

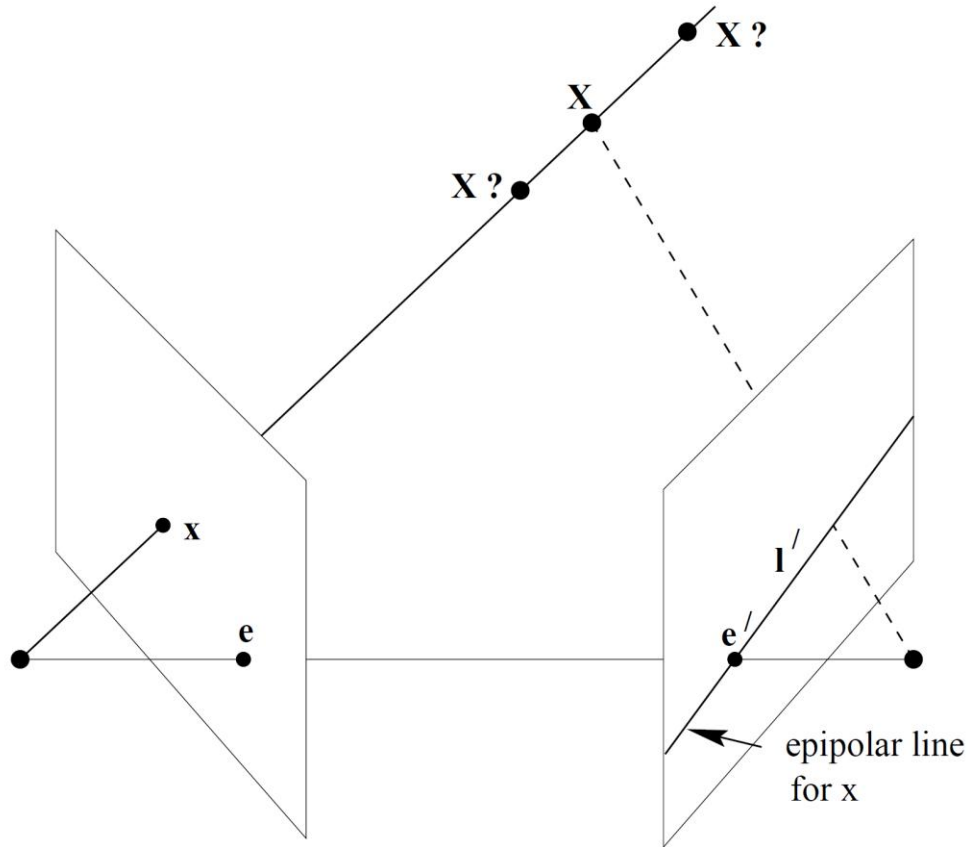
Structure from Motion I

CS 4391 Introduction Computer Vision

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The University of Texas at Dallas

