


# Lecture 5

## **Reconstruct 3D Geometry**

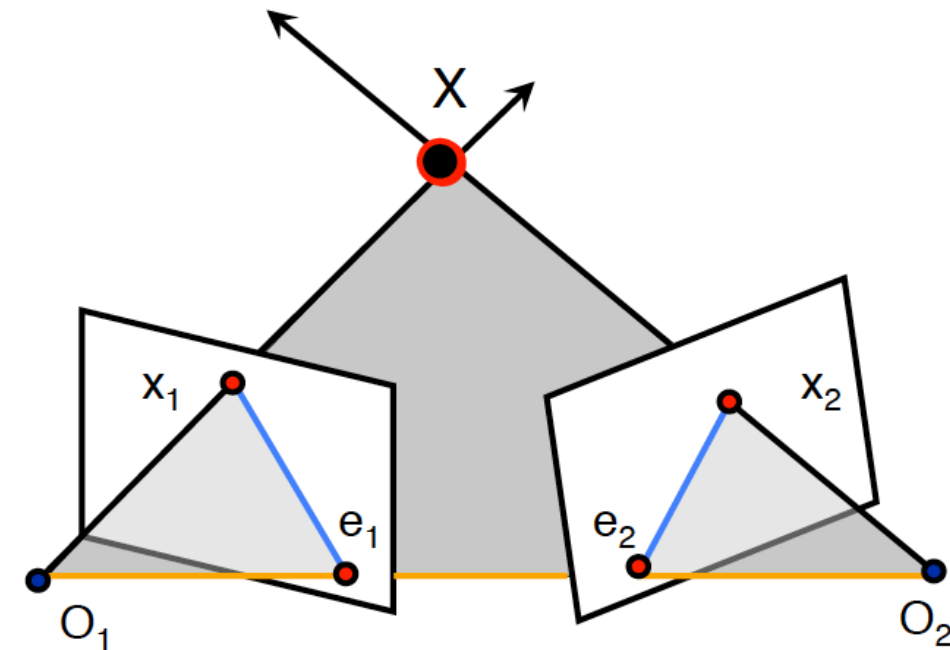
Liangliang Nan

# Today's Agenda

- Review of Epipolar Geometry 
- Image Matching (self study)
- Reconstruct 3D Geometry
  - 3D from 2 views
    - Estimate fundamental matrix
    - Recover relative pose
    - Triangulation
  - 3D from more views
    - Structure from motion
      - Bundle adjustment

# Review of Epipolar Geometry

- Epipolar Geometry
  - Baseline
    - The line between the two camera centers
  - Epipolar plane
    - The plane defined by  $X$ ,  $O_1$ , and  $O_2$
  - Epipoles
    - $\cap$  of baseline and image plane
    - Projection of the other camera center
  - Epipolar lines
    - $\cap$  of epipolar plane with the image plane



# Review of Epipolar Geometry

- Essential matrix
  - Canonical camera assumption

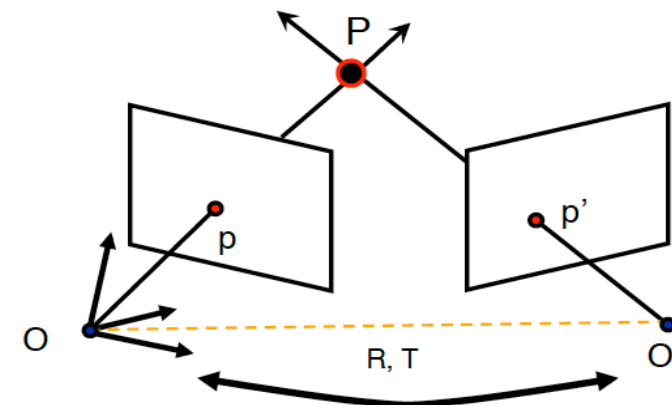
$$p'^T E p = 0, E = [T_x]R$$

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

- Fundamental matrix (most important concept in 3DV)

$$p'^T F p = 0, F = K'^{-T} [T_x] R K^{-1}$$

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

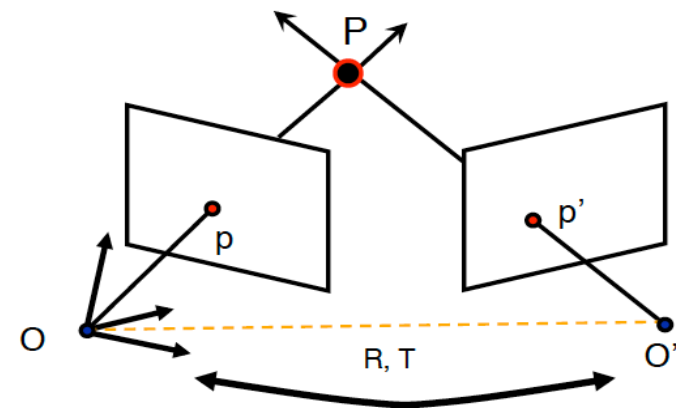




# Review of Epipolar Geometry

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

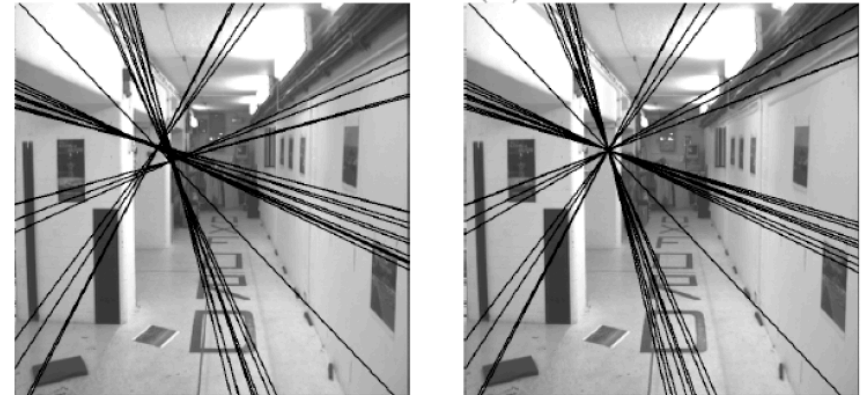
$$p'^T F p = 0, \quad F = K'^{-T} [T_{\times}] R K^{-1}$$



# Review of Epipolar Geometry

- Fundamental matrix
  - 3 by 3
  - homogeneous matrix
  - 7 degrees of freedom
    - 9 elements
    - scale ambiguity (scale doesn't matter)
    - $\det(F) = 0$
  - $\text{rank}(F) = 2$

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



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

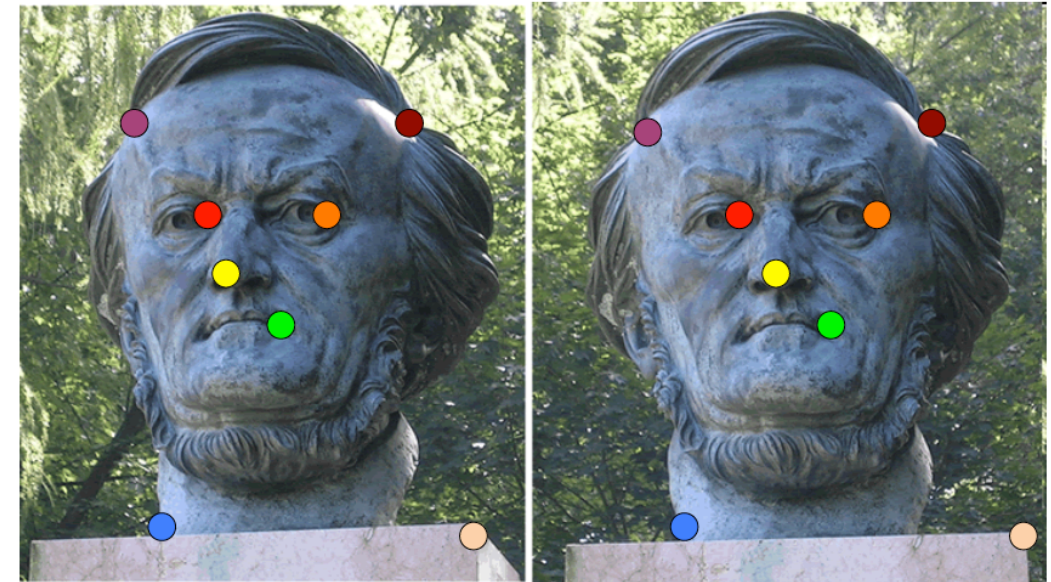
**Right:** Epipolar lines from corrected  $F$ .

