3D Computer Vision

Radim Šára Martin Matoušek

Center for Machine Perception Department of Cybernetics Faculty of Electrical Engineering Czech Technical University in Prague

https://cw.fel.cvut.cz/wiki/courses/tdv/start

http://cmp.felk.cvut.cz
mailto:sara@cmp.felk.cvut.cz
phone ext. 7203

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Open Informatics Master's Course

The Relative Orientation Problem

Problem: Given point triples (X_1, X_2, X_3) and (Y_1, Y_2, Y_3) in a general position in \mathbb{R}^3 such that the correspondence $X_i \leftrightarrow Y_i$ is known, determine the relative orientation (\mathbf{R}, \mathbf{t}) that maps \mathbf{X}_i to \mathbf{Y}_i , i.e.

$$\mathbf{Y}_i = \mathbf{R}\mathbf{X}_i + \underbrace{\mathbf{t}}_{i} \quad i = 1, 2, 3. \qquad \mathbf{k} \in \underbrace{\mathbf{T}}_{i}$$

Applies to:

- 3D scanners
- partial reconstructions from different viewpoints

Obs: Let the centroid be $\bar{\mathbf{X}} = \frac{1}{3} \sum_{i} \mathbf{X}_{i}$ and analogically for $\bar{\mathbf{Y}}$. Then $\bar{\mathbf{Y}} = \mathbf{R}\bar{\mathbf{X}} + \mathbf{t}$ Therefore

 $\mathbf{Z}_{i} \stackrel{\text{def}}{=} (\mathbf{Y}_{i} - \bar{\mathbf{Y}}) = \mathbf{R}(\mathbf{X}_{i} - \bar{\mathbf{X}}) \stackrel{\text{def}}{=} \mathbf{R}\mathbf{W}_{i}$ If all dot products are equal, $\mathbf{Z}_{i}^{\top}\mathbf{Z}_{j} = \mathbf{W}_{i}^{\top}\mathbf{W}_{j}$ for i, j = 1, 2, 3, we have $\mathbf{P}^{*} = [\mathbf{W}_{i} - \mathbf{V}_{i}] \stackrel{\text{def}}{=} \mathbf{R}_{i} = \mathbf{W}_{i}$ $\mathbf{R}^* = \begin{bmatrix} \mathbf{W}_1 & \mathbf{W}_2 & \mathbf{W}_3 \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{Z}_1 & \mathbf{Z}_2 & \mathbf{Z}_3 \end{bmatrix} \quad \mathbf{M} \quad \mathbf{W}_1^*$ Otherwise (in practice) we setup a minimization problem

$$\mathbf{R}^* = \arg\min_{\mathbf{R}} \sum_{i=1}^{3} \|\mathbf{Z}_i - \mathbf{R}\mathbf{W}_i\|^2 \quad \text{s.t.} \quad \mathbf{R}^\top \mathbf{R} = \mathbf{I}, \quad \det \mathbf{R} = 1$$

$$\arg\min_{\mathbf{R}} \sum_{i} \|\mathbf{Z}_{i} - \mathbf{R}\mathbf{W}_{i}\|^{2} = \arg\min_{\mathbf{R}} \sum_{i} \left(\|\mathbf{Z}_{i}\|^{2} - 2\mathbf{Z}_{i}^{\top}\mathbf{R}\mathbf{W}_{i} + \|\mathbf{W}_{i}\|^{2} \right) = \cdots$$
$$\cdots = \arg\max_{\mathbf{R}} \sum_{i=1}^{3} \mathbf{Z}_{i}^{\top}\mathbf{R}\mathbf{W}_{i}$$

3D Computer Vision: III. Computing with a Single Camera (p. 70/189) JOG CP R. Šára, CMP: rev. 20-Oct-2020 cont'd (What is Linear Algebra Telling Us?)

Obs 1: Let $\mathbf{A} : \mathbf{B} = \sum_{i,j} a_{ij} b_{ij}$ be the dot-product (Frobenius inner product) over real matrices. Then vec (A) T. vec (B) = $\mathbf{A} : \mathbf{B} = \mathbf{B} : \mathbf{A} = \operatorname{tr}(\mathbf{A}^{\top}\mathbf{B})$ A:B

Obs 2: (cyclic property for matrix trace)

