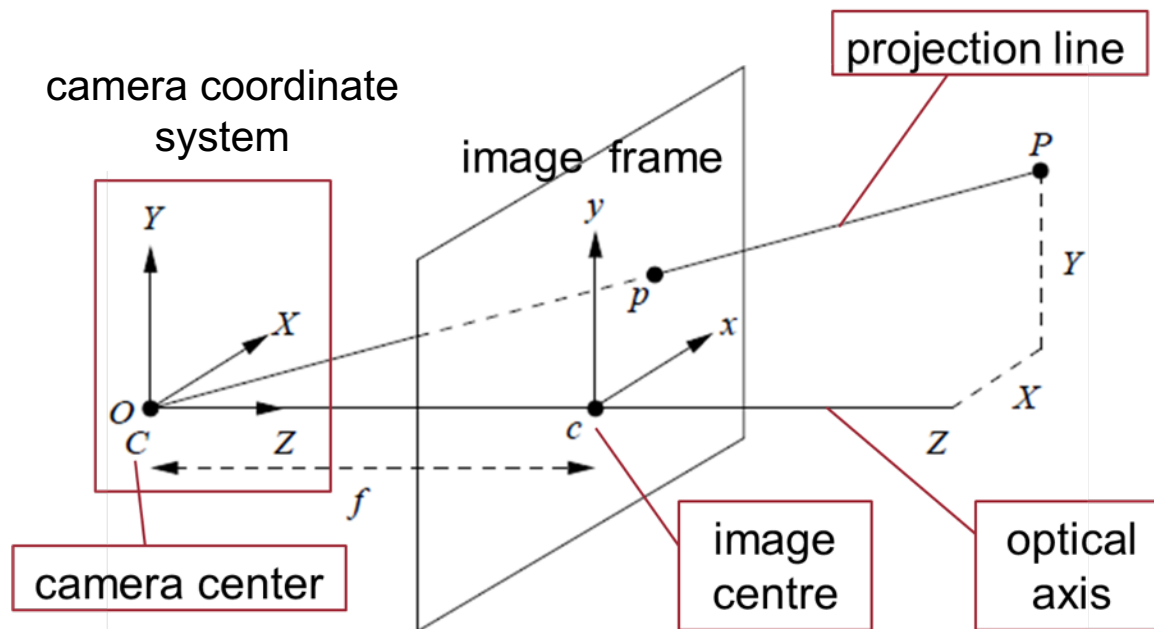


- **Review the lectures**
- **Assessment**

# Camera models

- Pinhole camera model



$$x = f \frac{X}{Z}, \quad y = f \frac{Y}{Z}$$

# Camera models

- Perspective projection model

- Camera sensor's pixels not exactly square

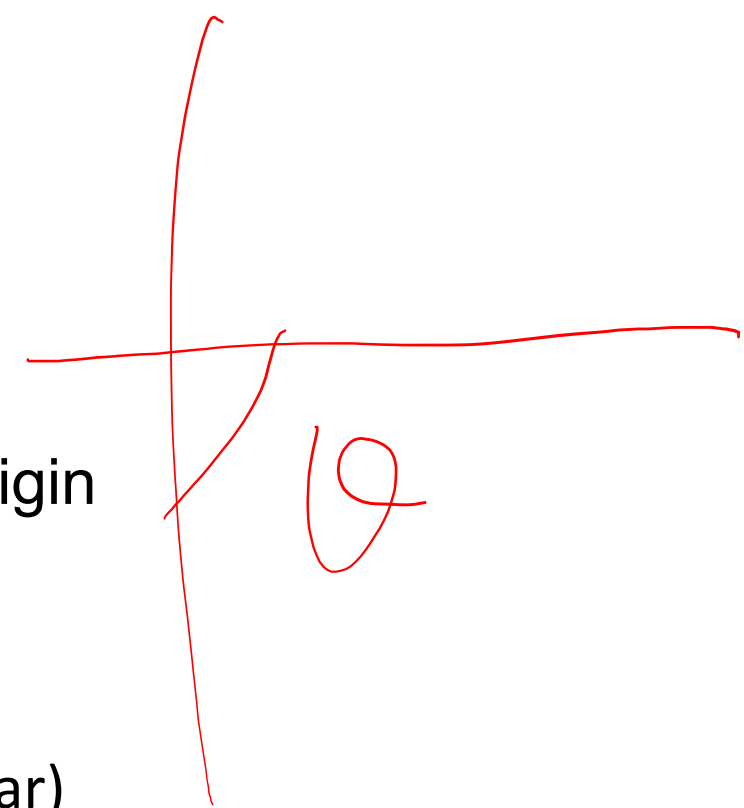
$$x = kf \frac{X}{Z}, \quad y = lf \frac{Y}{Z}$$