# Review of Epipolar Geometry

- Recover  $F$  from corresponding image points
  - 8 unknown parameters
  - Each point pair gives a single linear constraint

$$\begin{cases} p_i = (u_i, v_i, 1) \\ p'_i = (u'_i, v'_i, 1) \end{cases} + p'^T F p = 0,$$

$$\begin{bmatrix} u_i u'_i & v_i u'_i & u'_i & u_i v'_i & v_i v'_i & v'_i & u_i & v_i & 1 \end{bmatrix} \begin{bmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{bmatrix} = 0$$



# Review of Epipolar Geometry

- Recover  $F$  from corresponding image points
  - 8 unknown parameters
  - Each point pair gives a single linear constraint
  - 8-point algorithm (  $\geq 8$  pairs )
  - 7-point algorithm does exist but less popular

$$\begin{bmatrix}
 u_1 u'_1 & v_1 u'_1 & u'_1 & u_1 v'_1 & v_1 v'_1 & v'_1 & u_1 & v_1 & 1 \\
 u_2 u'_2 & v_2 u'_2 & u'_2 & u_2 v'_2 & v_2 v'_2 & v'_2 & u_2 & v_2 & 1 \\
 u_3 u'_3 & v_3 u'_3 & u'_3 & u_3 v'_3 & v_3 v'_3 & v'_3 & u_3 & v_3 & 1 \\
 u_4 u'_4 & v_4 u'_4 & u'_4 & u_4 v'_4 & v_4 v'_4 & v'_4 & u_4 & v_4 & 1 \\
 u_5 u'_5 & v_5 u'_5 & u'_5 & u_5 v'_5 & v_5 v'_5 & v'_5 & u_5 & v_5 & 1 \\
 u_6 u'_6 & v_6 u'_6 & u'_6 & u_6 v'_6 & v_6 v'_6 & v'_6 & u_6 & v_6 & 1 \\
 u_7 u'_7 & v_7 u'_7 & u'_7 & u_7 v'_7 & v_7 v'_7 & v'_7 & u_7 & v_7 & 1 \\
 u_8 u'_8 & v_8 u'_8 & u'_8 & u_8 v'_8 & v_8 v'_8 & v'_8 & u_8 & v_8 & 1
 \end{bmatrix}
 \begin{bmatrix}
 F_{11} \\
 F_{12} \\
 F_{13} \\
 F_{21} \\
 F_{22} \\
 F_{23} \\
 F_{31} \\
 F_{32} \\
 F_{33}
 \end{bmatrix}
 = 0
 \quad W \mathbf{f} = 0$$

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    - Triangulation
  - 3D from more views
    - Structure from motion
      - Bundle adjustment





# Image Matching

- SIFT, Surf ...
- RANSAC



# Image Matching

- SIFT



**David Lowe**

Computer Science Dept., [University of British Columbia](#)

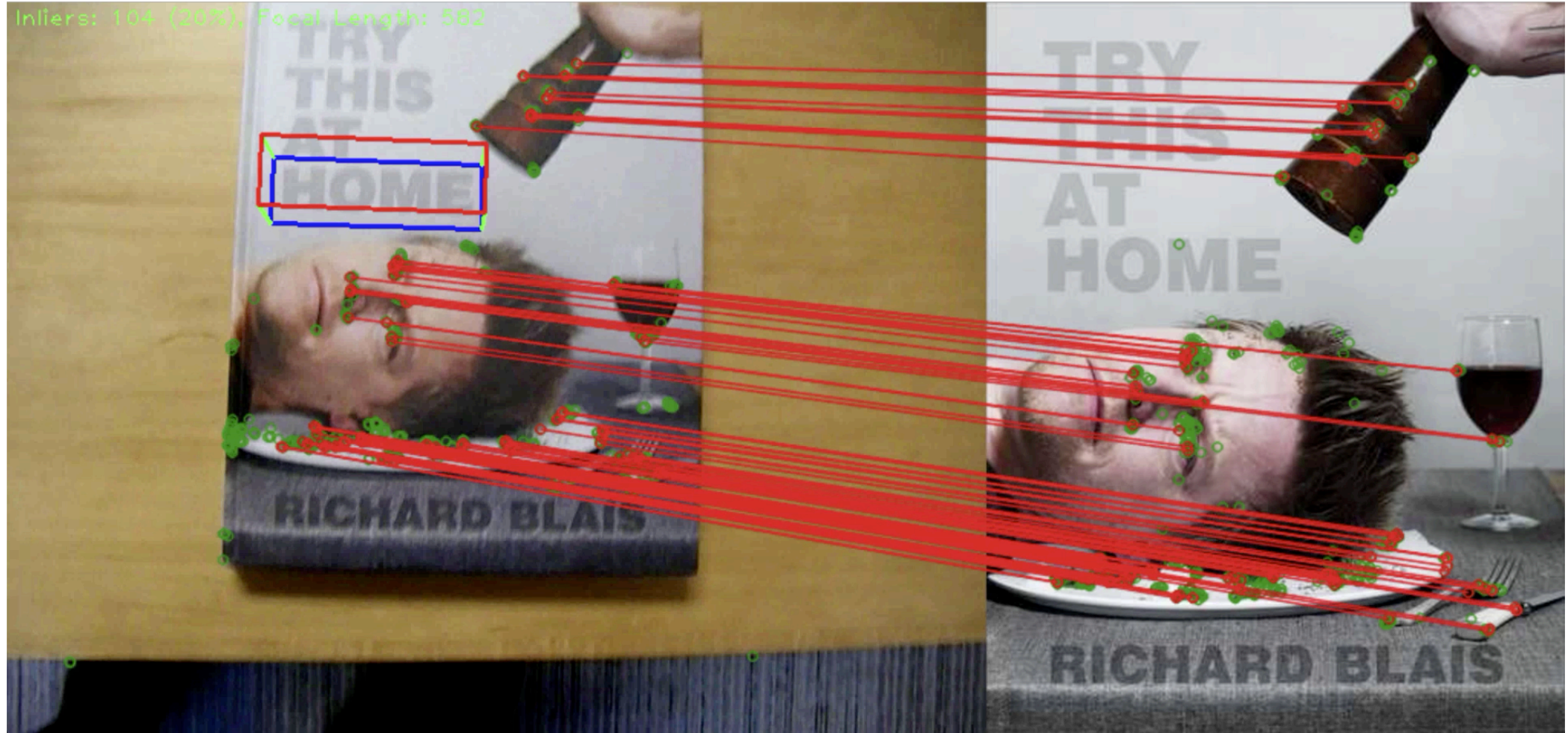
Verified email at cs.ubc.ca - [Homepage](#)

[Computer Vision](#) [Object Recognition](#)

