

Computer Vision: Lecture 6

2023-11-16

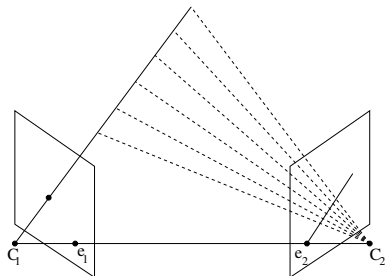
Recap

If $P_1 = (I \mid \mathbf{0})$ and $P_2 = (A \mid \mathbf{t})$:

$$\bar{\mathbf{x}}^T \underbrace{[\mathbf{t}]_{\times} \mathbf{A}}_{:=F} \mathbf{x} = 0$$

$F\mathbf{x}$ — epipolar line in image 2, $F^T \mathbf{e}_2 = \mathbf{0}$

$F^T \bar{\mathbf{x}}$ — epipolar line in image 1, $F\mathbf{e}_1 = \mathbf{0}$



Uncalibrated Structure from Motion with 2 cameras:

- Solve for F using 8-point solver
- Extract cameras from F (Today's Lecture)
- Triangulate 3D points

Today's Lecture

Two view geometry

- Computing cameras from F
- The calibrated case: The Essential Matrix
- The 8-point algorithm (again)
- Computing the cameras from E .

Camera matrices from F

- We assume $P_1 = (I \mid \mathbf{0})$
 - Projective ambiguity
- Can you determine $P_2 = (A \mid \mathbf{t})$ such that $F = [\mathbf{t}]_{\times} A$?
- Geometric intuition does not help...
- One choice is given by

$$P_2 = ([\mathbf{e}_2]_{\times} F \mid \mathbf{e}_2)$$

$\mathbf{e}_2 \in \text{null}(F^T)$ is the 2nd epipole (image of camera 1 in camera 2)

- Recall skew-symmetric matrix from last lecture

$$[\mathbf{a}]_{\times} := \begin{pmatrix} 0 & -a_3 & a_2 \\ a_3 & 0 & -a_1 \\ -a_2 & a_1 & 0 \end{pmatrix} \quad [\mathbf{a}]_{\times} + [\mathbf{a}]_{\times}^T = 0$$

- How can we prove that?

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Camera matrices from F

- Claim: for given F we can choose $P_1 = (I \mid \mathbf{0})$ and $P_2 = ([\mathbf{e}_2]_{\times} F \mid \mathbf{e}_2)$

- Let $\begin{pmatrix} \mathbf{X} \\ \mu \end{pmatrix} \in \mathbb{P}^3$ $\mathbf{X} \in \mathbb{R}^3$

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Question

Camera center 2

What is the camera center of $P_2 = ([\mathbf{e}_2]_{\times} \mathbf{F} \mid \mathbf{e}_2)$?

Hint: recall that $\mathbf{F}\mathbf{e}_1 = \mathbf{0}$.

Solution:

- Camera center $\begin{pmatrix} \mathbf{C}_2 \\ \mu \end{pmatrix} \in \mathbb{P}^3$:

$$\begin{aligned} P_2 \begin{pmatrix} \mathbf{C}_2 \\ \mu \end{pmatrix} = \mathbf{0} &\iff [\mathbf{e}_2]_{\times} \mathbf{F} \mathbf{C}_2 + \mu \mathbf{e}_2 = \mathbf{0} \\ &\implies \mathbf{C}_2 = \mathbf{e}_1 \wedge \mu = 0 \end{aligned}$$

- A point $\begin{pmatrix} \mathbf{e}_1 \\ 0 \end{pmatrix}$ at infinity!

You may get a gist that projective reconstruction may look strange

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Camera matrices from F

General solution

For given F we can choose

$$P_1 = (I \mid \mathbf{0})$$

$$P_2 = ([\mathbf{e}_2]_{\times} F + \mathbf{e}_2 \mathbf{v}^T \mid \lambda \mathbf{e}_2)$$

for any $\mathbf{v} \in \mathbb{R}^3$ and $\lambda \in \mathbb{R}$.