1

$$\mathbf{R} : \mathbf{M} = \mathbf{R} : (\mathbf{U}\mathbf{D}\mathbf{V}^{\top}) = \operatorname{tr}(\mathbf{R}^{\top}\mathbf{U}\mathbf{D}\mathbf{V}^{\top}) = \operatorname{tr}(\mathbf{V}^{\top}\mathbf{R}^{\top}\mathbf{U}\mathbf{D}) = (\mathbf{U}^{\top}\mathbf{R}\mathbf{V}) : \mathbf{D}$$

cont'd: The Algorithm

We are solving

$$\mathbf{R}^* = \arg \max_{\mathbf{R}} \sum_{i} \mathbf{Z}_{i}^{\top} \mathbf{R} \mathbf{W}_{i} = \arg \max_{\mathbf{R}} \left(\mathbf{U}^{\top} \mathbf{R} \mathbf{V} \right) : \mathbf{D}$$

- A particular solution is found as follows:
 - $\mathbf{U}^{\top}\mathbf{R}\mathbf{V}$ must be (1) orthogonal, and most similar to (2) diagonal, (3) positive definite
 - Since U, V are orthogonal matrices then the solution to the problem is among $\mathbf{R}^* = \mathbf{U} \mathbf{S} \mathbf{V}^\top$, where S is diagonal and orthogonal, i.e. one of

 $\pm \operatorname{diag}(1,1,1), \quad \pm \operatorname{diag}(1,-1,-1), \quad \pm \operatorname{diag}(-1,1,-1), \quad \pm \operatorname{diag}(-1,-1,1)$

- + $\mathbf{U}^{\top}\mathbf{V}$ is not necessarily positive definite
- We choose ${\bf S}$ so that $({\bf R}^*)^\top {\bf R}^* = {\bf I}$

1. Compute matrix $\mathbf{M} = \sum_{i} \mathbf{Z}_{i} \mathbf{W}_{i}^{\top}$.

- 2. Compute SVD $\mathbf{M} = \mathbf{U}\mathbf{D}\mathbf{V}^{\top}$.
- 3. Compute all $\mathbf{R}_k = \mathbf{U}\mathbf{S}_k\mathbf{V}^{\top}$ that give $\mathbf{R}_k^{\top}\mathbf{R}_k = \mathbf{I}$.
- 4. Compute $\mathbf{t}_k = \bar{\mathbf{Y}} \mathbf{R}_k \bar{\mathbf{X}}$.
 - The algorithm can be used for more than 3 points
 - Triple pairs can be pre-filtered based on motion invariants (lengths, angles)
 - The P3P problem is very similar but not identical

Module IV

Computing with a Camera Pair

- Ocamera Motions Inducing Epipolar Geometry
- Estimating Fundamental Matrix from 7 Correspondences
- Estimating Essential Matrix from 5 Correspondences
- Triangulation: 3D Point Position from a Pair of Corresponding Points

covered by

[1] [H&Z] Secs: 9.1, 9.2, 9.6, 11.1, 11.2, 11.9, 12.2, 12.3, 12.5.1
 [2] H. Li and R. Hartley. Five-point motion estimation made easy. In *Proc ICPR* 2006, pp. 630–633

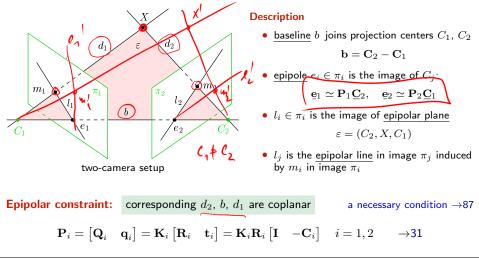
additional references

H. Longuet-Higgins. A computer algorithm for reconstructing a scene from two projections. *Nature*, 293 (5828):133–135, 1981.

► Geometric Model of a Camera Pair

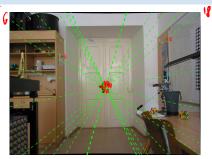
Epipolar geometry:

- brings constraints necessary for inter-image matching
- its parametric form encapsulates information about the relative pose of two cameras



Epipolar Geometry Example: Forward Motion



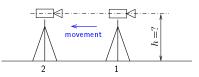




- red: correspondences
- green: epipolar line pairs per correspondence

image 2 click on the image to see their IDs same ID in both images

How high was the camera above the floor?



