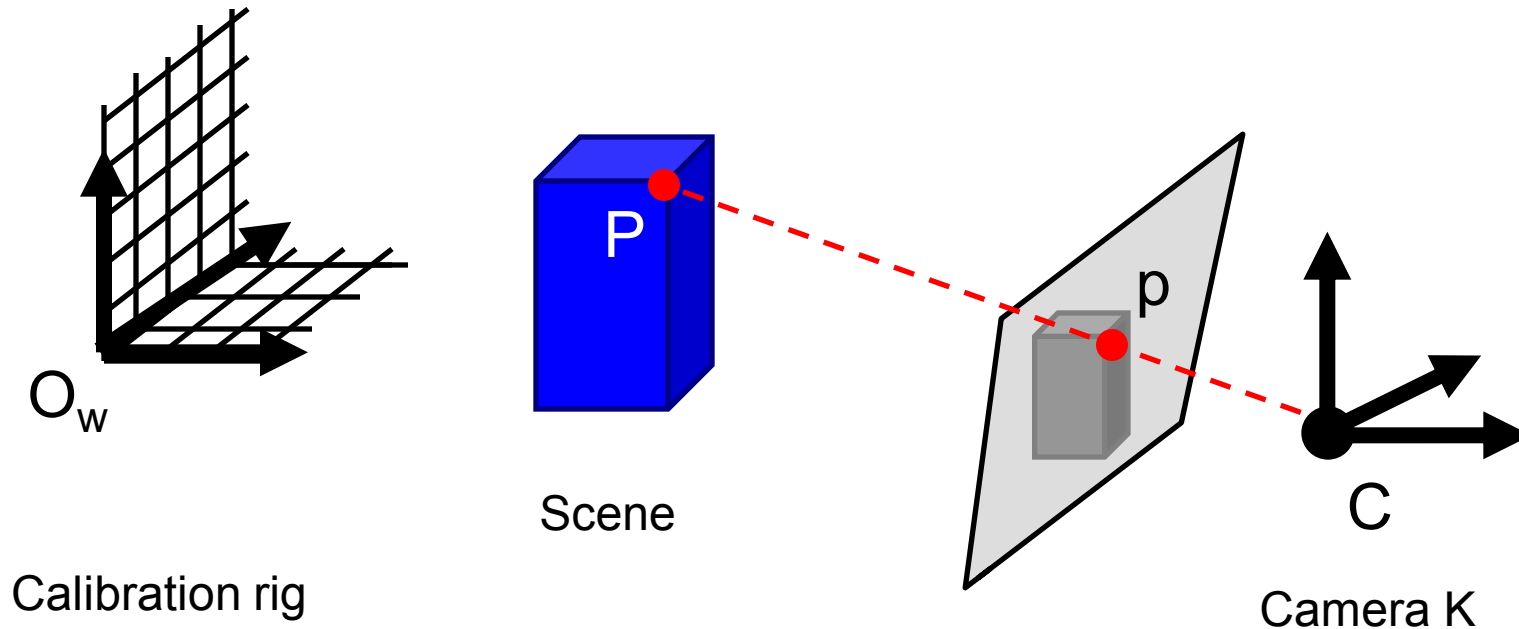


# EPIPOLAR GEOMETRY

The slides are from several sources through James Hays (Brown);  
Silvio Savarese (U. of Michigan); Svetlana Lazebnik (U. Illinois);  
Bill Freeman and Antonio Torralba (MIT), including their own slides.

# Recovering structure from a single view



Why is it so difficult?

Intrinsic ambiguity of the mapping from 3D to image in 2D.

see example...

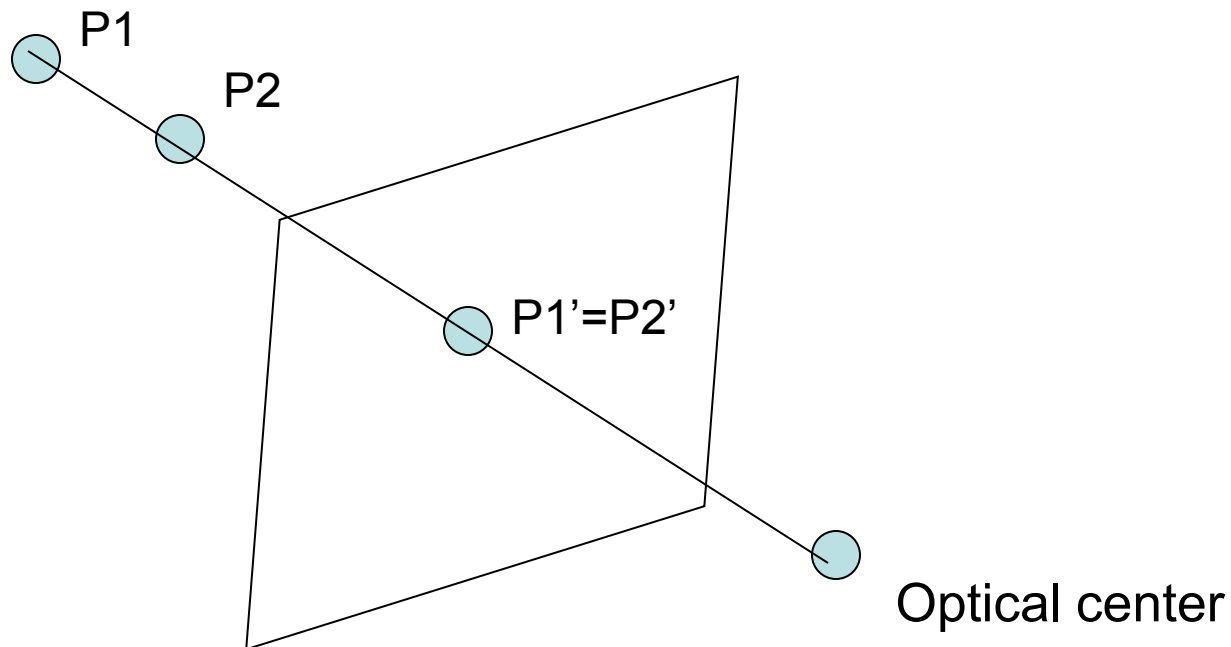
Is this an illusion of 3D to 2D?



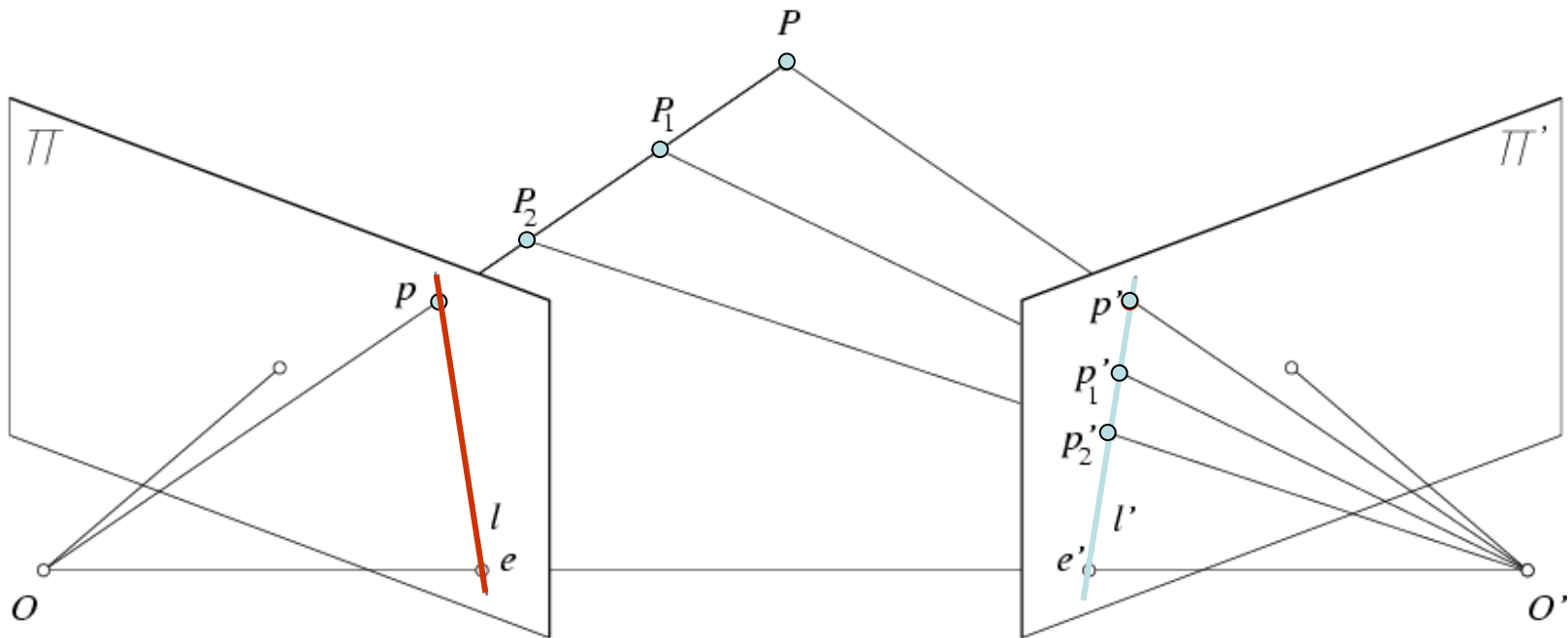
Courtesy slide S. Lazebnik

# Why multiple views?

- Structure and depth are inherently ambiguous from single views.



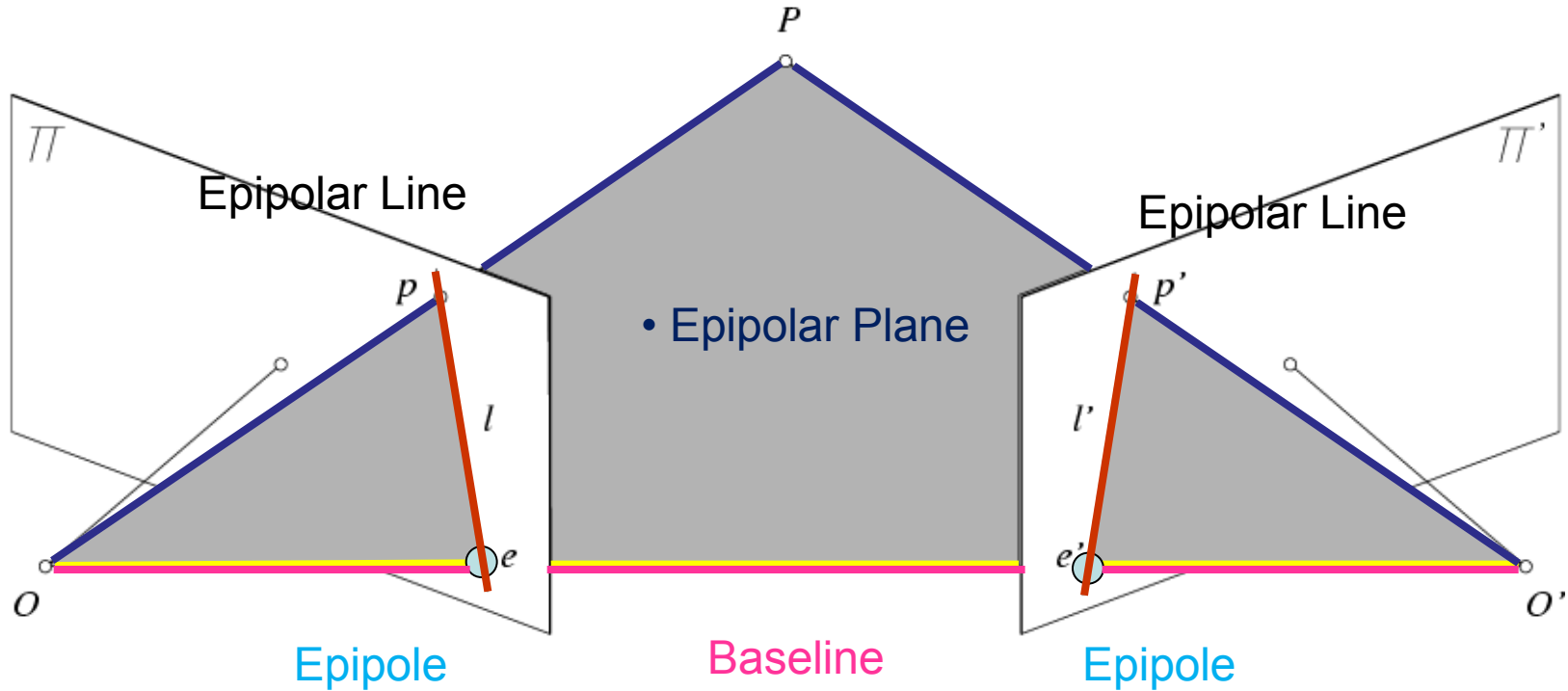
# Epipolar constraint



Geometry of two views constrains where the corresponding pixel for some image point in the first view *must occur* in the second view.

