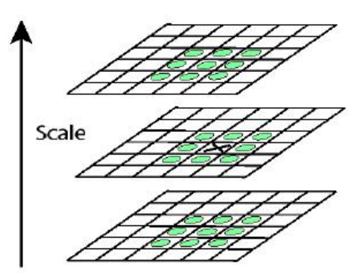
SIFT Feature Calculation

- Take the region around a keypoint according to its scale
- Rotate and align with the previously calculated orientation
- 8 orientation bins calculated at 4x4 bin array
- 8 x 4 x 4 = 128 dimension feature

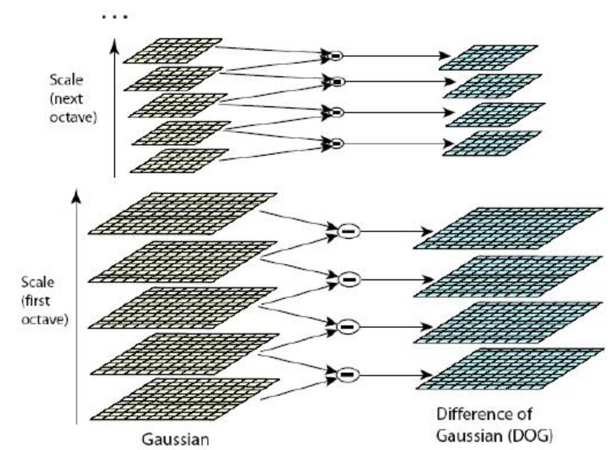


Local Extrema in DoG Images

- Minima
- Maxima
- 26 neighbourhood



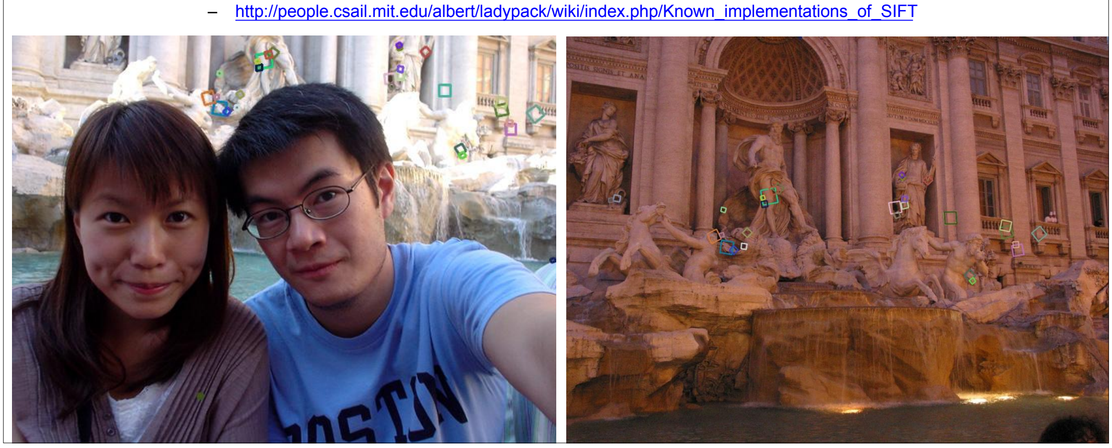
Efficient DoG Computation using Gaussian Scale Pyramid



Properties of 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



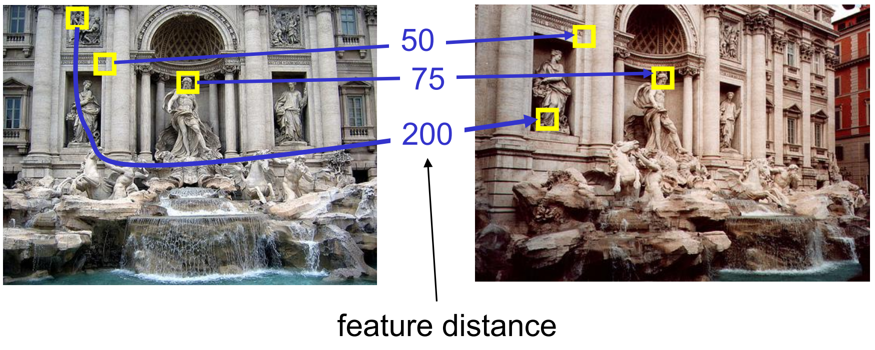
Feature matching

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

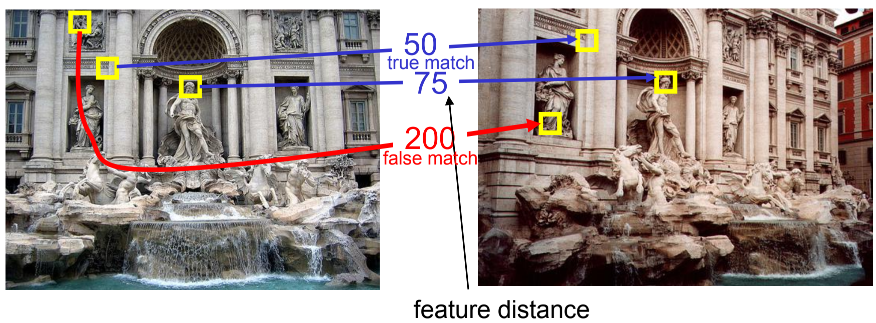
1. Define distance function that compares two descriptors
2. Test all the features in I_2, find the one with min distance

Evaluating the results

How can we measure the performance of a feature matcher?



True/false positives

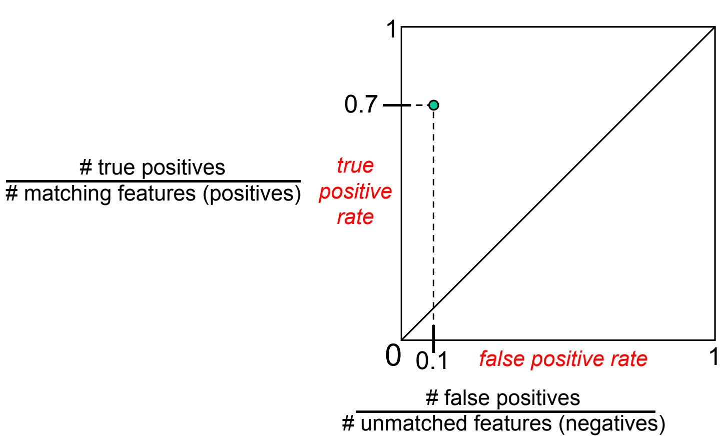


The distance threshold affects performance

- 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?

