

# Multiple-view Geometry 3

Triangulation, Resection, Bundle Adjustment

RRC Summer Sessions

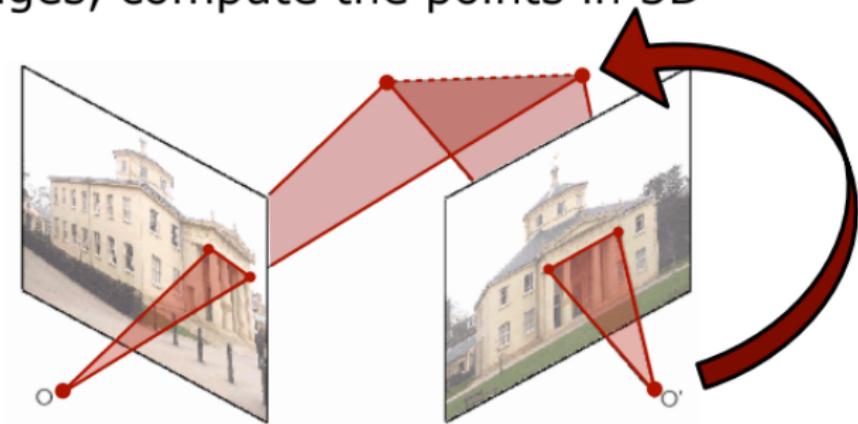
## Last class

- ▶ Elements of epipolar geometry - epipolar plane, epipoles, epipolar axis, epipolar lines
- ▶ Given an image point in the first view, how does it constrain the position of the corresponding point in the second view
- ▶ Essential matrix as a special case of the fundamental matrix, and its decomposition into  $R, S_b$
- ▶ Estimation of the fundamental matrix using the normalized 8-point algorithm
- ▶ Robust estimation using RANSAC

# Triangulation

# Triangulation

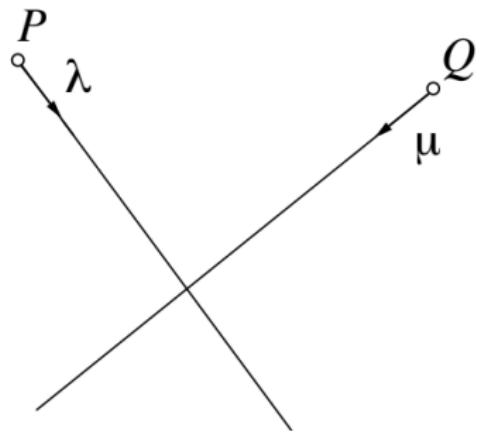
Given the relative orientation of two images, compute the points in 3D



Courtesy: Stachniss

# Triangulation

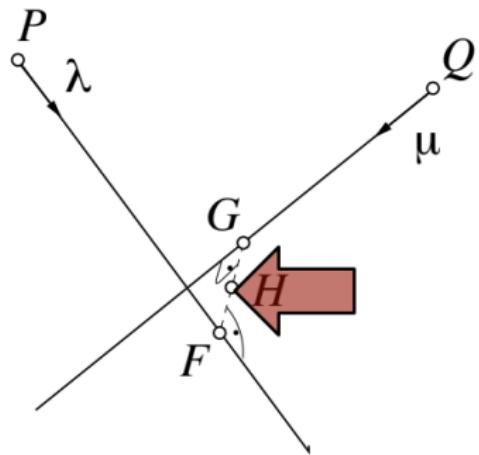
Geometric



Courtesy: Stachniss

# Triangulation

Geometric



Courtesy: Stachniss

# Triangulation

## Geometric

- Equation for two lines in 3D

$$f = p + \lambda r \quad g = q + \mu s$$

- with the points  $p = X_{O'}$   $q = X_{O''}$
- and the directions (calibrated camera)

$$r = R'^T k \mathbf{x}' \quad s = R''^T k \mathbf{x}''$$

- with  $k \mathbf{x}' = (x', y', c)^T$   $k \mathbf{x}'' = (x'', y'', c)^T$

Courtesy: Stachniss

# Triangulation

## Geometric

### Geometric Solution

- The shortest connection requires that FG is orthogonal to both lines
- This leads to the constraint

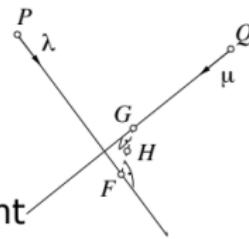
$$(f - g) \cdot r = 0 \quad (f - g) \cdot s = 0$$

which directly leads to

$$(q + \lambda s - p - \mu r) \cdot s = 0$$

$$(q + \lambda s - p - \mu r) \cdot r = 0$$

- Two equations, two unknowns



Courtesy: Stachniss

# Triangulation

## Geometric

- By solving the equations

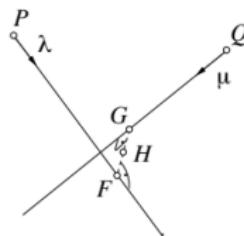
$$(q + \lambda s - p - \mu r) \cdot s = 0$$

$$(q + \lambda s - p - \mu r) \cdot r = 0$$

we obtain  $\lambda, \mu$

- $\lambda, \mu$  directly yield F and G

- We compute H as the middle of the line connecting F and G



Courtesy: Stachniss

# Triangulation

## Algebraic

We use a linear triangulation method that is analogous to DLT.

