Reconnaissance d’objets et vision artificielle 2010

Instance-level recognition II.

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Announcements

Class web-page:

http://www.di.ens.fr/willow/teaching/recvis10/

Assignment 1 is due next Tuesday, Oct 19th 2010!

Assignment 2 out: Stitching photo-mosaics

http://www.di.ens.fr/willow/teaching/recvis10/assignment2/

Matlab tutorial – Fri 15/10 13:30-15:00

Location: 23 Avenue d'Italie.

http://www.di.ens.fr/willow/contact.php

Instance-level recognition

Last time:

- Local invariant features (last lecture – C.Schmid)

Today:

- Camera geometry – review (J. Ponce)
- Correspondence, matching and recognition with local features, efficient visual search (J. Sivic)

Next week:

- Very large scale visual indexing – (C. Schmid)

Outline – the rest of the lecture

Part 1. Image matching and recognition with local features

- **Correspondence**
- **Semi-local and global geometric relations**
- **Robust estimation – RANSAC and Hough Transform**

Part 2. Going large-scale

- Approximate nearest neighbour matching
- Bag-of-visual-words representation
- Efficient visual search and extensions
- Applications

Image matching and recognition with local features

The goal: establish correspondence between two or more images

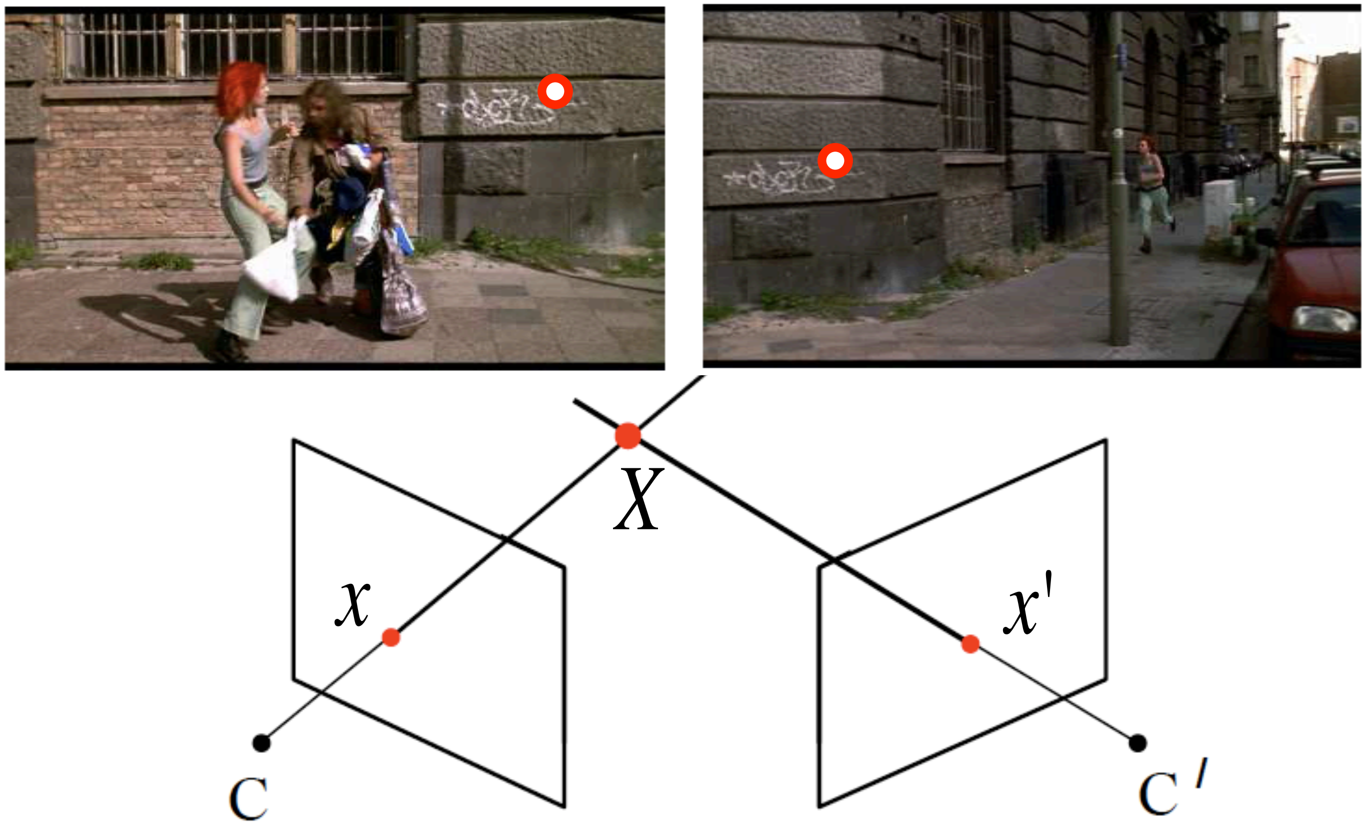


Image points x and x' are in correspondence if they are projections of the same 3D scene point X.

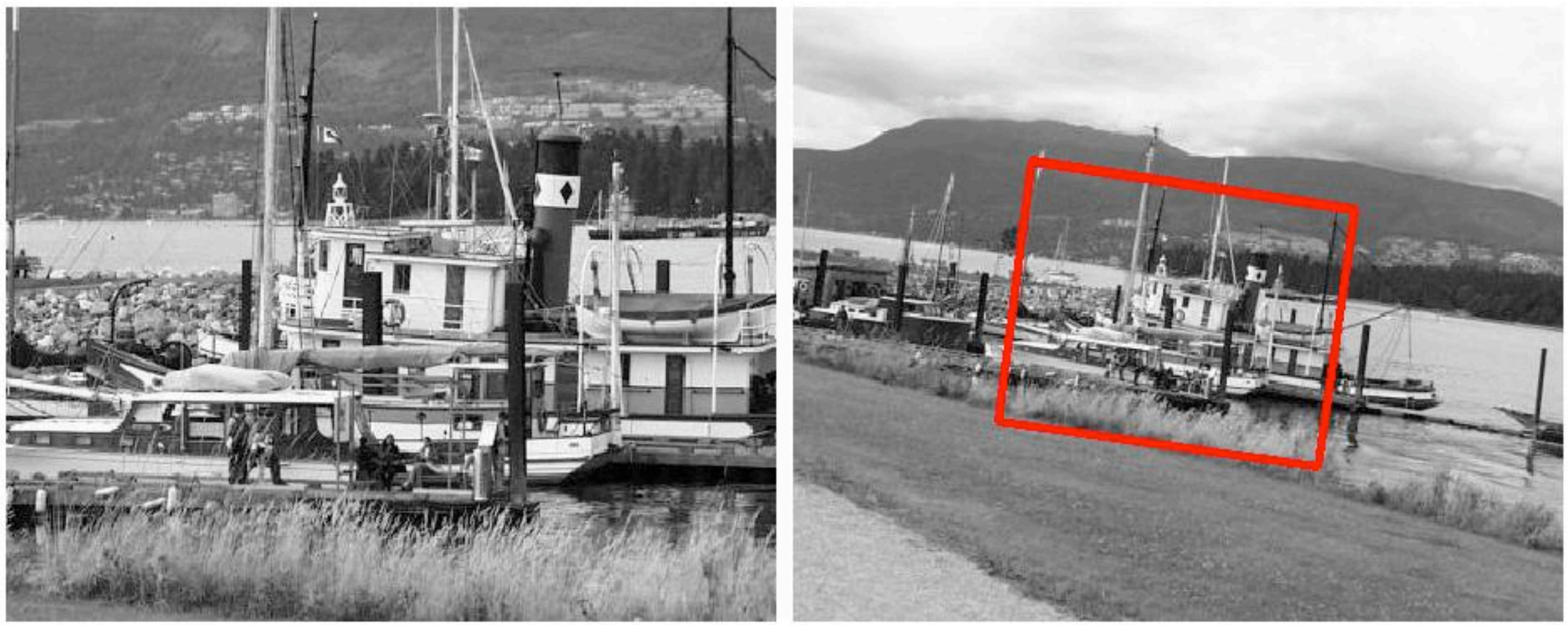
Images courtesy A. Zisserman

Example I: Wide baseline matching

Establish correspondence between two (or more) images.

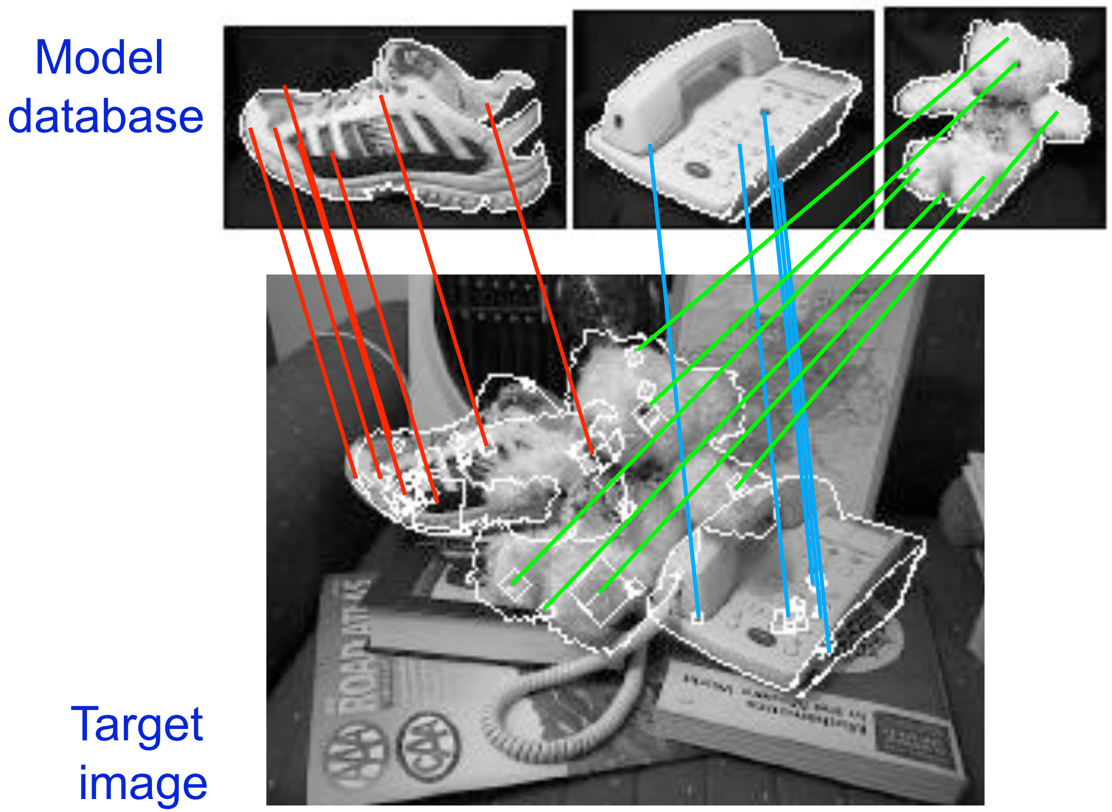
Useful in visual geometry: Camera calibration, 3D reconstruction, Structure and motion estimation, …

Scale/affine – invariant regions: SIFT, Harris-Laplace, etc.



Example II: Object recognition

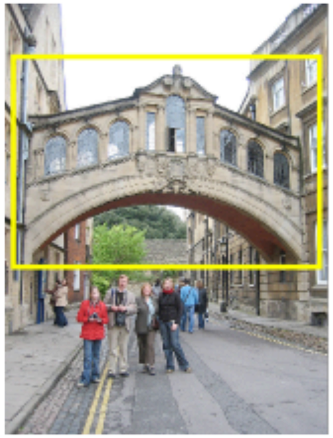
Establish correspondence between the target image and (multiple) images in the model database.



