

Geometry for Computer Vision Lecture 6b Sample Consensus Strategies

Per-Erik Forssén



Overview

- Issues with standard RANSAC
- Maximum-likelihood scoring
- LO-RANSAC
- Preemptive RANSAC
- DEGENSAC

Not covered here: All the other variants RANDOMIZED RANSAC, G-SAC, NAPSAC etc. Paper to read for next week: PROSAC



RANSAC issues

In lecture 3 we introduced RANSAC (Fischler&Bolles 81).

- It finds a **model with maximal support** in the presence of **outliers**
- Approach: randomly generate hypotheses and score them.

Most novelties since 1981 covered in thesis by: Ondrej Chum, *Two-View Geometry Estimation by Random Sample and Consensus*, July 2005



RANSAC issues

```
S - correspondence set, K - number of trials
  for k=1:K
      s=sample draw minimal(S)
      m=model estimate(s)
      [v,inliers]=model score(m,S)
      if v>best v
         best inlier set=inliers
         best v=v
         best m=m
      end
  end
```



RANSAC issue #1

Underlying optimization problem:

$$\varepsilon = \sum_{k} \sum_{l} v_k ||\mathbf{x}_{kl} - \operatorname{proj}(\mathbf{X}_k, \theta_l)||^2 \quad v_k \in \{0, 1\}$$

score is a discrete inlier count:

$$s = \sum_{k} v_k$$

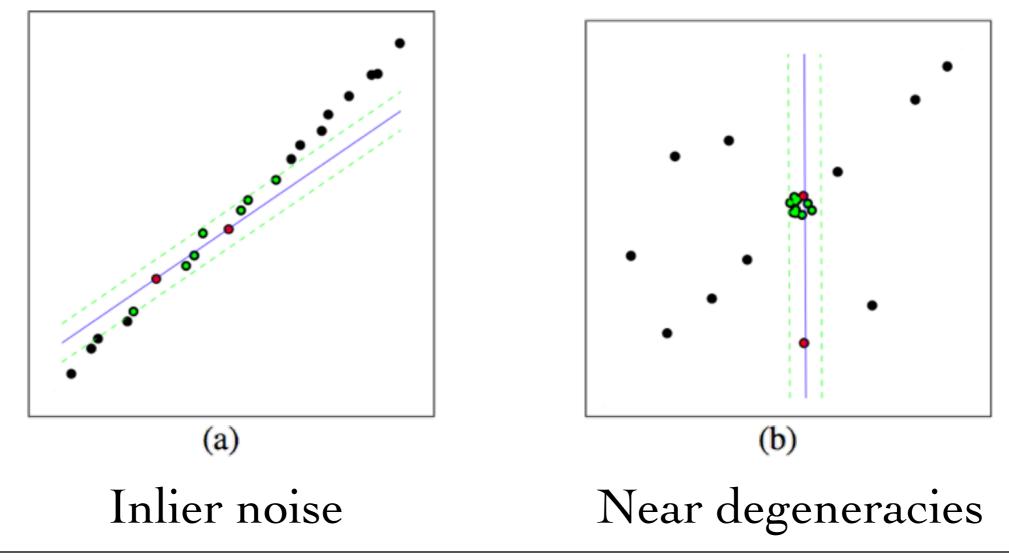
there may be many equally good optima!





RANSAC issues #2 and #3

Two more problems with the original approach:





RANSAC issue #3

Near degeneracies can be dealt with by sampling non-randomly, e.g.

 DEGENSAC, for F estimation in plane dominant scenes. Chum et al., *Two-view Geometry estimation unaffected by a Dominant Plane*, CVPR05



RANSAC issue #3

Near degeneracies can be dealt with by sampling non-randomly, e.g.

- DEGENSAC, for F estimation in plane dominant scenes. Chum et al., *Two-view Geometry estimation unaffected by a Dominant Plane*, CVPR05
- Distance constraint for points used in E estimation. Hedborg et al., Fast and Accurate Structure and Motion Estimation, ISVC09 Reduces #iterations by 50% in forward motion.