- ▶ Given a pair of corresponding points  $x = PX$  and  $x' = P'X$ , we form a system of linear equations  $AX = 0$ .
- ▶ We get three equations for each image point, of which two are linearly independent, by taking the cross product  $x \times PX = 0$ .
- ▶ Taking two equations from each image, we get a total of four

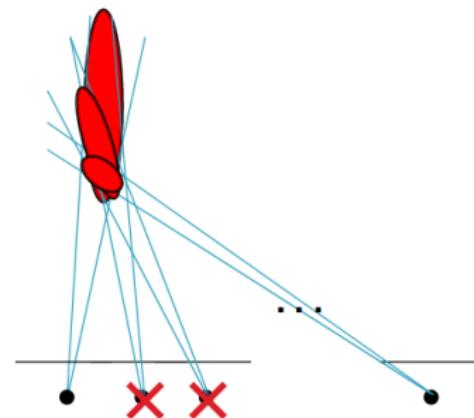
equations.  $A = \begin{bmatrix} xp^{3T} - p^{1T} \\ yp^{3T} - p^{2T} \\ x'p'^{3T} - p'^{1T} \\ y'p'^{3T} - p'^{2T} \end{bmatrix}$

- ▶ The solution for  $X$  is the singular vector corresponding to the smallest singular value of  $A$ .

# Triangulation

## Keyframe selection

- ▶ The std. deviation of the distances of the triangulated 3D point from all rays gives an idea of the quality of the 3D point.
- ▶ When frames are taken at nearby intervals, the 3D point typically exhibit large uncertainty.
- ▶ To avoid this, we skip adjacent frames until the average uncertainty of the 3D points decreases below a certain threshold. The selected frames are called *keyframes*.



Courtesy: Scaramuzza

## Computing relative scale

- ▶ To estimate the trajectory of the agent, different transformations (with different scales) need to be concatenated together.
- ▶ To do this, the relative scales for the subsequent transformations are computed.
- ▶ One way to do this is to triangulate 3D points  $X_{k-1}, X_k$  from two subsequent image pairs. The relative scale is then,

$$r = \frac{\|X_{k-1,i} - X_{k-1,j}\|}{\|X_{k,i} - X_{k,j}\|}$$

- ▶ For robustness, the scale ratios for many point pairs are computed and their mean (or median) is used.
- ▶ The translation vector  $t_k$  is then scaled with this ratio.

# Recap

## Visual odometry

### Algorithm 1. VO from 2-D-to-2-D correspondences.

- 1) Capture new frame  $I_k$
- 2) Extract and match features between  $I_{k-1}$  and  $I_k$
- 3) Compute essential matrix for image pair  $I_{k-1}, I_k$
- 4) Decompose essential matrix into  $R_k$  and  $t_k$ , and form  $T_k$
- 5) Compute relative scale and rescale  $t_k$  accordingly
- 6) Concatenate transformation by computing  $C_k = C_{k-1} T_k$
- 7) Repeat from 1).

Courtesy: Scaramuzza

# Recall

## Visual Odometry

We saw motion estimation from two sets of corresponding features  $f_k, f_{k-1}$  can be done in three different methods,

- ▶ 2D-2D - Both  $f_{k-1}, f_k$  are in 2D
- ▶ 3D-2D -  $f_{k-1}$  are in 3D,  $f_k$  are their corresponding reprojections in image  $I_k$
- ▶ 3D-3D - Both  $f_{k-1}, f_k$  are in 3D

# Recall

## Visual Odometry

We saw motion estimation from two sets of corresponding features  $f_k, f_{k-1}$  can be done in three different methods,

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- ▶ 3D-3D - Both  $f_{k-1}, f_k$  are in 3D

# Resection

# Resection

PnP

## Camera 3D Registration Perspective-n-Point Algorithm



3D point cloud via triangulation



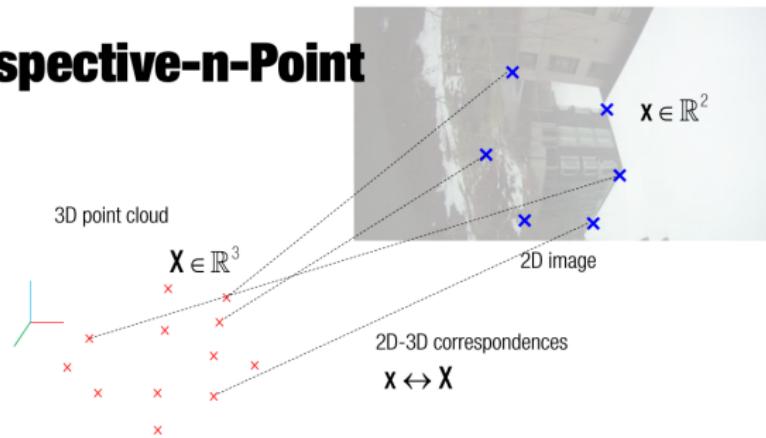
Where?