[D. Lowe, 1999]

Example III: Visual search

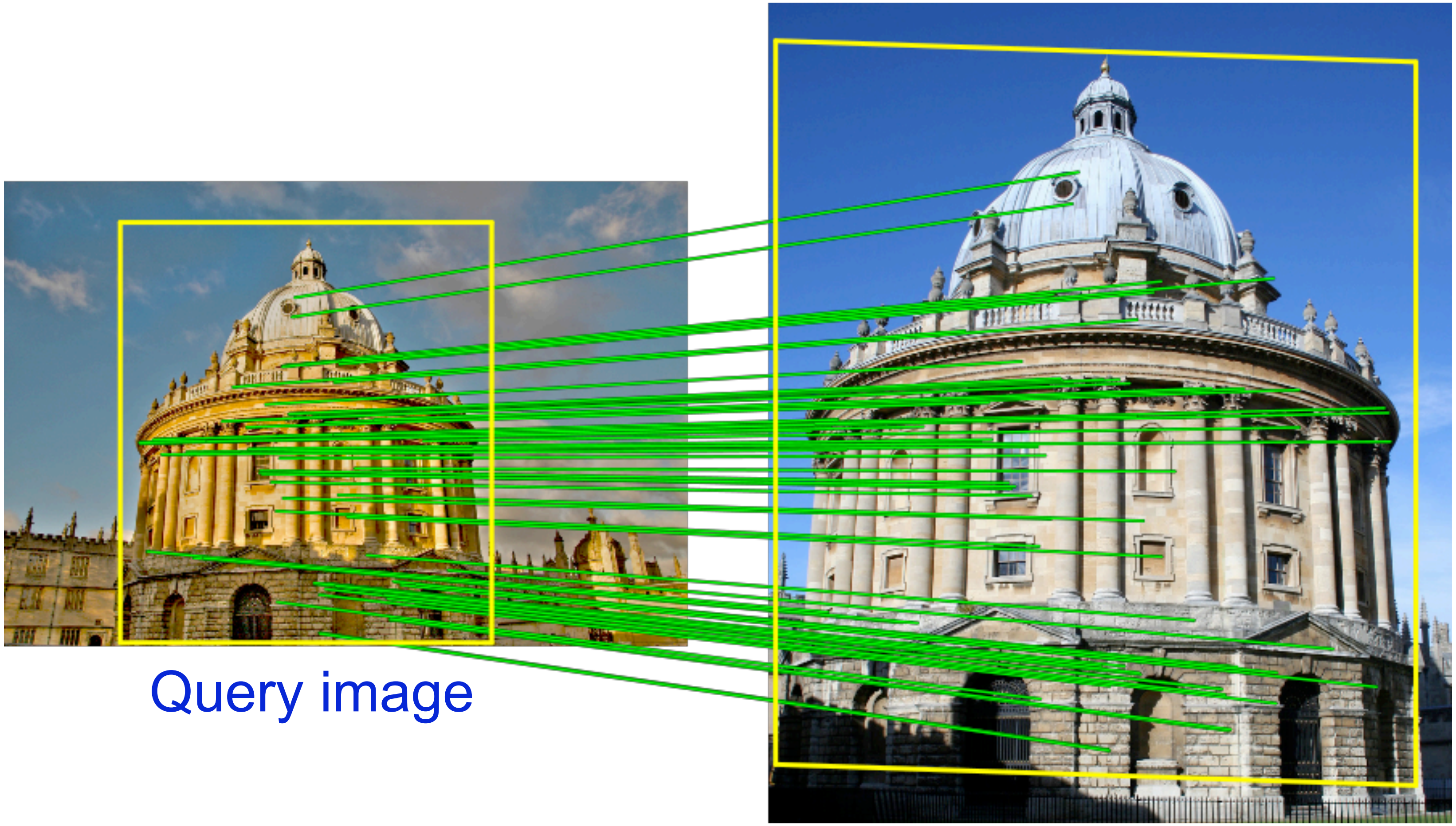
Given a query image, find images depicting the same place / object in a large unordered image collection.



Find these landmarks

...in these images and 1M more

Establish correspondence between the query image and all images from the database depicting the same object / scene.



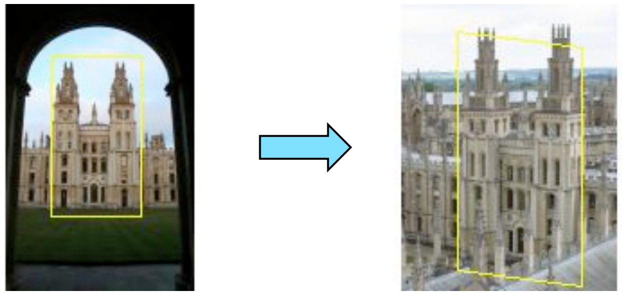
Query image

Database image(s)

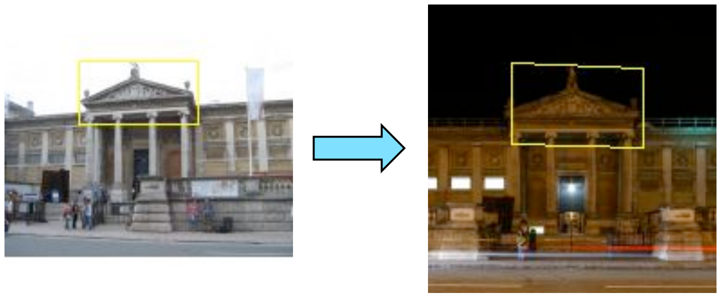
Why is it difficult?

Want to establish correspondence despite possibly large changes in scale, viewpoint, lighting and partial occlusion

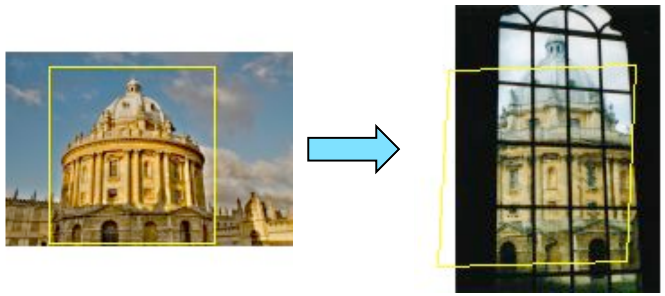
Scale



Viewpoint



Lighting



Occlusion

… and the image collection can be very large (e.g. 1M images)

Approach

Pre-processing (last lecture):

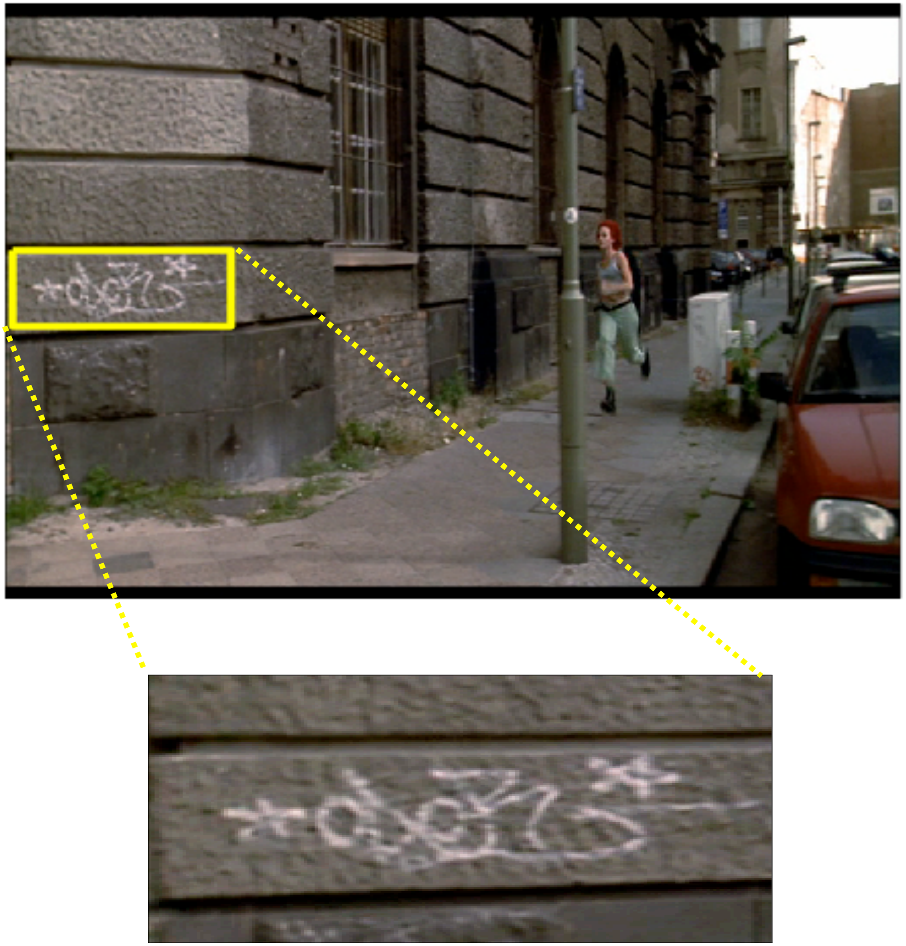
- Detect local features.
- Extract descriptor for each feature.

Matching:

1. Establish tentative (putative) correspondences based on local appearance of individual features (their descriptors).

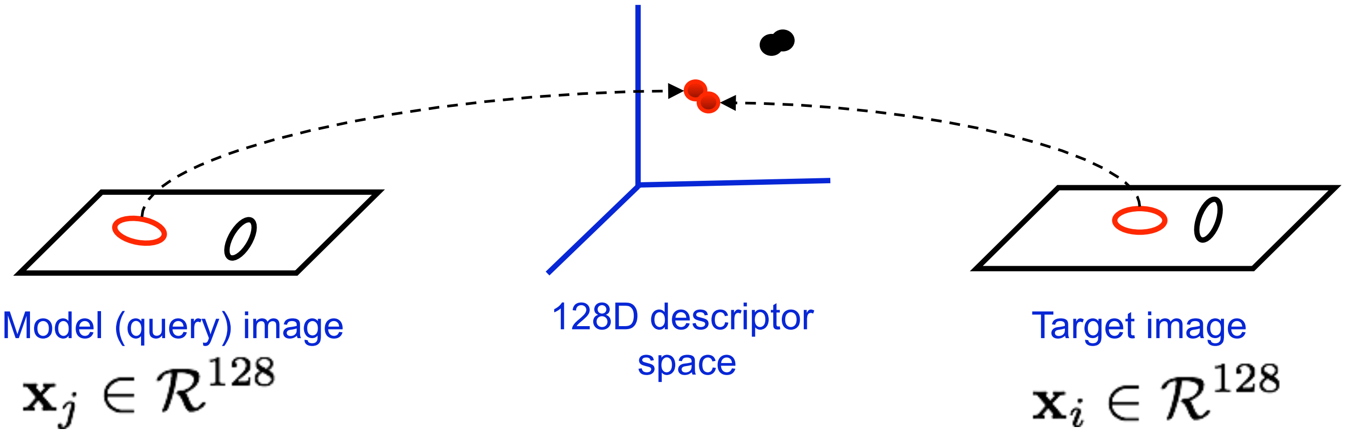
2. Verify matches based on semi-local / global geometric relations.

Example I: Two images -“Where is the Graffiti?”



Step 1. Establish tentative correspondence

Establish tentative correspondences between object model image and target image by nearest neighbour matching on SIFT vectors



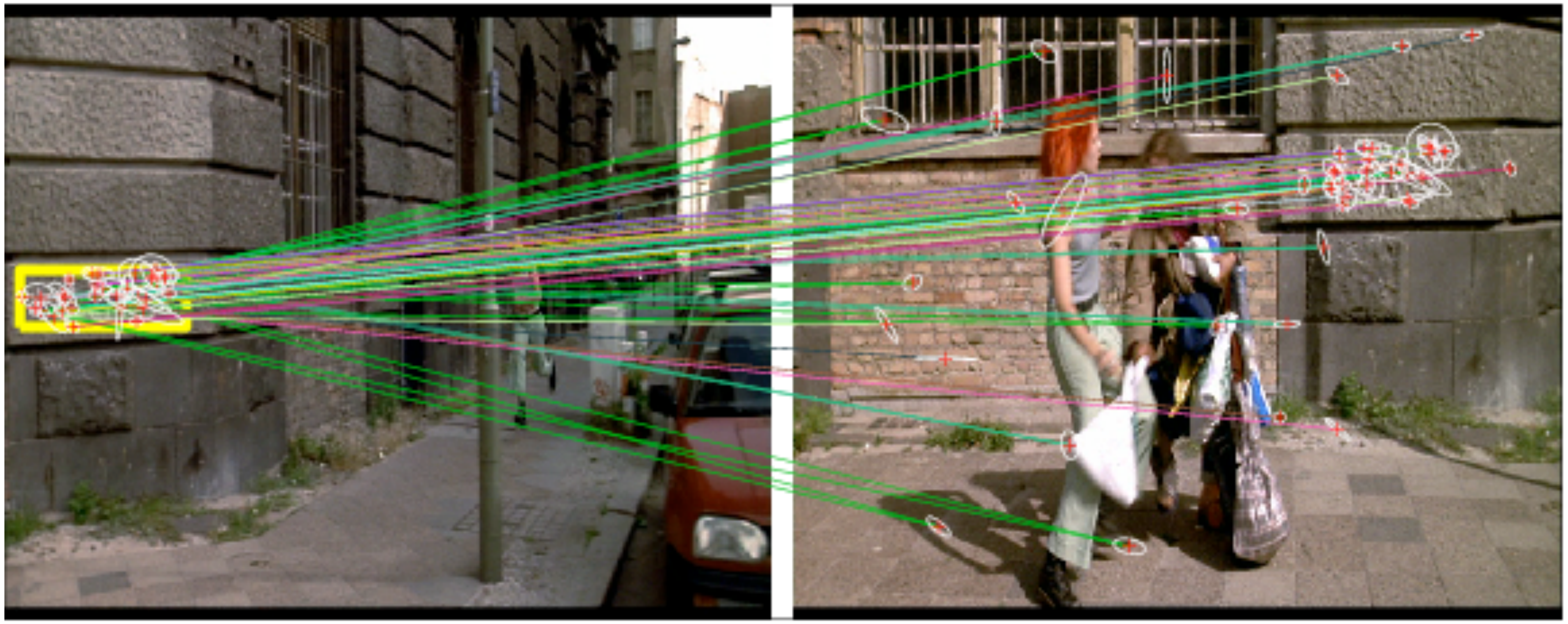
Need to solve some variant of the "nearest neighbor problem" for all feature vectors, $\mathbf{x}_j \in \mathcal{R}^{128}$, in the query image:

$$\forall j \; NN(j) = \arg\min_i ||\mathbf{x}_i - \mathbf{x}_j||,$$

where, $\mathbf{x}_i \in \mathcal{R}^{128}$, are features in the target image.

Can take a long time if many target images are considered.