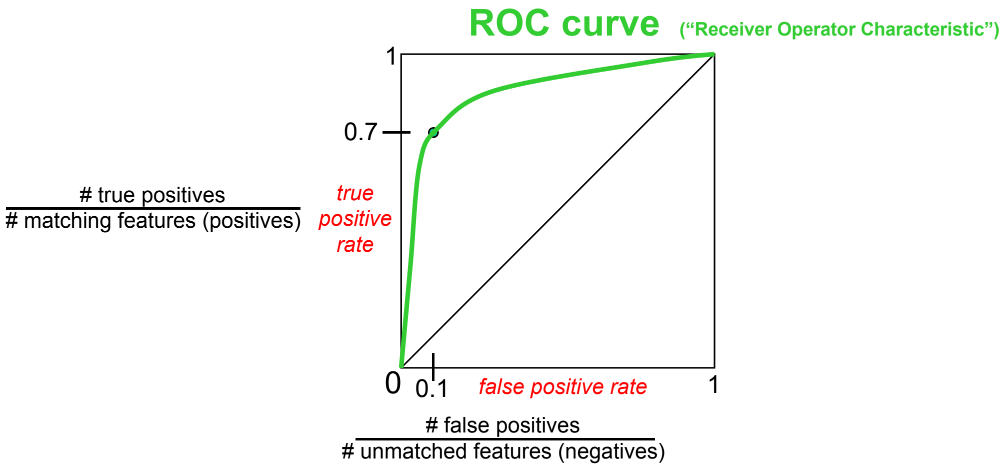
Evaluating the results

How can we measure the performance of a feature matcher?



Evaluating the results

How can we measure the performance of a feature matcher?



ROC Curves

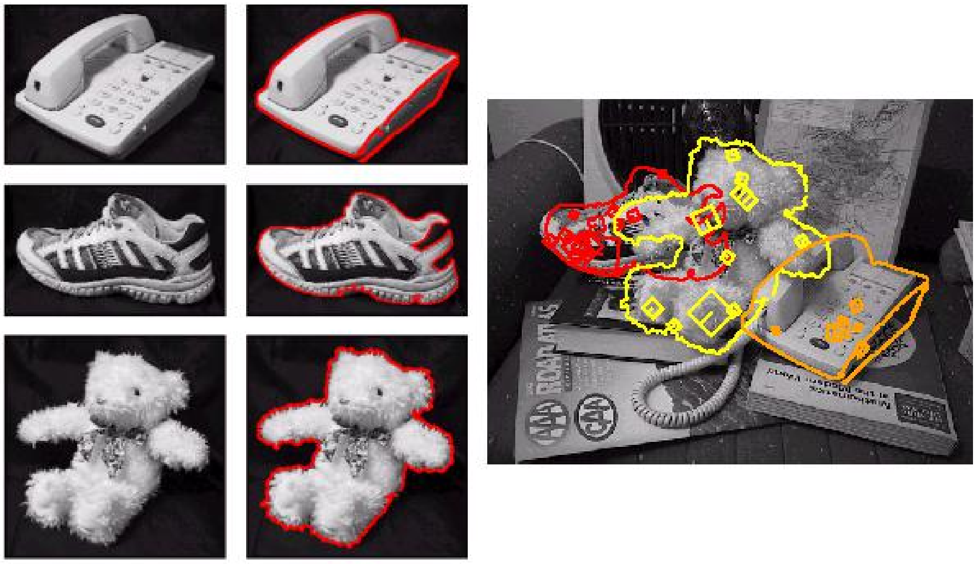
- Generated by counting # current/incorrect matches, for differentthreholds
- Want to maximize area under the curve (AUC)
- Useful for comparing different feature matching methods

Lots of applications

Features are used for:

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

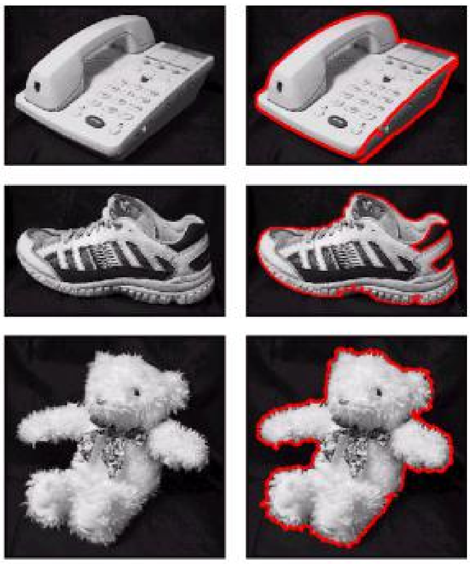
Object recognition (David Lowe)

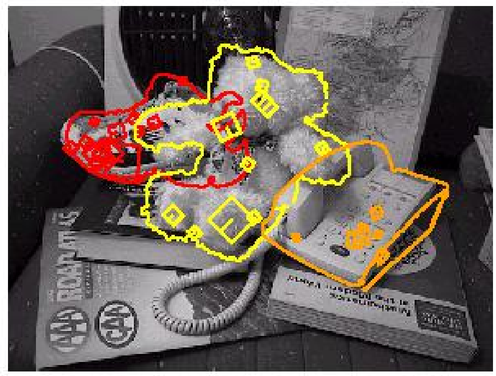


Feature Detectors – Classic and State of the Art

Feature	Detection	Extraction	OpenCV	Published
Harris	Yes	No	Yes	1988
KLT	Yes	No	Yes	1994
LBP	No	Yes	Yes	1994
SIFT	Yes	Yes	Yes	IJCV 2004
FAST	Yes	No	Yes	ECCV 2006
SURF	Yes	Yes	Yes	CVIU 2008
BRIEF	No	Yes	~	ECCV 2010
ORB	Yes	Yes	Yes	ICCV 2011
BRISK	Yes	Yes	Yes	ICCV 2011
FREAK	Yes	Yes	Yes	CVPR 2012