- For given F we have a 4-parameter family of solutions P_2 even after fixing $P_1 = (I \mid \mathbf{0})$
- $P_1 = (I \mid \mathbf{0})$ and $P_2 = (A \mid \mathbf{t})$... “canonical camera pair”
- We may apply a projective transformation $H \in \mathbb{R}^{4 \times 4}$

$$P'_1 = P_1 H$$

$$P'_2 = P_2 H$$

Will not affect F

Relative Orientation: The Calibrated Case

Problem Formulation

Given two sets of corresponding (normalized) points $\{\mathbf{x}_i\}$ and $\{\bar{\mathbf{x}}_i\}$, compute camera matrices $P_1 = (R_1 \mid T_1)$, $P_2 = (R_2 \mid T_2)$ and 3D-points $\{\mathbf{X}_i\}$ such that

$$\lambda_i \mathbf{x}_i = P_1 \mathbf{X}_i$$

and

$$\bar{\lambda}_i \bar{\mathbf{x}}_i = P_2 \mathbf{X}_i.$$

Relative Orientation: Problem Formulation

Simplification

If $P_1 = (R_1 \mid T_1)$, $P_2 = (R_2 \mid T_2)$, apply the (Euclidean) transformation

$$H = \begin{pmatrix} R_1^\top & -R_1^\top T_1 \\ \mathbf{0}^\top & 1 \end{pmatrix}.$$

Then

$$P_1 H = (R_1 \mid T_1) \begin{pmatrix} R_1^\top & -R_1^\top T_1 \\ \mathbf{0}^\top & 1 \end{pmatrix} = (I \mid \mathbf{0})$$

Hence, we may assume that the cameras are

$$P_1 = (I \mid \mathbf{0})$$

$$P_2 = (R \mid T).$$

The Essential Matrix

The Essential Matrix

The camera pair $P_1 = (I \mid \mathbf{0})$ and $P_2 = (R \mid \mathbf{T})$ has the fundamental matrix

$$E = [\mathbf{T}]_{\times} R$$

E is called the essential matrix.

- R has 3 dof, \mathbf{T} 3 dof, but the scale is arbitrary, therefore E has 5 d.o.f.
- E has $\det(E) = 0$
- E has two nonzero equal singular values.

The Essential Matrix

The 8-point algorithm (again)

- Extract at least 8 point correspondences.
- Normalize the coordinates (multiply with K^{-1} , K inner parameters).
- Form M and solve

$$\min_{\mathbf{v}: \|\mathbf{v}\|=1} \|\mathbf{M}\mathbf{v}\|^2$$

using SVD.

- Reshape $\mathbf{v} \in \mathbb{R}^9$ to $\mathbf{E} \in \mathbb{R}^{3 \times 3}$
- Enforce constraints on \mathbf{E}
 - Ensure that $\det(\mathbf{E}) = 0$
 - \mathbf{E} has two nonzero equal singular values
- Compute a pair of cameras from \mathbf{E} .
- Compute the scene points (triangulation).

The Essential Matrix

Issues

Resulting E may not have $\det(E) = 0$ and two nonzero equal singular values.
Pick the closest essential matrix.

Can be solved using `svd`, in matlab:

```
[U,S,V] = svd(E);  
s = (S(1,1)+S(2,2))/2;  
S = diag([s s 0]);  
E = U*S*V';
```

Note: Since the scale of the essential matrix is arbitrary we may assume that $s = 1$. We can therefore always use $S = \text{diag}([1 \ 1 \ 0])$.

Computing the cameras from E

Goal

Find $P_2 = (R \mid T)$ such that $E = [T]_{\times} R$.

