Beyond RANSAC

By marginalization in (23) we have lost constraints on M (eg. uniqueness). One can choose a better model when not marginalizing:

$$\pi(M, \mathbf{F}, E, D) = \underbrace{p(E \mid M, \mathbf{F})}_{\text{geometric error}} \cdot \underbrace{p(D \mid M)}_{\text{similarity}} \cdot \underbrace{p(\mathbf{F})}_{\text{prior}} \cdot \underbrace{P(M)}_{\text{constraints}}$$

this is a global model: decisions on m_{ij} are no longer independent!

In the MH scheme

- one can work with full $p(M, \mathbf{F} \mid E, D)$, then $S = (M, \mathbf{F})$
  - explicit labeling m_{ij} can be done by, e.g. sampling from

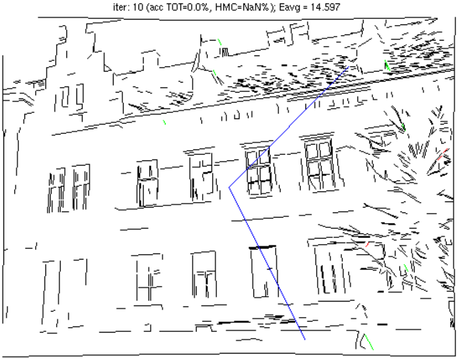
    $$q(m_{ij} \mid \mathbf{F}) \sim \big((1 - P_0)\, p_1(e_{ij} \mid \mathbf{F}),\; P_0\, p_0(e_{ij} \mid \mathbf{F})\big)$$

    when $P(M)$ uniform then always accepted, $a = 1$ ⊛ derive
  - we can compute the posterior probability of each match $p(m_{ij})$ by histogramming m_{ij} from $\{S_i\}$
  - local optimization can then use explicit inliers and $p(m_{ij})$
- error can be estimated for elements of $\mathbf{F}$ from $\{S_i\}$ — does not work in RANSAC!
- large error indicates problem degeneracy — this is not directly available in RANSAC
- good conditioning is not a requirement — we work with the entire distribution $p(\mathbf{F})$
- one can find the most probable number of epipolar geometries (homographies or other models) — by reversible jump MCMC and model selection

  if there are multiple models explaining data, RANSAC will return one of them randomly

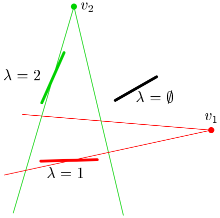
Example: MH Sampling for a More Complex Problem

Task: Find two vanishing points from line segments detected in input image. Principal point is known, square pixel.



video

- primitives = line segments
- latent variables
  1. each line has a vanishing point label $\lambda_i \in \{\emptyset, 1, 2\}$, $\emptyset$ represents an outlier
  2. 'mother line' parameters θ_L (they pass through their vanishing points)
- explicit variables
  1. two unknown vanishing points v_1, v_2
- marginal proposals (v_i fixed, v_j proposed)
- minimal sample $s = 2$



$$\arg\min_{v_1, v_2, \Lambda, \theta_L} V(v_1, v_2, \Lambda, L \mid S)$$

simplifications

- vanishing points restricted to the set of all pairwise segment intersections
- mother lines fixed by segment centroid (then θ_L uniquely given by λ_i)

Module VI

3D Structure and Camera Motion

covered by

[1] [H&Z] Secs: 9.5.3, 10.1, 10.2, 10.3, 12.1, 12.2, 12.4, 12.5, 18.1

[2] Triggs, B. et al. Bundle Adjustment—A Modern Synthesis. In *Proc ICCV Workshop on Vision Algorithms.* Springer-Verlag. pp. 298–372, 1999.

additional references

D. Martinec and T. Pajdla. Robust Rotation and Translation Estimation in Multiview Reconstruction. In *Proc CVPR*, 2007

M. I. A. Lourakis and A. A. Argyros. SBA: A Software Package for Generic Sparse Bundle Adjustment. ACM Trans Math Software 36(1):1–30, 2009.