Recall Fundamental Matrix



- Epipolar line $\mathbf{l}' = F \mathbf{x}$
 $\mathbf{l} = F^T \mathbf{x}'$

- Fundamental matrix

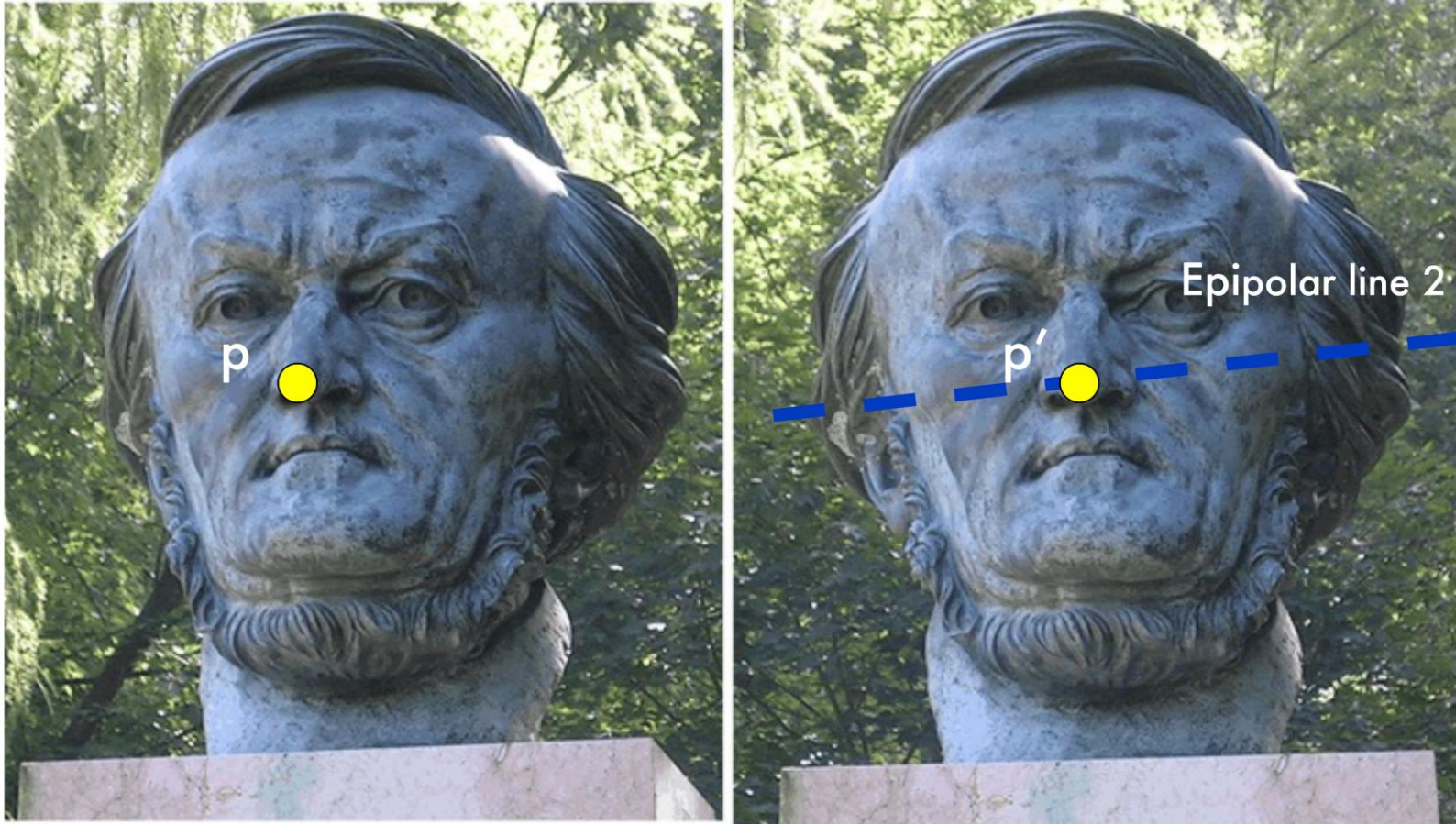