- Image center or **principal point**  $c$  may not be at origin

$$x = f_x \frac{X}{Z} + c_x, \quad y = f_y \frac{Y}{Z} + c_y$$

- Distortion (image frame may not be exactly rectangular)

$$x = f_x \frac{X}{Z} - f_x \cot \theta \frac{Y}{Z} + c_x, \quad y = \frac{f_y}{\sin \theta} \frac{Y}{Z} + c_y$$



# Camera models

- Perspective projection model
  - Intrinsic parameters

$$\tilde{\mathbf{x}} = \frac{1}{Z} \mathbf{K} \mathbf{X}, \quad \mathbf{K} = \begin{bmatrix} f_x & -f_x \cot \theta & c_x \\ 0 & \frac{f_y}{\sin \theta} & c_y \\ 0 & 0 & 1 \end{bmatrix}$$



$$\mathbf{K} = \begin{bmatrix} f_x & s & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix}$$

Intrinsic parameter matrix

# Camera models

- Perspective projection model
  - Extrinsic parameters
    - Camera coordinate system is not aligned with world coordinate system
    - Camera can move and rotate

$${}^C\mathbf{X} = {}^C_W\mathbf{R} {}^W\mathbf{X} + {}^C_W\mathbf{T}$$

# Camera models

- Perspective projection model

$$\mathbf{P}' = \mathcal{M} \mathbf{P}_w$$
$$= \mathcal{K} \begin{bmatrix} \mathcal{R} & \mathbf{T} \end{bmatrix} \mathbf{P}_w$$

Internal (intrinsic) parameters

External (extrinsic) parameters

# Camera Calibration

- Recovering  $K$
- Recovering  $R$  and  $T$

$$\begin{aligned} \mathbf{P}' &= \mathcal{M} \mathbf{P}_w \\ &= \mathcal{K} \begin{bmatrix} \mathcal{R} & \mathbf{T} \end{bmatrix} \mathbf{P}_w \end{aligned}$$

Internal (intrinsic) parameters

External (extrinsic) parameters

# Camera Calibration

- How many parameters to recover?

- 5 intrinsic parameters

- 2 for focal length
- 2 for offset
- 1 for skewness

- 6 extrinsic parameters

- 3 for rotation
- 3 for translation

$$\mathbf{K} = \begin{bmatrix} \alpha & -\alpha \cot \theta & u_o \\ 0 & \frac{\beta}{\sin \theta} & v_o \\ 0 & 0 & 1 \end{bmatrix}$$

$$\mathbf{R} = \begin{bmatrix} \mathbf{r}_1^T \\ \mathbf{r}_2^T \\ \mathbf{r}_3^T \end{bmatrix}$$

$$\mathbf{T} = \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix}$$

$$\begin{aligned} \mathbf{P}' &= \mathcal{M} \mathbf{P}_w \\ &= \mathbf{K} \begin{bmatrix} \mathbf{R} & \mathbf{T} \end{bmatrix} \mathbf{P}_w \end{aligned}$$



# Camera Calibration

- 11 parameters to recover
- Corresponding 3D-2D point pairs
  - Each 3D-2D point pair -> 2 constraints
  - 11 unknown -> 6 point correspondence
  - Use more to handle noisy data

$$\mathbf{p}_i = \begin{bmatrix} u_i \\ v_i \end{bmatrix} = M\mathbf{P}_i = \begin{bmatrix} \frac{\mathbf{m}_1 \mathbf{P}_i}{\mathbf{m}_3 \mathbf{P}_i} \\ \frac{\mathbf{m}_2 \mathbf{P}_i}{\mathbf{m}_3 \mathbf{P}_i} \end{bmatrix} \quad \begin{aligned} u_i(\mathbf{m}_3 \mathbf{P}_i) - \mathbf{m}_1 \mathbf{P}_i &= 0 \\ v_i(\mathbf{m}_3 \mathbf{P}_i) - \mathbf{m}_2 \mathbf{P}_i &= 0 \end{aligned}$$