Courtesy: Jianbo Shi

# Resection

PnP

## Perspective-n-Point

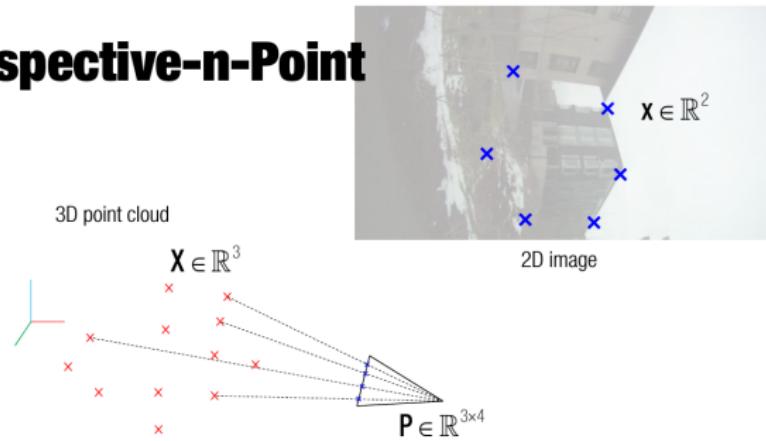


Courtesy: Jianbo Shi

# Resection

PnP

## Perspective-n-Point

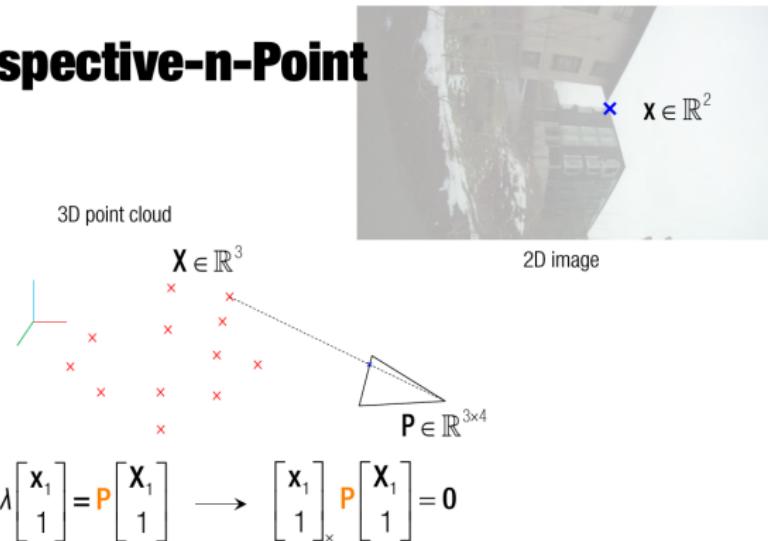


Courtesy: Jianbo Shi

# Resection

PnP

## Perspective-n-Point

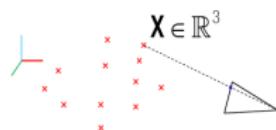


Courtesy: Jianbo Shi

# Resection

PnP

## Perspective-n-Point



2D image

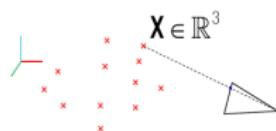
$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix}_x \begin{bmatrix} P_1 \\ P_2 \\ P_3 \end{bmatrix} \tilde{x}$$

Courtesy: Jianbo Shi

# Resection

PnP

## Perspective-n-Point



2D image

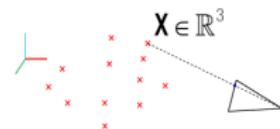
$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix}_x \begin{bmatrix} P_1 \\ P_2 \\ P_3 \end{bmatrix} \tilde{X} = \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}_x \begin{bmatrix} P_1 \tilde{X} \\ P_2 \tilde{X} \\ P_3 \tilde{X} \end{bmatrix}$$

Courtesy: Jianbo Shi

# Resection

PnP

## Perspective-n-Point



2D image

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix}_x \begin{bmatrix} \mathbf{P}_1 \\ \mathbf{P}_2 \\ \mathbf{P}_3 \end{bmatrix} \tilde{\mathbf{X}} = \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}_x \begin{bmatrix} \mathbf{P}_1 \tilde{\mathbf{X}} \\ \mathbf{P}_2 \tilde{\mathbf{X}} \\ \mathbf{P}_3 \tilde{\mathbf{X}} \end{bmatrix} = \begin{bmatrix} 0 & -1 & v \\ 1 & 0 & -u \\ -v & u & 0 \end{bmatrix} \begin{bmatrix} \tilde{\mathbf{X}}^\top \\ \mathbf{0}_{1 \times 4} \\ \tilde{\mathbf{X}}^\top \\ \mathbf{0}_{1 \times 4} \\ \mathbf{0}_{1 \times 4} \end{bmatrix} \begin{bmatrix} \mathbf{P}_1^\top \\ \mathbf{P}_2^\top \\ \mathbf{P}_3^\top \end{bmatrix} =$$

Courtesy: Jianbo Shi

# Resection

PnP

## Perspective-n-Point



2D image

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix}_{\times} \begin{bmatrix} \mathbf{P}_1 \\ \mathbf{P}_2 \\ \mathbf{P}_3 \end{bmatrix} \tilde{\mathbf{X}} = \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}_{\times} \begin{bmatrix} \mathbf{P}_1 \tilde{\mathbf{X}} \\ \mathbf{P}_2 \tilde{\mathbf{X}} \\ \mathbf{P}_3 \tilde{\mathbf{X}} \end{bmatrix} = \begin{bmatrix} 0 & -1 & v \\ 1 & 0 & -u \\ -v & u & 0 \end{bmatrix} \begin{bmatrix} \tilde{\mathbf{X}}^T \\ \mathbf{0}_{1 \times 4} \\ \tilde{\mathbf{X}}^T \\ \mathbf{0}_{1 \times 4} \\ \mathbf{0}_{1 \times 4} \\ \tilde{\mathbf{X}}^T \end{bmatrix} \begin{bmatrix} \mathbf{P}_1^T \\ \mathbf{P}_2^T \\ \mathbf{P}_3^T \end{bmatrix} =$$

