

The logo of the University of Bonn, featuring a blue square with a white curved line and a grey square.

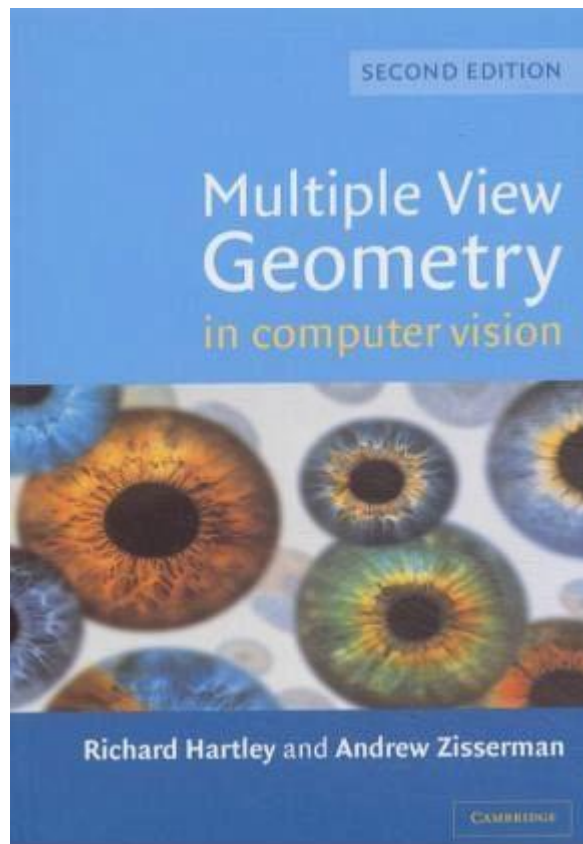
UNIVERSITÄT **BONN**

Juergen Gall

Camera Calibration  
MA-INF 2201 - Computer Vision  
WS24/25

# MA-INF 2206 - Seminar Vision

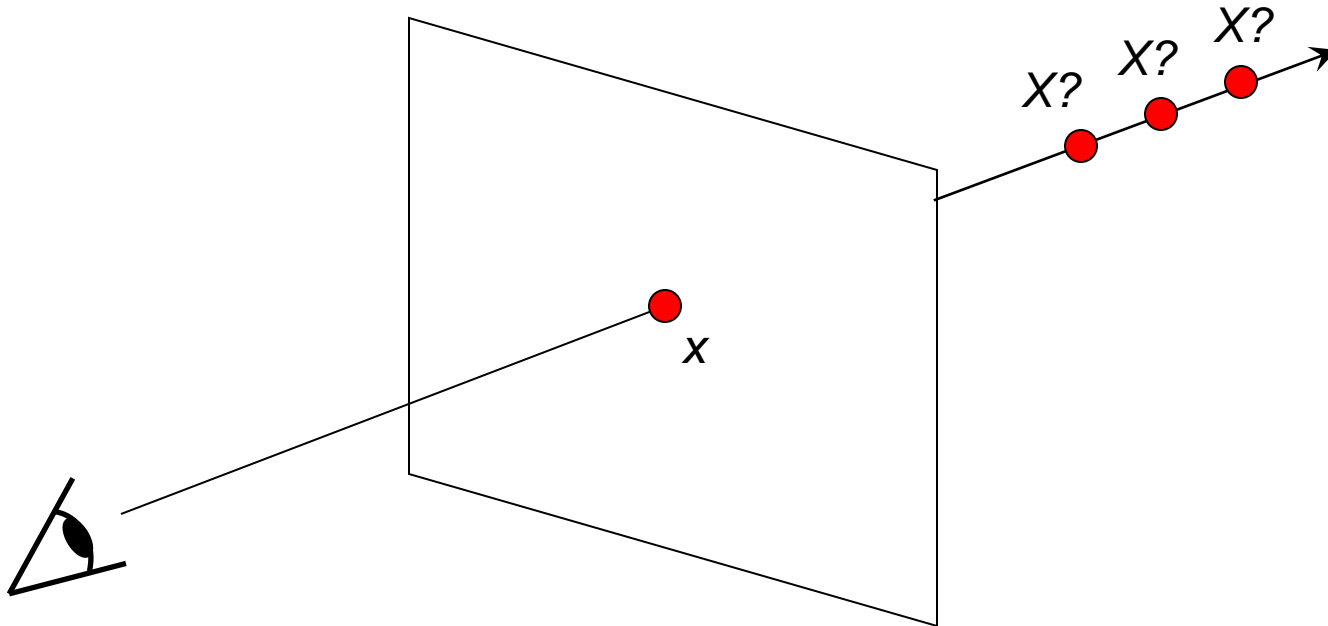
- First meeting: Friday, 24.1., 11:45, Friedrich-Hirzebruch Allee 5, HS 3
- Second meeting: Friday, 31.1., 11:45, Friedrich-Hirzebruch Allee 5, HS 3



Multiple View Geometry in Computer Vision, Second Edition, Richard Hartley and Andrew Zisserman, Cambridge University Press, March 2004.

# Our goal: Recovery of 3D structure

Recovery of structure from one image is inherently ambiguous



# Our goal: Recovery of 3D structure

We will need multi-view geometry

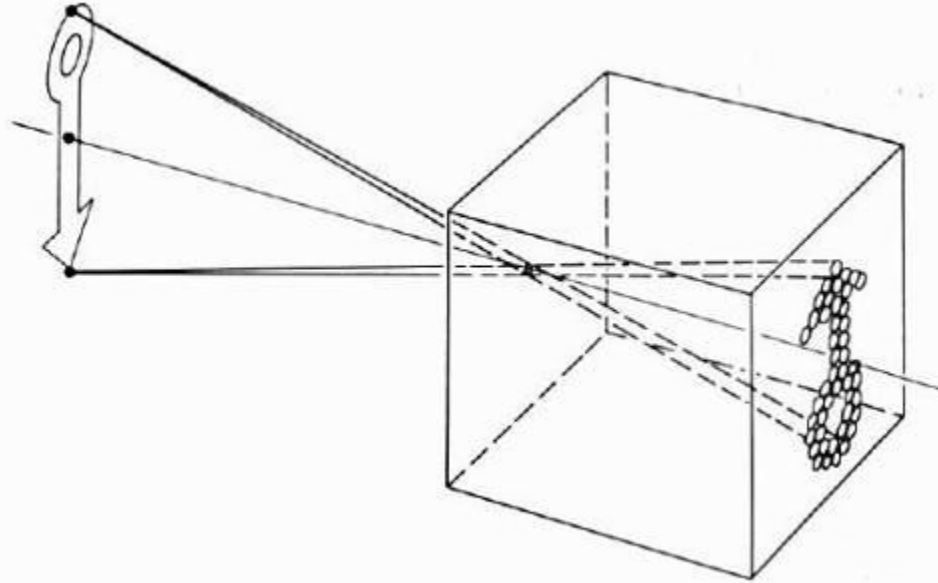


# Cameras





# Pinhole camera model



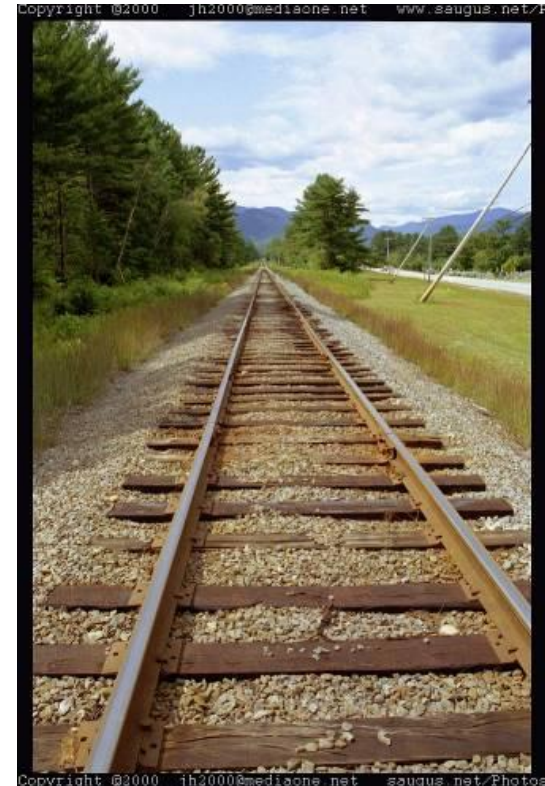
## Pinhole model:

- Captures pencil of rays – all rays through a single point
- The point is called Center of Projection (focal point)
- The image is formed on the Image Plane

# Vanishing points

Each direction in space has its own vanishing point

- All lines going in that direction converge at that point
- Exception: directions parallel to the image plane



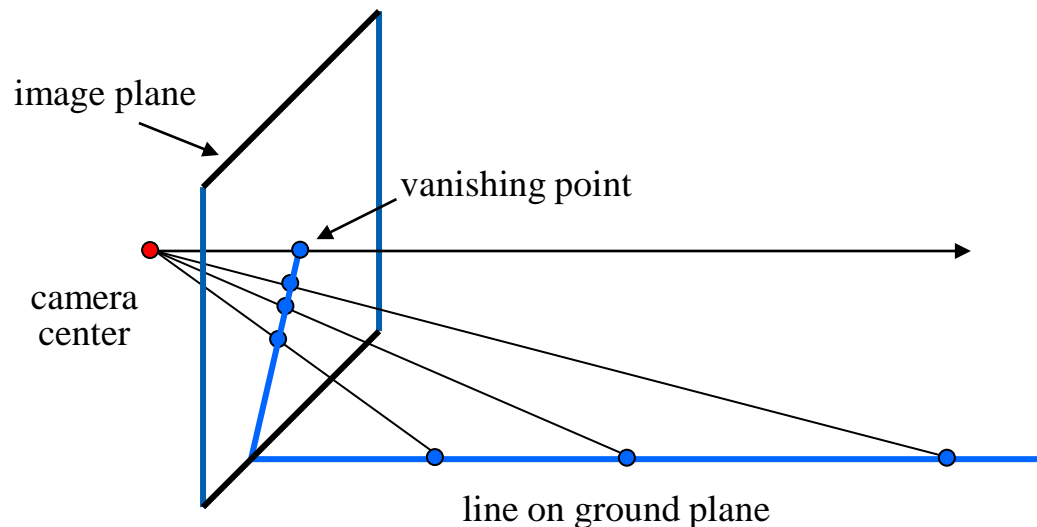


# Vanishing points

Each direction in space has its own vanishing point

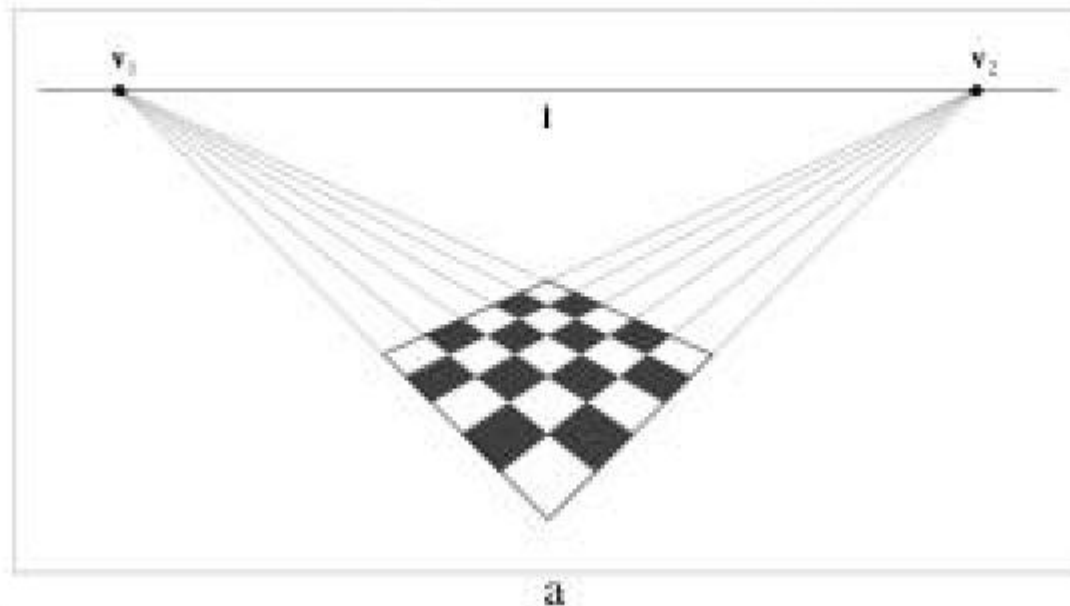
- All lines going in that direction converge at that point
- Exception: directions parallel to the image plane

How do we construct the vanishing point of a line?



# Vanishing points

- Each direction in space has its own vanishing point
  - All lines going in that direction converge at that point
  - Exception: directions parallel to the image plane
- How do we construct the vanishing point of a line?
  - What about the vanishing line of a plane?



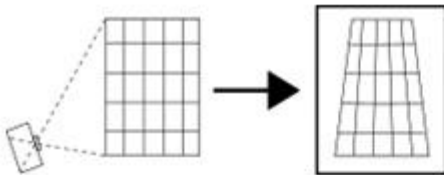
# Perspective distortion

Problem for architectural photography: converging verticals

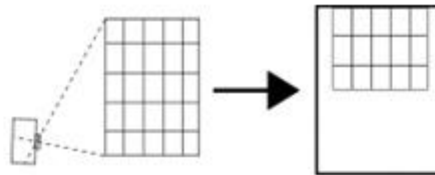


# Perspective distortion

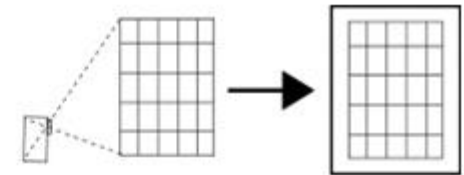
Problem for architectural photography: converging verticals



Tilting the camera upwards results in converging verticals

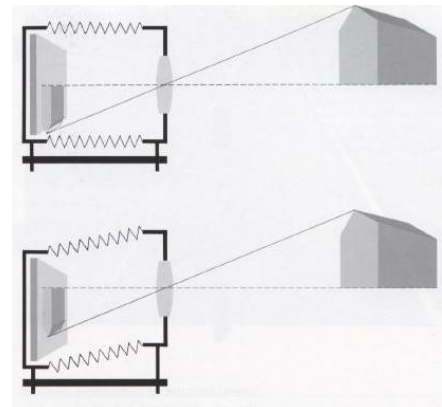
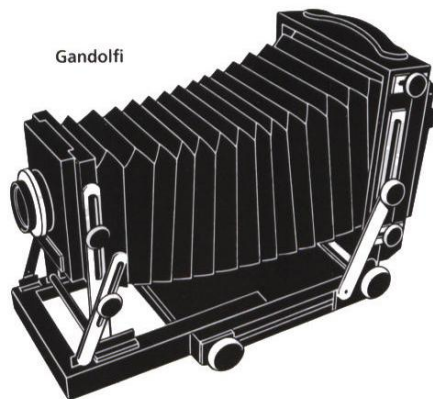


Keeping the camera level, with an ordinary lens, captures only the bottom portion of the building



Shifting the lens upwards results in a picture of the entire subject

Solution: view camera (lens shifted w.r.t. film)



[http://en.wikipedia.org/wiki/Perspective\\_correction\\_lens](http://en.wikipedia.org/wiki/Perspective_correction_lens)

# Perspective distortion

Problem for architectural photography: converging verticals

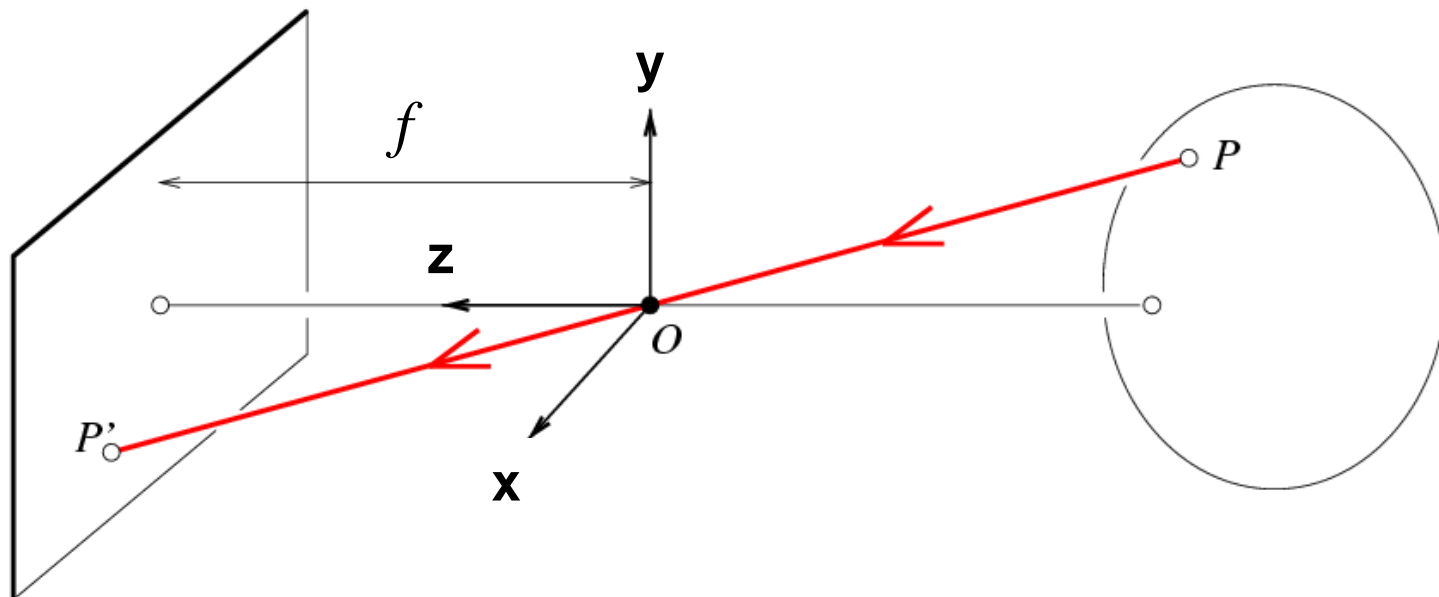
Result:



# Modeling projection

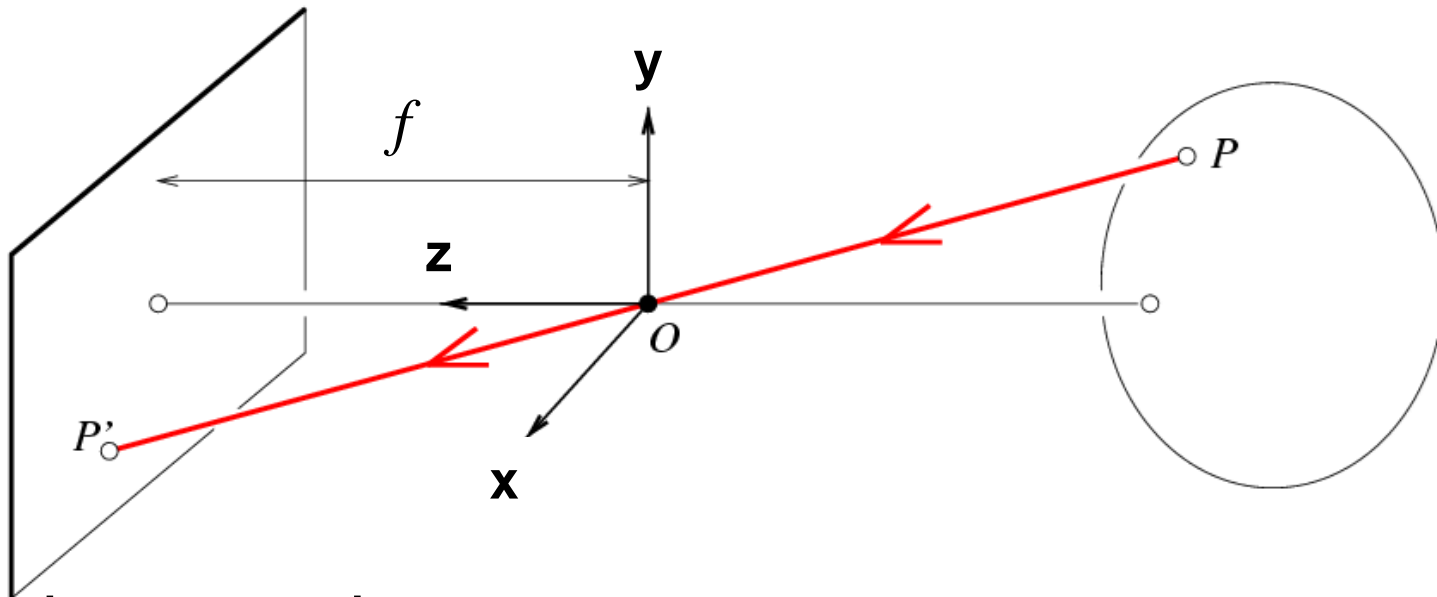
## The coordinate system

- The optical center ( $O$ ) is at the origin
- The image plane is parallel to  $xy$ -plane (perpendicular to  $z$  axis)





# Modeling projection



## • Projection equations

- Compute intersection with image plane of ray from  $\mathbf{P} = (x, y, z)$  to  $\mathbf{O}$
- Derived using similar triangles

$$(x, y, z) \rightarrow \left(f \frac{x}{z}, f \frac{y}{z}, f\right)$$

- We get the projection by throwing out the last coordinate:

$$(x, y, z) \rightarrow \left(f \frac{x}{z}, f \frac{y}{z}\right)$$

# Homogeneous coordinates

$$(x, y, z) \rightarrow \left(f \frac{x}{z}, f \frac{y}{z}\right)$$

Is this a linear transformation?

Trick: add one more coordinate:

$$(x, y) \Rightarrow \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

homogeneous image  
coordinates

$$(x, y, z) \Rightarrow \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

homogeneous scene  
coordinates

Converting *from* homogeneous coordinates

$$\begin{bmatrix} x \\ y \\ w \end{bmatrix} \Rightarrow (x/w, y/w) \qquad \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} \Rightarrow (x/w, y/w, z/w)$$

# Perspective Projection Matrix

Projection is a matrix multiplication using homogeneous coordinates

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1/f & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} = \begin{bmatrix} x \\ y \\ z/f \end{bmatrix} \Rightarrow \left( f \frac{x}{z}, f \frac{y}{z} \right)$$

divide by the third coordinate

# Perspective Projection Matrix

Projection is a matrix multiplication using homogeneous coordinates

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1/f & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} = \begin{bmatrix} x \\ y \\ z/f \end{bmatrix} \Rightarrow \left( f \frac{x}{z}, f \frac{y}{z} \right)$$

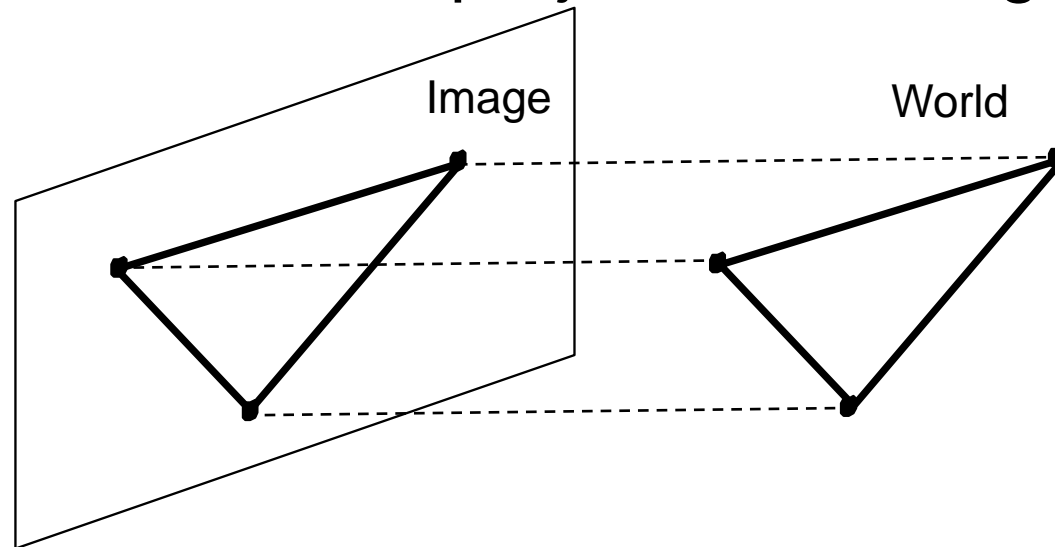
divide by the third coordinate

In practice: lots of coordinate transformations...

$$\begin{pmatrix} \text{2D point} \\ (3 \times 1) \end{pmatrix} = \begin{pmatrix} \text{Camera to pixel coord. trans. matrix} \\ (3 \times 3) \end{pmatrix} \begin{pmatrix} \text{Perspective projection matrix} \\ (3 \times 4) \end{pmatrix} \begin{pmatrix} \text{World to camera coord. trans. matrix} \\ (4 \times 4) \end{pmatrix} \begin{pmatrix} \text{3D point} \\ (4 \times 1) \end{pmatrix}$$

# Orthographic Projection

- Distance from center of projection to image plane is infinite



- Also called “parallel projection”
- What’s the projection matrix?

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} = \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \Rightarrow (x, y)$$

# Building a real camera





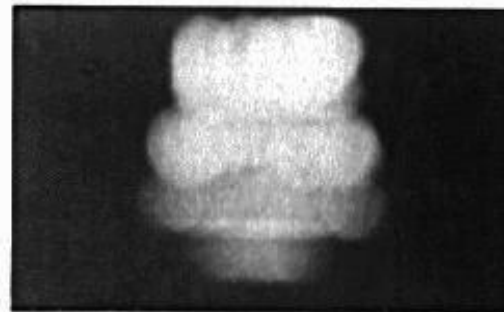
# Home-made pinhole camera



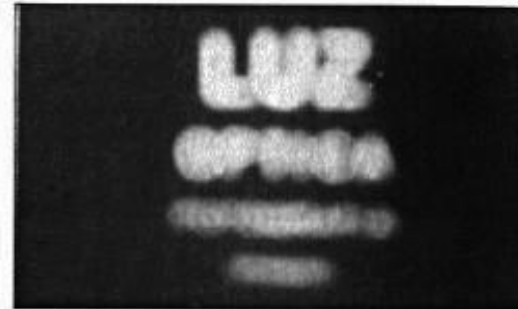
Why so  
blurry?