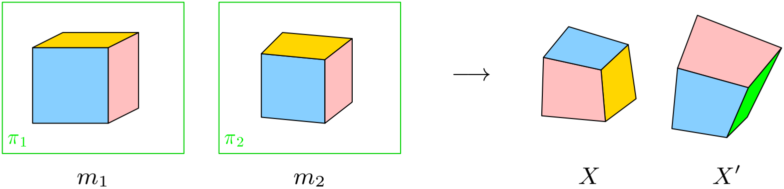
►The Projective Reconstruction Theorem

Observation: Unless $\mathbf{P}_i$ are constrained, then for any number of cameras $i = 1, \ldots, k$

$$\underline{\mathbf{m}}_i \simeq \mathbf{P}_i \underline{\mathbf{X}} = \underbrace{\mathbf{P}_i \mathbf{H}^{-1}}_{\mathbf{P}'_i} \underbrace{\mathbf{H}\underline{\mathbf{X}}}_{\underline{\mathbf{X}}'} = \mathbf{P}'_i \underline{\mathbf{X}}'$$

- when $\mathbf{P}_i$ and $\underline{\mathbf{X}}$ are both determined from correspondences (including calibrations $\mathbf{K}_i$), they are given up to a common 3D homography $\mathbf{H}$

  (translation, rotation, scale, shear, pure perspectivity)



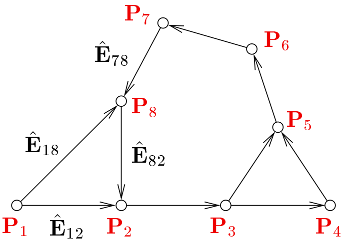
- when cameras are internally calibrated ($\mathbf{K}_i$ known) then $\mathbf{H}$ is restricted to a similarity since it must preserve the calibrations $\mathbf{K}_i$ [H&Z, Secs. 10.2, 10.3], [Longuet-Higgins 1981]

  (translation, rotation, scale)

▶Reconstructing Camera Systems

Problem: Given a set of p decomposed pairwise essential matrices $\hat{\mathbf{E}}_{ij} = [\hat{\mathbf{t}}_{ij}]_\times \hat{\mathbf{R}}_{ij}$ and calibration matrices $\mathbf{K}_i$ reconstruct the camera system $\mathbf{P}_i$, $i = 1, \ldots, k$

→80 and →145 on representing $\mathbf{E}$



We construct calibrated camera pairs $\hat{\mathbf{P}}_{ij} \in \mathbb{R}^{6,4}$ →128

$$\hat{\mathbf{P}}_{ij} = \begin{bmatrix} \mathbf{K}_i^{-1}\hat{\mathbf{P}}_i \\ \mathbf{K}_j^{-1}\hat{\mathbf{P}}_j \end{bmatrix} = \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \hat{\mathbf{R}}_{ij} & \hat{\mathbf{t}}_{ij} \end{bmatrix} \in \mathbb{R}^{6,4}$$

- singletons i, j correspond to graph nodes — k nodes
- pairs ij correspond to graph edges — p edges

$\hat{\mathbf{P}}_{ij}$ are in different coordinate systems but these are related by similarities $\hat{\mathbf{P}}_{ij}\mathbf{H}_{ij} = \mathbf{P}_{ij}$

$$\underbrace{\begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \hat{\mathbf{R}}_{ij} & \hat{\mathbf{t}}_{ij} \end{bmatrix}}_{\mathbb{R}^{6,4}} \underbrace{\begin{bmatrix} \mathbf{R}_{ij} & \mathbf{t}_{ij} \\ \mathbf{0}^\top & s_{ij} \end{bmatrix}}_{\mathbf{H}_{ij} \in \mathbb{R}^{4,4}} \overset{!}{=} \underbrace{\begin{bmatrix} \mathbf{R}_i & \mathbf{t}_i \\ \mathbf{R}_j & \mathbf{t}_j \end{bmatrix}}_{\mathbb{R}^{6,4}} \tag{28}$$