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Cross Products and Maps by Skew-Symmetric 3×3 Matrices

• There is an equivalence $\mathbf{b} \times \mathbf{m} = ([\mathbf{b}]_{\times})\mathbf{m}$, where $[\mathbf{b}]_{\times}$ is a 3×3 skew-symmetric matrix

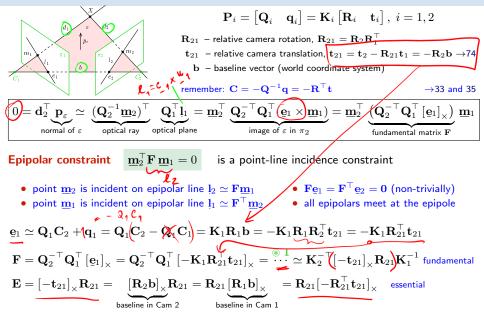
$$\begin{bmatrix} \mathbf{b} \end{bmatrix}_{\times} = \begin{bmatrix} 0 & -b_3 & b_2 \\ b_3 & 0 & -b_1 \\ -b_2 & b_1 & 0 \end{bmatrix}, \quad \text{assuming } \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

Some properties

(1) $[\mathbf{b}]_{\times}^{\top} = -[\mathbf{b}]_{\times}$ the general antisymmetry property 2. A is skew-symmetric iff $\mathbf{x}^{\top} \mathbf{A} \mathbf{x} = 0$ for all \mathbf{x} skew-sym mtx generalizes cross products (3) $[\mathbf{b}]_{\vee}^{3} = -\|\mathbf{b}\|^{2} \cdot [\mathbf{b}]_{\vee}$ Frobenius norm $(\|\mathbf{A}\|_F = \sqrt{\operatorname{tr}(\mathbf{A}^{\top}\mathbf{A})} = \sqrt{\sum_{i,j} |a_{ij}|^2})$ **4.** $\|[\mathbf{b}]_{\times}\|_{E} = \sqrt{2} \|\mathbf{b}\|$ C57.6=0 5. $[\mathbf{b}]_{\vee}\mathbf{b} = \mathbf{0}$ $\mathbf{b} \star \mathbf{b} = \mathbf{0}$ **6**. rank $[\mathbf{b}]_{\sim} = 2$ iff $\|\mathbf{b}\| > 0$ check minors of $[\mathbf{b}]_{\vee}$ (7) eigenvalues of $[\mathbf{b}]_{\checkmark}$ are $(0, \lambda, -\lambda)$ 0 (8) for any 3×3 regular \mathbf{B} : $\mathbf{B}^{\top}[\mathbf{B}\mathbf{z}]_{\mathbf{v}}\mathbf{B} = \det \mathbf{B}[\mathbf{z}]_{\mathbf{v}}$ follows from the factoring on \rightarrow 39 (2) in particular: if $\mathbf{R}\mathbf{R}^{ op} = \mathbf{I}$ then $[\mathbf{R}\mathbf{b}]_{ imes} = \mathbf{R}[\mathbf{b}]_{ imes}\mathbf{R}^{ op}$

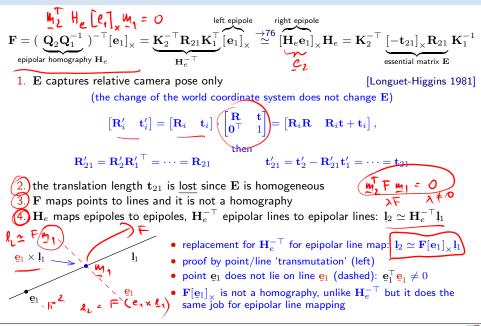
- note that if \mathbf{R}_b is rotation about \mathbf{b} then $\mathbf{R}_b\mathbf{b} = \mathbf{b}$
- note $[\mathbf{b}]_{ imes}$ is not a homography; it is not a rotation matrix it is the logarithm of a rotation mtx

Expressing Epipolar Constraint Algebraically

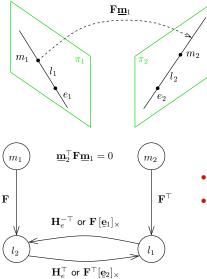


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► The Structure and the Key Properties of the Fundamental Matrix



Summary: Relations and Mappings Involving Fundamental Matrix



$0 = \underline{\mathbf{m}}_2^\top \mathbf{F} \underline{\mathbf{m}}_1$	
$\underline{\mathbf{e}}_1 \simeq \operatorname{null}(\mathbf{F}),$	$\underline{\mathbf{e}}_2 \simeq \operatorname{null}(\mathbf{F}^\top)$
$\mathbf{\underline{e}}_1\simeq \mathbf{H}_e^{-1}\mathbf{\underline{e}}_2$	$\mathbf{\underline{e}}_2\simeq\mathbf{H}_e\mathbf{\underline{e}}_1$
$\underline{\mathbf{l}}_1\simeq \mathbf{F}^\top \underline{\mathbf{m}}_2$	$\mathbf{l}_2\simeq \mathbf{F}\mathbf{\underline{m}}_1$
$\mathbf{l}_1\simeq \mathbf{H}_e^{ op}\mathbf{l}_2$	$\mathbf{l}_2 \simeq \mathbf{H}_e^{- op} \mathbf{l}_1$
$\mathbf{l}_1 \simeq \mathbf{F}^{ op} [\mathbf{\underline{e}}_2]_{ imes} \mathbf{l}_2$	$\mathbf{l}_2\simeq \mathbf{F}[\mathbf{\underline{e}}_1]_{\times}\mathbf{l}_1$