 FOLLOW

TITLE	CITED BY	YEAR
<p><a href="#">Distinctive image features from scale-invariant keypoints</a>            DG Lowe            International journal of computer vision 60 (2), 91-110</p>	61454	2004

# Image Matching





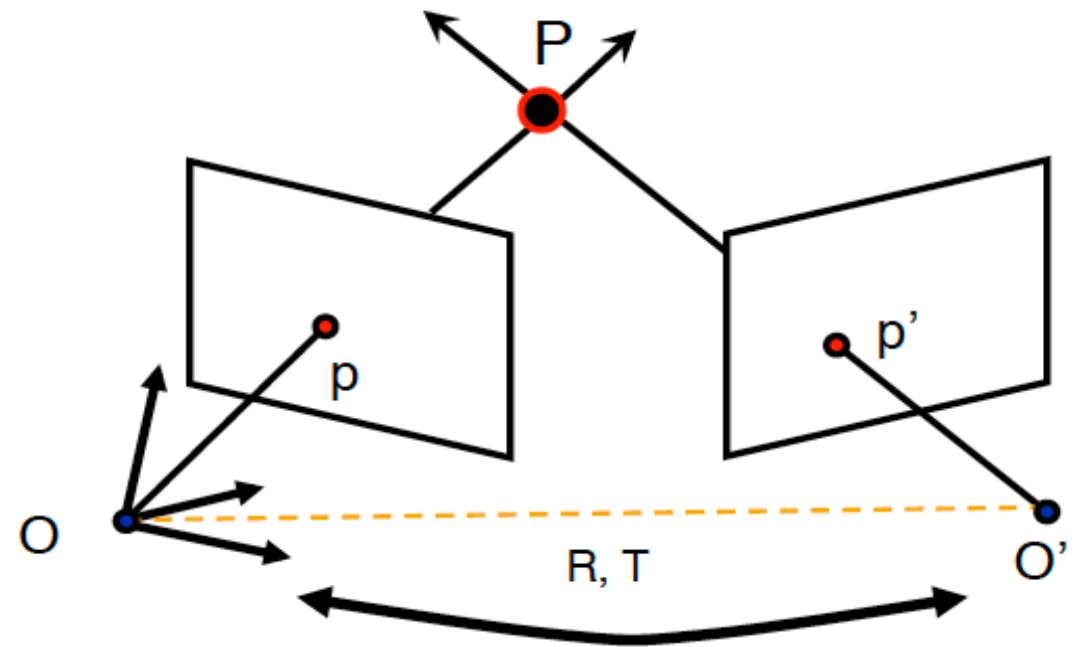
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# 3D from 2 Views

- The general idea

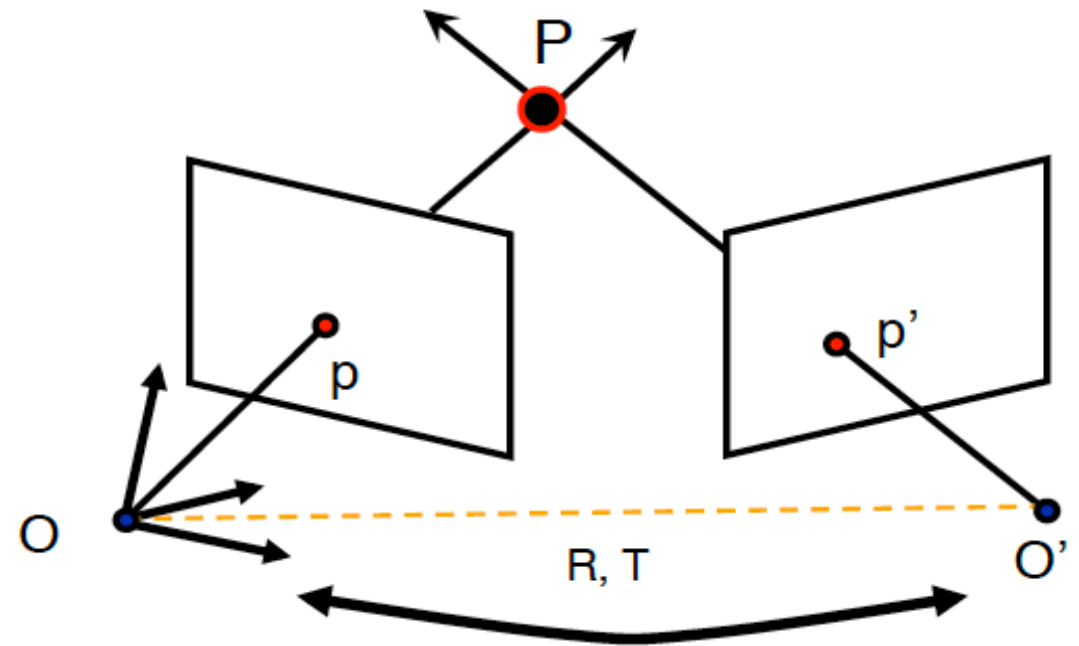


# 3D from 2 Views

- What information is needed?
  - Corresponding image points
    - Image matching techniques
  - Intrinsic camera parameters
    - Camera calibration
  - Extrinsic camera parameters
    - Recover from image points?

$$p'^T F p = 0,$$

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



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    - Structure from motion
      - Bundle adjustment
- Image Matching



# Recover F from Matched Image Points

- 8-point algorithm ( $\geq 8$  point pairs)
  - Sensitive to noise
  - Sensitive to origin of coordinates
  - Sensitive to scales



Same scale, different origins



Image taken using different focal lengths

# Recover F from Matched Image Points

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

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

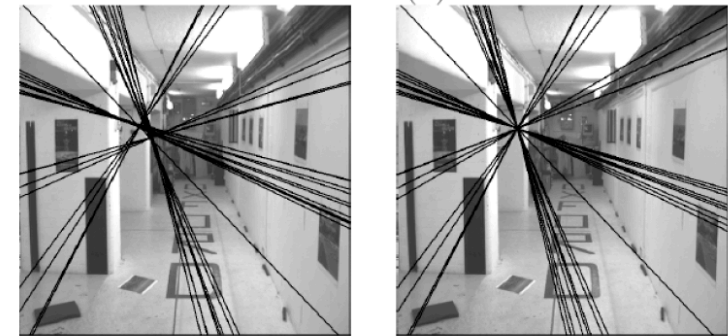
# Recover F from Matched Image Points

- 8-point algorithm ( $\geq 8$  point pairs)
- Normalized 8-point algorithm
  - Idea: normalize before constructing the equations
  - Construct linear system using the normalized points
    - Same as in the original 8-point algorithm
  - Solve using SVD
    - Same as in the original 8-point algorithm

# Recover F from Matched Image Points

- 8-point algorithm ( $\geq 8$  point pairs)
- Normalized 8-point algorithm
  - Idea: normalize before constructing the equations
  - Construct linear system using the normalized points
  - Solve using SVD
  - Constraint enforcement
    - $\text{rank}(F) = 2$

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 before constructing the equations
  - Construct linear system using the normalized points
  - Solve using SVD
  - Constraint enforcement

- $\text{rank}(F) = 2$

$$\hat{F} = U\Sigma V^T \quad F = U \begin{bmatrix} \Sigma_1 & 0 & 0 \\ 0 & \Sigma_2 & 0 \\ 0 & 0 & 0 \end{bmatrix} V^T$$

# Recover F from Matched Image Points

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

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

See handout on “Epipolar geometry”

$$F = T'^T F_q T$$

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  - 3D from more views
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      - Bundle adjustment