$$\begin{bmatrix} \mathbf{0}_{1 \times 4} & -\tilde{\mathbf{X}}^T & v\tilde{\mathbf{X}}^T \\ \tilde{\mathbf{X}}^T & \mathbf{0}_{1 \times 4} & -u\tilde{\mathbf{X}}^T \\ -v\tilde{\mathbf{X}}^T & u\tilde{\mathbf{X}}^T & \mathbf{0}_{1 \times 4} \end{bmatrix} \begin{bmatrix} \mathbf{P}_1^T \\ \mathbf{P}_2^T \\ \mathbf{P}_3^T \end{bmatrix} = \mathbf{0}$$

3x12 matrix

Courtesy: Jianbo Shi

# Resection

PnP

## Perspective-n-Point



$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix}_{\times} \begin{bmatrix} P_1 \\ P_2 \\ P_3 \end{bmatrix} \tilde{X} = \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}_{\times} \begin{bmatrix} P_1 \tilde{X} \\ P_2 \tilde{X} \\ P_3 \tilde{X} \end{bmatrix} = \begin{bmatrix} 0 & -1 & v \\ 1 & 0 & -u \\ -v & u & 0 \end{bmatrix} \begin{bmatrix} \tilde{X}^T \\ 0_{1 \times 4} \\ \tilde{X}^T \\ 0_{1 \times 4} \\ 0_{1 \times 4} \\ \tilde{X}^T \end{bmatrix} \begin{bmatrix} P_1^T \\ 0_{1 \times 4} \\ P_2^T \\ 0_{1 \times 4} \\ P_3^T \\ \tilde{X}^T \end{bmatrix} =$$

$$\begin{bmatrix} 0_{1 \times 4} & -\tilde{X}^T & v\tilde{X}^T \\ \tilde{X}^T & 0_{1 \times 4} & -u\tilde{X}^T \\ -v\tilde{X}^T & u\tilde{X}^T & 0_{1 \times 4} \end{bmatrix} \begin{bmatrix} P_1^T \\ P_2^T \\ P_3^T \end{bmatrix} = 0$$

3x12 matrix

$$\begin{array}{c|c|c} A & | & 0 \\ \hline & | & | \\ & x & = \end{array}$$

Courtesy: Jianbo Shi

# Resection

PnP

## Perspective-n-Point



$$x \in \mathbb{R}^2$$

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix}_x \begin{bmatrix} P_1 \\ P_2 \\ P_3 \end{bmatrix} \tilde{X} = \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}_x \begin{bmatrix} P_1 \tilde{X} \\ P_2 \tilde{X} \\ P_3 \tilde{X} \end{bmatrix} = \begin{bmatrix} 0 & -1 & v \\ 1 & 0 & -u \\ -v & u & 0 \end{bmatrix} \begin{bmatrix} \tilde{X}^T \\ \mathbf{0}_{1 \times 4} \\ \tilde{X}^T \\ \mathbf{0}_{1 \times 4} \\ \mathbf{0}_{1 \times 4} \\ \tilde{X}^T \end{bmatrix} \begin{bmatrix} P_1^T \\ P_2^T \\ P_3^T \end{bmatrix} =$$

$$\begin{bmatrix} \mathbf{0}_{1 \times 4} & -\tilde{X}^T & v\tilde{X}^T \\ \tilde{X}^T & \mathbf{0}_{1 \times 4} & -u\tilde{X}^T \\ -v\tilde{X}^T & u\tilde{X}^T & \mathbf{0}_{1 \times 4} \end{bmatrix} \begin{bmatrix} P_1^T \\ P_2^T \\ P_3^T \end{bmatrix} = \mathbf{0}$$

3x12 matrix (rank 2)

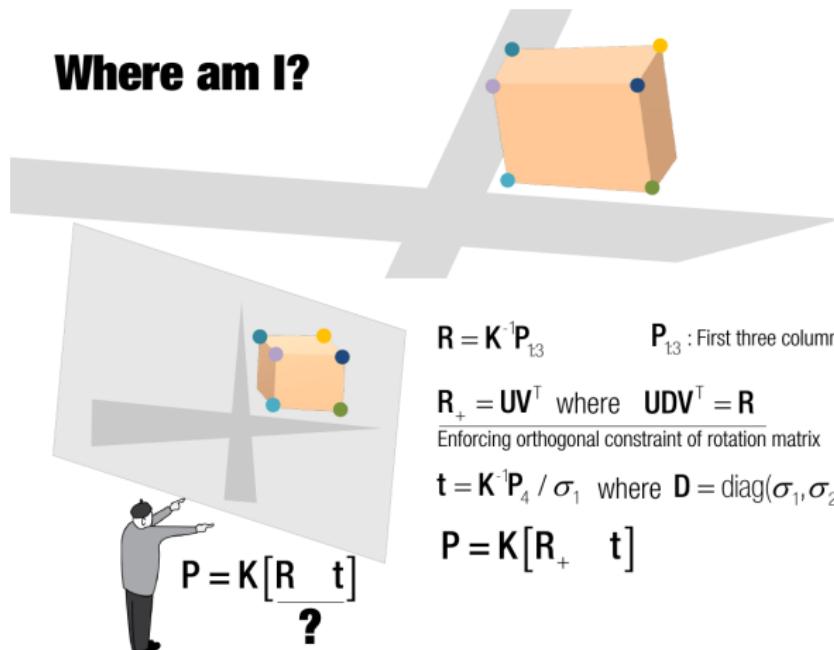
$$\begin{array}{c|c} \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_6 \end{matrix} & \begin{matrix} x \\ \vdots \end{matrix} \\ \hline & \begin{matrix} 0 \\ 0 \\ \vdots \\ 0 \end{matrix} \end{array}$$

