Multiview Geometry

Reading: [AZ] Chapter: 4 “Estimation – 2D perspective transformations
Chapter: 9 “Epipolar Geometry and the Fundamental Matrix Transformation”
Chapter: 11 “Computation of the Fundamental Matrix F”
[FP] Chapter: 7 “Stereopsis”
Chapter: 8 “Structure from Motion”

Some slides in this lecture are courtesy to Prof. Silvio Savarese

Agenda

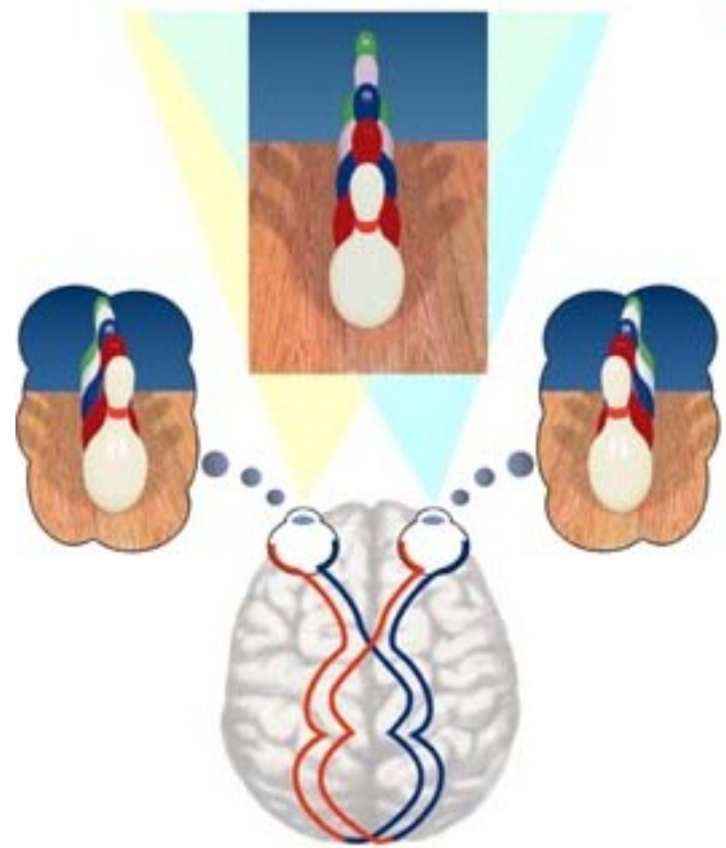
- Why is stereo useful?
- Epipolar constraints
- Fundamental matrix
- Estimating F

Recovering structure from a single view

Intrinsic ambiguity of the mapping from 3D to image (2D)

Courtesy slide S. Lazebnik

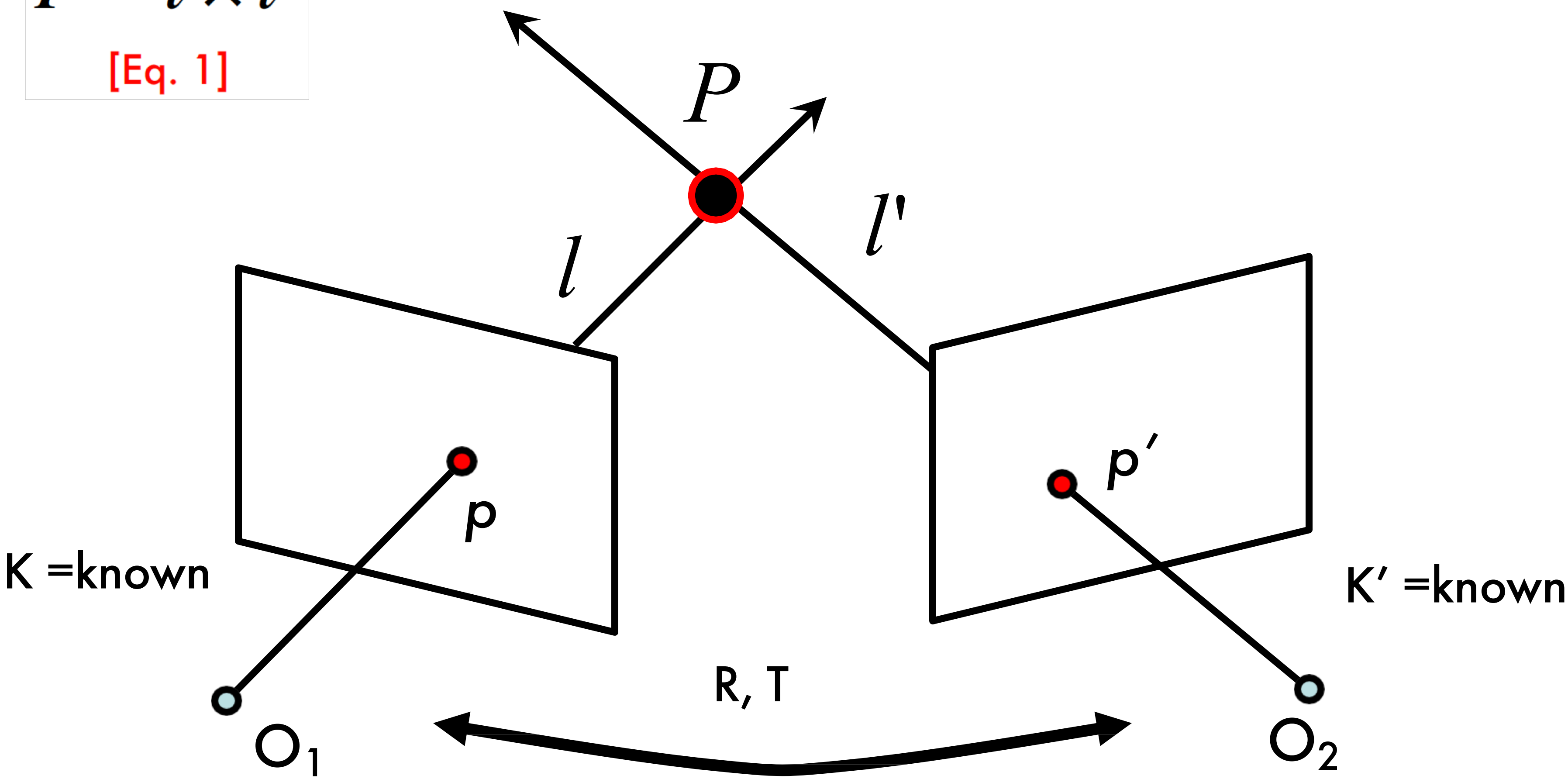
Two eyes help!



Two eyes help!

$$P = l \times l'$$

[Eq. 1]