- $\mathbf{F}[\underline{\mathbf{e}}_1]_{\times}$ maps lines to lines but it is not a homography
- $\mathbf{H}_e = \mathbf{Q}_2 \mathbf{Q}_1^{-1}$ is the epipolar homography \rightarrow 78 $\mathbf{H}_e^{-\top}$ maps epipolar lines to epipolar lines, where

$$\mathbf{H}_e = \mathbf{Q}_2 \mathbf{Q}_1^{-1} = \mathbf{K}_2 \mathbf{R}_{21} \mathbf{K}_1^{-1}$$

you have seen this ${\rightarrow}59$

▶ Representation Theorem for Fundamental Matrices

Def: F is fundamental when $\mathbf{F} \simeq \left(\mathbf{H}^{-\top}[\underline{\mathbf{e}}_1]_{\times}\right)$ where **H** is regular and $\underline{\mathbf{e}}_1 \simeq \operatorname{null} \mathbf{F} \neq \mathbf{0}$.

Theorem: A 3×3 matrix **A** is fundamental iff it is of rank 2.

Proof.

<u>Direct</u>: By the geometry, **H** is full-rank, $\underline{\mathbf{e}}_1 \neq \mathbf{0}$, hence $\mathbf{H}^{-\top}[\underline{\mathbf{e}}_1]_{\times}$ is a 3×3 matrix of rank 2. <u>Converse</u>:

- 1. let $\mathbf{A} = \mathbf{U}\mathbf{D}\mathbf{V}^{\top}$ be the SVD of \mathbf{A} of rank 2; then $\mathbf{D} = \operatorname{diag}(\lambda_1, \lambda_2, 0), \ \lambda_1 \ge \lambda_2 > 0$
- 2. we write $\mathbf{D} = \mathbf{BC}$, where $\mathbf{B} = \text{diag}(\lambda_1, \lambda_2, \lambda_3)$, $\mathbf{C} = \text{diag}(1, 1, 0)$, $\lambda_3 = \lambda_2$ (w.l.o.g.)
- 3. then $\mathbf{A} = \mathbf{UBCV}^{\top} = \mathbf{UBCWV}^{\top} \mathbf{V}^{\top}$ with \mathbf{W} rotation

4. we look for a rotation W that maps C to a skew-symmetric S, i.e. $\mathbf{S} = \mathbf{CW}$

5. then
$$\mathbf{W} = \begin{bmatrix} 0 & \alpha & 0 \\ -\alpha & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$
, $|\alpha| = 1$, and $\mathbf{S} = [\mathbf{s}]_{\times}$, $\mathbf{s} = (0, 0, 1)$

$$\mathbf{A} = \mathbf{U}\mathbf{B}[\mathbf{s}]_{\times}\mathbf{W}^{\top}\mathbf{V}^{\top} = \overset{\circledast}{\cdots} = \underbrace{\mathbf{U}\mathbf{B}(\mathbf{V}\mathbf{W})^{\top}}_{\simeq \mathbf{H}^{-\top}} [\mathbf{v}_{3}]_{\times} \simeq \underbrace{[\mathbf{H}\mathbf{v}_{3}]_{\times}}_{\simeq [\mathbf{u}_{3}]_{\times}} \mathbf{H},$$
(12)

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7. H regular, $Av_3 = 0$, $u_3A = 0$ for $v_3 \neq 0$, $u_3 \neq 0$

- we also got a (non-unique: $lpha=\pm 1$) decomposition formula for fundamental matrices
- it follows there is no constraint on F except the rank

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▶ Representation Theorem for Essential Matrices

Theorem

Let E be a 3×3 matrix with SVD $\mathbf{E} = \mathbf{U}\mathbf{D}\mathbf{V}^{\mathsf{T}}$. Then E is essential iff $\mathbf{D} \simeq \operatorname{diag}(1,1,0)$.

Proof.