It must be  $\{A @ A\}^\wedge$  carved out by a plane connecting the world point and the optical centers.

# Epipolar geometry



# Epipolar geometry: terms

- **Baseline:** line joining the camera centers.
  - **Epipole:** point of intersection of baseline with image plane.
  - **Epipolar plane:** plane containing baseline and world point.
  - **Epipolar line:** intersection of epipolar plane with the image plane.
- 
- All epipolar lines in an image intersect at the epipole... or, an epipolar plane intersects the left and right image planes in epipolar lines.

*Why is the epipolar constraint useful?*

# Epipolar constraint



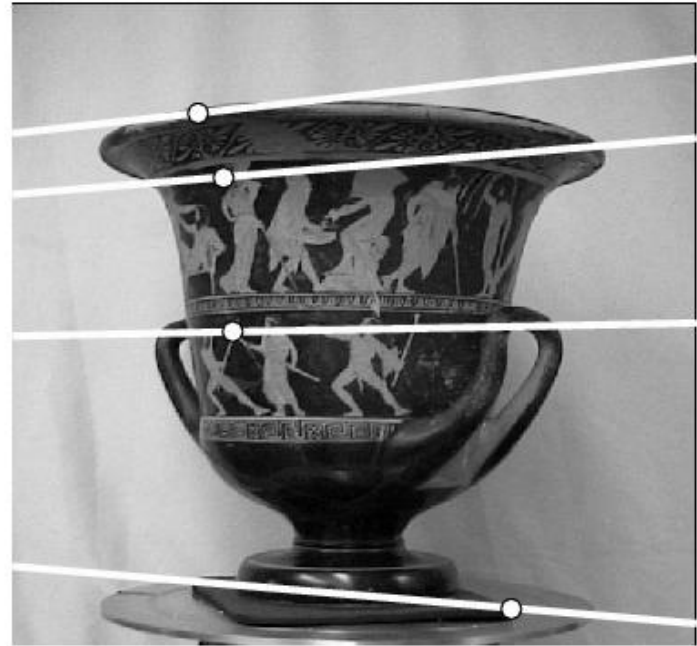
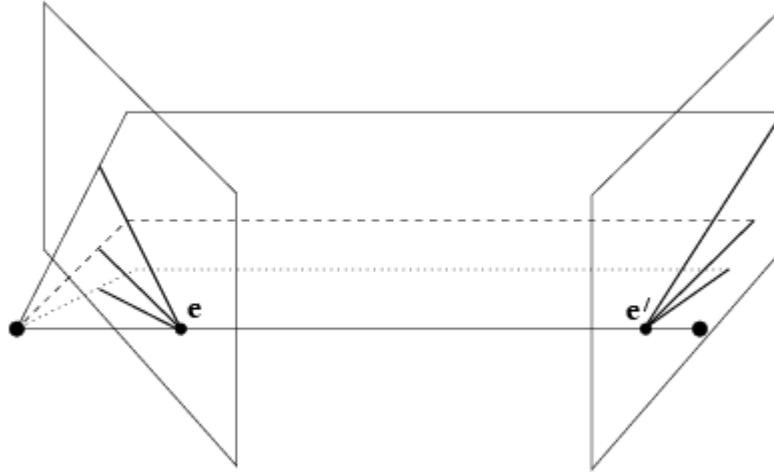
Reduces the correspondence problem to a 1D search in the second image along an epipolar line.



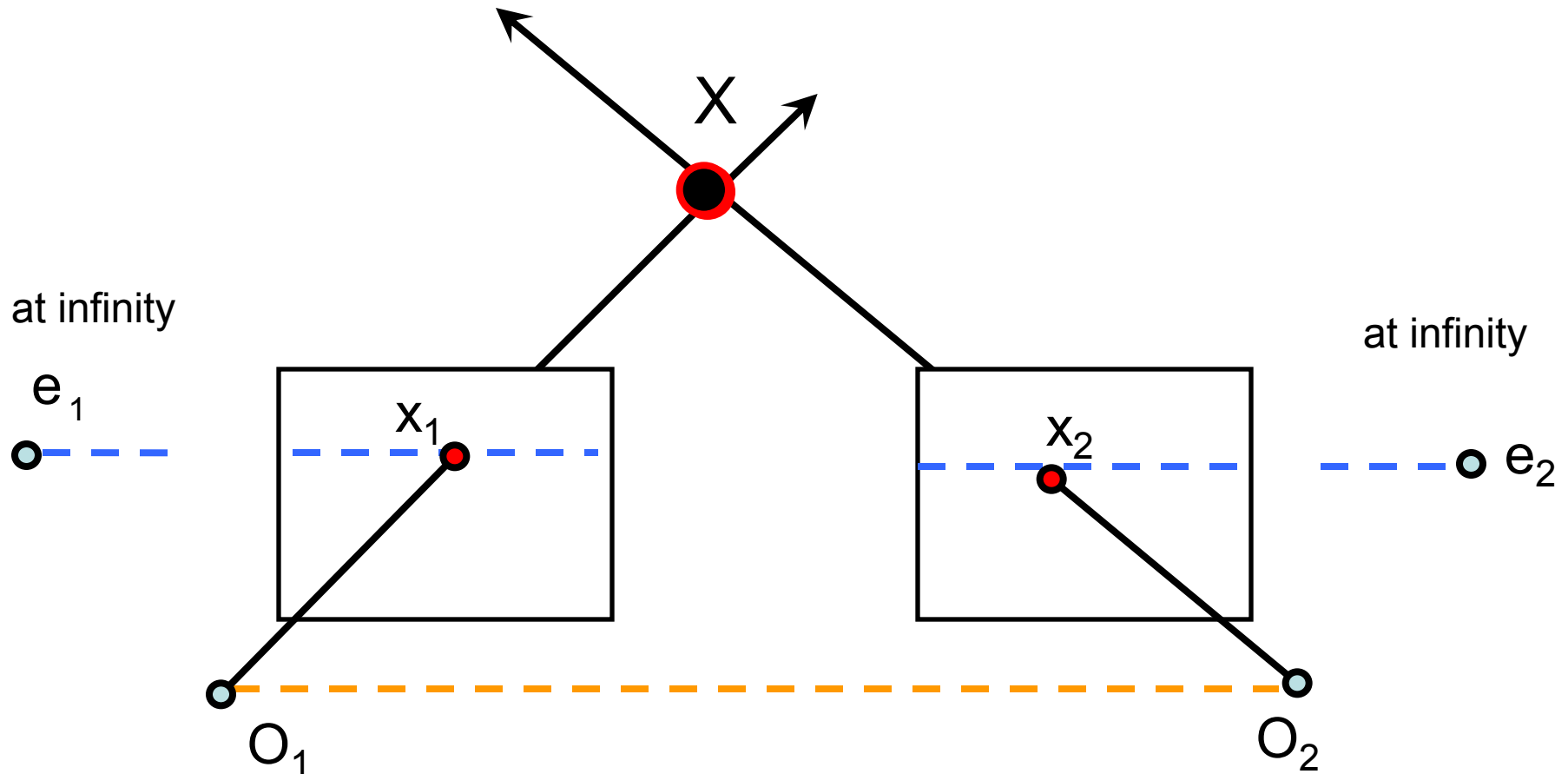
Two examples:



# Converging cameras have finite epipoles.

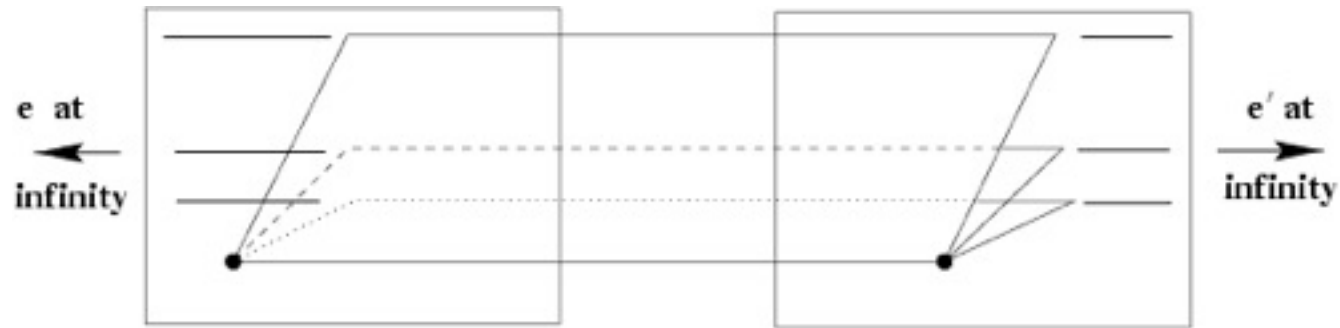


# Parallel cameras have epipoles at infinity.



- Baseline intersects the image plane at infinity.
- *Epipoles are at infinity.*
- Epipolar lines are parallel to x axis.

In parallel cameras search is only along x coord.



# Motion perpendicular to image plane

---



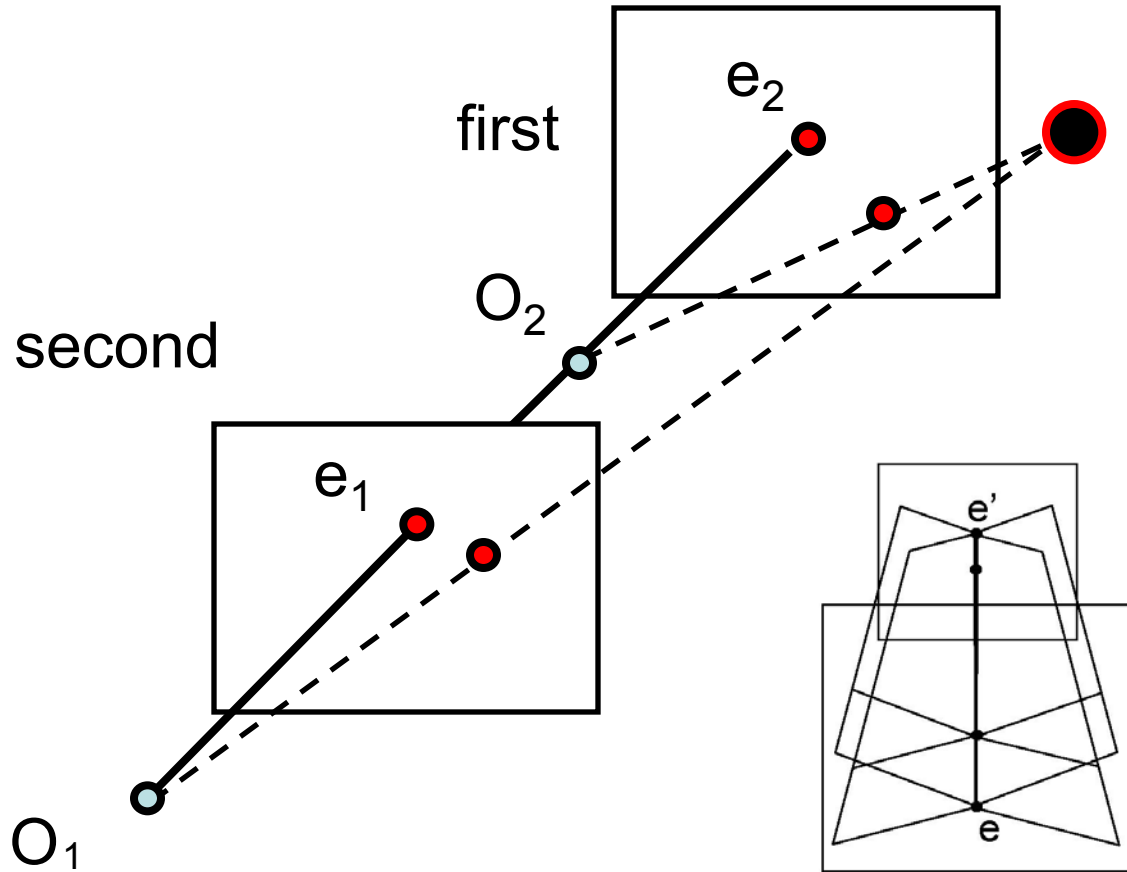
# Motion perpendicular to image plane

---

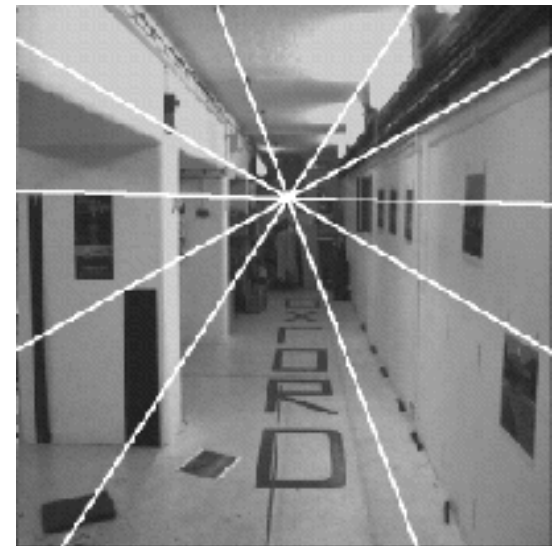
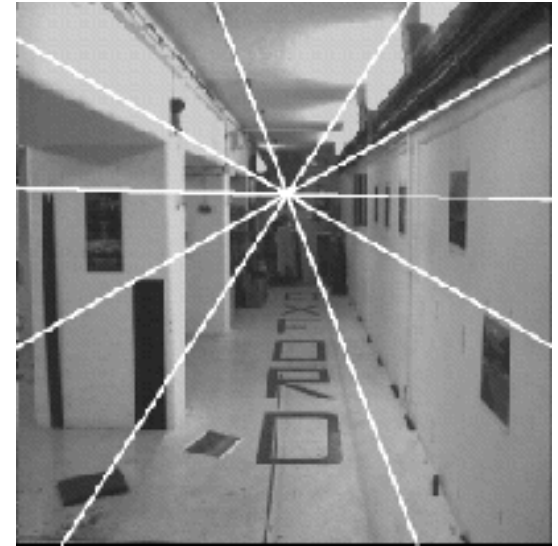


forward

# Forward translation



- The epipoles have same position in both images.
- Epipole here is called FOE (focus of expansion).