$$F = [\mathbf{e}']_{\times} P' P^+$$

3x3

Epipole $\mathbf{e}' = (P' C)$

$$P^+ = P^T (P P^T)^{-1}$$

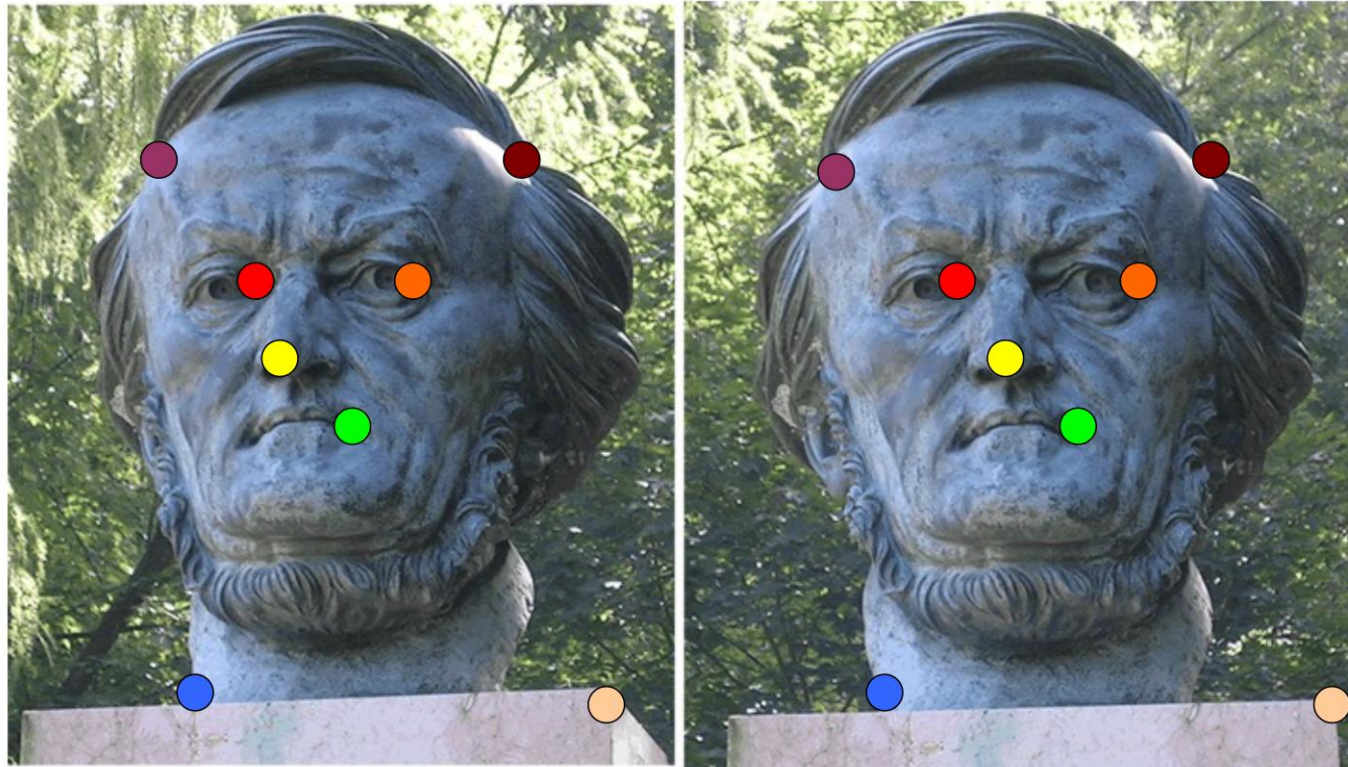
Why the Fundamental Matrix is Useful?