<http://www.debevec.org/Pinhole/>

# Shrinking the aperture



2 mm



1 mm



0.6mm



0.35 mm

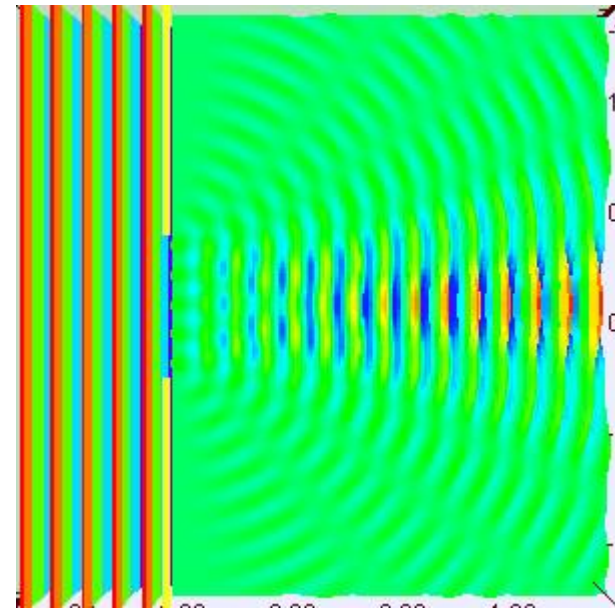
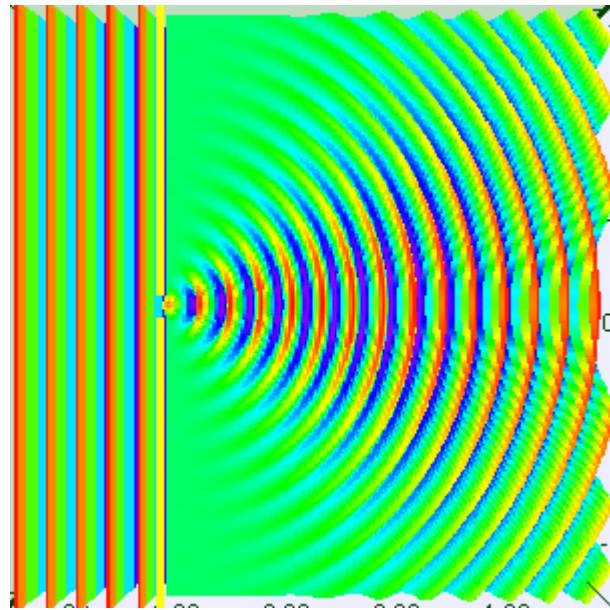


0.15 mm



0.07 mm

# Shrinking aperture

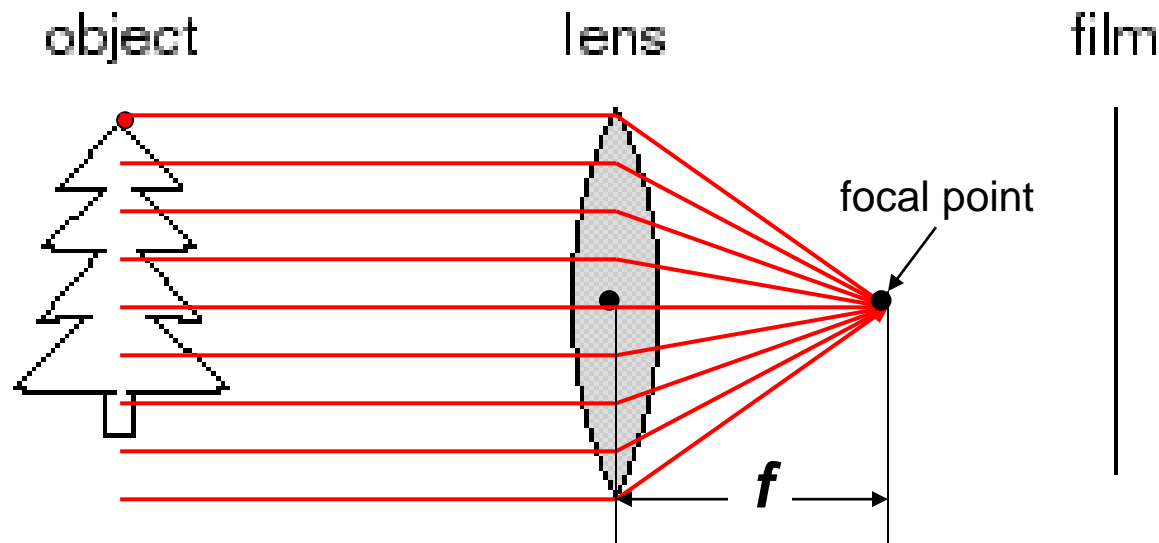


# Adding a lens

A lens focuses light onto the film

– Thin lens model:

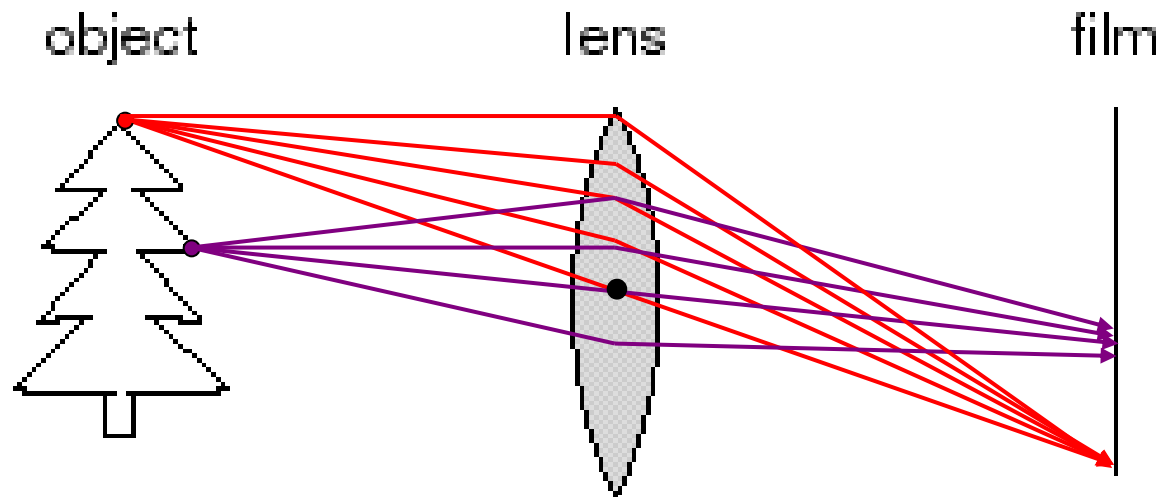
- Rays passing through the center are not deviated (pinhole projection model still holds)
- All parallel rays converge to one point on a plane located at the focal length  $f$



# Adding a lens

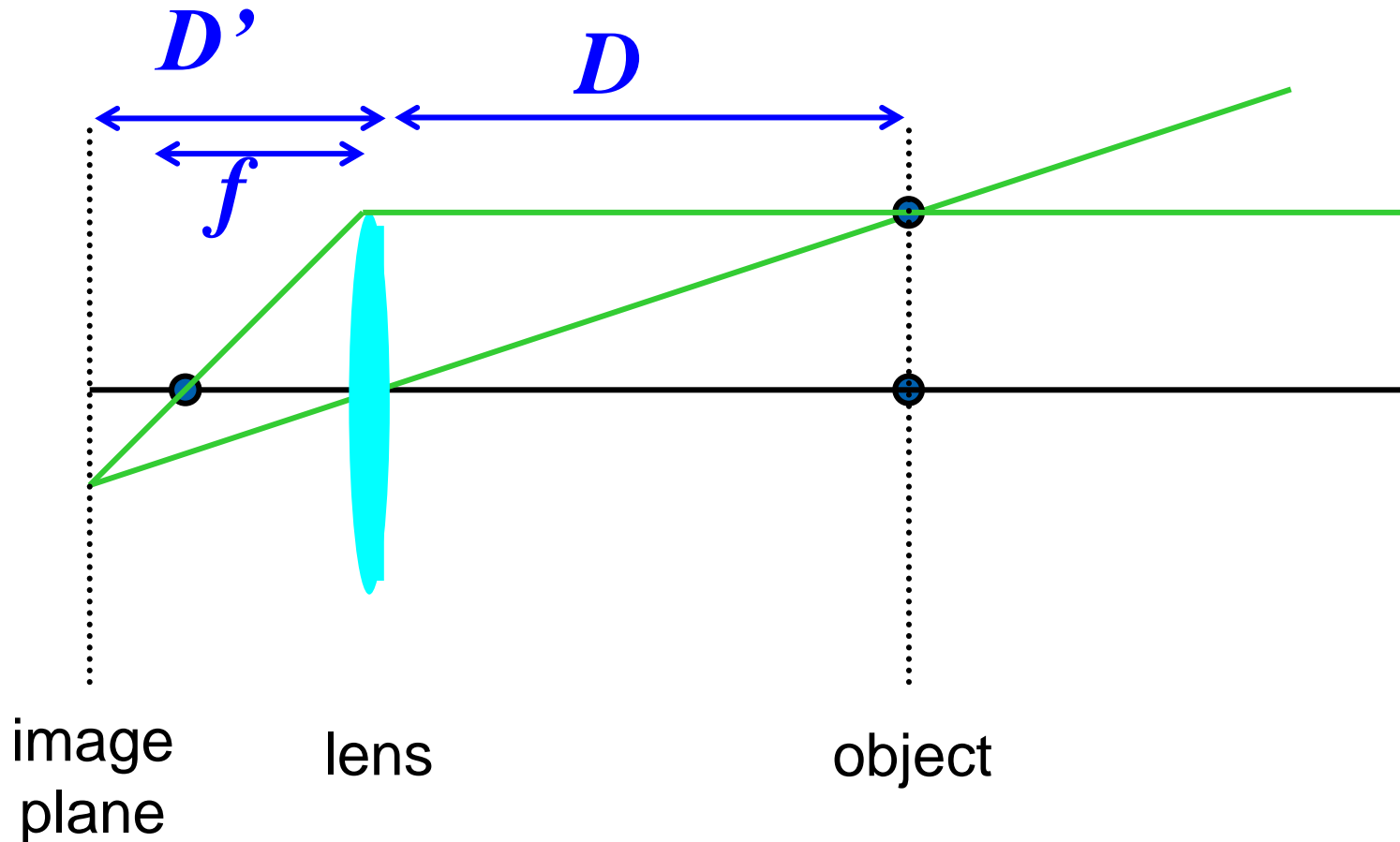
A lens focuses light onto the film

- There is a specific distance at which objects are “in focus”



# Thin lens formula

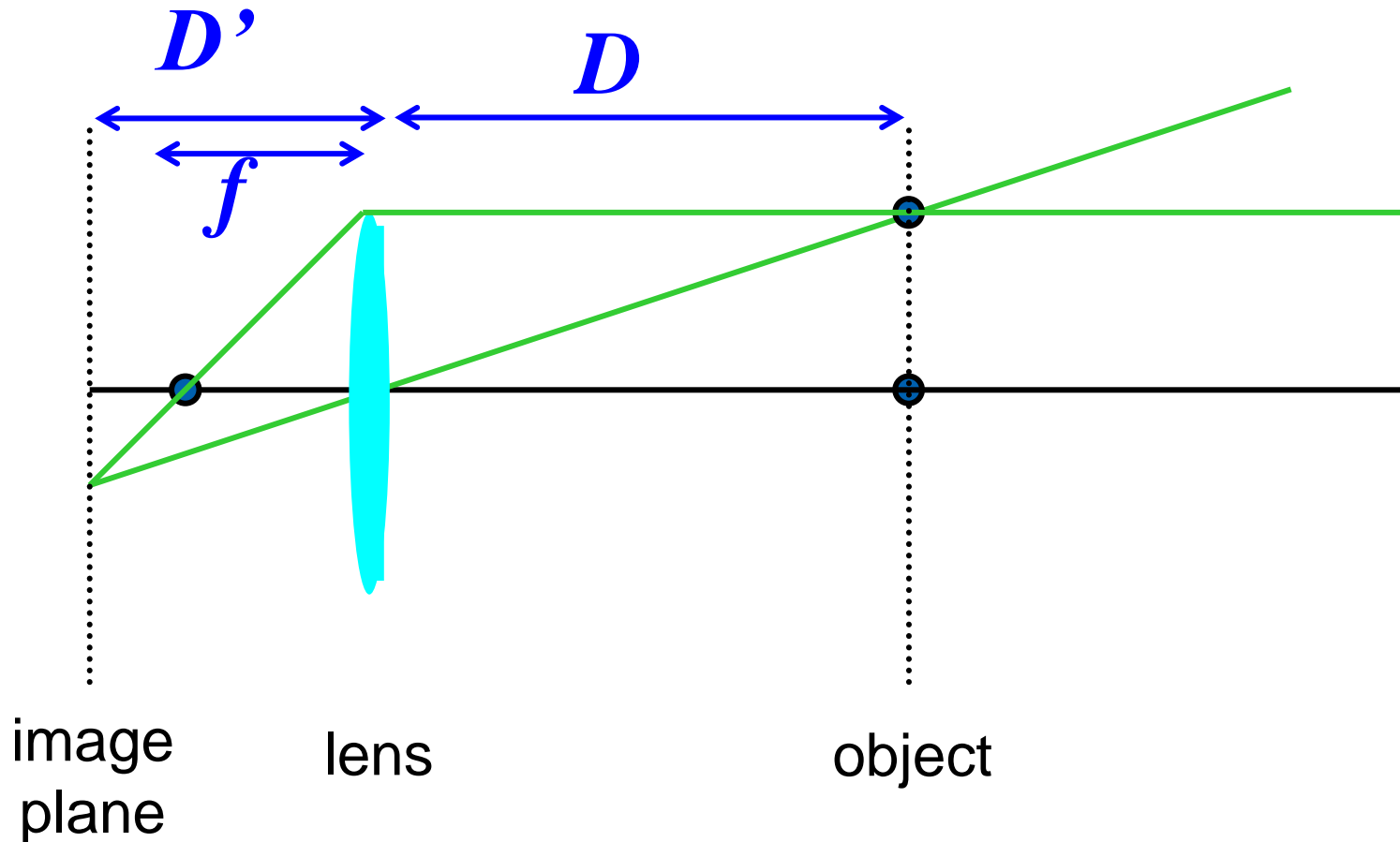
What is the relation between the focal length ( $f$ ), the distance of the object from the optical center ( $D$ ), and the distance at which the object will be in focus ( $D'$ )?





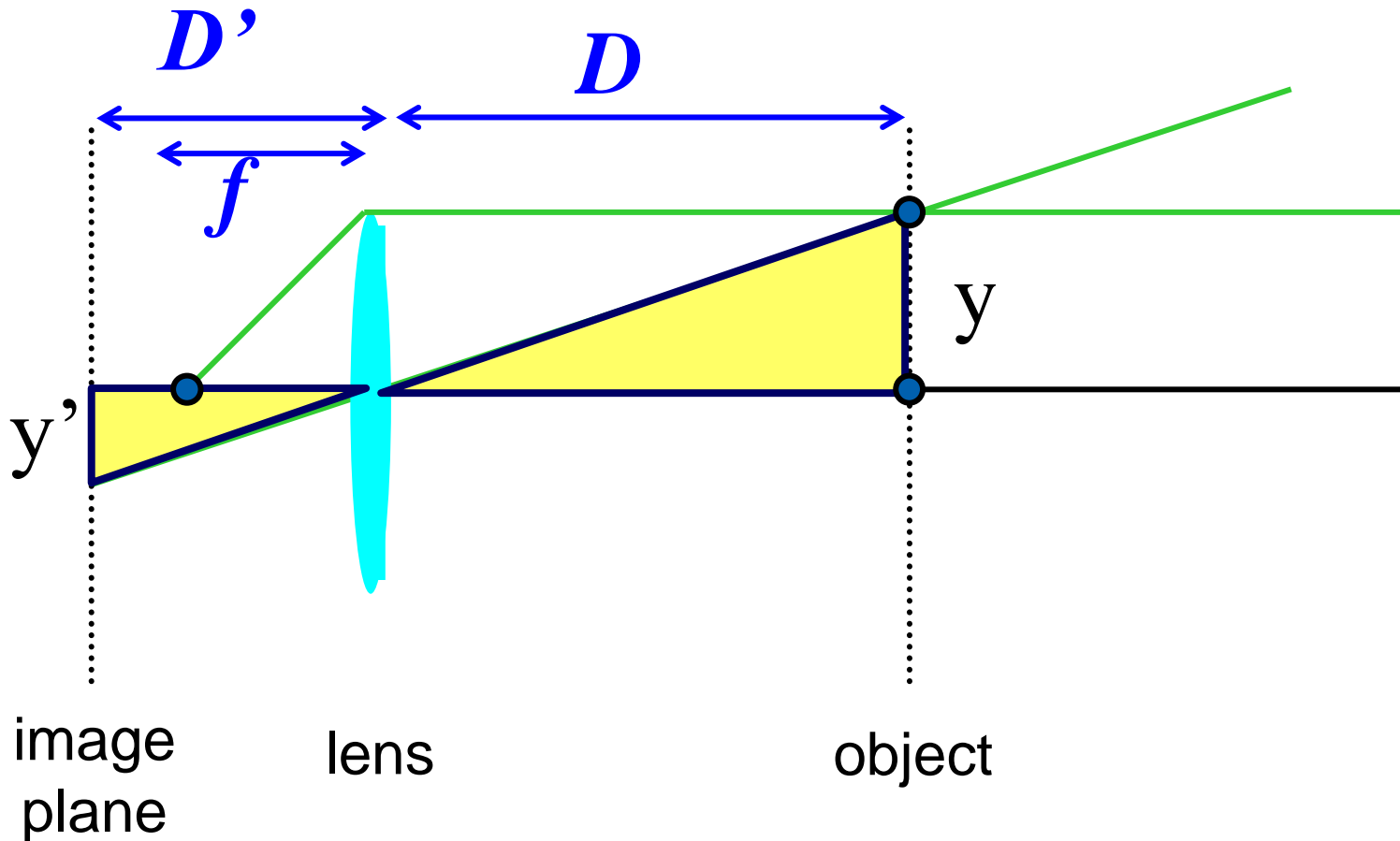
# Thin lens formula

Similar triangles everywhere!



# Thin lens formula

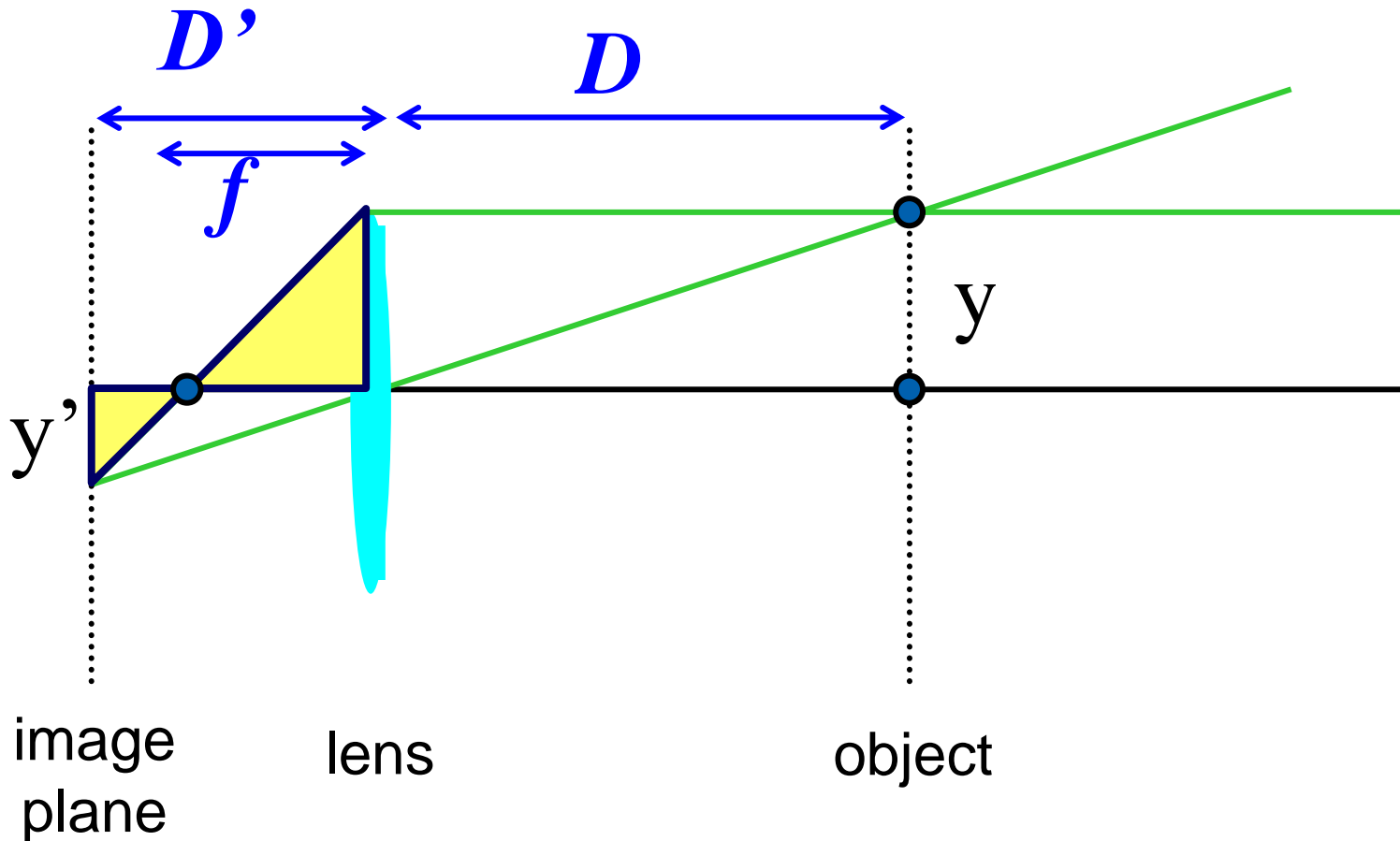
Similar triangles everywhere!  $y'/y = D'/D$



# Thin lens formula

Similar triangles everywhere!

$$y'/y = D'/D$$

$$y'/y = (D' - f)/f$$


# Thin lens formula

Similar triangles everywhere!

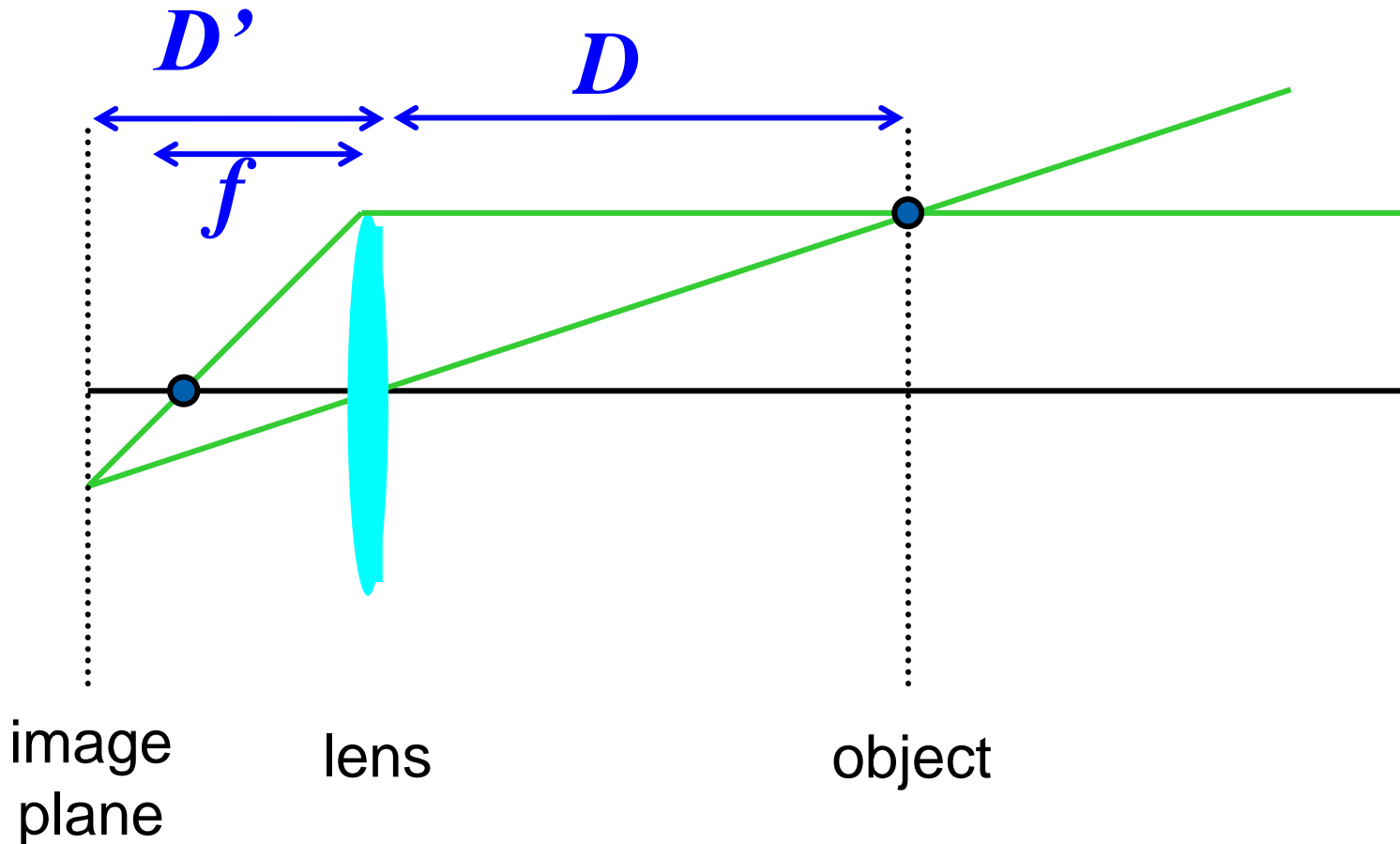
$$y'/y = D'/D$$

$$y'/y = (D' - f)/f$$

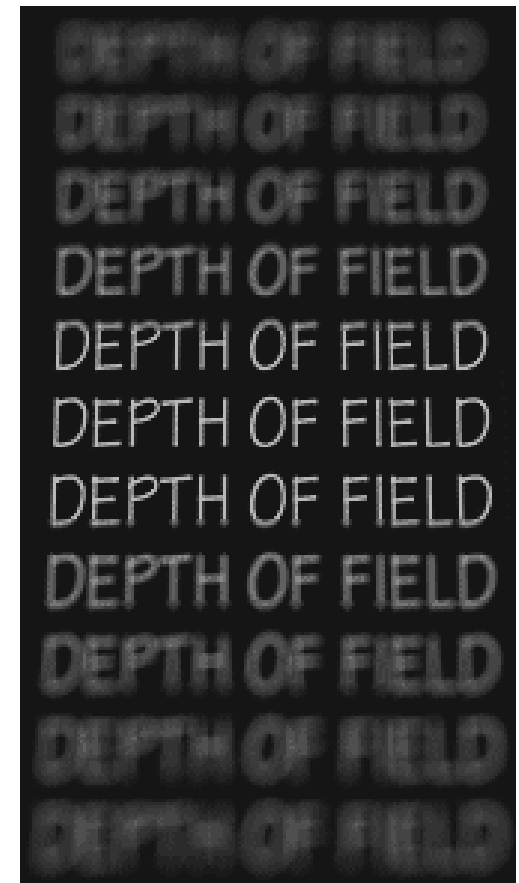
# Thin lens formula

$$\frac{1}{D'} + \frac{1}{D} = \frac{1}{f}$$

Any point satisfying the thin lens equation is in focus.