Courtesy: Jianbo Shi

# Resection

PnP

## Where am I?



Courtesy: Jianbo Shi

# Resection

PnP

## Camera 3D Registration Perspective-n-Point Algorithm



Courtesy: Jianbo Shi

# Resection

## P3P

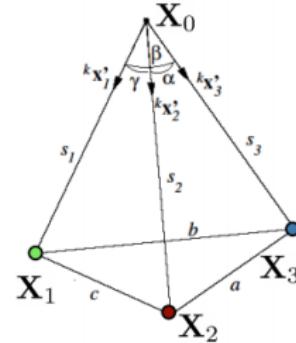
- ▶ For robust estimation, *perspective-from-three-points* is the standard method, and can be seen as the minimal case of the PnP method.
- ▶ The method typically returns four solutions that can be disambiguated using one or more additional points.
- ▶ Like PnP, various approaches have been proposed. Current state of the art is *Lambda Twist P3P*. We'll look at the earliest approach (Grunert 1841).

# Resection

P3P

- We start with the direct solution

- Grunert 1841
- Analogous to planar resection
- 2 steps
  - 1. Estimate length of projection rays
  - 2. Estimate orientation



Courtesy: Stachniss

# Resection

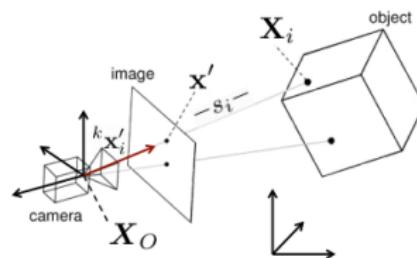
P3P

- Coordinates of object points within the camera system are given by

$$s_i N({}^k \mathbf{x}'_i) = R(\mathbf{X}_i - \mathbf{X}_O) \quad i = 1, 2, 3$$

**spherical normalization**

$$N(\mathbf{x}) = \frac{\mathbf{x}}{|\mathbf{x}|}$$



Courtesy: Stachniss

# Resection

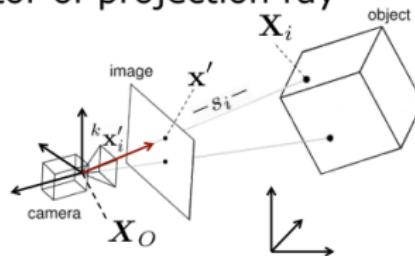
P3P

- Coordinates of object points within the camera system are given by

$$s_i \mathbf{N}({}^k \mathbf{x}'_i) = R(\mathbf{X}_i - \mathbf{X}_O) \quad i = 1, 2, 3$$

- From image coordinates we obtain the directional vector of projection ray

$${}^k \mathbf{x}'_i = \mathbf{K}^{-1} \mathbf{x}'_i$$

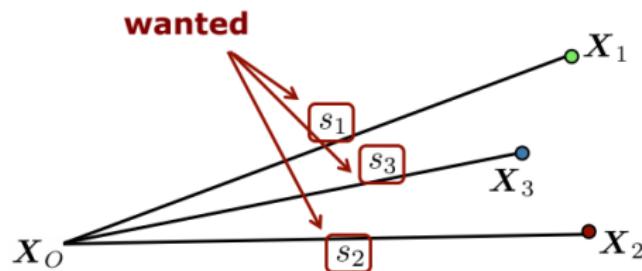


Courtesy: Stachniss

# Resection

P3P

## 1. Get length of projection rays



Courtesy: Stachniss

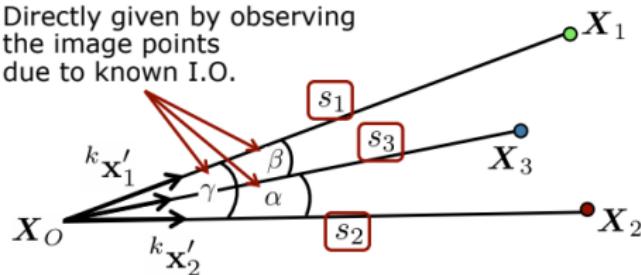
# Resection

P3P

## 1. Get length of projection rays

$$\begin{aligned} {}^k \mathbf{x}'_i &= \mathbf{K}^{-1} \mathbf{x}'_i \\ \alpha &= \arccos({}^k \mathbf{x}'_2, {}^k \mathbf{x}'_3) \\ \beta &= \arccos({}^k \mathbf{x}'_3, {}^k \mathbf{x}'_1) \\ \gamma &= \arccos({}^k \mathbf{x}'_1, {}^k \mathbf{x}'_2) \end{aligned}$$

Directly given by observing  
the image points  
due to known I.O.