Outline:

- Ensure that E has the SVD

$$E = U \Sigma V^T = U \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix} V^T$$

where $\det(UV^T) = 1$

- Compute a factorization $E = SR$ where S is skew symmetric and R a rotation
- Compute a T such that $[T]_{\times} = S$
- Form the camera $P_2 = (R \mid T)$

Decomposing E

- First decompose $\Sigma = \underbrace{Z}_{\text{skew sym.}} \underbrace{W}_{\text{orthogonal}} \iff \Sigma W^T = Z$

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} w_{11} & w_{21} & w_{31} \\ w_{12} & w_{22} & w_{32} \\ w_{13} & w_{23} & w_{33} \end{pmatrix} = \begin{pmatrix} w_{11} & w_{21} & w_{31} \\ w_{12} & w_{22} & w_{32} \\ 0 & 0 & 0 \end{pmatrix} \stackrel{!}{=} \begin{pmatrix} 0 & -z_3 & z_2 \\ z_3 & 0 & -z_1 \\ -z_2 & z_1 & 0 \end{pmatrix}$$

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- Two solutions $\Sigma = ZW = Z^T W^T$, where

$$W = \begin{pmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} \qquad Z = \begin{pmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

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Decomposing E

- Two solutions for E

$$\begin{aligned} E &= U\Sigma V^T = UZ WV^T = \overbrace{UZU^T}^{S_1} \overbrace{UWV^T}^{R_1} \\ E &= U\Sigma V^T = UZ^T W^T V^T = \underbrace{UZ^T U^T}_{S_2} \underbrace{UW^T V^T}_{R_2} \end{aligned}$$

- A “twisted pair”
- Ex: show that S_1 and S_2 are skew symmetric and that R_1 and R_2 are rotations

The Twisted Pair

- $S_1 = -S_2$ (i.e. are the same up to scale)
- Next step: find \mathbf{T} such that $[\mathbf{T}]_{\times} = S_1$
- $[\mathbf{T}]_{\times} \mathbf{T} = 0 \implies \mathbf{T} \in \text{null}(S_1) = \text{null}(\mathbf{U}\mathbf{Z}\mathbf{U}^{\top})$

$$\mathbf{T} = \mathbf{U}(:, 3)$$

- Or read it directly from S_1

$$S_1 = [\mathbf{T}]_{\times} := \begin{pmatrix} 0 & -T_3 & T_2 \\ T_3 & 0 & -T_1 \\ -T_2 & T_1 & 0 \end{pmatrix}$$

- Overall: $P_1(\mathbf{I} \mid \mathbf{0})$ and 4 possible solutions:

$$P_2 = (\mathbf{U}\mathbf{W}\mathbf{V}^{\top} \mid \pm \mathbf{T}) \quad \text{or} \quad P_2 = (\mathbf{U}\mathbf{W}^{\top}\mathbf{V}^{\top} \mid \pm \mathbf{T})$$

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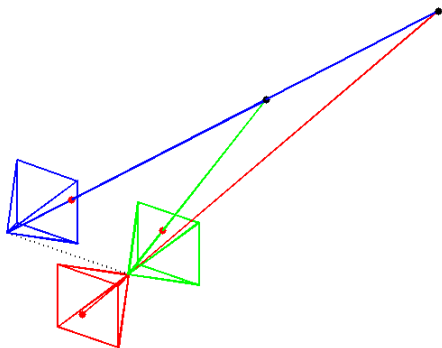
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The Twisted Pair: Example

$P_2 = (I \mid \mathbf{T})$ or $P_2 = (R_2 \mid \mathbf{T})$:

$$R_2 = \begin{pmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$\mathbf{T} = \begin{pmatrix} -1 \\ 0 \\ 0 \end{pmatrix}$$

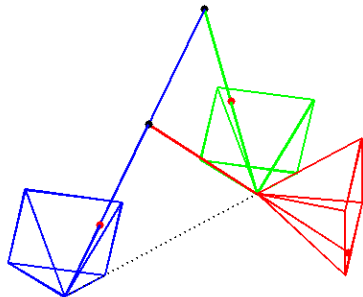


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$$\mathbf{T} = \begin{pmatrix} 0 \\ -1 \\ -1 \end{pmatrix}$$