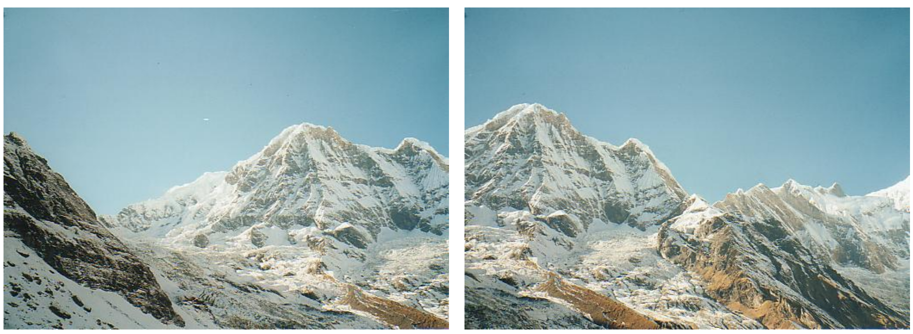
Object recognition (David Lowe)



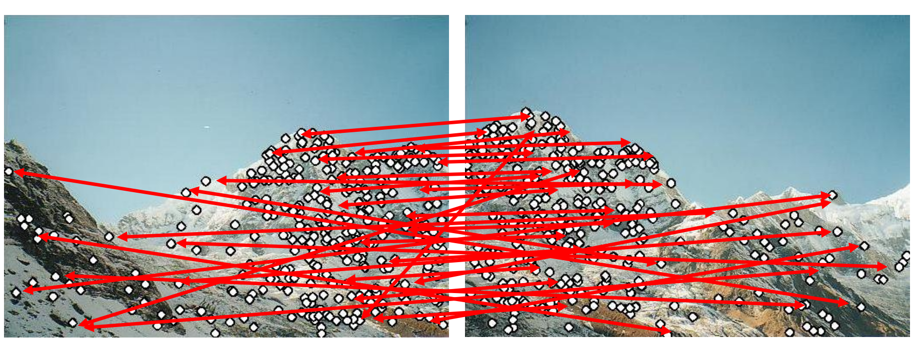


How do we build panorama？

- We need to match (align) images



Feature-based alignment outline



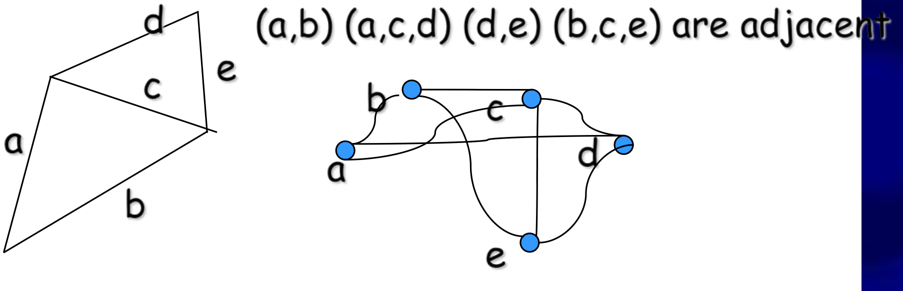
- Extract features
- Compute *putative matches*

Feature-based alignment outline

- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation *T*
  - *Verify* transformation (search for other matches consistent with *T*)

Relational Graphs

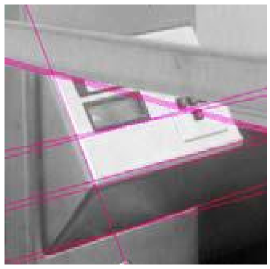
- Features and their relationships can be organized by using a <u>*relational graph.*</u>



•Graph matching algorithms ➔ Exponential cost !!!!!