Courtesy: Stachniss

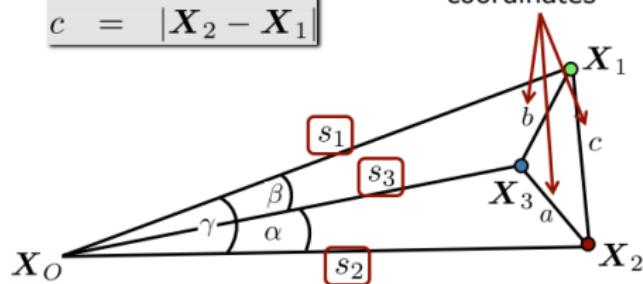
# Resection

P3P

## 1. Get length of projection rays

$$\begin{aligned}a &= |\mathbf{X}_3 - \mathbf{X}_2| \\b &= |\mathbf{X}_1 - \mathbf{X}_3| \\c &= |\mathbf{X}_2 - \mathbf{X}_1|\end{aligned}$$

Given through  
known tie point  
coordinates



Courtesy: Stachniss

# Resection

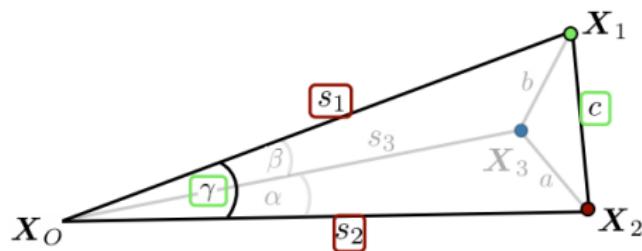
P3P

## Use the Law of Cosines

In triangle  $X_0, X_1, X_2$

$$s_1^2 + s_2^2 - 2s_1s_2 \cos \gamma = c^2$$

wanted      known



Courtesy: Stachniss

# Resection

P3P

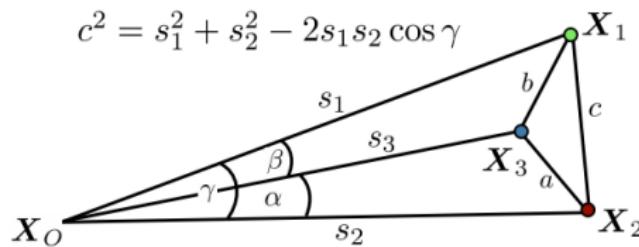
## Use the Law of Cosines

analogous solutions

$$a^2 = s_2^2 + s_3^2 - 2s_2s_3 \cos \alpha$$

$$b^2 = s_1^2 + s_3^2 - 2s_1s_3 \cos \beta$$

$$c^2 = s_1^2 + s_2^2 - 2s_1s_2 \cos \gamma$$



Courtesy: Stachniss

### Estimate distances

- We start from:

$$a^2 = s_2^2 + s_3^2 - 2s_2s_3 \cos \alpha$$

- Define:  $u = \frac{s_2}{s_1}$        $v = \frac{s_3}{s_1}$

- Substitute:  $a^2 = s_1^2(u^2 + v^2 - 2uv \cos \alpha)$

- Rearrange to get the distance:

$$s_1^2 = \frac{a^2}{u^2 + v^2 - 2uv \cos \alpha}$$

Courtesy: Stachniss

# Resection

P3P

## Rearrange again

- Solve one equation for  $u$  put into the other

$$s_1^2 = \frac{a^2}{u^2 + v_2^2 - 2uv \cos \alpha}$$

$$s_1^2 = \frac{b^2}{1 + v^2 - 2v \cos \beta}$$

$$s_1^2 = \frac{c^2}{1 + u^2 - 2u \cos \gamma}$$


**Results in an fourth degree polynomial**

$$A_4v^4 + A_3v^3 + A_2v^2 + A_1v + A_0 = 0$$

Courtesy: Stachniss

# Resection

P3P

## Forth degree polynomial

$$A_4 v^4 + A_3 v^3 + A_2 v^2 + A_1 v + A_0 = 0$$

$$A_4 = \left( \frac{a^2 - c^2}{b^2} - 1 \right)^2 - \frac{4c^2}{b^2} \cos^2 \alpha$$

$$\begin{aligned} A_3 &= 4 \left[ \frac{a^2 - c^2}{b^2} \left( 1 - \frac{a^2 - c^2}{b^2} \right) \cos \beta \right. \\ &\quad \left. - \left( 1 - \frac{a^2 + c^2}{b^2} \right) \cos \alpha \cos \gamma + 2 \frac{c^2}{b^2} \cos^2 \alpha \cos \beta \right] \end{aligned}$$

Courtesy: Stachniss

# Resection

P3P

## Forth degree polynomial

$$A_4v^4 + A_3v^3 + \boxed{A_2}v^2 + A_1v + A_0 = 0$$

$$\begin{aligned} A_2 &= 2 \left[ \left( \frac{a^2 - c^2}{b^2} \right)^2 - 1 + 2 \left( \frac{a^2 - c^2}{b^2} \right)^2 \cos^2 \beta \right. \\ &\quad + 2 \left( \frac{b^2 - c^2}{b^2} \right) \cos^2 \alpha \\ &\quad - 4 \left( \frac{a^2 + c^2}{b^2} \right) \cos \alpha \cos \beta \cos \gamma \\ &\quad \left. + 2 \left( \frac{b^2 - a^2}{b^2} \right) \cos^2 \gamma \right] \end{aligned}$$

