

Basics on Computer Vision

Jikai Wang



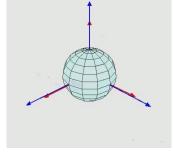
3D Transformation

3D Rotation Representations

Rotation matrix

$$R_{3\times3} = \begin{bmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{bmatrix}$$

Euler angles



$$\omega = \theta \hat{n}$$

Unit quaternion

$$q = w + xi + yj + zk$$

3D Euclidean Transformation SE(3)

3D Rotation + 3D translation

$$x' = Rx + t$$

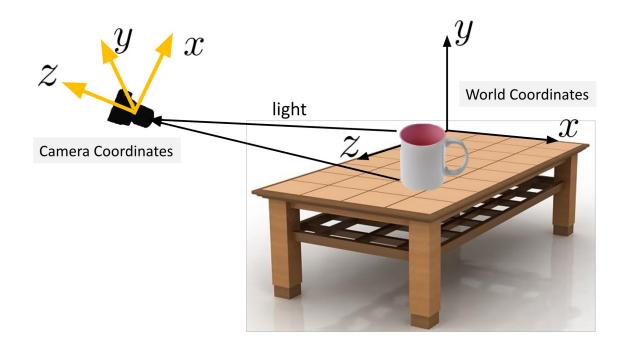
$$x' = [R|t]\bar{x}$$

$$\bar{x} = (x, y, z, 1)$$



Perspective Camera Model

Perspective Camera Model



Camera intrinsics

$$K = \begin{bmatrix} \alpha_x & s & x_0 \\ & \alpha_y & y_0 \\ & & 1 \end{bmatrix}$$

Camera extrinsics

$$\mathbf{X}_{ ext{cam}} = R\mathbf{X} + \mathbf{t}$$

Camera Projection Matrix

$$P = K[R|\mathbf{t}]$$

World space point to image plane pixel

$$\mathbf{x} = P\mathbf{X}$$

Camera space point to image plane pixel

$$\mathbf{x} = K[I|\mathbf{0}]\mathbf{X}_{cam}$$

Back-projection to a 3D Point in Camera Coordinates

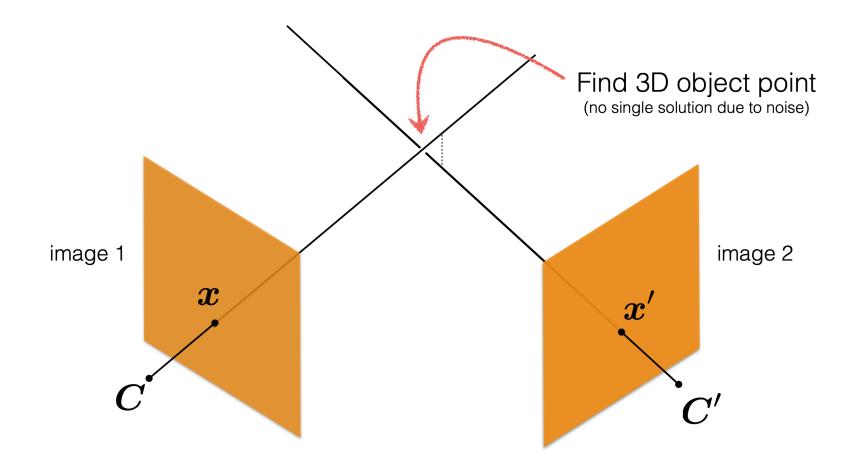
$$K = egin{bmatrix} f_x & 0 & c_x \ 0 & f_y & c_y \ 0 & 0 & 1 \end{bmatrix}$$

$$K^{-1} = egin{bmatrix} 1/f_x & 0 & -c_x/f_x \ 0 & 1/f_y & -c_y/f_y \ 0 & 0 & 1 \end{bmatrix}$$

$$egin{bmatrix} x \ y \ z \end{bmatrix} = K^{-1} \cdot egin{bmatrix} u \ v \ 1 \end{bmatrix} \cdot z$$

$$egin{bmatrix} x \ y \ z \end{bmatrix} = egin{bmatrix} (u-c_x) \cdot rac{z}{f_x} \ (v-c_y) \cdot rac{z}{f_y} \ z \end{bmatrix}$$

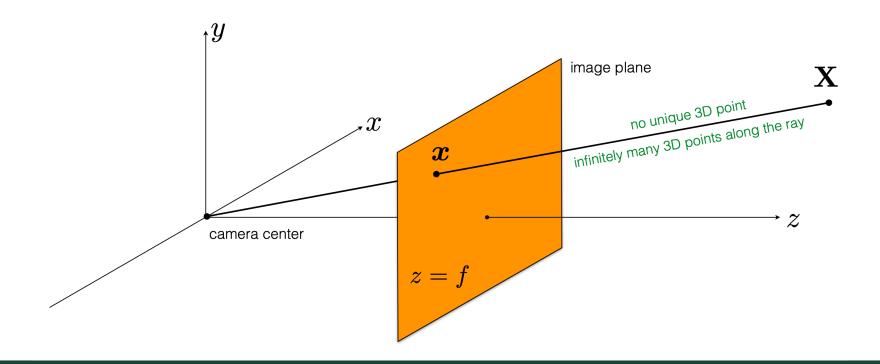






- Given:
 - A set of matched points $\{x_i, x_i'\}$
 - And camera matrices P, P'
- Estimate:
 - The 3D point *X*

