

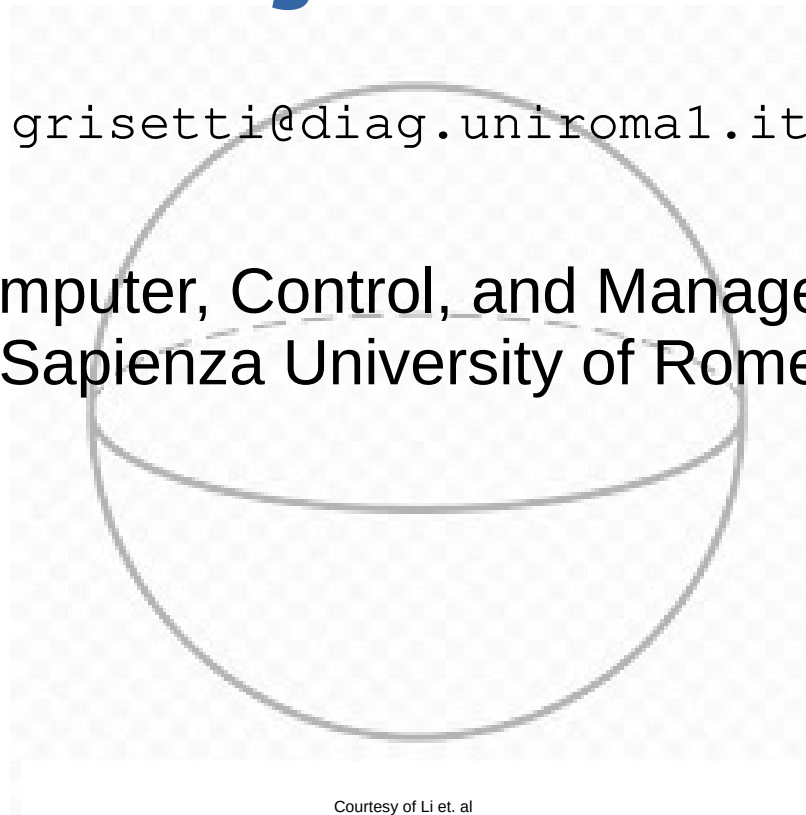
Probabilistic Robotics Course

Mini Recap of Epipolar Geometry on Unit Sphere

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Lines

Line in the space described as an offset \mathbf{p} , and a direction \mathbf{d} . The points in the line are spanned by scalar ascissa s .

$$\mathbf{l}_0 = \mathbf{p}_0 + \mathbf{d}_0 s_0$$

Transforming a line by T : R, t , transforms the point and rotates the direction:

$$\mathbf{T} = [\mathbf{R} \ \mathbf{t}]$$

$$\mathbf{l}_1 = \mathbf{T} \cdot \mathbf{l}_0 = \underbrace{\mathbf{R}\mathbf{p}_0 + \mathbf{t}}_{\mathbf{p}_1} + \underbrace{\mathbf{R}\mathbf{d}_0}_{\mathbf{d}_1} s_0$$

Lines, closest point

Lines in the space do not always intersect

Given two lines, can find the closest point by looking for the pair of \mathbf{s} for which the corresponding points in the line are the closest

$$\begin{aligned}\Delta(s_0, s_1) &= \mathbf{p}_0 + \mathbf{d}_0 s_0 - \mathbf{p}_1 - \mathbf{d}_1 s_1 \\ &= \underbrace{(\mathbf{p}_0 - \mathbf{p}_1)}_{\Delta \mathbf{p}} + \underbrace{(\mathbf{d}_0 \mid -\mathbf{d}_1)}_{\Delta \mathbf{D}} \underbrace{\begin{pmatrix} s_0 \\ s_1 \end{pmatrix}}_{\mathbf{s}}\end{aligned}$$

$$\begin{aligned}\mathbf{s}^* &= \underset{\mathbf{s}}{\operatorname{argmin}} \|\Delta \mathbf{p} + \Delta \mathbf{D} \mathbf{s}\|^2 \\ &= -(\Delta \mathbf{D}^T \Delta \mathbf{D})^{-1} \Delta \mathbf{D}^T \Delta \mathbf{p}\end{aligned}$$