Problem with matching on local descriptors alone



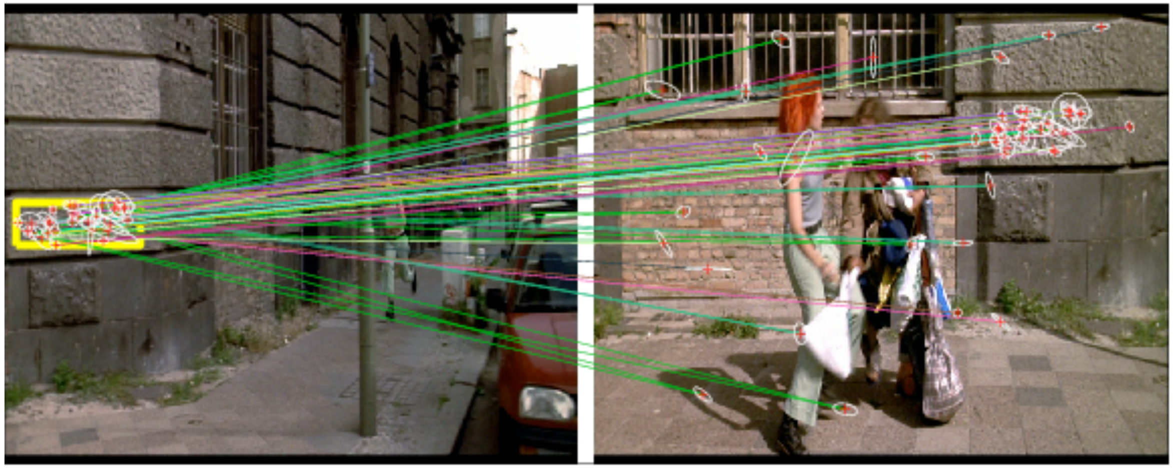
- too much individual invariance
- each region can affine deform independently (by different amounts)
- Locally appearance can be ambiguous

Solution: use semi-local and global spatial relations to verify matches.

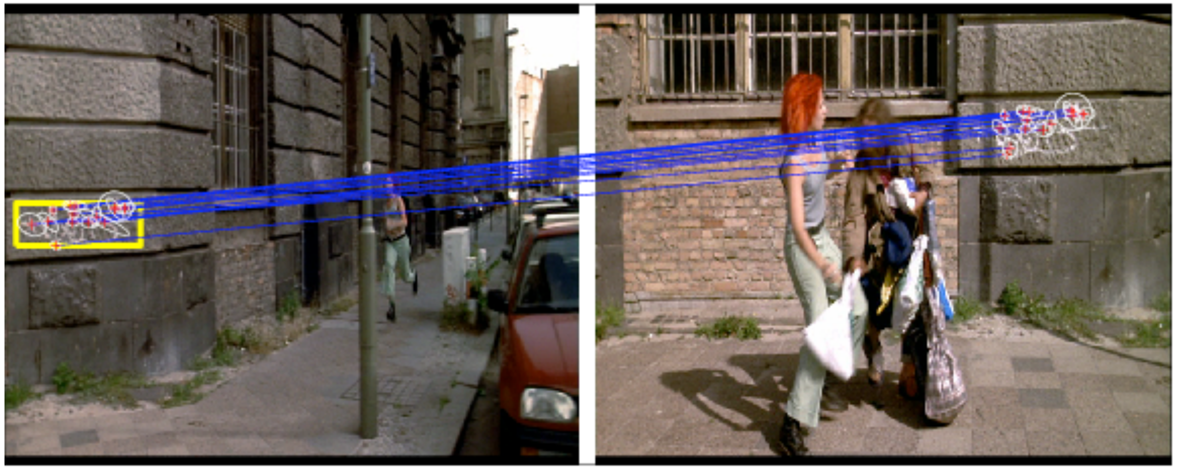
Example I: Two images -“Where is the Graffiti?”

Initial matches

Nearest-neighbor search based on appearance descriptors alone.



After spatial verification



Step 2: Spatial verification (now)

1. Semi-local constraints

   Constraints on spatially close-by matches

2. Global geometric relations

   Require a consistent global relationship between all matches

Semi-local constraints: Example I. – neighbourhood consensus

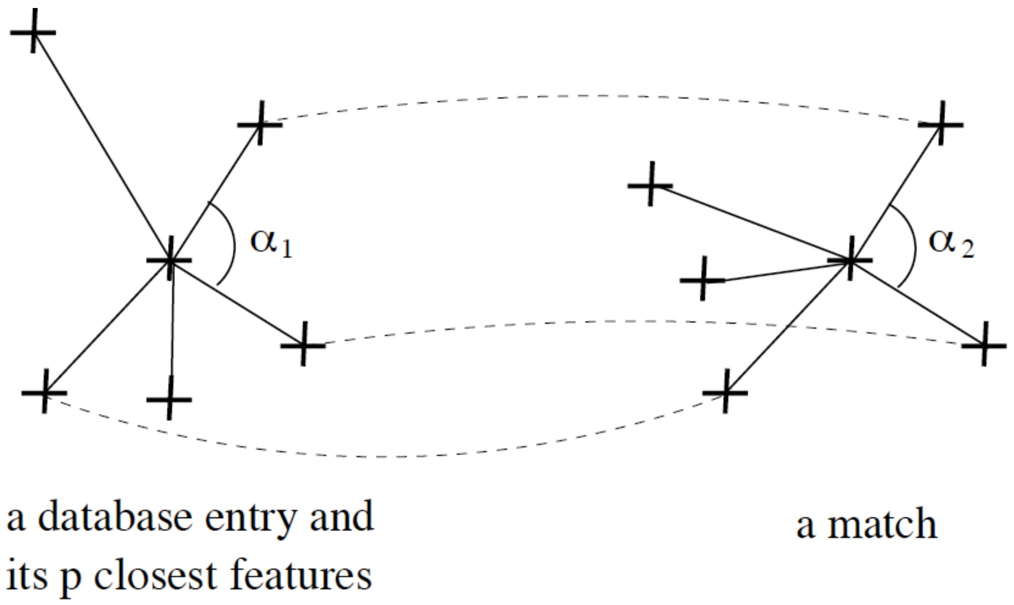
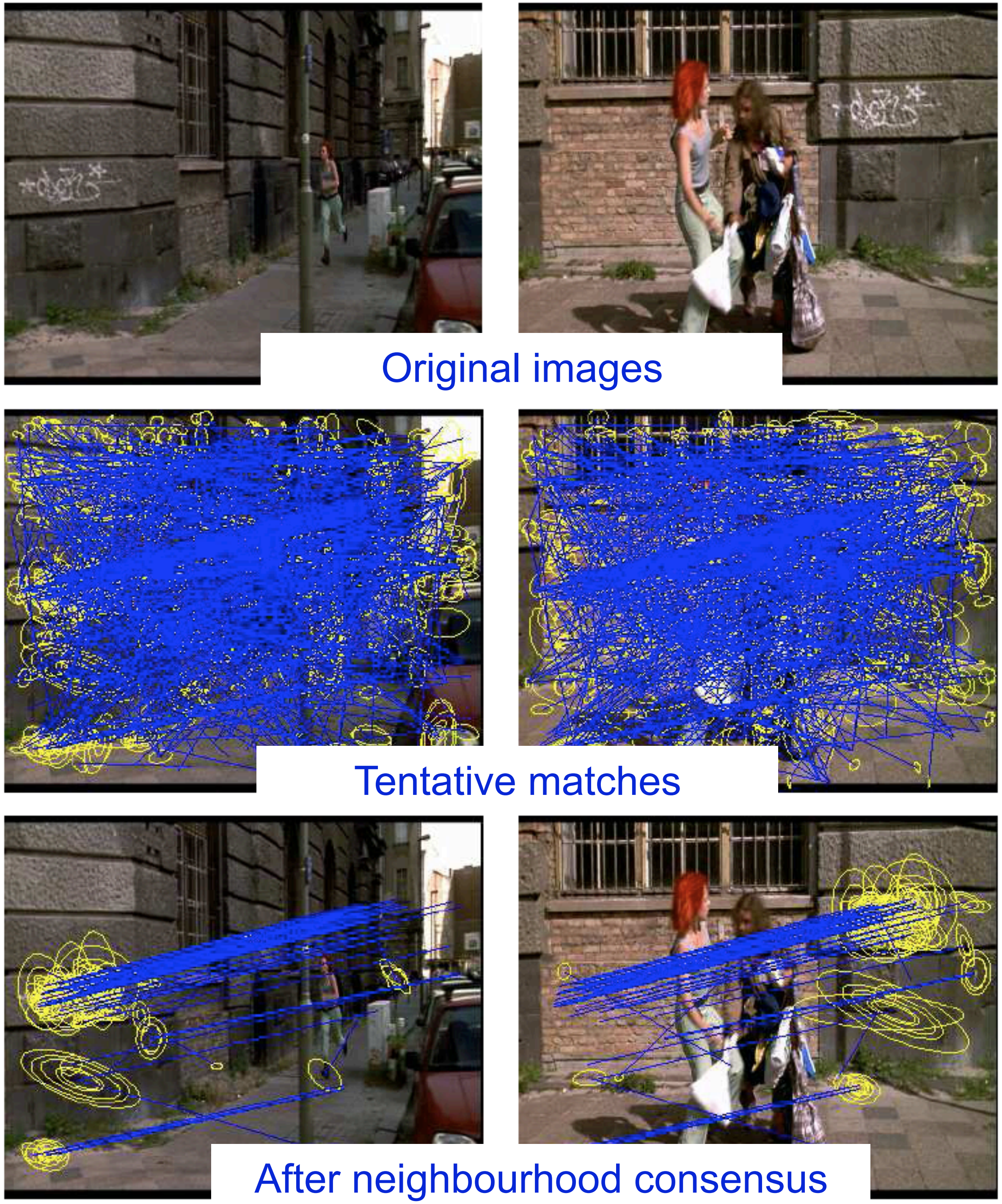


Fig. 4. Semi-local constraints : neighbours of the point have to match and angles have to correspond. Note that not all neighbours have to be matched correctly.

[Schmid&Mohr, PAMI 1997]

Semi-local constraints:

Example I. – neighbourhood consensus



[Schaffalitzky & Zisserman, CIVR 2004]

Semi-local constraints: Example II.

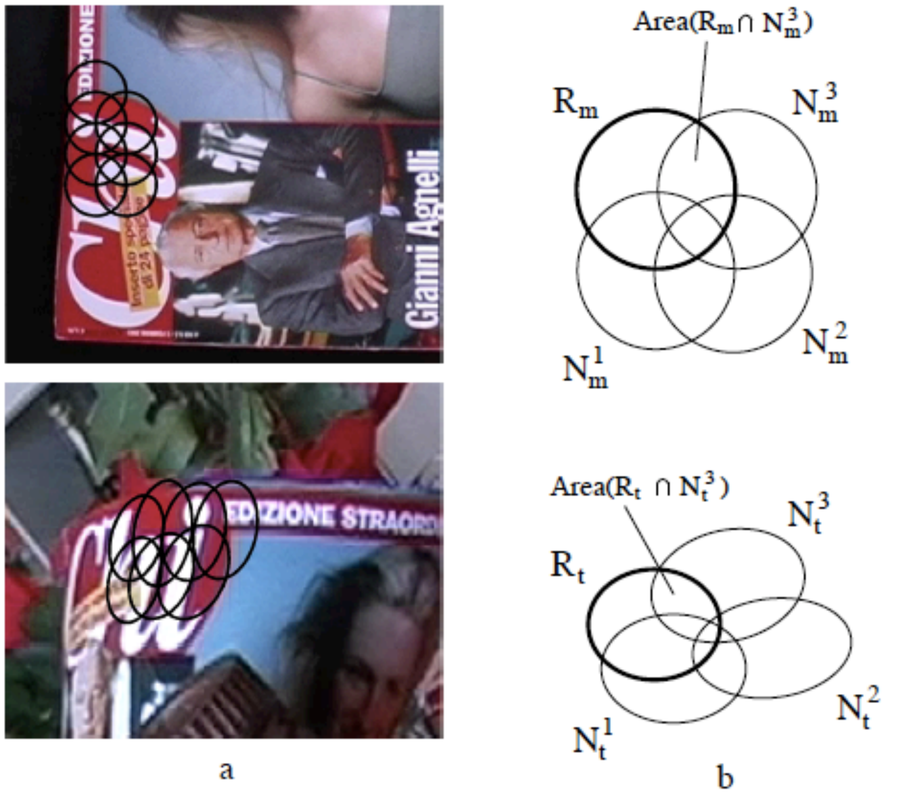


Figure 5: *Surface contiguity filter. a) the pattern of intersection between neighboring correct region matches is preserved by transformations between the model and the test images, because the surface is contiguous and smooth. b) the filter evaluates this property by testing the conservation of the area ratios.*

[Ferrari et al., IJCV 2005]

Model image

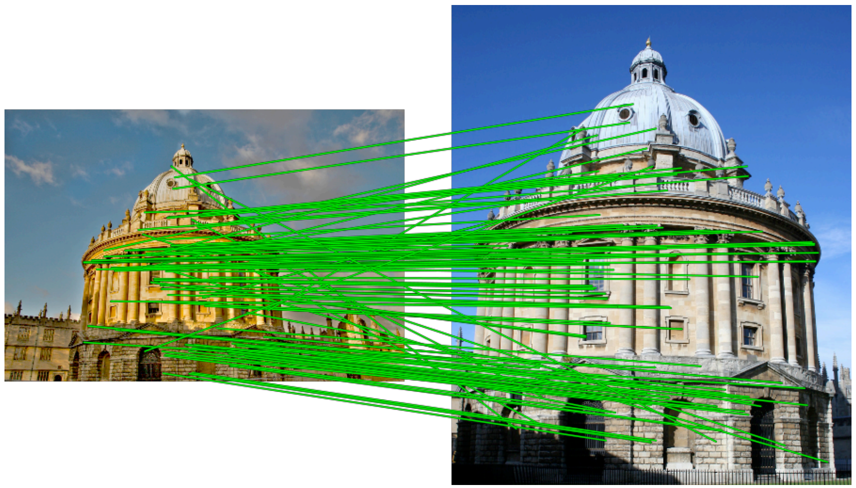
Matched image

Matched image

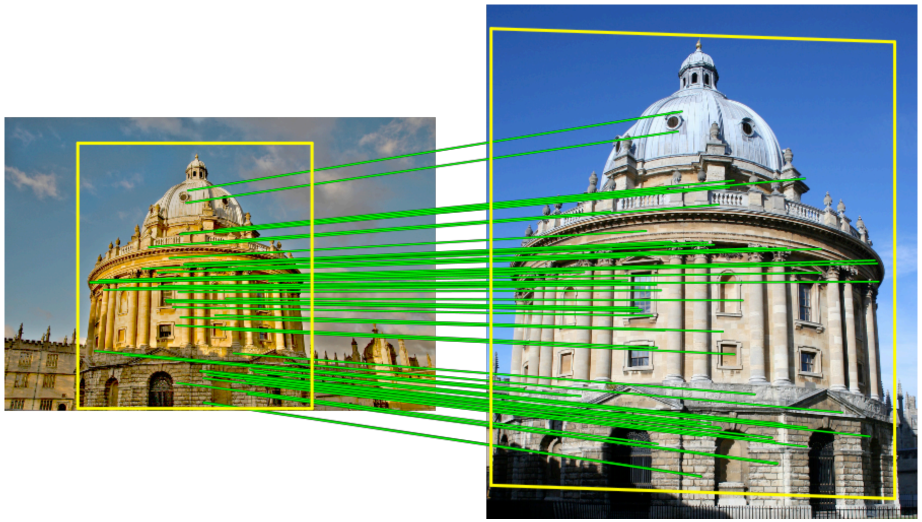
Geometric verification with global constraints

- All matches must be consistent with a global geometric relation / transformation.