- (28) is a linear system of $24p$ eqs. in $7p + 6k$ unknowns — $7p \sim (\mathbf{t}_{ij}, \mathbf{R}_{ij}, s_{ij})$, $6k \sim (\mathbf{R}_i, \mathbf{t}_i)$
- each $\mathbf{P}_i$ appears on the right side as many times as is the degree of node $\mathbf{P}_i$ — eg. P_5 3-times

Eq. (28) implies $\begin{bmatrix} \mathbf{R}_{ij} \\ \hat{\mathbf{R}}_{ij}\mathbf{R}_{ij} \end{bmatrix} = \begin{bmatrix} \mathbf{R}_i \\ \mathbf{R}_j \end{bmatrix} \qquad \begin{bmatrix} \mathbf{t}_{ij} \\ \hat{\mathbf{R}}_{ij}\mathbf{t}_{ij} + s_{ij}\hat{\mathbf{t}}_{ij} \end{bmatrix} = \begin{bmatrix} \mathbf{t}_i \\ \mathbf{t}_j \end{bmatrix}$

- $\mathbf{R}_{ij}$ and $\mathbf{t}_{ij}$ can be eliminated:

$$\hat{\mathbf{R}}_{ij}\mathbf{R}_i = \mathbf{R}_j, \qquad \hat{\mathbf{R}}_{ij}\mathbf{t}_i + s_{ij}\hat{\mathbf{t}}_{ij} = \mathbf{t}_j, \qquad s_{ij} > 0 \tag{29}$$

- note transformations that do not change these equations — assuming no error in $\hat{\mathbf{R}}_{ij}$

  1. $\mathbf{R}_i \mapsto \mathbf{R}_i\mathbf{R}$, 2. $\mathbf{t}_i \mapsto \sigma\,\mathbf{t}_i$ and $s_{ij} \mapsto \sigma s_{ij}$, 3. $\mathbf{t}_i \mapsto \mathbf{t}_i + \mathbf{R}_i\mathbf{t}$

- the global frame is fixed, e.g. by selecting

$$\mathbf{R}_1 = \mathbf{I}, \qquad \sum_{i=1}^{k} \mathbf{t}_i = \mathbf{0}, \qquad \frac{1}{p}\sum_{i,j} s_{ij} = 1 \tag{30}$$

- rotation equations are decoupled from translation equations
- in principle, s_{ij} could correct the sign of $\hat{\mathbf{t}}_{ij}$ from essential matrix decomposition →80
  but $\mathbf{R}_i$ cannot correct the α sign in $\hat{\mathbf{R}}_{ij}$
  $\Rightarrow$ therefore make sure all points are in front of cameras and constrain $s_{ij} > 0$; →82

+ pairwise correspondences are sufficient
− suitable for well-distributed cameras only (dome-like configurations)

otherwise intractable or numerically unstable

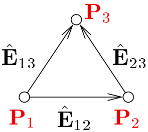
Finding The Rotation Component in Eq. (29): A Global Algorithm

Task: Solve $\hat{\mathbf{R}}_{ij}\mathbf{R}_i = \mathbf{R}_j$, $i, j \in V$, $(i, j) \in E$ where $\mathbf{R}$ are a 3×3 rotation matrix each.
Per columns $c = 1, 2, 3$ of $\mathbf{R}_j$:

$$\hat{\mathbf{R}}_{ij}\mathbf{r}_i^c - \mathbf{r}_j^c = \mathbf{0}, \qquad \text{for all } i,\ j \tag{31}$$