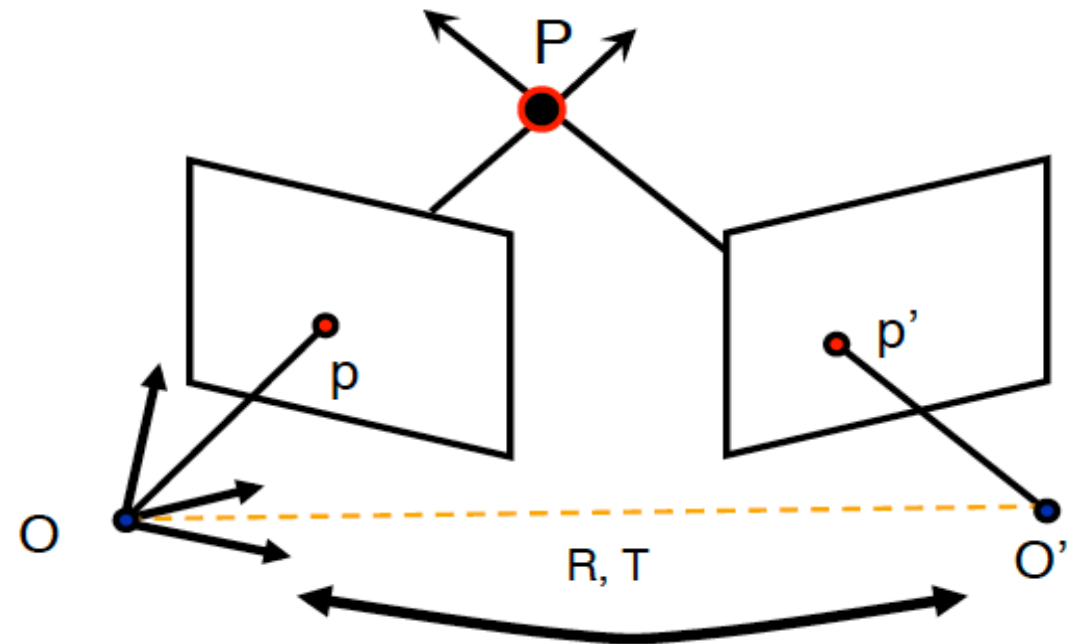


# Relative Pose from Fundamental Matrix

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

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

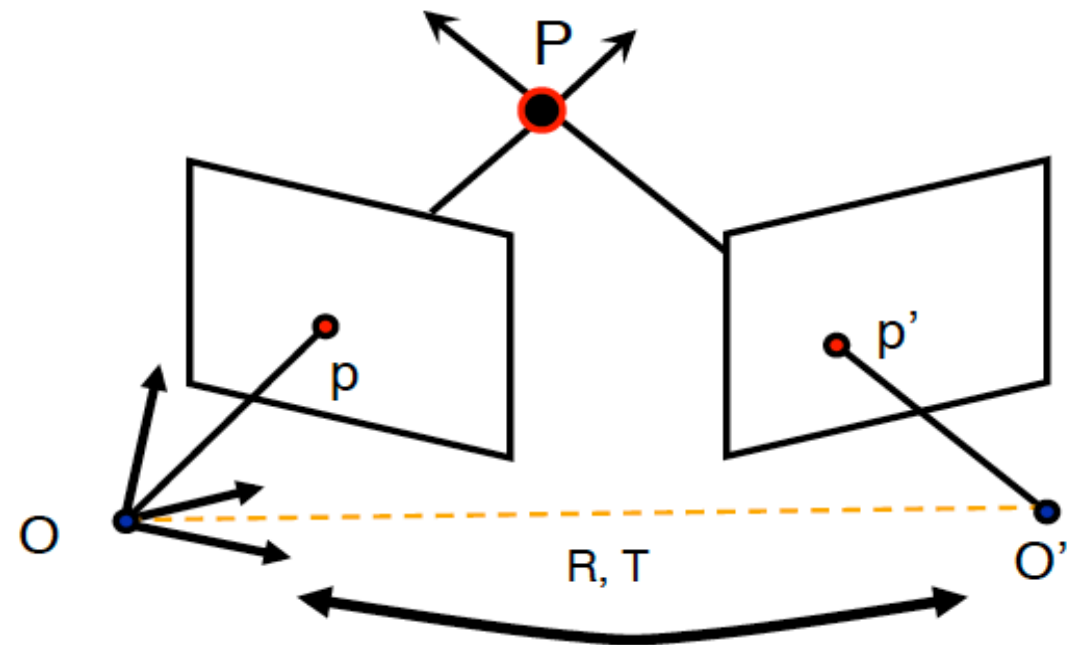
$$E = [t_{\times}] R = K'^T F K$$



# Relative Pose from Fundamental Matrix

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

$$E = [t_{\times}]R$$



# Relative Pose from Fundamental Matrix

- Essential matrix from fundamental matrix
- Relative pose from essential matrix
  - SVD of E

$$W = \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad Z = \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad E = U\Sigma V^T$$

# Relative Pose from Fundamental Matrix

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

- SVD of E

- determinant(R) > 0

- Two potential values

$$W = \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad Z = \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad E = U\Sigma V^T$$

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

# 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

$$W = \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad Z = \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad E = U\Sigma V^T$$

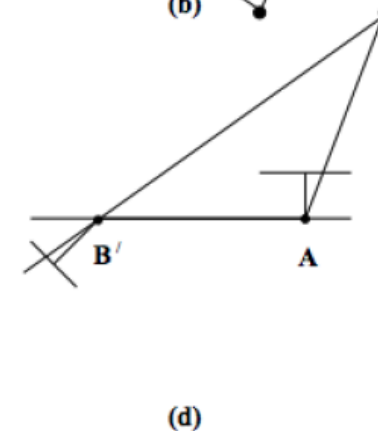
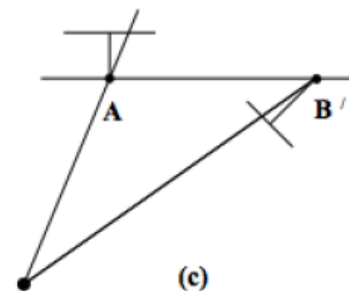
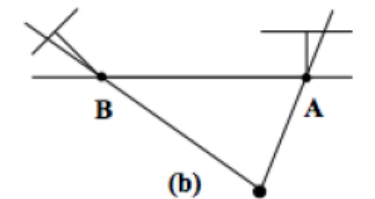
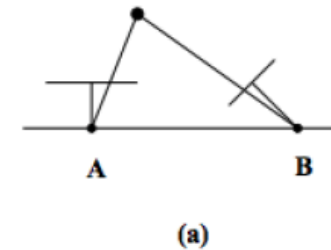
$$R = (\det UWV^T)UWV^T \text{ or } (\det UW^TV^T)UW^TV^T$$

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



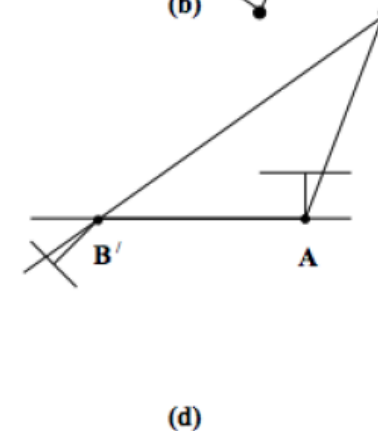
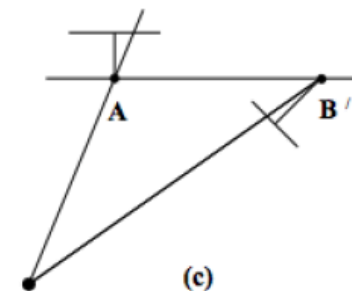
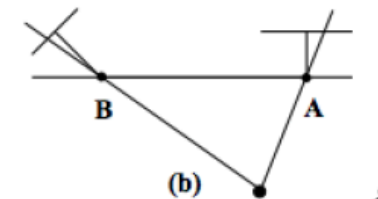
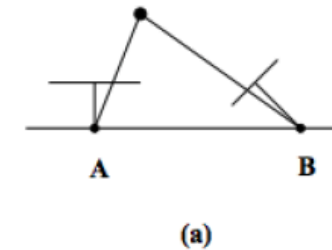
# Relative Pose from Fundamental Matrix