- Need to simultaneously (i) estimate the geometric relation / transformation and (ii) the set of consistent matches



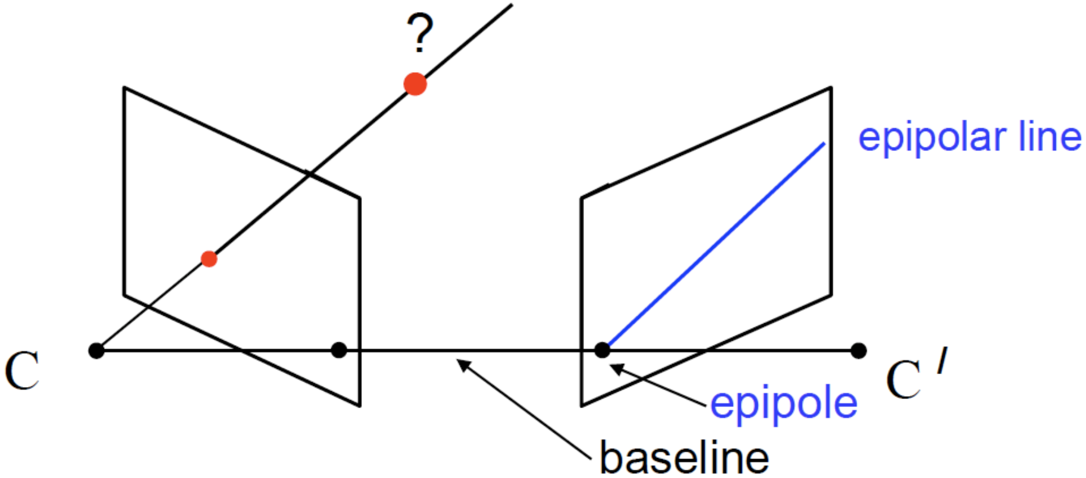
Tentative matches

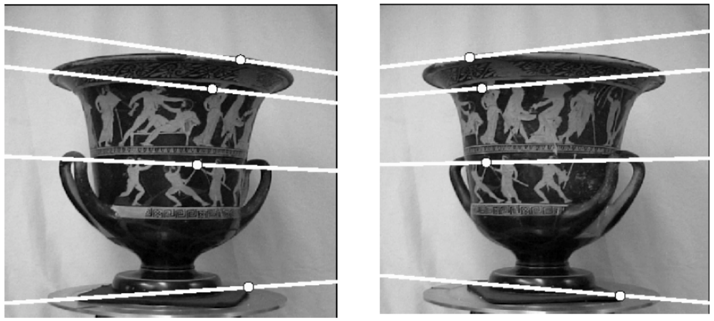


Matches consistent with an affine transformation

Epipolar geometry (not considered here)

In general, two views of a 3D scene are related by the epipolar constraint.





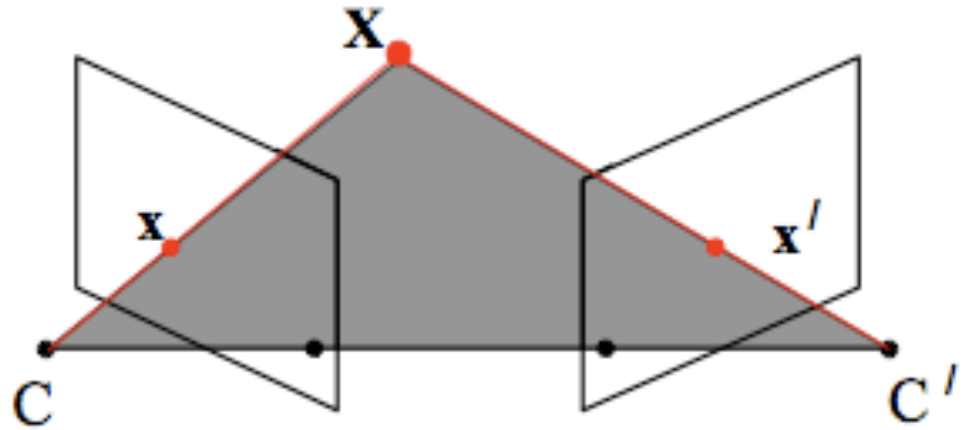
- A point in one view "generates" an epipolar line in the other view
- The corresponding point lies on this line.

Slide credit: A. Zisserman

Epipolar geometry (not considered here)

Algebraically, the epipolar constraint can be expressed as

$$\mathbf{x}'^{\top}\mathbf{F}\mathbf{x} = 0$$



where

- x, x' are homogeneous coordinates (3-vectors) of **corresponding** image points.

- F is a 3x3, rank 2 homogeneous matrix with 7 degrees of freedom, called the **fundamental matrix**.

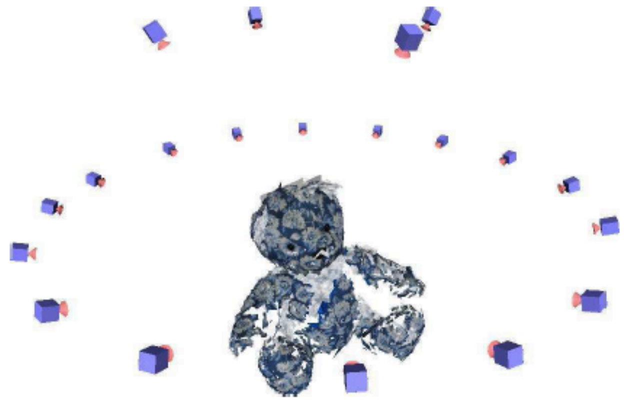
Slide credit: A. Zisserman

3D constraint: example (not considered here)

- Matches must be consistent with a 3D model

3 (out of 20) images used to build the 3D model

(a)



Recovered 3D model

Object recognized in a previously unseen pose

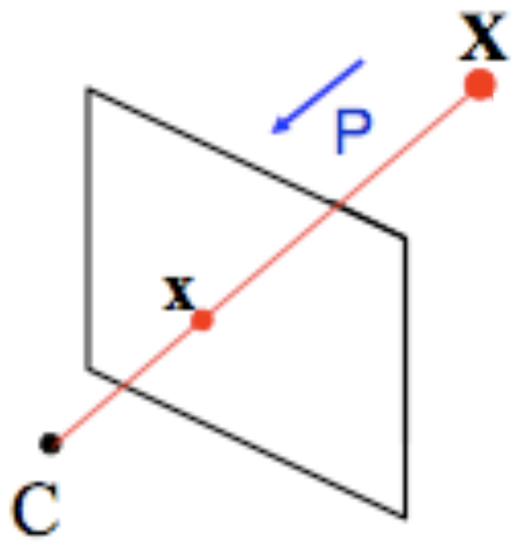
Recovered pose

(d)

[Lazebnik, Rothganger, Schmid, Ponce, CVPR'03]

3D constraint: example (not considered here)

With a given 3D model (set of known X's) and a set of measured image points x, the goal is to find find camera matrix P and a set of geometrically consistent correspondences x↔X.



$$\mathbf{x} = \mathrm{P}\mathbf{X}$$

P : 3 × 4 matrix

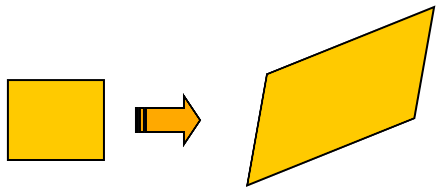
$\mathbf{X}$: 4-vector

$\mathbf{x}$: 3-vector

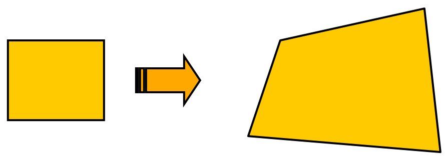
2D transformation models

Similarity
(translation,
scale, rotation)

Affine



Projective
(homography)



Estimating 2D geometric relations - outline

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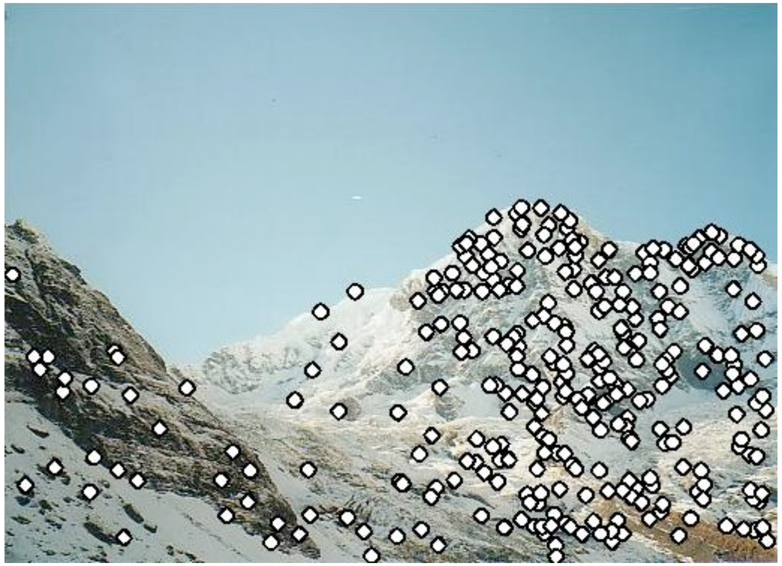
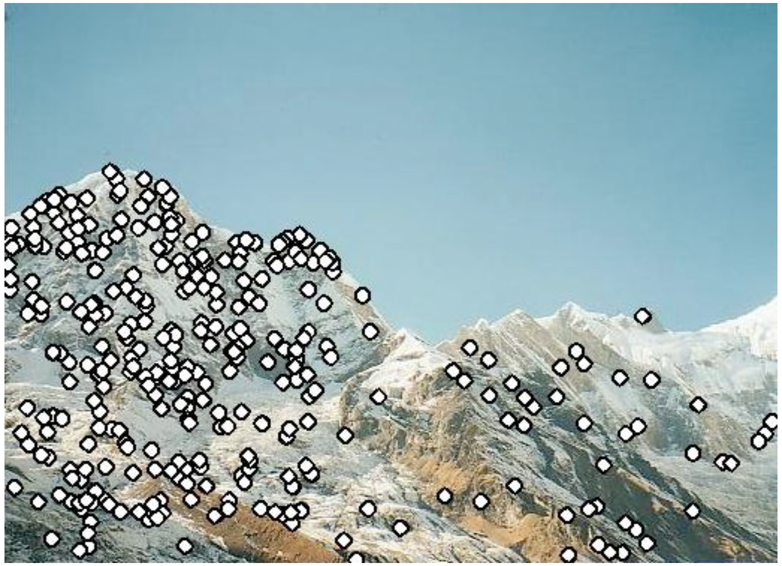
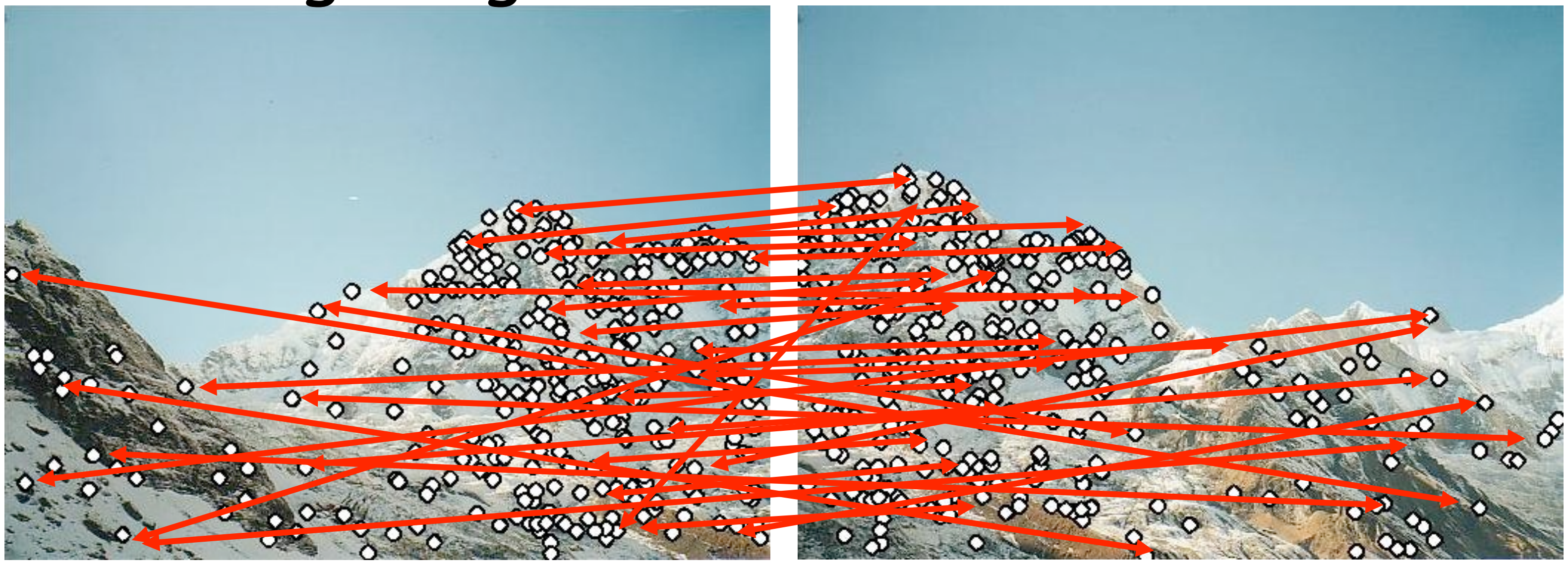