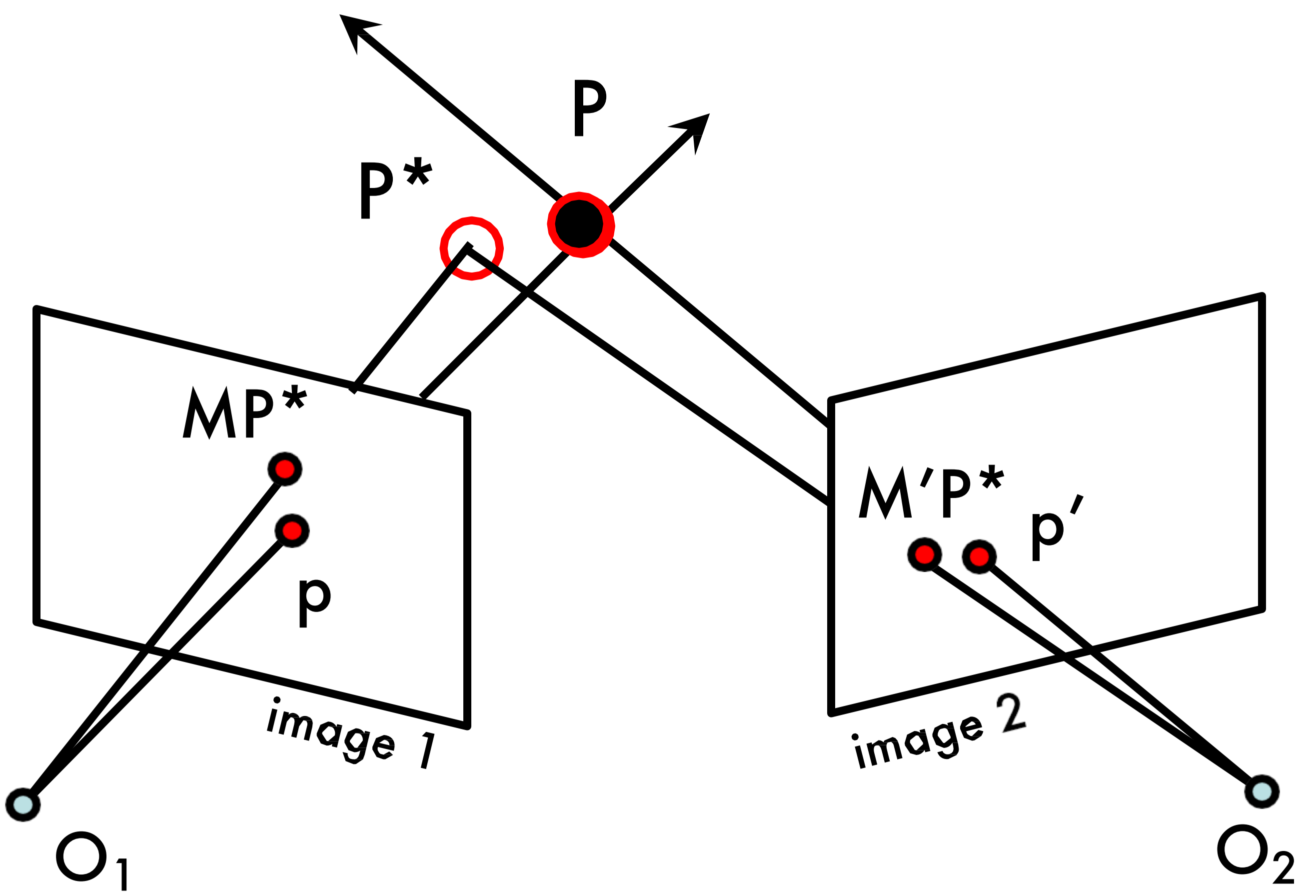


This is called triangulation

Triangulation

- Find P* that minimizes

$$d(p, M\ P^*) + d(p', M'P^*) \quad \text{[Eq. 2]}$$



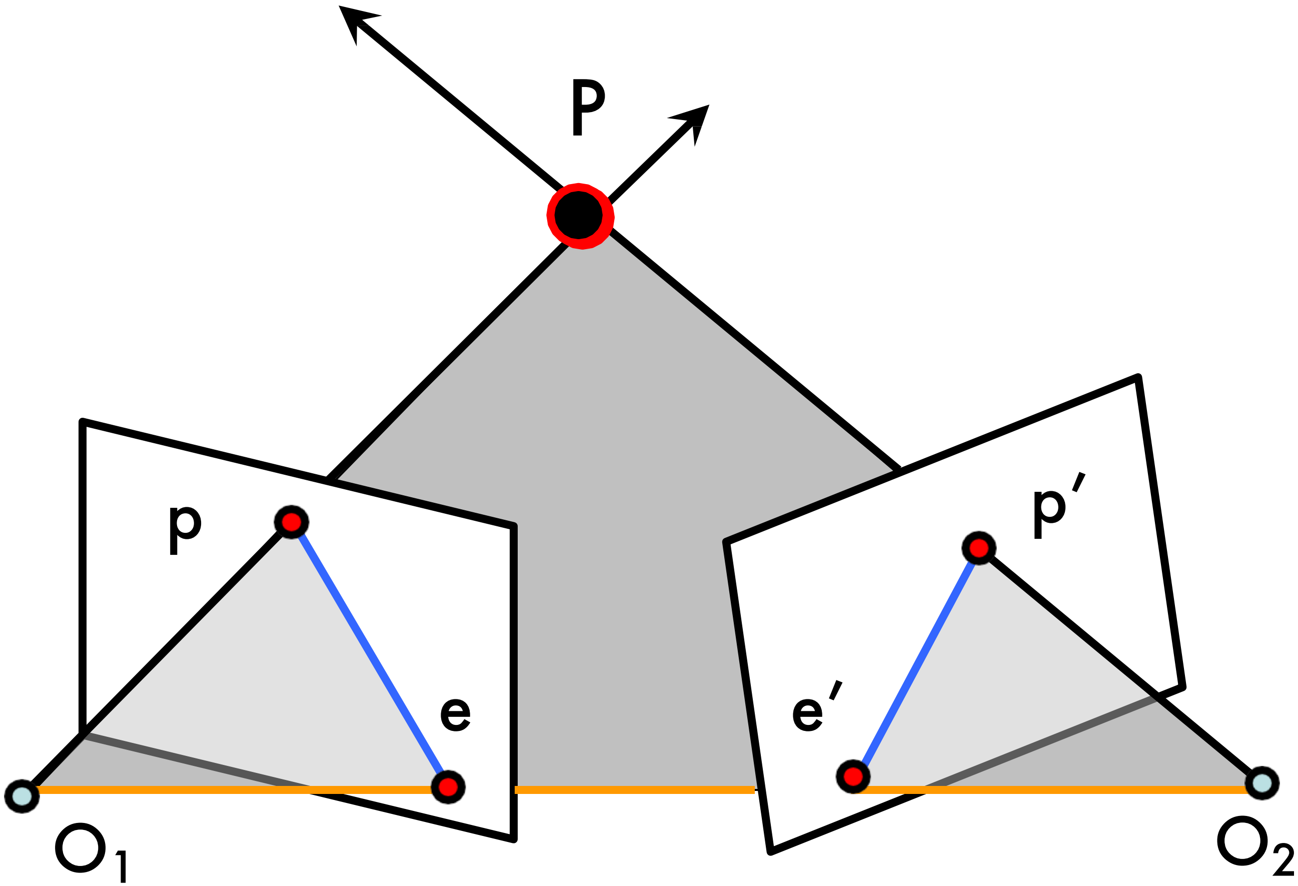
Multi (stereo)-view geometry

- **Camera geometry:** Given corresponding points in two images, find camera matrices, position and pose.
- **Scene geometry:** Find coordinates of 3D point from its projection into 2 or multiple images.
- **Correspondence:** Given a point p in one image, how can I find the corresponding point p’ in another one?

Agenda

- Why is stereo useful?
- **Epipolar constraints**
- Fundamental matrix
- Estimating F

Epipolar geometry

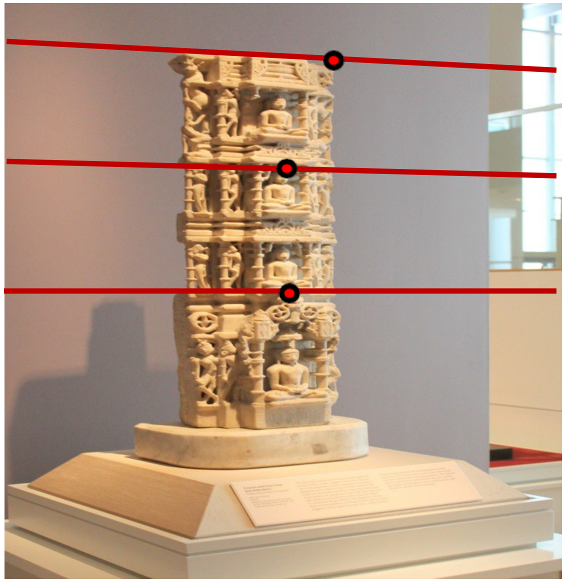


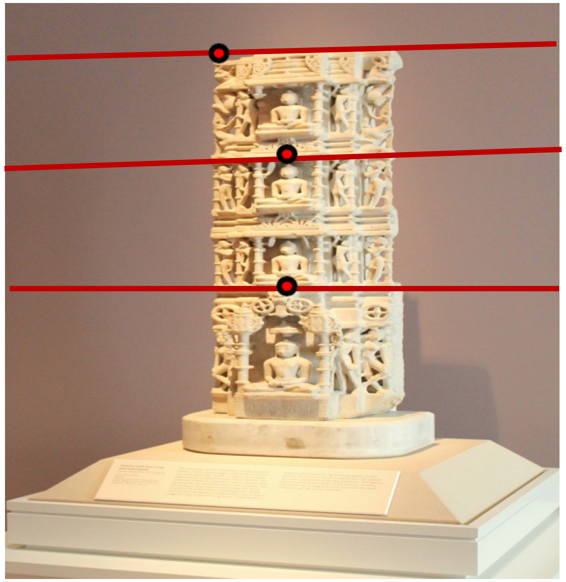
- Epipolar Plane
- Baseline
- Epipolar Lines
- Epipoles e, e′

  = intersections of baseline with image planes

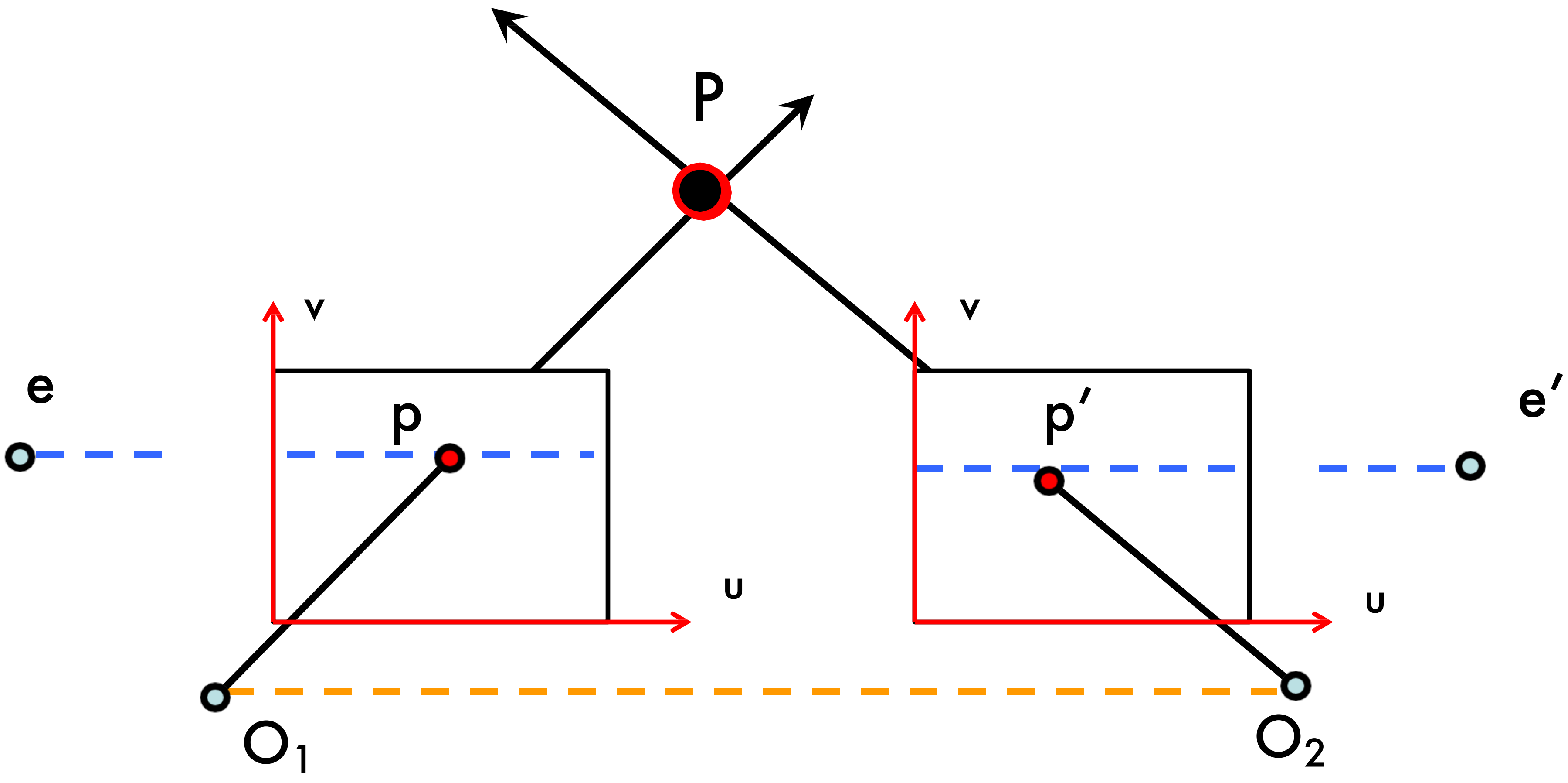
  = projections of the other camera center

Example of epipolar lines





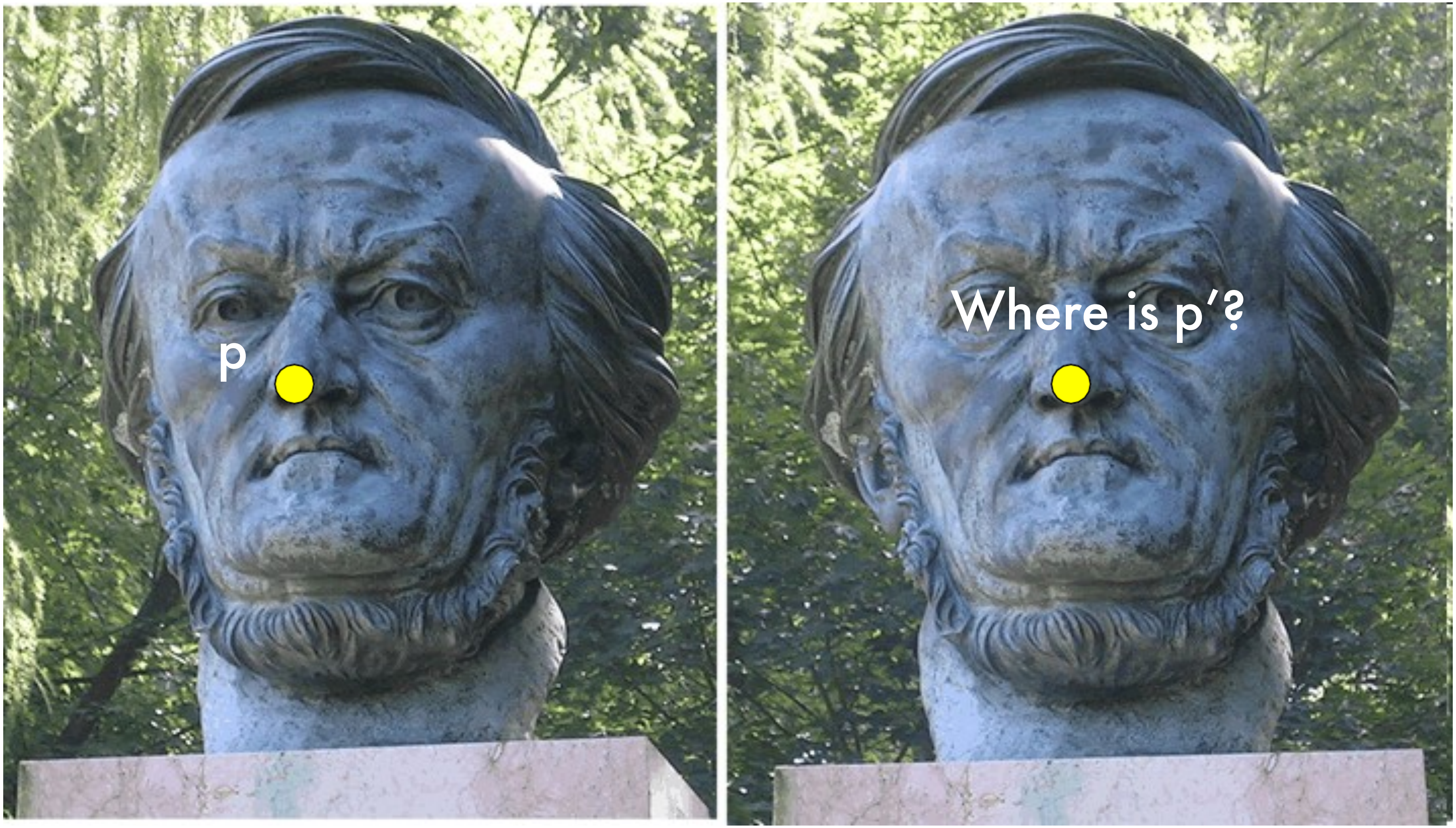
Example: Parallel image planes



- Baseline intersects the image plane at infinity
- Epipoles are at infinity
- Epipolar lines are parallel to u axis

