3D Computer Vision

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Open Informatics Master's Course

Expressing Epipolar Constraint Algebraically



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► The Structure and the Key Properties of the Fundamental Matrix

$$\mathbf{F} = \big(\underbrace{\mathbf{Q}_{2}\mathbf{Q}_{1}^{-1}}_{\text{epipolar homography }\mathbf{H}_{e}}\big)^{-\top} [\mathbf{e}_{1}]_{\times} = \underbrace{\mathbf{K}_{2}^{-\top}\mathbf{R}_{21}\mathbf{K}_{1}^{\top}}_{\mathbf{H}_{e}^{-\top}} [\mathbf{e}_{1}]_{\times} \xrightarrow{\rightarrow 76} [\mathbf{H}_{e}\mathbf{e}_{1}]_{\times} \mathbf{H}_{e} = \mathbf{K}_{2}^{-\top} \underbrace{[-\mathbf{t}_{21}]_{\times}\mathbf{R}_{21}}_{\text{essential matrix }\mathbf{E}} \mathbf{K}_{1}^{-1}$$

- 1. E captures relative camera pose only [Longuet-Higgins 1981] (the change of the world coordinate system does not change E) $\begin{bmatrix} \mathbf{R}'_i & \mathbf{t}'_i \end{bmatrix} = \begin{bmatrix} \mathbf{R}_i & \mathbf{t}_i \end{bmatrix} \cdot \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}^\top & \mathbf{1} \end{bmatrix} = \begin{bmatrix} \mathbf{R}_i \mathbf{R} & \mathbf{R}_i \mathbf{t} + \mathbf{t}_i \end{bmatrix},$ then $\mathbf{R}'_{21} = \mathbf{R}'_2 \mathbf{R}'_1^\top = \cdots = \mathbf{R}_{21}$ then $\mathbf{t}'_{21} = \mathbf{t}'_2 - \mathbf{R}'_{21} \mathbf{t}'_1 = \cdots = \mathbf{t}_{21}$
- 2. the translation length t_{21} is lost since E is homogeneous
- 3. F maps points to lines and it is not a homography
- 4. \mathbf{H}_e maps epipoles to epipoles, $\mathbf{H}_e^{-\top}$ epipolar lines to epipolar lines: $\mathbf{l}_2 \simeq \mathbf{H}_e^{-\top} \mathbf{l}_1$



another epipolar line map: $\mathbf{l}_2 \simeq \mathbf{F}[\mathbf{e}_1]_{\times} \mathbf{l}_1$

- proof by point/line 'transmutation' (left)
- point $\underline{\mathbf{e}}_1$ does not lie on line $\underline{\mathbf{e}}_1$ (dashed): $\underline{\mathbf{e}}_1^\top \underline{\mathbf{e}}_1 \neq 0$
- $\mathbf{F}[\underline{\mathbf{e}}_1]_{\times}$ is not a homography, unlike $\mathbf{H}_e^{-\top}$ but it does the same job for epipolar line mapping
- no need to decompose ${f F}$ to obtain ${f H}_e$

Summary: Relations and Mappings Involving Fundamental Matrix



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

• $\mathbf{F}[\underline{e}_1]_{\times}$ maps epipolar lines to epipolar 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 $\mathbf{F} \simeq \mathbf{H}^{-\top}[\mathbf{e}_1]_{\times}$, where H is regular and $\mathbf{e}_1 \simeq \operatorname{null} \mathbf{F} \neq \mathbf{0}$.

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 $\mathbf{B} = \operatorname{diag}(\lambda_1, \lambda_2, \lambda_3)$, $\mathbf{C} = \operatorname{diag}(1, 1, 0)$
- 3. then $\mathbf{A} = \mathbf{U}\mathbf{B}\mathbf{C}\mathbf{V}^\top = \mathbf{U}\mathbf{B}\mathbf{C}\underbrace{\mathbf{W}\mathbf{W}^\top}_{\mathbf{I}}\mathbf{V}^\top$ with \mathbf{W} rotation

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

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

6. we write

 \mathbf{v}_3 – 3rd column of $\mathbf{V},\,\mathbf{u}_3$ – 3rd column of \mathbf{U}