Extract features

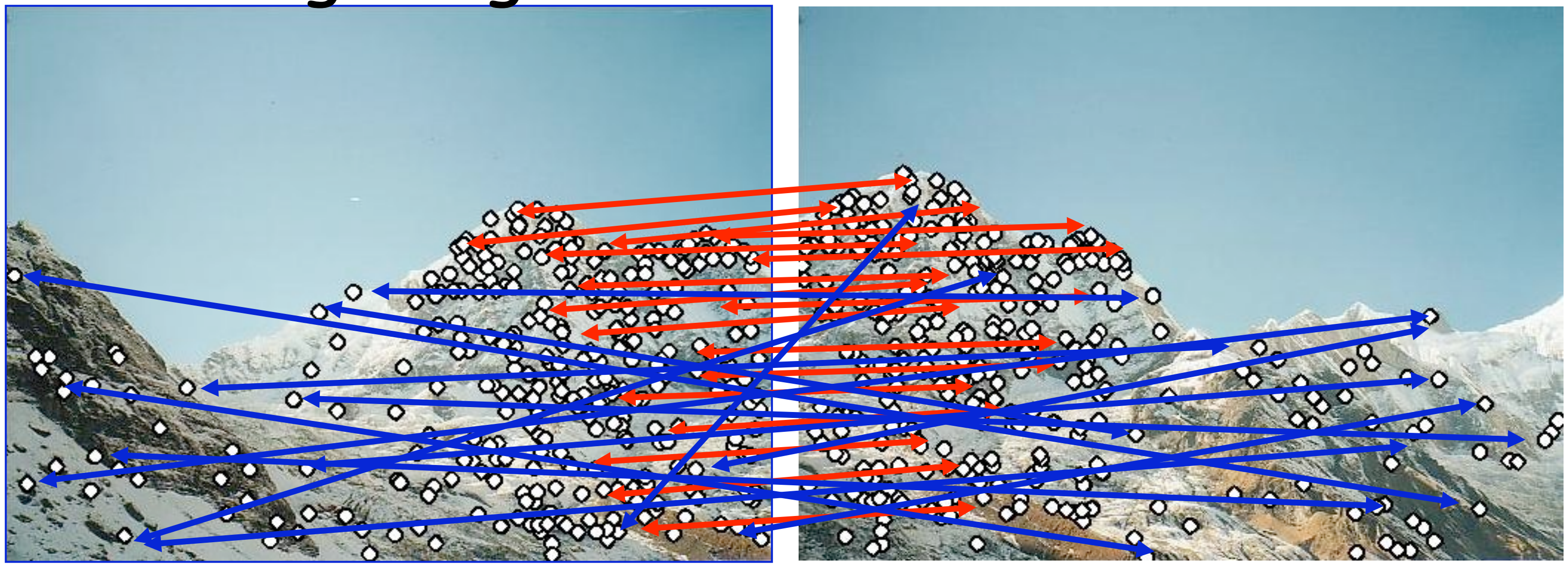
Estimating 2D geometric relations - outline



Extract features

Compute *putative matches*

Estimating 2D geometric relations - outline

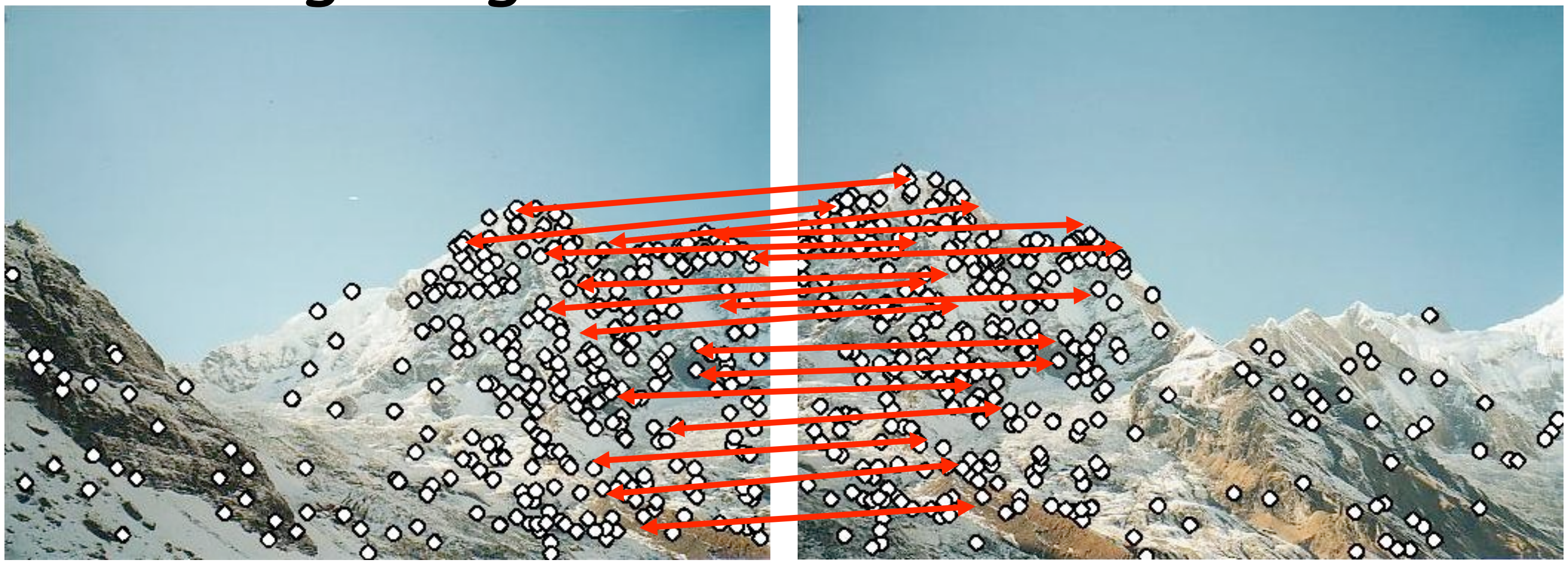


Extract features

Compute *putative matches*

Identify *outliers*

Estimating 2D geometric relations - outline



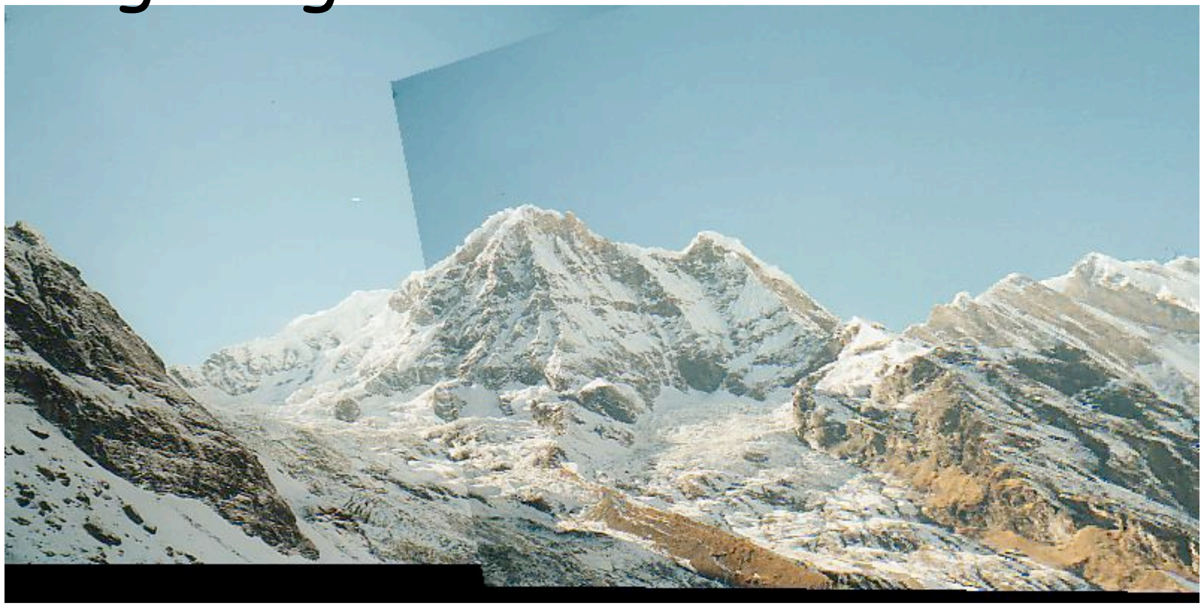
Extract features

Compute *putative matches*

Identify *outliers*

Estimate transformation from *inliers* (valid matches)

Estimating 2D geometric relations - outline



Extract features

Compute *putative matches*

Identify *outliers*

Estimate transformation from *inliers* (valid matches)

Example: estimating 2D affine transformation

- Simple fitting procedure (linear least squares)
- Approximates viewpoint changes for roughly planar objects and roughly orthographic cameras
- Can be used to initialize fitting for more complex models

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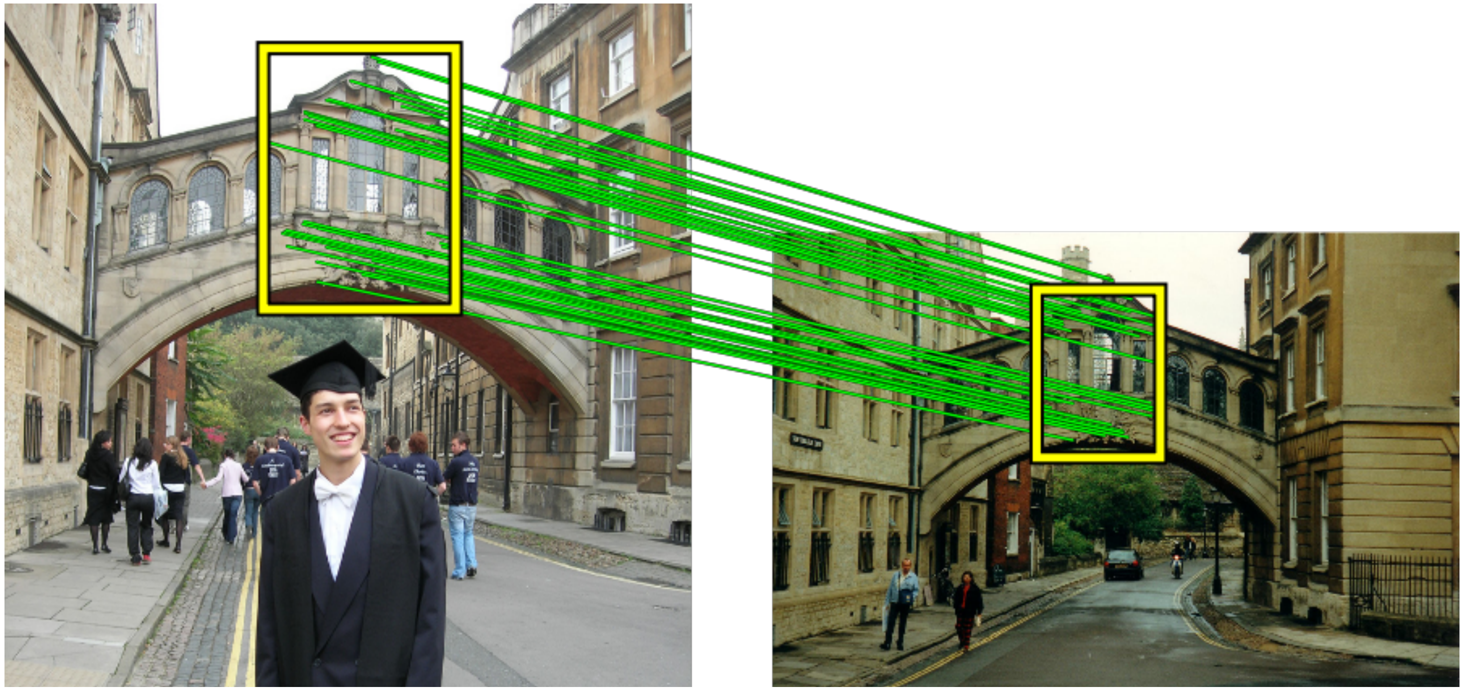
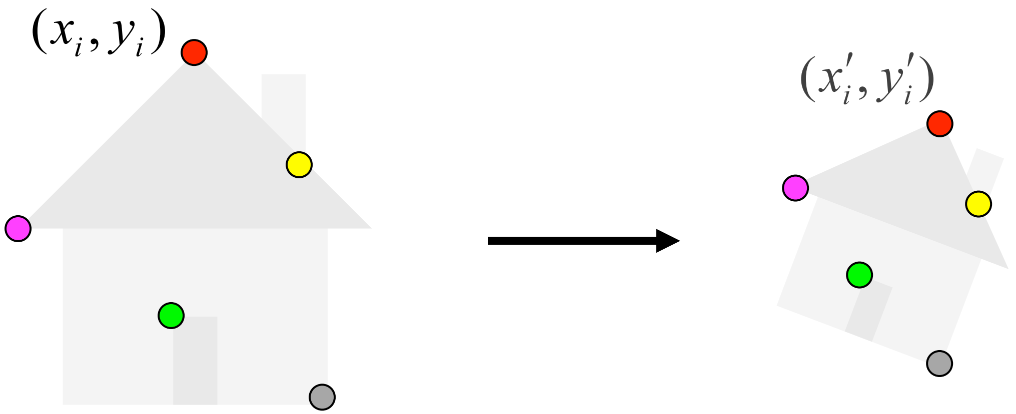