# Camera Calibration

- Solved using SVD

$$P\mathbf{m} = 0$$

SVD decomposition of P

$$U_{2n \times 12} D_{12 \times 12} V^T_{12 \times 12}$$

# Epipolar Geometry

- Essential matrix
  - Canonical camera

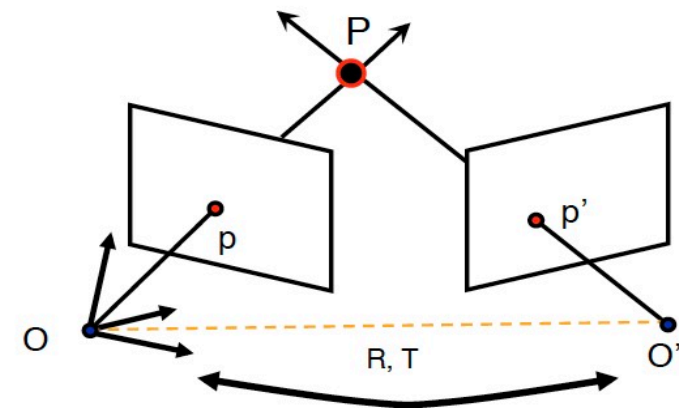
$$p'^T E p = 0, E = [T_{\times}]R$$

$$K = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

- Fundamental matrix

$$p'^T F p = 0, F = \left| K'^{-T} [T_{\times}] R K^{-1} \right|$$

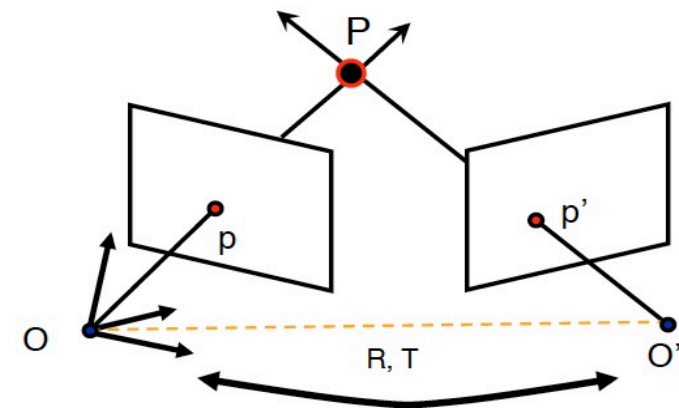
- Relate matching points of different views
  - No need 3D point location
  - No need intrinsic parameters
  - No need extrinsic parameters



# Epipolar Geometry

- Fundamental matrix
  - 3 by 3
  - homogeneous matrix
  - 7 degrees of freedom
    - 9 elements
    - scale doesn't matter (homogeneous matrix)
    - $\text{determinant}(F) = 0$

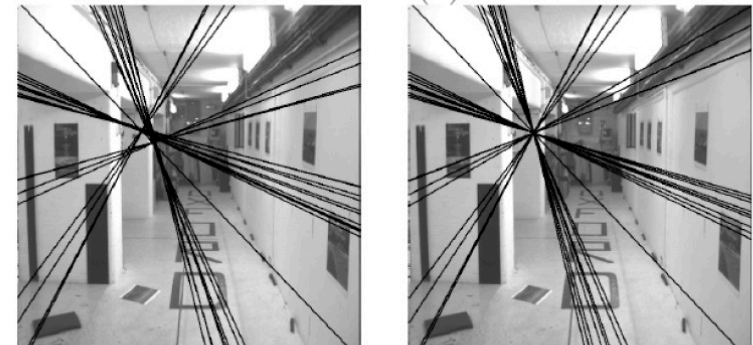
$$p'^T F p = 0, \quad F = K'^{-T} [T_{\times}] R K^{-1}$$



# Epipolar Geometry

- Fundamental matrix
  - 3 by 3
  - homogeneous matrix
  - 7 degrees of freedom
    - 9 elements
    - scale doesn't matter (homogeneous matrix))
    - determinant( $F$ ) = 0
      - rank( $F$ ) = 2

Fundamental matrix has rank 2 :  $\det(F) = 0$ .