$$l' = Fp$$

Estimating the Fundamental Matrix

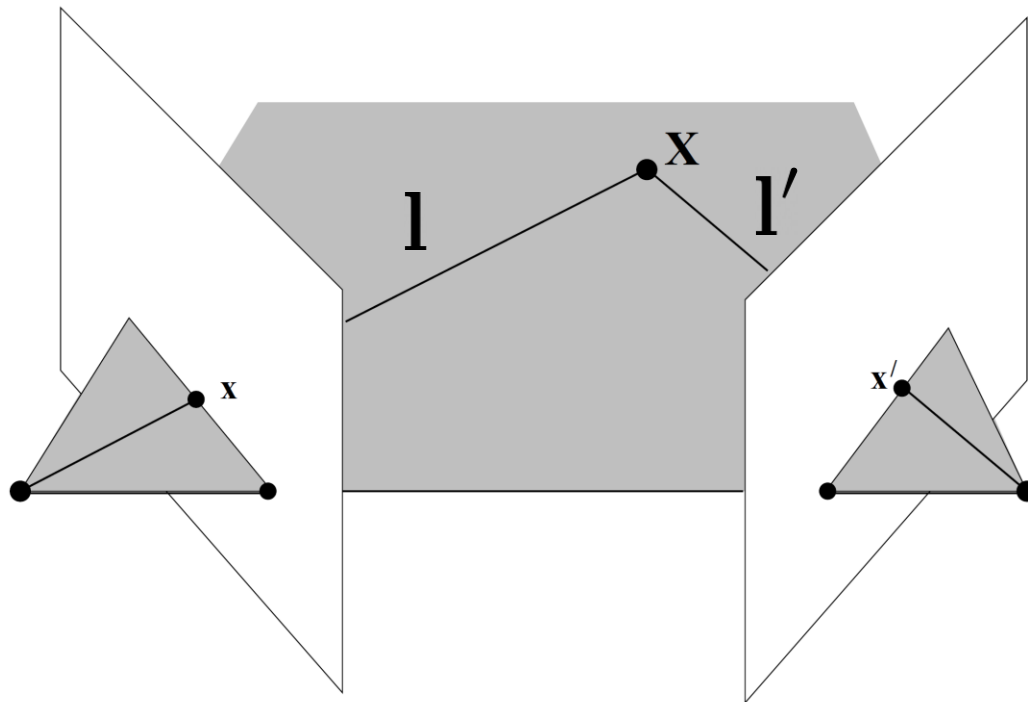
- The 8-point algorithm



$$\mathbf{l}' = F\mathbf{x}$$
$$\mathbf{x}'^T F \mathbf{x} = 0$$

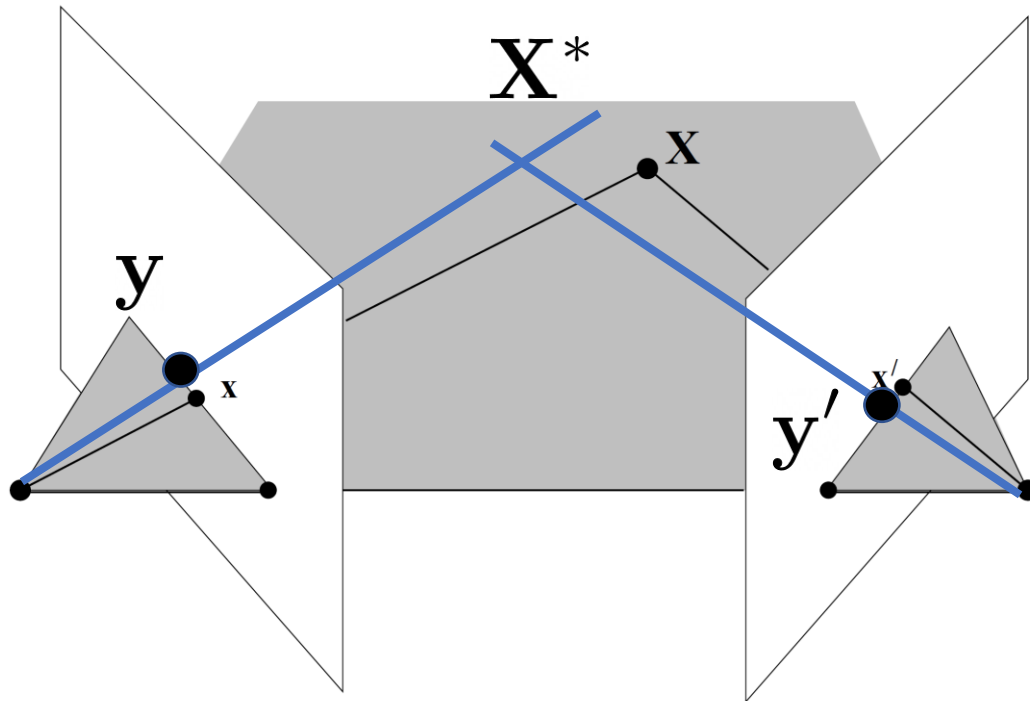
Triangulation

- Compute the 3D point given image correspondences



Intersection of two
backprojected lines

Triangulation



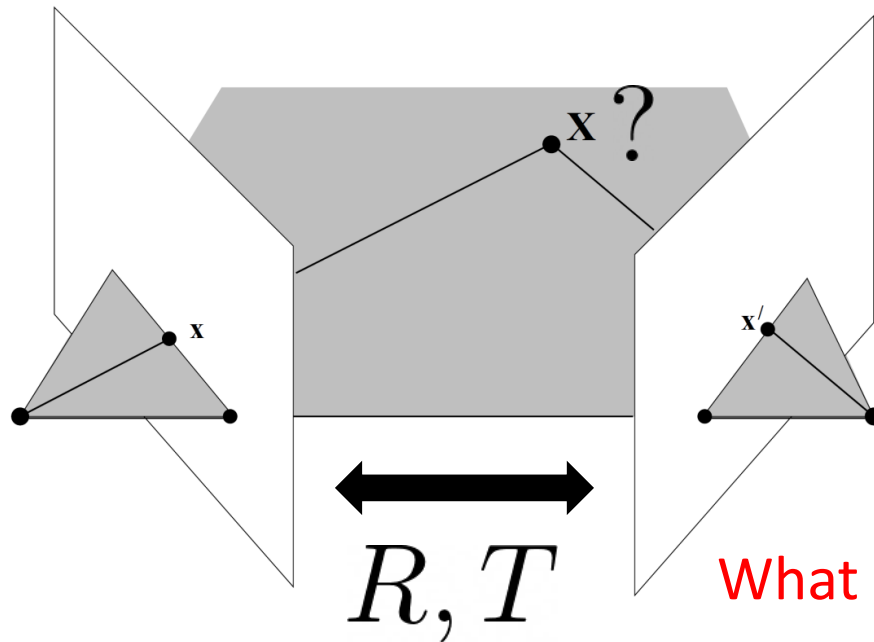
- In practice, we find the correspondences $y \ y'$
- The backprojected lines may not intersect
- Find X^* that minimizes

$$d(\mathbf{y}, P\mathbf{X}^*) + d(\mathbf{y}', P'\mathbf{X}^*)$$

Projection matrix

Triangulation

- Idea: using images from different views and feature matching
- Triangulation from pixel correspondences to compute 3D location



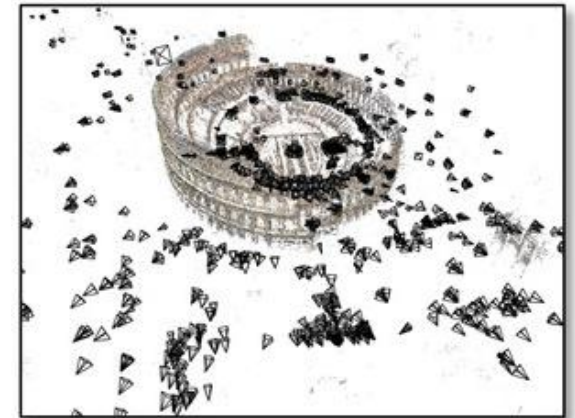
Given $\mathbf{X} \longleftrightarrow \mathbf{X}'$

Intersection of two
backprojected lines

What if unknow camera pose?