Matches consistent with an affine transformation

Fitting an affine transformation

Assume we know the correspondences, how do we get the transformation?



$$\begin{bmatrix} x_i' \\ y_i' \end{bmatrix} = \begin{bmatrix} m_1 & m_2 \\ m_3 & m_4 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} t_1 \\ t_2 \end{bmatrix}$$

$$\begin{bmatrix} & & \cdots & & & \\ x_i & y_i & 0 & 0 & 1 & 0 \\ 0 & 0 & x_i & y_i & 0 & 1 \\ & & \cdots & & & \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_1 \\ t_2 \end{bmatrix} = \begin{bmatrix} \cdots \\ x_i' \\ y_i' \\ \cdots \end{bmatrix}$$

Fitting an affine transformation

$$\begin{bmatrix} & & \cdots & & & \\ x_i & y_i & 0 & 0 & 1 & 0 \\ 0 & 0 & x_i & y_i & 0 & 1 \\ & & \cdots & & & \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_1 \\ t_2 \end{bmatrix} = \begin{bmatrix} \cdots \\ x_i' \\ y_i' \\ \cdots \end{bmatrix}$$

Linear system with six unknowns

Each match gives us two linearly independent equations: need at least three to solve for the transformation parameters

Dealing with outliers

The set of putative matches may contain a high percentage (e.g. 90%) of outliers

How do we fit a geometric transformation to a small subset of all possible matches?

Possible strategies:

- RANSAC
- Hough transform

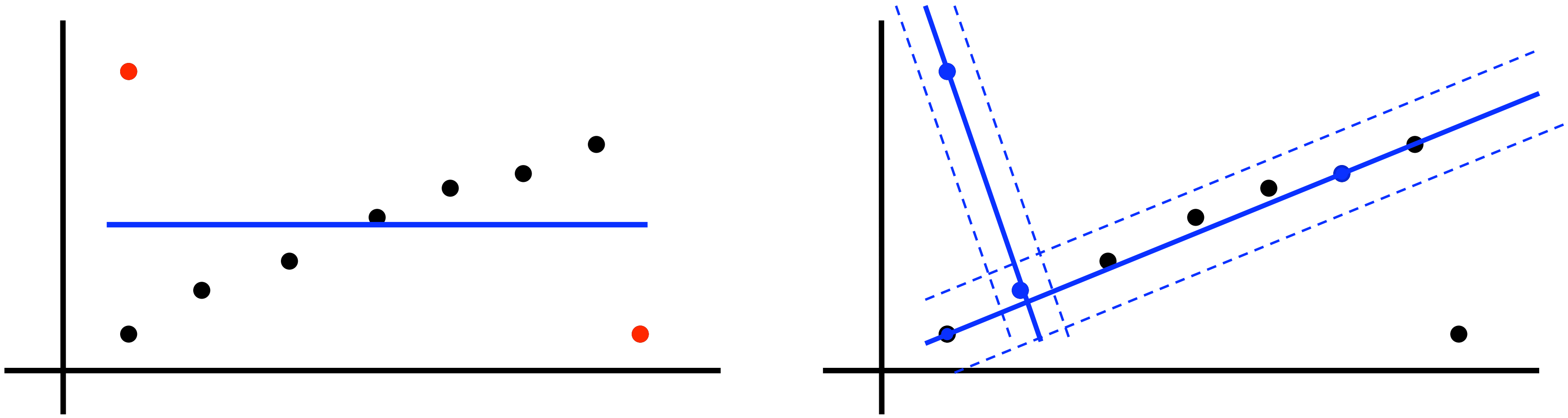
Strategy 1: RANSAC

RANSAC loop (Fischler & Bolles, 1981):

- Randomly select a *seed group* of matches
- Compute transformation from seed group
- Find *inliers* to this transformation
- If the number of inliers is sufficiently large, re-compute least-squares estimate of transformation on all of the inliers
- Keep the transformation with the largest number of inliers

Example: Robust line estimation - RANSAC

Fit a line to 2D data containing outliers



There are two problems

1. a line fit which minimizes perpendicular distance
2. a classification into inliers (valid points) and outliers

Solution: use robust statistical estimation algorithm RANSAC

(RANdom Sample Consensus) [Fishler & Bolles, 1981]

Slide credit: A. Zisserman

RANSAC robust line estimation

Repeat

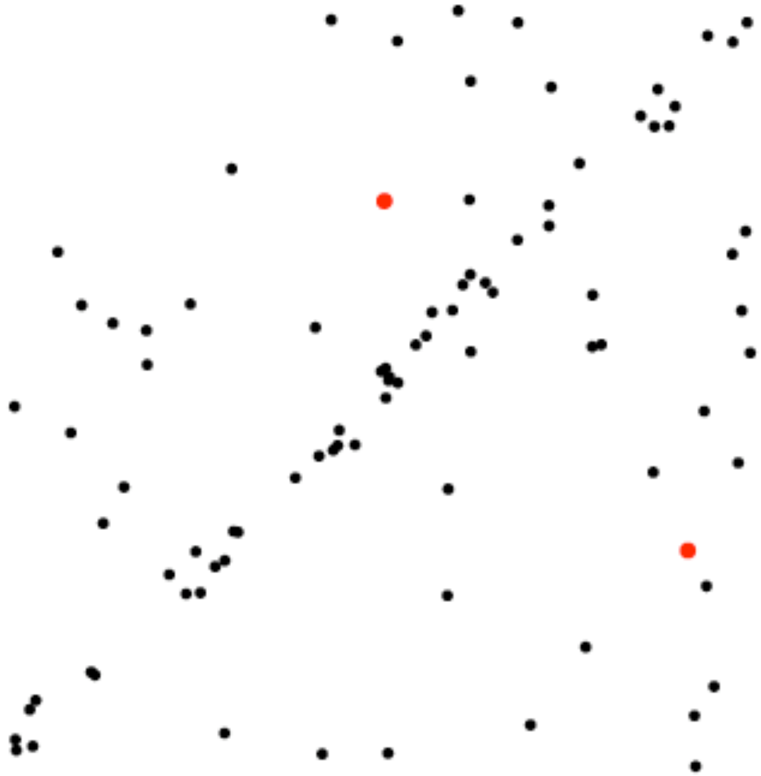
1. Select random sample of 2 points
2. Compute the line through these points
3. Measure support (number of points within threshold distance of the line)

Choose the line with the largest number of inliers

- Compute least squares fit of line to inliers (regression)

Slide credit: A. Zisserman

Slide credit: O. Chum



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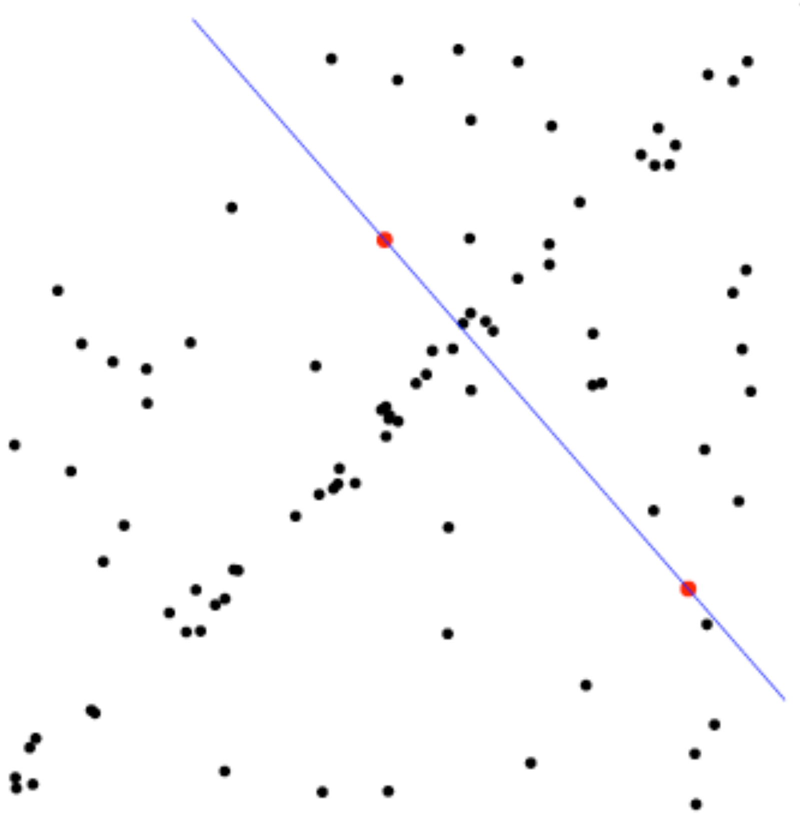

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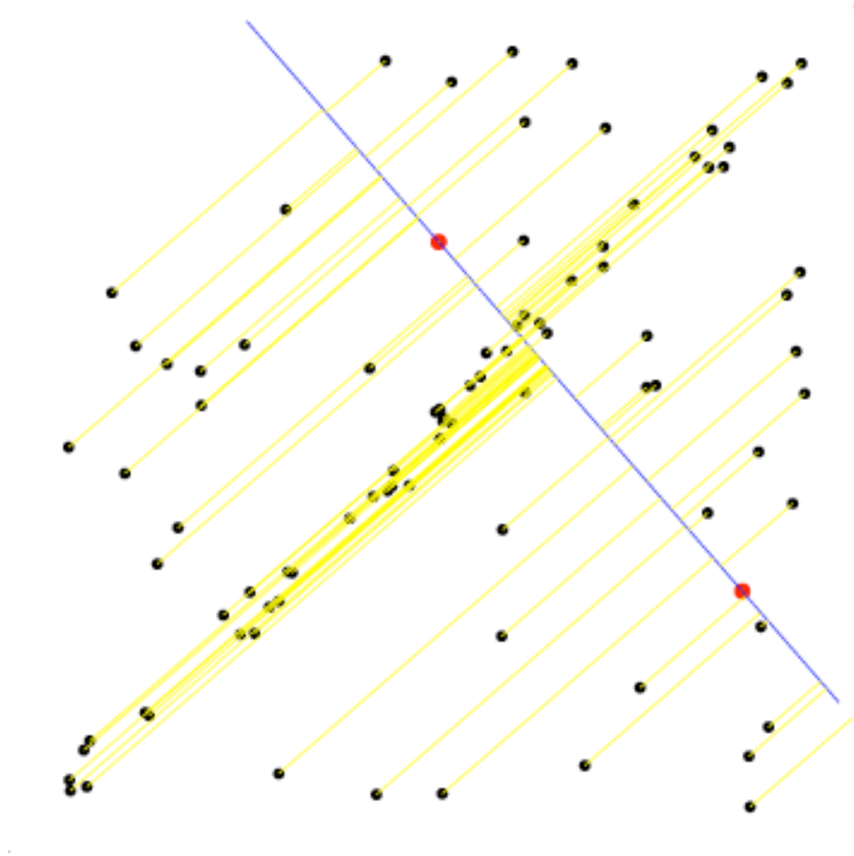