# A 3x3 matrix connects the two 2D images.

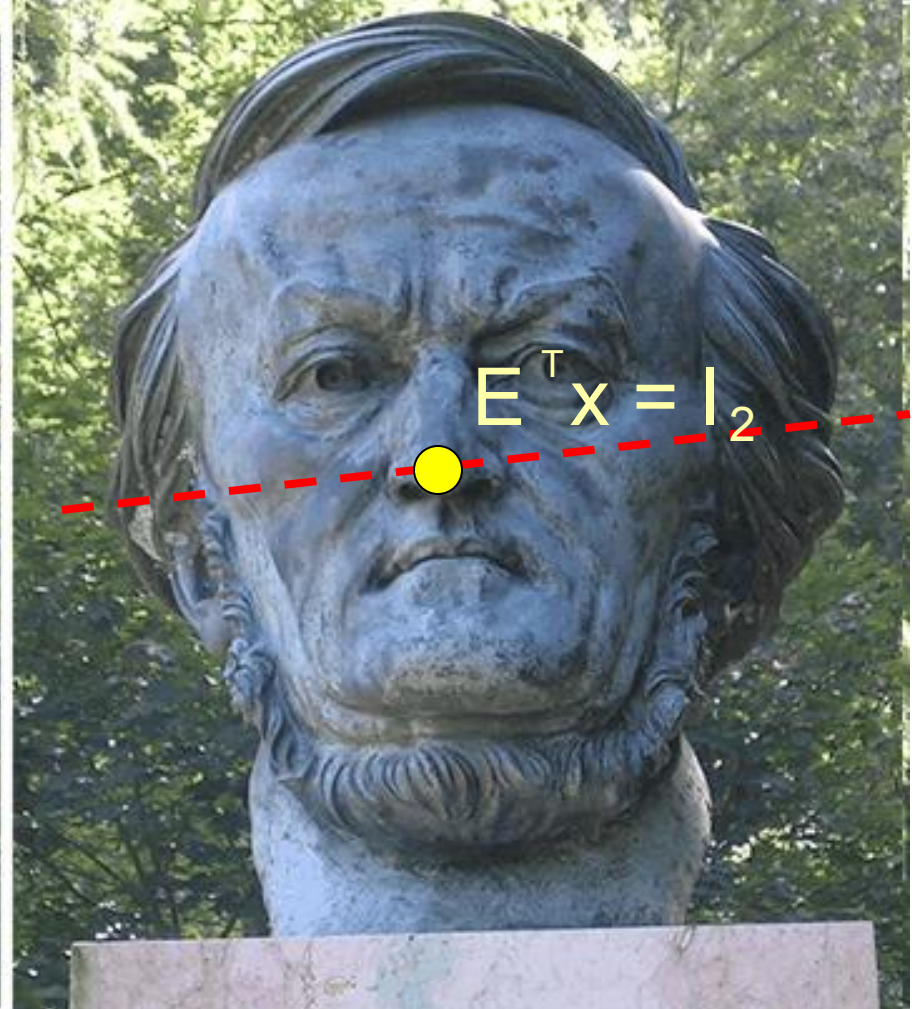
---

This matrix is called

- the “Essential Matrix”,  $E$ 
  - when image *intrinsic parameters* are known
- the “Fundamental Matrix”,  $F$ 
  - more the general uncalibrated case

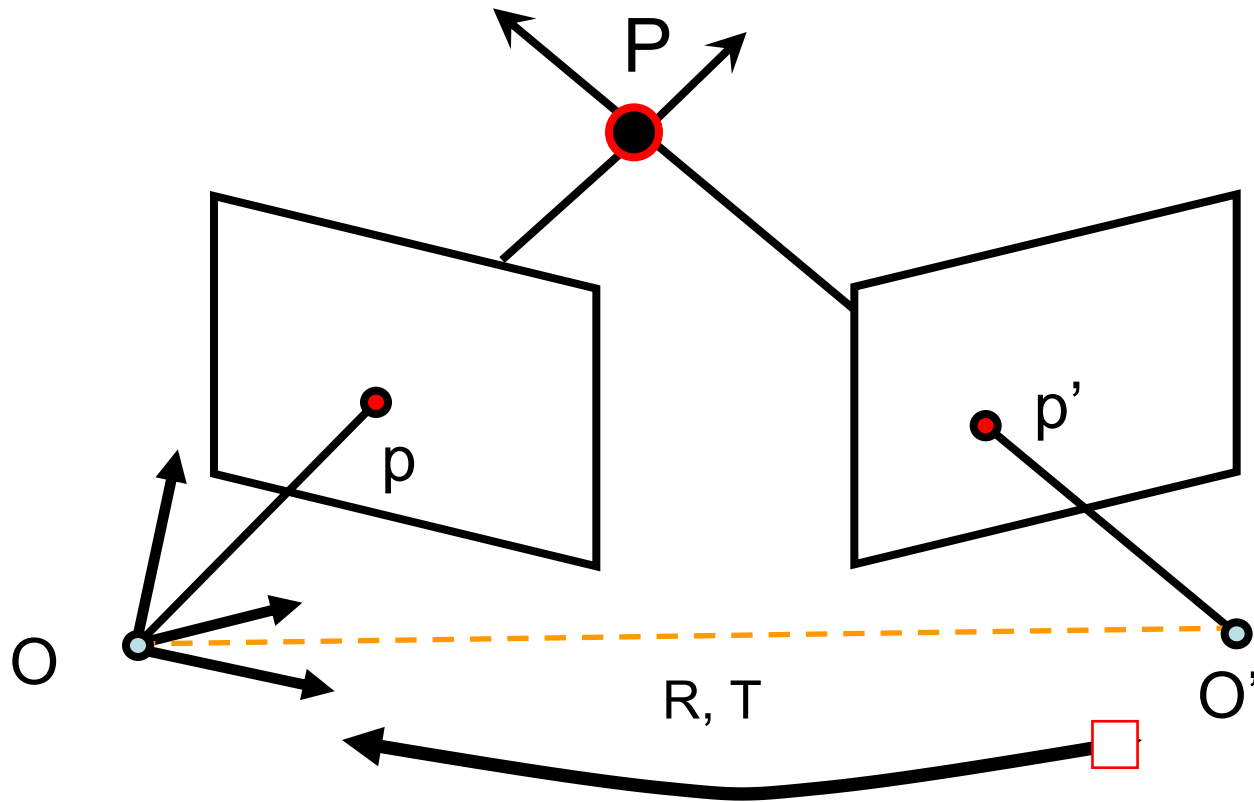


# Essential matrix: E



- Two views of the same object
- Suppose we know the camera positions and camera matrices ==> E matrix
- Given a point on left image, how can we find the corresponding point on right image?

# Epipolar Constraint - E matrix



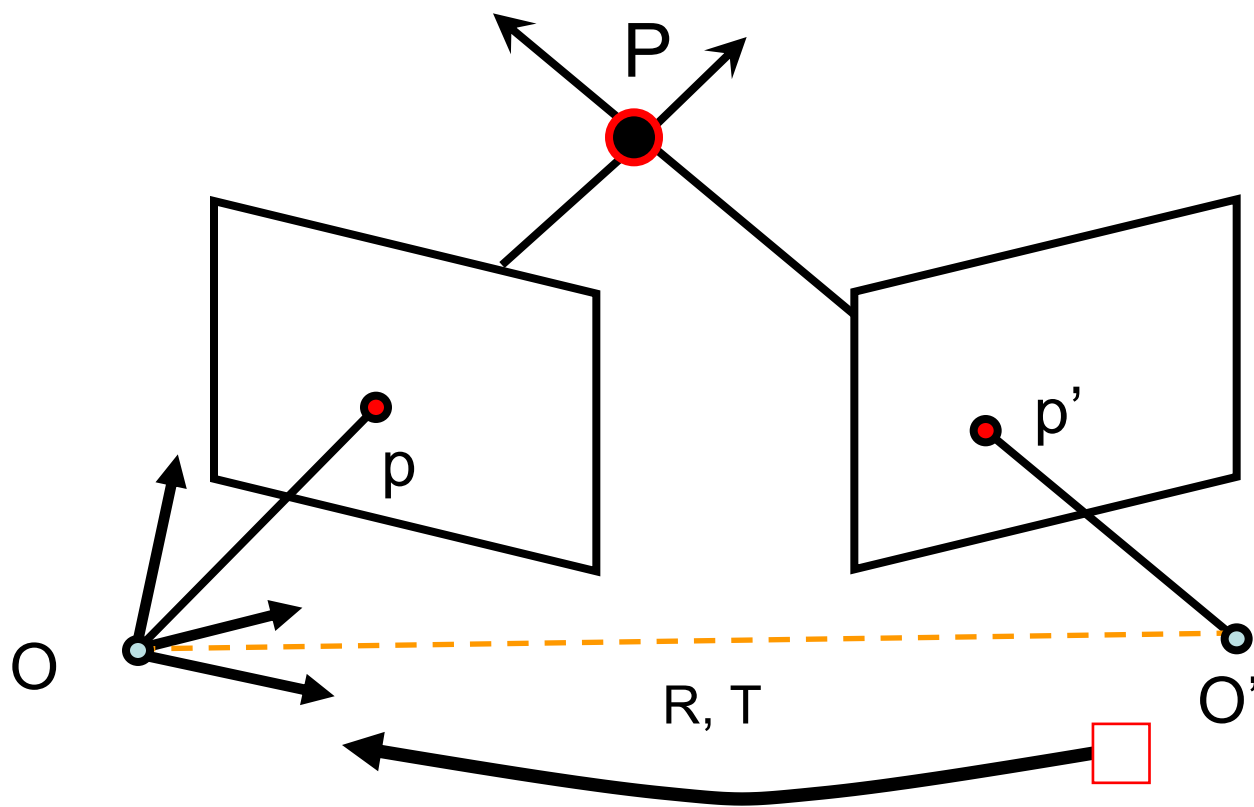
$$M = K \begin{bmatrix} I & 0 \end{bmatrix}$$