Scale Ambiguity

- Scale is arbitrary $\lambda \mathbf{E}$ is also a valid essential matrix

$$\lambda \mathbf{E} = [\lambda \mathbf{T}]_{\times} \mathbf{R}_1 = [\lambda \mathbf{T}]_{\times} \mathbf{R}_2$$

- Gives two solutions $\mathbf{P}_1 = (\mathbf{I} \mid \mathbf{0})$ and

$$\mathbf{P}_2 = (\mathbf{U} \mathbf{W} \mathbf{V}^{\top} \mid \lambda \mathbf{T}) \quad \text{or} \quad \mathbf{P}_2 = (\mathbf{U} \mathbf{W}^{\top} \mathbf{V}^{\top} \mid \lambda \mathbf{T})$$

- Scales *baseline* between camera centers and rescales scene

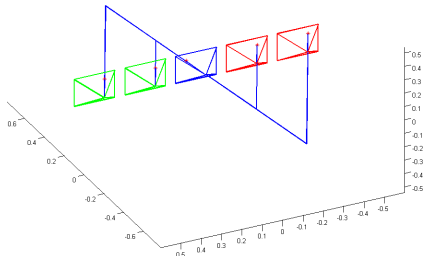
Scale Ambiguity: Example

$$P_2 = (I \mid \lambda T)$$

$$T = \begin{pmatrix} -1 \\ 0 \\ 0 \end{pmatrix}$$

Green — $\lambda > 0$

Red — $\lambda < 0$.



4 Solutions

4 possible 3D reconstructions

Conclusion: One of the 4 solutions

$$P_2 = (UWV^T \mid \mathbf{T})$$

$$P_2 = (UW^T V^T \mid \mathbf{T})$$

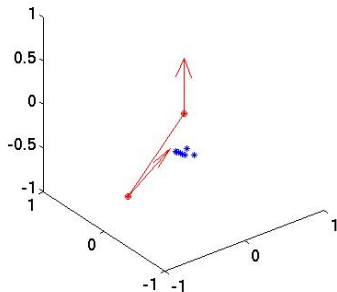
$$P_2 = (UWV^T \mid -\mathbf{T})$$

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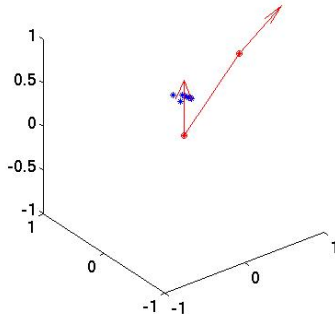
has points in front of both cameras.

- “Cheirality constraint”: 3D points have to lie in front of both cameras
- If not:
 - Wrong configuration
 - Noise in image points and numerical issues
 - Corresponding points are outliers, i.e. false positives