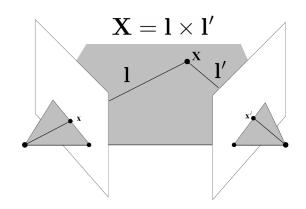
 Q1: Can we compute X from a single correspondence x? No! x = PX



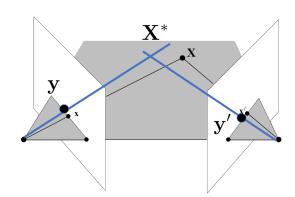
- Q2: Can we compute X from a two correspondences x and x'? Maybe x = PX
 - There will not be a point that satisfies both constraints because the measurements are usually noisy

$$x' = P'X$$
 $x = PX$

Need to find the **best fit**



Perfect measurements



Noisy measurements

- In practice, we find the correspondences
- Find *X** that minimizes $d(x, PX^*) + d(x', P'X^*)$

- Q2: Can we compute X from a two correspondences x and x'? Maybe x = PX
 - There will not be a point that satisfies both constraints because the measurements are usually noisy

$$x' = P'X$$
 $x = PX$

- Need to find the **best fit**
- Same ray direction but differs by a scale factor

$$x = \alpha PX$$

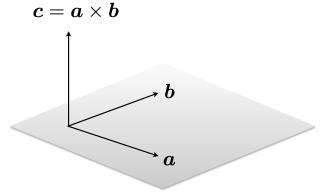
$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \alpha \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix} \begin{bmatrix} x \\ Y \\ Z \\ 1 \end{bmatrix}$$

Q3: How do we solve for unknowns in a similarity relation?

$$x = \alpha PX$$

- Direct Linear Transform:
 - Remove scale factor, convert to linear system and solve with **SVD** (Singular Value Decomposition).
 - Recall: Cross product of two vectors of same direction is zero

$$x \times x = 0$$



$$\mathbf{c} \cdot \mathbf{a} = 0$$
 $\mathbf{c} \cdot \mathbf{b} = 0$

$$m{a} imes m{b} = \left[egin{array}{c} a_2 b_3 - a_3 b_2 \ a_3 b_1 - a_1 b_3 \ a_1 b_2 - a_2 b_1 \end{array}
ight]$$

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$$x \times x = x \times \alpha PX = 0$$

Triangulation - Convert to Linear System

Rewrite x:

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \alpha \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} = \alpha \begin{bmatrix} - & p_1^T & - \\ - & p_2^T & - \\ - & p_3^T & - \end{bmatrix} X = \alpha \begin{bmatrix} p_1^T X \\ p_2^T X \\ p_3^T X \end{bmatrix}$$

 $x \times \alpha PX = 0$, because scaler α is **non-zero**, we **remove** α :

$$x \times PX = 0$$

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \times \begin{bmatrix} p_1^T X \\ p_2^T X \\ p_3^T X \end{bmatrix} = \begin{bmatrix} y p_3^T X - p_2^T X \\ p_1^T X - x p_3^T X \\ x p_2^T X - y p_1^T X \end{bmatrix} = \begin{bmatrix} y p_3^T - p_2^T \\ p_1^T - x p_3^T \\ x p_2^T - y p_1^T \end{bmatrix} X = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

Triangulation - Convert to Linear System

$$x \times PX = \begin{bmatrix} yp_3^T - p_2^T \\ p_1^T - xp_3^T \\ xp_2^T - yp_1^T \end{bmatrix} X = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

Observation: Third line is a linear combination of the first and second lines.

$$xp_2^T X - yp_1^T X = -x(yp_3^T - p_2^T) - y(p_1^T - xp_3^T)$$

$$\begin{bmatrix} yp_3^T - p_2^T \\ p_1^T - xp_3^T \\ xp_3^T - yp_4^T \end{bmatrix} X = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \Leftrightarrow \begin{bmatrix} yp_3^T - p_2^T \\ p_1^T - xp_3^T \end{bmatrix} X = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

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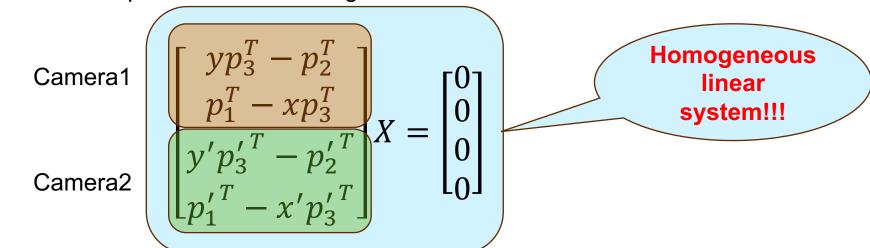
linear equations

$$\begin{bmatrix} yp_3^T - p_2^T \\ p_1^T - xp_3^T \\ xp_2^T - yp_3^T \end{bmatrix} X = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \Leftrightarrow \begin{bmatrix} yp_3^T - p_2^T \\ p_1^T - xp_3^T \end{bmatrix} X = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

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- Now we can make a system of linear equations
 - Concatenate the 2D points from both images: AX = 0



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- Now we can make a system of linear equations
 - Concatenate the 2D points from both images: AX = 0
- To solve AX = 0, we apply SVD on A

$$A = UWV^T \Longrightarrow AV = UWV^TV = UW$$

$$A[v_1, ..., \mathbf{y}] = U\begin{bmatrix} \sigma_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \mathbf{0} \end{bmatrix}$$

The last element y of V is the solution!!!