Underlying optimization problem:

$$\varepsilon = \sum_{k} \sum_{l} v_k ||\mathbf{x}_{kl} - \operatorname{proj}(\mathbf{X}_k, \theta_l)||^2 \quad v_k \in \{0, 1\}$$

score is a discrete inlier count:

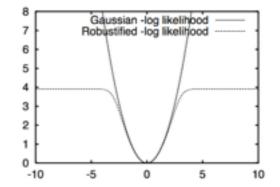
$$s = \sum_{k} v_k$$

there may be many equally good optima!



Better to use a robust error norm:

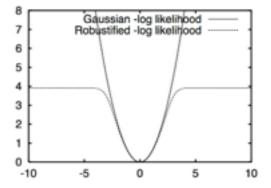
$$\varepsilon = \sum_{k} \sum_{l} \rho(\mathbf{x}_{kl} - \operatorname{proj}(\mathbf{X}_{k}, \theta_{l}))$$





Better to use a robust error norm:

$$\varepsilon = \sum_{k} \sum_{l} \rho(\mathbf{x}_{kl} - \operatorname{proj}(\mathbf{X}_{k}, \theta_{l}))$$



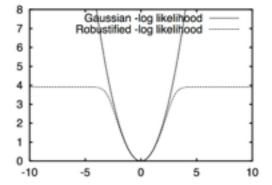
and as score, the minimum error (MLESAC):

$$s = -\varepsilon$$



Better to use a robust error norm:

$$\varepsilon = \sum_{k} \sum_{l} \rho(\mathbf{x}_{kl} - \operatorname{proj}(\mathbf{X}_{k}, \theta_{l}))$$



and as score, the minimum error (MLESAC):

 $s = -\varepsilon$

called maximum likelihood scoring

See: Torr & Zisserman, *MLESAC: A new robust estimator with application to estimating image geometry*, CVIU'00



Inlier noise means that the heuristic for number of samples to draw:

$$N = \log(1-p)/\log(1-w^s)$$

is overly optimistic.

A small modification makes the heuristic work again: Chum et al., *Locally Optimized RANSAC*, DAGM03



Small modification:

```
S - correspondence set, K - number of trials
  for k=1:K
       s=sample draw minimal(S)
       m=model estimate(s)
       [v,inliers]=model_score(m,S)
       if v>best v
           [inliers,v,m]=local_optimization(inliers,v,m)
          best inlier set=inliers
          best v=v
          best m=m
       end
  end
```



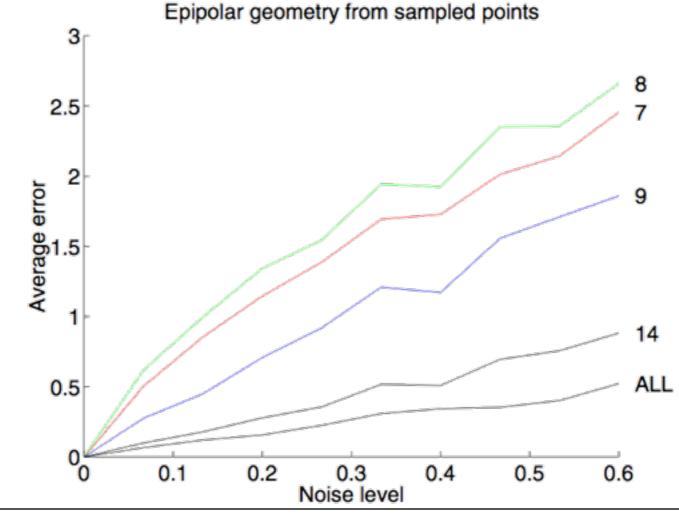
Chum tries four variants of local optimisation:

- 1. Linear estimation from all inliers
- 2. Iterative linear estimation with
- decreasing inlier threshold.
- 3. Inner RANSAC
- 4. Inner RANSAC with #2.