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$$\mathbf{A} = \mathbf{U}\mathbf{B}[\mathbf{s}]_{\times}\mathbf{W}^{\top}\mathbf{V}^{\top} = \stackrel{\text{(b)}}{\cdots} \stackrel{1}{=} \underbrace{\mathbf{U}\mathbf{B}(\mathbf{V}\mathbf{W})^{\top}}_{\simeq \mathbf{H}^{-\top}} [\mathbf{v}_{3}]_{\times} \simeq \underbrace{[\mathbf{H}\mathbf{v}_{3}]_{\times}}_{\simeq [\mathbf{u}_{3}]_{\times}} \mathbf{H},$$
(12)

- 7. H regular, $Av_3 = 0$, $u_3A = 0$ for $v_3 \neq 0$, $u_3 \neq 0$
- we also got a (non-unique: α , λ_3) decomposition formula for fundamental matrices
- it follows there is no constraint on F except for the rank

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▶ Representation Theorem for Essential Matrices

Theorem

Let E be a 3×3 matrix with SVD $\mathbf{E} = \mathbf{U}\mathbf{D}\mathbf{V}^{\top}$. 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 $\mathbf{B} = \lambda \mathbf{I}$. we have fixed the missing λ_3 in (12)

Then

$$\mathbf{R}_{21} = \mathbf{H}^{-\top} \simeq \mathbf{U} \mathbf{W}^{\top} \mathbf{V}^{\top} \simeq \mathbf{U} \mathbf{W} \mathbf{V}^{\top}$$

Converse:

 ${\bf E}$ is fundamental with

$$\mathbf{D} = \operatorname{diag}(\lambda, \lambda, 0) = \underbrace{\lambda \mathbf{I}}_{\mathbf{B}} \underbrace{\operatorname{diag}(1, 1, 0)}_{\mathbf{D}}$$

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

- $\mathbf{v}_3 \simeq \mathbf{R}_{21}^{-1} \mathbf{t}_{21}$ 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 \mathbf{t}_{21}

 $\mathbf{R}(\alpha) = \mathbf{U}\mathbf{W}\mathbf{V}^{\top}, \ \mathbf{R}(-\alpha) = \mathbf{U}\mathbf{W}^{\top}\mathbf{V}^{\top} \Rightarrow \mathbf{T} = \mathbf{R}(-\alpha)\mathbf{R}^{\top}(\alpha) = \cdots = \mathbf{U}\operatorname{diag}(-1, -1, 1)\mathbf{U}^{\top}$ which is a rotation by 180° about $\mathbf{u}_3 \simeq \mathbf{t}_{21}$: show that \mathbf{u}_3 is the rotation axis

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

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

see next for geometric interpretation

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► 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.



- <u>chirality constraint</u>: 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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►7-Point Algorithm for Estimating Fundamental Matrix

Problem: Given a set $\{(x_i, y_i)\}_{i=1}^k$ of k = 7 finite correspondences, estimate f. m. **F**.

$$\underline{\mathbf{y}}_i^{\top} \mathbf{F} \, \underline{\mathbf{x}}_i = 0, \ i = 1, \dots, k, \quad \underline{\mathsf{known}}: \ \underline{\mathbf{x}}_i = (u_i^1, v_i^1, 1), \ \underline{\mathbf{y}}_i = (u_i^2, v_i^2, 1)$$

terminology: correspondence = truth, later: match = algorithm's result; hypothesized corresp.

Solution:

$$\begin{split} \mathbf{y}_i^\top \mathbf{F} \, \mathbf{x}_i &= (\mathbf{y}_i \mathbf{x}_i^\top) : \mathbf{F} = \left(\operatorname{vec}(\mathbf{y}_i \mathbf{x}_i^\top) \right)^\top \operatorname{vec}(\mathbf{F}), & \text{rotation property of matrix trace} \to 71 \\ \operatorname{vec}(\mathbf{F}) &= \begin{bmatrix} f_{11} & f_{21} & f_{31} & \dots & f_{33} \end{bmatrix}^\top \in \mathbb{R}^9 & \text{column vector from matrix} \end{split}$$