**Left :** Uncorrected  $F$  – epipolar lines are not coincident.

**Right :** Epipolar lines from corrected  $F$ .

# Recover F from Matched Image Points

- 8-point algorithm ( $\geq 8$  point pairs)
- Normalized 8-point algorithm
  - Idea: normalize image points before constructing the equations
    - Translation: the centroid of the image points is at origin
    - Scaling: average distance of points from origin is  $\sqrt{2}$

$$q_i = T p_i \quad q'_i = T' p'_i$$

# Recover F from Matched Image Points

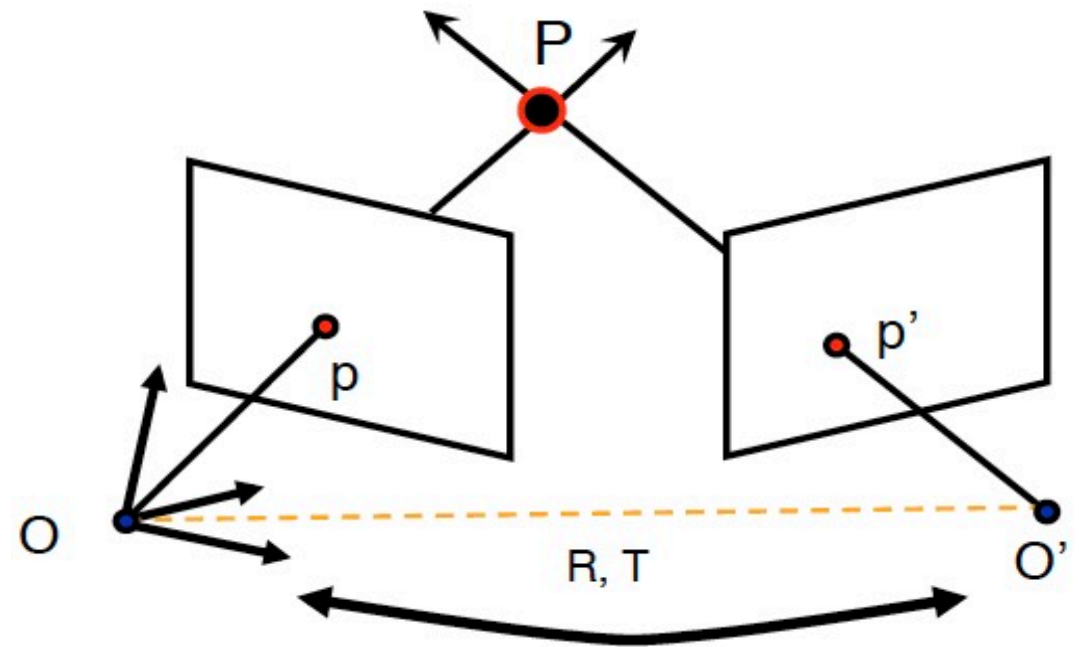
- 8-point algorithm ( $\geq 8$  point pairs)
- Normalized 8-point algorithm
  - Idea: normalize image points before constructing the equations
  - Construct linear system using the normalized points
  - Solve using SVD
  - Constraint enforcement
  - De-normalization

# Relative Pose from Fundamental Matrix

- Essential matrix from fundamental matrix
  - Known intrinsic parameters
    - Estimation
    - Calibration