Line Intersection

Two lines

$$l_0 : \mathbf{p}_0, \mathbf{d}_0$$

$$l_1 : \mathbf{p}_1, \mathbf{d}_1$$

The intersection condition specifies that the projection of

- the difference vector between any two points in the line (so we choose \mathbf{p}_0 and \mathbf{p}_1)
- along the vector $\mathbf{d}_0 \times \mathbf{d}_1$ orthogonal to both lines should be 0.

$$0 = (\mathbf{p}_0 - \mathbf{p}_1) \cdot (\mathbf{d}_0 \times \mathbf{d}_1)$$

Line Intersection

Both lines pass through a camera center in $\mathbf{p}=\mathbf{0}$

$$l_0 : \mathbf{p}_0 = 0, \mathbf{d}_0$$

$$l_1 : \mathbf{p}_1 = 0, \mathbf{d}_1$$

The second camera is at position $\mathbf{T} = [\mathbf{R}, \mathbf{t}]$

$$l'_1 : \mathbf{t}, \mathbf{R}\mathbf{d}_1$$

$$0 = \mathbf{t} \cdot (\mathbf{R}\mathbf{d}_1 \times \mathbf{d}_0)$$

Intersection condition

$$= \mathbf{d}_0 \cdot (\mathbf{t} \times (\mathbf{R}\mathbf{d}_1))$$

cross prod. identity $\mathbf{a} \cdot (\mathbf{b} \times \mathbf{c}) = \mathbf{c} \cdot (\mathbf{a} \times \mathbf{b})$

$$= \mathbf{d}_0 \cdot [\mathbf{t}]_{\times} \mathbf{R}\mathbf{d}_1$$

cross prod. to skew

$$= \mathbf{d}_1^T \underbrace{(\mathbf{R}^T [\mathbf{t}]_{\times})}_{\mathbf{E}} \mathbf{d}_0$$

transpose and negate

$$0 = \mathbf{d}_1 \mathbf{E} \mathbf{d}_0$$

Epipolar Constraint

Extracting **R** and **t** from **E**

E contains both **R** and **t**. To get them we need to decompose **E** in the product of a rotation matrix and a skew symmetric matrix.

Done by:

- Computing SVD
- Using the rearranging matrix **W**
- Extract **R** and **t** by identification
- 4 solutions for: **t**, **-t**, **W** and **W^T**
- Choose one by triangulating the points and pick the one with most points in front of camera

$$\mathbf{E} = \mathbf{R}^T [\mathbf{t}]_{\times} \text{rank}(\mathbf{E}) \leq 2$$

$$= \mathbf{U} \mathbf{S} \mathbf{V}^T \text{ s.t. } \mathbf{S} = \begin{pmatrix} \sigma_1 & & \\ & \sigma_2 & \\ & & 0 \end{pmatrix}$$

$$\mathbf{W} = \begin{pmatrix} & 1 & \\ -1 & & \\ & & 1 \end{pmatrix}$$

$$\mathbf{W} \mathbf{S} = \begin{pmatrix} & \sigma_2 & \\ -\sigma_1 & & \\ & & 0 \end{pmatrix}$$

$$\mathbf{W} \mathbf{S} \mathbf{W}^T = \mathbf{S}$$

$$\mathbf{E} = \mathbf{U} \mathbf{W} \mathbf{S} \mathbf{W}^T \mathbf{V}^T$$

$$= \underbrace{\mathbf{U} \mathbf{W} \mathbf{V}^T}_{\mathbf{R}} \underbrace{\mathbf{V} \mathbf{S} \mathbf{W}^T \mathbf{V}^T}_{[\mathbf{t}]_{\times}}$$

Estimating E (8 point)