$$P \rightarrow M P = \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}$$

homogeneous coordinates

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

$$P \rightarrow M' P = \begin{bmatrix} u' \\ v' \\ 1 \end{bmatrix}$$



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



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

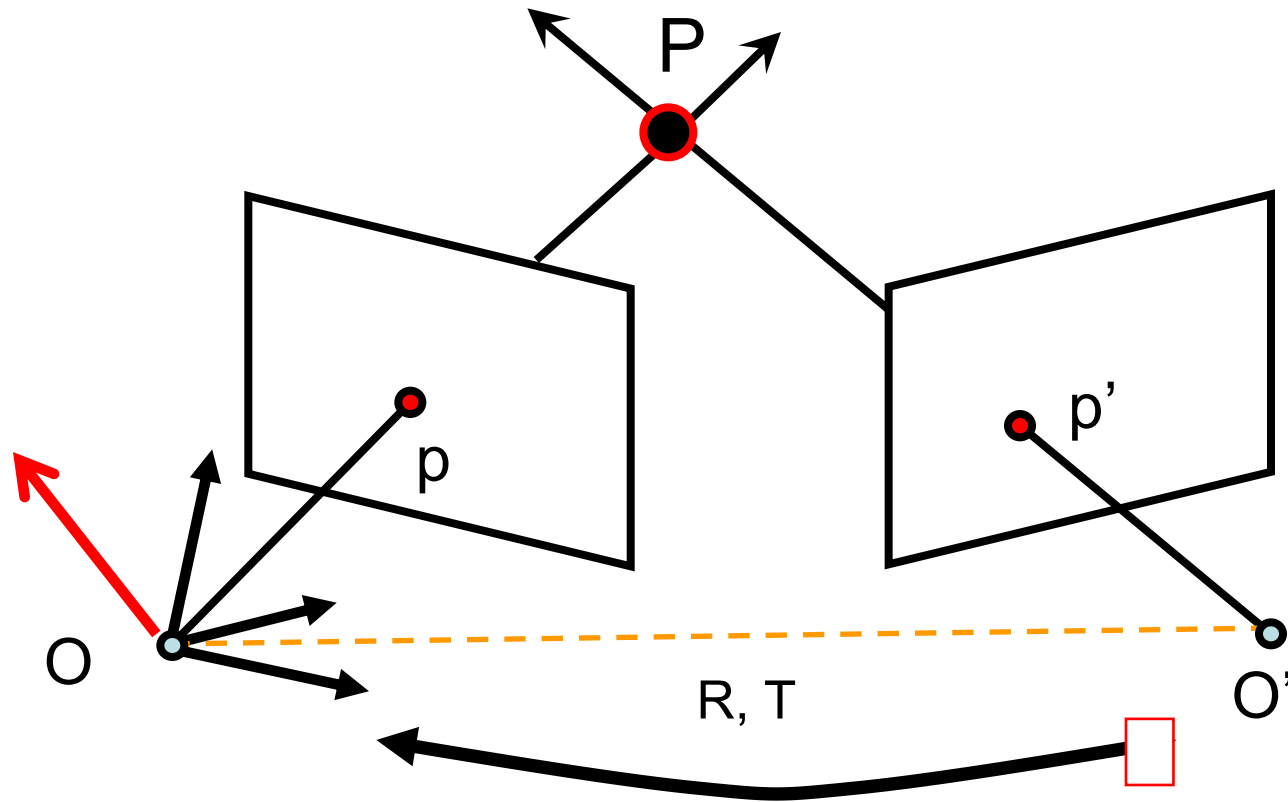
$K$  and  $K'$  are known  
(calibrated cameras)

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



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

In the epipolar plane we have



first camera coordinates

$$p^T \cdot [T \times (R p')] = 0$$

$$T \times (R p')$$

Perpendicular to epipolar plane

Cross products can be written as matrix multiplication.

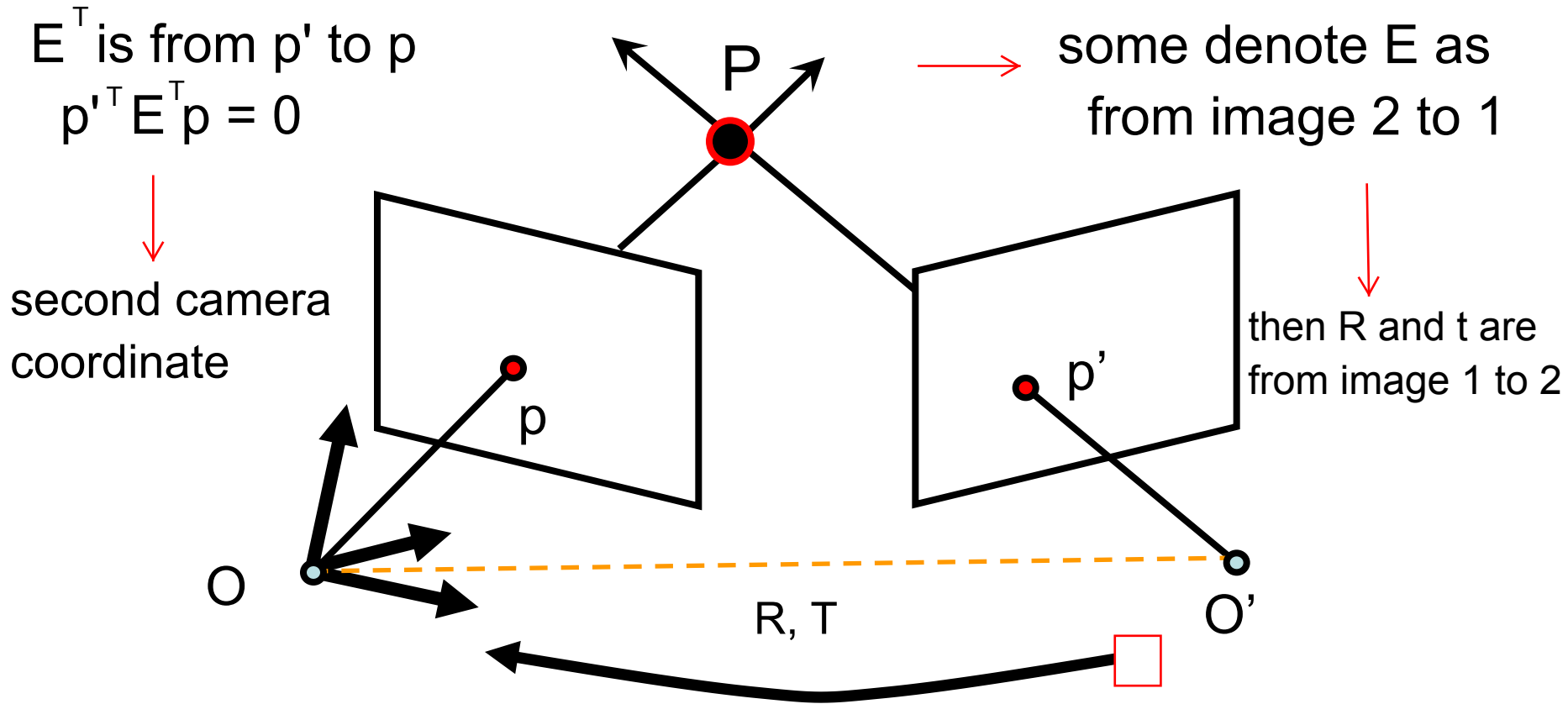
$$\mathbf{a} \times \mathbf{b} = \mathbf{A}\mathbf{b} = [\mathbf{a}]_{\times} \mathbf{b} = \begin{pmatrix} 0 & -a_3 & a_2 \\ a_3 & 0 & -a_1 \\ -a_2 & a_1 & 0 \end{pmatrix} \mathbf{b} = \begin{pmatrix} a_2b_3 - a_3b_2 \\ a_3b_1 - a_1b_3 \\ a_1b_2 - a_2b_1 \end{pmatrix}$$

...verify it

The matrix derived from  $\mathbf{a}$  is skew-symmetric.

The matrix is rank 2. The null vector is along the vector  $\mathbf{a}$ .

# Essential matrix



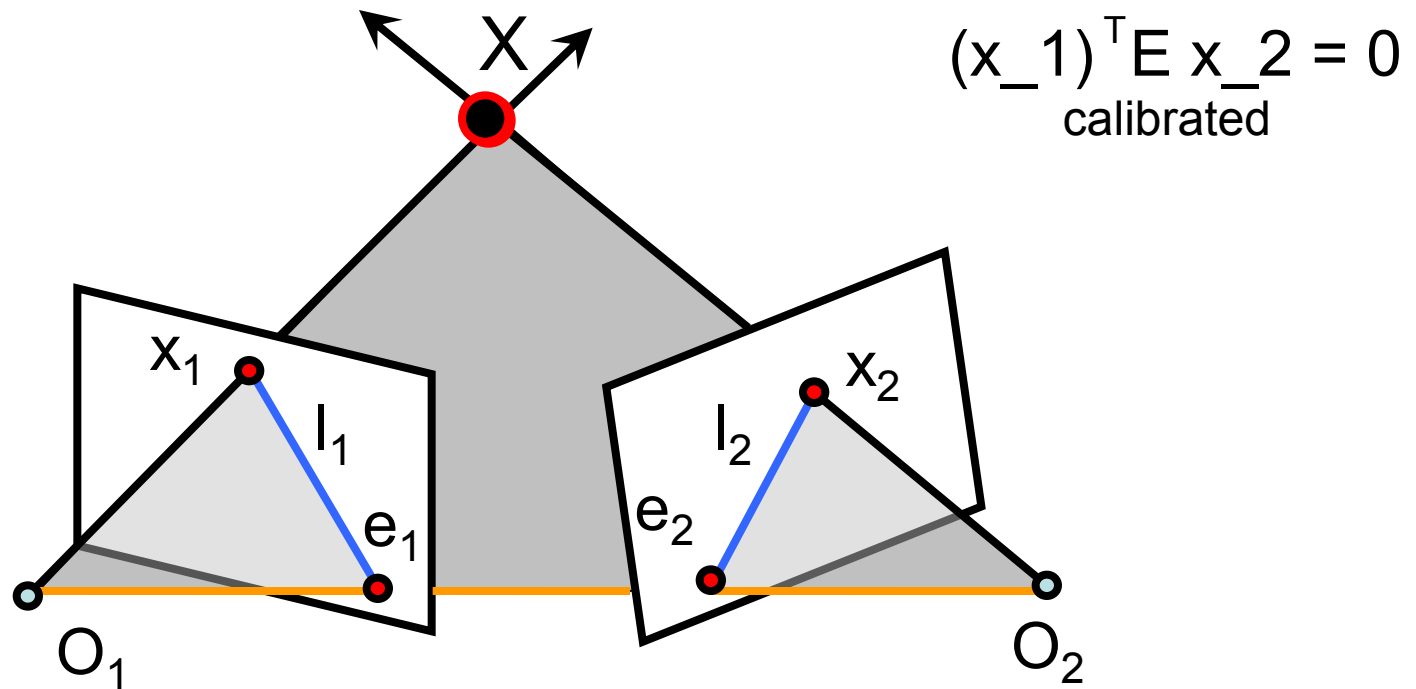
$$p^T \cdot [T \times (R p')] = 0 \rightarrow p^T \cdot [T]_{\times} \cdot R p' = 0$$

$E$  = essential matrix

$E$  is a rank 2 matrix!

(Longuet-Higgins, 1981)