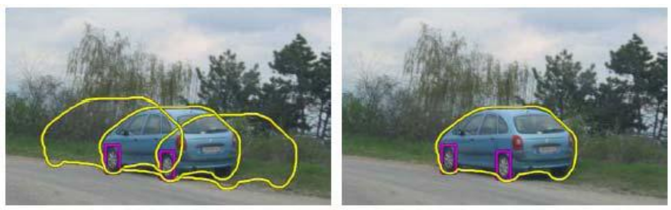
Fitting

- Choose a parametric model to represent a set of features



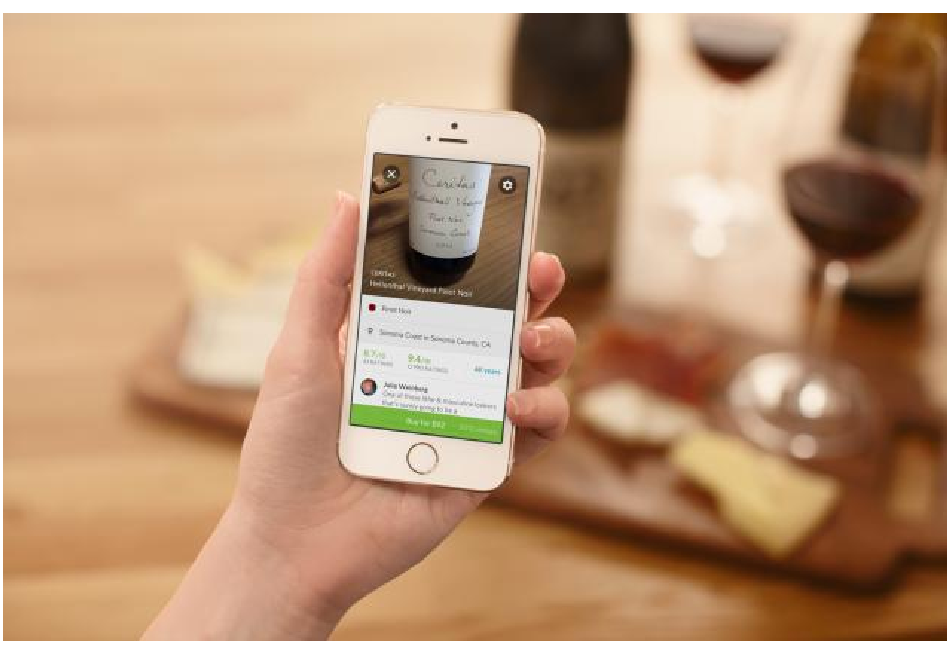
simple model: lines

simple model: circles



complicated model: car

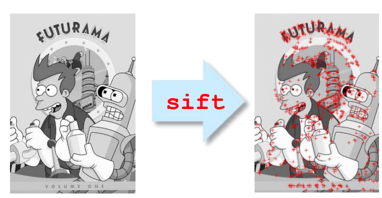
Source: K. Grauman



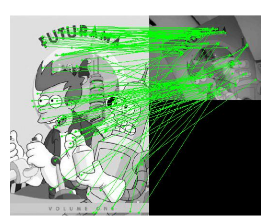
Once detected...
How do we match an object in an image?

Object matching in three steps

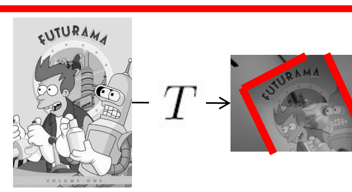
1. Detect features in the template and search images



2. Match features: find “similar-looking” features in the two images



3. Find a transformation T that explains the movement of the matched features



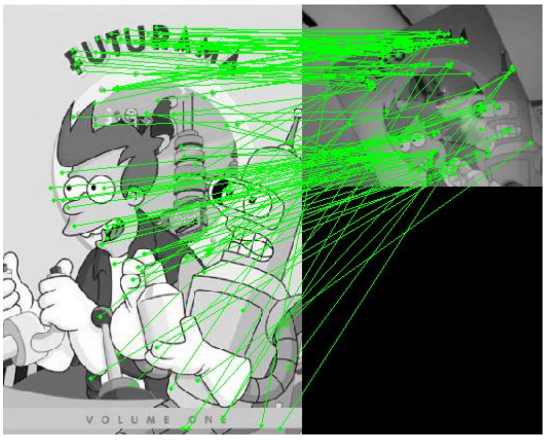
Affine transformations

- A *2D affine transformation* has the form:

$$T = \begin{bmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{bmatrix}$$

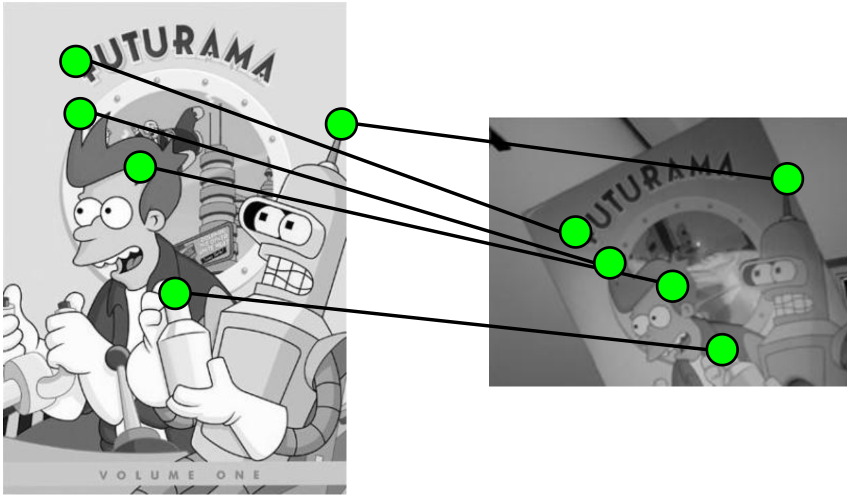
$$\begin{bmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} ax + by + c \\ dx + ey + f \\ 1 \end{bmatrix}$$

Fitting affine transformations



- We will fit an affine transformation to a set of feature matches
  - Problem: there are many incorrect matches

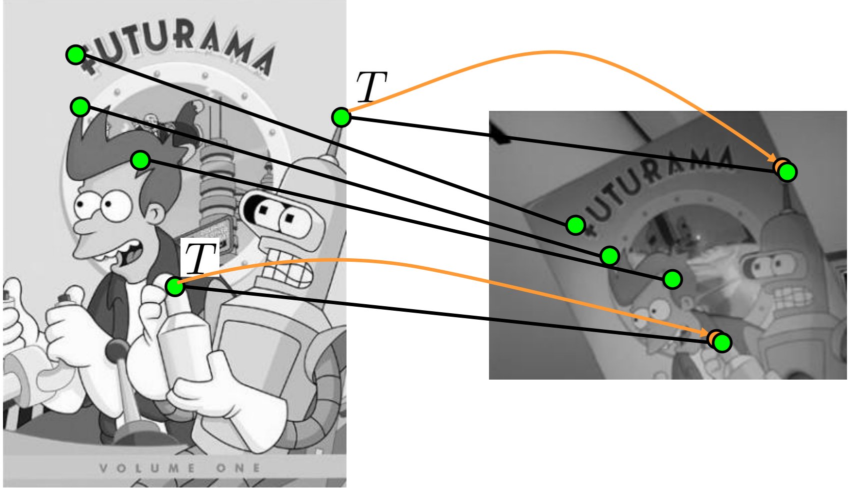
Very similar idea



- Given two images with a set of feature matches, how do we compute an affine transform between the two images?

