

Lab 4 introduction

General reminders

- Please be aware that you and your lab partner both need to join a lab group for every single lab. Otherwise the grade only gets assigned to the student who uploaded the lab.
- If you are working alone then you do not have to join a group, but we recommend that you do, as any comment you leave is going to be invisible to us from our main grading UI if you are not in a group.
- Ask questions in the discussion forum instead of individual emails to help others to benefit from your questions. Can be done anonymously.

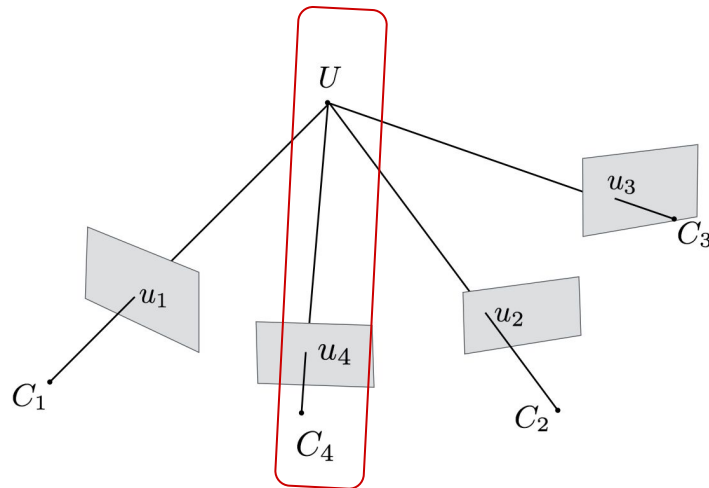
Study points

- From 2D-2D image correspondence to 2D image-3D point correspondence

2D-2D image corr.	2D-2D image corr.+camera matrix P
Affine transformation estimation	3D point estimation
<code>estimated_affine()</code>	<code>minimal_triangulation()</code>
<code>residual_lgths()</code>	<code>reprojection_error()</code>
<code>ransac_fit_affine()</code>	<code>ransac_triangulation()</code>
<code>ransac_fit_affine_ls()</code>	Least squares triangulation <i>*Don't forget that points with negative depth should be outliers</i>
	<code>compute_residuals()</code>
	<code>compute_jacobian()</code>
	<code>refine_triangulation()</code>

Ransac Triangulation

- Given: projection matrices P and 2D image points u
 - Inside RANSAC loop
 - Triangulate point using **minimal solver**
 - Determine inliers based on reprojection error
 - Refine point position by minimizing sum of squared errors.
 - **minimal_triangulation()**
 - One 2D-2D correspondence \leadsto 6 equations with 5 unknown parameters
 - How?
 - Hint: See lecture notes page 97



$$\lambda \mathbf{x} = \mathbf{P} \mathbf{X} \Leftrightarrow \begin{pmatrix} \lambda x \\ \lambda y \\ \lambda \end{pmatrix} = \begin{pmatrix} \mathbf{P}_1 \\ \mathbf{P}_2 \\ \mathbf{P}_3 \end{pmatrix} \mathbf{X}$$

Reprojection error

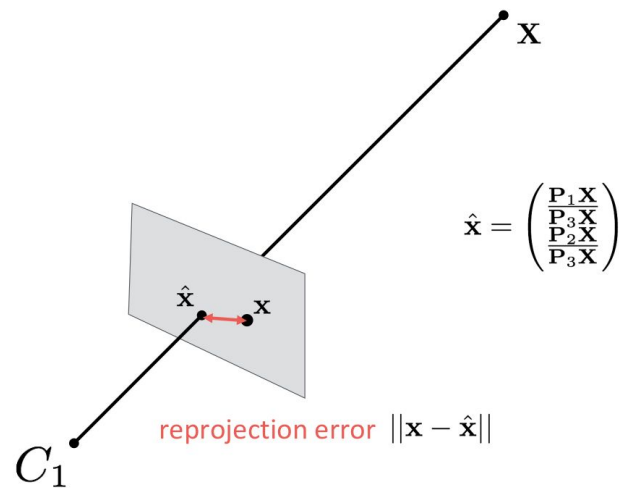
- `compute_residuals()` $\sim 2*N$

$$\lambda \hat{u} = \lambda \begin{pmatrix} \hat{x} \\ \hat{y} \\ 1 \end{pmatrix} = P\hat{U} = \begin{pmatrix} a^T \hat{U} \\ b^T \hat{U} \\ c^T \hat{U} \end{pmatrix} \quad \text{with } \lambda > 0$$

$$\lambda = c^T \hat{U}, \quad \hat{x} = \frac{a^T \hat{U}}{c^T \hat{U}} \quad \text{and} \quad \hat{y} = \frac{b^T \hat{U}}{c^T \hat{U}}, \quad \text{if } c^T \hat{U} > 0$$

$$r(\theta) = \begin{pmatrix} \hat{x} \\ \hat{y} \end{pmatrix} - \begin{pmatrix} x \\ y \end{pmatrix}, \quad \text{if } c^T \hat{U} > 0.$$

- `reprojection_error()` $\sim N$
 - The norm of the residual is reprojection error.
- See lecture notes page 98 for more details.



Refine triangulation

- After performing Ransac and removing the outliers.
 - How to use the remaining inlier measurements?
- Gauss-Newton algorithm
 - `compute_residual()`
 - `compute_jacobian()`
 - For loop is needed to construct J for different number of image points.
 - See lecture notes page 99 for more details.

$$\bar{r}(\theta) = \begin{pmatrix} r_{1,x}(\theta) \\ r_{1,y}(\theta) \\ r_{2,x}(\theta) \\ r_{2,y}(\theta) \\ \vdots \end{pmatrix}$$

$$J = \begin{pmatrix} \frac{\partial r_{1,x}}{\partial \theta_1} & \frac{\partial r_{1,x}}{\partial \theta_2} & \cdots \\ \frac{\partial r_{1,y}}{\partial \theta_1} & \frac{\partial r_{1,y}}{\partial \theta_2} & \cdots \\ \frac{\partial r_{2,x}}{\partial \theta_1} & \frac{\partial r_{2,x}}{\partial \theta_2} & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}.$$