# Depth of Field

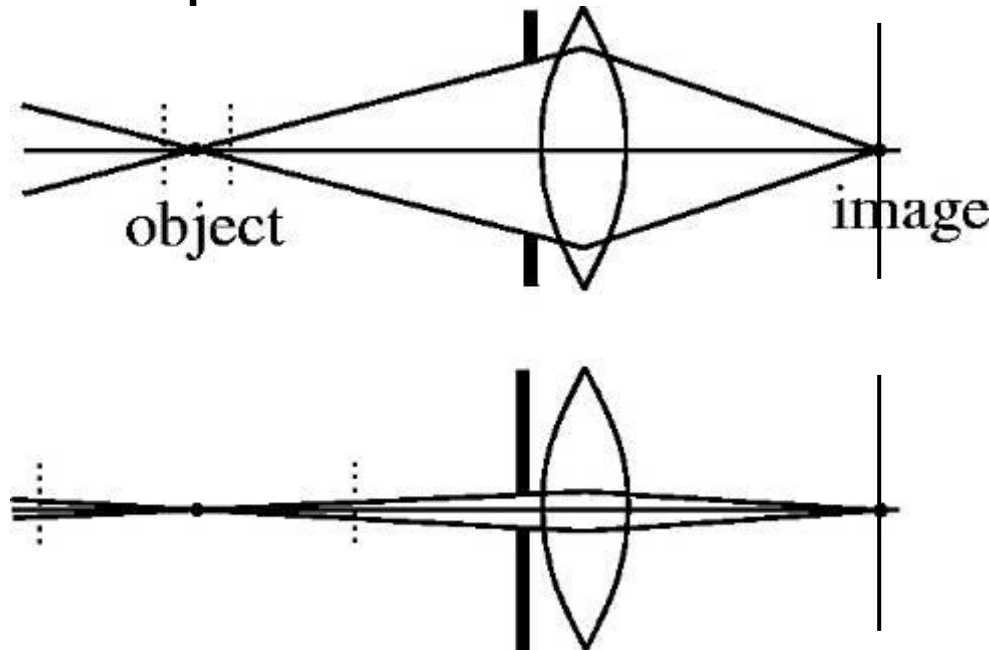




# How can we control the depth of field?

Changing the aperture size affects depth of field

- A smaller aperture increases the range in which the object is approximately in focus
- But small aperture reduces amount of light – need to increase exposure



# Varying the aperture

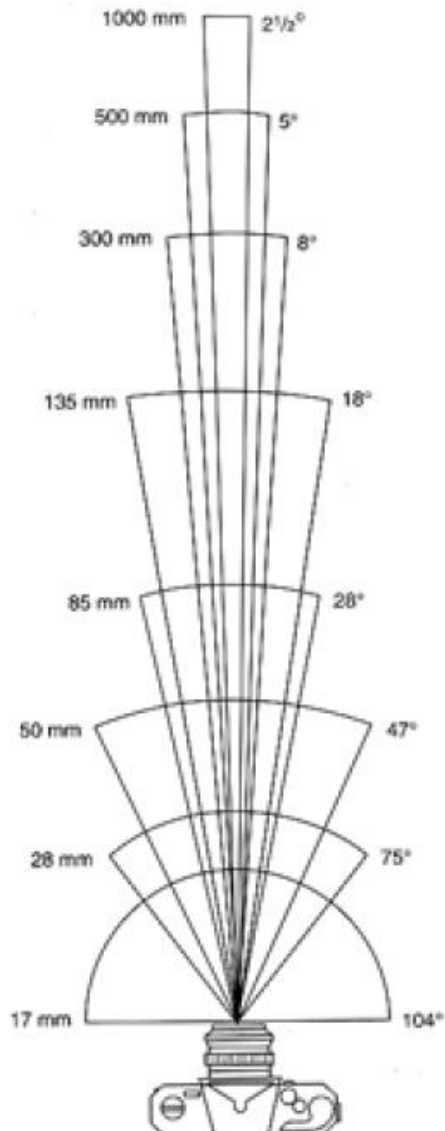


Large aperture = small DOF



Small aperture = large DOF

# Field of View



17mm



28mm

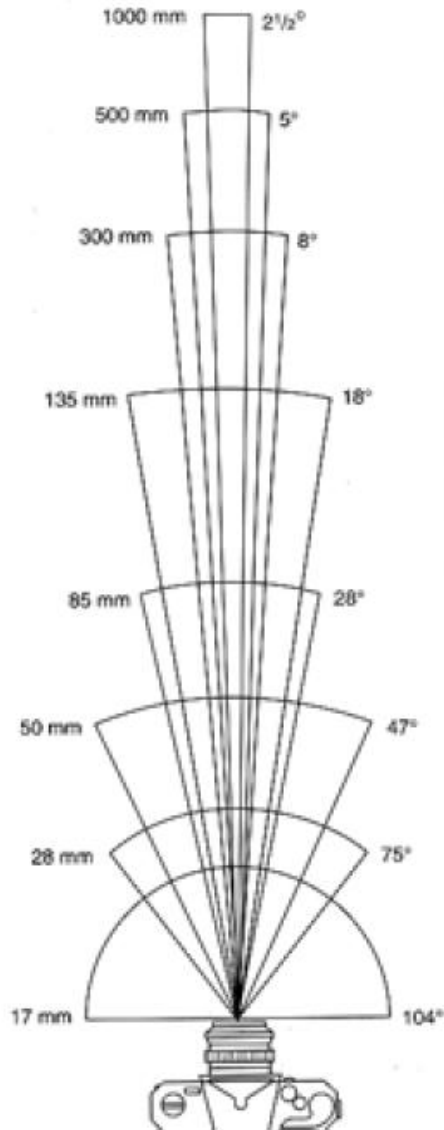


50mm

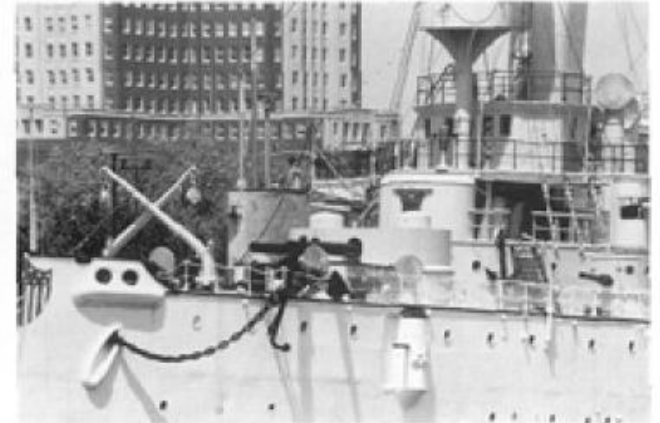


85mm

# Field of View



135mm



300mm



17mm

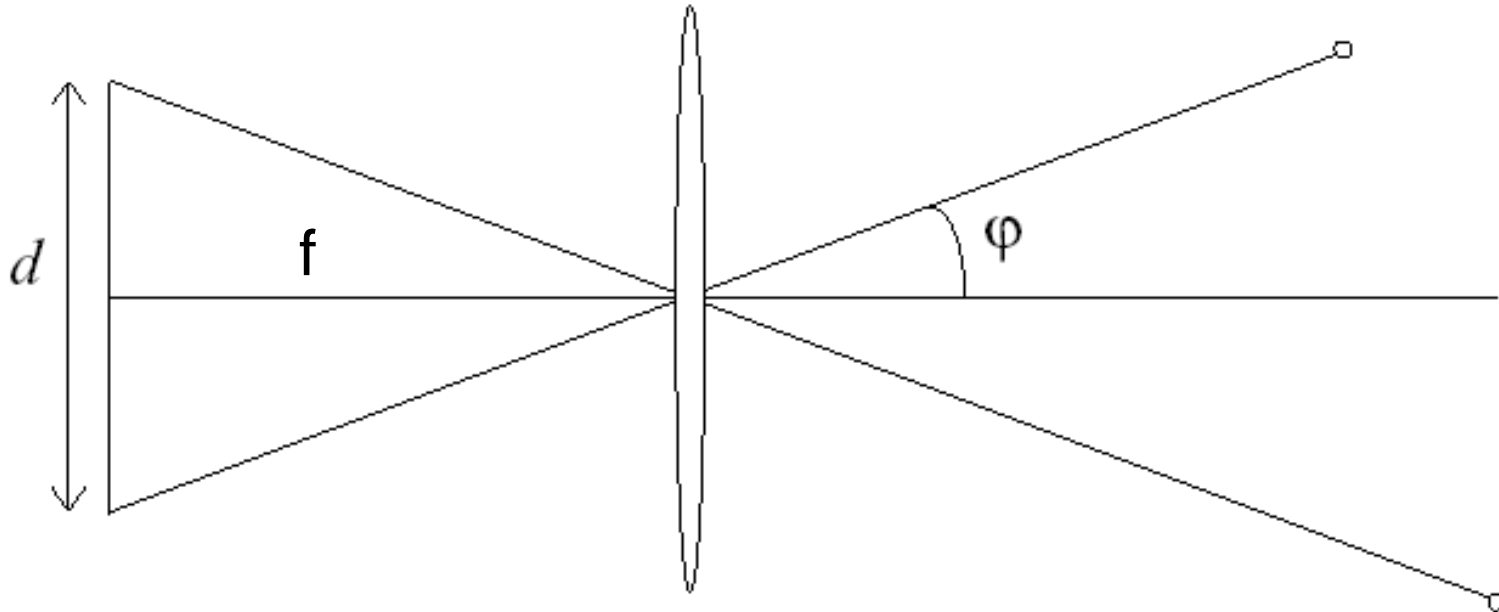


17mm

What does FOV depend on?



# Field of View

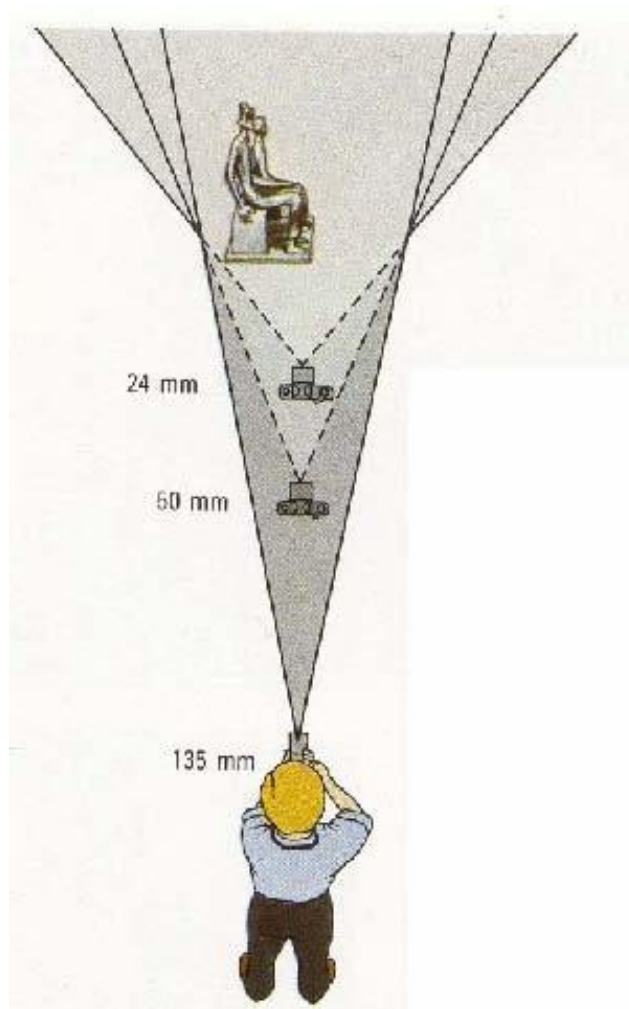


FOV depends on focal length and size of the camera retina

$$\varphi = \tan^{-1}\left(\frac{d}{2f}\right)$$

Smaller FOV = larger Focal Length

# Field of View / Focal Length

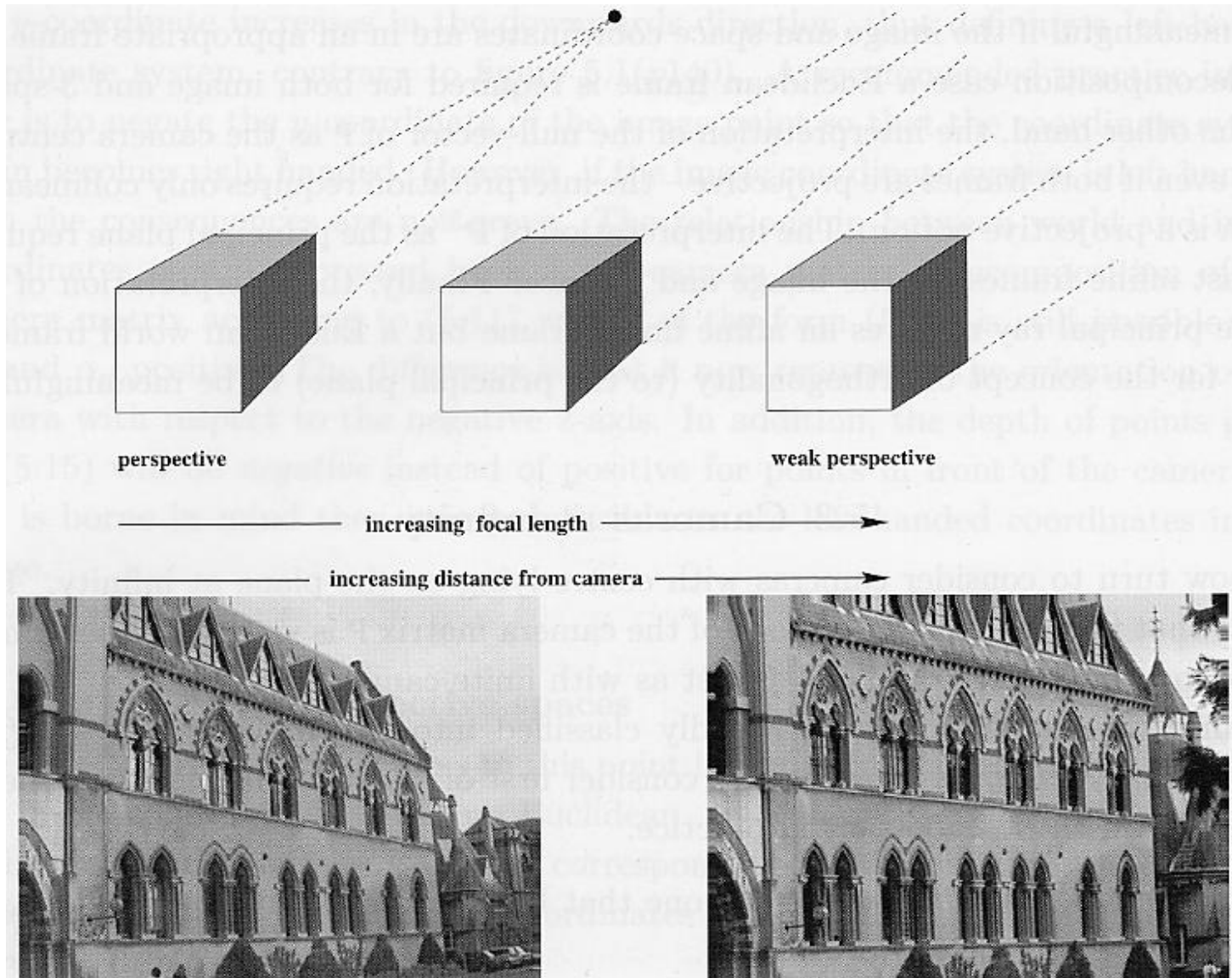


Large FOV, small  $f$   
Camera close to car



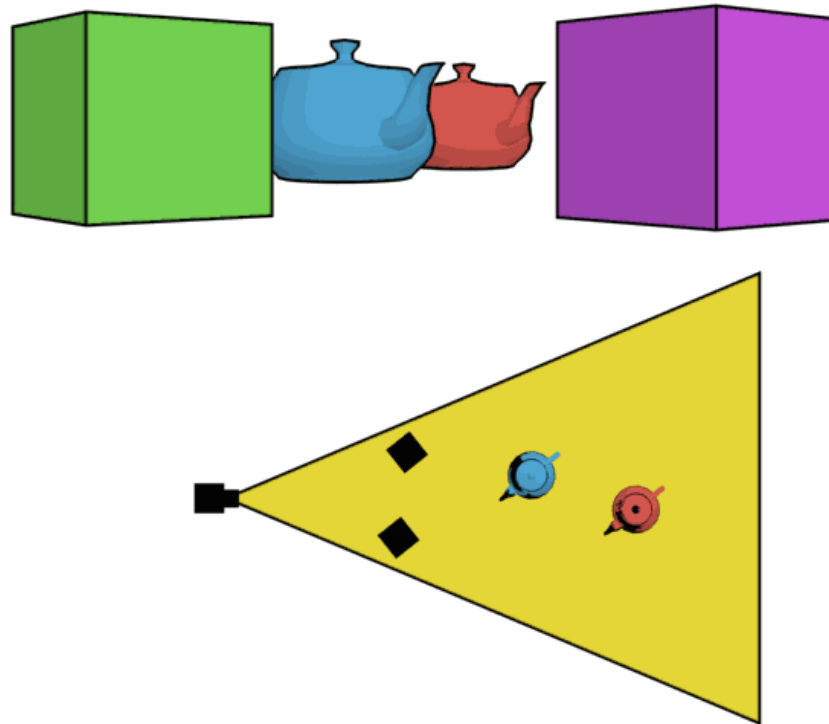
Small FOV, large  $f$   
Camera far from the car

# Approximating an affine camera



# The dolly zoom

Continuously adjusting the focal length while the camera moves away from (or towards) the subject




[http://en.wikipedia.org/wiki/Dolly\\_zoom](http://en.wikipedia.org/wiki/Dolly_zoom)



# Dolly zoom



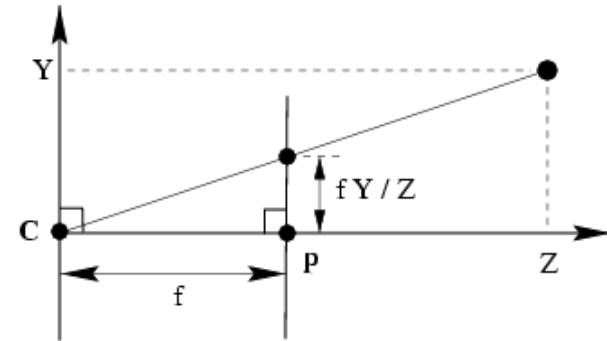
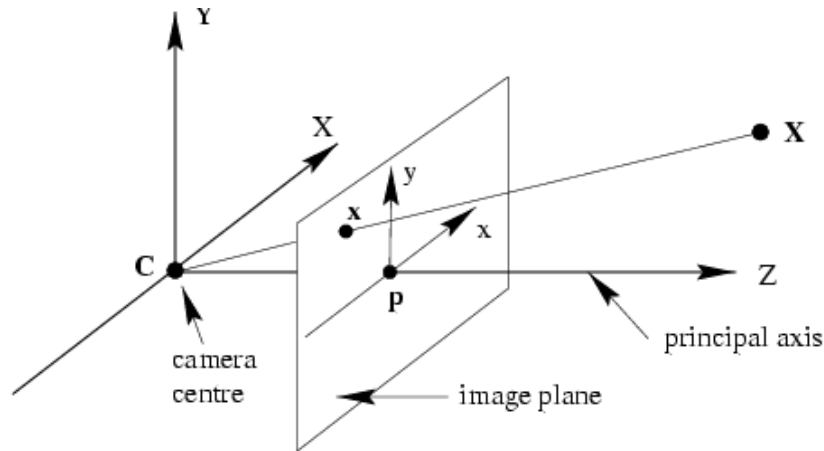
 Filereference: va\_vertigo\_001.max

3DSMax 2011+



*Filmeffekte*

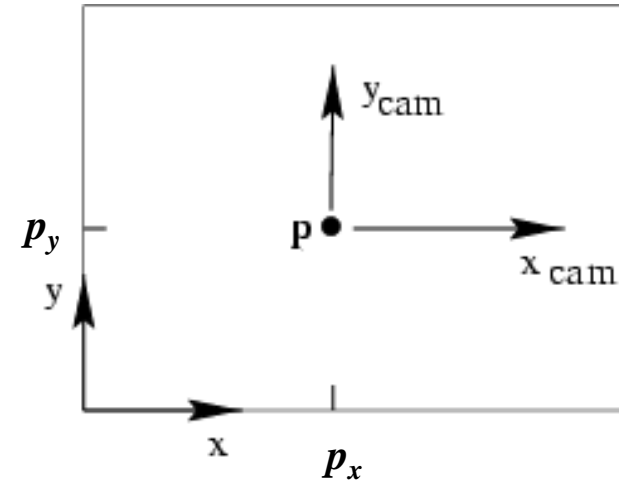
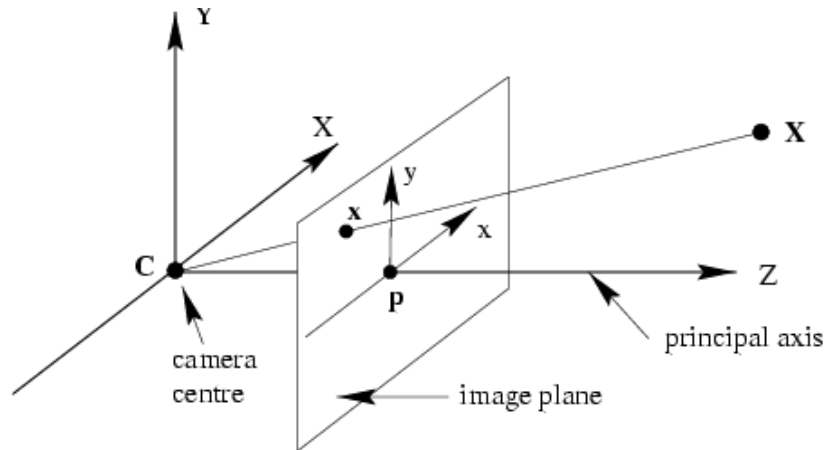
# Pinhole camera model



$$(X, Y, Z) \mapsto (fX/Z, fY/Z)$$

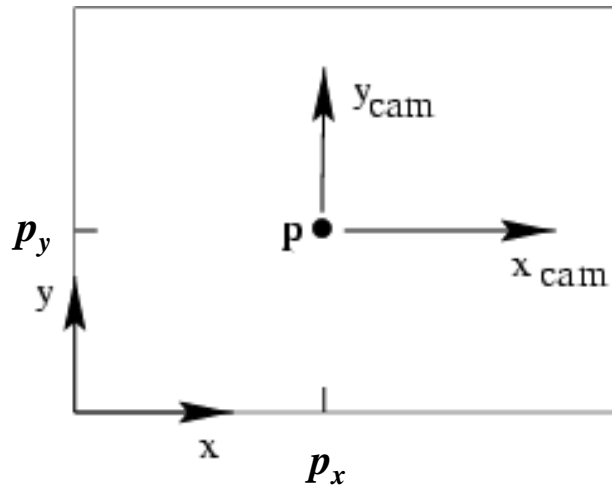
$$\begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix} \mapsto \begin{pmatrix} fX \\ fY \\ Z \end{pmatrix} = \begin{bmatrix} f & 0 \\ f & 0 \\ 1 & 0 \end{bmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix} \quad \mathbf{x} = \mathbf{P}\mathbf{X}$$

# Principal point



- Principal point ( $p$ ): point where principal axis intersects the image plane (origin of normalized coordinate system)
- Normalized coordinate system: origin is at the principal point
- Image coordinate system: origin is in the corner
- How to go from normalized coordinate system to image coordinate system?

# Principal point offset

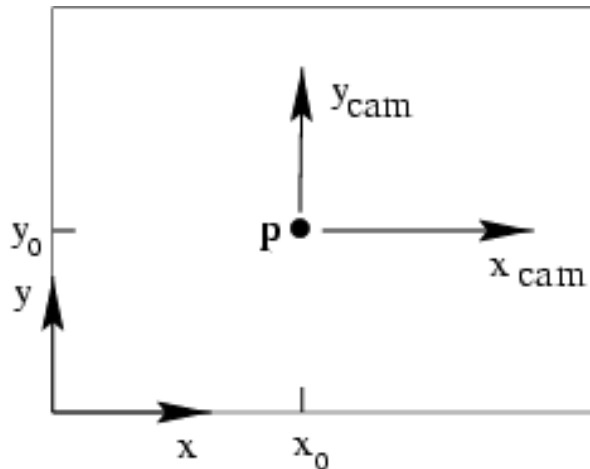


principal point:  $(p_x, p_y)$

$$(X, Y, Z) \mapsto (f X / Z + p_x, f Y / Z + p_y)$$

$$\begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix} \mapsto \begin{pmatrix} f X + Z p_x \\ f Y + Z p_y \\ Z \end{pmatrix} = \begin{bmatrix} f & p_x & 0 \\ & f & p_y & 0 \\ & & 1 & 0 \end{bmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

# Principal point offset



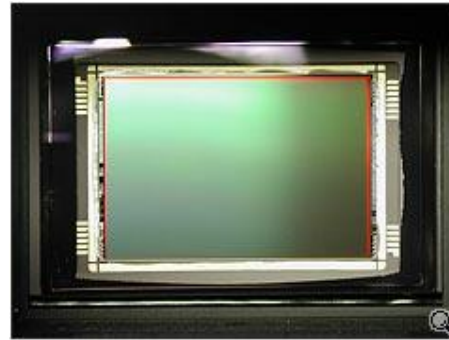
principal point:  $(p_x, p_y)$

$$\begin{pmatrix} fX + Zp_x \\ fY + Zp_y \\ Z \end{pmatrix} = \begin{bmatrix} f & p_x \\ & f & p_y \\ & & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ & 1 & 0 \\ & & 1 & 0 \end{bmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

$$K = \begin{bmatrix} f & p_x \\ & f & p_y \\ & & 1 \end{bmatrix} \text{ calibration matrix}$$

$$P = K[I \mid 0]$$

# Pixel coordinates



Pixel size:

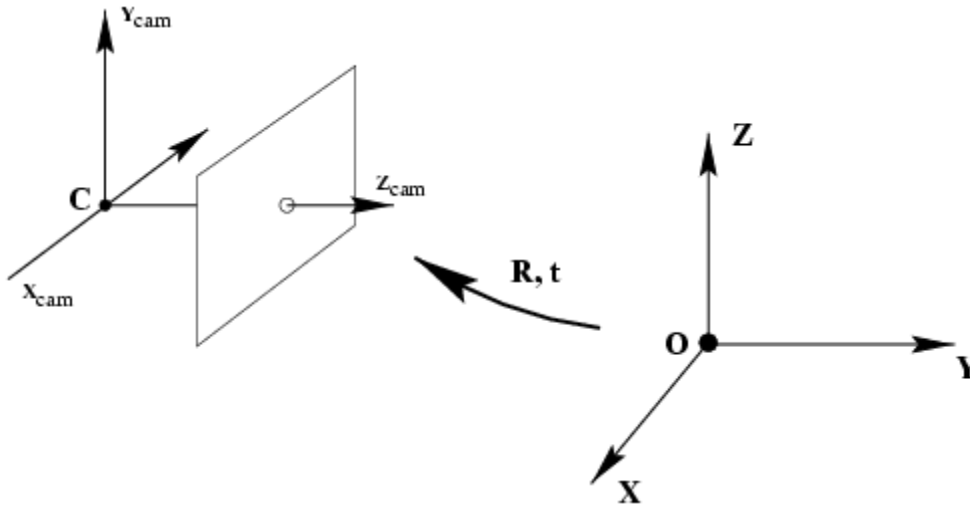
$$\frac{1}{m_x} \times \frac{1}{m_y}$$

$m_x$  pixels per meter in horizontal direction,  
 $m_y$  pixels per meter in vertical direction

$$K = \begin{bmatrix} m_x & & \\ & m_y & \\ & & 1 \end{bmatrix} \begin{bmatrix} f \\ f \\ 1 \end{bmatrix} = \begin{bmatrix} \alpha_x & & \beta_x \\ & \alpha_y & \beta_y \\ & & 1 \end{bmatrix}$$

pixels/m                      m                      pixels

# Camera rotation and translation



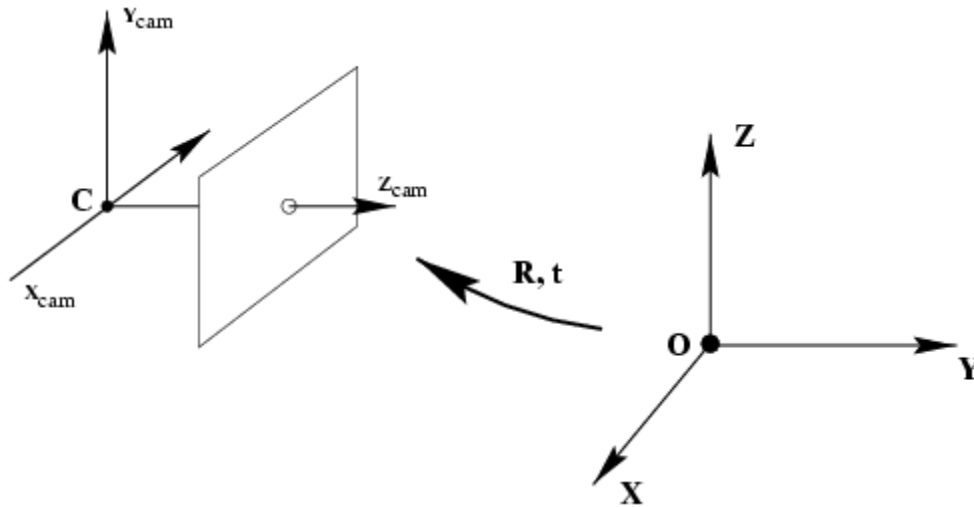
In general, the camera coordinate frame will be related to the world coordinate frame by a rotation and a translation

$$\tilde{\mathbf{X}}_{\text{cam}} = \mathbf{R}(\tilde{\mathbf{X}} - \tilde{\mathbf{C}})$$

coords. of point in camera frame     
 coords. of a point in world frame (nonhomogeneous)     
 coords. of camera center in world frame