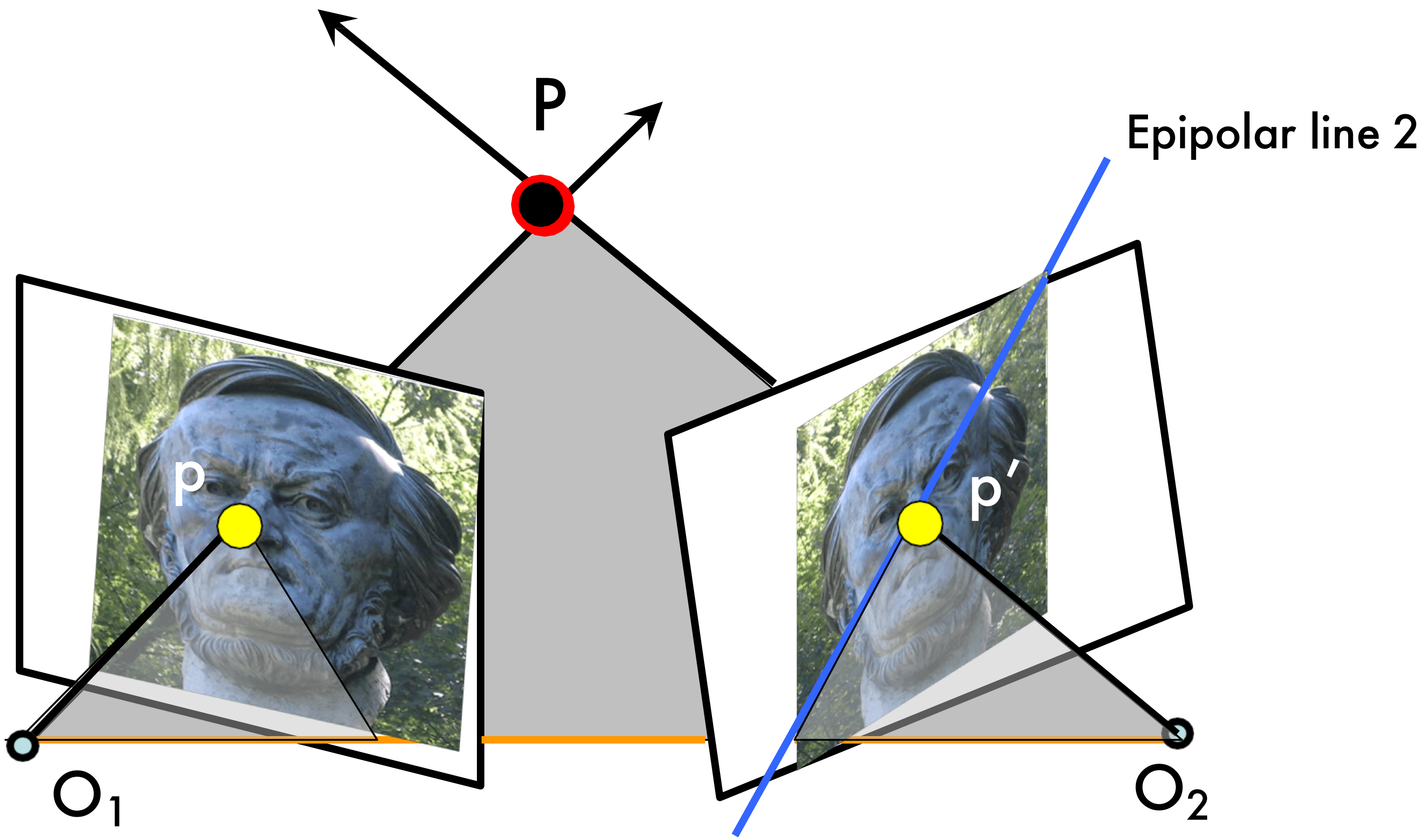
Example: Parallel Image Planes

Epipolar Constraint

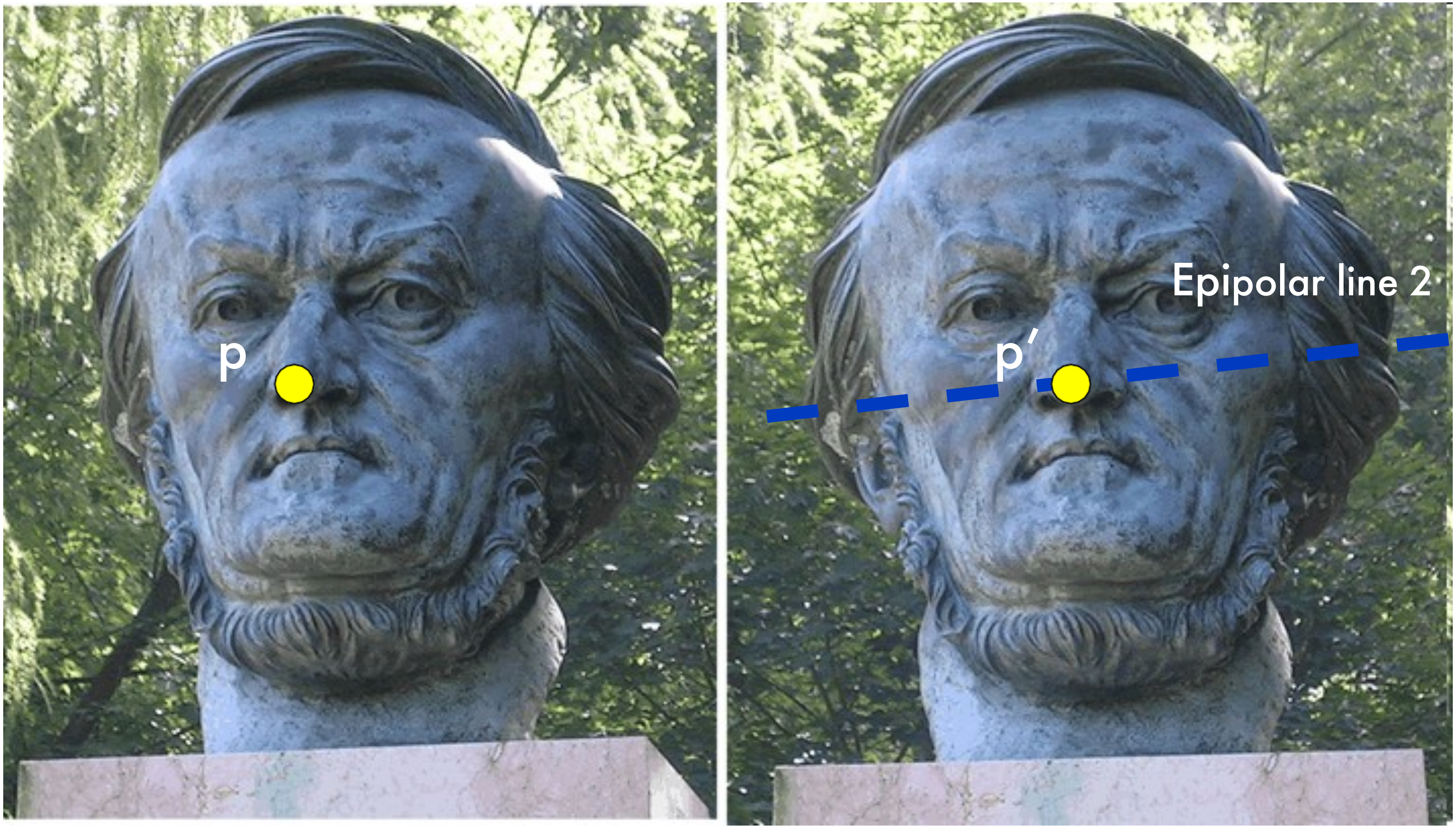


- Two views of the same object
- Given a point on left image, how can I find the corresponding point on right image?

Epipolar geometry

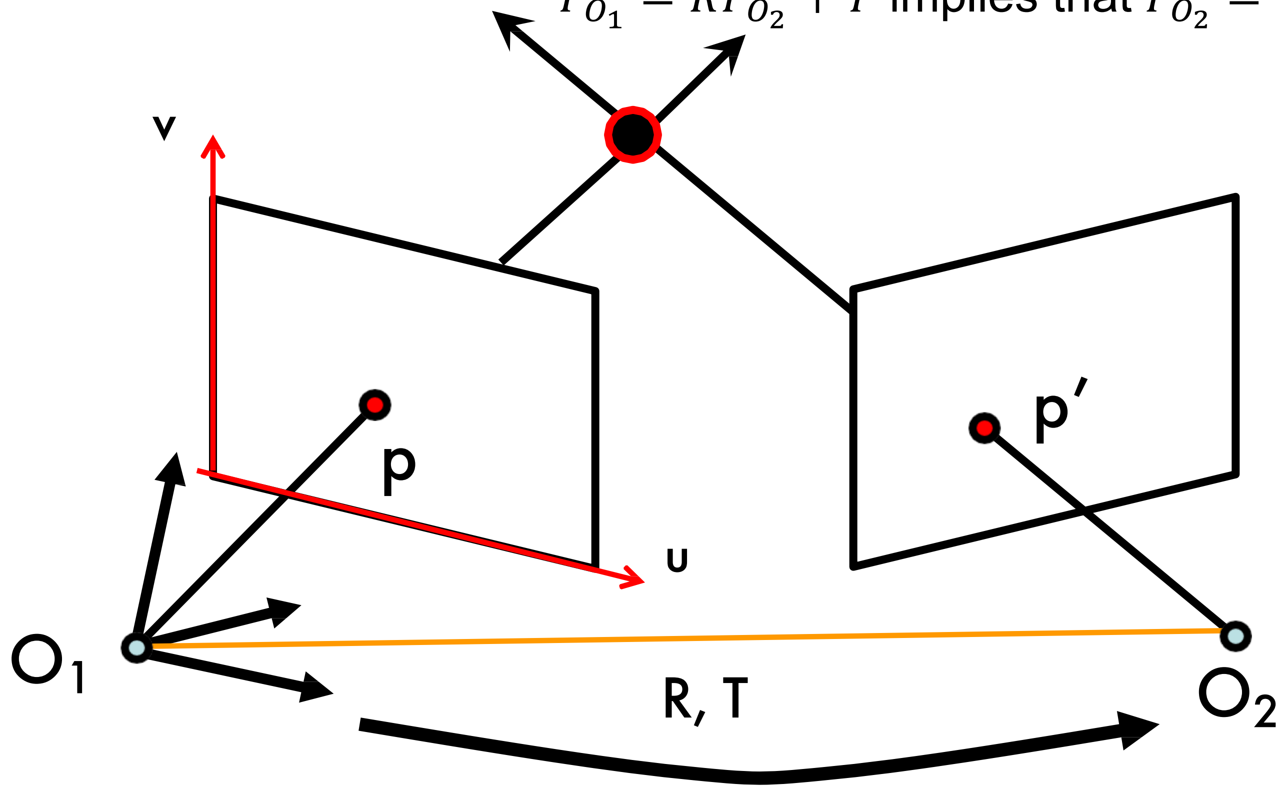


Epipolar Constraint



Epipolar Constraint

$P_{O_1} = RP_{O_2} + T$ implies that $P_{O_2} = [R^T, -R^T T] \begin{bmatrix} P_{O_1} \\ 1 \end{bmatrix}$