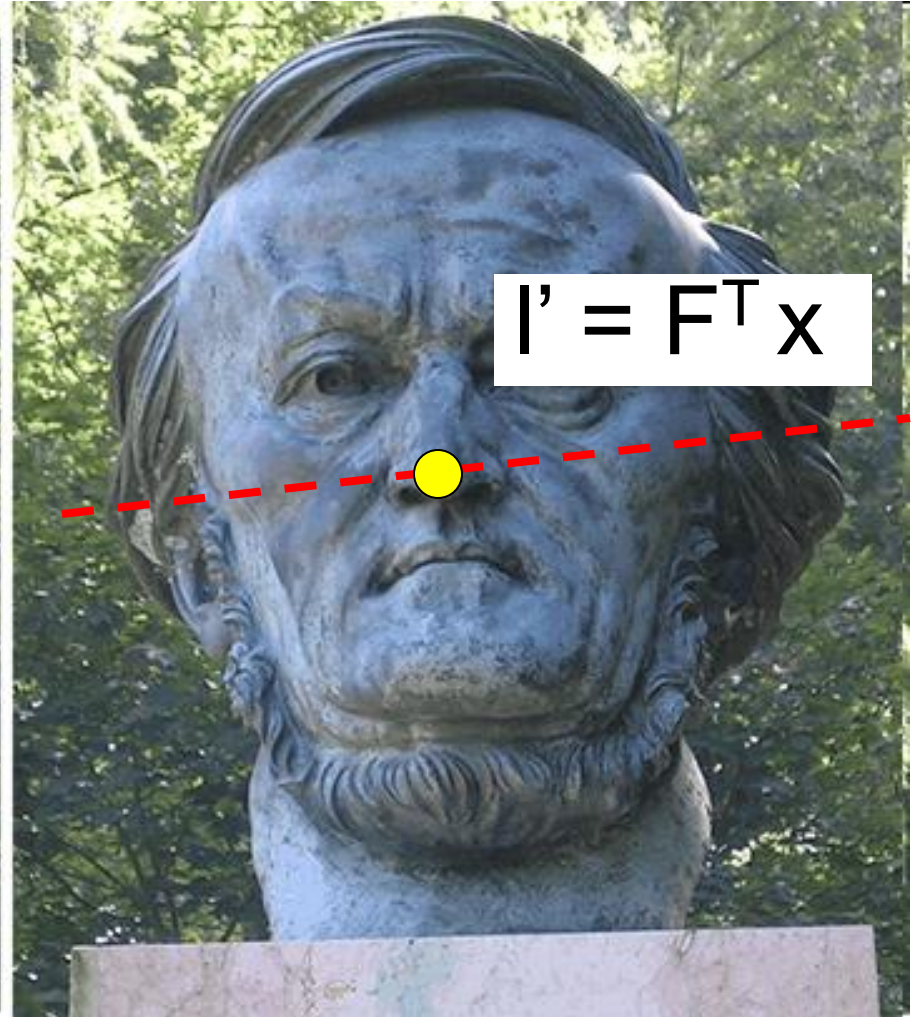
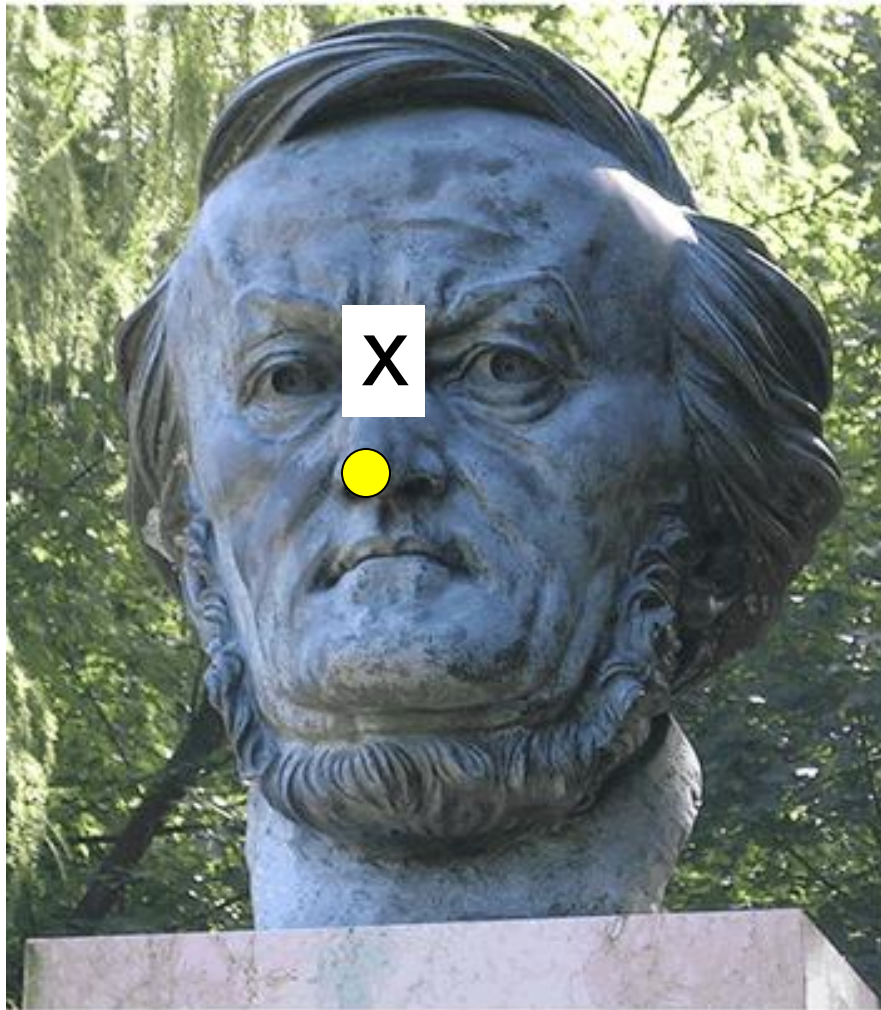
# Essential matrix properties



- $E x_2$  is the epipolar line associated with  $x_2$  ( $l_1 = E x_2$ )
- $E^T x_1$  is the epipolar line associated with  $x_1$  ( $l_2 = E^T x_1$ )
- $E$  is *singular (rank two)* -- two equal singular values are one.
- $E e_2 = 0$  and  $E^T e_1 = 0$   $l_1^T e_1 = (E x_2)^T e_1 = 0$  valid for any  $x_2$
- $E$  is 3x3 matrix with 5 DOF:  $3(R) + 3(t) - 1(\text{scale})$



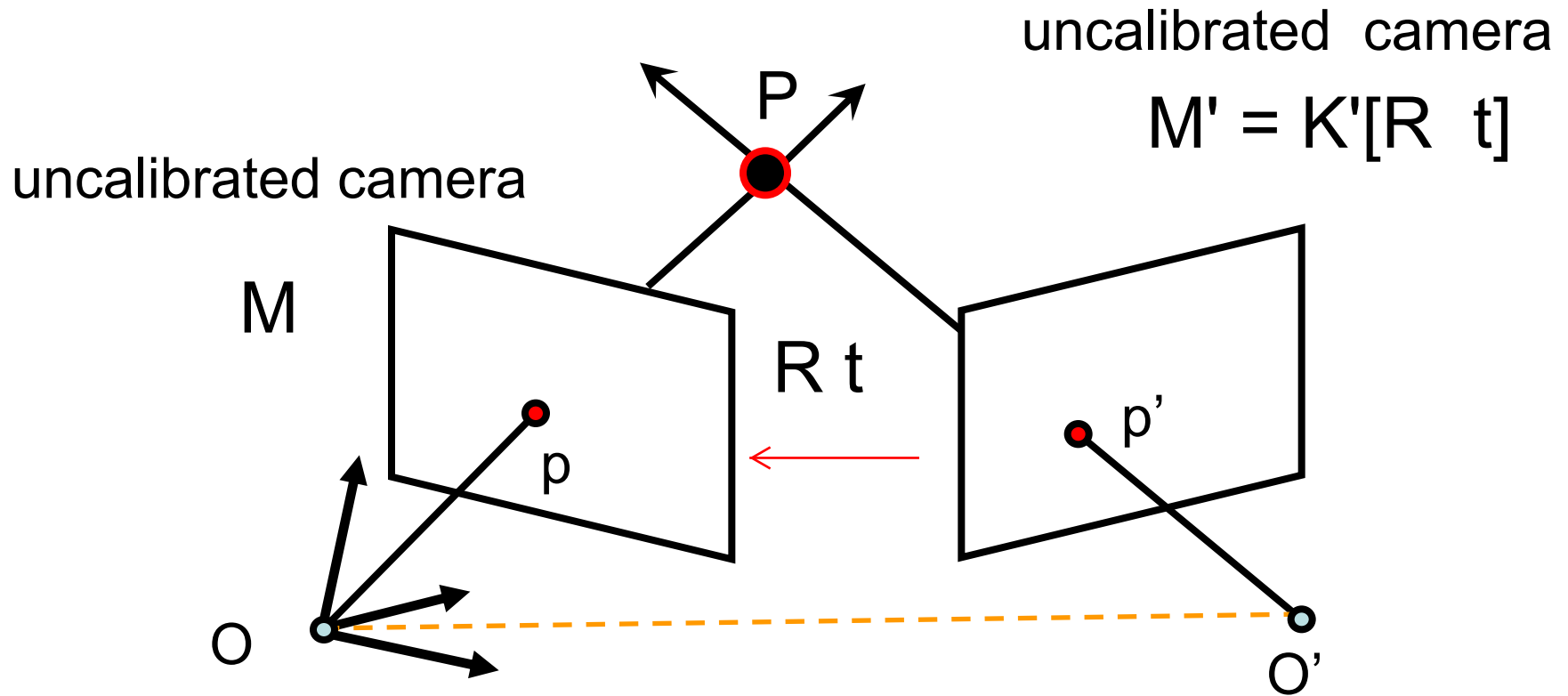
# Fundamental matrix: F



- Uncalibrated cameras.
- No additional information about the scene and camera is given ==> F matrix
- Given a point on left image, how can I find the corresponding point on right image?



# Epipolar Constraint - F matrix

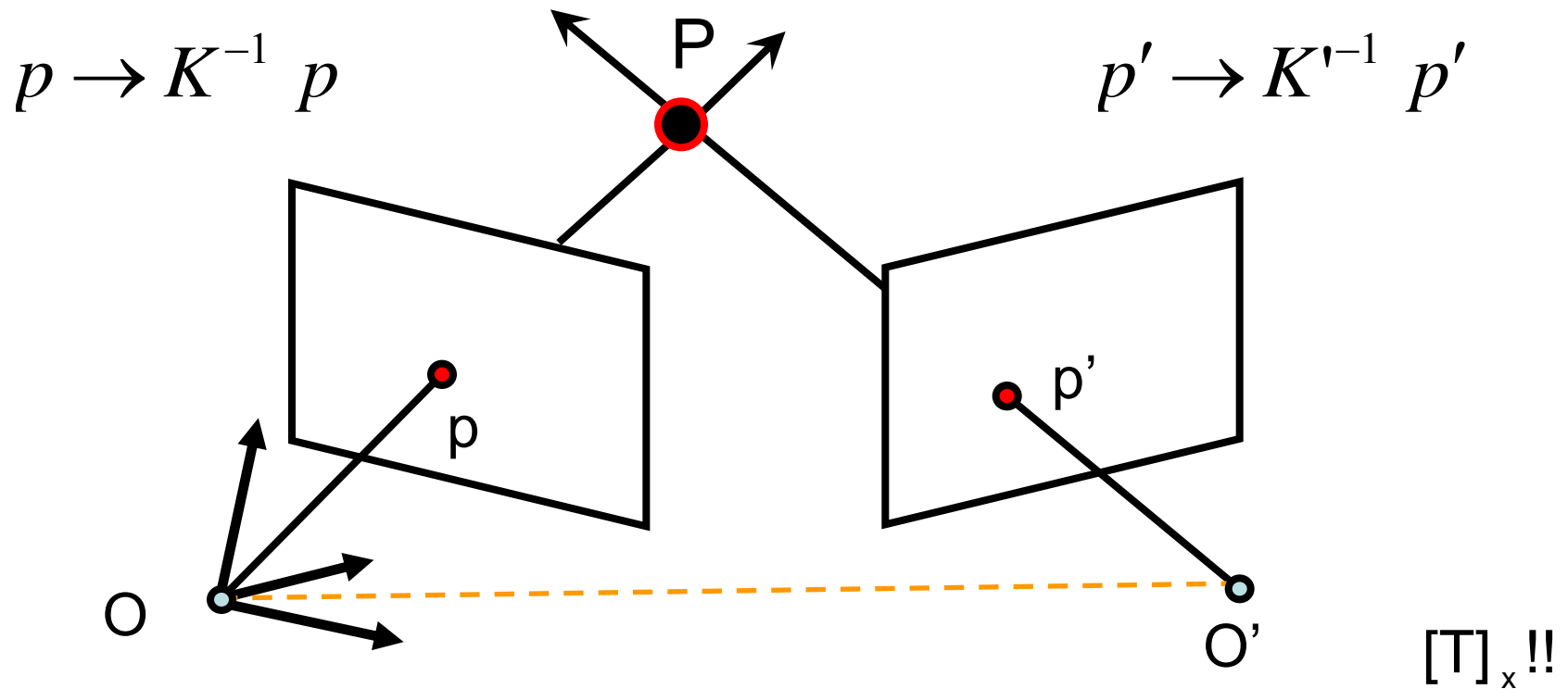


$$P \rightarrow M \rightarrow p = \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \quad \text{homogeneous coord.}$$