# Camera rotation and translation



In non-homogeneous coordinates:

$$\tilde{X}_{\text{cam}} = R(\tilde{X} - \tilde{C})$$

$$X_{\text{cam}} = \begin{bmatrix} R & -R\tilde{C} \\ 0 & 1 \end{bmatrix} \begin{pmatrix} \tilde{X} \\ 1 \end{pmatrix} = \begin{bmatrix} R & -R\tilde{C} \\ 0 & 1 \end{bmatrix} X$$

$$x = K[I \mid 0]X_{\text{cam}} = K[R \mid -R\tilde{C}]X \quad P = K[R \mid t], \quad t = -R\tilde{C}$$

# Camera parameters

- Intrinsic parameters
  - Principal point coordinates
  - Focal length
  - Pixel magnification factors

$$K = \begin{bmatrix} m_x & & \\ & m_y & \\ & & 1 \end{bmatrix} \begin{bmatrix} f & & \\ & f & \\ & & 1 \end{bmatrix} \begin{bmatrix} p_x \\ p_y \\ 1 \end{bmatrix} = \begin{bmatrix} \alpha_x & & \beta_x \\ & \alpha_y & \beta_y \\ & & 1 \end{bmatrix}$$

# Camera parameters

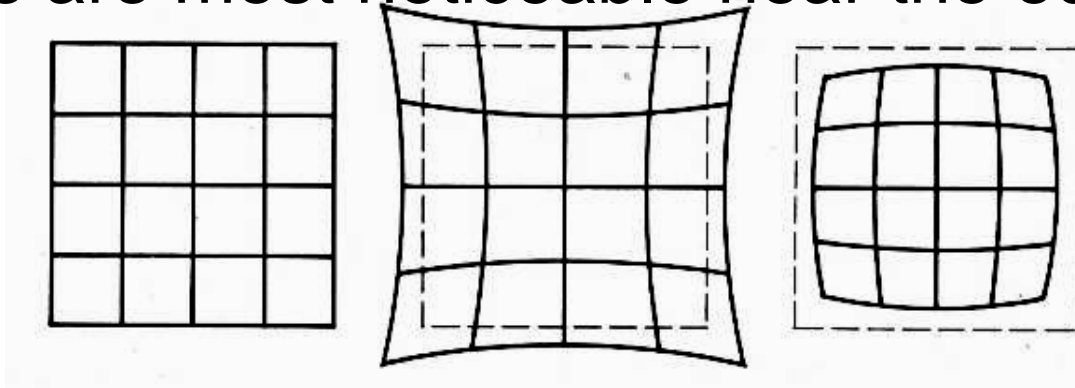
- Intrinsic parameters
  - Principal point coordinates
  - Focal length
  - Pixel magnification factors
  - *Skew (non-rectangular pixels)*

$$K = \begin{pmatrix} \alpha_x & \gamma & \beta_x \\ 0 & \alpha_y & \beta_y \\ 0 & 0 & 1 \end{pmatrix}$$

# Radial Distortion

Caused by imperfect lenses

Deviations are most noticeable near the edge of the lens



No distortion

Pin cushion

Barrel



# Fisheye lenses



Fisheye photo © 2006 Jarle Aasland  
Nikkor 6mm mounted on Nikon F3 body © 2006 Kazuo Koga

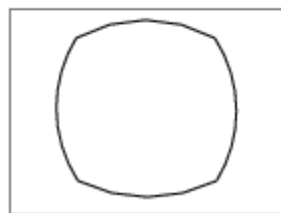
# Camera parameters

- Intrinsic parameters
  - Principal point coordinates
  - Focal length
  - Pixel magnification factors
  - *Skew (non-rectangular pixels)*
  - *Radial distortion*

$$K = \begin{pmatrix} \alpha_x & \gamma & \beta_x \\ 0 & \alpha_y & \beta_y \\ 0 & 0 & 1 \end{pmatrix}$$



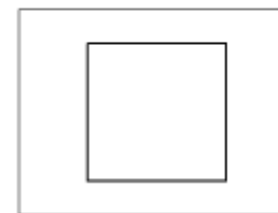
radial distortion



correction



linear image



# Radial distortion

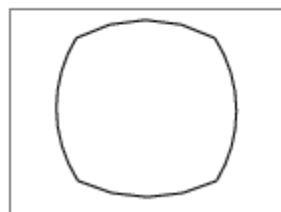
## Polynomial model

$$\begin{pmatrix} x_d \\ y_d \end{pmatrix} = L(\tilde{r}) \begin{pmatrix} \tilde{x} \\ \tilde{y} \end{pmatrix}$$

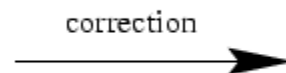
$$L(r) = 1 + \kappa_1 r + \kappa_2 r^2 + \kappa_3 r^3 + \dots$$



radial distortion

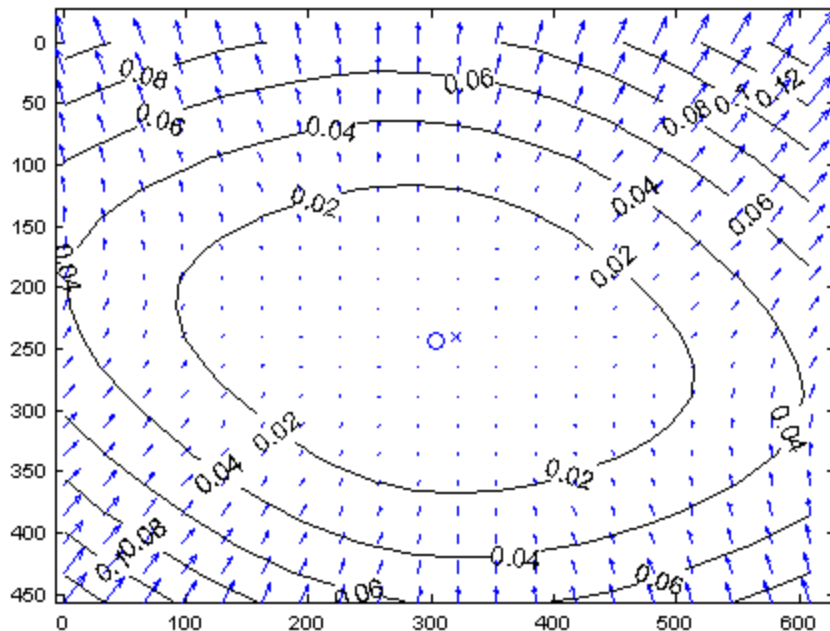


linear image

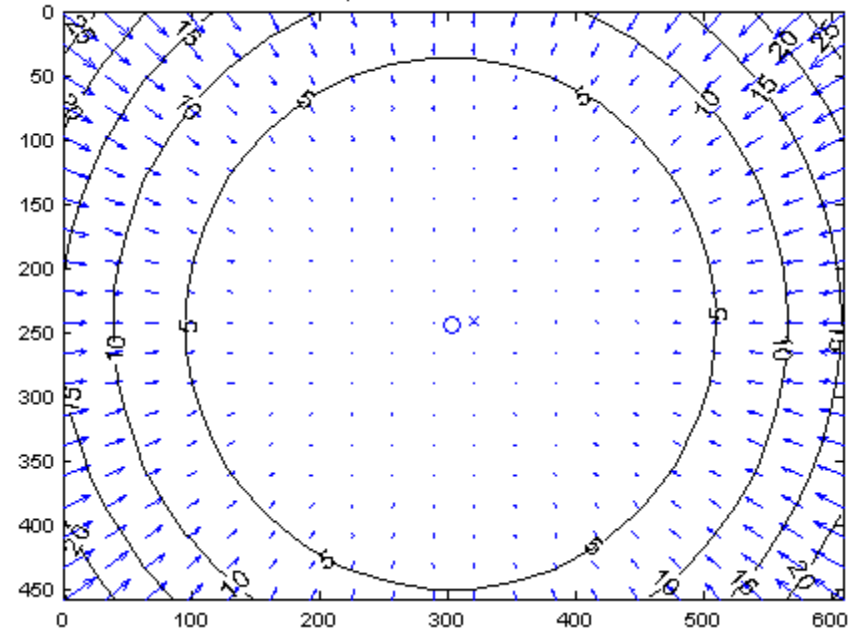


## Other models combine radial and tangential distortion

Tangential Component of the Distortion Model



Radial Component of the Distortion Model



$$\mathbf{x}_d = \begin{bmatrix} \mathbf{x}_d(1) \\ \mathbf{x}_d(2) \end{bmatrix} = \left( 1 + kc(1)r^2 + kc(2)r^4 + kc(5)r^6 \right) \mathbf{x}_n + d\mathbf{x}$$

$$d\mathbf{x} = \begin{bmatrix} 2kc(3)xy + kc(4)(r^2 + 2x^2) \\ kc(3)(r^2 + 2y^2) + 2kc(4)xy \end{bmatrix}$$



# Camera parameters

## Intrinsic parameters

- Principal point coordinates
- Focal length
- Pixel magnification factors
- Skew (non-rectangular pixels)
- Radial distortion

## Extrinsic parameters

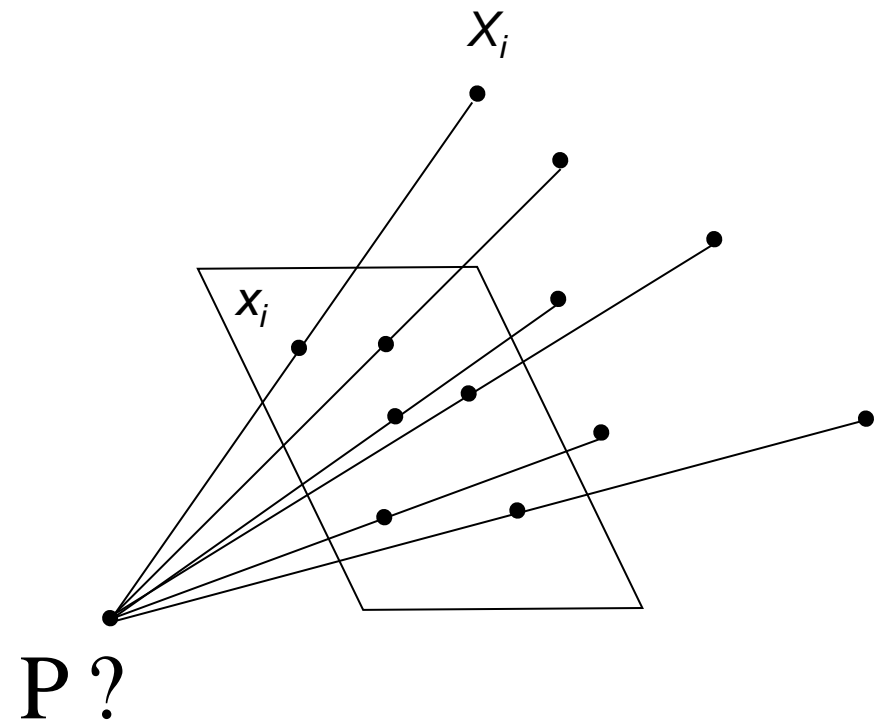
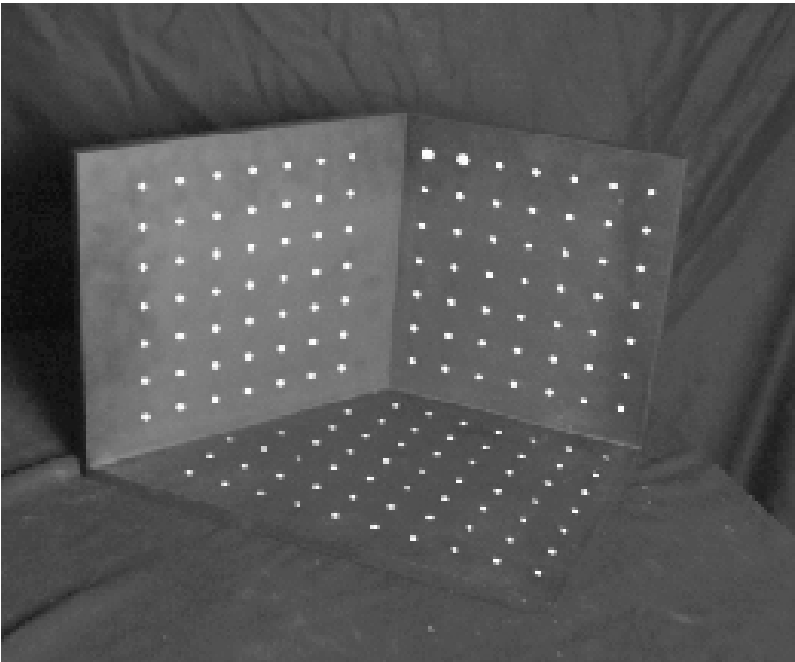
- Rotation and translation relative to world coordinate system

$$\mathbf{x} = \mathbf{K} \begin{bmatrix} \mathbf{R} & \mathbf{t} \end{bmatrix} \mathbf{X}$$

$$\begin{bmatrix} \lambda x \\ \lambda y \\ \lambda \end{bmatrix} = \begin{bmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

# Camera calibration

Given  $n$  points with known 3D coordinates  $X_i$  and known image projections  $x_i$ , estimate the camera parameters



# Camera calibration: Linear method

$$\lambda \mathbf{x}_i = \mathbf{P} \mathbf{X}_i \quad \mathbf{x}_i \times \mathbf{P} \mathbf{X}_i = 0 \quad \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix} \times \begin{bmatrix} \mathbf{P}_1^T \mathbf{X}_i \\ \mathbf{P}_2^T \mathbf{X}_i \\ \mathbf{P}_3^T \mathbf{X}_i \end{bmatrix} = 0$$

$$\mathbf{a} \times \mathbf{b} = [\mathbf{a}]_{\times} \mathbf{b} = \begin{bmatrix} 0 & -a_3 & a_2 \\ a_3 & 0 & -a_1 \\ -a_2 & a_1 & 0 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

$$\begin{bmatrix} 0 & -\mathbf{X}_i^T & y_i \mathbf{X}_i^T \\ \mathbf{X}_i^T & 0 & -x_i \mathbf{X}_i^T \\ -y_i \mathbf{X}_i^T & x_i \mathbf{X}_i^T & 0 \end{bmatrix} \begin{pmatrix} \mathbf{P}_1 \\ \mathbf{P}_2 \\ \mathbf{P}_3 \end{pmatrix} = 0$$

Two linearly independent equations

# Camera calibration: Linear method

$$\begin{bmatrix} 0^T & \mathbf{X}_1^T & -y_1 \mathbf{X}_1^T \\ \mathbf{X}_1^T & 0^T & -x_1 \mathbf{X}_1^T \\ \dots & \dots & \dots \\ 0^T & \mathbf{X}_n^T & -y_n \mathbf{X}_n^T \\ \mathbf{X}_n^T & 0^T & -x_n \mathbf{X}_n^T \end{bmatrix} \begin{pmatrix} \mathbf{P}_1 \\ \mathbf{P}_2 \\ \mathbf{P}_3 \end{pmatrix} = 0 \quad \mathbf{A}\mathbf{p} = 0$$

- $\mathbf{P}$  has 11 degrees of freedom (12 parameters, but scale is arbitrary)
- One 2D/3D correspondence gives us two linearly independent equations
- Homogeneous least squares
- 6 correspondences needed for a minimal solution

# Camera calibration: Linear method

Advantages: easy to formulate and solve

Disadvantages

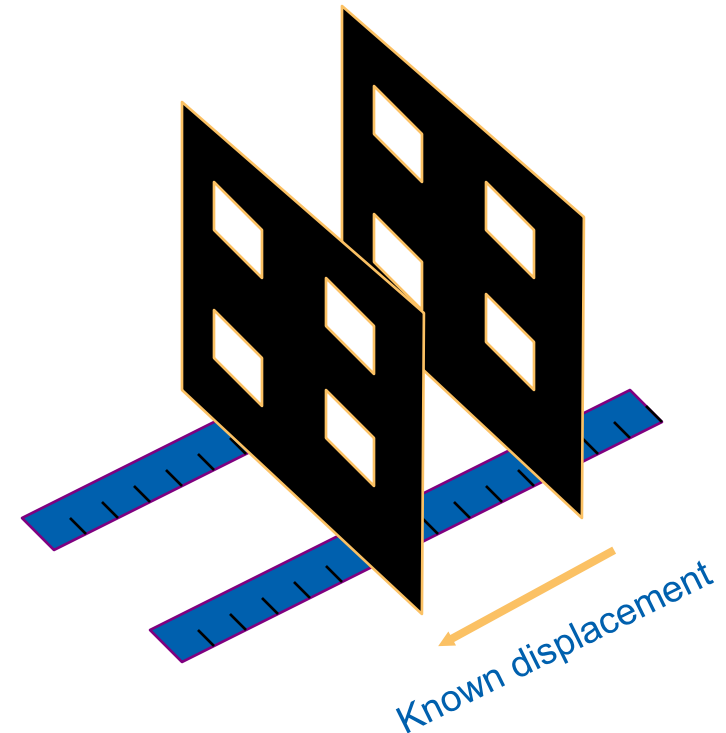
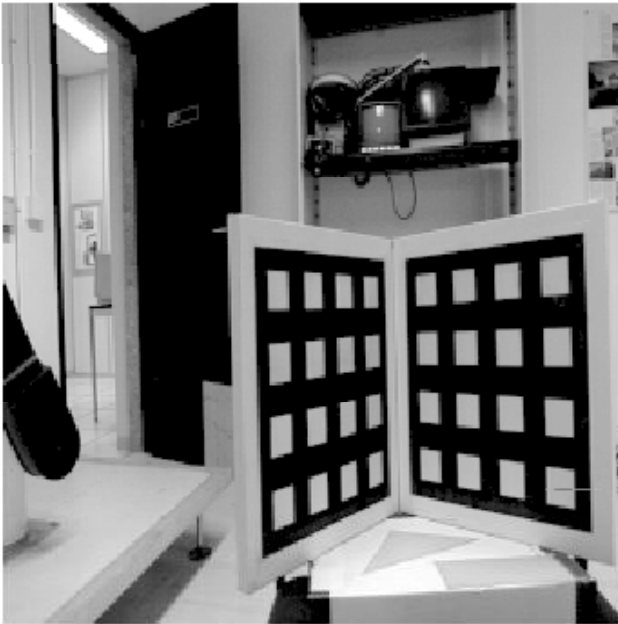
- Doesn't directly tell you camera parameters
- Doesn't model radial distortion
- Can't impose constraints, such as known focal length and orthogonality

Non-linear methods are preferred

- Define error as difference between projected points and measured points
- Minimize error using Newton's method or other non-linear optimization

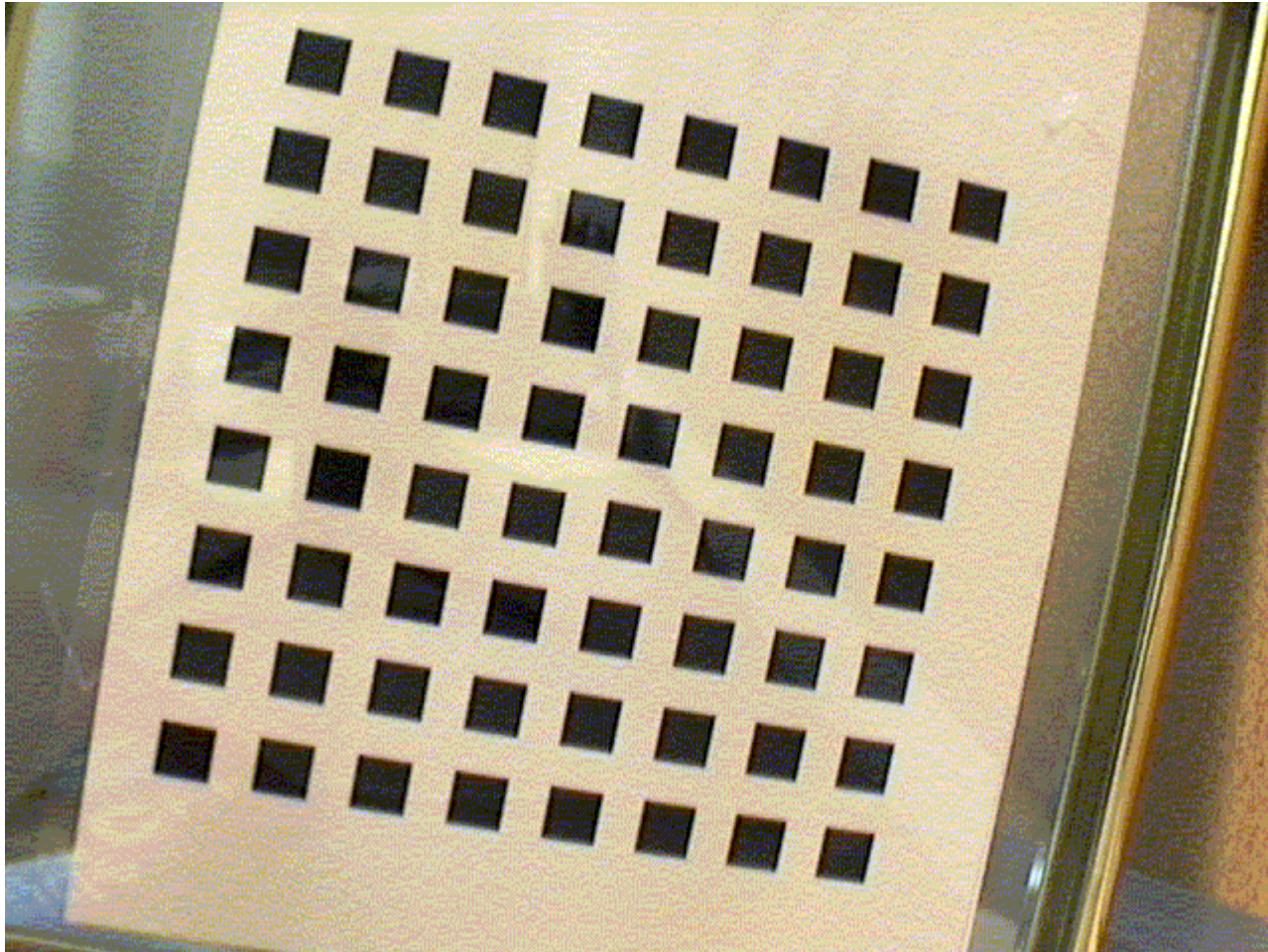
# Calibration Object

Use precisely known 3D points



Shortcoming: Not flexible

# Intrinsic Calibration with Planes





# Intrinsic Calibration with Planes

Use only one plane

- Print a pattern on a paper
- Attach the paper on a planar surface
- Show the plane freely a few times to the camera

Advantages

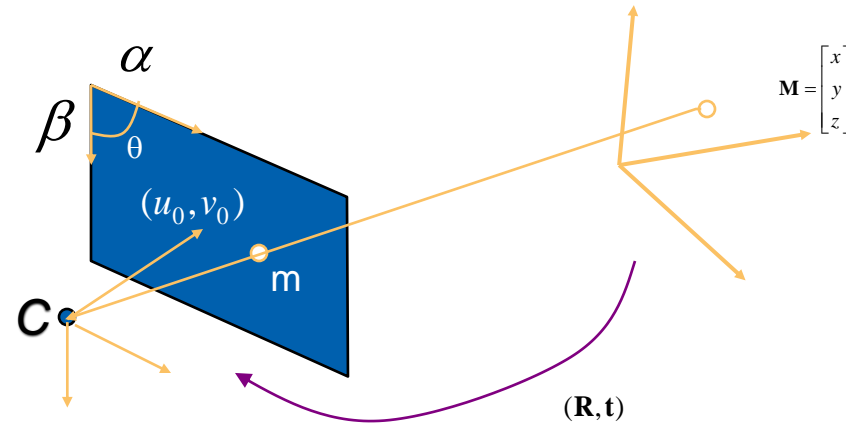
- Flexible
- Robust

Implementation in OpenCV or Matlab toolbox:

[http://www.vision.caltech.edu/bouguetj/calib\\_doc/](http://www.vision.caltech.edu/bouguetj/calib_doc/)

[ Z. Zhang. Flexible Camera Calibration by Viewing a Plane from Unknown Orientations. ICCV99 ]