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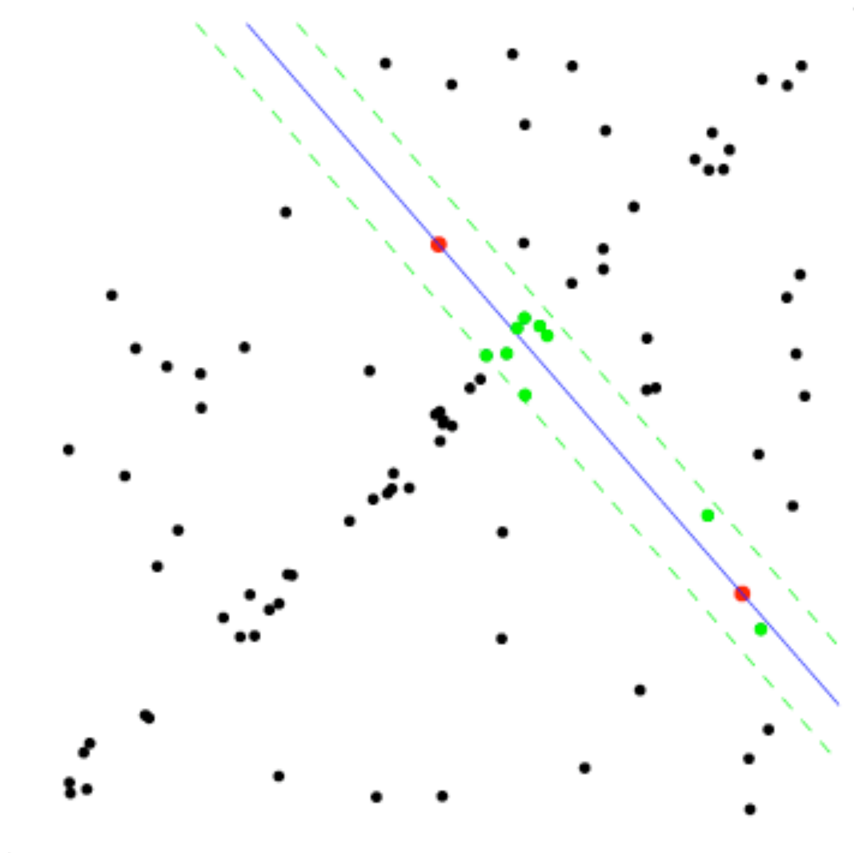

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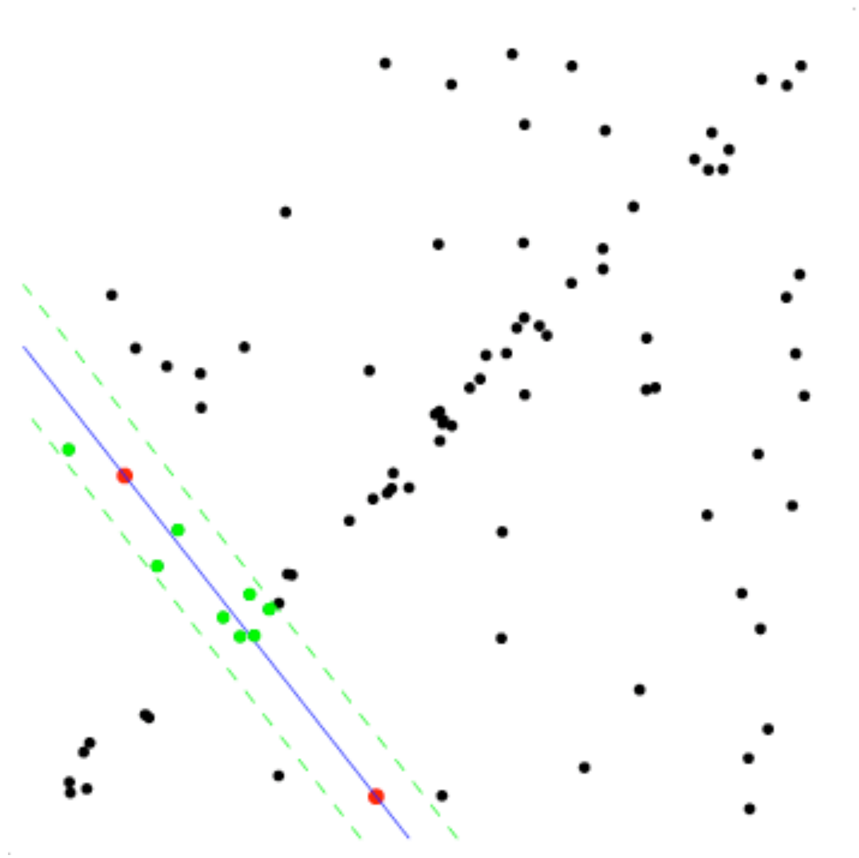

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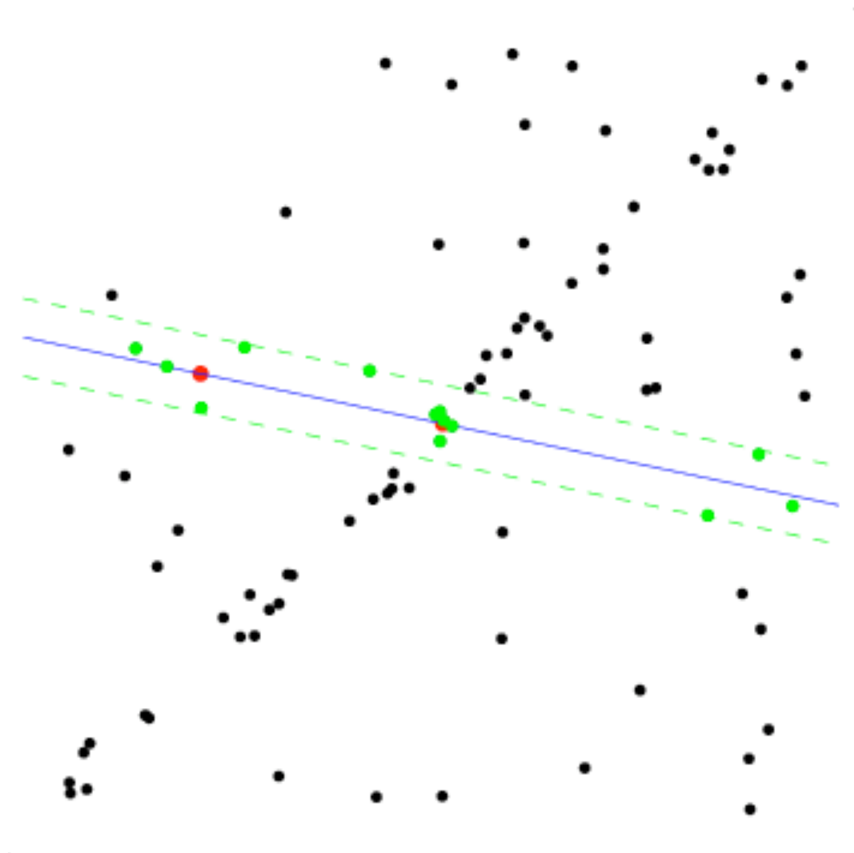

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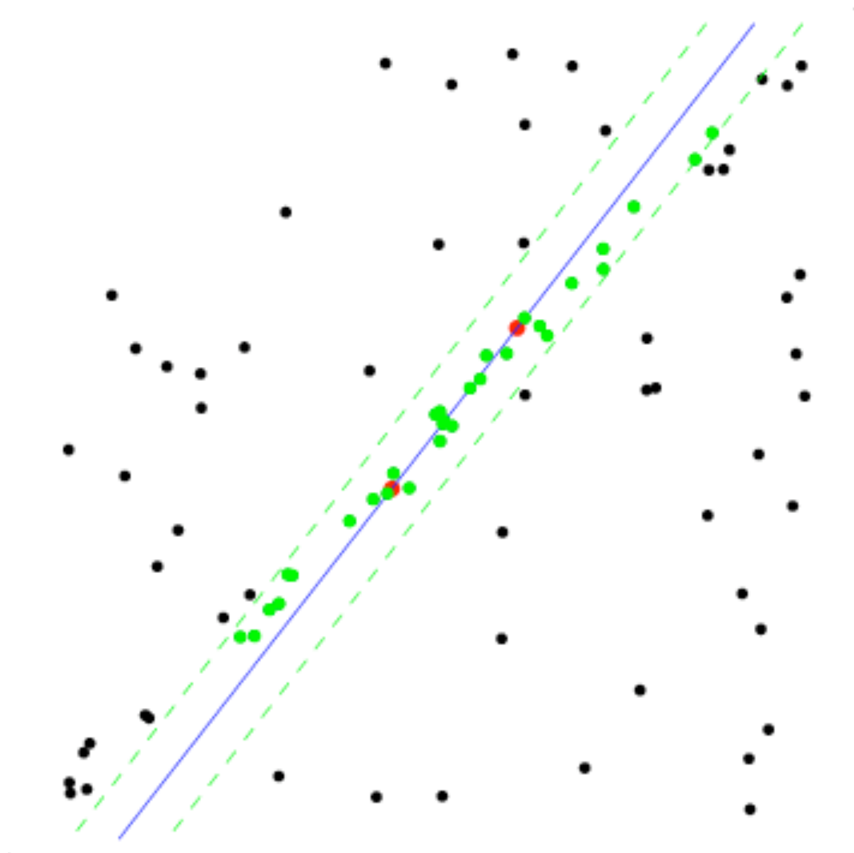

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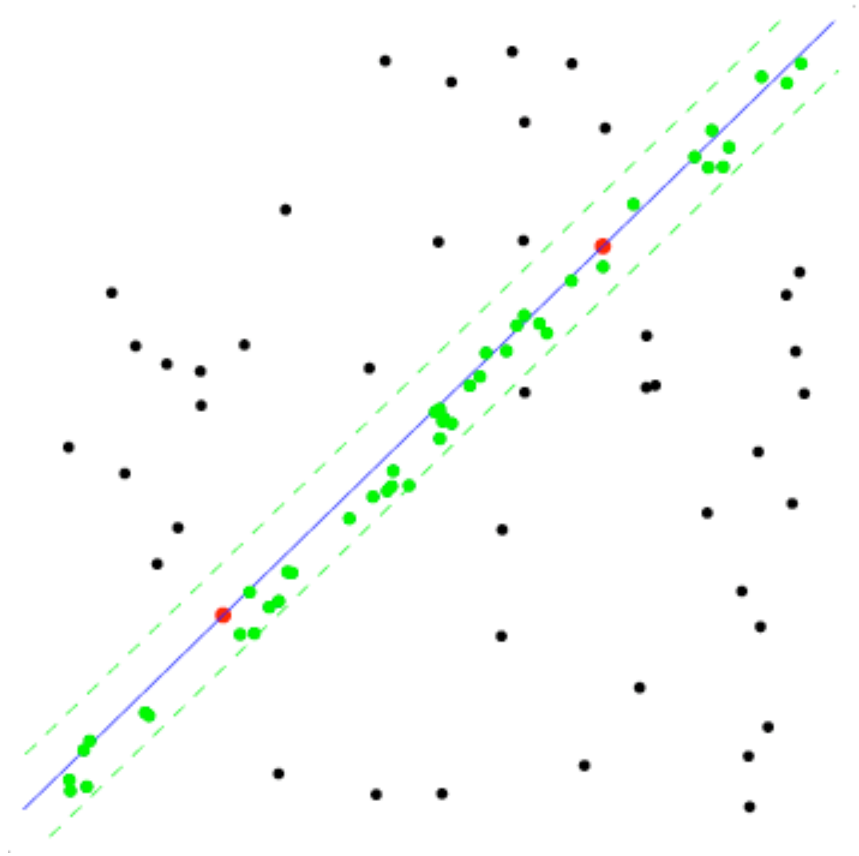


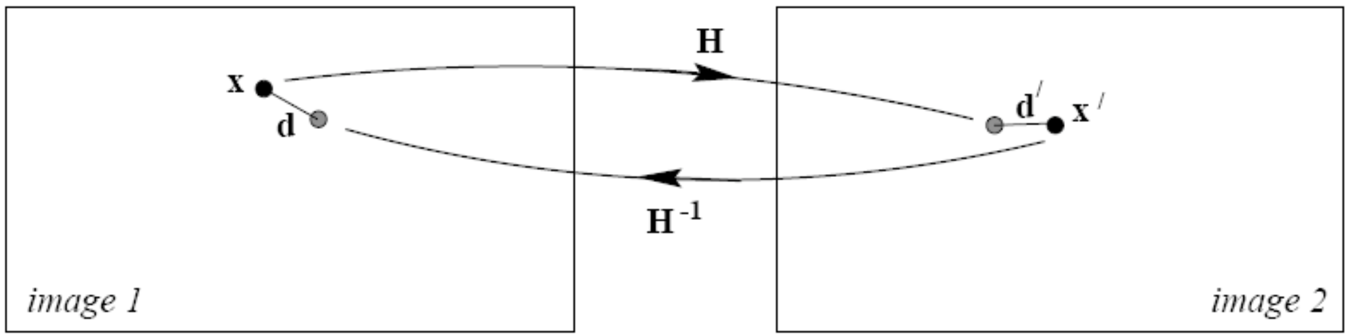
Slide credit: O. Chum

Algorithm summary – RANSAC robust estimation of 2D affine transformation

Repeat

1. Select 3 point to point correspondences
2. Compute H (2x2 matrix) + t (2x1) vector for translation
3. Measure support (number of inliers within threshold distance, i.e. $d^2_{transfer} < t$)

$$d^2_{\text{transfer}} = d(\mathbf{x}, \mathtt{H}^{-1}\mathbf{x}')^2 + d(\mathbf{x}', \mathtt{H}\mathbf{x})^2$$



Choose the (H,t) with the largest number of inliers

(Re-estimate (H,t) from all inliers)

How many samples?

Number of samples *N*

- Choose *N* so that, with probability *p*, at least one random sample is free from outliers
- e.g.:
  - > p=0.99
  - > outlier ratio: *e*

Probability a randomly picked point is an inlier

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

Probability of all points in a sample (of size s) are inliers

Source: M. Pollefeys

How many samples?