$$M = \boxed{K} \begin{bmatrix} I & 0 \end{bmatrix} \quad (3 \times 4)$$

unknown

# F matrix derived from E matrix

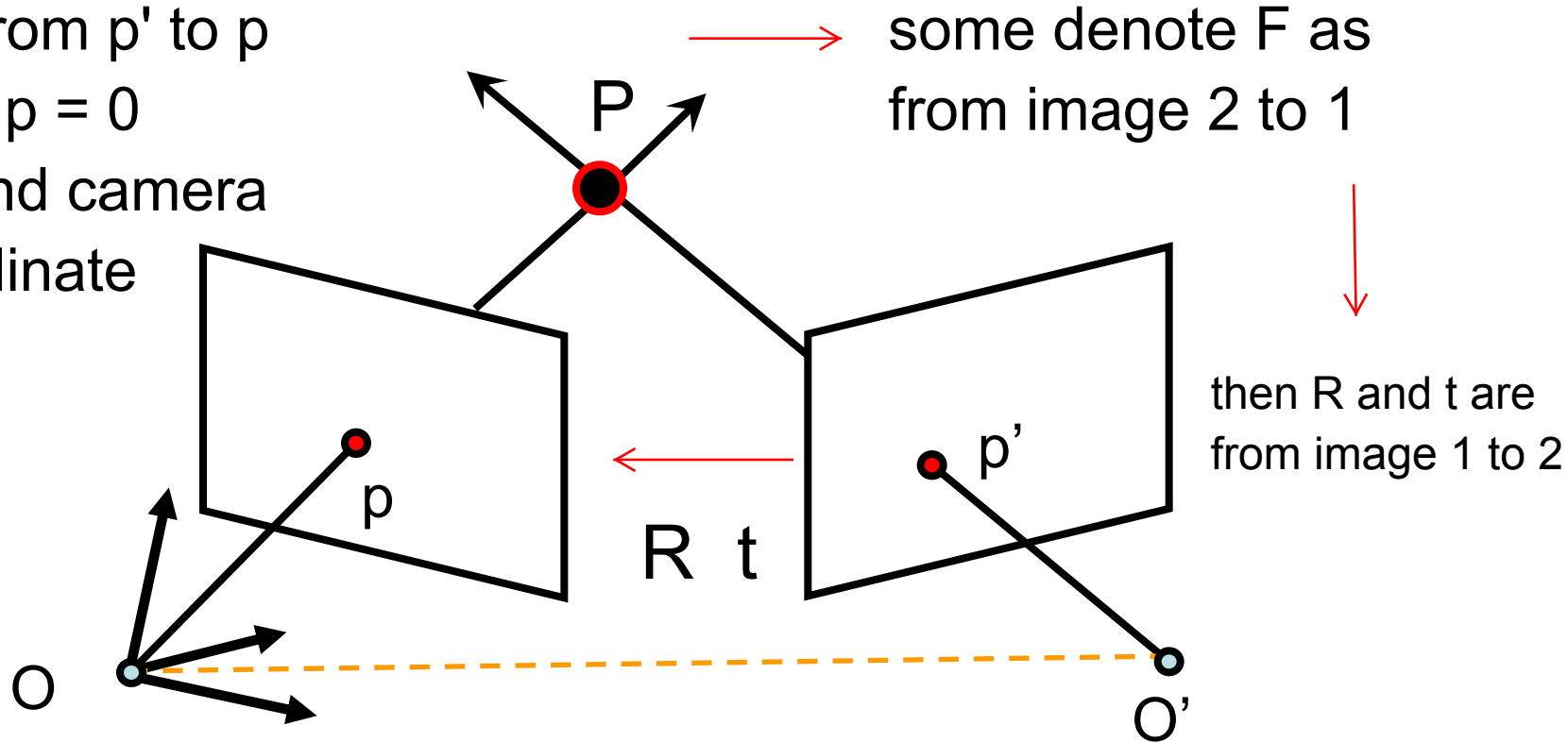


$$p^T \cdot [T_x] \cdot R p' = 0 \rightarrow (K^{-1} p)^T \cdot [T_x] \cdot R K'^{-1} p' = 0$$

$$p^T \boxed{K^{-T} \cdot [T_x] \cdot R K'^{-1}} p' = 0 \rightarrow p^T \boxed{F} p' = 0 \quad \text{rank 2}$$

# Fundamental matrix

$F^T$  is from  $p'$  to  $p$   
 $p'^T F^T p = 0$   
 second camera  
 coordinate



some denote  $F$  as  
 from image 2 to 1

then  $R$  and  $t$  are  
 from image 1 to 2

$$p^T F p' = 0 \quad (\text{Faugeras and Luong, 1992})$$

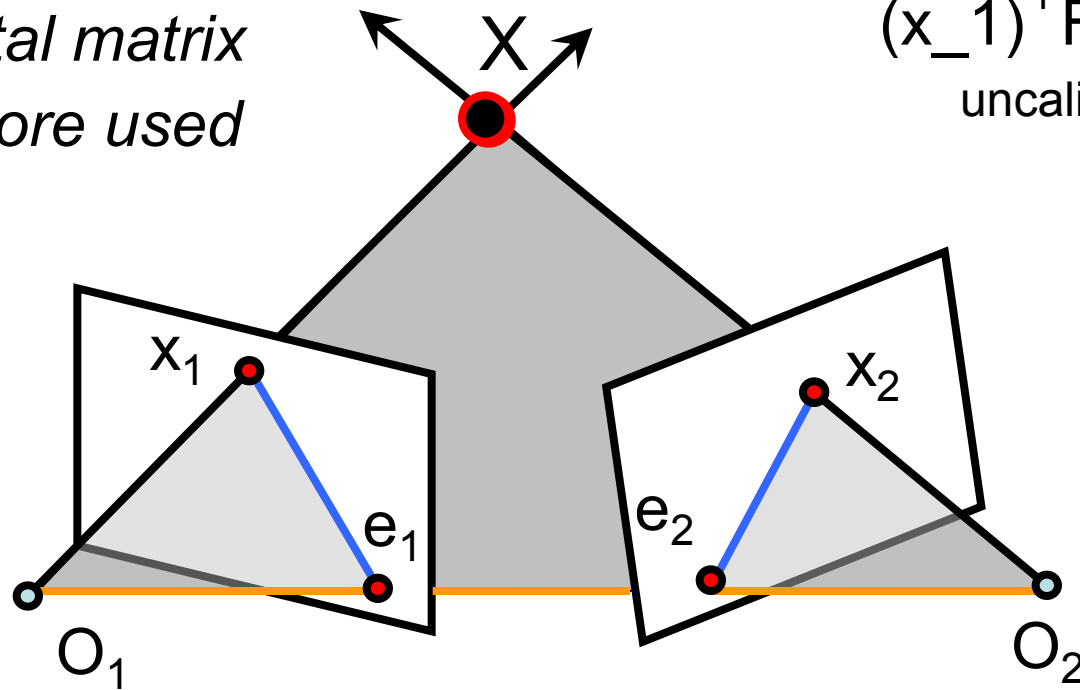
*The fundamental matrix has a projective ambiguity.* Two pairs of camera matrices  $(P, P')$  and  $(\tilde{P}, \tilde{P}')$  give the same  $F$  if  $\tilde{P} = PH$  and  $\tilde{P}' = P'H$  where  $H$  is a  $4 \times 4$  nonsingular matrix.

# Fundamental matrix properties

*fundamental matrix  
is much more used*

$$(x_1)^T F x_2 = 0$$

uncalibrated



- $F x_2$  is the epipolar line associated with  $x_2$  ( $l_1 = F x_2$ )
- $F^T x_1$  is the epipolar line associated with  $x_1$  ( $l_2 = F^T x_1$ )
- $F$  is *singular (rank two)*
- $F e_2 = 0$  and  $F^T e_1 = 0$
- $F$  is 3x3 matrix with 7 DOF:  $9 - 1(\text{rank } 2) - 1(\text{scale})$

# The eight-point algorithm of F (linear)

$$\mathbf{x} = (u, v, 1)^T, \quad \mathbf{x}' = (u', v', 1)^T$$

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

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

Minimize:

$$\sum_{i=1}^N (x_i^T F x'_i)^2$$

under the constraint

$$F_{33} = 1$$

can be an other  $F_{ij}$  constraint also

# Estimating F

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

• Homogeneous system  $\mathbf{W} \mathbf{f} = 0$

• Rank 8  $\longrightarrow$  A non-zero solution exists (unique)

• If  $N > 8$   $\longrightarrow$  Lsq. solution by SVD  $\longrightarrow \hat{\mathbf{F}}$   
 $\|\mathbf{f}\| = 1$  rank 3 solution

Taking into account the rank-2 constraint.

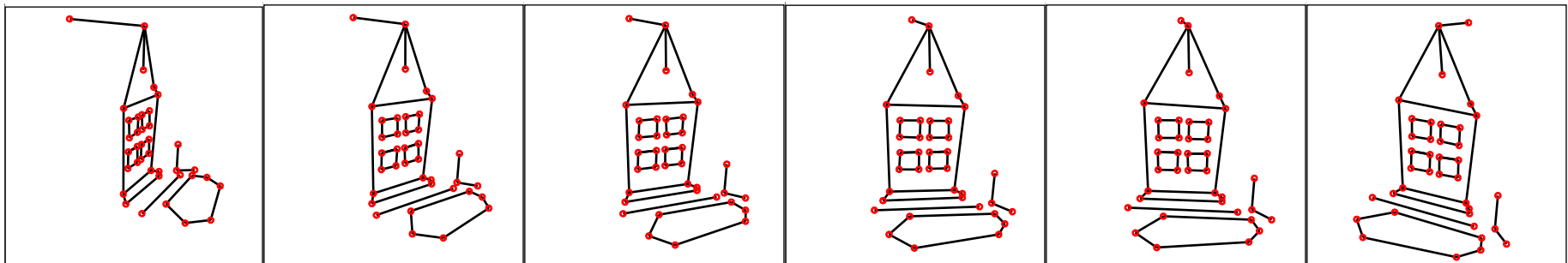
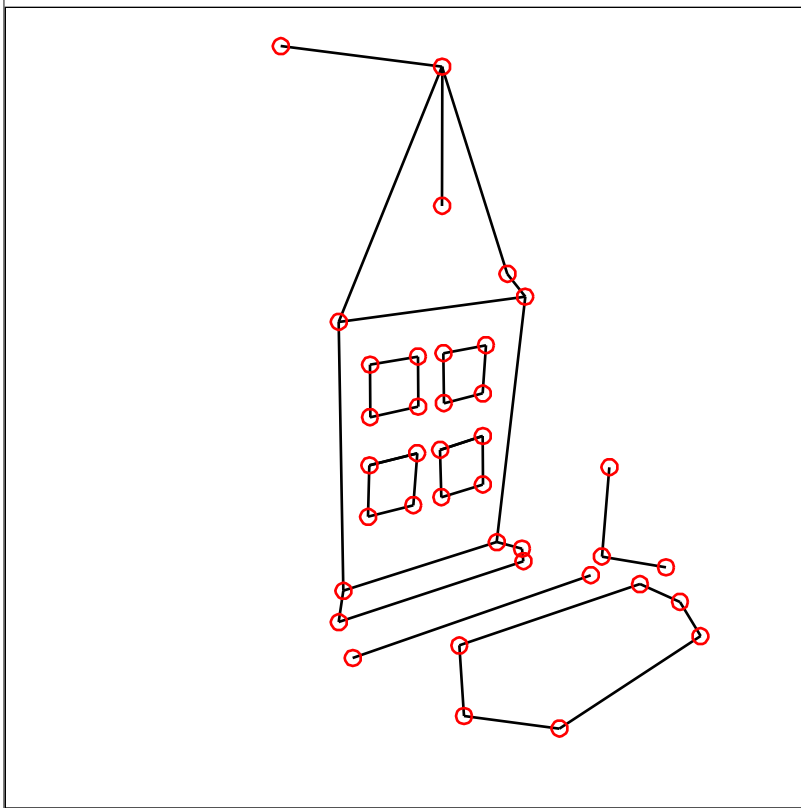
$$\mathbf{p}^T \hat{\mathbf{F}} \mathbf{p}' = 0$$

The estimated  $\hat{\mathbf{F}}$  have full rank ( $\det(\hat{\mathbf{F}}) \neq 0$ )  
but  $\mathbf{F}$  should have rank=2 instead.

Find  $\mathbf{F}$  that minimizes  $\left\| \mathbf{F} - \hat{\mathbf{F}} \right\| = 0$   
Frobenius norm (\*)  
subject to  $\det(\mathbf{F})=0$

*Taking the first two s.v. and the three equal zero.*

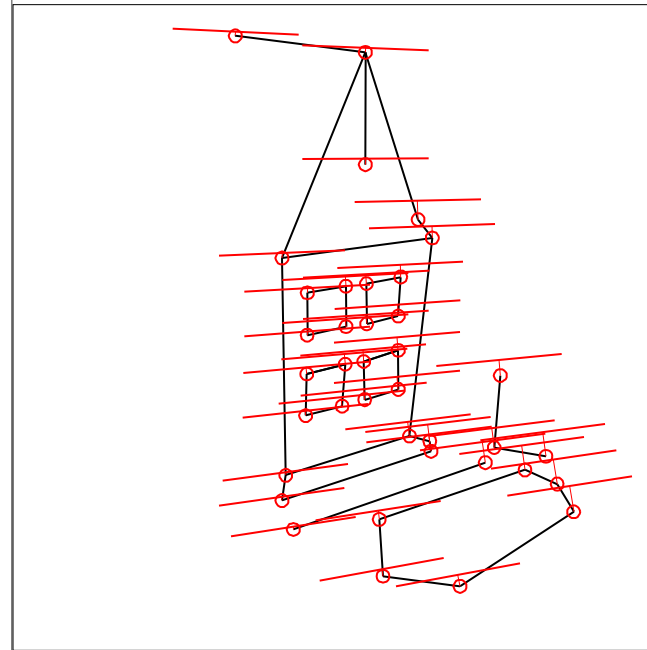
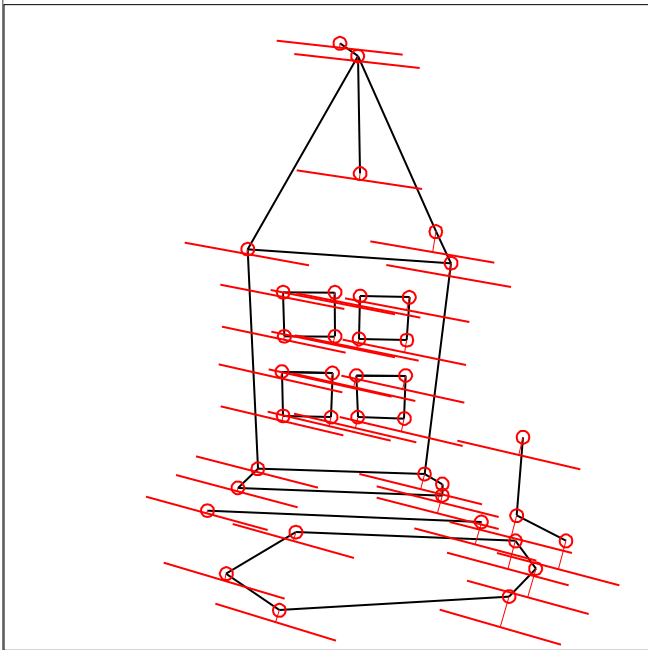
(\*) Sqrt root of the sum of squares of all entries



Example of F recovery

Data courtesy of R. Mohr and B. Boufama.