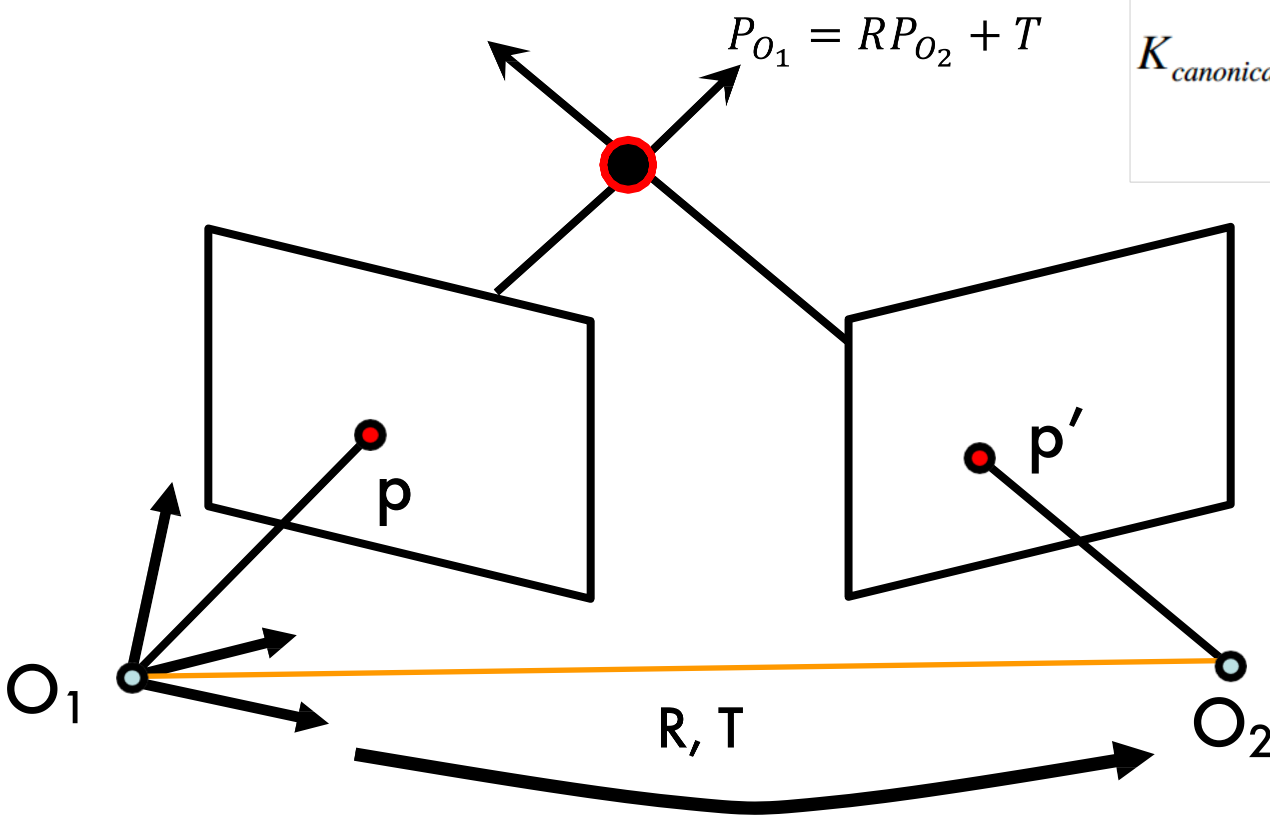
$$M = K\begin{bmatrix} I & 0 \end{bmatrix} \qquad M' = K'\begin{bmatrix} R^T & -R^T T \end{bmatrix}$$

$$M\,P = \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = p \quad \text{[Eq. 3]} \qquad M'\,P = \begin{bmatrix} u' \\ v' \\ 1 \end{bmatrix} = p' \quad \text{[Eq. 4]}$$

here, P means P_{O_1} here, P also means P_{O_1}

Epipolar Constraint

$$K_{canonical} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$



$$M = K\begin{bmatrix} I & 0 \end{bmatrix}$$

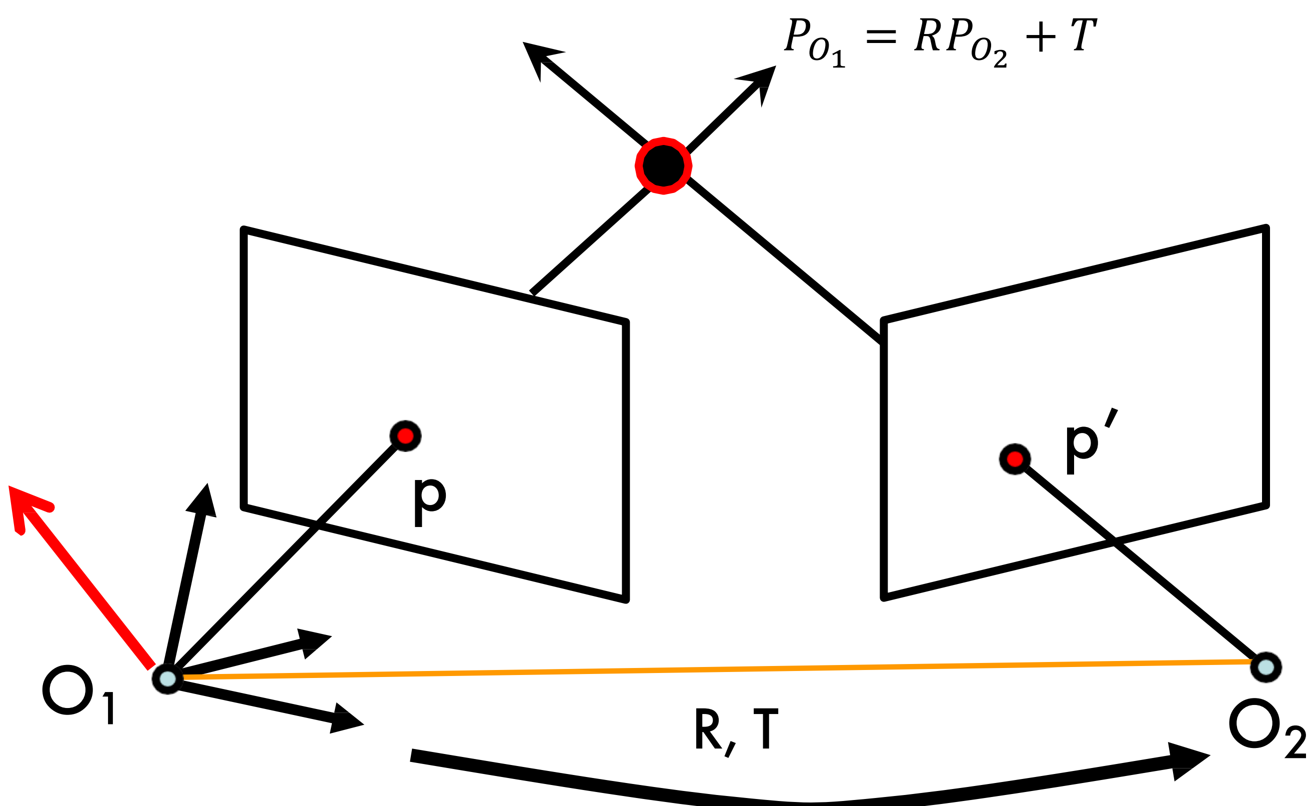
K = K′ are known
(canonical cameras)

$$M' = K'\begin{bmatrix} R^T & -R^T T \end{bmatrix}$$

$$M = \begin{bmatrix} I & 0 \end{bmatrix} \quad \text{[Eq. 5]}$$

$$M' = \begin{bmatrix} R^T & -R^T T \end{bmatrix} \quad \text{[Eq. 6]}$$

Epipolar Constraint



(actually, convert retina plane metric coordinate $\begin{bmatrix} x' \\ y' \end{bmatrix}$ in 2D as $\mathrm{p}' = \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix}$ in 3D with unit distance to O_2)

p′ in first camera reference system is $= R\,p' + T$

$T \times ((R\,p') + T) = T \times (R\,p')$ is perpendicular to epipolar plane

$$\rightarrow p^T \cdot [T \times (R\,p')] = 0 \quad \textbf{[Eq. 7]}$$

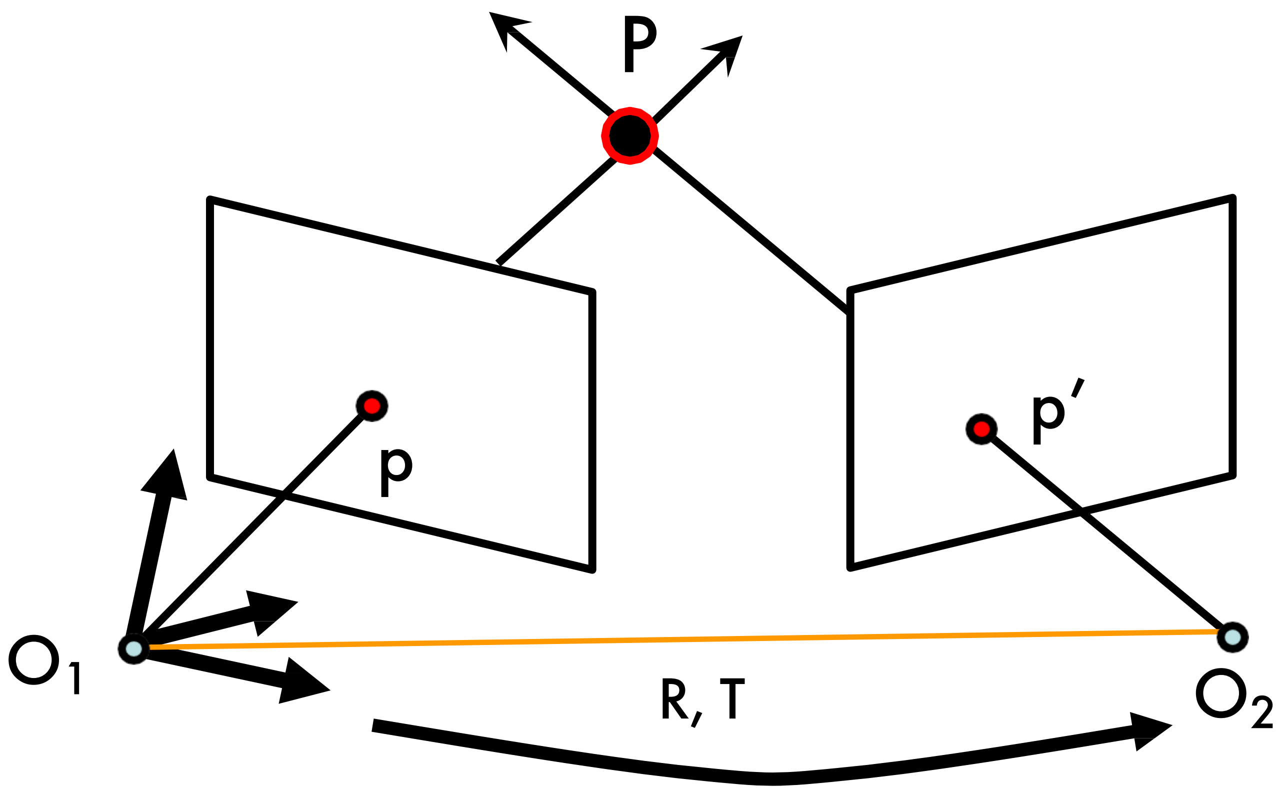
Cross product as matrix multiplication

$$\mathbf{a} \times \mathbf{b} = \begin{bmatrix} 0 & -a_z & a_y \\ a_z & 0 & -a_x \\ -a_y & a_x & 0 \end{bmatrix} \begin{bmatrix} b_x \\ b_y \\ b_z \end{bmatrix} = [\mathbf{a}_\times]\mathbf{b}$$

$$[a_\times] = -[a_\times]^T$$

"skew-symmetric matrix"