Number of samples *N*

- Choose *N* so that, with probability *p*, at least one random sample is free from outliers
- e.g.:
  - > *p*=0.99
  - > outlier ratio: *e*

Probability that all N samples (of size s) are corrupted (contain an outlier)

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

Probability of at least one point in a sample (of size s) is an outlier

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

	proportion of outliers e						
s	5%	10%	20%	30%	40%	50%	90%
1	2	2	3	4	5	6	43
2	2	3	5	7	11	17	458
3	3	4	7	11	19	35	4603
4	3	5	9	17	34	72	4.6e4
5	4	6	12	26	57	146	4.6e5
6	4	7	16	37	97	293	4.6e6
7	4	8	20	54	163	588	4.6e7
8	5	9	26	78	272	1177	4.6e8

Source: M. Pollefeys

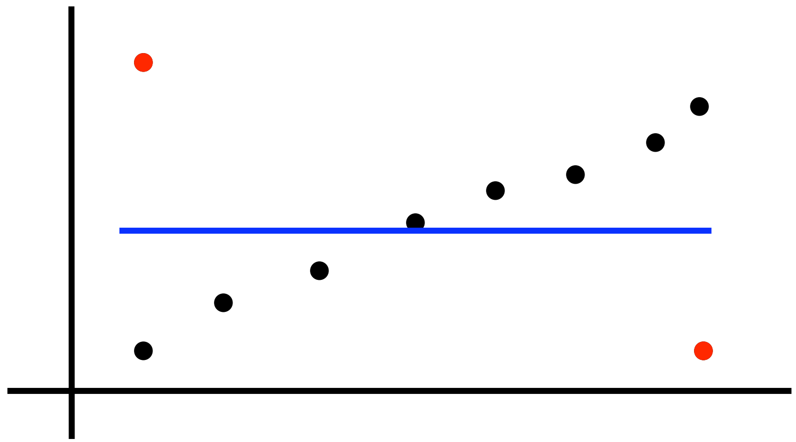
Example: line fitting

$p = 0.99$

$s = ?$

$e = ?$

$N = ?$



Source: M. Pollefeys

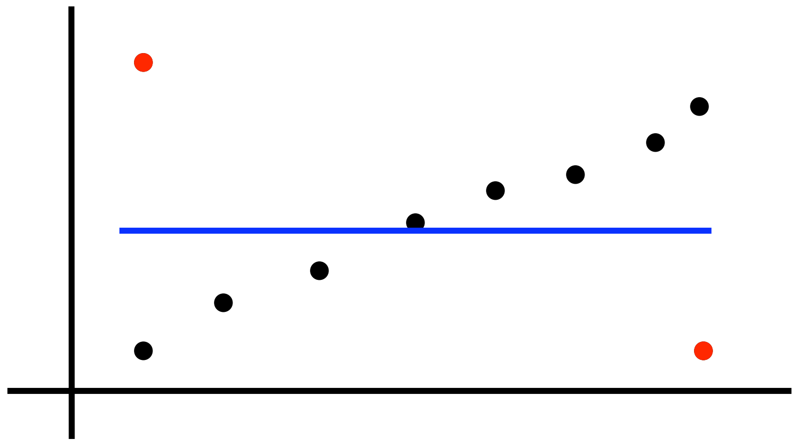
Example: line fitting

p = 0.99

s = 2

e = 2/10 = 0.2

N = 5



Compare with exhaustively trying all point pairs:

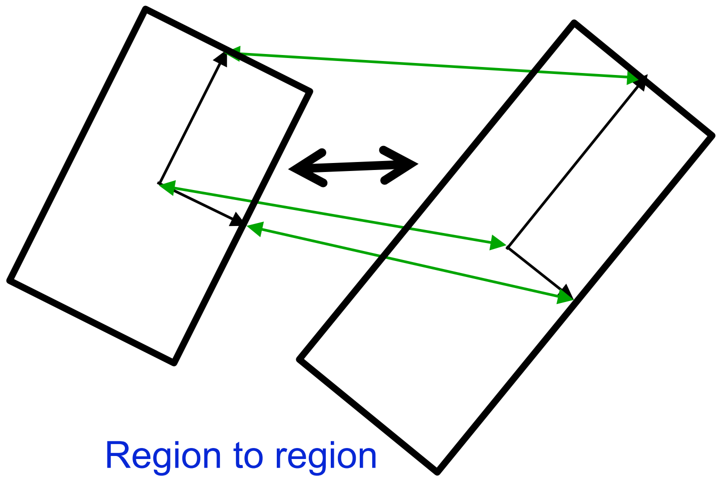
$$\binom{10}{2} = 10*9 / 2 = 45$$

	proportion of outliers e						
s	5%	10%	20%	30%	40%	50%	90%
1	2	2	3	4	5	6	43
2	2	3	5	7	11	17	458
3	3	4	7	11	19	35	4603
4	3	5	9	17	34	72	4.6e4
5	4	6	12	26	57	146	4.6e5
6	4	7	16	37	97	293	4.6e6
7	4	8	20	54	163	588	4.6e7
8	5	9	26	78	272	1177	4.6e8

Source: M. Pollefeys

How to reduce the number of samples needed?

1. Reduce the proportion of outliers.
2. Reduce the sample size
   - use simpler model (e.g. similarity instead of affine tnf.)
   - use local information (e.g. a region to region correspondence is equivalent to (up to) 3 point to point correspondences).



Region to region correspondence

Number of samples *N*

	proportion of outliers e						
s	5%	10%	20%	30%	40%	50%	90%
1	2	2	3	4	5	6	43
2	2	3	5	7	11	17	458
3	3	4	7	11	19	35	4603
4	3	5	9	17	34	72	4.6e4
5	4	6	12	26	57	146	4.6e5
6	4	7	16	37	97	293	4.6e6
7	4	8	20	54	163	588	4.6e7
8	5	9	26	78	272	1177	4.6e8

RANSAC (references)

M. Fischler and R. Bolles, “Random Sample Consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography,” Comm. ACM, 1981

R. Hartley and A. Zisserman, Multiple View Geometry in Computer Vision, 2nd ed., 2004.

Extensions:

B. Tordoff and D. Murray, “Guided Sampling and Consensus for Motion Estimation, ECCV’03

D. Nister, “Preemptive RANSAC for Live Structure and Motion Estimation, ICCV’03

Chum, O.; Matas, J. and Obdrzalek, S.: Enhancing RANSAC by Generalized Model Optimization, ACCV’04

Chum, O.; and Matas, J.: Matching with PROSAC - Progressive Sample Consensus , CVPR 2005

Philbin, J., Chum, O., Isard, M., Sivic, J. and Zisserman, A.: Object retrieval with large vocabularies and fast spatial matching, CVPR’07

Chum, O. and Matas. J.: Optimal Randomized RANSAC, PAMI’08

Strategy 2: Hough Transform

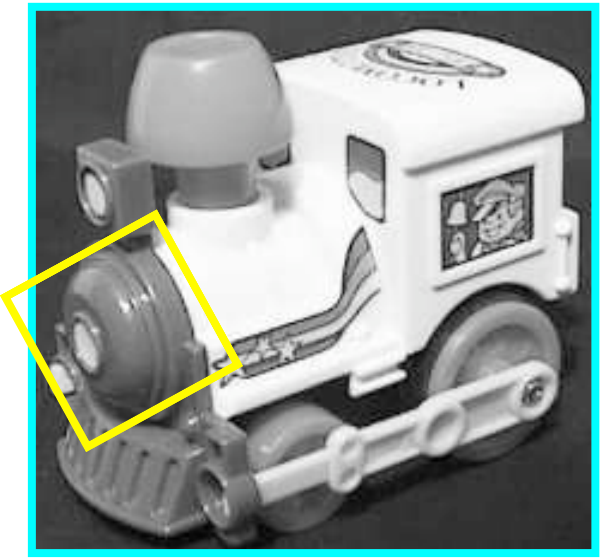
- Origin: Detection of straight lines in cluttered images
- Can be generalized to arbitrary shapes
- Can extract feature groupings from cluttered images in linear time.
- Illustrate on extracting sets of local features consistent with a similarity transformation.

Hough transform for object recognition

Suppose our features are scale- and rotation-covariant

- Then a single feature match provides an alignment hypothesis (translation, scale, orientation)

model



Target image

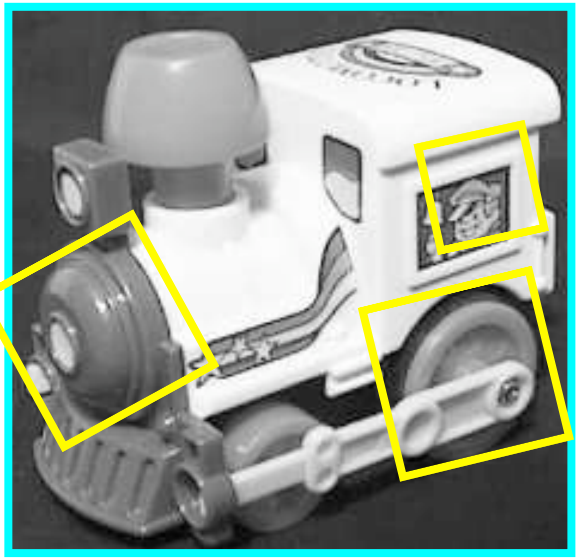
David G. Lowe. **“Distinctive image features from scale-invariant keypoints”,** *IJCV* 60 (2), pp. 91-110, 2004.

Hough transform for object recognition

Suppose our features are scale- and rotation-covariant

- Then a single feature match provides an alignment hypothesis (translation, scale, orientation)
- Of course, a hypothesis obtained from a single match is unreliable
- Solution: Coarsely quantize the transformation space. Let each match vote for its hypothesis in the quantized space.

model

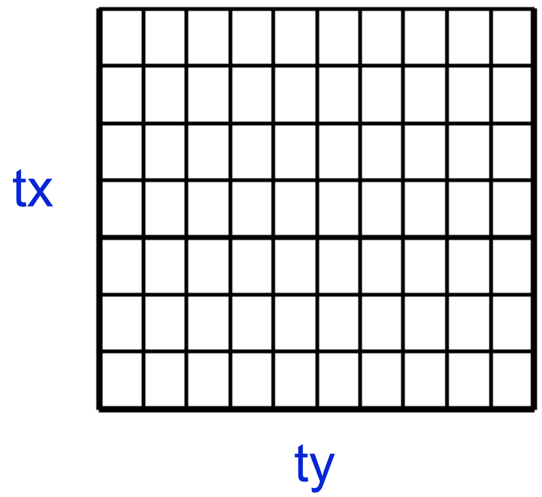


David G. Lowe. **“Distinctive image features from scale-invariant keypoints”,** *IJCV* 60 (2), pp. 91-110, 2004.

Basic algorithm outline

1. Initialize accumulator H to all zeros
2. For each tentative match
   compute transformation hypothesis: tx, ty, s, θ
   H(tx,ty,s,θ) = H(tx,ty,s,θ) + 1
   end
   end
3. Find all bins (tx,ty,s,θ) where H(tx,ty,s,θ) has at least three votes

H: 4D-accumulator array (only 2-d shown here)



- Correct matches will consistently vote for the same transformation while mismatches will spread votes.
- Cost: Linear scan through the matches (step 2), followed by a linear scan through the accumulator (step 3).

Hough transform details (D. Lowe's system)

Training phase: For each model feature, record 2D location, scale, and orientation of model (relative to normalized feature frame)

Test phase: Let each match between a test and a model feature vote in a 4D Hough space

- Use broad bin sizes of 30 degrees for orientation, a factor of 2 for scale, and 0.25 times image size for location
- Vote for two closest bins in each dimension

Find all bins with at least three votes and perform geometric verification

- Estimate least squares *affine* transformation
- Use stricter thresholds on transformation residual
- Search for additional features that agree with the alignment

Hough transform in object recognition (references)

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

D. Lowe, "Distinctive image features from scale-invariant keypoints", *IJCV* 60 (2), 2004.

H. Jegou, M. Douze, C. Schmid, Hamming embedding and weak geometric consistency for large scale image search, ECCV'2008

Extensions (object category detection):

B. Leibe, A. Leonardis, and B. Schiele., Combined Object Categorization and Segmentation with an Implicit Shape Model, in ECCV'04 Workshop on Statistical Learning in Computer Vision, Prague, May 2004.

S. Maji and J. Malik, Object Detection Using a Max-Margin Hough Tranform, CVPR'2009

A. Lehmann, B. Leibe, L. Van Gool. Fast PRISM: Branch and Bound Hough Transform for Object Class Detection, IJCV (to appear), 2010.

O. Barinova, V. Lempitsky, P. Kohli, On the Detection of Multiple Object Instances using Hough Transforms, CVPR, 2010

Comparison

Hough Transform

Advantages

- Can handle high percentage of outliers (>95%)
- Extracts groupings from clutter in linear time

Disadvantages

- Quantization issues
- Only practical for small number of dimensions (up to 4)

Improvements available

- Probabilistic Extensions
- Continuous Voting Space
- Can be generalized to arbitrary shapes and objects

RANSAC

Advantages

- General method suited to large range of problems
- Easy to implement
- "Independent" of number of dimensions

Disadvantages

- Basic version only handles moderate number of outliers (<50%)

Many variants available, e.g.

- PROSAC: Progressive RANSAC [Chum05]
- Preemptive RANSAC [Nister05]

Slide credit: K. Grauman, B. Leibe

Outline – the rest of the lecture

Part 1.

Correspondence

Semi-local and global geometric relations

Robust estimation – RANSAC and Hough Transform

Part 2.

Approximate nearest neighbour matching

Bag-of-visual-words representation

Efficient visual search and extensions

Applications