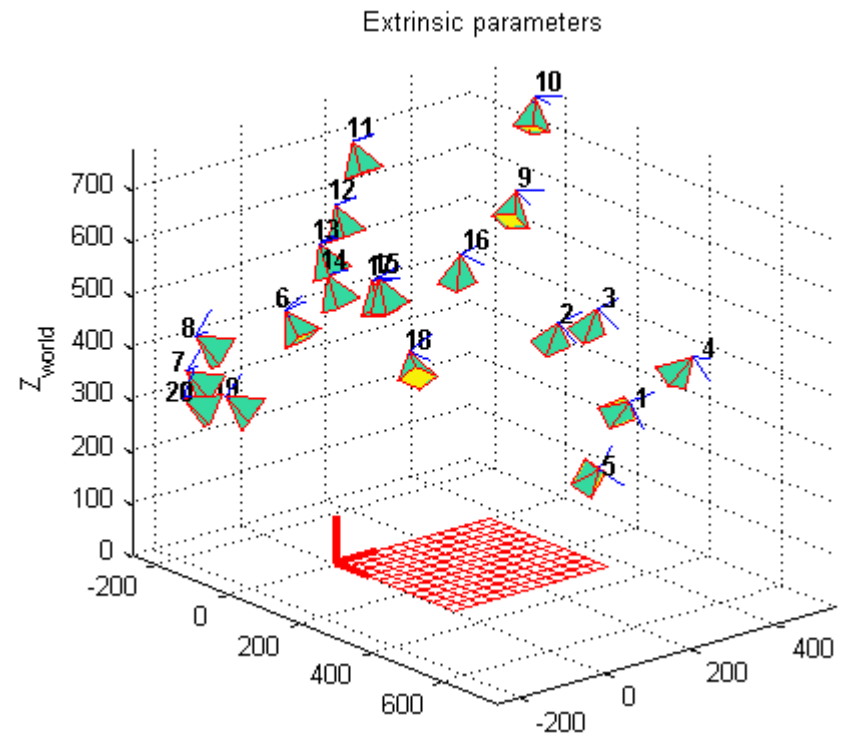
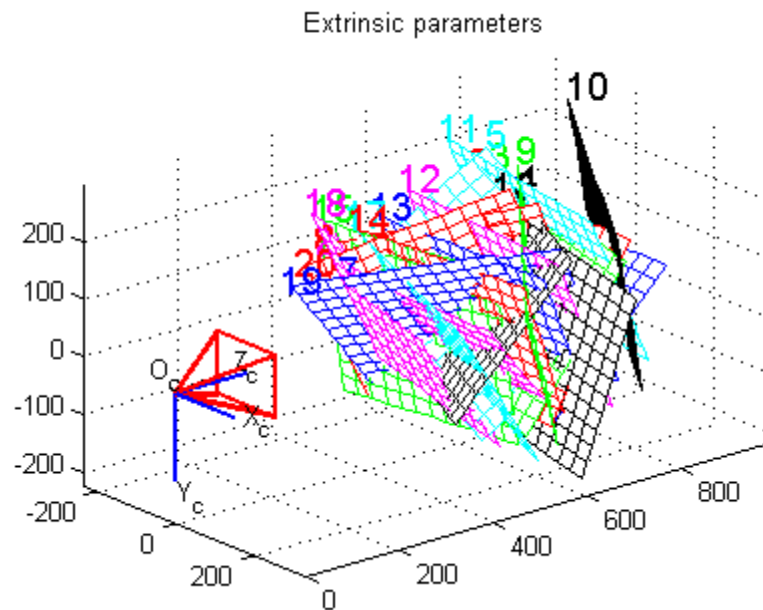
# Camera Model



$$\underbrace{s \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}}_{\tilde{\mathbf{m}}} = \underbrace{\begin{bmatrix} \alpha & \gamma & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix}}_{\mathbf{A}} \underbrace{\begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{r}_3 & \mathbf{t} \end{bmatrix}}_{[\mathbf{R} \quad \mathbf{t}]} \underbrace{\begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}}_{\tilde{\mathbf{M}}}$$

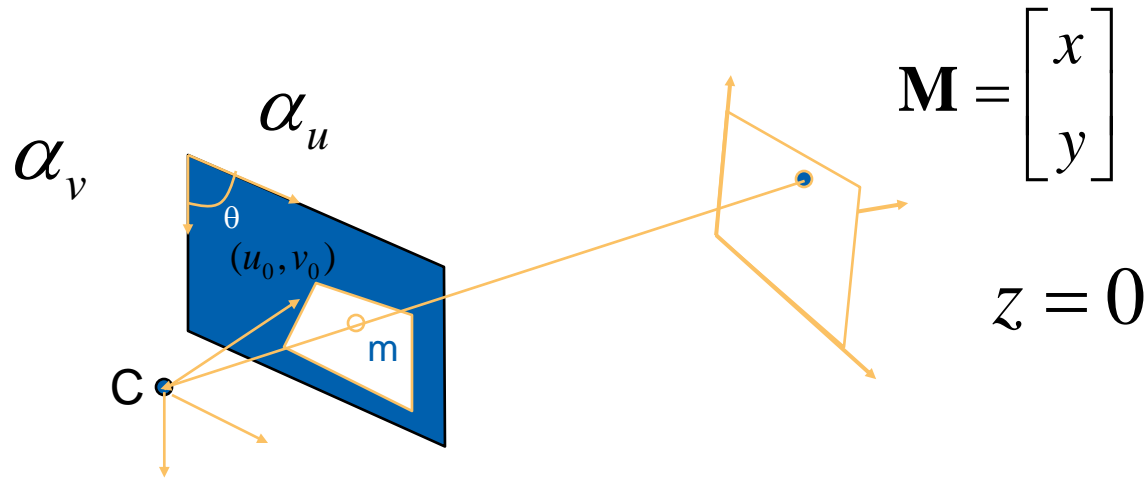
# Calibration process

## Extrinsic parameters



# Plane projection

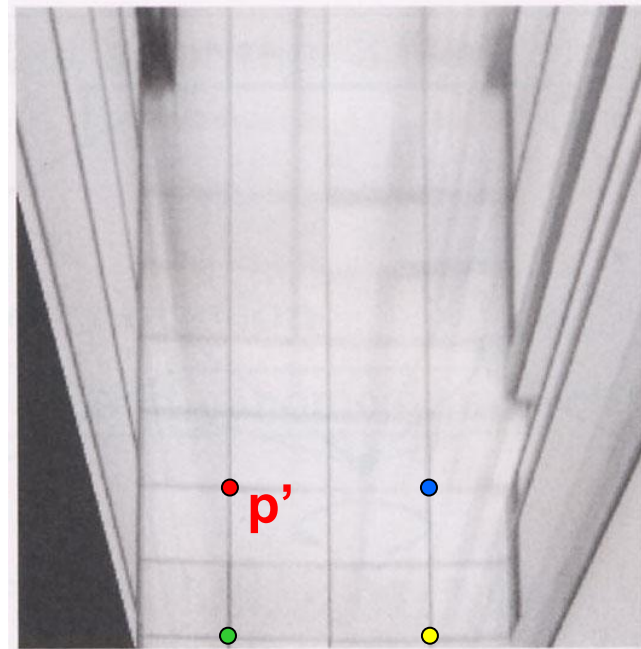
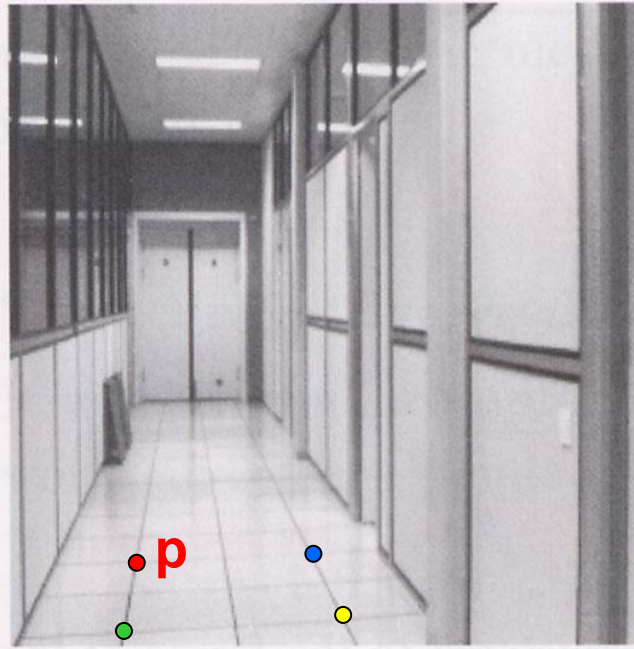
For convenience, assume the plane at  $z = 0$ .



The relation between image points and model points is then given by a homography  $\mathbf{H}$ :

$$s\tilde{\mathbf{m}} = \mathbf{H}\tilde{\mathbf{M}} \quad \text{with} \quad \mathbf{H} = \mathbf{A} \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{t} \end{bmatrix} \quad \mathbf{A} \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{r}_3 & \mathbf{t} \end{bmatrix} \begin{bmatrix} X \\ Y \\ 0 \\ 1 \end{bmatrix} = \mathbf{A} \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{t} \end{bmatrix} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}$$

# Recall: Image rectification



# What do we get from one image?

We can obtain two equations in 6 intermediate homogeneous parameters.

Given  $\mathbf{H}$ , which is defined up to a scale factor,

And let  $\mathbf{H} = [\mathbf{h}_1 \quad \mathbf{h}_2 \quad \mathbf{h}_3]$ , we have

$$[\mathbf{h}_1 \quad \mathbf{h}_2 \quad \mathbf{h}_3] = \lambda \mathbf{A} [\mathbf{r}_1 \quad \mathbf{r}_2 \quad \mathbf{t}]$$

This yields

$$\mathbf{h}_1^T \mathbf{A}^{-T} \mathbf{A}^{-1} \mathbf{h}_2 = 0$$

$$\mathbf{h}_1^T \mathbf{A}^{-T} \mathbf{A}^{-1} \mathbf{h}_1 = \mathbf{h}_2^T \mathbf{A}^{-T} \mathbf{A}^{-1} \mathbf{h}_2$$

# Linear Equations

Let

$$\mathbf{B} = \mathbf{A}^{-T} \mathbf{A}^{-1} = \begin{bmatrix} B_{11} & B_{12} & B_{13} \\ B_{21} & B_{22} & B_{23} \\ B_{31} & B_{32} & B_{33} \end{bmatrix} \quad \leftarrow \text{symmetric}$$

Define  $\mathbf{b} = [B_{11} \ B_{12} \ B_{22} \ B_{13} \ B_{23} \ B_{33}]$  up to a scale factor

Rewrite

$$\mathbf{h}_1^T \mathbf{A}^{-T} \mathbf{A}^{-1} \mathbf{h}_2 = 0$$

$$\mathbf{h}_1^T \mathbf{A}^{-T} \mathbf{A}^{-1} \mathbf{h}_1 = \mathbf{h}_2^T \mathbf{A}^{-T} \mathbf{A}^{-1} \mathbf{h}_2$$

as linear equations:

$$\begin{bmatrix} \mathbf{v}_{12}^T \\ (\mathbf{v}_{11} - \mathbf{v}_{22})^T \end{bmatrix} \mathbf{b} = \mathbf{0}$$

$$\mathbf{v}_{ij} = [h_{i1}h_{j1}, h_{i1}h_{j2} + h_{i2}h_{j1}, h_{i2}h_{j2}, \\ h_{i3}h_{j1} + h_{i1}h_{j3}, h_{i3}h_{j2} + h_{i2}h_{j3}, h_{i3}h_{j3}]^T$$

# Camera parameters

## Intrinsic camera parameters

$$v_0 = (B_{12}B_{13} - B_{11}B_{23}) / (B_{11}B_{22} - B_{12}^2)$$

$$\lambda = B_{33} - [B_{13}^2 + v_0(B_{12}B_{13} - B_{11}B_{23})] / B_{11}$$

$$\alpha = \sqrt{\lambda / B_{11}}$$

$$\beta = \sqrt{\lambda B_{11} / (B_{11}B_{22} - B_{12}^2)}$$

$$c = -B_{12}\alpha^2\beta / \lambda$$

$$u_0 = cv_0 / \alpha - B_{13}\alpha^2 / \lambda .$$

$$\mathbf{A} = \begin{pmatrix} \alpha & c & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{pmatrix}$$

## Rotation and translation

$$\mathbf{r}_1 = \lambda \mathbf{A}^{-1} \mathbf{h}_1, \mathbf{r}_2 = \lambda \mathbf{A}^{-1} \mathbf{h}_2, \mathbf{r}_3 = \mathbf{r}_1 \times \mathbf{r}_2, \mathbf{t} = \lambda \mathbf{A}^{-1} \mathbf{h}_3$$

$$\lambda = 1 / \|\mathbf{A}^{-1} \mathbf{h}_1\| = 1 / \|\mathbf{A}^{-1} \mathbf{h}_2\|$$



# Distortion

Distortion model ((x,y) undistorted image coordinates):

$$\begin{aligned}\check{x} &= x + x[k_1(x^2 + y^2) + k_2(x^2 + y^2)^2] \\ \check{y} &= y + y[k_1(x^2 + y^2) + k_2(x^2 + y^2)^2]\end{aligned}$$

Converted to pixels by:

$$\begin{aligned}\check{u} &= u_0 + \alpha\check{x} + c\check{y} \\ \check{v} &= v_0 + \beta\check{y}\end{aligned} \quad A = \begin{pmatrix} \alpha & c & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{pmatrix}$$

gives

$$\begin{aligned}\check{u} &= u + (u - u_0)[k_1(x^2 + y^2) + k_2(x^2 + y^2)^2] \\ \check{v} &= v + (v - v_0)[k_1(x^2 + y^2) + k_2(x^2 + y^2)^2]\end{aligned}$$

i.e. distortion model centered at  $u_0$  and  $v_0$ .

# Distortion

Distortion model ((x,y) undistorted image coordinates):

$$\check{x} = x + x[k_1(x^2 + y^2) + k_2(x^2 + y^2)^2]$$

$$\check{y} = y + y[k_1(x^2 + y^2) + k_2(x^2 + y^2)^2]$$

Centered at  $u_0$  and  $v_0$ :

$$\check{u} = u + (u - u_0)[k_1(x^2 + y^2) + k_2(x^2 + y^2)^2]$$

$$\check{v} = v + (v - v_0)[k_1(x^2 + y^2) + k_2(x^2 + y^2)^2]$$

Solution:

$$\underbrace{\begin{bmatrix} (u-u_0)(x^2+y^2) & (u-u_0)(x^2+y^2)^2 \\ (v-v_0)(x^2+y^2) & (v-v_0)(x^2+y^2)^2 \end{bmatrix}}_{\mathbf{D}} \begin{bmatrix} k_1 \\ k_2 \end{bmatrix} = \underbrace{\begin{bmatrix} \check{u}-u \\ \check{v}-v \end{bmatrix}}_{\mathbf{d}}$$

$$\mathbf{k} = (\mathbf{D}^T \mathbf{D})^{-1} \mathbf{D}^T \mathbf{d}$$

# Non-linear optimization

In practice, closed-form solution is used for initialization of non-linear optimization problem

$$\sum_{i=1}^n \sum_{j=1}^m \|\mathbf{m}_{ij} - \check{\mathbf{m}}(\mathbf{A}, k_1, k_2, \mathbf{R}_i, \mathbf{t}_i, \mathbf{M}_j)\|^2$$

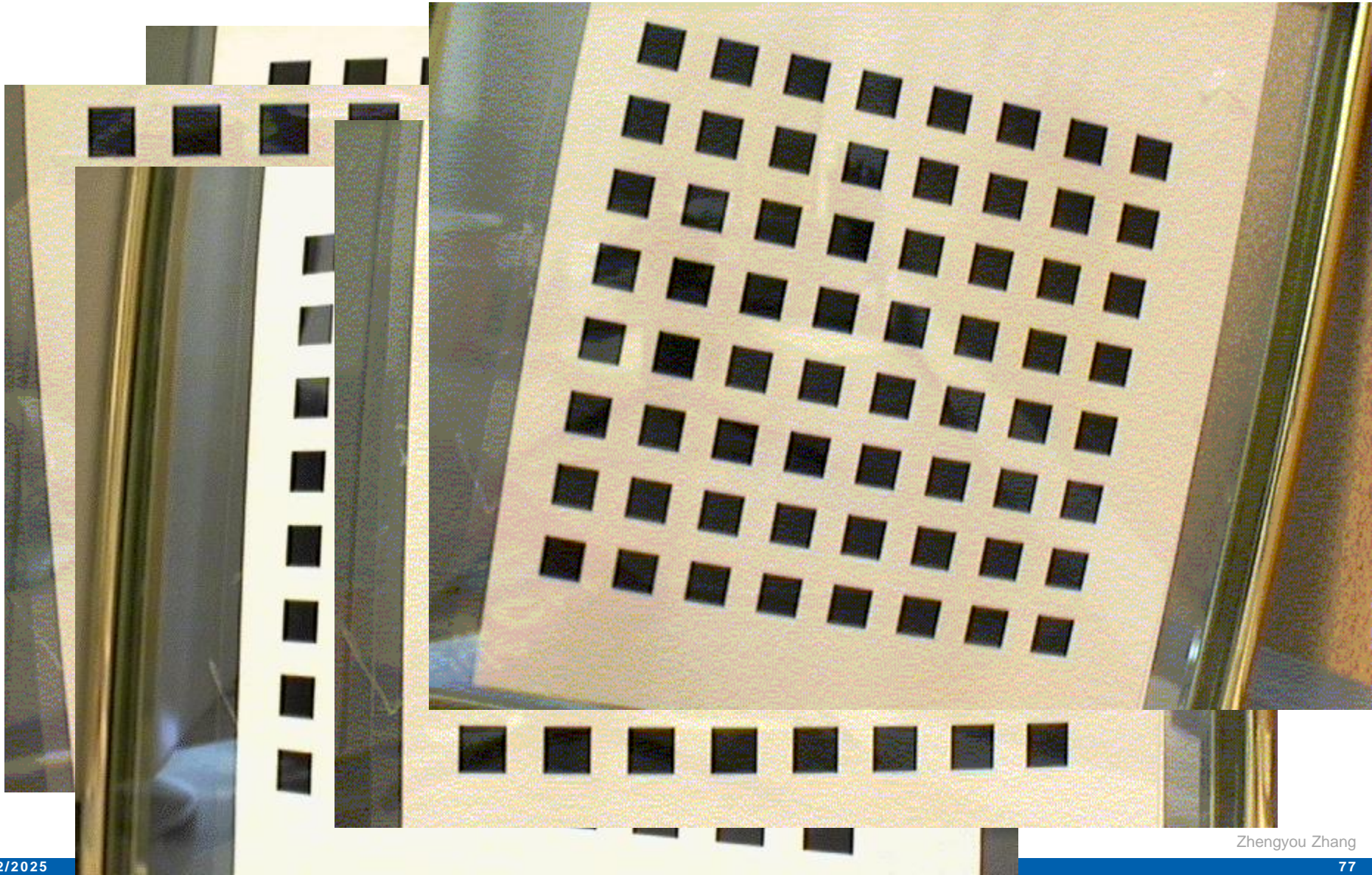
Solved with Levenberg-Marquardt algorithm.

Without skew at least 2 images are needed, the more the better.

# Summary

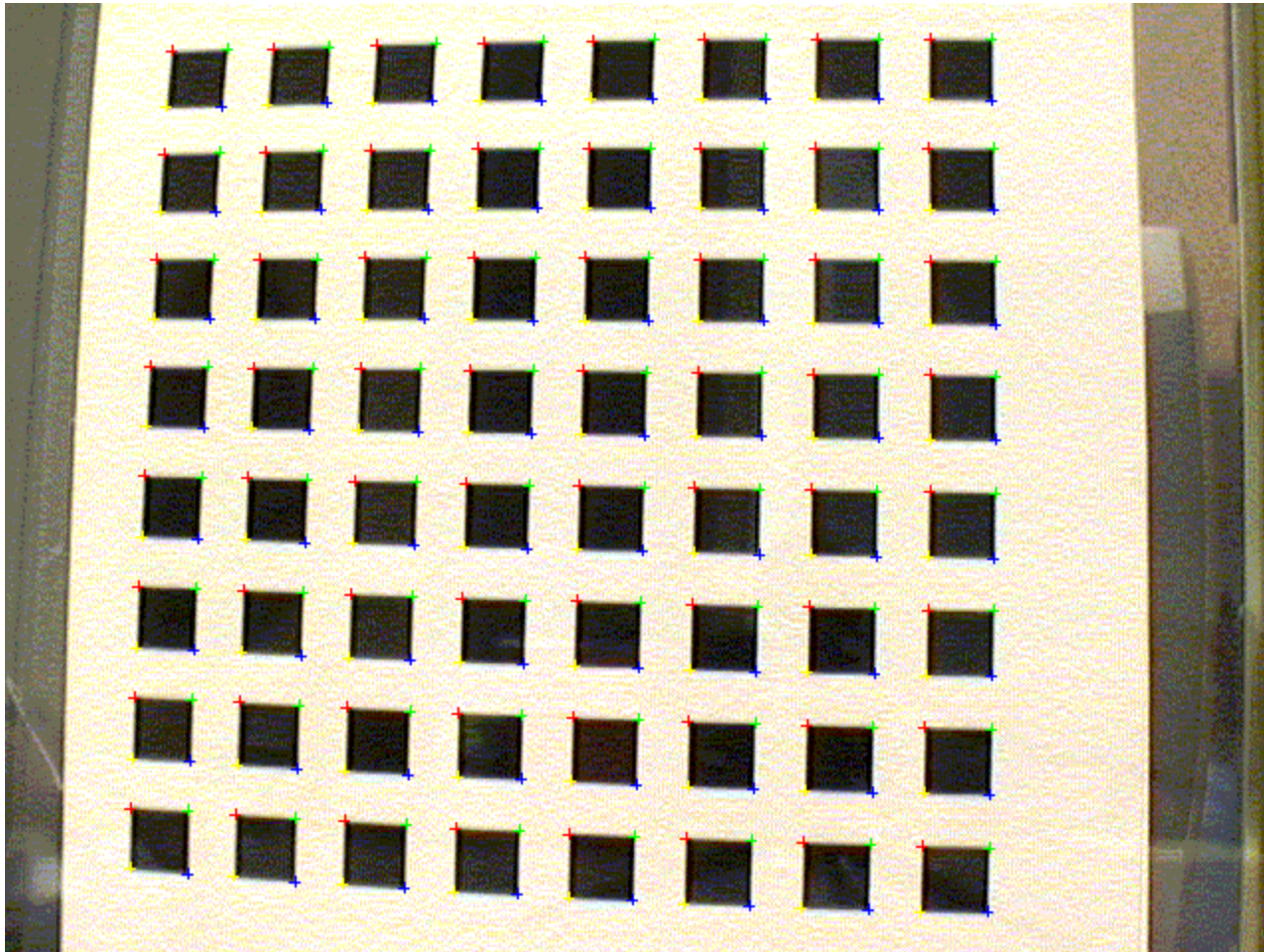
- Show the plane under  $n$  different orientations ( $n > 1$ )
- Estimate the  $n$  homography matrices  
*(analytic solution followed by MLE)*
- Solve analytically the 6 intermediate parameters  
*(defined up to a scale factor)*
- Extract the five intrinsic parameters
- Compute the extrinsic parameters
- Refine all parameters with MLE

# Experimental results

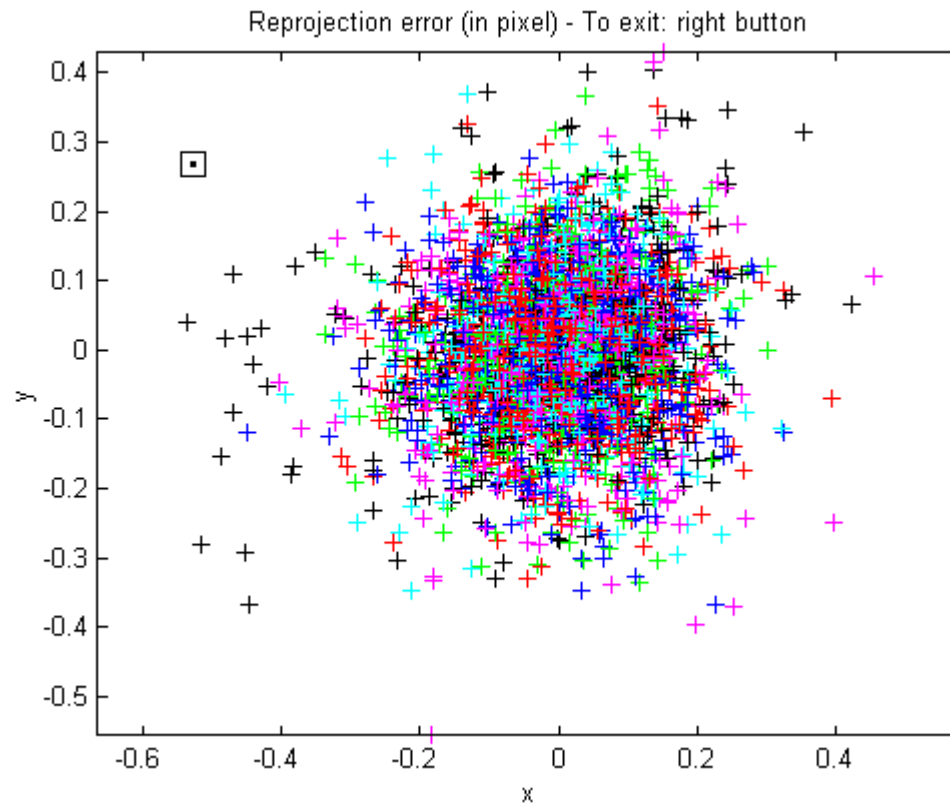




# Extracted corner points



# Reprojection error



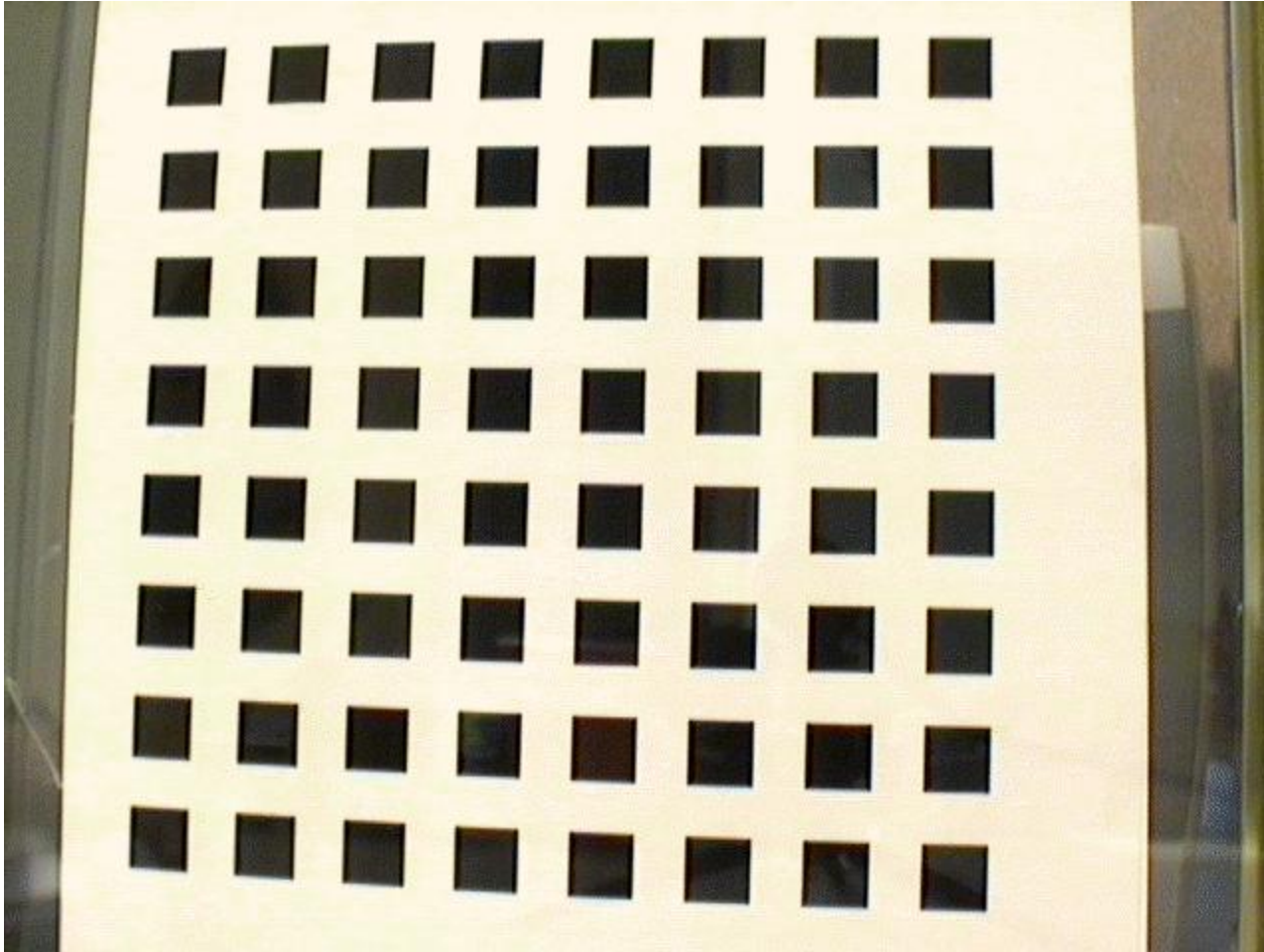
# Number of images

Table 1: Results with real data of 2 through 5 images

nb	2 images			3 images			4 images			5 images		
	initial	final	$\sigma$	initial	final	$\sigma$	initial	final	$\sigma$	initial	final	$\sigma$
$\alpha$	825.59	830.47	4.74	917.65	830.80	2.06	876.62	831.81	1.56	877.16	832.50	1.41
$\beta$	825.26	830.24	4.85	920.53	830.69	2.10	876.22	831.82	1.55	876.80	832.53	1.38
$\gamma$	0	0	0	2.2956	0.1676	0.109	0.0658	0.2867	0.095	0.1752	0.2045	0.078
$u_0$	295.79	307.03	1.37	277.09	305.77	1.45	301.31	304.53	0.86	301.04	303.96	0.71
$v_0$	217.69	206.55	0.93	223.36	206.42	1.00	220.06	206.79	0.78	220.41	206.59	0.66
$k_1$	0.161	-0.227	0.006	0.128	-0.229	0.006	0.145	-0.229	0.005	0.136	-0.228	0.003
$k_2$	-1.955	0.194	0.032	-1.986	0.196	0.034	-2.089	0.195	0.028	-2.042	0.190	0.025
RMS	0.761	0.295		0.987	0.393		0.927	0.361		0.881	0.335	