- Essential matrix from fundamental matrix
- Relative pose from essential matrix
  - R: two potential values
  - T: two potential values



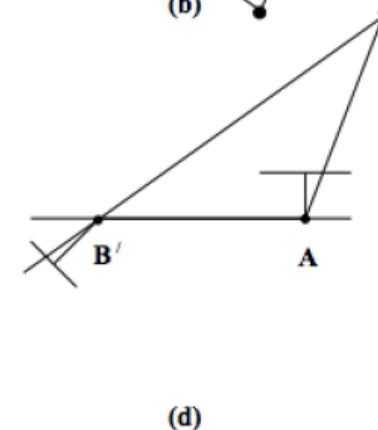
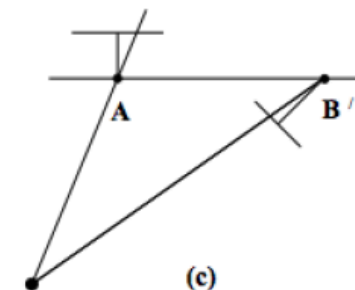
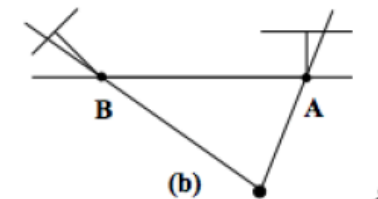
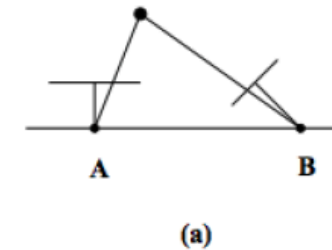
# Relative Pose from Fundamental Matrix

- 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



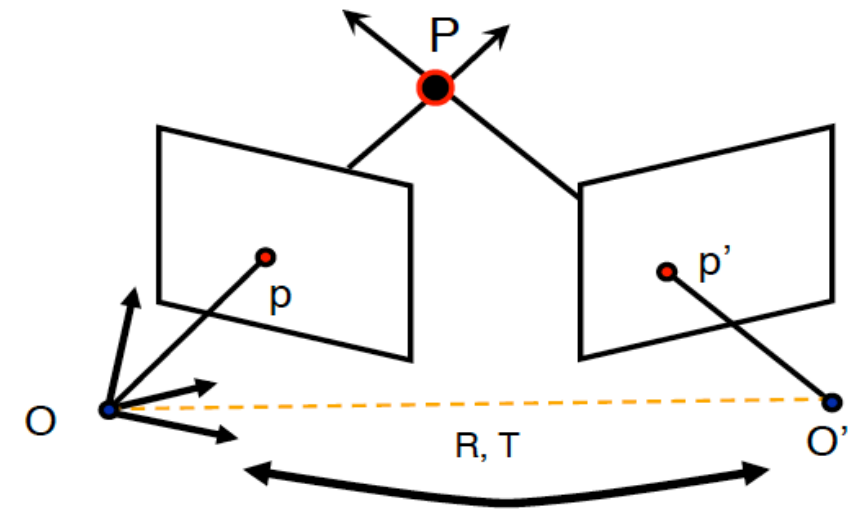
# Relative Pose from Fundamental Matrix

- 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




# 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
    - First camera
      - $P.z > 0$  ?
    - Second camera
      - P in 2<sup>nd</sup> camera's coordinate system:  $Q = R * P + t$
      - $Q.z > 0$  ?

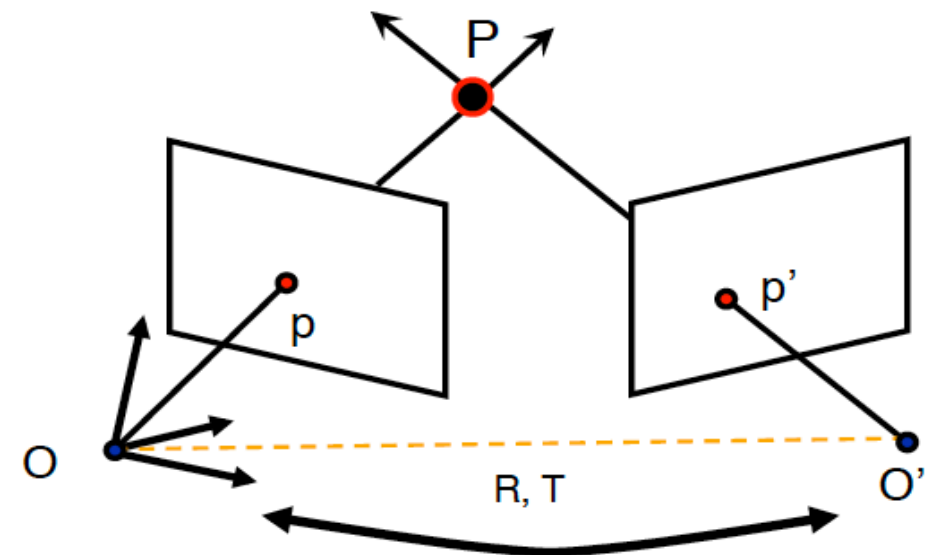


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- Review of Epipolar Geometry
- Image Matching (self study)
- Reconstruct 3D Geometry
  - 3D from 2 views
    - Estimate fundamental matrix
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    - Triangulation 
  - 3D from more views
    - Structure from motion
      - Bundle adjustment

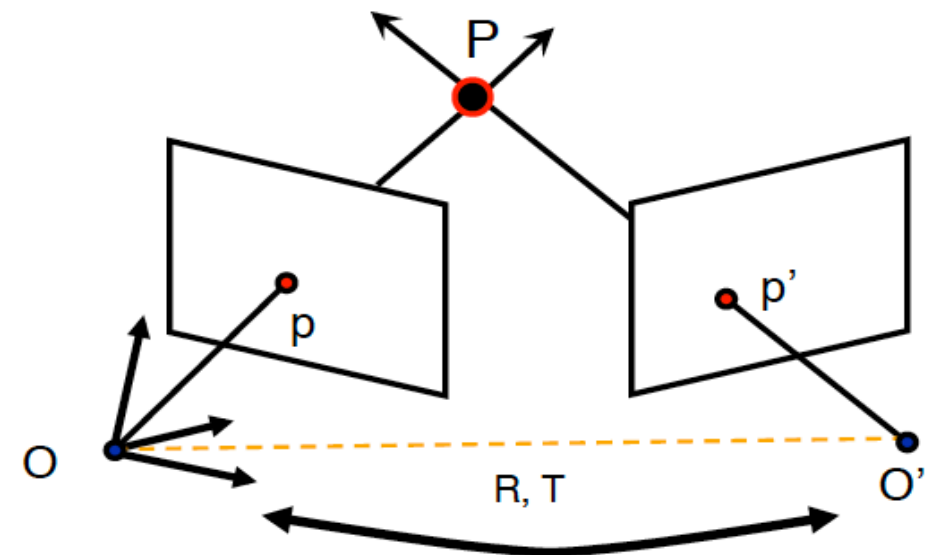
# Triangulation

- Find coordinates of 3D point from its projection into two views
  - Known camera intrinsic parameters ( $K$ )
  - Known relative orientation ( $R$ ) and offset ( $T$ )