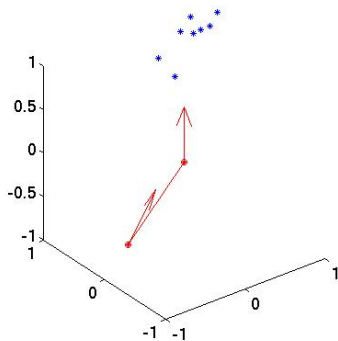
4 Solutions: Example



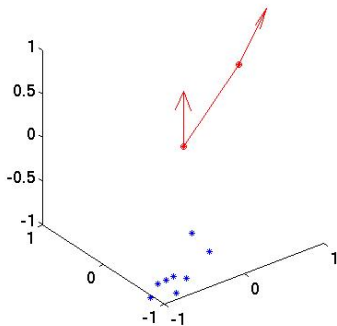
4 Solutions: Example



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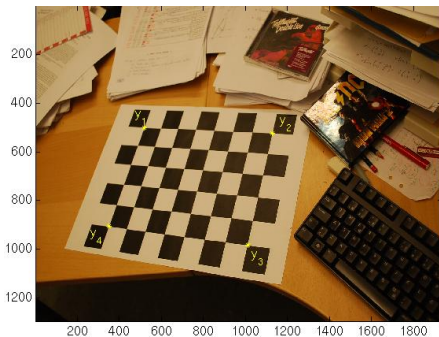
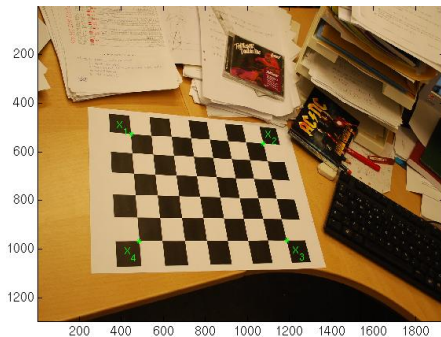


4 Solutions: Example



Homographies: Calibrated Setup

Remember homographies?



Homographies: Calibrated Setup

- Let $P_1 = (I \mid \mathbf{0})$, $P_2 = (R \mid \mathbf{T})$ and $\Pi = (\mathbf{n}, d)$
- Points $\mathbf{X} \in \mathbb{R}^3$ on the plane satisfy $\mathbf{n}^\top \mathbf{X} + d = 0$
- Image point \mathbf{x} in camera 1: $\mathbf{X} = \lambda \mathbf{x}$
- Now $\mathbf{X} \in \Pi$:

$$\lambda \mathbf{n}^\top \mathbf{x} + d = 0 \implies \lambda = -\frac{d}{\mathbf{n}^\top \mathbf{x}} \wedge \mathbf{X} = -\frac{d}{\mathbf{n}^\top \mathbf{x}} \mathbf{x}$$

- Corresponding image point in camera 2:

$$P_2 \begin{pmatrix} \mathbf{X} \\ 1 \end{pmatrix} = R\mathbf{X} + \mathbf{T} = -R \frac{d}{\mathbf{n}^\top \mathbf{x}} \mathbf{x} + \mathbf{T} \sim R\mathbf{x} - \frac{\mathbf{T}\mathbf{n}^\top \mathbf{x}}{d} = \underbrace{\left(R - \frac{\mathbf{T}\mathbf{n}^\top}{d} \right)}_{=H} \mathbf{x}$$

Homography in the calibrated setup

For a canonical camera pair, $P_1 = (I \mid \mathbf{0})$ and $P_2 = (R \mid \mathbf{T})$, and 3D plane $\Pi = (\mathbf{n}, d)$ the induced homography is given by $H = R - \frac{1}{d} \mathbf{T}\mathbf{n}^\top$.

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Homographies: Calibrated Setup

- Comparison of d.o.f.
 - Homography H has 8 d.o.f.
 - R , T and Π together have $3+(3-1)+(4-1) = 8$ d.o.f.
- Given R , T and Π there is a unique (up to scale) $H = R - \frac{1}{d}Tn^\top$
- Can we extract R , T and Π from a given H ?

Homography decomposition

A homography H estimated from *normalized* image points has two solutions for R , T and Π such that $H = R_i - \frac{1}{d_i}T_i n_i^\top$ for $i = 1, 2$.

- Matlab routine will be provided
- Python
 - Convert Matlab routine, or
 - `num, Rs, Ts, Ns = cv2.decomposeHomographyMat(H, K)` (with $K = I$)
- Finding out which solution is the correct one is not always straightforward
 - More at the project presentation

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Lab sessions today: MTI2, MTI4, SB-D020, SB-D409

- Next time: Robust Estimation.
- Work on Assignment 2.

More reading:

- Szeliski, Section 11.3 on Two-View Structure from Motion.