Fitting an affine transformation

- In other words:
  - Find 2D affine xform T that maps points in image 1 as close as possible to their matches in image 2



Multi-variable fitting

- Let's consider 2D affine transformations
  - maps a 2D point to another 2D point

$$T = \begin{bmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{bmatrix}$$

- We have a set of n matches

$[\ x_1\ y_1\ ] \rightarrow [\ x_1'\ y_1'\ ]$
$[\ x_2\ y_2\ ] \rightarrow [\ x_2'\ y_2'\ ]$
$[\ x_3\ y_3\ ] \rightarrow [\ x_3'\ y_3'\ ]$
…
$[\ x_n\ y_n\ ] \rightarrow [\ x_n'\ y_n'\ ]$

Fitting an affine transformation

- Consider just one match

$[\ x_1\ y_1\ ] \rightarrow [\ x_1'\ y_1'\ ]$

$$\begin{bmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} = \begin{bmatrix} x_1' \\ y_1' \\ 1 \end{bmatrix}$$

$$\mathbf{ax_1 + by_1 + c = x_1'}$$
$$\mathbf{dx_1 + ey_1 + f = y_1'}$$

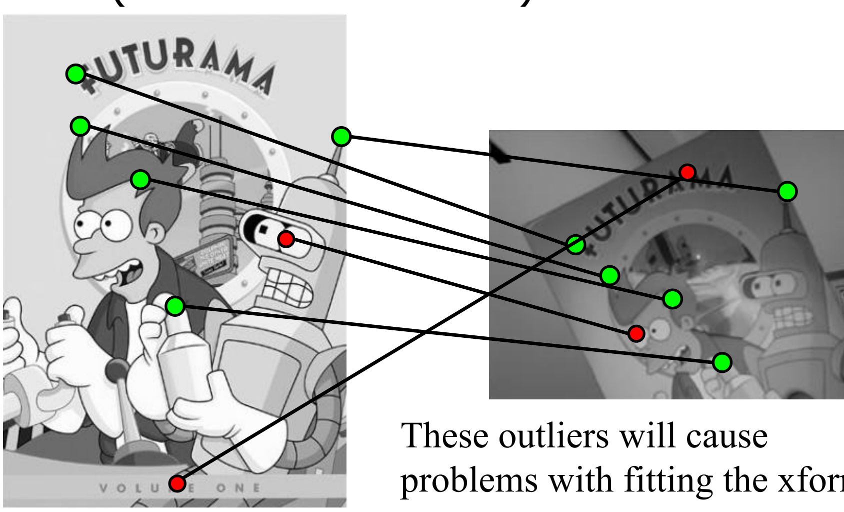
- 2 equations, 6 unknowns → we need at least 3 matches, but can fit n using least squares

Fitting an affine transformation

- This is just a bigger linear system, still (relatively) easy to solve
- Really just two linear systems with 3 equations each (one for a,b,c, the other for d,e,f)

Back to fitting

- Just like in the case of fitting a line or computing a median, we have some bad data (incorrect matches)



These outliers will cause problems with fitting the xform

Dealing with outliers

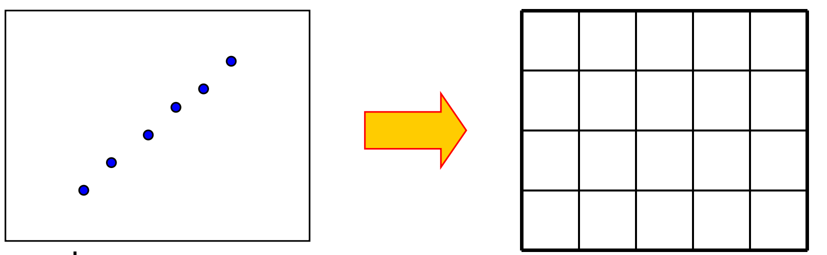
- The set of putative matches contains a very high percentage of outliers
- Geometric fitting strategies:
  - Hough transform
  - RANSAC

Hough Transform (Voting schemes)

- Let each feature vote for all the models that are compatible with it
- Hopefully the noise features will not vote consistently for any single model
- Missing data doesn't matter as long as there are enough features remaining to agree on a good model

Hough transform

- An early type of voting scheme
- General outline:
  - Discretize parameter space into bins
  - For each feature point in the image, put a vote in every bin in the parameter space that could have generated this point
  - Find bins that have the most votes



P.V.C. Hough, *Machine Analysis of Bubble Chamber Pictures,* Proc. Int. Conf. High Energy Accelerators and Instrumentation, 1959

Fitting an affine transformation

Consider just one match

$[\ x_1\ y_1\ ] \rightarrow [\ x_1'\ y_1'\ ]$

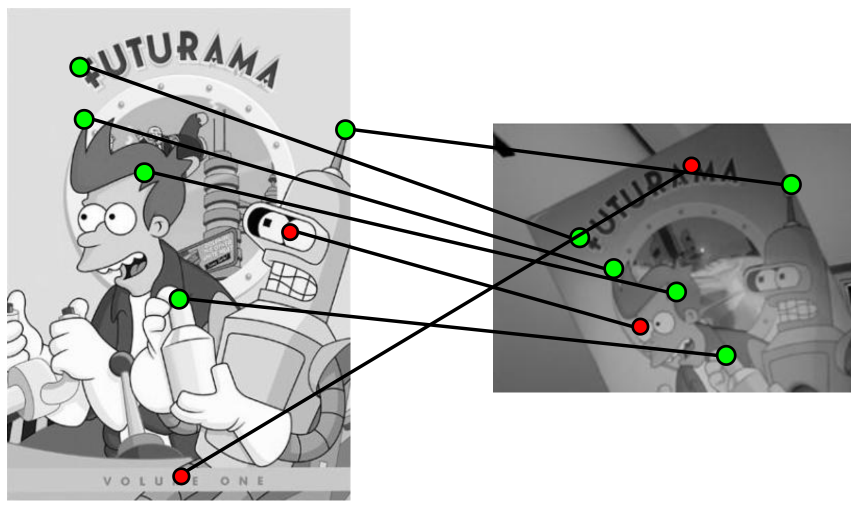
$$\begin{bmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} = \begin{bmatrix} x_1' \\ y_1' \\ 1 \end{bmatrix}$$