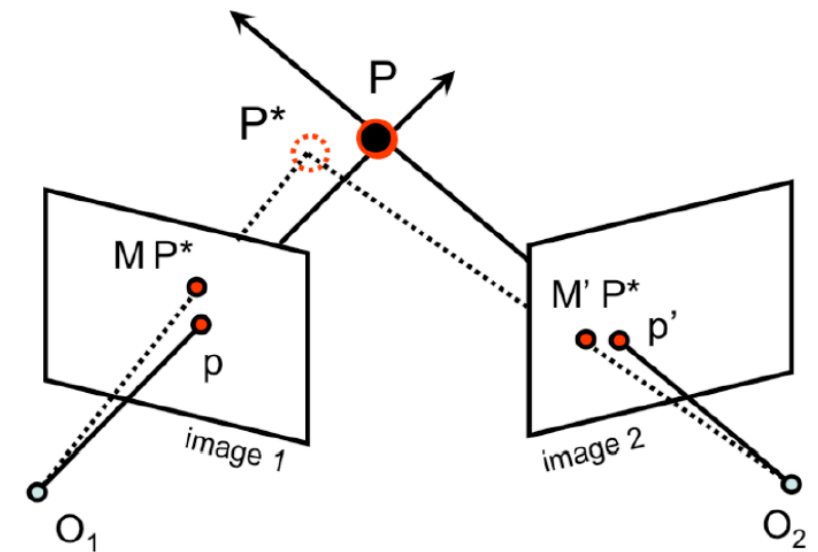
# Triangulation

- Find coordinates of 3D point from its projection into two views
  - Known camera intrinsic parameters ( $K$ )
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  - In theory,  $P$  is  $\cap$  of the two lines of sight



# Triangulation

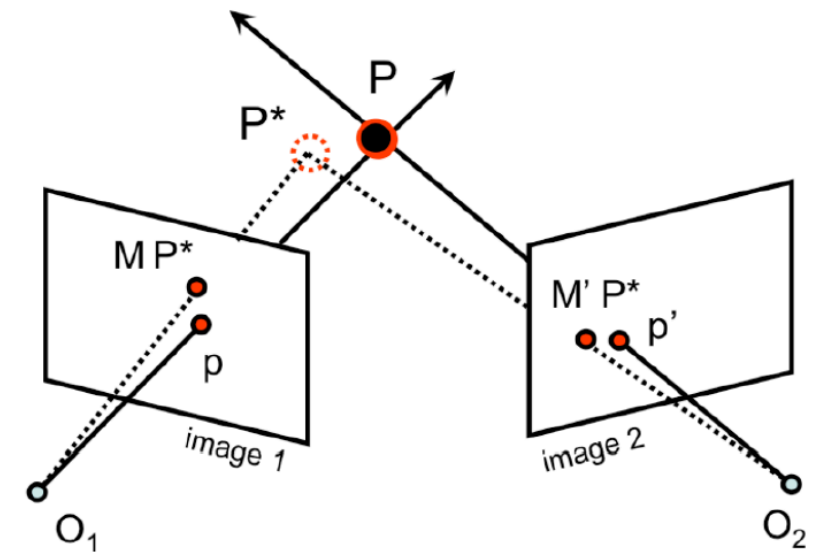
- Find coordinates of 3D point from its projection into two views
  - Known camera intrinsic parameters ( $K$ )
  - Known relative orientation ( $R$ ) and offset ( $T$ )
  - In theory,  $P$  is  $\cap$  of the two lines of sight
    - Straightforward and mathematically sound
    - Do not work well
 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





# 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

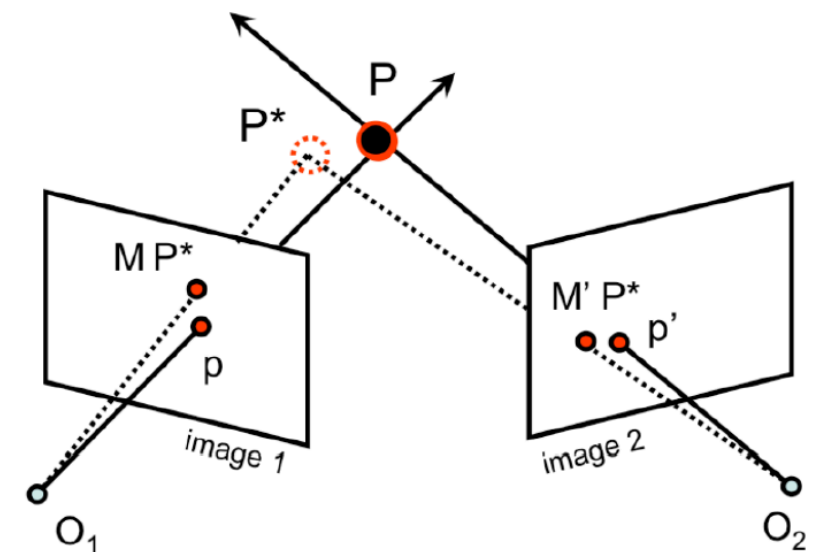
Two image points

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

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

By the definition of the cross product

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



# A Linear Method for Triangulation

## Two image points

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

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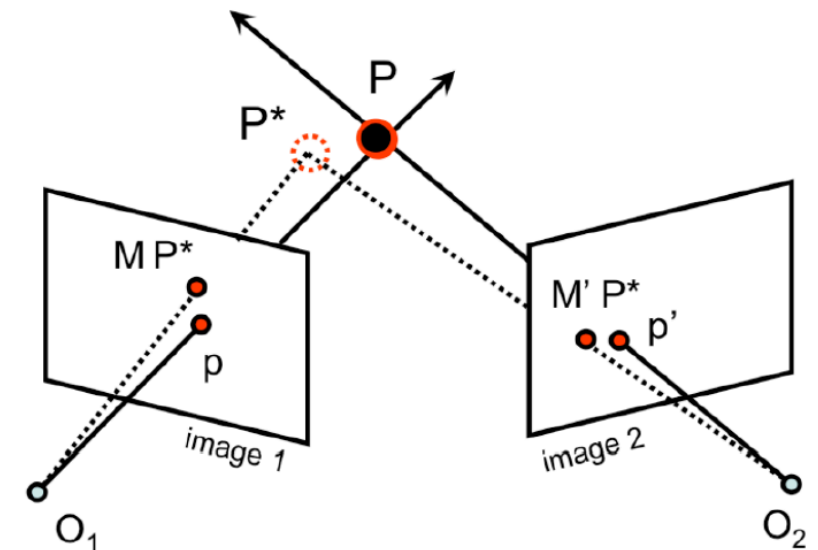


Similar constraints can also be formulated for  $p'$  and  $M'$ .

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

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

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



# 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

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

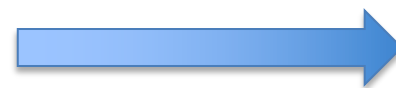
Similar constraints can also be formulated for  $p'$  and  $M'$ .