Find the matrix that better satisfies the intersection constraint between all correspondences

$$\mathbf{E} = \begin{pmatrix} e_{11} & e_{12} & e_{13} \\ e_{21} & e_{22} & e_{23} \\ e_{31} & e_{32} & e_{33} \end{pmatrix} \quad \mathbf{e} = \begin{pmatrix} e_{11} \\ e_{12} \\ \vdots \\ e_{33} \end{pmatrix}$$

$$\mathbf{d}'^T \mathbf{E} \mathbf{d} = 0$$

$$\mathbf{e}^* = \operatorname{argmin}_{\mathbf{e}} \sum_i \|\mathbf{d}'^{[i]T} \mathbf{E} \mathbf{d}^{[i]}\|^2$$

$$\mathbf{E} = \mathbf{0} \text{ trivial solution, enforce } \|\mathbf{e}\| = 1$$

Estimating E (8 point)

$$\mathbf{d}'^T \mathbf{E} \mathbf{d} = \underbrace{(x'x \ x'y \ x'z \ y'x \ y'y \ y'z \ z'x \ z'y \ z'z)}_{\mathbf{A}} \underbrace{\begin{pmatrix} e_{11} \\ e_{12} \\ \vdots \\ e_{33} \end{pmatrix}}_{\mathbf{e}}$$

$$\begin{aligned} \mathbf{e}^* &= \underset{\mathbf{e}}{\operatorname{argmin}} \sum_i \mathbf{e}^T \mathbf{A}^{[i]T} \mathbf{A}^{[i]} \mathbf{e} \\ &= \underset{\mathbf{e}}{\operatorname{argmin}} \mathbf{e}^T \underbrace{\left(\sum_i \mathbf{A}^{[i]T} \mathbf{A}^{[i]} \right)}_{\mathbf{H}} \mathbf{e} \end{aligned}$$

$$\text{s.t. } \mathbf{e}^T \mathbf{e} = 1$$

Estimating E (8 point)

Constrained minimization using Lagrange multipliers

$$\mathcal{L}(\mathbf{e}, \lambda) = \mathbf{e}^T \mathbf{H} \mathbf{e} - \lambda(\mathbf{e}^T \mathbf{e} - 1)$$

$$\frac{\partial \mathcal{L}(\mathbf{e}, \lambda)}{\partial \mathbf{e}} = 2\mathbf{H}\mathbf{e} - 2\lambda\mathbf{e} = \mathbf{0}$$

$$\frac{\partial \mathcal{L}(\mathbf{e}, \lambda)}{\partial \lambda} = \mathbf{e}^T \mathbf{e} - 1 = 0$$

$\mathbf{H}\mathbf{e} = \lambda\mathbf{e}$ \mathbf{e} : is an eigenvector of \mathbf{H}

$$\mathbf{e}_j^T \mathbf{H} \mathbf{e}_j = \mathbf{e}_j^T \lambda_j \mathbf{e}_j = \lambda_j \text{ cost}$$

Considerations

Using the 8 points algorithm, we need 8 correspondences.

- The E matrix has only 5 DOF.
- There are more complex solutions that require less points (7, 6 and 5) to compute E
- In fact the algorithm is commonly used to estimate the Fundamental matrix \mathbf{F} , that incorporates also the camera matrix \mathbf{K}

How to get T ?

From a set of points in the image compute the direction vectors (or something proportional to them), by undoing the effects of the camera matrix \mathbf{K}

Estimate the essential from these directions

Compute the 4 solutions for R and t and for each triangulate the points. Choose the solution with most admissible points

- In front of camera
- In camera frustum

Conclusions

Short recap of how to get a reconstruction (up to a scale) from a set of directions.

Improvements include

- Use an algorithm requiring less correspondences to compute \mathbf{E}
- Normalize the points in the image plane to get a better conditioned system

This lesson does not substitute in any way a proper computer vision course. Its main purpose is to provide those students that had no contact with the subject with some basic knowledge within one hour.