Mean errors:  
10.0pixel  
and 9.1pixel

This are large errors...

# The problem with eight-point algorithm

---

250906.36	183269.57	921.81	200931.10	146766.13	738.21	272.19	198.81
2692.28	131633.03	176.27	6196.73	302975.59	405.71	15.27	746.79
416374.23	871684.30	935.47	408110.89	854384.92	916.90	445.10	931.81
191183.60	171759.40	410.27	416435.62	374125.90	893.65	465.99	418.65
48988.86	30401.76	57.89	298604.57	185309.58	352.87	846.22	525.15
164786.04	546559.67	813.17	1998.37	6628.15	9.86	202.65	672.14
116407.01	2727.75	138.89	169941.27	3982.21	202.77	838.12	19.64
135304.50	75411.13	190.72	411350.03	229127.70	603.79	601.20	379.40

$$\begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \end{pmatrix} = - \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}$$

Poor numerical conditioning.

*Can be fixed by rescaling the data before estimation.*

Can be used for any DLT type algorithm.

More sophisticated nonlinear methods after the 8-point algorithm exist, but we will not cover.

# RESCALING BY NORMALIZATION

You have  $i = 1, \dots, n$  points  $\mathbf{x}_i$ . The mean of these points is

$$\bar{\mathbf{x}} = \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i$$

which is translated to the origin  $(0, 0)$  by the vector  $-\bar{\mathbf{x}}$ . The new coordinated of a point are  $\tilde{\mathbf{x}}_i = \mathbf{x}_i - \bar{\mathbf{x}}$ .

Compute the mean squared distance of the points from the center

$$a^2 = \frac{1}{n} \sum_{i=1}^n \tilde{\mathbf{x}}_i^\top \tilde{\mathbf{x}}_i$$

and move the square norm equal to 2 by multiplying the components of the original point  $\sqrt{2}/a$ . This is the scaling. The translation are the mean coordinates with opposite sign multiplied with  $\sqrt{2}/a$ .

In the homogeneous 2D coordinates

$$\mathbf{T} = \frac{\sqrt{2}}{a} \begin{bmatrix} 1 & 0 & -\bar{x}_1 \\ 0 & 1 & -\bar{x}_2 \\ 0 & 0 & \frac{a}{\sqrt{2}} \end{bmatrix} \quad \mathbf{T}\mathbf{x}_i = \begin{bmatrix} \frac{\sqrt{2}}{a}(x_{i1} - \bar{x}_1) \\ \frac{\sqrt{2}}{a}(x_{i2} - \bar{x}_2) \\ 1 \end{bmatrix}$$

a 2D similarity transformation.

# The normalized eight-point algorithm

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(Hartley, 1995)

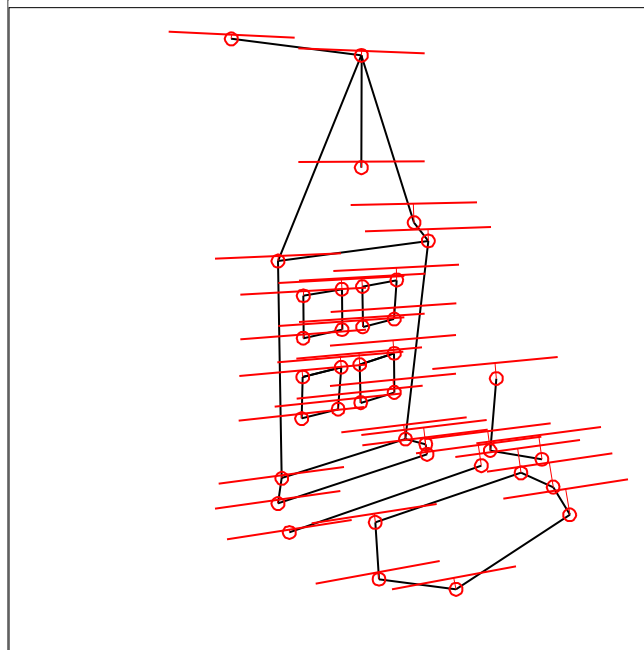
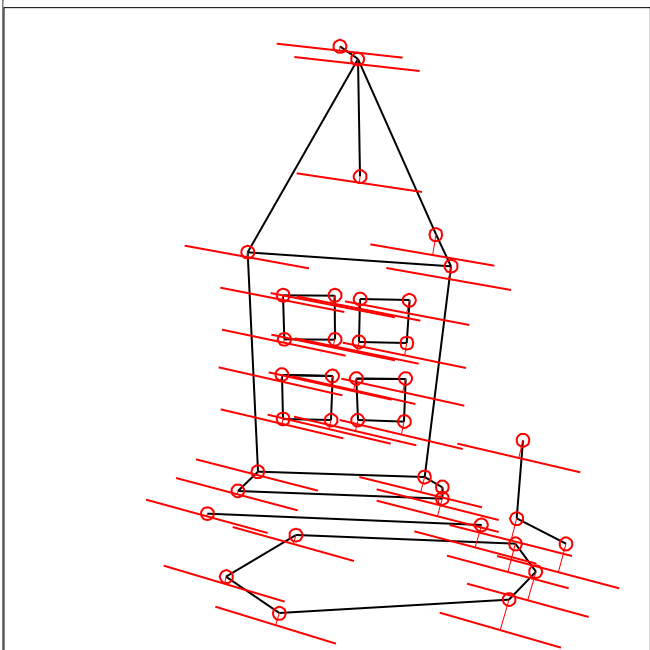
- Center the image data at the origin, and scale it so the *mean squared distance* between the origin and the data points is 2 pixels.
- Use the eight-point algorithm to compute  $F$  from the *normalized points*,  $n\_1$  and  $n\_2$ .
- *Enforce the rank-2 constraint.* For example, take SVD of  $F$  and throw out the smallest singular value.
- *Transform fundamental matrix back to original units:* if  $T$  and  $T'$  are the normalizing transformations in the two images, then the fundamental matrix in original coordinates is  $T^T F T'$ .

Isotropic translation (mean to origin)  
and scale in each image separately.

$$x\_1 = T^{-1} n\_1 \quad x\_2 = T'^{-1} n\_2$$

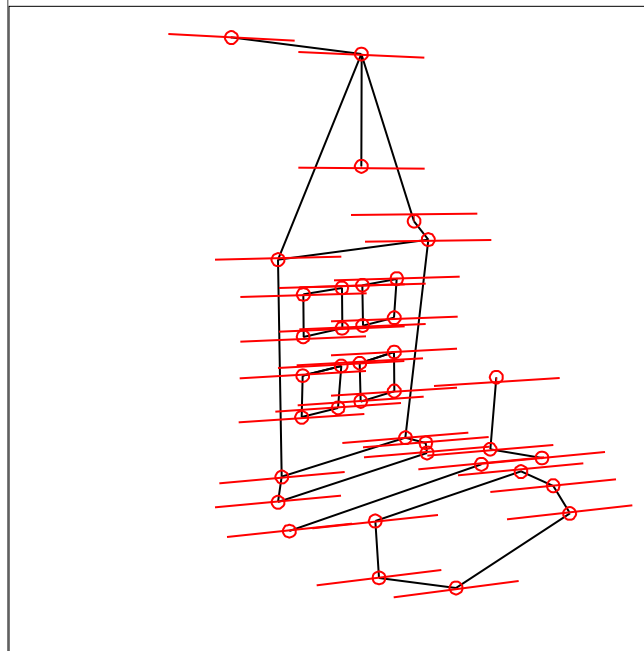
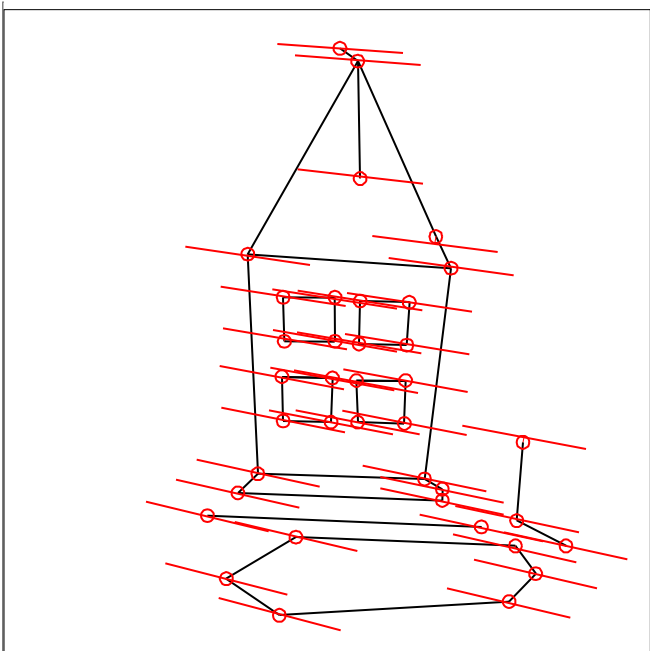
$$(n\_1)^T \underbrace{T^{-T} F T'^{-1}}_{\text{given}} n\_2 = 0 \quad \Rightarrow \text{final } F$$