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

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

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

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



$$AP = 0$$

# 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

$$AP = 0$$

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

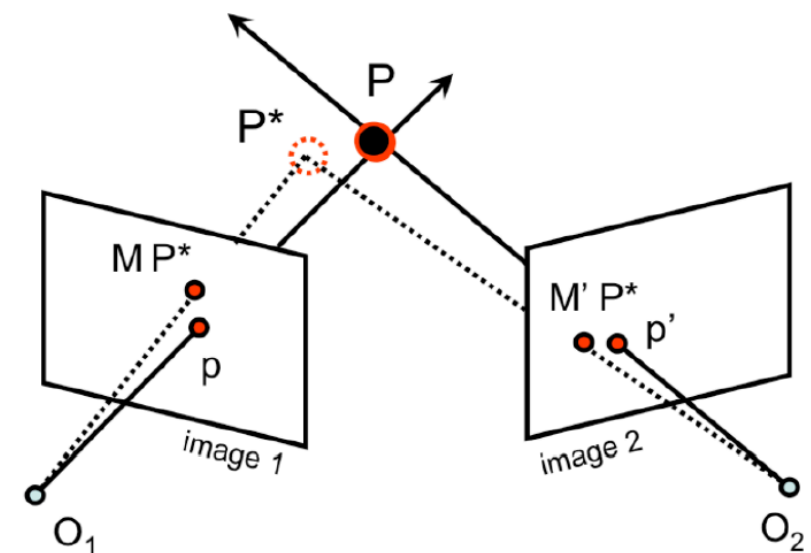
# The Non-linear Method for Triangulation

- Minimize the reprojection error

$$\min_{\hat{P}} \sum_i \|M\hat{P}_i - p_i\|^2 + \|M'\hat{P}_i - p_i'\|^2$$

Reprojection error

- Gauss-Newton's method
- Levenberg-Marquardt



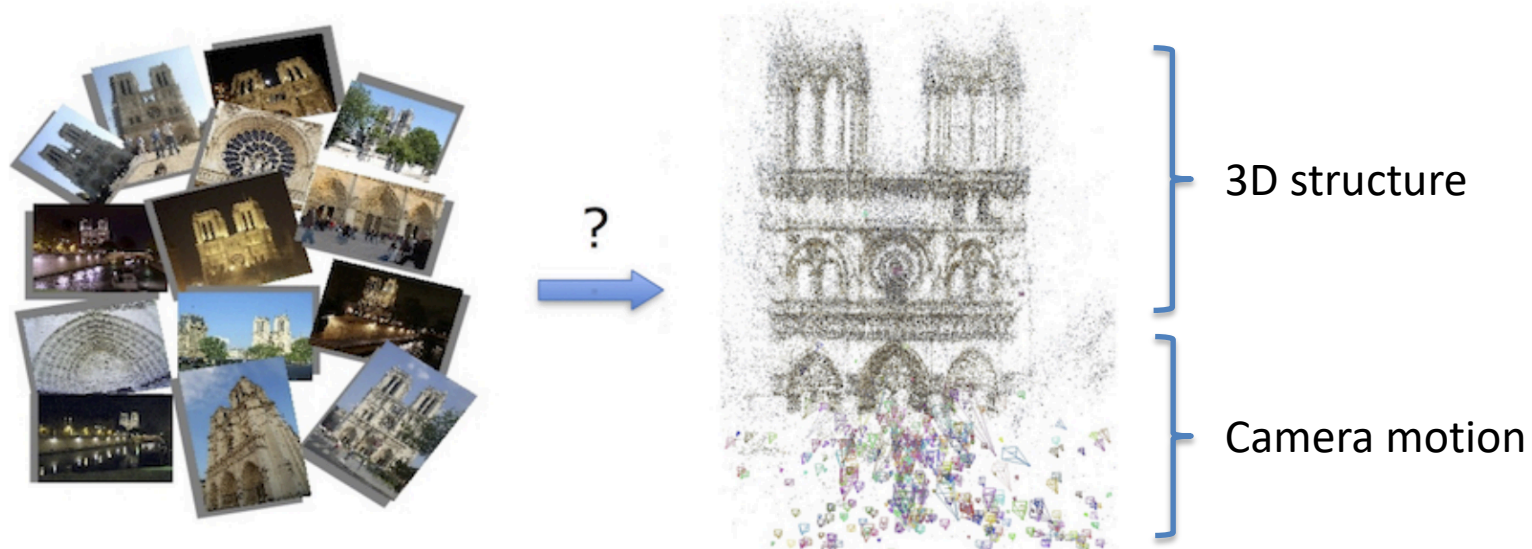
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# Structure from Motion

- Structure?
  - 3D geometry of the scene/object
- Motion?
  - Camera locations and orientations

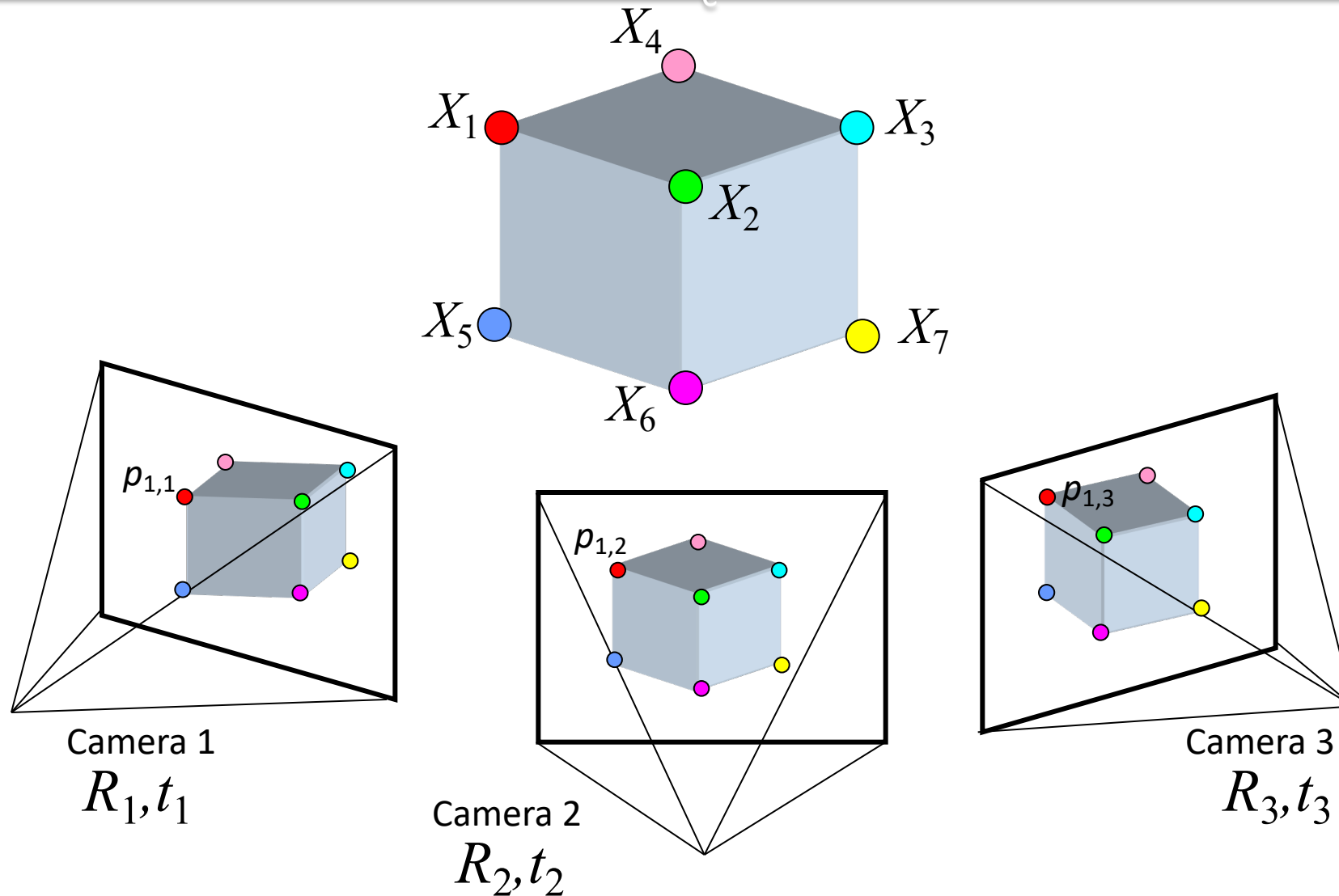




# Structure from Motion

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

# Structure from Motion



# Bundle Adjustment

- Minimize sum of squared re-projection errors:

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

# Bundle Adjustment

- Minimize sum of squared re-projection errors:

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

- Minimizing this function is called *bundle adjustment*
  - Optimized using non-linear least squares,  
e.g. Levenberg-Marquardt

# Bundle Adjustment

- Minimize sum of squared re-projection errors:

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

- Minimizing this function is called *bundle adjustment*
- Initialization
  - From chained 2-view reconstruction
    - Relative motion can be estimated from the corresponding images points
    - 3D points can be estimated from the relative motion using triangulation
  - Global optimization techniques when the poses and the 3D structure are initialized arbitrarily.