$$\mathbf{D} = \begin{bmatrix} \left(\operatorname{vec}(\mathbf{y}_{1}\mathbf{x}_{1}^{\top}) \right)^{\top} \\ \left(\operatorname{vec}(\mathbf{y}_{2}\mathbf{x}_{2}^{\top}) \right)^{\top} \\ \left(\operatorname{vec}(\mathbf{y}_{3}\mathbf{x}_{3}^{\top}) \right)^{\top} \\ \left(\operatorname{vec}(\mathbf{y}_{3}\mathbf{x}_{3}^{\top}) \right)^{\top} \\ \vdots \\ \left(\operatorname{vec}(\mathbf{y}_{k}\mathbf{x}_{k}^{\top}) \right)^{\top} \end{bmatrix} = \begin{bmatrix} u_{1}^{1}u_{1}^{2} & u_{1}^{1}v_{1}^{2} & u_{1}^{1} & u_{1}^{2}v_{1}^{1} & v_{1}^{1}v_{1}^{2} & v_{1}^{1} & u_{1}^{2} & v_{1}^{2} & 1 \\ u_{2}^{1}u_{2}^{2} & u_{2}^{1}v_{2}^{2} & u_{2}^{1} & u_{2}^{1}v_{2}^{2} & v_{2}^{1} & v_{2}^{1}v_{2}^{2} & v_{2}^{2} & 1 \\ u_{3}^{1}u_{3}^{2} & u_{3}^{1}v_{3}^{2} & u_{3}^{1} & u_{3}^{2}v_{3}^{1} & v_{3}^{1}v_{3}^{2} & v_{3}^{1} & u_{3}^{2} & v_{3}^{2} & 1 \\ \vdots & & & & & & & & \\ u_{k}^{1}u_{k}^{2} & u_{k}^{1}v_{k}^{2} & u_{k}^{1} & u_{k}^{2}v_{k}^{1} & v_{k}^{1}v_{k}^{2} & v_{k}^{1} & u_{k}^{2} & v_{k}^{2} & 1 \end{bmatrix} \in \mathbb{R}^{k,9} \end{bmatrix}$$

 $\mathbf{D}\operatorname{vec}(\mathbf{F}) = \mathbf{0}$

►7-Point Algorithm Continued

 $\mathbf{D} \operatorname{vec}(\mathbf{F}) = \mathbf{0}, \quad \mathbf{D} \in \mathbb{R}^{k,9}$

- for k = 7 we have a rank-deficient system, the null-space of D is 2-dimensional
- but we know that $\det \mathbf{F} = 0$, hence
 - **1**. find a basis of the null space of **D**: \mathbf{F}_1 , \mathbf{F}_2
 - 2. get up to 3 real solutions for α from

 $det(\boldsymbol{\alpha}\mathbf{F}_1 + (1-\boldsymbol{\alpha})\mathbf{F}_2) = 0 \qquad \text{cubic equation in } \boldsymbol{\alpha}$

- 3. get up to 3 fundamental matrices $\mathbf{F}_i = \alpha_i \mathbf{F}_1 + (1 \alpha_i) \mathbf{F}_2$
- 4. if rank $\mathbf{F}_i < 2$ for all i = 1, 2, 3 then fail
- the result may depend on image (domain) transformations

٠	normalization improves conditioning	→92
•	this gives a good starting point for the full algorithm	\rightarrow 104
•	dealing with mismatches need not be a part of the 7-point algorithm	\rightarrow 105

by SVD or QR factorization

A Note on Oriented Epipolar Constraint

- a tighter epipolar constraint preserves orientations
- requires all points and cameras be on the same side of the plane at infinity



 $(\underline{\mathbf{e}}_2 \times \underline{\mathbf{m}}_2) \stackrel{+}{\sim} \mathbf{F} \, \underline{\mathbf{m}}_1$

notation: $\underline{\mathbf{m}} \stackrel{+}{\sim} \underline{\mathbf{n}}$ means $\underline{\mathbf{m}} = \lambda \underline{\mathbf{n}}, \ \lambda > 0$

- we can read the constraint as $(\underline{\mathbf{e}}_2 imes \underline{\mathbf{m}}_2) \ totolog \leftarrow \mathbf{H}_e^{- op} (\mathbf{e}_1 imes \underline{\mathbf{m}}_1)$
- note that the constraint is not invariant to the change of either sign of \mathbf{m}_i
- all 7 correspondence in 7-point alg. must have the same sign
- this may help reject some wrong matches, see ightarrow 105
- an even more tight constraint: scene points in front of both cameras

see later

[Chum et al. 2004]

expensive

this is called chirality constraint

Thank You