Structure from Motion

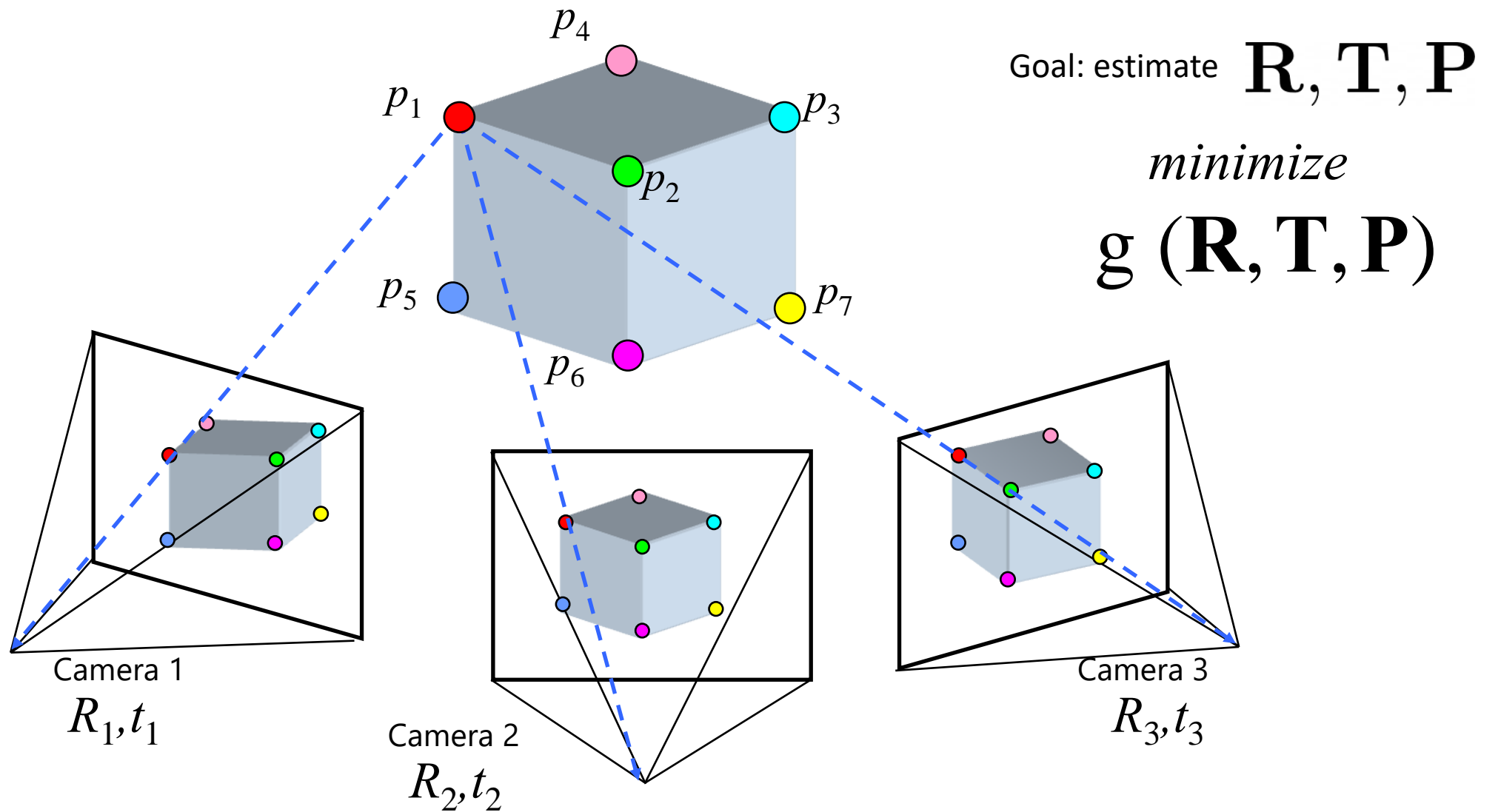
- Input
 - A set of images from different views
- Output
 - 3D Locations of all feature points in a world frame
 - Camera poses of the images



Structure from Motion



Structure from motion



Structure from Motion

- Minimize sum of squared reprojection errors

$$g(\mathbf{X}, \mathbf{R}, \mathbf{T}) = \sum_{i=1}^m \sum_{j=1}^n w_{ij} \cdot \left\| \underbrace{\mathbf{P}(\mathbf{x}_i, \mathbf{R}_j, \mathbf{t}_j)}_{\text{predicted image location}} - \underbrace{\begin{bmatrix} u_{i,j} \\ v_{i,j} \end{bmatrix}}_{\text{observed image location}} \right\|^2$$

m points, n images

Indicator variable:

is point i visible in image j?

Projection

$$\begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = \mathbf{R}\mathbf{x} + \mathbf{t}$$

$$u' = f_x \frac{x'}{z'} + p_x$$

$$v' = f_y \frac{y'}{z'} + p_y$$

$$\begin{bmatrix} u' \\ v' \end{bmatrix} = \mathbf{P}(\mathbf{x}, \mathbf{R}, \mathbf{t})$$

Structure from Motion

- How to minimize

$$g(\mathbf{X}, \mathbf{R}, \mathbf{T}) = \sum_{i=1}^m \sum_{j=1}^n w_{ij} \cdot \left\| \mathbf{P}(\mathbf{x}_i, \mathbf{R}_j, \mathbf{t}_j) - \begin{bmatrix} u_{i,j} \\ v_{i,j} \end{bmatrix} \right\|^2$$

- A non-linear least squares problem (why?)
 - E.g. Levenberg-Marquardt

The Levenberg-Marquardt Algorithm

- Nonlinear least squares $\hat{\beta} \in \operatorname{argmin}_{\beta} S(\beta) \equiv \operatorname{argmin}_{\beta} \sum_{i=1}^m [y_i - f(x_i, \beta)]^2$
 $n \times 1$

- An iterative algorithm

- Start with an initial guess β_0
- For each iteration $\beta \leftarrow \beta + \delta$

- How to get δ ?