Epipolar Constraint



$$p^T \cdot \left[T \times (R\,p') \right] = 0 \rightarrow$$

[Eq. 8]

$$p^T \cdot \boxed{[T_\times] \cdot R}\; p' = 0$$

[Eq. 9]

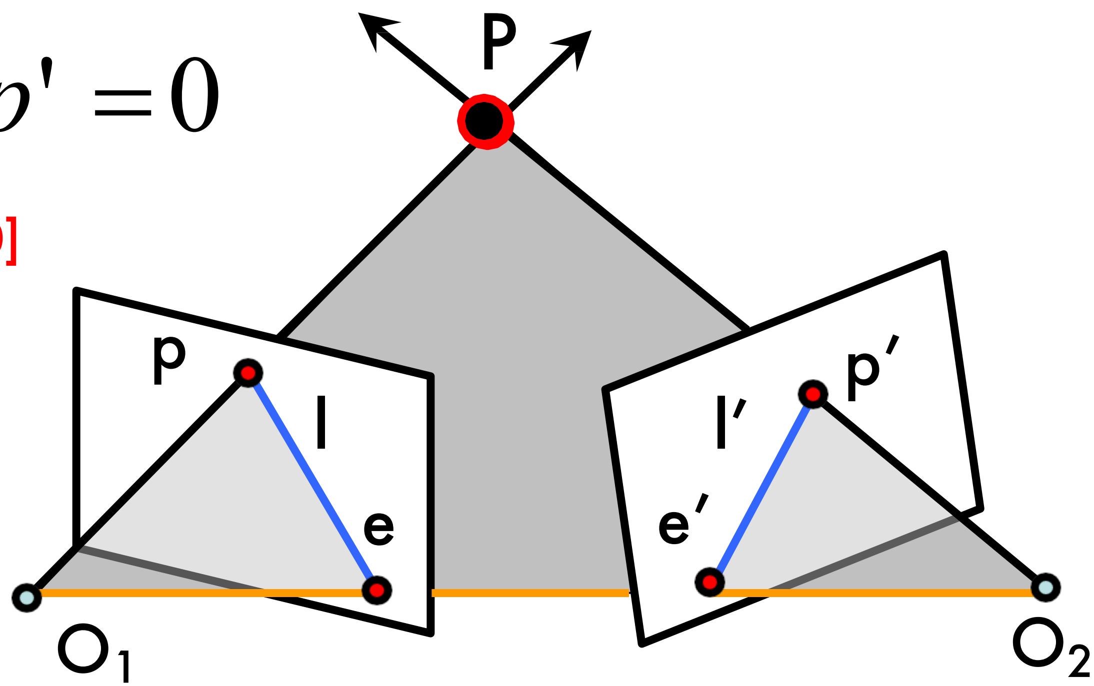
E = Essential matrix

(Longuet-Higgins, 1981)

Epipolar Constraint

$$p^T \cdot E\, p' = 0$$

[Eq. 10]

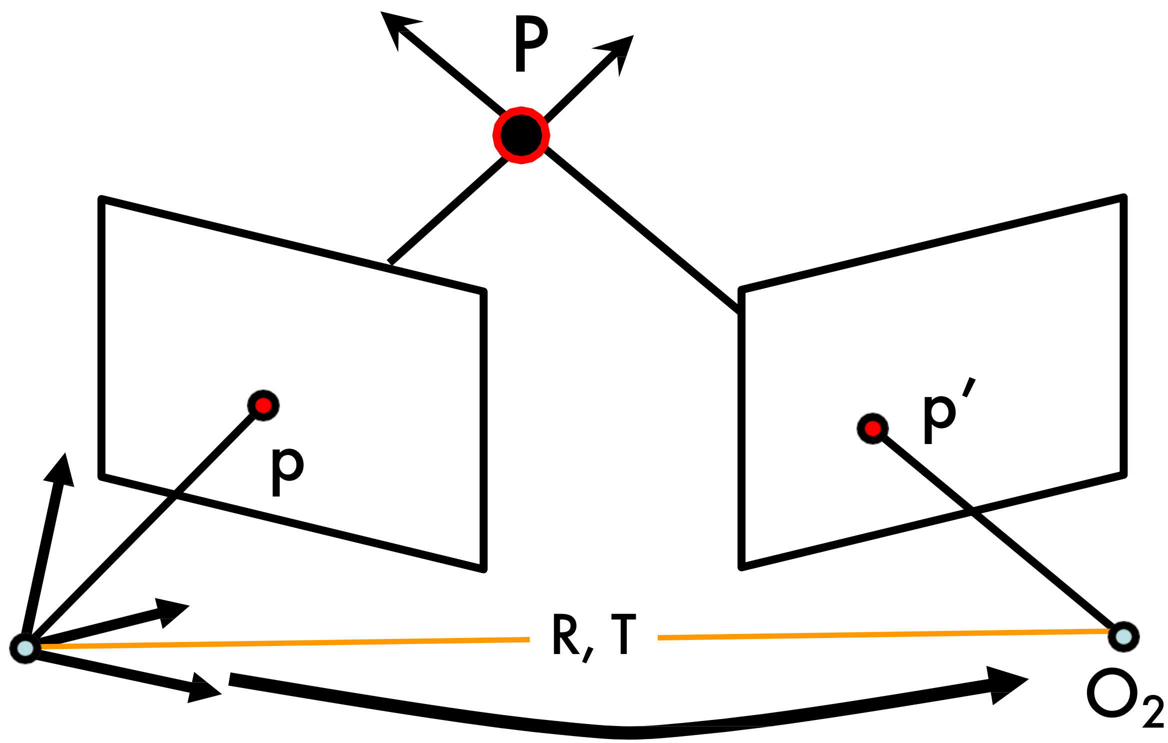


- l = E p′ is the epipolar line associated with p′
- l′ = E^T p is the epipolar line associated with p
- E e′ = 0 and E^T e = 0
- E is 3x3 matrix; 5 DOF
- E is singular (rank two)

Agenda

- Why is stereo useful?
- Epipolar constraints
- **Fundamental matrix**
- Estimating F

Epipolar Constraint



$$M = K\begin{bmatrix} I & 0 \end{bmatrix} \qquad M' = K'\begin{bmatrix} R^T & -R^T T \end{bmatrix}$$

"ideal" camera

$$p_c = K^{-1}\, p \quad \text{[Eq. 11]} \qquad p'_c = K'^{-1}\, p' \quad \text{[Eq. 12]}$$

Goal: Cancel the adjustment made by K which was to accommodate the device

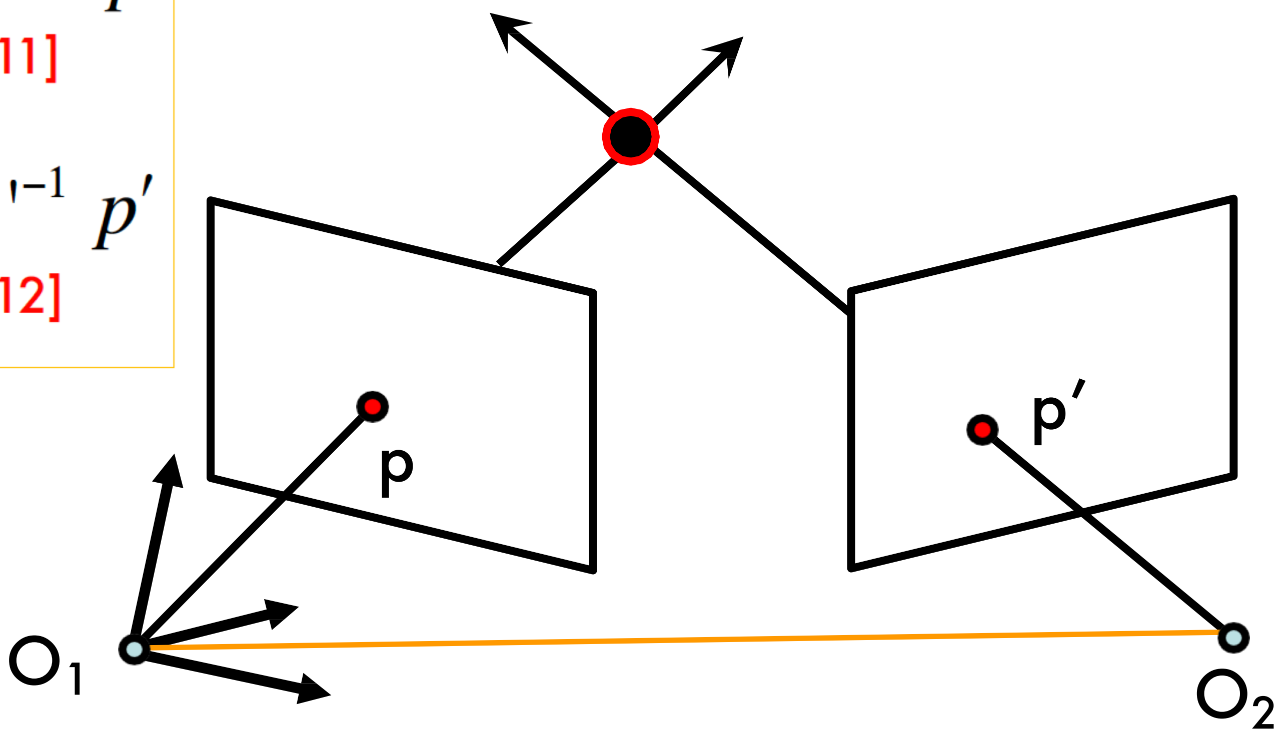
Epipolar Constraint

$$p_c = K^{-1}\ p$$

[Eq. 11]

$$p_c' = K'^{-1}\ p'$$

[Eq. 12]