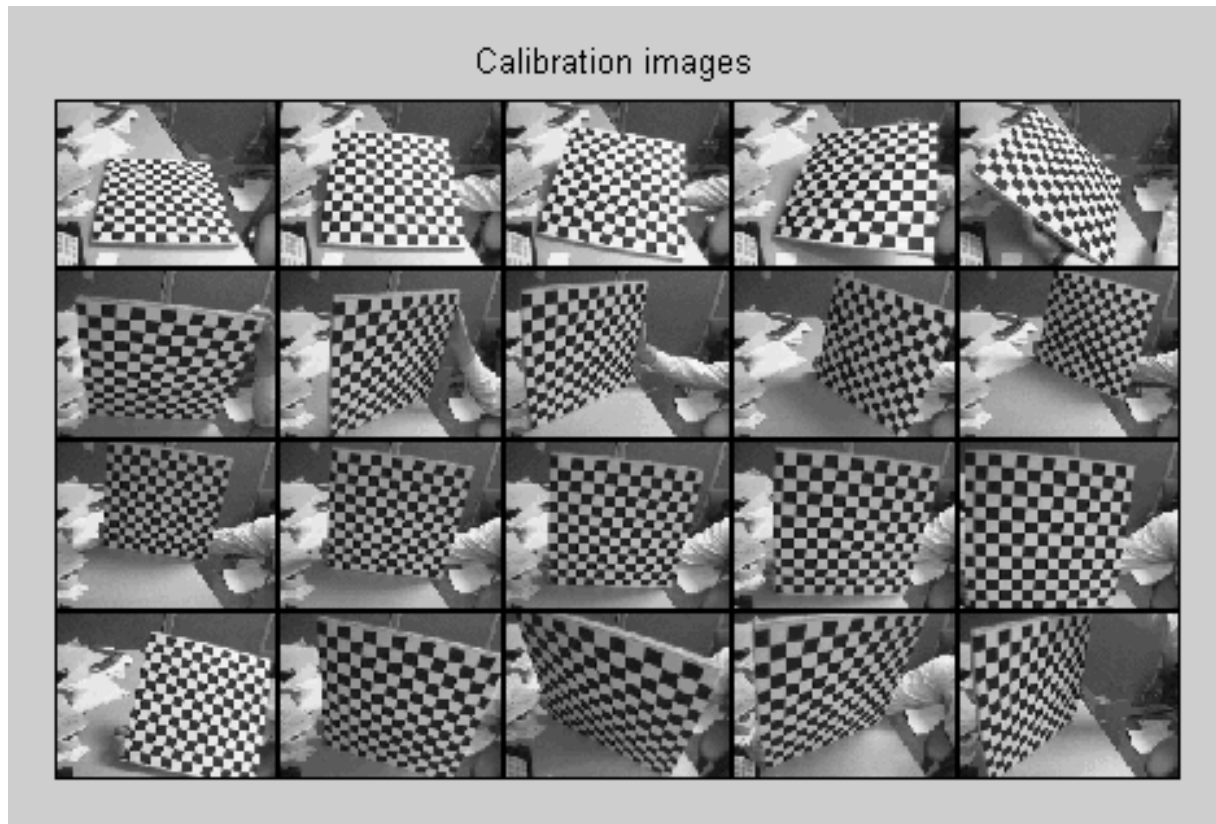
# Correction of Radial Distortion



**Original image**

# Calibration process

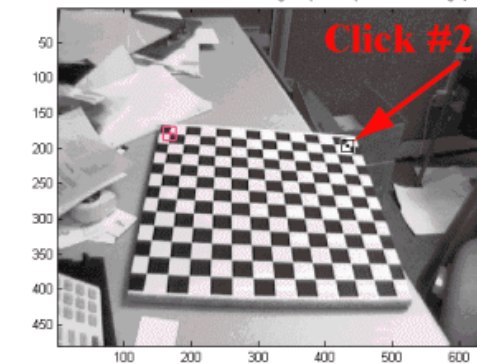
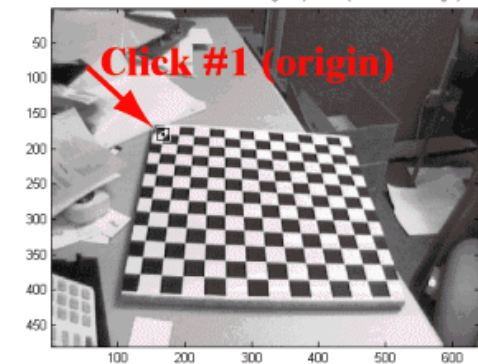
## Capture images



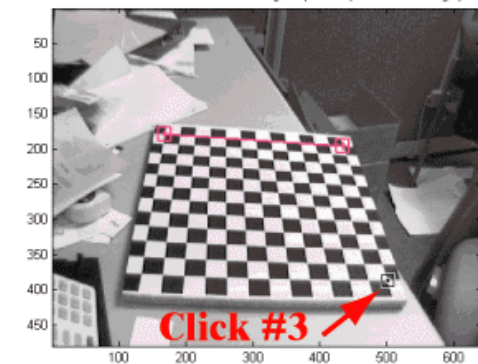
# Calibration process

Click on four corners, corners extracted automatically

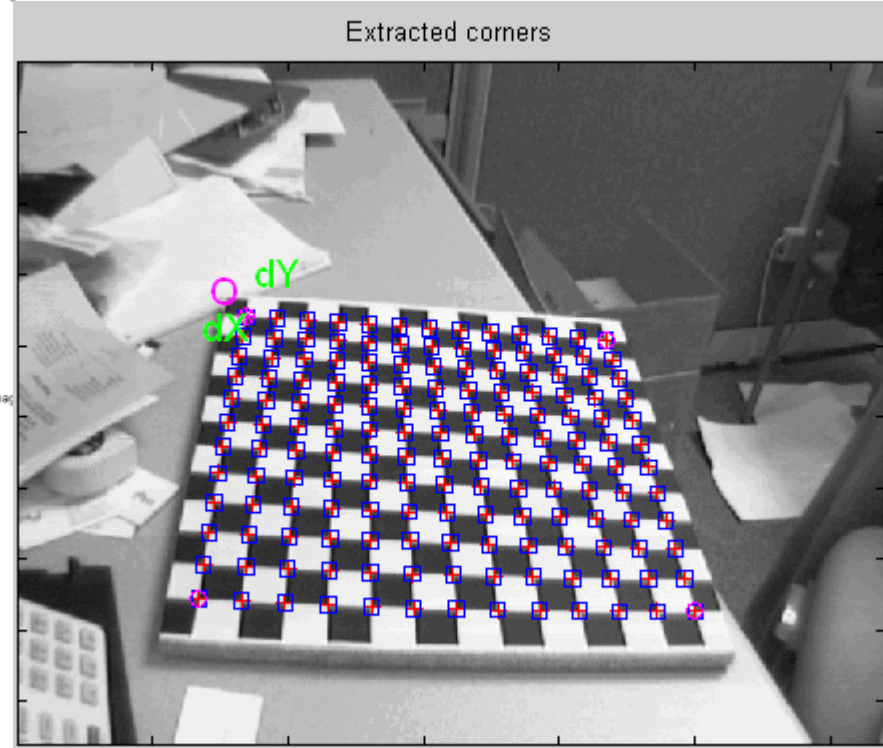
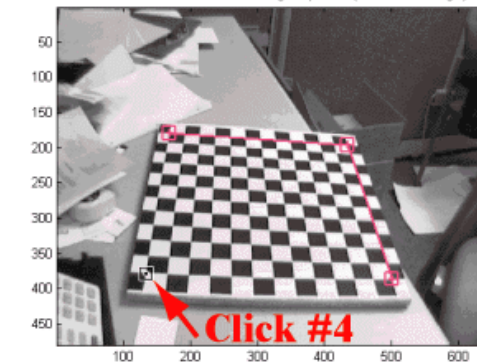
Click on the four extreme corners of the rectangular pattern (first corner = origin)... Image 1



Click on the four extreme corners of the rectangular pattern (first corner = origin)... Image 1

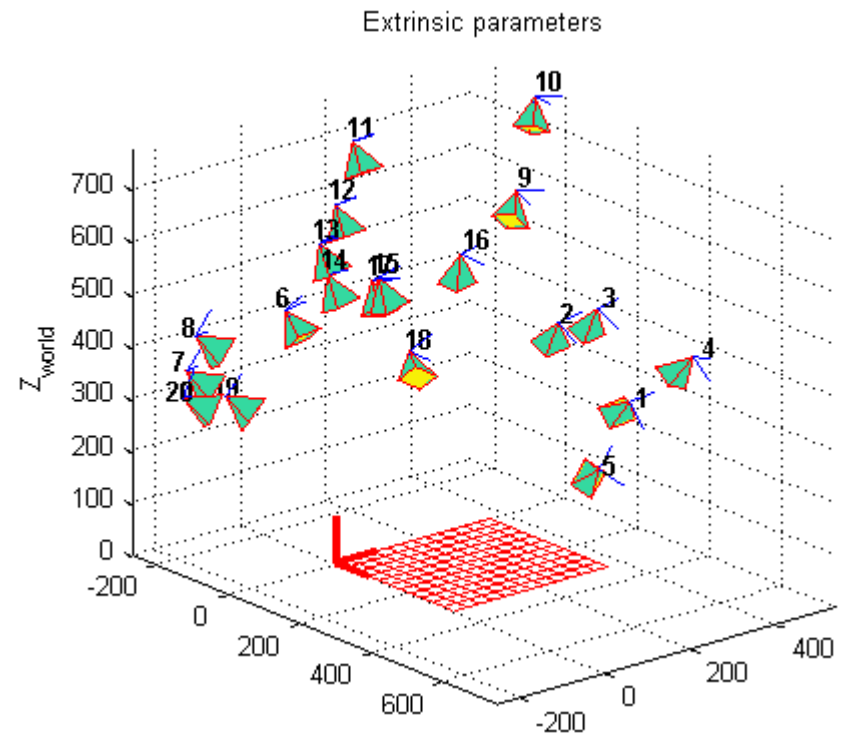
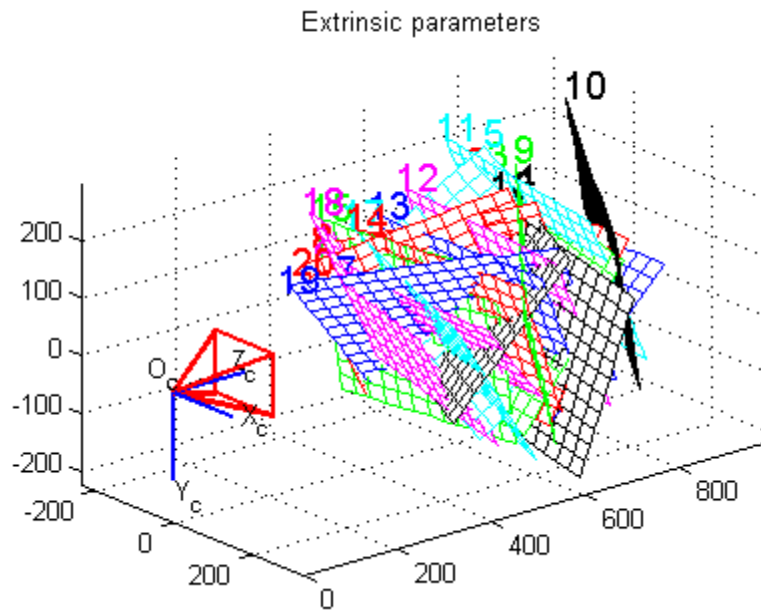


Click on the four extreme corners of the rectangular pattern (first corner = origin)... Image 1



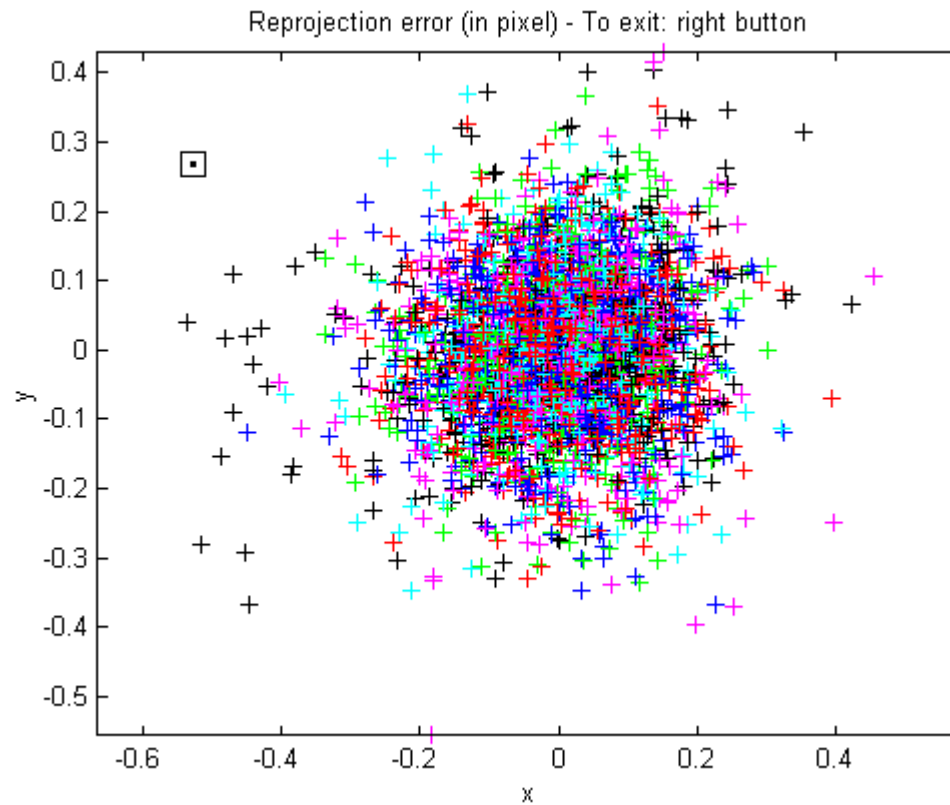
# Calibration process

## Extrinsic parameters



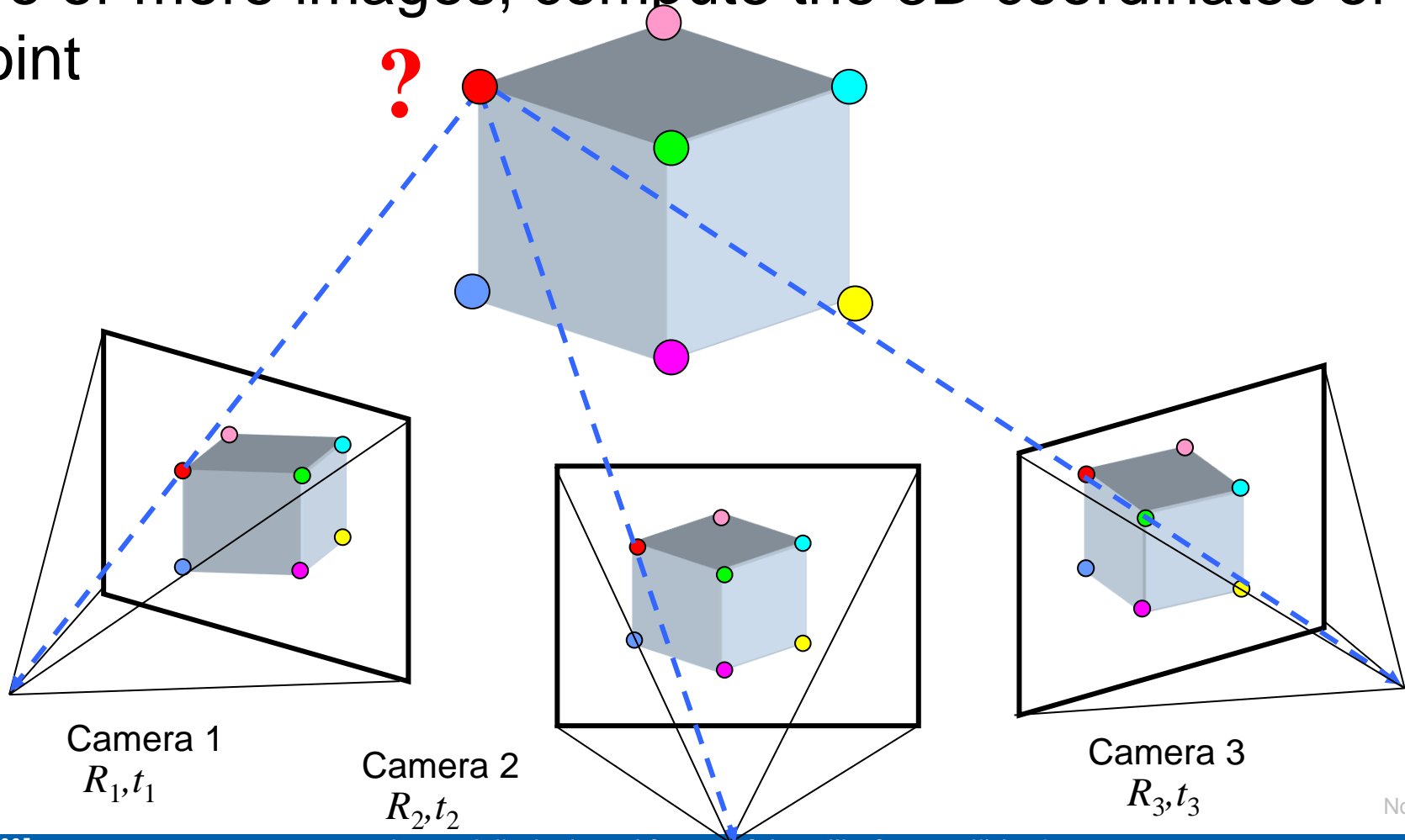
# Calibration process

## Reprojection error



# Multi-view geometry problems

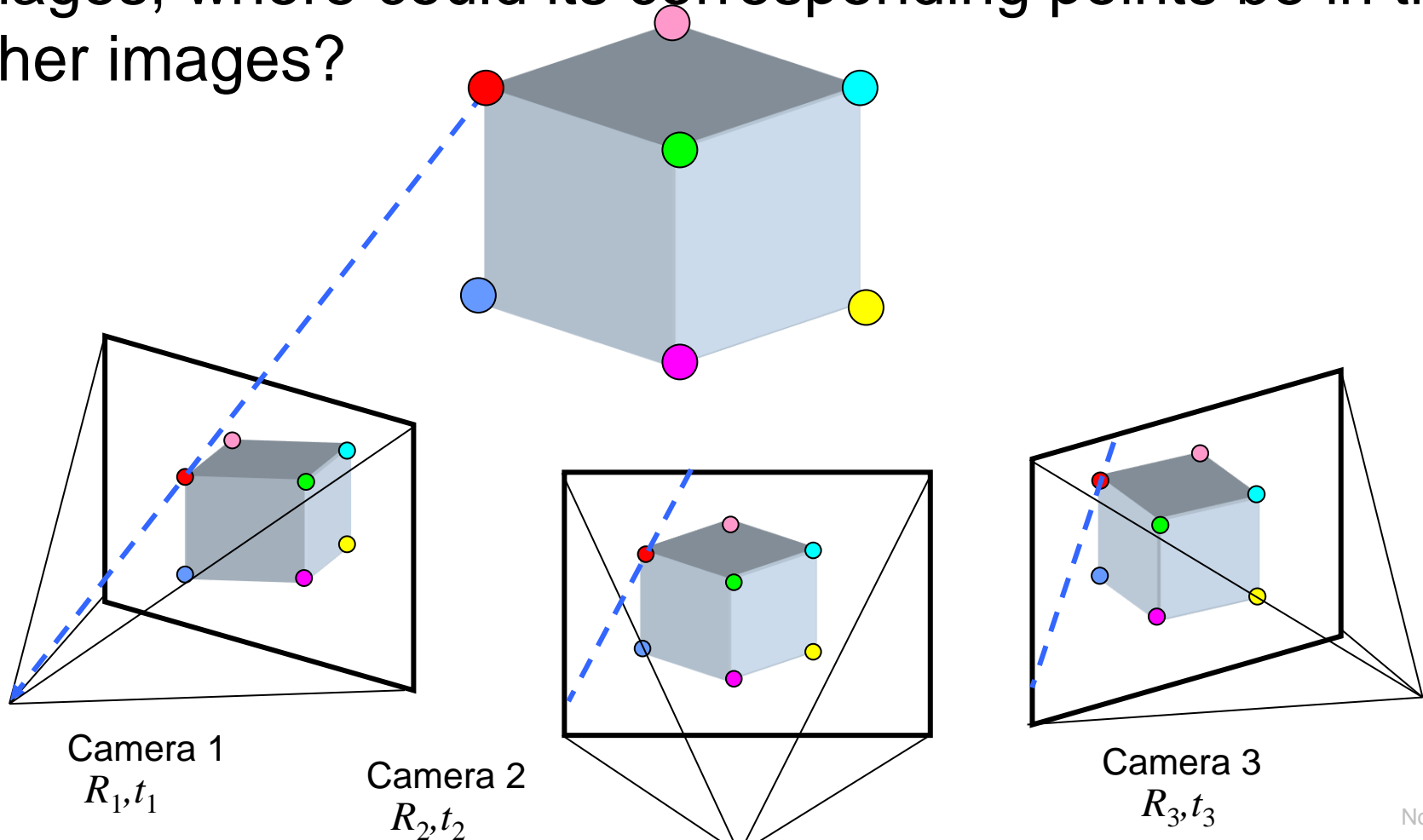
**Structure:** Given projections of the same 3D point in two or more images, compute the 3D coordinates of that point





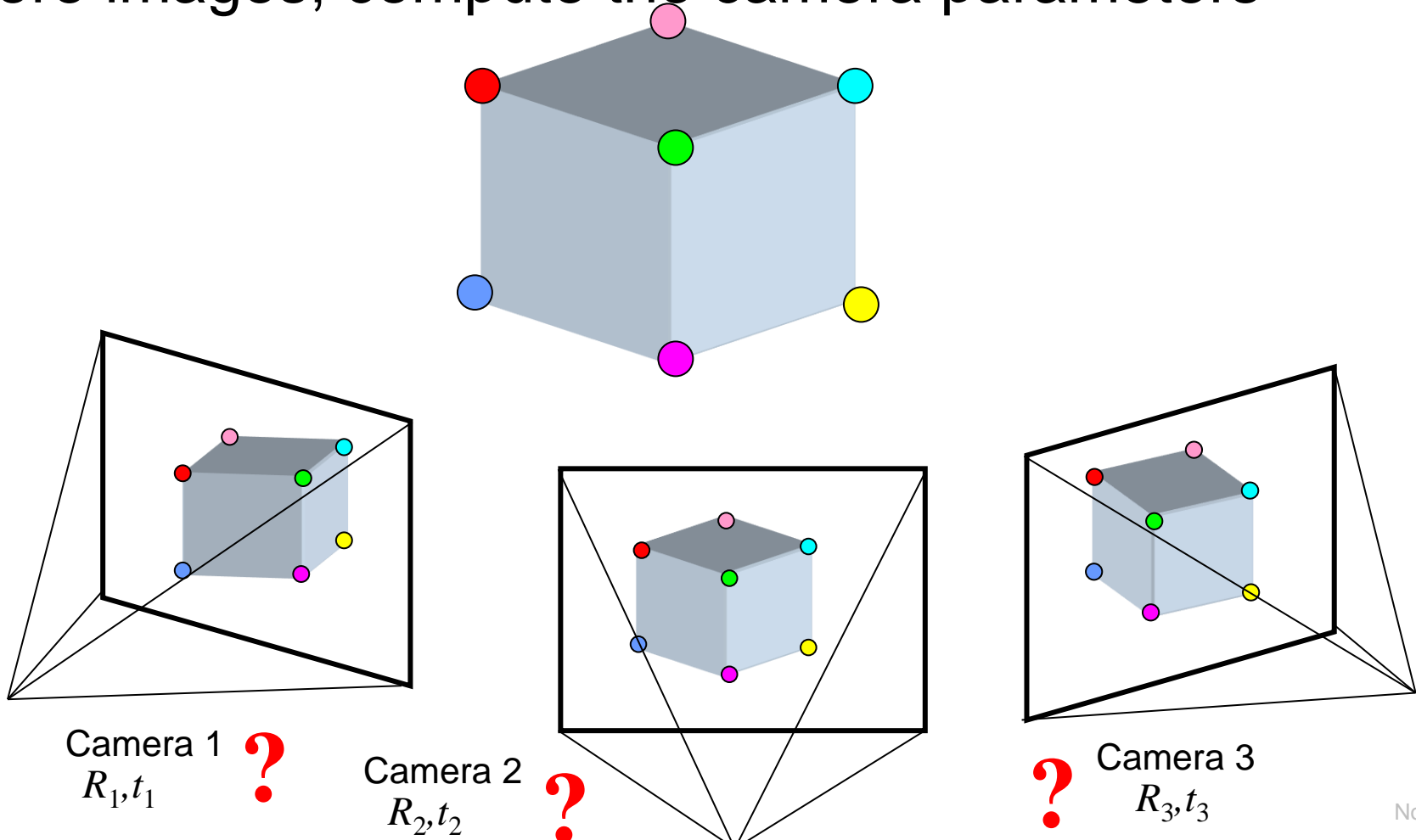
# Multi-view geometry problems

**Stereo correspondence:** Given a point in one of the images, where could its corresponding points be in the other images?