$$F = K'^{-T} [t_{\times}] R K^{-1}$$

$$E = [t_{\times}] R = K'^T F K$$





# Relative Pose from Fundamental Matrix

- Essential matrix from fundamental matrix
- Relative pose from essential matrix

- SVD of E

- determinant(R) > 0

- Two potential values

- T up to a sign

- Two potential values

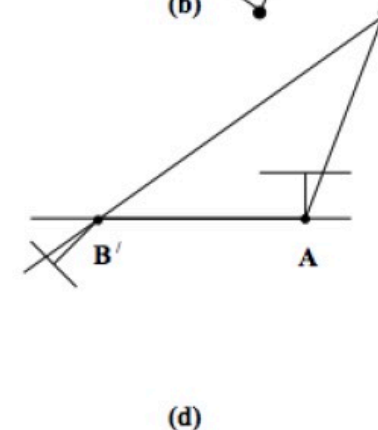
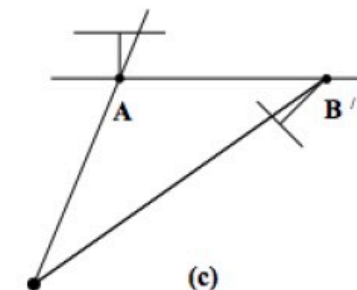
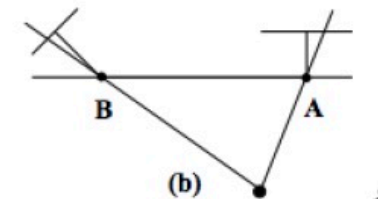
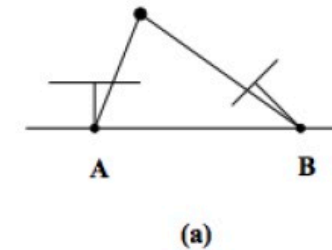
$$E = U\Sigma V^T$$

$$R = (\det UWV^T)UWV^T \text{ or } (\det UW^TV^T)UW^TV^T$$

$$t = \pm U \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = \pm u_3$$

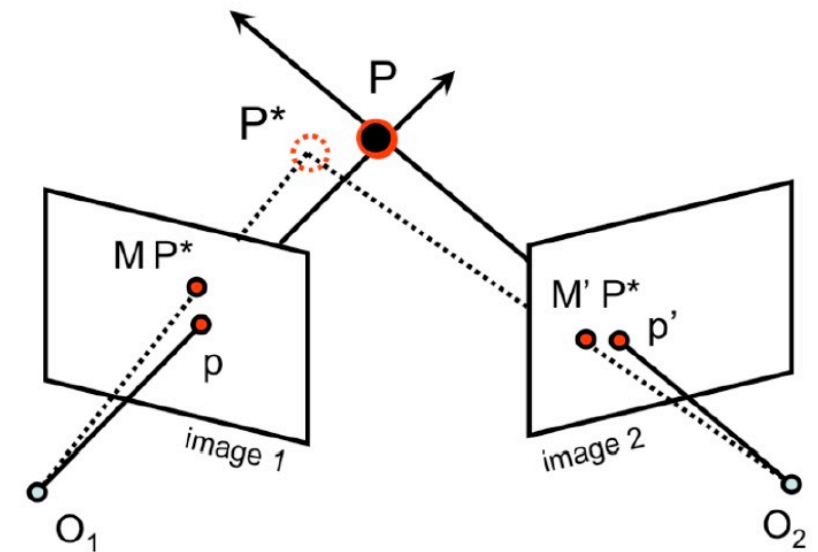
# Relative Pose from Fundamental Matrix

- Essential matrix from fundamental matrix
- Relative pose from essential matrix
  - R: two potential values
  - T: two potential values
  - 3D points must be in front of both cameras
    - Reconstruct 3D points
      - using all potential pairs of R and t
    - Count the number of points in front of cameras
    - The pair giving max front points is correct



# Triangulation

- Find coordinates of 3D point from its projection into two views
  - Known camera intrinsic parameters ( $K$ )
  - Known relative orientation ( $R$ ) and offset ( $T$ )
  - In theory,  $P$  is  $\cap$  of the two lines of sight
    - Straightforward and mathematically sound
    - Do not work well
      - Noisy in observation
      - $K$ ,  $R$ ,  $T$  are not precise
  - A linear method for triangulation
  - A non-linear method for triangulation