Courtesy: Stachniss

# Resection

P3P

## Forth degree polynomial

$$A_4v^4 + A_3v^3 + A_2v^2 + \boxed{A_1}v + \boxed{A_0} = 0$$

$$\begin{aligned} A_1 &= 4 \left[ - \left( \frac{a^2 - c^2}{b^2} \right) \left( 1 + \frac{a^2 - c^2}{b^2} \right) \cos \beta \right. \\ &\quad + \frac{2a^2}{b^2} \cos^2 \gamma \cos \beta \\ &\quad \left. - \left( 1 - \left( \frac{a^2 + c^2}{b^2} \right) \right) \cos \alpha \cos \gamma \right] \end{aligned}$$

$$A_0 = \left( 1 + \frac{a^2 - c^2}{b^2} \right)^2 - \frac{4a^2}{b^2} \cos^2 \gamma$$

Courtesy: Stachniss

### Forth degree polynomial

$$A_4v^4 + A_3v^3 + A_2v^2 + A_1v + A_0 = 0$$

➤ Solve for  $v$  to get  $s_1, s_2, s_3$

$$s_1^2 = \frac{b^2}{1+v^2-2v \cos \beta}$$

$$s_3 = v \ s_1$$

$$a^2 = s_2^2 + s_3^2 - 2s_2s_3 \cos \alpha \Rightarrow s_2 = \dots$$

**Problem:**

**Up to 4 possible solutions !**

$$\{s_1, s_2, s_3\}_{1\dots 4}$$

Courtesy: Stachniss

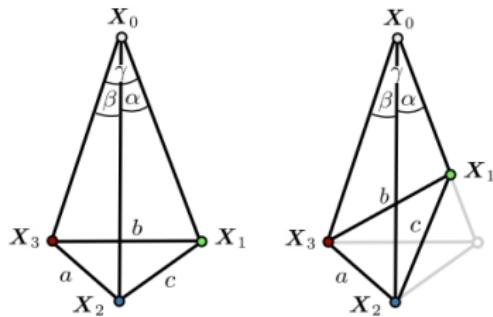
# Resection

P3P

## Four Solutions

- Example:

- Assume  $a = b = c$     $\alpha = \beta = \gamma$
- Tilting the rectangle  $\Delta(X_1, X_2, X_3)$  has no effect on  $(a, b, c)$  and  $(\alpha, \beta, \gamma)$

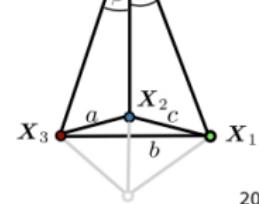
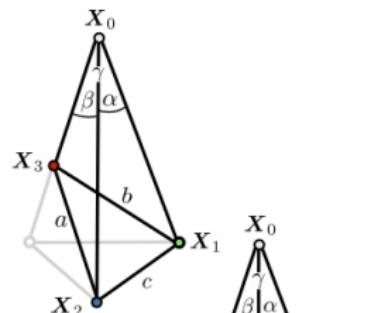
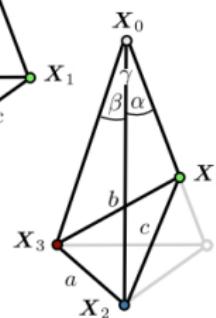
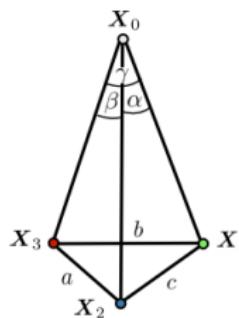


Courtesy: Stachniss

# Resection

P3P

## Four Solutions



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Courtesy: Stachniss

### How to get rid of ambiguity?

- Approximate solution, e.g. from GPS
- Use 4<sup>th</sup> points to confirm the right solution



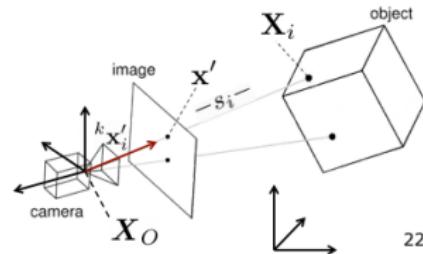
**Unique solution for**

$s_1, s_2, s_3$

Courtesy: Stachniss

## 2. Orientation of the Camera

- Given:
  - Distances to tie points
- Task:
  - Estimate 6 parameters of E.O.



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Courtesy: Stachniss

# Resection

## P3P

- ▶ We now have two sets of 3 corresponding 3-D points. We want to find the transformation that best aligns the two sets.

$$\arg \min_{T_k} \sum_i \|X_k^i - T_k X_{k-1}^i\|$$

- ▶  $R_k = VU^T$  where  $USV^T = svd((X_{k-1} - \overline{X_{k-1}})(X_k - \overline{X_k})^T)$
- ▶  $t_k = \overline{X_k} - R\overline{X_{k-1}}$
- ▶ where  $\cdot$  stands for the mean value
- ▶ Details: Least-squares fitting of two 3D point-sets by Arun et al.