- fix c and denote $\mathbf{r}^c = \left[\mathbf{r}_1^c, \mathbf{r}_2^c, \ldots, \mathbf{r}_k^c\right]^\top$ c-th columns of all rotation matrices stacked; $\mathbf{r}^c \in \mathbb{R}^{3k}$
- then (31) becomes $\mathbf{D}\,\mathbf{r}^c = \mathbf{0}$ $\quad\mathbf{D} \in \mathbb{R}^{3p,3k}$
- $3p$ equations for $3k$ unknowns $\to p \geq k$ $\quad$ in a 1-connected graph we have to fix $\mathbf{r}_1^c = [1, 0, 0]$

Ex: $(k = p = 3)$



$\to$

$$\begin{aligned} \hat{\mathbf{R}}_{12}\mathbf{r}_1^c - \mathbf{r}_2^c &= \mathbf{0} \\ \hat{\mathbf{R}}_{23}\mathbf{r}_2^c - \mathbf{r}_3^c &= \mathbf{0} \\ \hat{\mathbf{R}}_{13}\mathbf{r}_1^c - \mathbf{r}_3^c &= \mathbf{0} \end{aligned}$$

$\to$

$$\mathbf{D}\,\mathbf{r}^c = \begin{bmatrix} \hat{\mathbf{R}}_{12} & -\mathbf{I} & \mathbf{0} \\ \mathbf{0} & \hat{\mathbf{R}}_{23} & -\mathbf{I} \\ \hat{\mathbf{R}}_{13} & \mathbf{0} & -\mathbf{I} \end{bmatrix} \begin{bmatrix} \mathbf{r}_1^c \\ \mathbf{r}_2^c \\ \mathbf{r}_3^c \end{bmatrix} = \mathbf{0}$$

- must hold for any c

Idea: [Martinec & Pajdla CVPR 2007]

1. find the space of all $\mathbf{r}^c \in \mathbb{R}^{3k}$ that solve (31) $\quad\mathbf{D}$ is sparse, use `[V,E] = eigs(D'*D,3,0);` (Matlab)
2. choose 3 unit orthogonal vectors in this space $\quad$ 3 smallest eigenvectors
3. find closest rotation matrices per cam. using SVD $\quad$ because $\|\mathbf{r}^c\| = 1$ is necessary but insufficient
   $\mathbf{R}_i^* = \mathbf{U}\mathbf{V}^\top$, where $\mathbf{R}_i = \mathbf{U}\mathbf{D}\mathbf{V}^\top$

- global world rotation is arbitrary

Finding The Translation Component in Eq. (29)

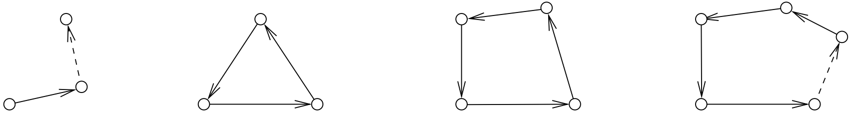
From (29) and (30): $d \leq 3$ – rank of camera center set, p – #pairs, k – #cameras

$$\hat{\mathbf{R}}_{ij}\mathbf{t}_i + s_{ij}\hat{\mathbf{t}}_{ij} - \mathbf{t}_j = \mathbf{0}, \qquad \sum_{i=1}^{k} \mathbf{t}_i = \mathbf{0}, \qquad \sum_{i,j} s_{ij} = p, \qquad s_{ij} > 0, \qquad \mathbf{t}_i \in \mathbb{R}^d$$

- in rank d: $d \cdot p + d + 1$ equations for $d \cdot k + p$ unknowns $\rightarrow p \geq \frac{d(k-1)-1}{d-1} \stackrel{\text{def}}{=} Q(d,k)$

Ex: Chains and circuits construction from sticks of known orientation and unknown length?