#3 and #4 worked best, and #4 came close to the heuristically expected #samples.



The inner RANSAC step uses non-minimal sample sets. Errors for linear **F** estimation:





Open source

Lebeda, Matas, Chum, *Fixing the Locally Optimized RANSAC*, BMVC'12

- C/C++ library available on the web. Source code on request. The "Fixes" are:
 - Maximum likelihood scoring (i.e. MLESAC)
 Iterative Reweighted Least-Squares on random subsets of bounded size (7xmin subset)



David Nister, Preemptive RANSAC for live structure and motion estimation, ICCV03

Total time for RANSAC is given by: $t = k(t_M + E[m_S]t_V)$

k- #iterations t_M-model estimation time, t_V-verification time. m_S - #models/iteration



David Nister, Preemptive RANSAC for live structure and motion estimation, ICCV03

Total time for RANSAC is given by: $t = k(t_M + E[m_S]t_V)$

k- #iterations t_M-model estimation time, t_V-verification time. m_S - #models/iteration If many correspondences, t_V will dominate.



Idea: Do a probabilistic verification instead. $t = k(t_M + E[m_S]t_V)$

- In a real-time system, t is fixed, so if we reduce t_v we may increase k.
- Preemptive RANSAC does this by evaluating all hypotheses in parallel.
- In each step, a fixed number of most promising hypotheses are kept.



Preemptive RANSAC:

- 1. Generate f(1) hypotheses in parallel.
- 2. For n=1 to N
- Evaluate f(n) hypotheses ona random correspondence
- Keep the f(n+1) best hypothesesaccording to accumulated score.

f(1)=M and $f(n+1) \leq f(n)$



- f(n) the preemption function $f(n) = \lfloor M2^{-\lfloor \frac{n}{B} \rfloor} \rfloor$
- B block size (f only changes every B steps)
- M number of models NAccumulated scoring $L(m) = \sum_{n=1}^{N} \rho(n,m)$ Log-likelihood of sample *n* given model *m*



Chum, et al., *Two-view Geometry Estimation Unaffected by a Dominant Plane*, CVPR'05

Planar dominant scenes are also problematic





Actually, the **F** estimation problem is even worse than it might appear, as 5 points in a plane +2 **arbitrary** correspondences gives an **F** compatible with the plane.



Actually, the F estimation problem is even worse than it might appear, as 5 points in a plane +2 *arbitrary* correspondences gives an F compatible with the plane.

In le5 we saw that if all seven points are in a plane, then

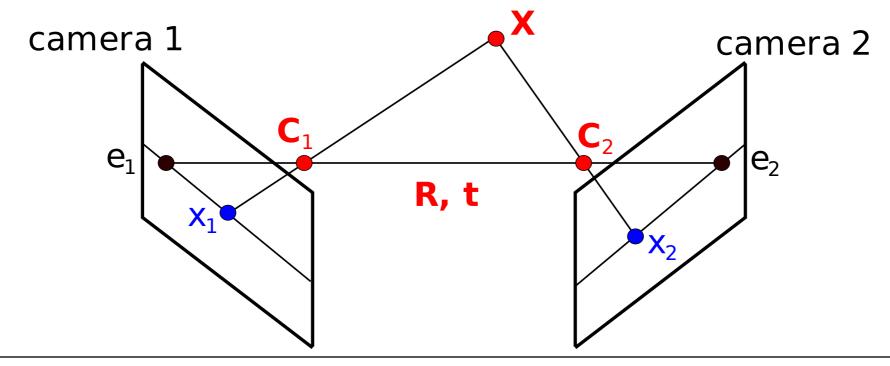
$$\mathbf{x}_k^T \mathbf{F} \mathbf{y}_k = 0, \ \mathbf{x}_k = \mathbf{H} \mathbf{y}_k, \quad k = 1 \dots 7$$