$$ax_1 + by_1 + c = x_1'$$
$$dx_1 + ey_1 + f = y_1'$$

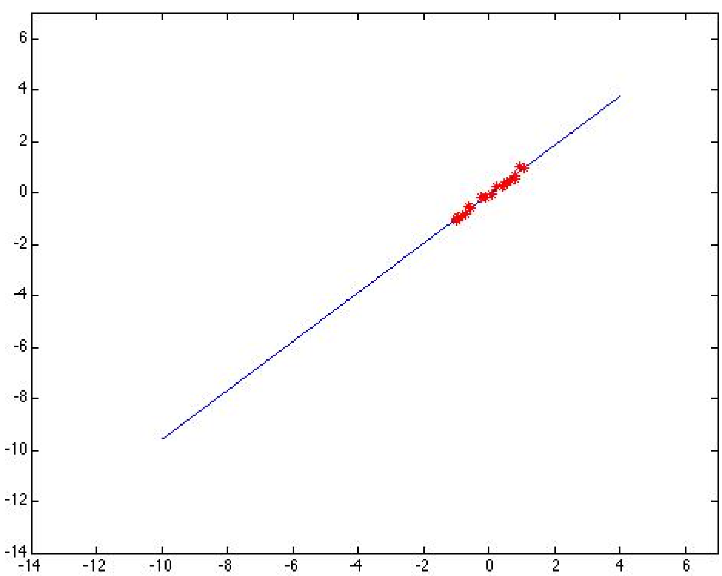
Acumule votes in the [a,b,c] and the [d,e,f] Hough arrays.

Remember the curse of dimensionality

RANSAC

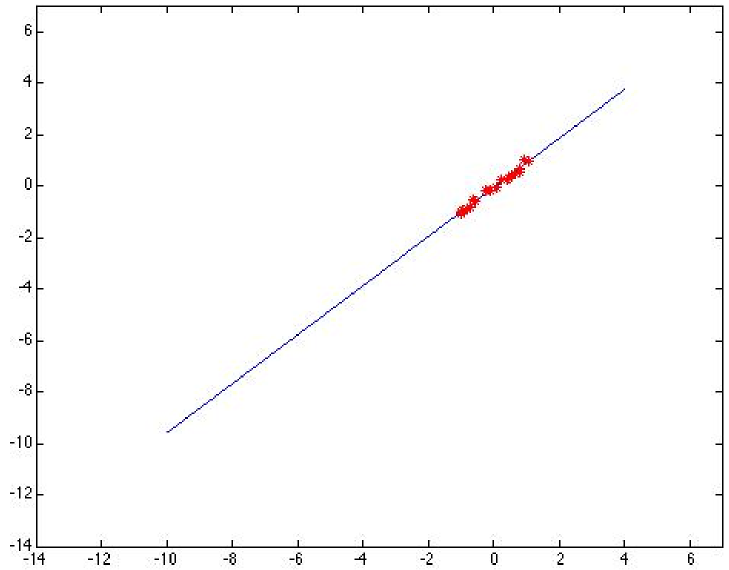


A toy example: fitting a line



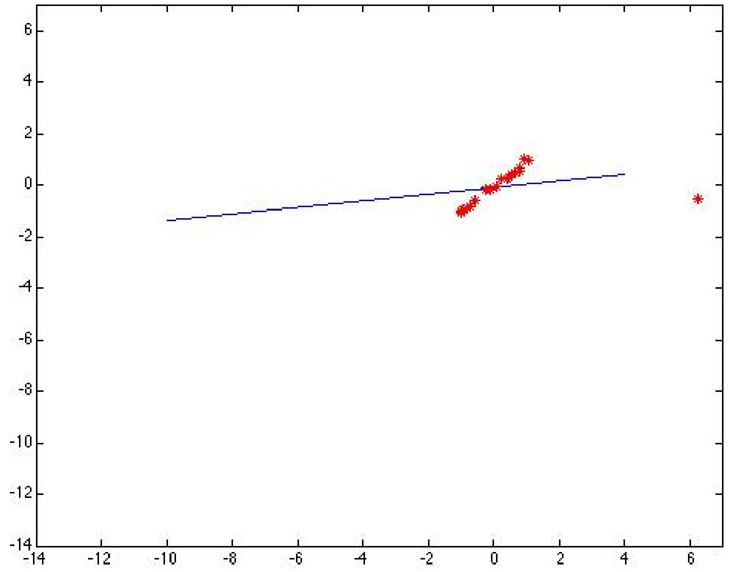
Least squares: Robustness to noise

Least squares fit to the red points:



Least squares: Robustness to noise

Least squares fit with an outlier:



Problem: squared error heavily penalizes outliers

RANSAC

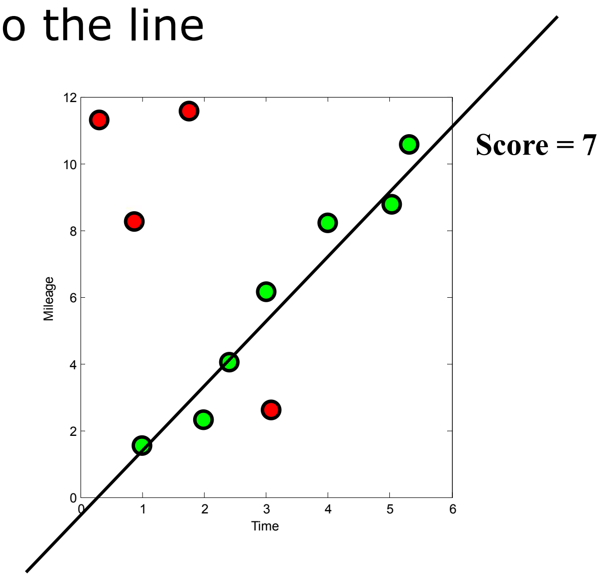
- Robust fitting can deal with a few outliers – what if we have very many?
- Random sample consensus (RANSAC): Very general framework for model fitting in the presence of outliers
- Outline
  - Choose a small subset of points uniformly at random
  - Fit a model to that subset
  - Find all remaining points that are "close" to the model and reject the rest as outliers
  - Do this many times and choose the best model

M. A. Fischler, R. C. Bolles. Random Sample Consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography. Comm. of the ACM, Vol 24, pp 381-395, 1981.