# Multi-view geometry problems

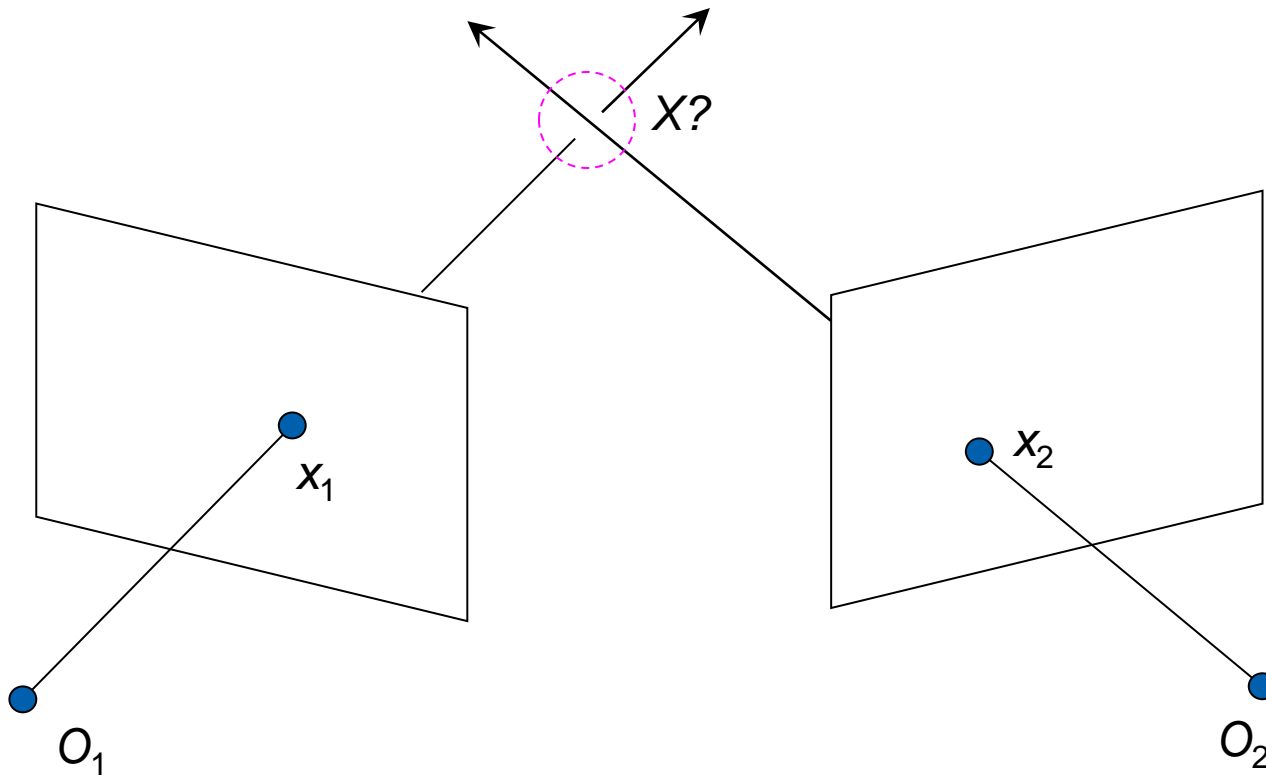
**Motion:** Given a set of corresponding points in two or more images, compute the camera parameters





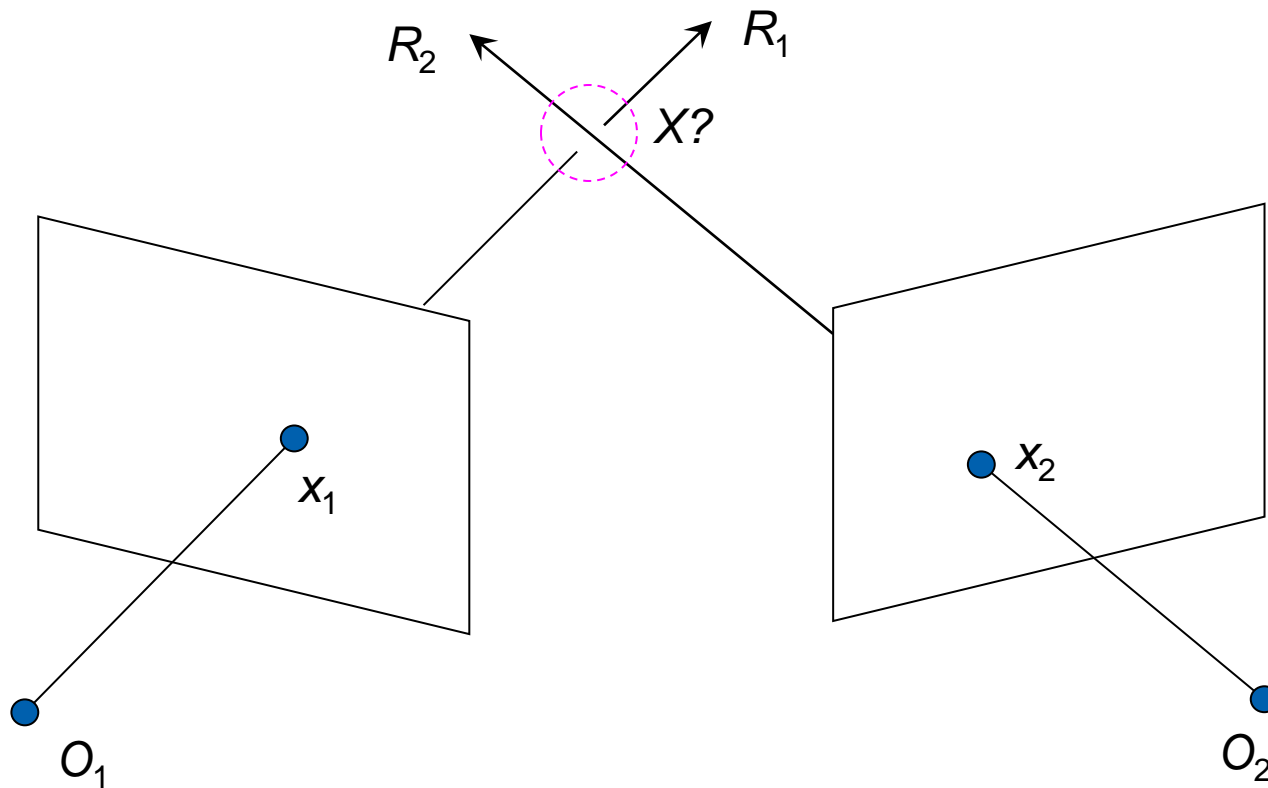
# Triangulation

Given projections of a 3D point in two or more images (with known camera matrices), find the coordinates of the point



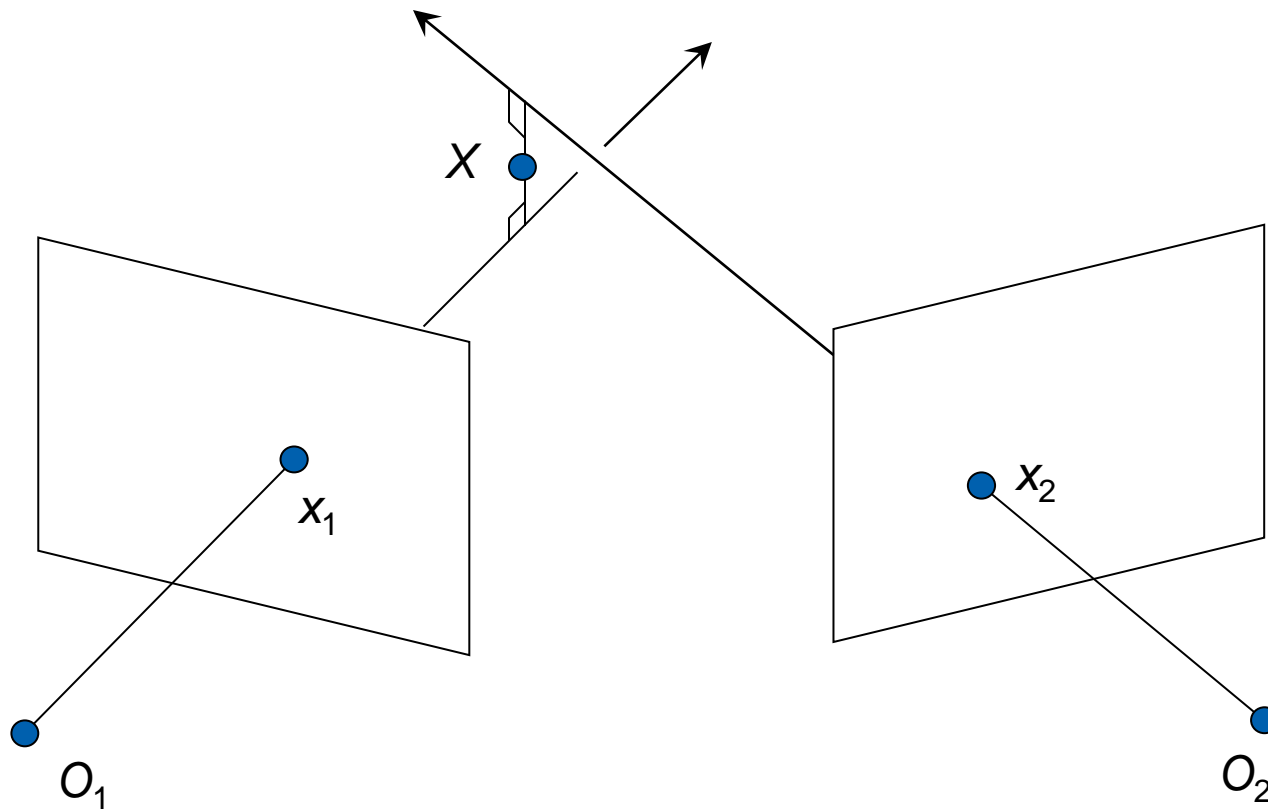
# Triangulation

We want to intersect the two visual rays corresponding to  $x_1$  and  $x_2$ , but because of noise and numerical errors, they don't meet exactly



# Triangulation: Geometric approach

Find shortest segment connecting the two viewing rays and let  $X$  be the midpoint of that segment



# Triangulation: Linear approach

$$\begin{array}{lll} \lambda_1 \mathbf{x}_1 = \mathbf{P}_1 \mathbf{X} & \mathbf{x}_1 \times \mathbf{P}_1 \mathbf{X} = 0 & [\mathbf{x}_{1\times}] \mathbf{P}_1 \mathbf{X} = 0 \\ \lambda_2 \mathbf{x}_2 = \mathbf{P}_2 \mathbf{X} & \mathbf{x}_2 \times \mathbf{P}_2 \mathbf{X} = 0 & [\mathbf{x}_{2\times}] \mathbf{P}_2 \mathbf{X} = 0 \end{array}$$

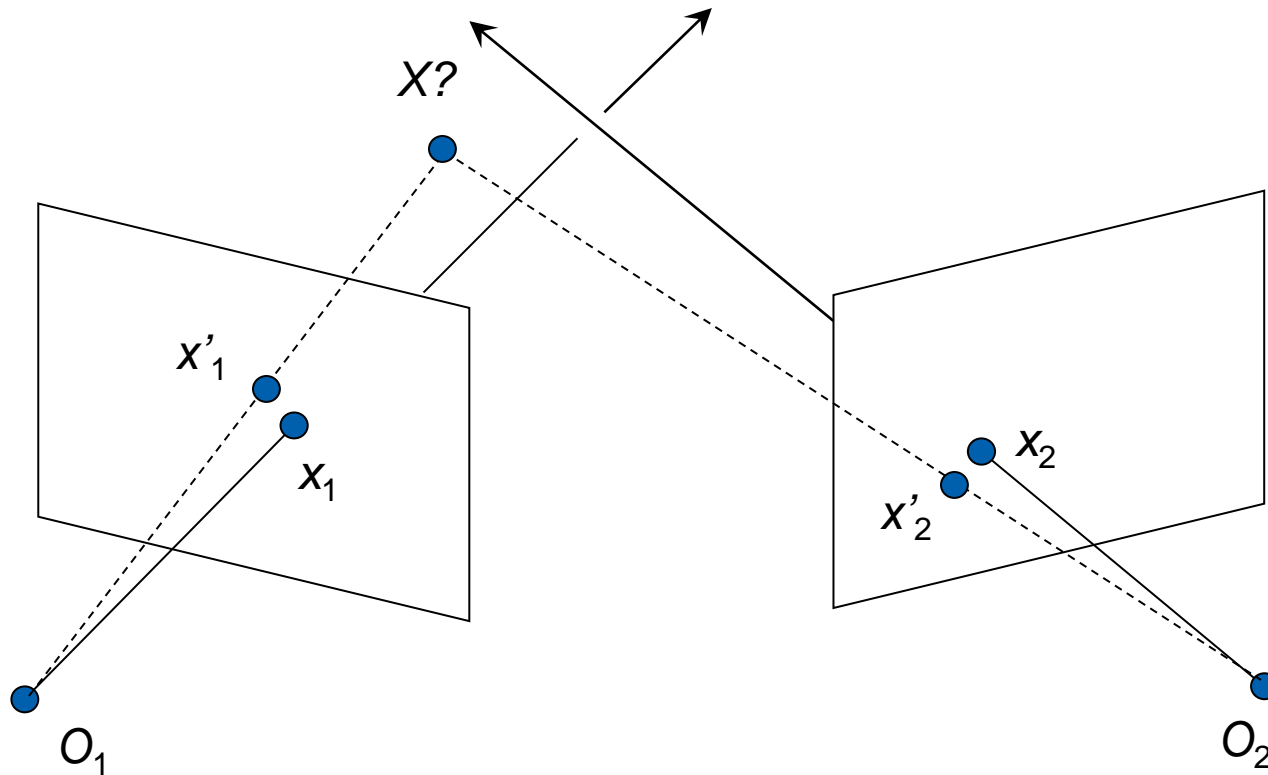
Cross product as matrix multiplication:

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

# Triangulation: Nonlinear approach

- Find  $X$  that minimizes

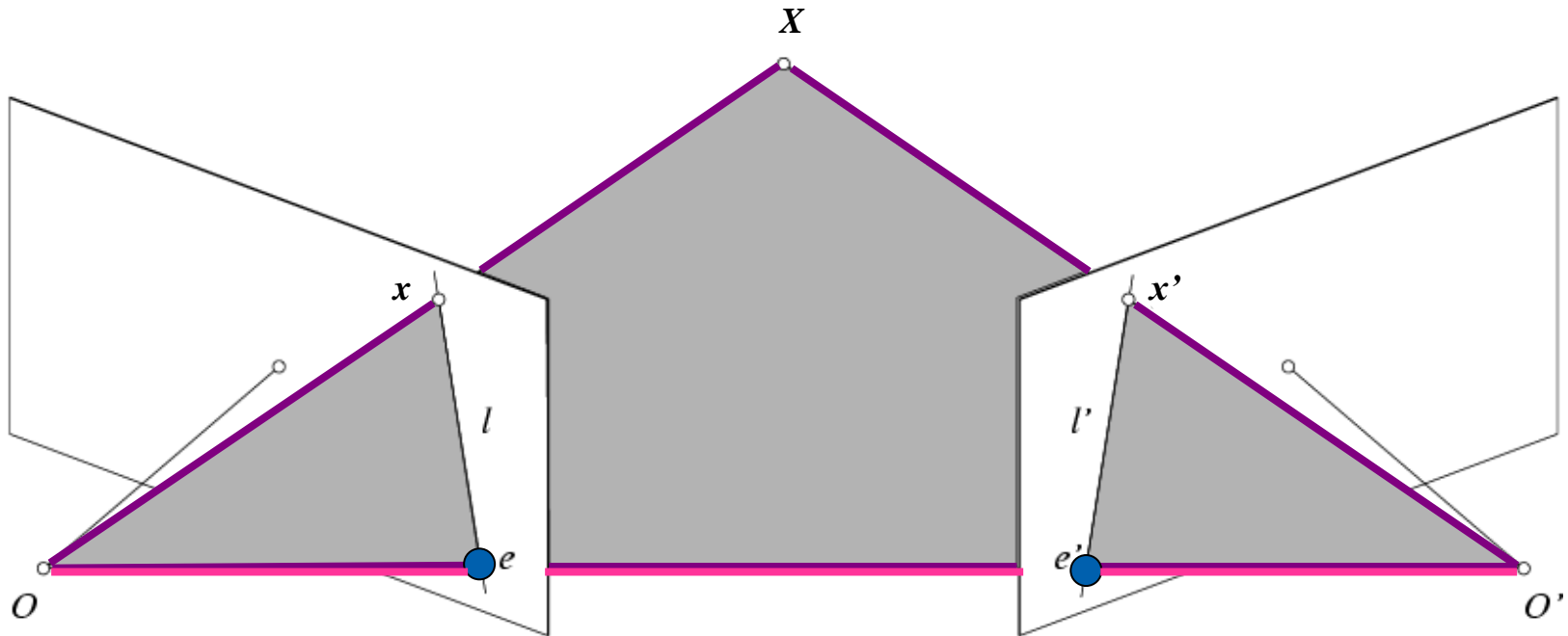
$$d^2(x_1, P_1 X) + d^2(x_2, P_2 X)$$



# Two-view geometry

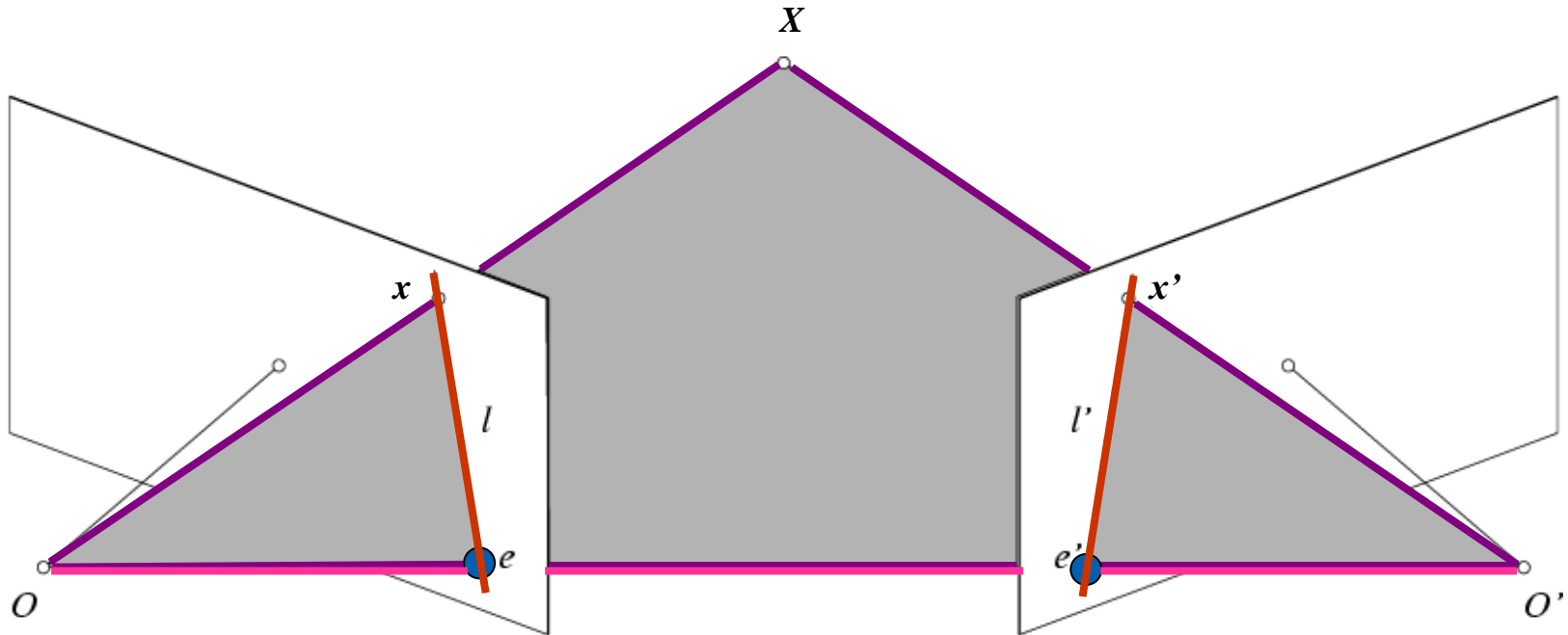


# Epipolar geometry



- **Baseline** – line connecting the two camera centers
- **Epipolar Plane** – plane containing baseline (1D family)
- **Epipoles**  
 = intersections of baseline with image planes  
 = projections of the other camera center

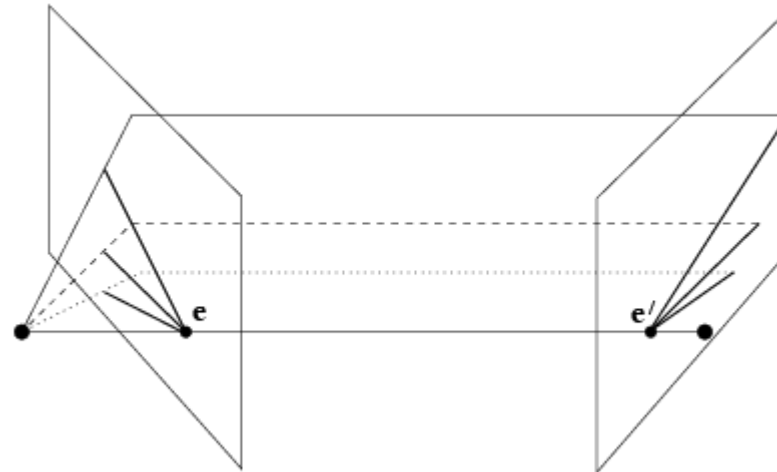
# Epipolar geometry



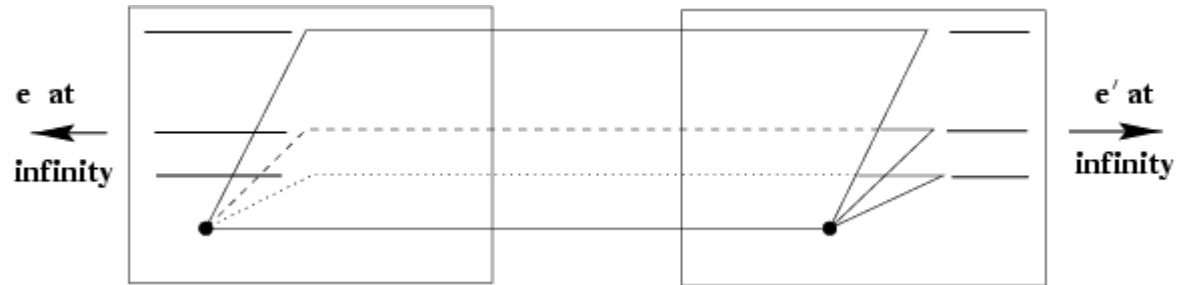
- **Baseline** – line connecting the two camera centers
- **Epipolar Plane** – plane containing baseline (1D family)
- **Epipoles**  
= intersections of baseline with image planes  
= projections of the other camera center
- **Epipolar Lines** - intersections of epipolar plane with image planes (always come in corresponding pairs)



# Example: Converging cameras



# Example: Motion parallel to image plane



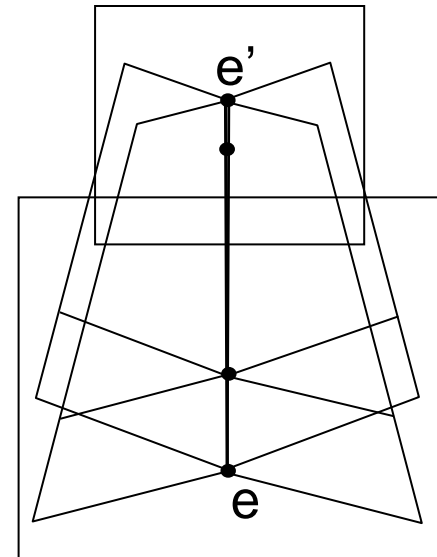
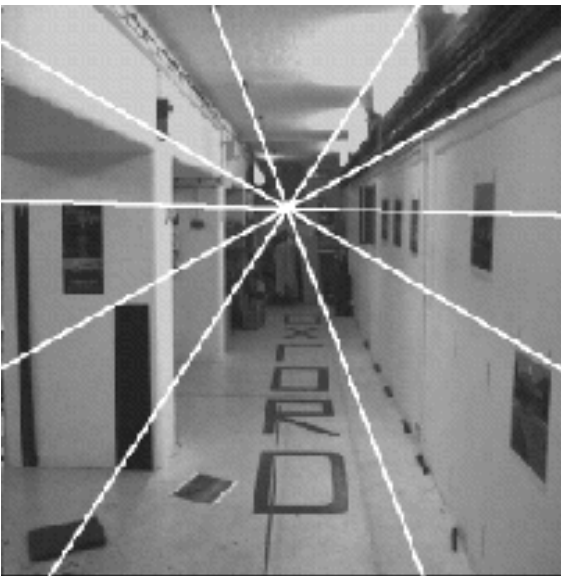
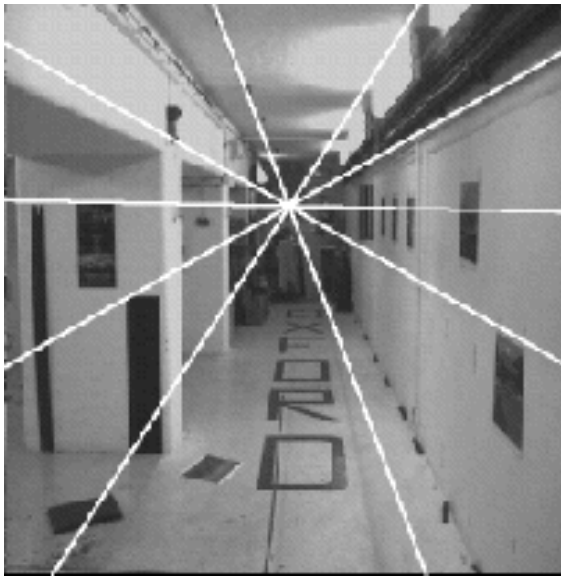
# Example: Motion perpendicular to image plane



# Example: Motion perpendicular to image plane



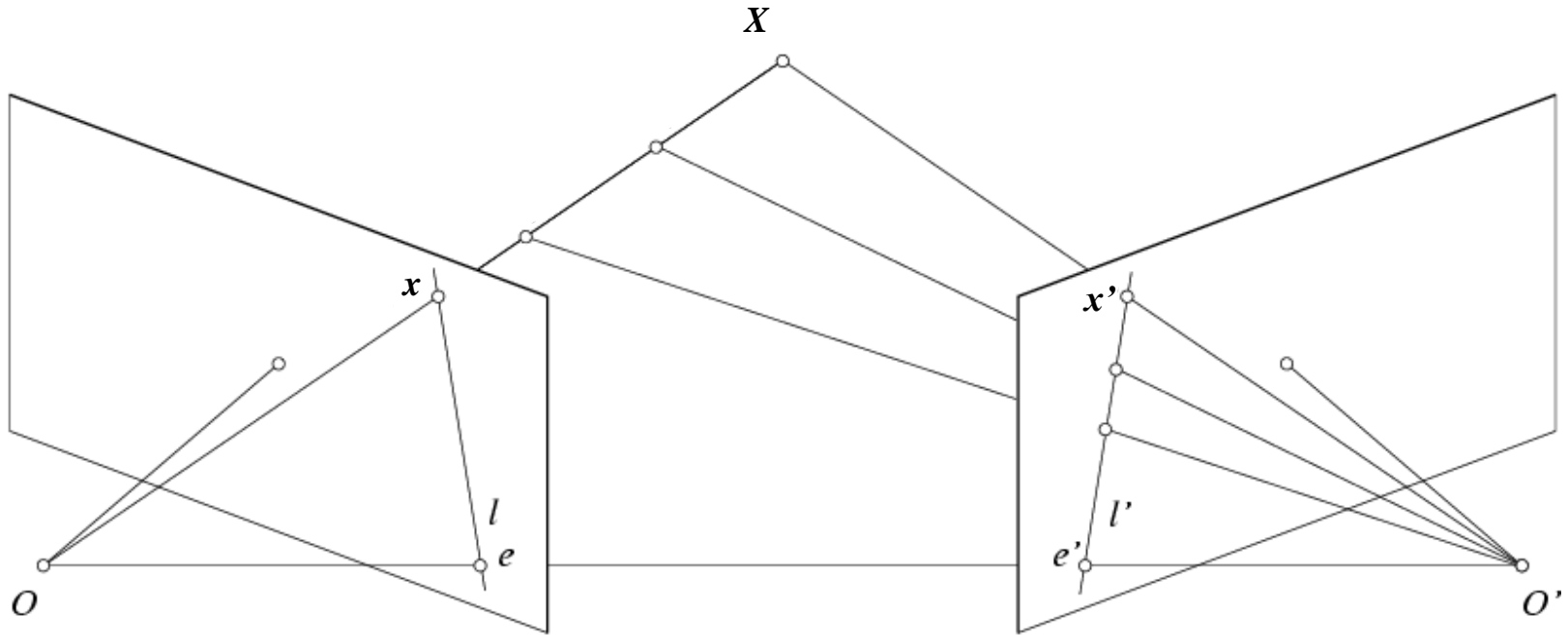
# Example: Motion perpendicular to image plane



Epipole has same coordinates in both images.