and $\mathbf{F} = [\mathbf{e}]_{\times} \mathbf{H}$ for any epipole \mathbf{e}



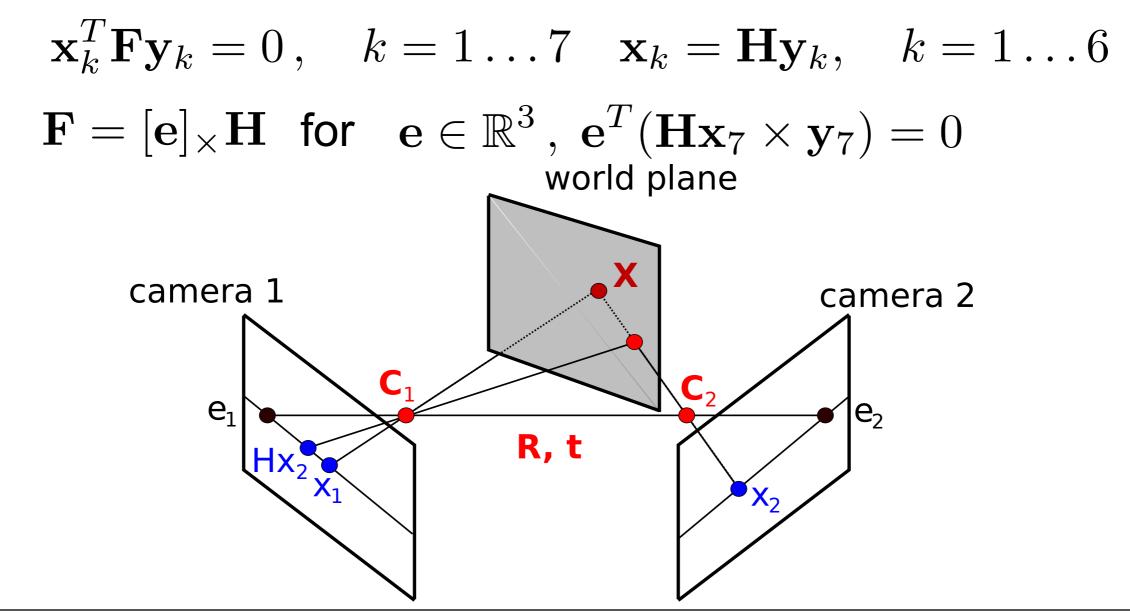
If six points are in a plane

 $\mathbf{x}_k^T \mathbf{F} \mathbf{y}_k = 0, \quad k = 1 \dots 7 \quad \mathbf{x}_k = \mathbf{H} \mathbf{y}_k, \quad k = 1 \dots 6$ $\mathbf{F} = [\mathbf{e}]_{\times} \mathbf{H} \text{ for } \mathbf{e} \in \mathbb{R}^3, \ \mathbf{e}^T (\mathbf{H} \mathbf{x}_7 \times \mathbf{y}_7) = 0$





If six points are in a plane





If six points are in a plane

 $\mathbf{x}_k^T \mathbf{F} \mathbf{y}_k = 0, \quad k = 1 \dots 7 \quad \mathbf{x}_k = \mathbf{H} \mathbf{y}_k, \quad k = 1 \dots 6$ $\mathbf{F} = [\mathbf{e}]_{\times} \mathbf{H} \text{ for } \mathbf{e} \in \mathbb{R}^3, \ \mathbf{e}^T (\mathbf{H} \mathbf{x}_7 \times \mathbf{y}_7) = 0$

For *five* points in the plane

$$\mathbf{x}_6 \times (\mathbf{H}\mathbf{y}_6)$$
 and $\mathbf{x}_7 \times (\mathbf{H}\mathbf{y}_7)$

define two lines that intersect in **e**. **F** will have all points consistent with **H** as inliers.