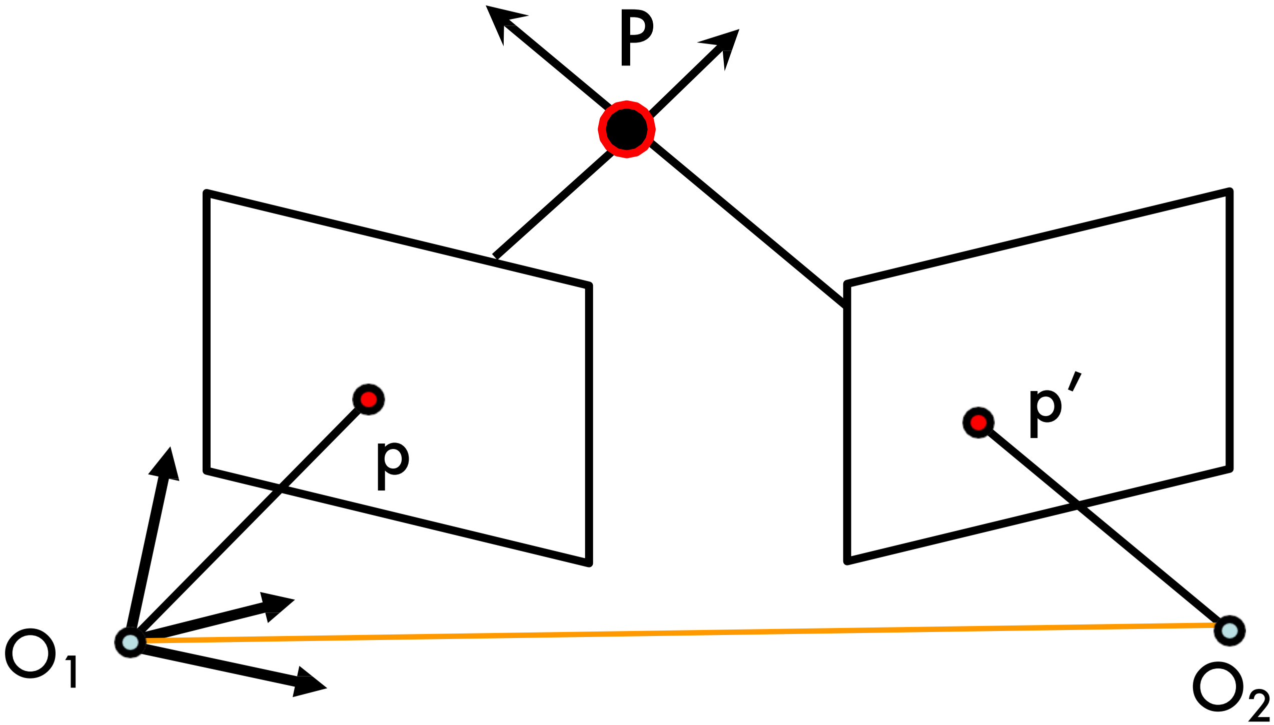
[Eq.9]

$$p_c^T \cdot [T_\times] \cdot R\ p_c' = 0 \rightarrow (\mathrm{K}^{-1}\ \mathrm{p})^{\mathrm{T}} \cdot [\mathrm{T}_\times] \cdot \mathrm{R}\ \mathrm{K}'^{-1}\ \mathrm{p}' = 0$$

$$\mathrm{p}^{\mathrm{T}}\ \boxed{\mathrm{K}^{-\mathrm{T}} \cdot [\mathrm{T}_\times] \cdot \mathrm{R}\ \mathrm{K}'^{-1}}\ \mathrm{p}' = 0 \rightarrow \mathrm{p}^{\mathrm{T}}\ \boxed{\mathrm{F}}\ \mathrm{p}' = 0$$

[Eq. 13]

Epipolar Constraint



[Eq. 13] $$\boxed{\mathrm{p}^{\mathrm{T}}\,\mathrm{F}\,\mathrm{p}' = 0}$$

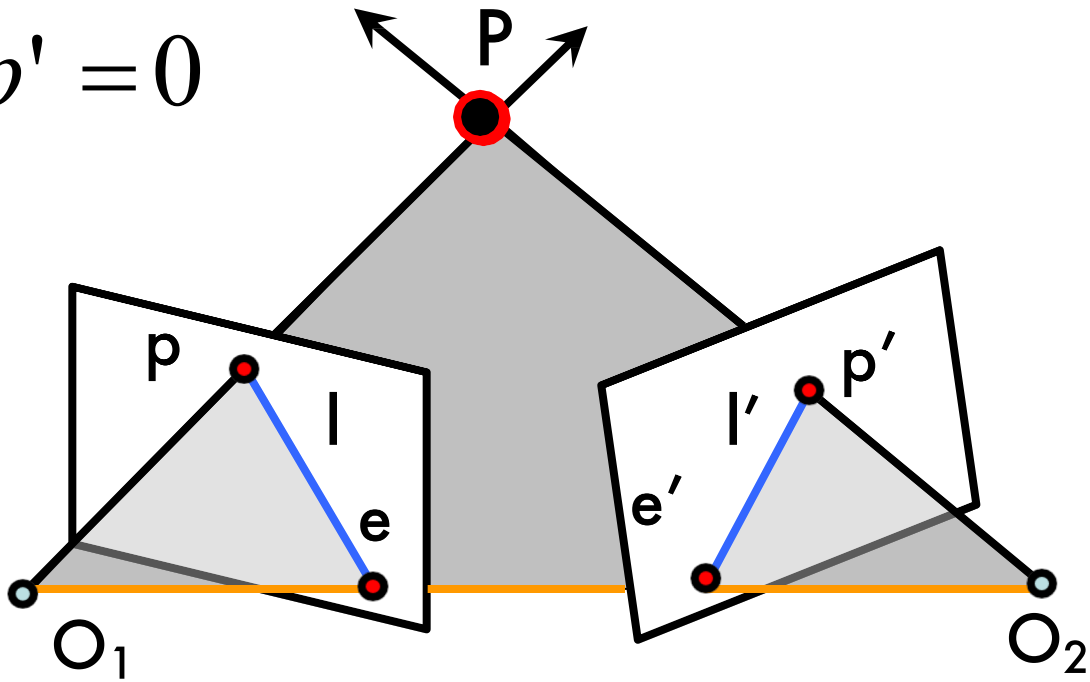
$$F = K^{-T} \cdot [T_{\times}] \cdot R\, K'^{-1}$$

[Eq. 14]

F = Fundamental Matrix
(Faugeras and Luong, 1992)

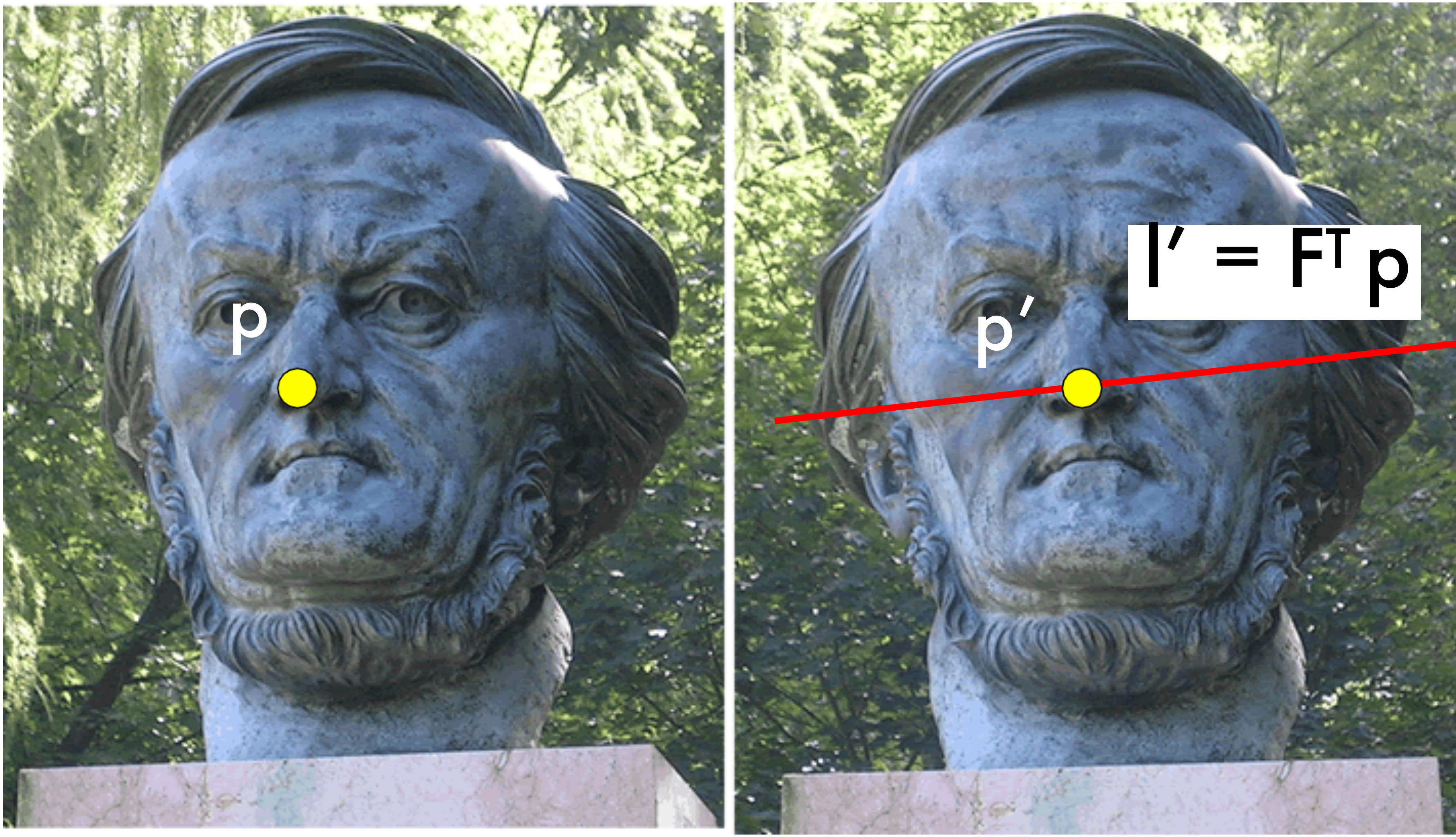
Epipolar Constraint

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



- $l = F\,p'$ is the epipolar line associated with p'
- $l' = F^T p$ is the epipolar line associated with p
- $F\,e' = 0$ and $F^T e = 0$
- F is 3x3 matrix; 7 DOF
- F is singular (rank two)

Why F is useful?



- Suppose F is known
- No additional information about the scene and camera is given
- Given a point on left image, we can compute the corresponding epipolar line in the second image

Why F is useful?

- F captures information about the epipolar geometry of 2 views + camera parameters

- MORE IMPORTANTLY: F gives constraints on how the scene changes under view point transformation (without reconstructing the scene!)