Without transformation



Mean errors:  
10.0pixel  
and 9.1pixel

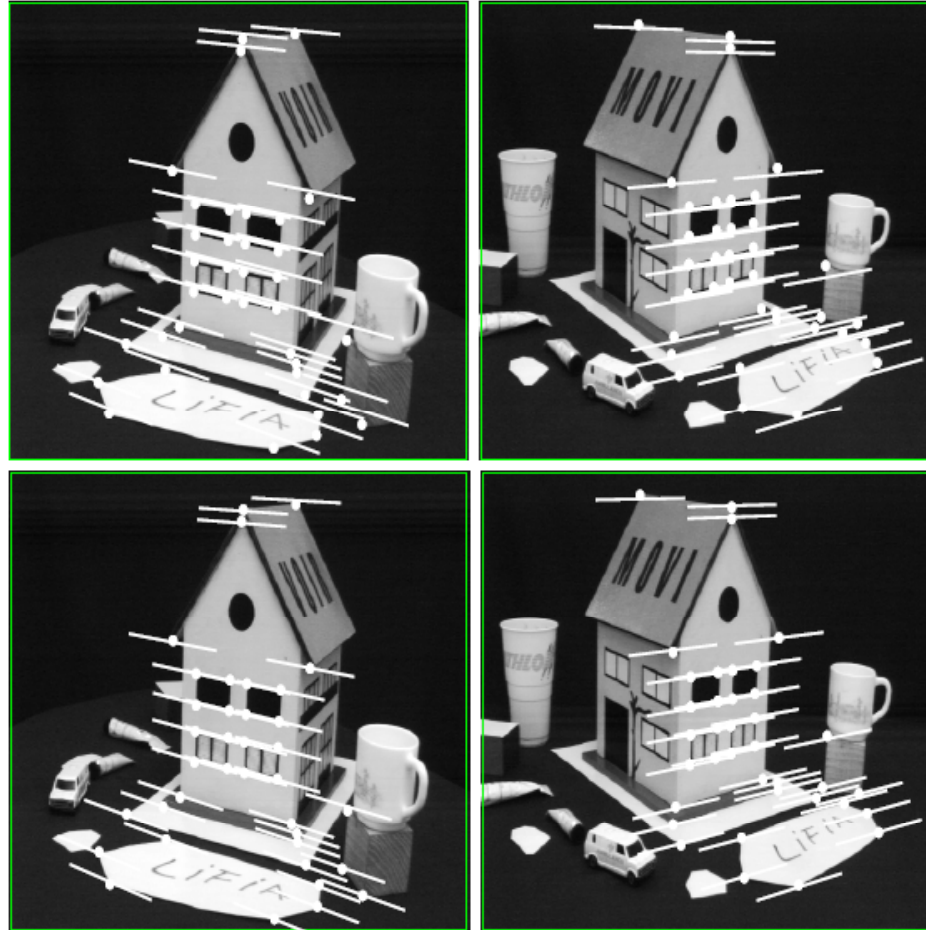
With transformation



Mean errors:  
1.0pixel  
and 0.9pixel

# Comparison of estimation algorithms

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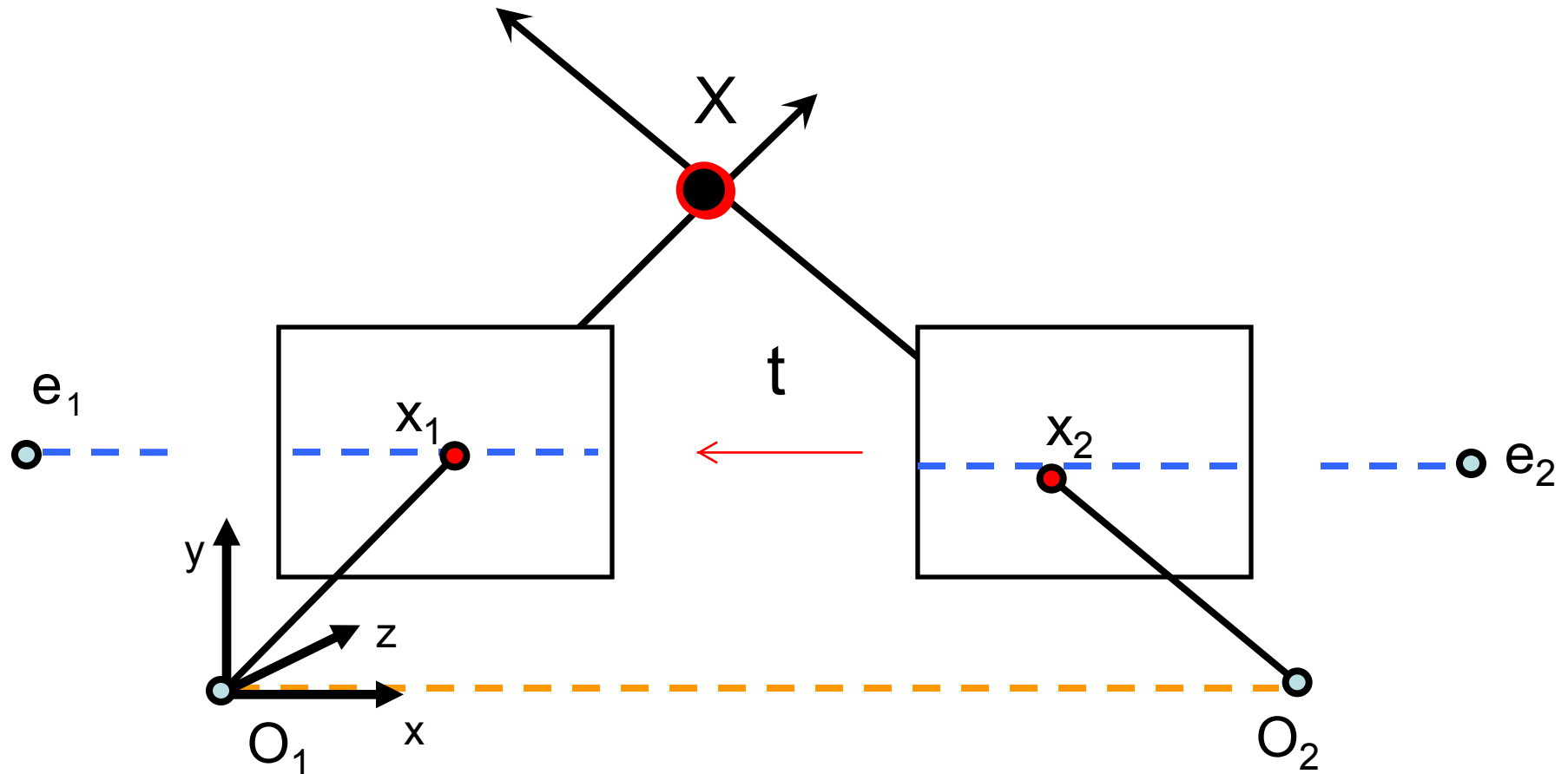
	8-point	Normalized 8-point	Nonlinear least squares
Av. Dist. 1	2.33 pixels	0.92 pixel	0.86 pixel
Av. Dist. 2	2.18 pixels	0.85 pixel	0.80 pixel

# From epipolar geometry to camera calibration

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- Estimating the fundamental matrix is known as “weak calibration”.
- If *we know* the calibration matrices of the two cameras, we can estimate the essential matrix:  $E = K^T F K'$  (see F from E slide)
- The essential matrix can give us the relative rotation and translation between the cameras, with 5 point pairs.

# Example: Parallel calibrated images



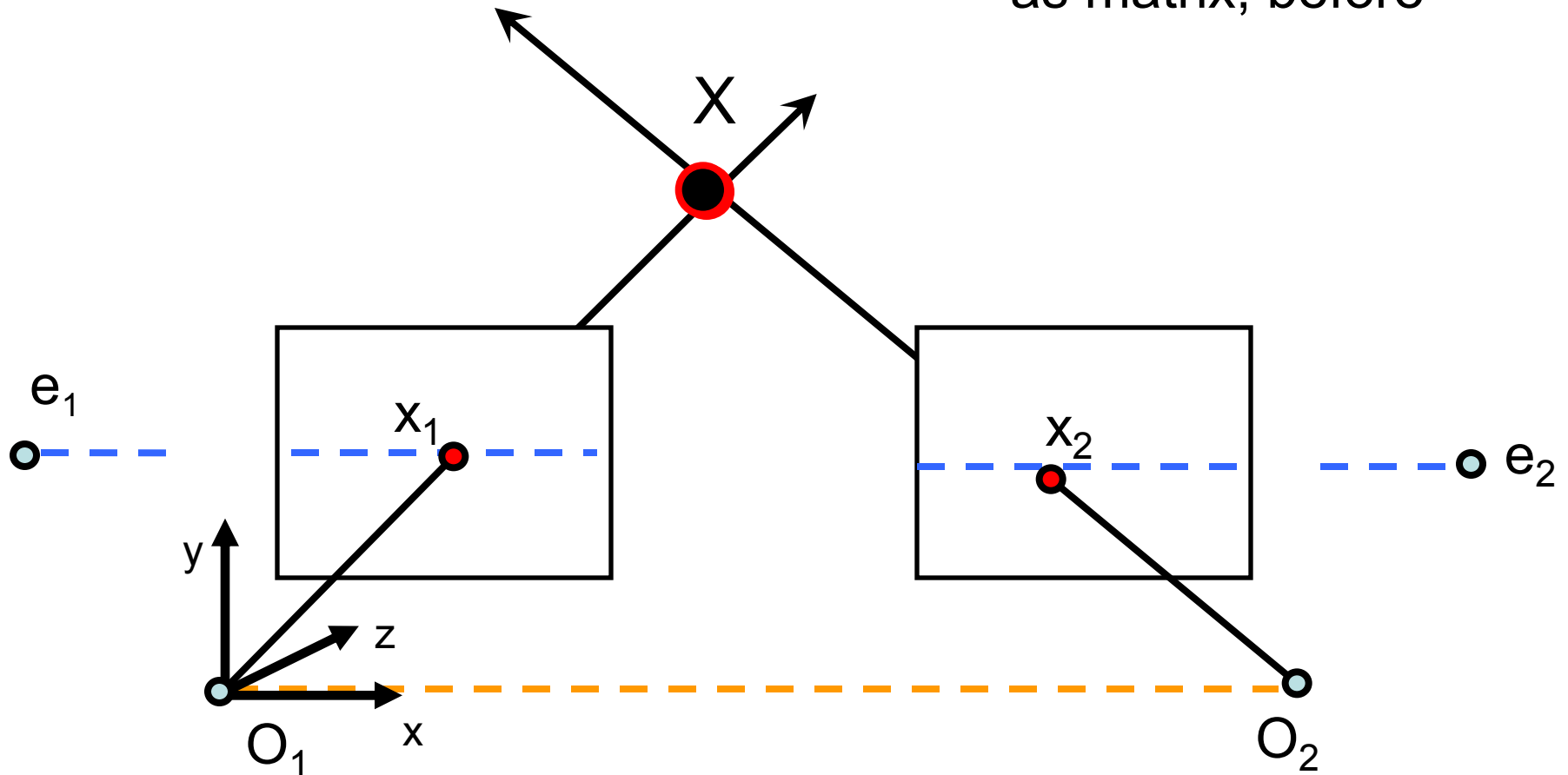
$K_1 = K_2 = \text{known}$   
 $x$  parallel to  $O_1O_2$

$E = ?$

Hint :  
 $R = I$       $t = (T, 0, 0)$



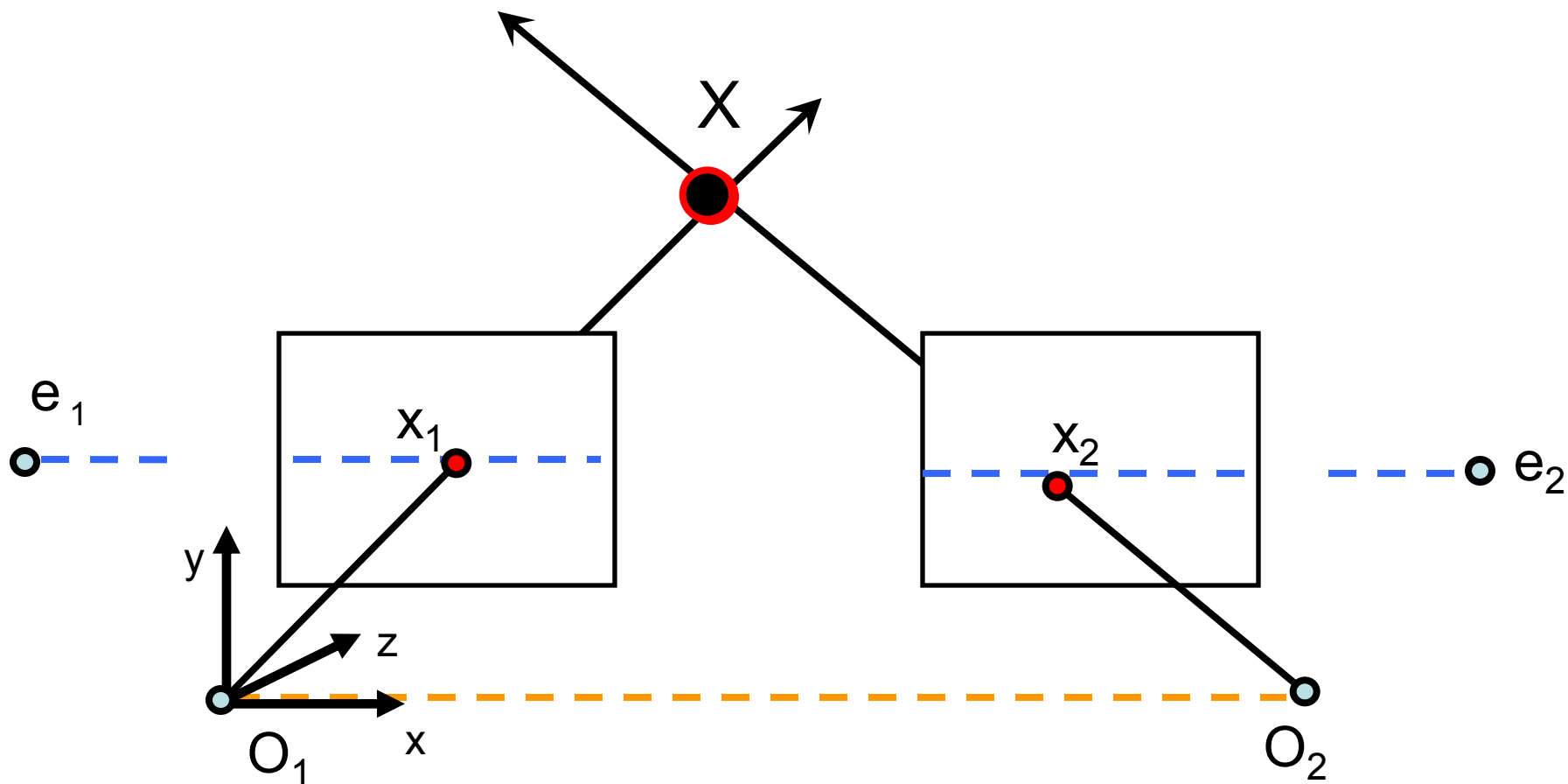
see cross-product  
as matrix, before



$K_1=K_2 = \text{known}$   
 $x$  parallel to  $O_1O_2$

$E=?$

$$E = [t_x]R = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -T \\ 0 & T & 0 \end{bmatrix}$$



Epipolar constraint reduces to  $\rightarrow y = y'$

*In stereo vision that will be a big help.*