# Bundle Adjustment

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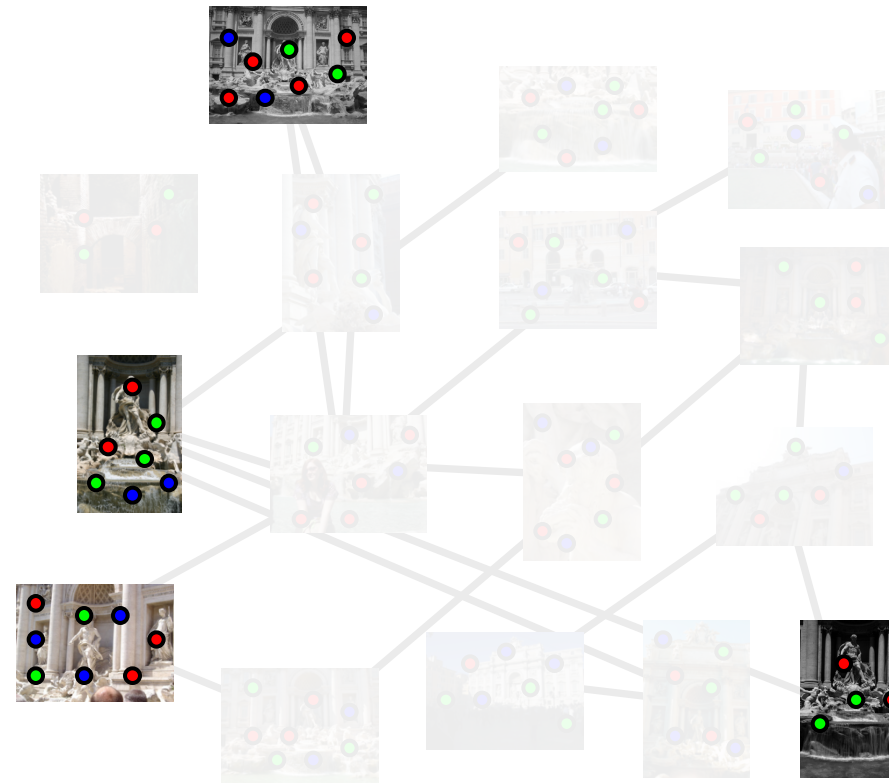
- What are the variables?
  - Camera intrinsic parameters, extrinsic parameters
  - Coordinates of the 3D points
- How many variables per camera?
- How many variables per point?

500 input photos

100,000 3D points

= Very large optimization problem

# Incremental SfM



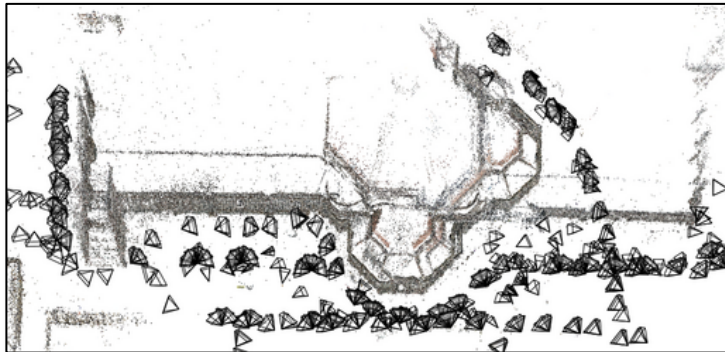
# Structure from Motion





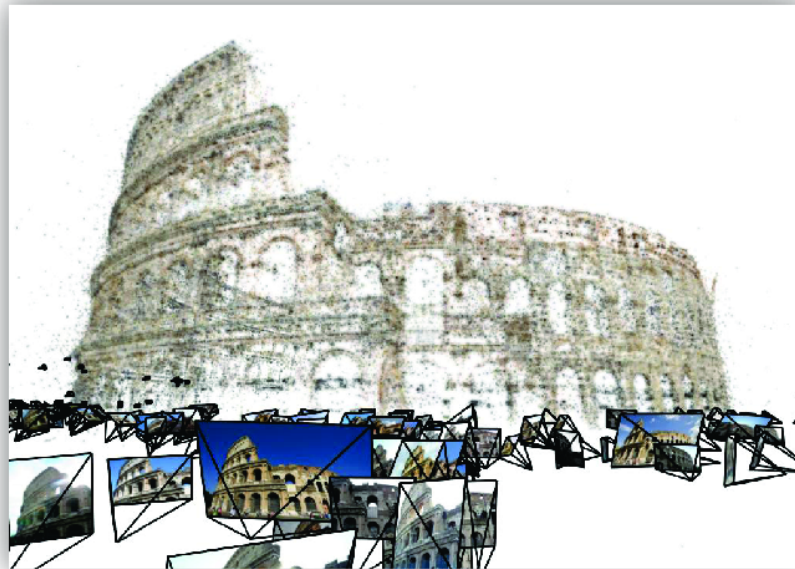
# Failure Cases

- Repetitive structures

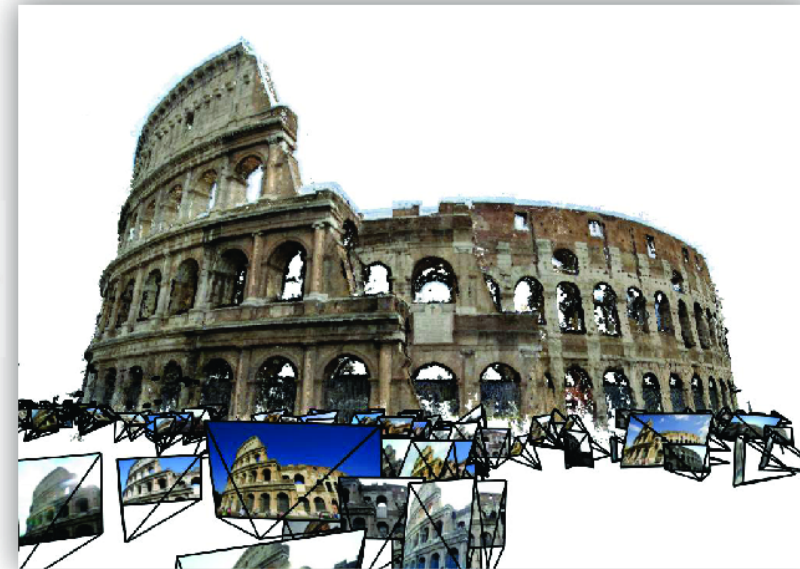


# Next Lecture

- Multi-view Stereo
  - Obtaining dense point clouds



Images + camera information



Dense 3d point cloud