- Powerful tool in:
    - 3D reconstruction
    - Multi-view object/scene matching

Agenda

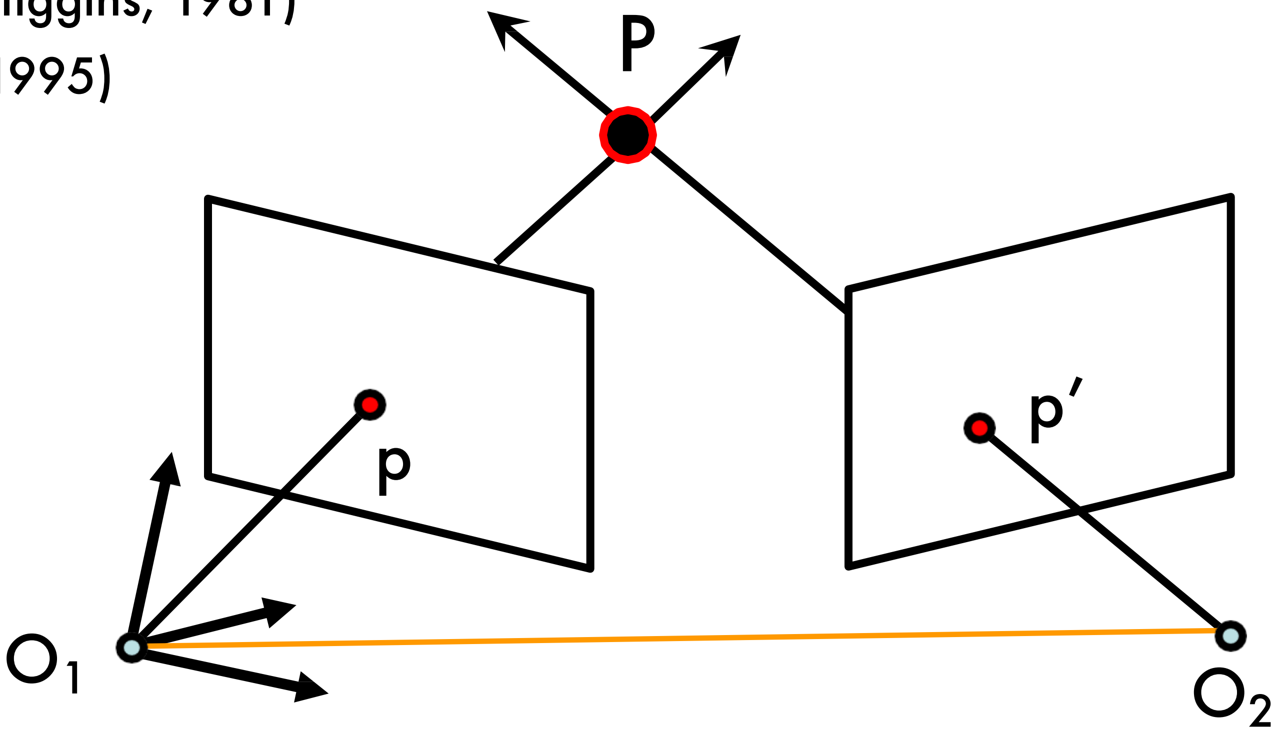
- Why is stereo useful?
- Epipolar constraints
- Fundamental matrix
- **Estimating F**

Estimating F

The Eight-Point Algorithm

(Longuet-Higgins, 1981)

(Hartley, 1995)



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

Estimating F

[Eq. 13] $\mathrm{p}^{\mathrm{T}}\,\mathrm{F}\,\mathrm{p}' = 0$ ➡

$$p = \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \quad p' = \begin{bmatrix} u' \\ v' \\ 1 \end{bmatrix}$$

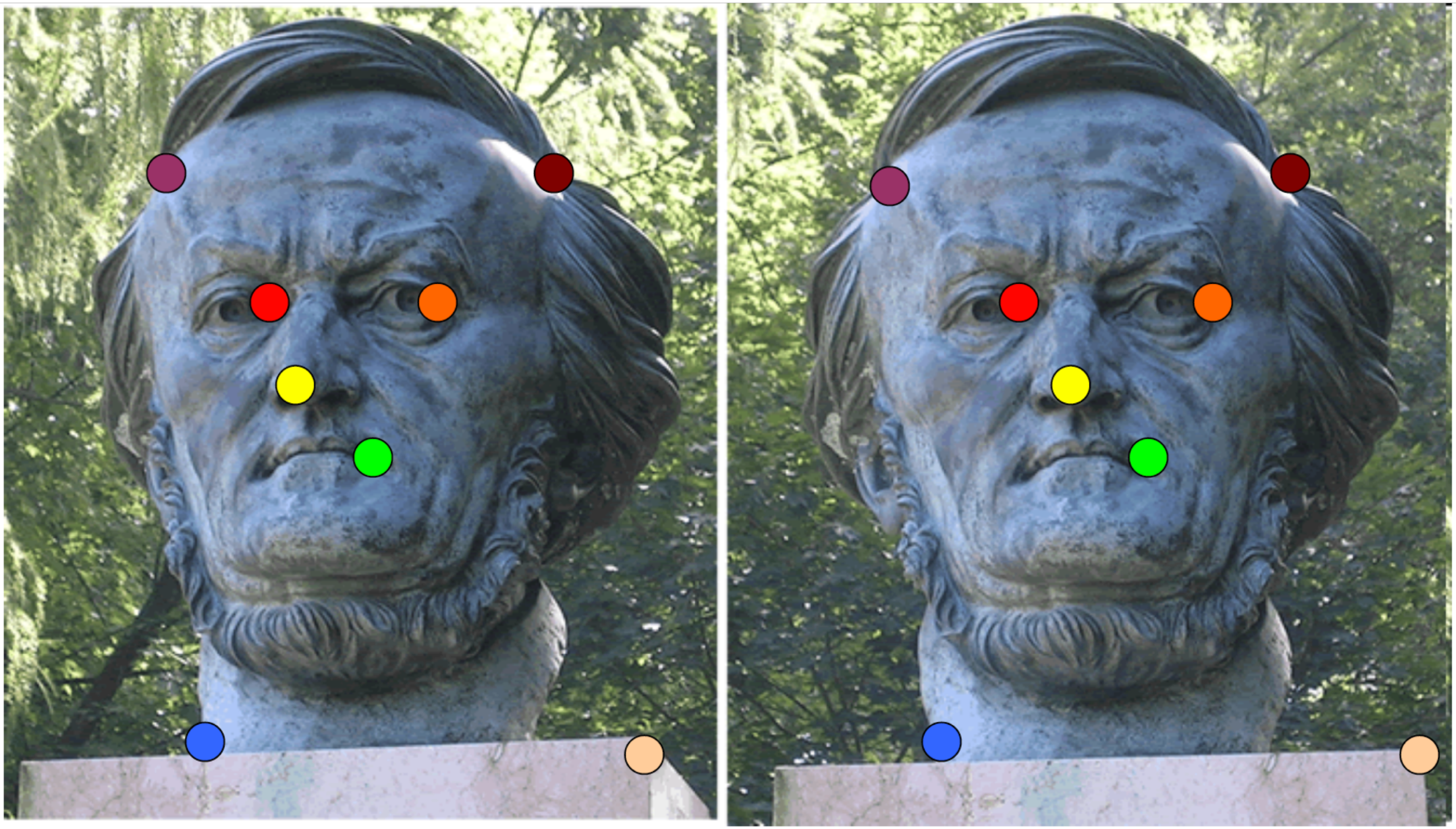
$$(u, v, 1)\begin{pmatrix} F_{11} & F_{12} & F_{13} \\ F_{21} & F_{22} & F_{23} \\ F_{31} & F_{32} & F_{33} \end{pmatrix}\begin{pmatrix} u' \\ v' \\ 1 \end{pmatrix} = 0$$

➡ $$(uu', uv', u, vu', vv', v, u', v', 1)\begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix} = 0$$

[Eq. 14]

Let's take 8 corresponding points

Estimating F



Estimating F

$$\left(u_i u'_i, u_i v'_i, u_i, v_i u'_i, v_i v'_i, v_i, u'_i, v_i', 1\right)\begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix} = 0 \qquad \text{[Eq. 14]}$$

Estimating F

$$\underbrace{\begin{pmatrix} u_1u'_1 & u_1v'_1 & u_1 & v_1u'_1 & v_1v'_1 & v_1 & u'_1 & v'_1 & 1 \\ u_2u'_2 & u_2v'_2 & u_2 & v_2u'_2 & v_2v'_2 & v_2 & u'_2 & v'_2 & 1 \\ u_3u'_3 & u_3v'_3 & u_3 & v_3u'_3 & v_3v'_3 & v_3 & u'_3 & v'_3 & 1 \\ u_4u'_4 & u_4v'_4 & u_4 & v_4u'_4 & v_4v'_4 & v_4 & u'_4 & v'_4 & 1 \\ u_5u'_5 & u_5v'_5 & u_5 & v_5u'_5 & v_5v'_5 & v_5 & u'_5 & v'_5 & 1 \\ u_6u'_6 & u_6v'_6 & u_6 & v_6u'_6 & v_6v'_6 & v_6 & u'_6 & v'_6 & 1 \\ u_7u'_7 & u_7v'_7 & u_7 & v_7u'_7 & v_7v'_7 & v_7 & u'_7 & v'_7 & 1 \\ u_8u'_8 & u_8v'_8 & u_8 & v_8u'_8 & v_8v'_8 & v_8 & u'_8 & v'_8 & 1 \end{pmatrix}}_{\mathbf{W}} \underbrace{\begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix}}_{\mathbf{f}} = 0$$

[Eqs. 15]

- Homogeneous system $\mathbf{W}\,\mathbf{f} = 0$
- Rank 8 $\longrightarrow$ A non-zero solution exists (unique)
- If N>8 $\longrightarrow$ Lsq. solution by SVD! $\longrightarrow \hat{\mathrm{F}}$

  $\|\mathbf{f}\| = 1$

$\hat{F}$ satisfies: $p^T \hat{F} p' = 0$

and estimated $\hat{F}$ may have full rank ($\det(\hat{F}) \neq 0$)

But remember: fundamental matrix is Rank2

Find F that minimizes $\|F - \hat{F}\| = 0$

Frobenius norm (*)

Subject to rank(F)=2

SVD (again!) can be used to solve this problem

(*) Sq. root of the sum of squares of all entries

Find F that minimizes $\left\|F - \hat{F}\right\| = 0$

Frobenius norm (*)

Subject to det(F)=0

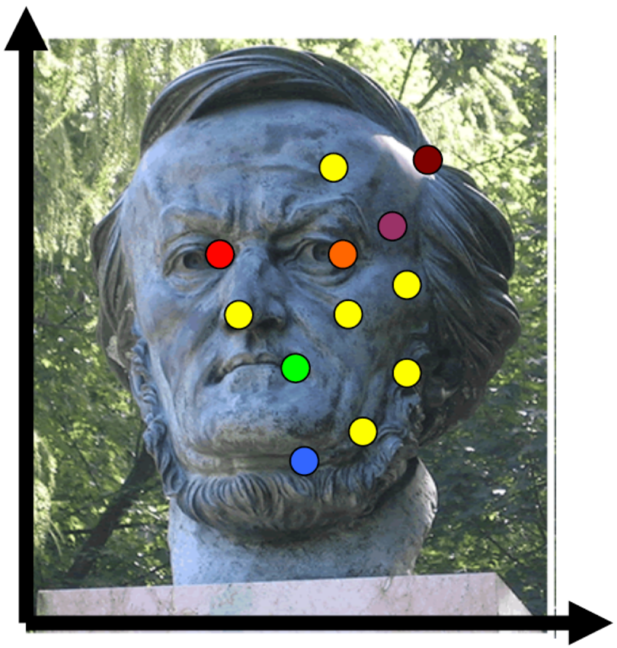
$$F = U\begin{bmatrix} s_1 & 0 & 0 \\ 0 & s_2 & 0 \\ 0 & 0 & 0 \end{bmatrix}V^T$$

Where:

$$U\begin{bmatrix} s_1 & 0 & 0 \\ 0 & s_2 & 0 \\ 0 & 0 & s_3 \end{bmatrix}V^T = SVD(\hat{F})$$

[HZ] pag 281, chapter 11, "Computation of F"

Problems with the 8-Point Algorithm



$$\mathbf{W}\,\mathbf{f} = 0,$$
$$\|\mathbf{f}\| = 1$$

$$\xrightarrow{\text{Lsq solution by SVD}} \mathrm{F}$$

- Recall the structure of W:
  - do we see any potential (numerical) issue?