Direct:

If E is an essential matrix, then the epipolar homography matrix is a rotation matrix (\rightarrow 78), hence $\mathbf{H}^{-\top} \simeq \mathbf{UB}(\mathbf{VW})^{\top}$ in (12) must be (λ -scaled) orthogonal, therefore $\mathbf{B} = \lambda \mathbf{I}$.

Converse:

E is fundamental with $\mathbf{D} = \lambda \operatorname{diag}(1, 1, 0)$ then we do not need B (as if $\mathbf{B} = \lambda \mathbf{I}$) in (12) and $\mathbf{U}(\mathbf{V}\mathbf{W})^{\top}$ is orthogonal, as required.

Essential Matrix Decomposition

We are decomposing \mathbf{E} to $\mathbf{E} \simeq [-\mathbf{t}_{21}]_{\times} \mathbf{R}_{21} = \mathbf{R}_{21} [-\mathbf{R}_{21}^{\top} \mathbf{t}_{21}]_{\times}$ [H&Z, sec. 9.6]

- 1. compute SVD of $\mathbf{E}^{(1)} = \mathbf{U}\mathbf{D}\mathbf{V}^{\top}$ and verify $\mathbf{D} = \lambda \operatorname{diag}(1, 1, 0)$
- 2. ensure $U,\,V$ are rotation matrices by $U\mapsto \det(U)U,\,V\mapsto \det(V)V$
- compute

$$\mathbf{R}_{21} = \mathbf{U} \underbrace{\begin{bmatrix} 0 & \alpha & 0 \\ -\alpha & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{\mathbf{W}} \mathbf{V}^{\top}, \quad \mathbf{t}_{21} = -\beta \, \mathbf{u}_3, \qquad |\alpha| = 1, \quad \beta \neq 0$$
(13)

Notes

 $\mathbf{\hat{v}}_3 \simeq \mathbf{R}_{21}^\top \mathbf{t}_{21}$ by (12), hence $\mathbf{R}_{21} \mathbf{v}_3 \simeq \mathbf{t}_{21} \simeq \mathbf{u}_3$ since it must fall in left null space by $\mathbf{E} \simeq [\mathbf{u}_3]_{\times} \mathbf{R}_{21}$

- \mathbf{t}_{21} is recoverable up to scale β and direction $\operatorname{sign}\beta$
- the result for \mathbf{R}_{21} is unique up to $\alpha = \pm 1$

despite non-uniqueness of SVD

• the change of sign in lpha rotates the solution by 180° about ${f t}_{21}$

 $\mathbf{R}(\alpha) = \mathbf{U}\mathbf{W}\mathbf{V}^{\top}, \ \mathbf{R}(-\alpha) = \mathbf{U}\mathbf{W}^{\top}\mathbf{V}^{\top} \Rightarrow \mathbf{R}(-\alpha)\mathbf{R}^{\top}(\alpha) = \cdots = \mathbf{U}\operatorname{diag}(-1, -1, 1)\mathbf{U}^{\top} = \mathbf{R}(-\alpha)\mathbf{R}^{\top}(\alpha) = \mathbf{U}\operatorname{diag}(-1, -1, 1)\mathbf{U}^{\top} = \mathbf{U}\operatorname{diag}(-1, -1, 1)\mathbf{U}\operatorname{diag}(-1, -1, 1)\mathbf{U}$

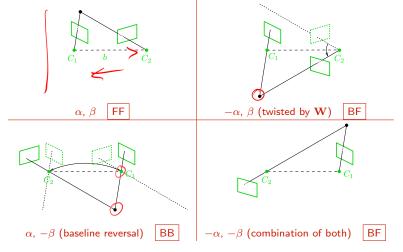
$$\mathbf{U}\operatorname{diag}(-1,-1,1)\mathbf{U}^{\mathsf{T}}\mathbf{u}_{3} = \mathbf{U}\begin{bmatrix} -1 & 0 & 0\\ 0 & -1 & 0\\ 0 & 0 & 1 \end{bmatrix}\begin{bmatrix} 0\\ 0\\ 1 \end{bmatrix} = \mathbf{u}_{3}$$

• 4 solution sets for 4 sign combinations of α , β

see next for geometric interpretation

► Four Solutions to Essential Matrix Decomposition

Transform the world coordinate system so that the origin is in Camera 2. Then $t_{21} = -b$ and W rotates about the baseline b.



- chirality constraint: all 3D points are in front of both cameras
- this singles-out the upper left case

[H&Z, Sec. 9.6.3]

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Thank You