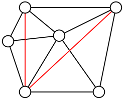
$p = k - 1$ | $k = p = 3$ | $k = p = 4$ | $k = p > 4$



$k \leq 2$ for any d | $3 \geq d \geq 2$: non-collinear ok | $3 \geq d \geq 3$: non-planar ok | $3 \geq d \geq k-1$: impossible

- equations insufficient for chains, trees, or when $d = 1$ collinear cameras
- 3-connectivity implies sufficient equations for $d = 3$ cams. in general pos. in 3D
  - s-connected graph has $p \geq \lceil \frac{sk}{2} \rceil$ edges for $s \geq 2$, hence $p \geq \lceil \frac{3k}{2} \rceil \geq Q(3,k) = \frac{3k}{2} - 2$
- 4-connectivity implies sufficient eqns. for any k when $d = 2$ coplanar cams
  - since $p \geq \lceil 2k \rceil \geq Q(2,k) = 2k - 3$
  - maximal planar tringulated graphs have $p = 3k - 6$ and give a solution for $k \geq 3$

maximal planar triangulated graph example:



cont'd

Linear equations in (29) and (30) can be rewritten to

$$\mathbf{D}\mathbf{t} = \mathbf{0}, \qquad \mathbf{t} = \left[\mathbf{t}_1^\top, \mathbf{t}_2^\top, \ldots, \mathbf{t}_k^\top, s_{12}, \ldots, s_{ij}, \ldots\right]^\top$$

for $d = 3$: $\mathbf{t} \in \mathbb{R}^{3k+p}$, $\mathbf{D} \in \mathbb{R}^{3p,3k+p}$ is sparse

$$\mathbf{t}^* = \arg\min_{\mathbf{t},\, s_{ij}>0} \mathbf{t}^\top \mathbf{D}^\top \mathbf{D}\, \mathbf{t}$$

- this is a quadratic programming problem (mind the constraints!)

```
z = zeros(3*k+p,1);
t = quadprog(D.'*D, z, diag([zeros(3*k,1); -ones(p,1)]), z);
```

- but check the rank first!

▶Solving Eq. (29) by Stepwise Gluing

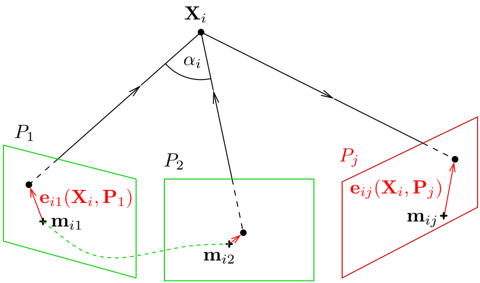
Given: Calibration matrices $\mathbf{K}_j$ and tentative correspondences per camera triples.

Initialization

1. initialize camera cluster $\mathcal{C}$ with P_1, P_2,
2. find essential matrix $\mathbf{E}_{12}$ and matches M_{12} by the 5-point algorithm →87
3. construct camera pair

$$\mathbf{P}_1 = \mathbf{K}_1 \begin{bmatrix} \mathbf{I} & \mathbf{0} \end{bmatrix}, \ \mathbf{P}_2 = \mathbf{K}_2 \begin{bmatrix} \mathbf{R} & \mathbf{t} \end{bmatrix}$$

4. compute 3D reconstruction $\{X_i\}$ per match from M_{12} →104
5. initialize point cloud $\mathcal{X}$ with $\{X_i\}$ satisfying chirality constraint $z_i > 0$ and apical angle constraint $|\alpha_i| > \alpha_T$



Attaching camera $P_j \notin \mathcal{C}$

1. select points $\mathcal{X}_j$ from $\mathcal{X}$ that have matches to P_j
2. estimate $\mathbf{P}_j$ using $\mathcal{X}_j$, RANSAC with the 3-pt alg. (P3P), projection errors $\mathbf{e}_{ij}$ in $\mathcal{X}_j$ →66
3. reconstruct 3D points from all tentative matches from P_j to all P_l, $l \neq k$ that are not in $\mathcal{X}$
4. filter them by the chirality and apical angle constraints and add them to $\mathcal{X}$
5. add P_j to $\mathcal{C}$
6. perform bundle adjustment on $\mathcal{X}$ and $\mathcal{C}$

coming next →136

Thank You