Slide: S. Lazebnik

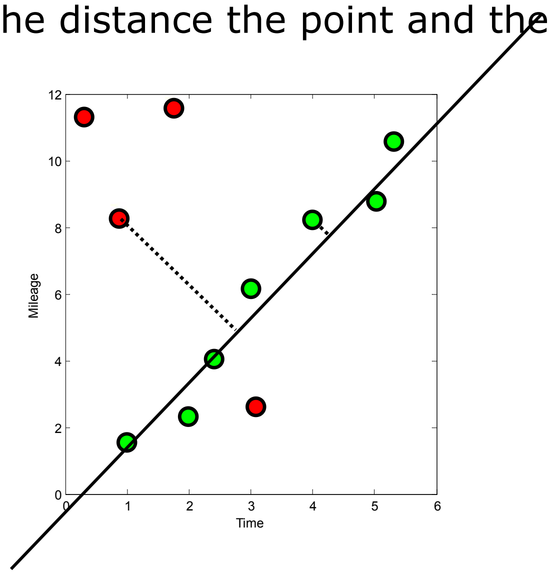
Testing goodness

- Idea: *count* the number of points that are "close" to the line



Testing goodness

- How can we tell if a point agrees with a line?
- Compute the distance the point and the line, and threshold



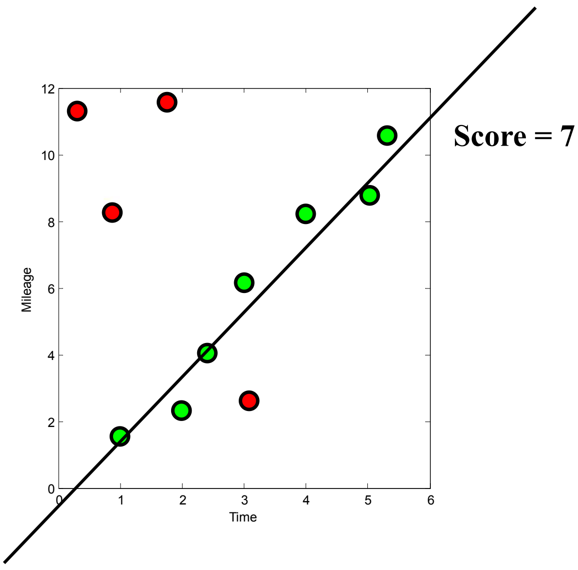
Testing goodness

- If the distance is small, we call this point an *inlier* to the line
- If the distance is large, it's an *outlier* to the line
- For an inlier point and a good line, this distance will be close to (but not exactly) zero
- For an outlier point or bad line, this distance will probably be large

- Objective function: find the line with the most inliers (or the fewest outliers)

Optimizing for inlier count

- How do we find the best possible line?



RANSAC for line fitting

Repeat ***N*** times:

- Pick ***s*** points uniformly at random (s=2)
- Fit line to these ***s*** points
- Find inliers to this line among the remaining points (i.e., points whose distance from the line is less than ***t***)
- If there are ***d*** or more inliers, accept the line and refit using all inliers

Choosing the parameters

- Initial number of points *s*
    - Typically minimum number needed to fit the model
- Distance threshold *t*
- Probability *p*, that at least one random sample is free from outliers after N iterations.(e.g: p=0'99)
- Outlier ratio e.

$$\boxed{\left(1-(1-e)^s\right)^N = 1-p}$$

$$N = \log(1-p)/\log\left(1-(1-e)^s\right)$$

	proportion of outliers e						
s	5%	10%	20%	25%	30%	40%	50%
2	2	3	5	6	7	11	17
3	3	4	7	9	11	19	35
4	3	5	9	13	17	34	72
5	4	6	12	17	26	57	146
6	4	7	16	24	37	97	293
7	4	8	20	33	54	163	588
8	5	9	26	44	78	272	1177

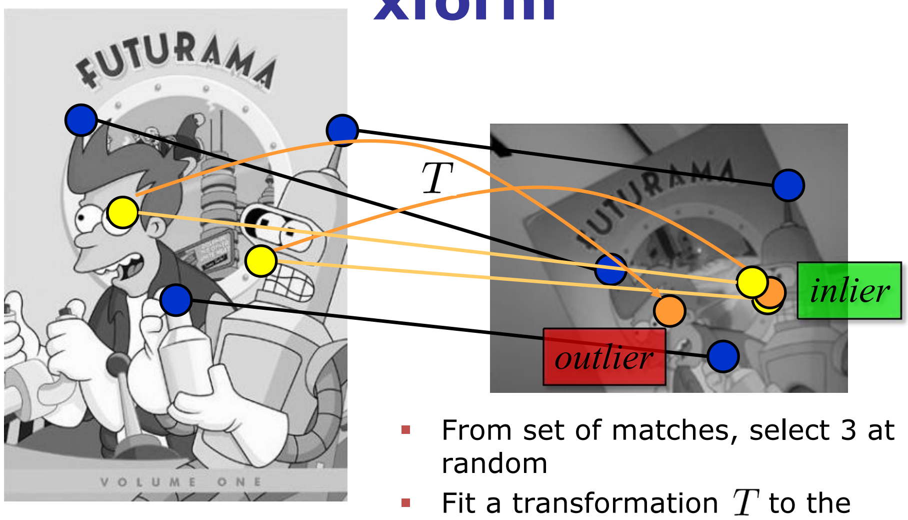
Adaptively determining the number of samples

- Inlier ratio *e* is often unknown a priori, so pick worst case, e.g. 50%, and adapt if more inliers are found, e.g. 80% would yield *e*=0.2
- Adaptive procedure:
    - *N*=∞, *sample_count* =0
    - While *N* >*sample_count*
        - Choose a sample and count the number of inliers
        - Set e = 1 – (number of inliers)/(total number of points)
        - Recompute *N* from *e:*

$$N = \log(1-p)/\log\left(1-(1-e)^s\right)$$

        - Increment the *sample_count* by 1

Generating and testing an xform



- From set of matches, select 3 at random
- Fit a transformation T to the selected matches
- Count inliers

Transform Fitting Algorithm (RANSAC)

1. Select 3 putative matches at random
2. Solve for the affine transformation T
3. Count the number of matches that are inliers to *T*
4. If *T* has the highest number of inliers so far, save it
5. Recompute N
6. Repeat for N rounds, return the best *T*

How do we solve for T given 3 matches?