# A Linear Method for Triangulation

## Two image points

$$p = MP = (x, y, 1)$$

$$p' = M'P = (x', y', 1)$$

By the definition of the cross product

$$p \times (MP) = 0$$

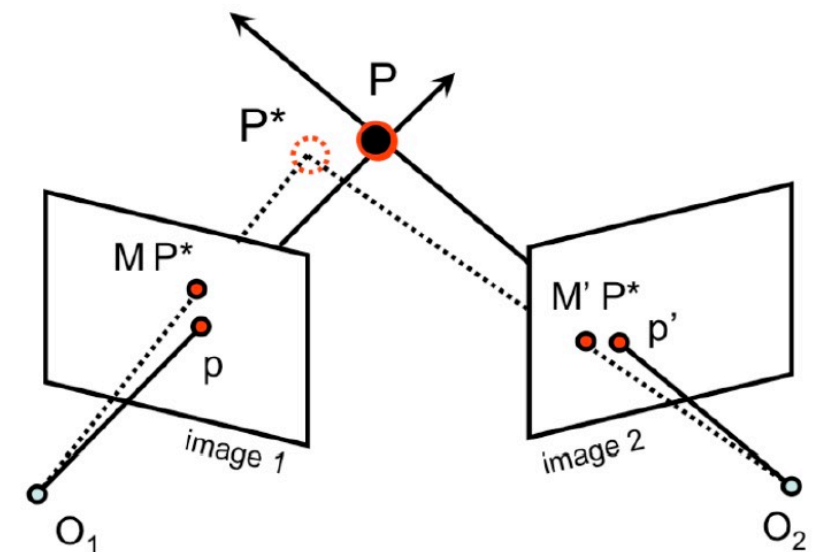


Similar constraints can also be formulated for  $p'$  and  $M'$ .

$$x(M_3P) - (M_1P) = 0$$

$$y(M_3P) - (M_2P) = 0$$

$$x(M_2P) - y(M_1P) = 0$$



# A Linear Method for Triangulation

## Two image points

$$p = MP = (x, y, 1)$$

$$p' = M'P = (x', y', 1)$$

By the definition of the cross product

$$p \times (MP) = 0$$

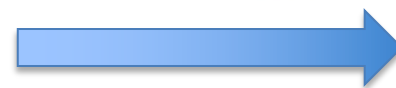
Similar constraints can also be formulated for  $p'$  and  $M'$ .

$$x(M_3P) - (M_1P) = 0$$

$$y(M_3P) - (M_2P) = 0$$

$$x(M_2P) - y(M_1P) = 0$$

$$A = \begin{bmatrix} xM_3 - M_1 \\ yM_3 - M_2 \\ x'M_3' - M_1' \\ y'M_3' - M_2' \end{bmatrix}$$



$$AP = 0$$

# A Linear Method for Triangulation

- Advantages
  - Easy to solve and very efficient
  - Any number of corresponding image points
  - Can handle multiple views
  - Used as initialization to advanced methods

$$AP = 0$$

$$A = \begin{bmatrix} xM_3 - M_1 \\ yM_3 - M_2 \\ x'M'_3 - M'_1 \\ y'M'_3 - M'_2 \end{bmatrix}$$

# Structure from Motion

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- Structure
  - 3D geometry of the scene/object
- Motion
  - Camera locations and orientations
- Structure from Motion
  - Simultaneously recovering structure and motion

# Bundle Adjustment

- Minimize sum of squared re-projection errors:

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



# Advanced topics

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- Lecture 7
  - Multi-view stereo
  - Deep learning for MVS
- Lecture 8
  - Machine learning basics and semantic segmentation

- **Review the lectures**
- **Assessment**



# Assignments vs. final exam

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- Assignments – 40%
- Final exam – 60%
  - 09:00 – 11:30, April 12 (Monday)
  - Open book
  - Three types of questions
    - Multiple choice questions with a single correct answer
    - Multiple choice questions with  $\geq 2$  correct answers
    - Open questions

# Example questions

- Multiple choice questions with a single correct answer

Which of the following statement regarding camera calibration is correct?

- (a) Camera calibration requires at least 6 3D-2D point correspondences.
- (b) Camera calibration requires at least 8 3D-2D point correspondences.
- (c) Camera calibration requires at least 8 pairs of corresponding image points.
- (d) Camera calibration can be solved using SVD decomposition of the projection matrix.

# Example questions

- Multiple choice questions with a single correct answer
- Multiple choice questions with  $\geq 2$  correct answers

Which of the following operations will change the camera intrinsic parameters?

- (a) When zooming in.
- (b) When rotating the camera around its local origin.
- (c) When changing the resolution of the image.
- (d) When the camera is moved.

# Example questions

- Multiple choice questions with a single correct answer
- Multiple choice questions with  $\geq 2$  correct answers
- Open questions

For camera calibration, how do you determine the sign of the intermediate parameter  $\rho$ . How does an incorrect sign of  $\rho$  affect the subsequent calculation of the intrinsic and extrinsic camera parameters?

- 
- Q&A session
    - 13:45 – 15:30, April 6 (Tuesday)