Problems with the 8-Point Algorithm

$$\mathbf{W}\mathbf{f} = 0$$

$$\begin{pmatrix} u_1u'_1 & u_1v'_1 & u_1 & v_1u'_1 & v_1v'_1 & v_1 & u'_1 & v'_1 & 1 \\ u_2u'_2 & u_2v'_2 & u_2 & v_2u'_2 & v_2v'_2 & v_2 & u'_2 & v'_2 & 1 \\ u_3u'_3 & u_3v'_3 & u_3 & v_3u'_3 & v_3v'_3 & v_3 & u'_3 & v'_3 & 1 \\ u_4u'_4 & u_4v'_4 & u_4 & v_4u'_4 & v_4v'_4 & v_4 & u'_4 & v'_4 & 1 \\ u_5u'_5 & u_5v'_5 & u_5 & v_5u'_5 & v_5v'_5 & v_5 & u'_5 & v'_5 & 1 \\ u_6u'_6 & u_6v'_6 & u_6 & v_6u'_6 & v_6v'_6 & v_6 & u'_6 & v'_6 & 1 \\ u_7u'_7 & u_7v'_7 & u_7 & v_7u'_7 & v_7v'_7 & v_7 & u'_7 & v'_7 & 1 \\ u_8u'_8 & u_8v'_8 & u_8 & v_8u'_8 & v_8v'_8 & v_8 & u'_8 & v'_8 & 1 \end{pmatrix} \begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix} = 0$$

- Highly un-balanced (not well conditioned)
- Values of W must have similar magnitude
- This creates problems during the SVD decomposition

HZ pag 108

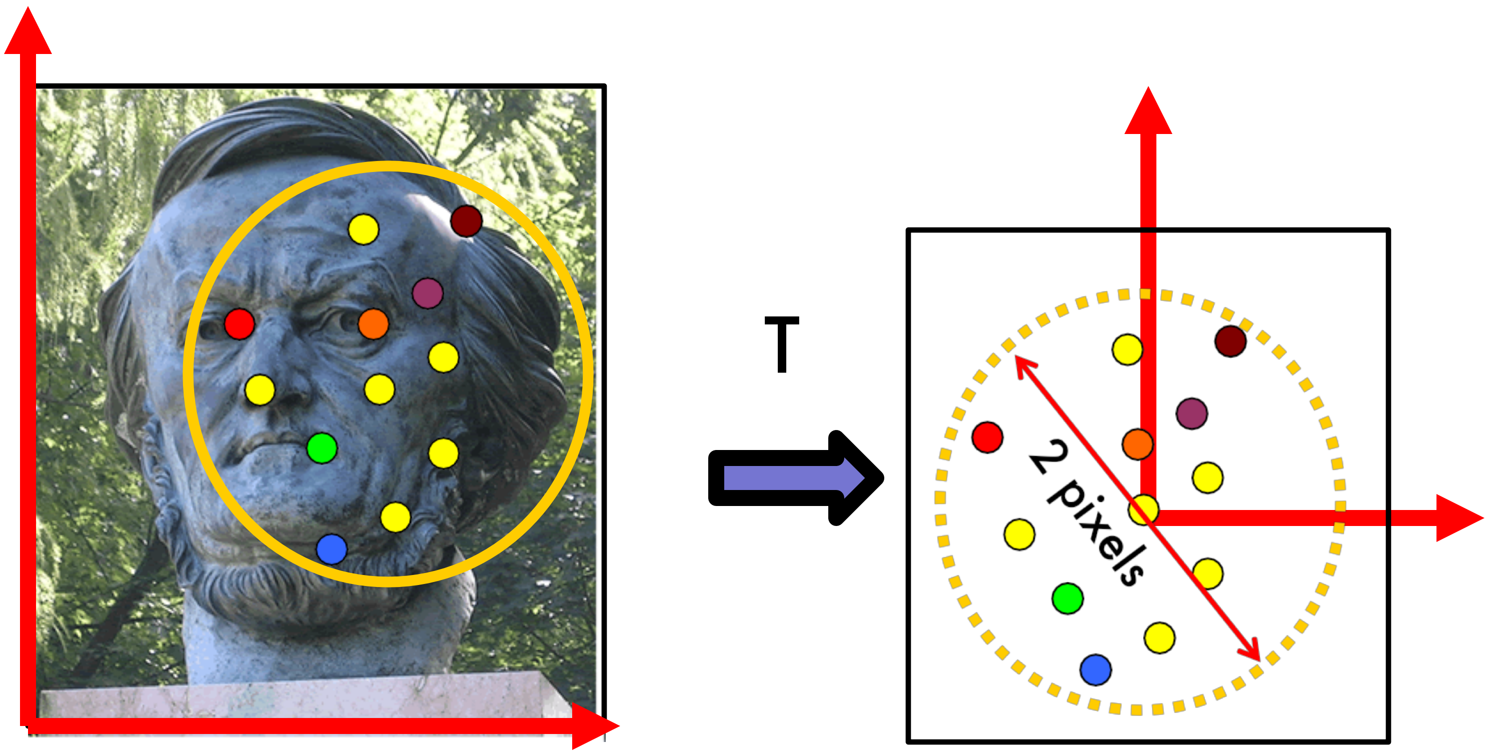
Normalization

IDEA: Transform image coordinates such that the matrix W becomes better conditioned **(pre-conditioning)**

For each image, apply a transformation T (translation and scaling) acting on image coordinates such that:

- Origin = centroid of image points
- Mean square distance of the image points from origin is ~2 pixels

Example of normalization

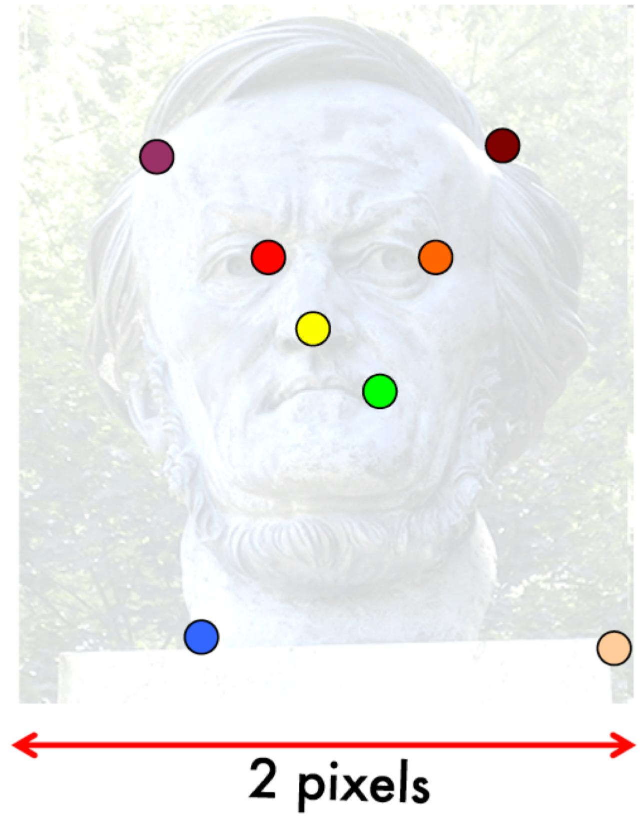


Coordinate system of the image before applying T

Coordinate system of the image after applying T

- Origin = centroid of image points
- Mean square distance of the image points from origin is ~2 pixels

Normalization



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

The Normalized Eight-Point Algorithm

1. Compute T and T′ for image 1 and 2, respectively
2. Normalize coordinates in images 1 and 2:

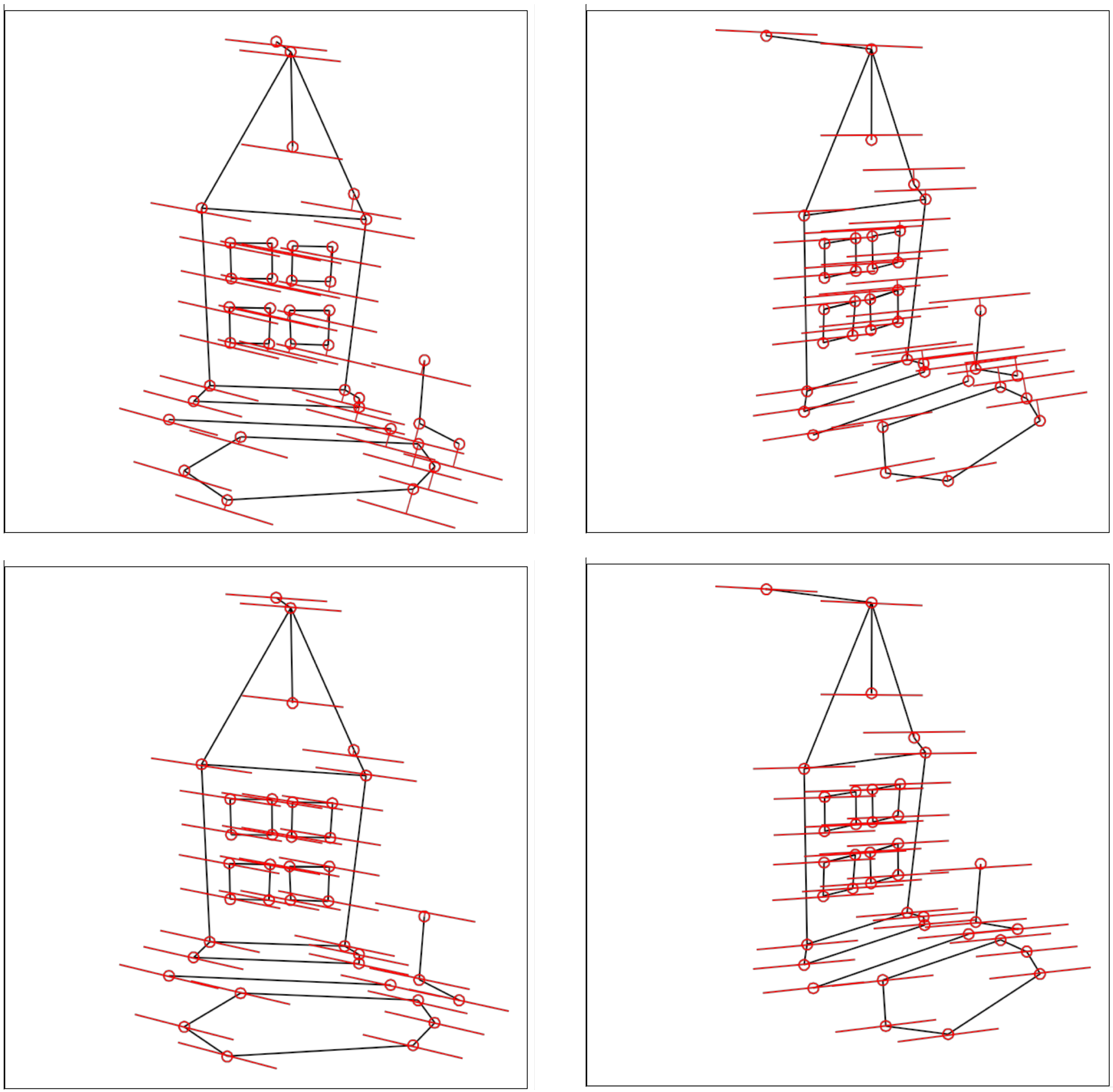
$$q_i = T\ p_i \qquad q_i' = T'\ p_i'$$

2. Use the eight-point algorithm to compute $\hat{F}_q$ from the corresponding points q_i and q_i' .

1. Enforce the rank-2 constraint: $\rightarrow \mathrm{F_q}$ such that:

$$\begin{cases} \mathrm{q^T F_q\ q' = 0} \\ \mathrm{det(F_q) = 0} \end{cases}$$

2. De-normalize F_q: $F = T^T F_q\ T'$



Without normalization

Mean errors:
10.0pixel
9.1pixel

With normalization

Mean errors:
1.0pixel
0.9pixel