- Three matches give a linear system with six equations:

$[\ x_1\ y_1\ ] \rightarrow [\ x_1'\ y_1'\ ]$

$$ax_1 + by_1 + c = x_1'$$
$$dx_1 + ey_1 + f = y_1'$$

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$[\ x_3\ y_3\ ] \rightarrow [\ x_3'\ y_3'\ ]$

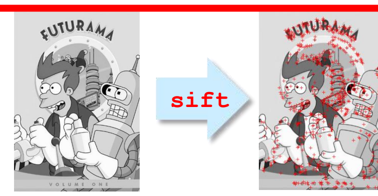
$$ax_3 + by_3 + c = x_3'$$
$$dx_3 + ey_3 + f = y_3'$$

Randomized algorithms

- Very common in computer science
  - In this case, we avoid testing an infinite set of possible lines, or all $O(n^2)$ lines generated by pairs of points
- These algorithms find the right answer with some probability
- Often work very well in practice

Object matching in three steps

1. Detect features in the template and search images



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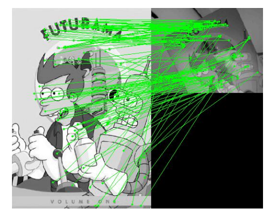

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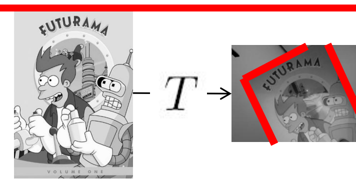
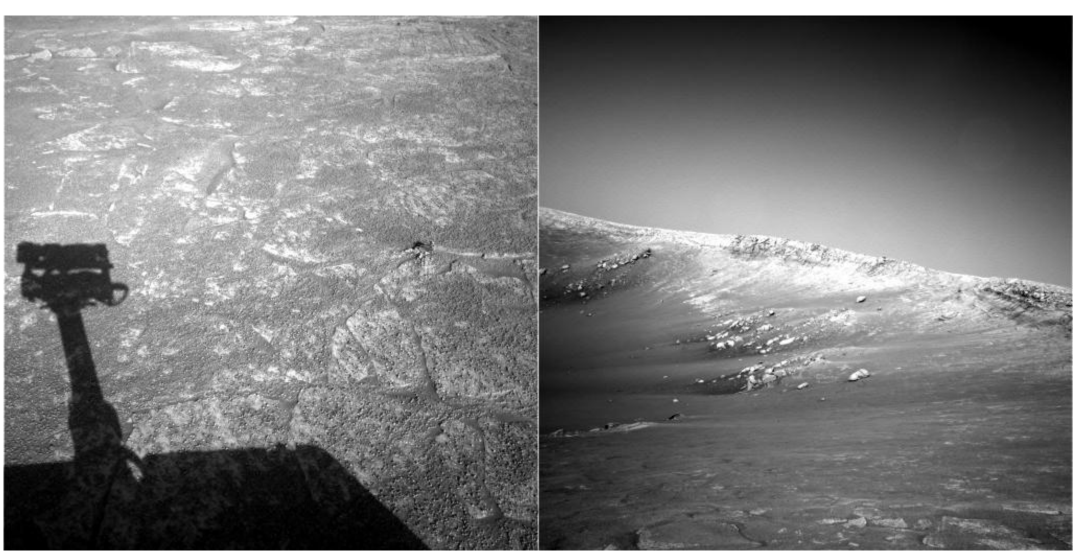
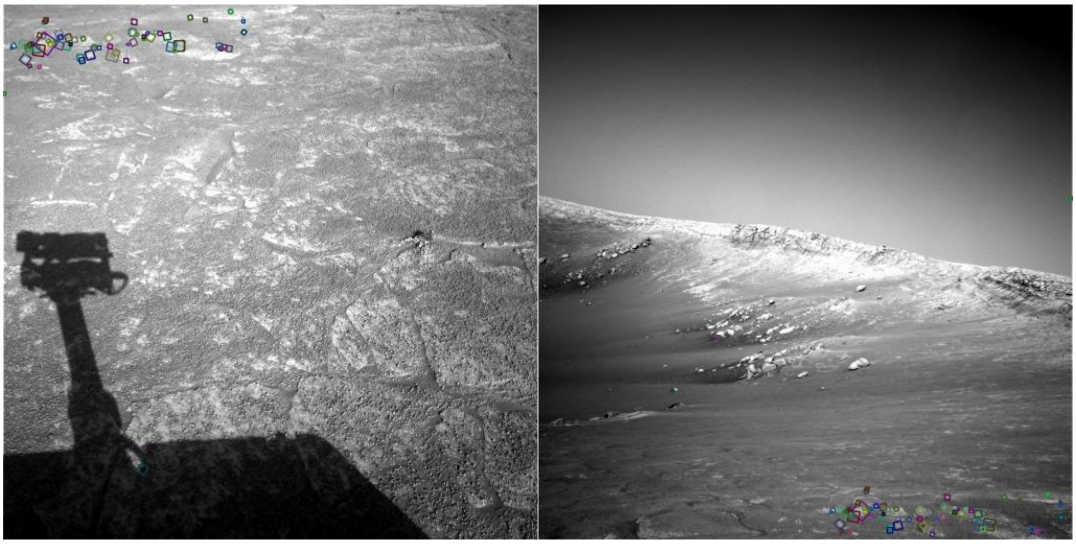


Do these two images overlap?



NASA Mars Rover images

Answer below



NASA Mars Rover images