If six points are in a plane

 $\mathbf{x}_k^T \mathbf{F} \mathbf{y}_k = 0, \quad k = 1 \dots 7 \quad \mathbf{x}_k = \mathbf{H} \mathbf{y}_k, \quad k = 1 \dots 6$ $\mathbf{F} = [\mathbf{e}]_{\times} \mathbf{H} \text{ for } \mathbf{e} \in \mathbb{R}^3, \ \mathbf{e}^T (\mathbf{H} \mathbf{x}_7 \times \mathbf{y}_7) = 0$

For *five* points in the plane

$$\mathbf{x}_6 \times (\mathbf{H}\mathbf{y}_6)$$
 and $\mathbf{x}_7 \times (\mathbf{H}\mathbf{y}_7)$

define two lines that intersect in e. F will have all points consistent with H as inliers.
Also used in plane+parallax algorithm



Degensac - detection

From **F** and $\{\mathbf{x}_k \leftrightarrow \mathbf{y}_k\}_{k=1}^3$ we can compute a homography $\mathbf{H} = \mathbf{A} - \mathbf{e}_1 (\mathbf{M}^{-1} \mathbf{b})^T$

where $\mathbf{A} = [\mathbf{e}_1]_{\times} \mathbf{F}$ $\mathbf{M} = [\mathbf{x}_1 \ \mathbf{x}_2 \ \mathbf{x}_3]^T$

and $b_k = (\mathbf{x}_k \times \mathbf{A}\mathbf{y}_k)^T (\mathbf{x}_k \times \mathbf{e}_1) ||\mathbf{x}_k \times \mathbf{e}_1||^{-2}$



Degensac - detection

From **F** and $\{\mathbf{x}_k \leftrightarrow \mathbf{y}_k\}_{k=1}^3$ we can compute a homography $\mathbf{H} = \mathbf{A} - \mathbf{e}_1 (\mathbf{M}^{-1} \mathbf{b})^T$

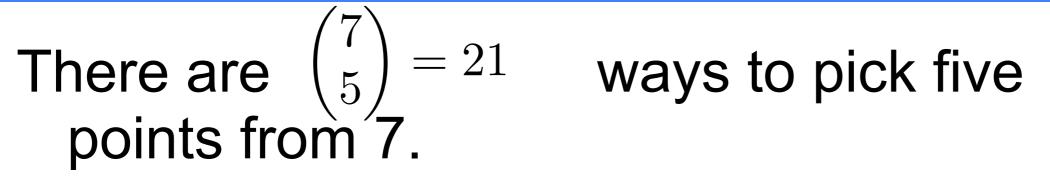
where
$$\mathbf{A} = [\mathbf{e}_1]_{\times} \mathbf{F}$$
 $\mathbf{M} = [\mathbf{x}_1 \ \mathbf{x}_2 \ \mathbf{x}_3]^T$

and
$$b_k = (\mathbf{x}_k \times \mathbf{A}\mathbf{y}_k)^T (\mathbf{x}_k \times \mathbf{e}_1) ||\mathbf{x}_k \times \mathbf{e}_1||^{-2}$$

This **H** is now checked for two additional inliers. If found, **F** is said to be **H**-degenerate



Degensac - detection



But, if we pick the 3 points that define H as $\{1, 2, 3\}, \{4, 5, 6\}, \{1, 2, 7\}, \{4, 5, 7\}, \{3, 6, 7\}$

We will have covered all 21 permutations.

Thus at most **five H** need to be computed and tested to find out if **F** is **H**degenerate.



DEGENSAC algorithm

1. Select 7 random correspondences and estimate F

- 2. IF best support this far
- 3. IF H-degeneracy
- 4. Do inner RANSAC and estimate F
 from H and 2 correspondences
 that are inconsistent with H
 (Plane+Parallax algorithm)
- IF new F has even bigger support, store F
 ELSE store H



Paper to discuss next week...

Ondrej Chum and Jiri Matas, Matching with PROSAC -- Progressive Sample Consensus, CVPR'05