# Bundle Adjustment

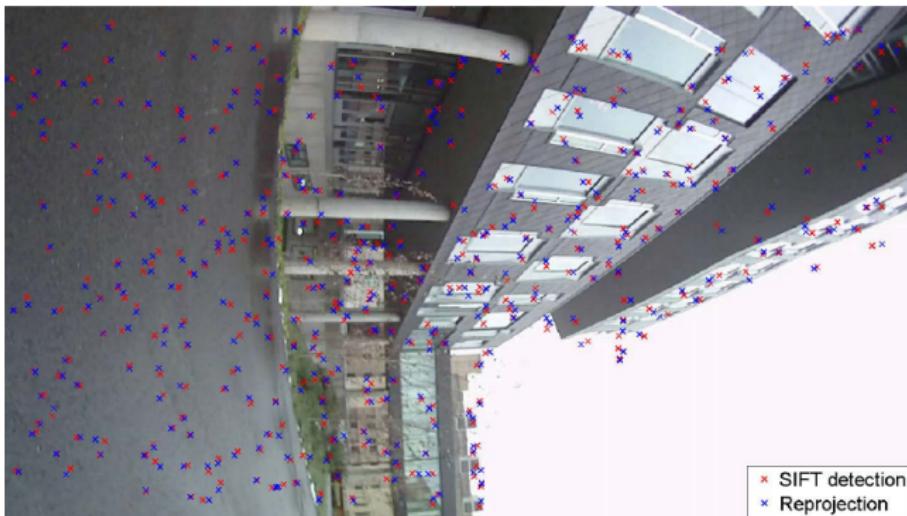
## Bundle Adjustment

- ▶ To reduce the drift and improve the accuracy of the local trajectory in VO, we run an optional iterative refinement step, called bundle adjustment.
- ▶ This is equivalent to building a local map in SLAM, but only to improve the local consistency of the trajectory.
- ▶ This is a non-linear optimization problem where we minimize the sum of the squared reprojection errors of the reconstructed 3D points over the last  $m$  images. This is technically called *windowed-bundle adjustment*.

$$\arg \min_{X_j, P_i} \sum_{i=1}^M \sum_{j=1}^N \|x_{ij} - P_i X_j\|^2$$

where  $P_i$  is the  $i$ th view,  $x_{ij}$  is the image of the  $j$ th point in the  $i$ th view.

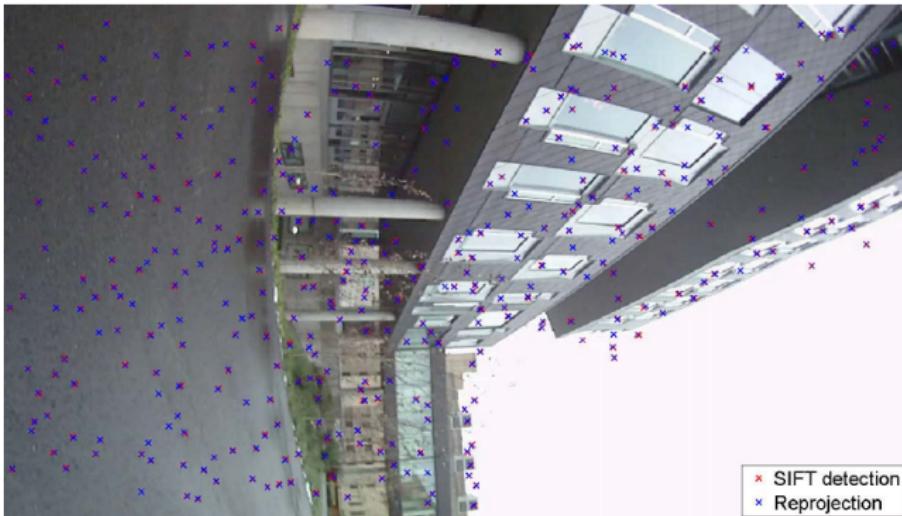
## Geometric Refinement Before Bundle Adjustment



Courtesy: Jianbo Shi

# Bundle adjustment

## Geometric Refinement After Bundle Adjustment



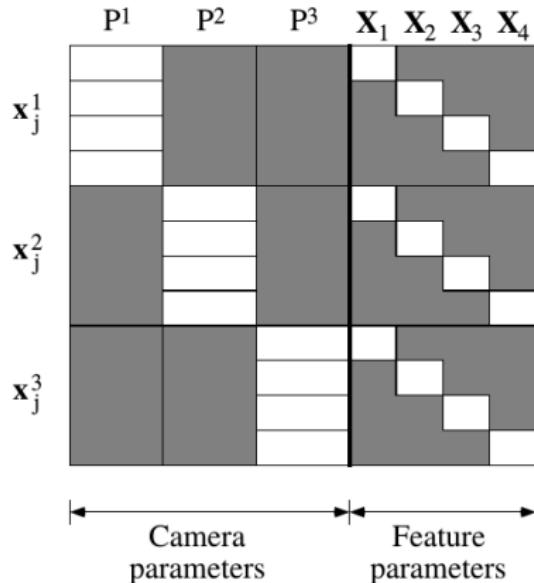
Courtesy: Jianbo Shi

# Bundle Adjustment

- ▶ Bundle here refers to the bundles of light rays leaving each 3D feature and converging on the camera centre, which are then adjusted optimally with respect to both feature and camera parameters.
- ▶ It is typically solved using the Levenberg Marquardt solver. Refer to - Bundle Adjustment by Triggs et al.- for an extensive survey on different approaches to solve the problem.

# Bundle Adjustment

Structure of the Jacobian for a typical BA problem,



# Quiz

<https://bit.ly/2Wm8K8M>