- Linear approximation $f(x_i, \beta + \delta) \approx f(x_i, \beta) + \mathbf{J}_i \delta$. $\mathbf{J}_i = \frac{\partial f(x_i, \beta)}{\partial \beta}$ $1 \times n$

- Find δ to minimize the objective $S(\beta + \delta) \approx \sum_{i=1}^m [y_i - f(x_i, \beta) - \mathbf{J}_i \delta]^2$

Best to minimize the objective

Wikipedia

The Levenberg-Marquardt Algorithm

- Vector notation for $S(\boldsymbol{\beta} + \boldsymbol{\delta}) \approx \sum_{i=1}^m [y_i - f(x_i, \boldsymbol{\beta}) - \mathbf{J}_i \boldsymbol{\delta}]^2$

$$\begin{aligned} S(\boldsymbol{\beta} + \boldsymbol{\delta}) &\approx \|\mathbf{y} - \mathbf{f}(\boldsymbol{\beta}) - \mathbf{J}\boldsymbol{\delta}\|^2 \\ &= [\mathbf{y} - \mathbf{f}(\boldsymbol{\beta}) - \mathbf{J}\boldsymbol{\delta}]^T [\mathbf{y} - \mathbf{f}(\boldsymbol{\beta}) - \mathbf{J}\boldsymbol{\delta}] \\ &= [\mathbf{y} - \mathbf{f}(\boldsymbol{\beta})]^T [\mathbf{y} - \mathbf{f}(\boldsymbol{\beta})] - [\mathbf{y} - \mathbf{f}(\boldsymbol{\beta})]^T \mathbf{J}\boldsymbol{\delta} - (\mathbf{J}\boldsymbol{\delta})^T [\mathbf{y} - \mathbf{f}(\boldsymbol{\beta})] + \boldsymbol{\delta}^T \mathbf{J}^T \mathbf{J}\boldsymbol{\delta} \\ &= [\mathbf{y} - \mathbf{f}(\boldsymbol{\beta})]^T [\mathbf{y} - \mathbf{f}(\boldsymbol{\beta})] - 2[\mathbf{y} - \mathbf{f}(\boldsymbol{\beta})]^T \mathbf{J}\boldsymbol{\delta} + \boldsymbol{\delta}^T \mathbf{J}^T \mathbf{J}\boldsymbol{\delta}. \end{aligned}$$

Take derivation with respect to $\boldsymbol{\delta}$ and set to zero $(\mathbf{J}^T \mathbf{J}) \boldsymbol{\delta} = \mathbf{J}^T [\mathbf{y} - \mathbf{f}(\boldsymbol{\beta})]$

<https://www.cs.ubc.ca/~schmidtm/Courses/340-F16/linearQuadraticGradients.pdf>

Levenberg's contribution $(\mathbf{J}^T \mathbf{J} + \lambda \mathbf{I}) \boldsymbol{\delta} = \mathbf{J}^T [\mathbf{y} - \mathbf{f}(\boldsymbol{\beta})]$ damped version

$$\boldsymbol{\beta} \leftarrow \boldsymbol{\beta} + \boldsymbol{\delta}$$

Wikipedia

Structure from Motion

$$g(\mathbf{X}, \mathbf{R}, \mathbf{T}) = \sum_{i=1}^m \sum_{j=1}^n \underbrace{w_{ij}}_{\substack{\text{indicator variable:} \\ \text{is point } i \text{ visible in image } j?}} \cdot \left\| \underbrace{\mathbf{P}(\mathbf{x}_i, \mathbf{R}_j, \mathbf{t}_j)}_{\substack{\text{predicted} \\ \text{image location}}} - \underbrace{\begin{bmatrix} u_{i,j} \\ v_{i,j} \end{bmatrix}}_{\substack{\text{observed} \\ \text{image location}}} \right\|^2$$

$$\beta = (\mathbf{X}, \mathbf{R}, \mathbf{T})$$

How to get the initial estimation β_0 ?

Random guess is not a good idea.

Next Lecture

Further Reading

- Chapter 11, Computer Vision, Richard Szeliski
- Build Rome in One Day <https://grail.cs.washington.edu/rome/>
- Structure from Motion Revisited <https://colmap.github.io/index.html>