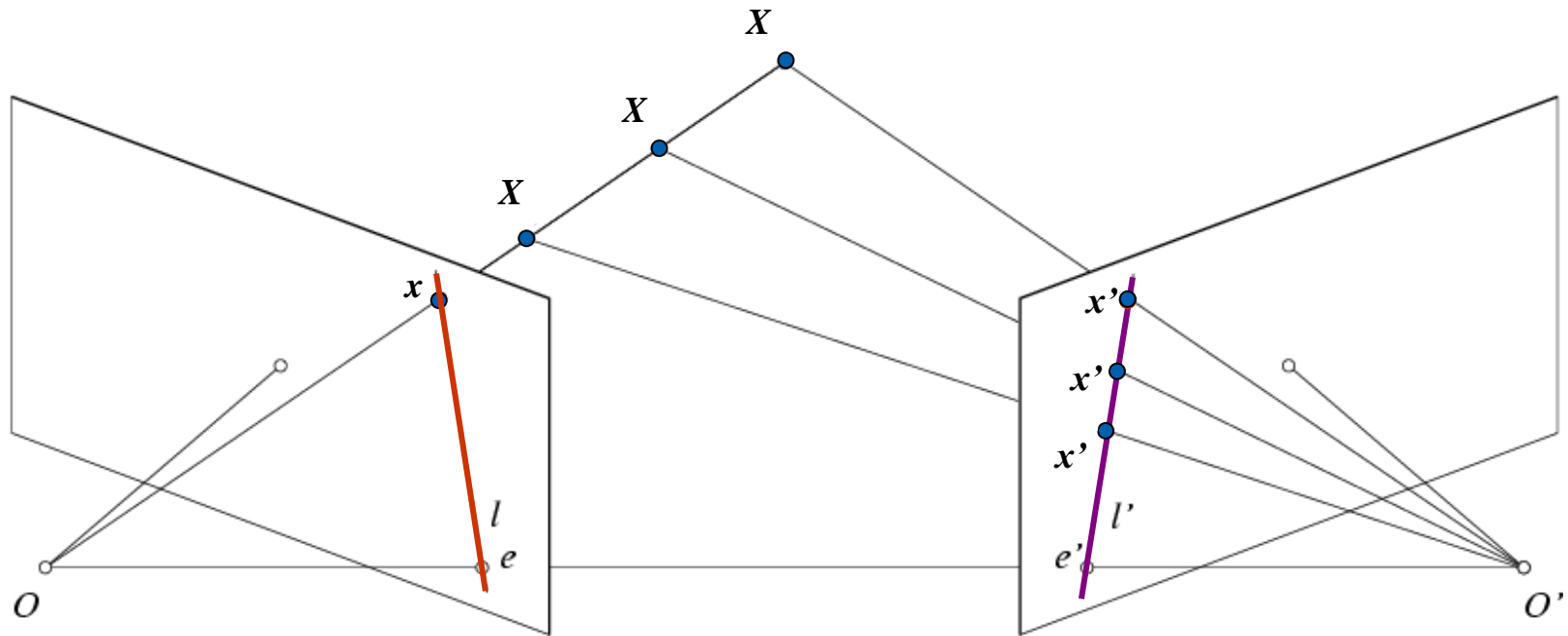
Points move along lines radiating from  $e$ :  
“Focus of expansion”

# Epipolar constraint



If we observe a point  $x$  in one image, where can the corresponding point  $x'$  be in the other image?

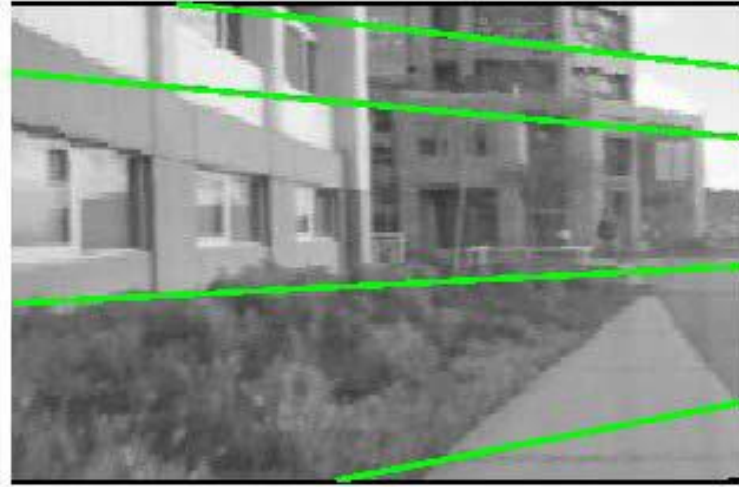
# Epipolar constraint



Potential matches for  $x$  have to lie on the corresponding epipolar line  $l'$ .

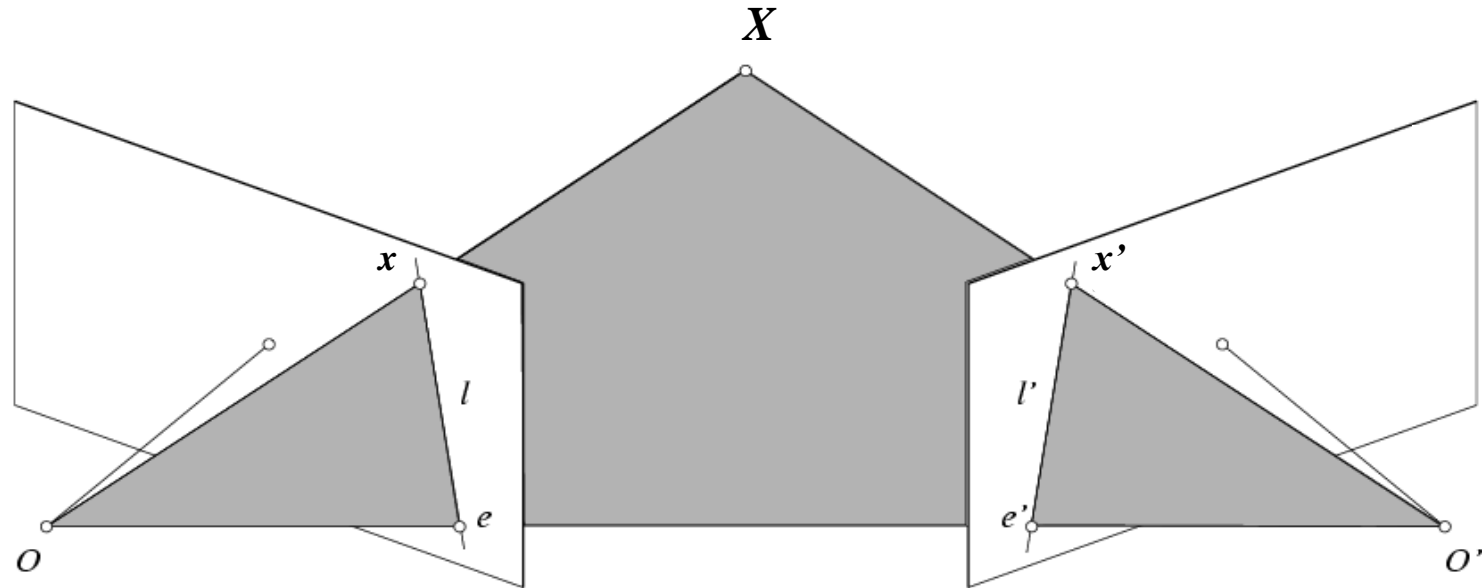
Potential matches for  $x'$  have to lie on the corresponding epipolar line  $l$ .

# Epipolar constraint example



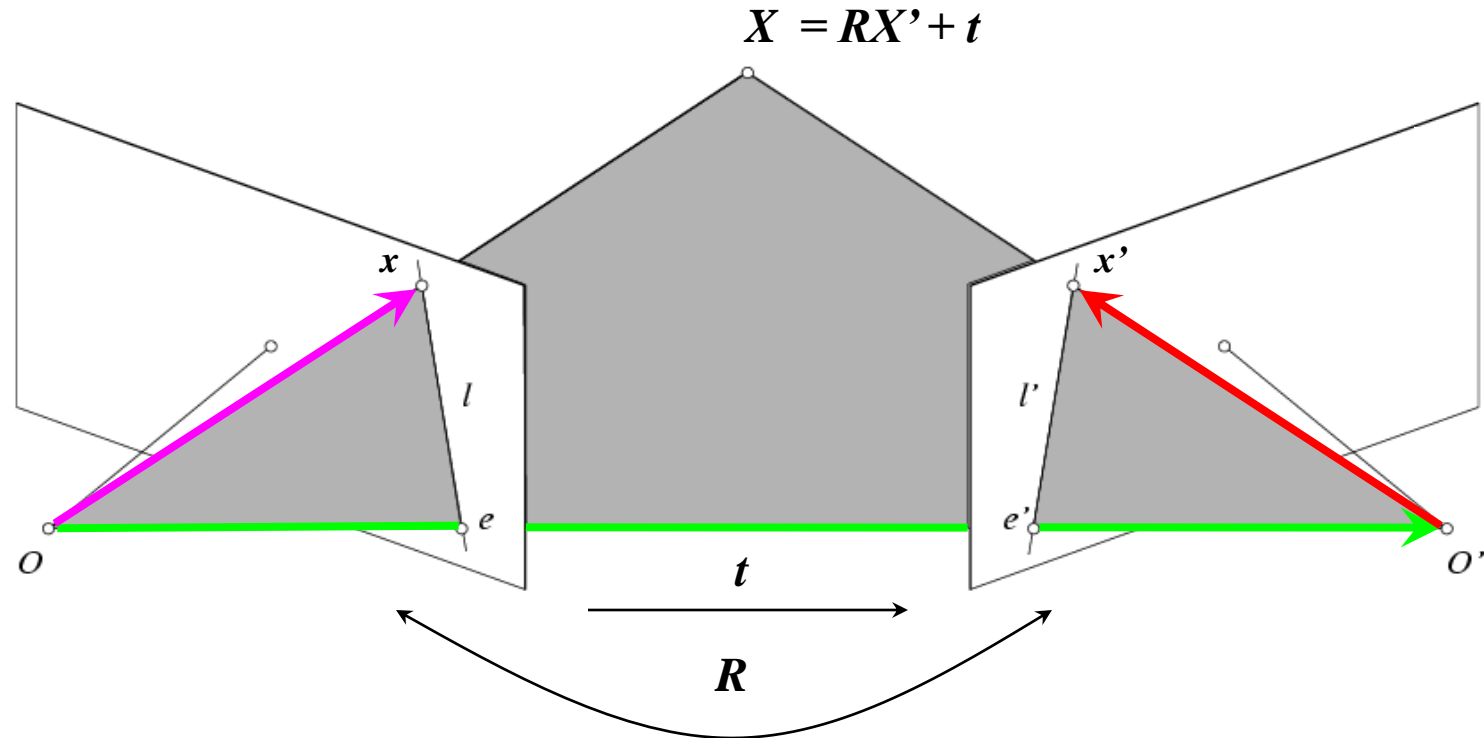


# Epipolar constraint: Calibrated case



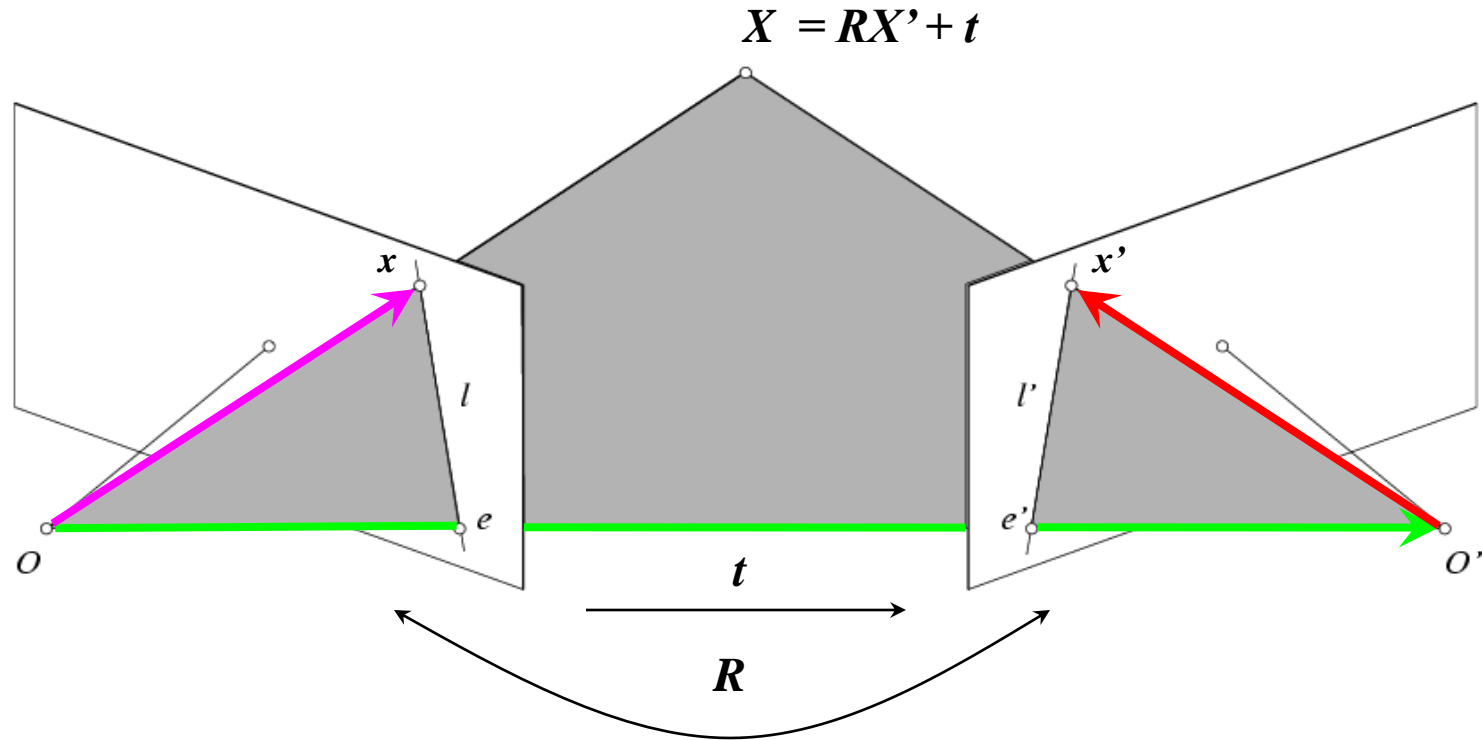
- Assume that the intrinsic and extrinsic parameters of the cameras are known
- We can multiply the projection matrix of each camera (and the image points) by the inverse of the calibration matrix to get normalized image coordinates
- We can also set the global coordinate system to the coordinate system of the first camera. Then the projection matrix of the first camera is  $[I \mid \mathbf{0}]$ .

# Epipolar constraint: Calibrated case



- $X'$  is  $X$  in the second camera's coordinate system
- Projections of  $X$  and  $X'$  by homogeneous vectors  $x$  and  $x'$
- The vectors  $x$ ,  $t$ , and  $Rx'$  are coplanar

# From geometry to algebra

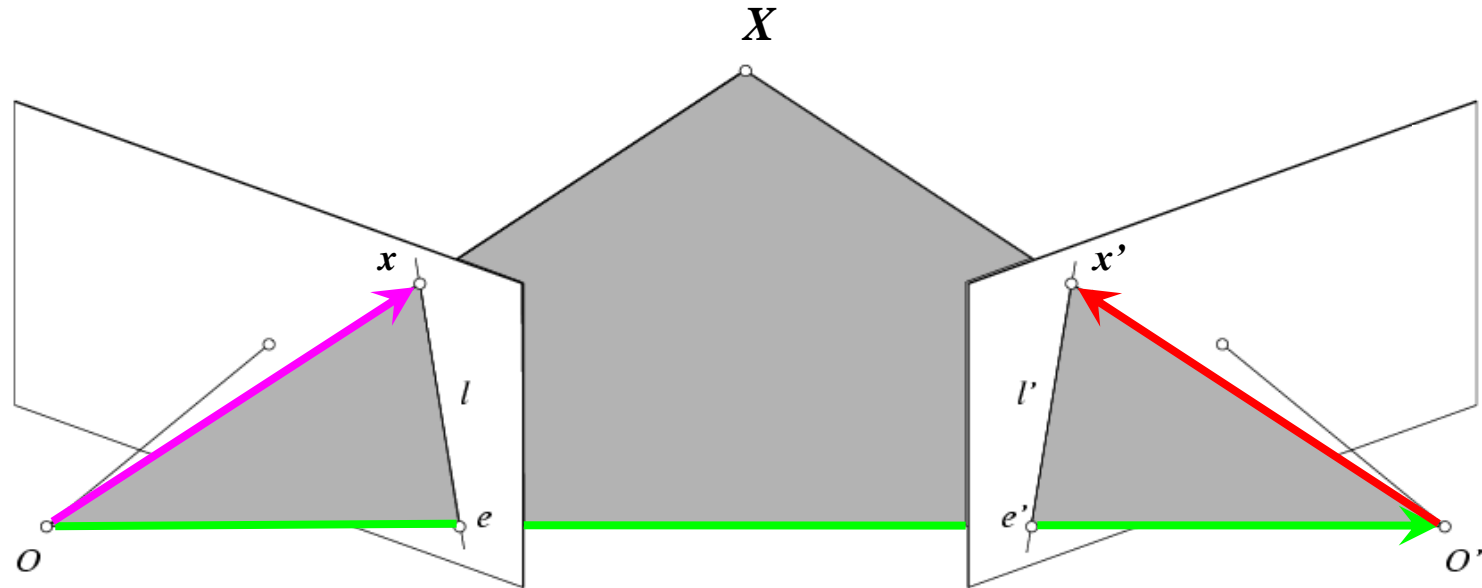


$$\boxed{\mathbf{X}} = \boxed{\mathbf{R}}\boxed{\mathbf{X}'} + \boxed{\mathbf{T}}$$

$$\underbrace{\mathbf{T} \times \mathbf{X}}_{\text{Normal to the plane}} = \mathbf{T} \times \mathbf{R}\mathbf{X}'$$

$$\begin{aligned} \mathbf{X} \cdot (\mathbf{T} \times \mathbf{X}) &= \mathbf{X} \cdot (\mathbf{T} \times \mathbf{R}\mathbf{X}') \\ &= 0 \end{aligned}$$

# Epipolar constraint: Calibrated case

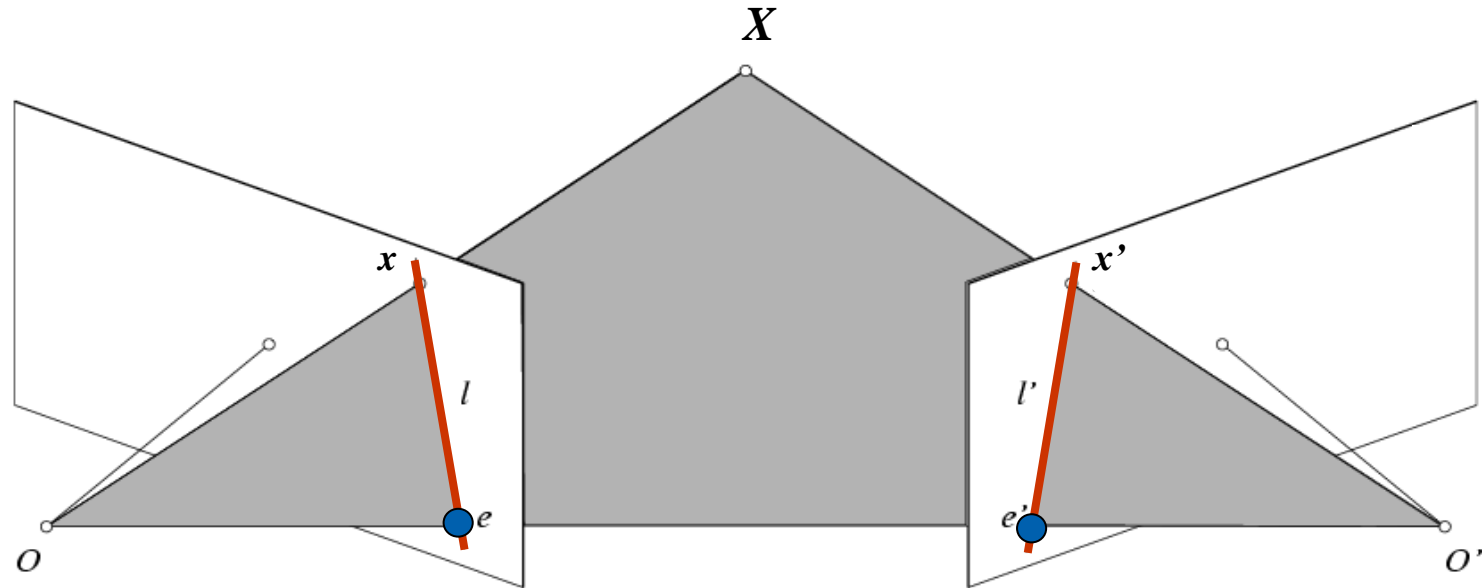


$$x \cdot [t \times (Rx')] = 0 \quad \Rightarrow \quad x^T E x' = 0 \quad \text{with} \quad E = [t_{\times}] R$$



**Essential Matrix**  
(Longuet-Higgins, 1981)

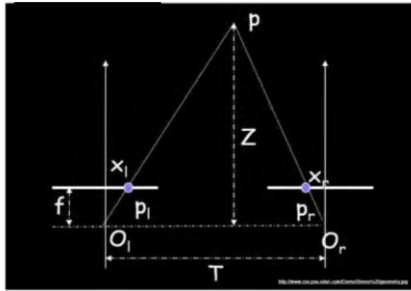
# Epipolar constraint: Calibrated case



$$x \cdot [t \times (Rx')] = 0 \quad \Rightarrow \quad x^T E x' = 0 \quad \text{with} \quad E = [t_x] R$$

- $E x'$  is the epipolar line associated with  $x'$  ( $l = E x'$ )
- $E^T x$  is the epipolar line associated with  $x$  ( $l' = E^T x$ )
- $E e' = 0$  and  $E^T e = 0$
- $E$  is singular (rank two)
- $E$  has five degrees of freedom

# Essential matrix example: parallel cameras



$$\mathbf{R} =$$

$$\mathbf{T} =$$

$$\mathbf{E} = [\mathbf{T} \ \mathbf{x}] \mathbf{R} =$$

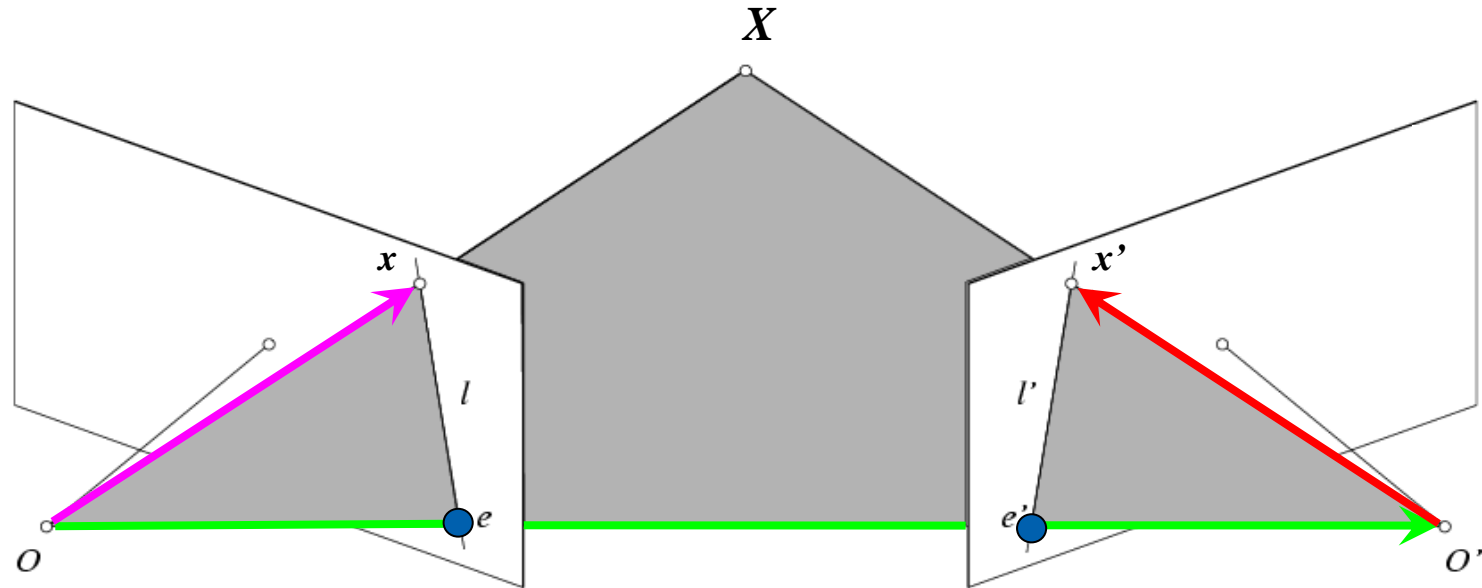
$$\mathbf{p} = [x, y, f]$$

$$\mathbf{p}' = [x', y', f]$$

$$\mathbf{p}'^T \mathbf{E} \mathbf{p} = 0$$

For the parallel cameras,  
image of any point must lie  
on same horizontal line in  
each image plane.

# Epipolar constraint: Uncalibrated case



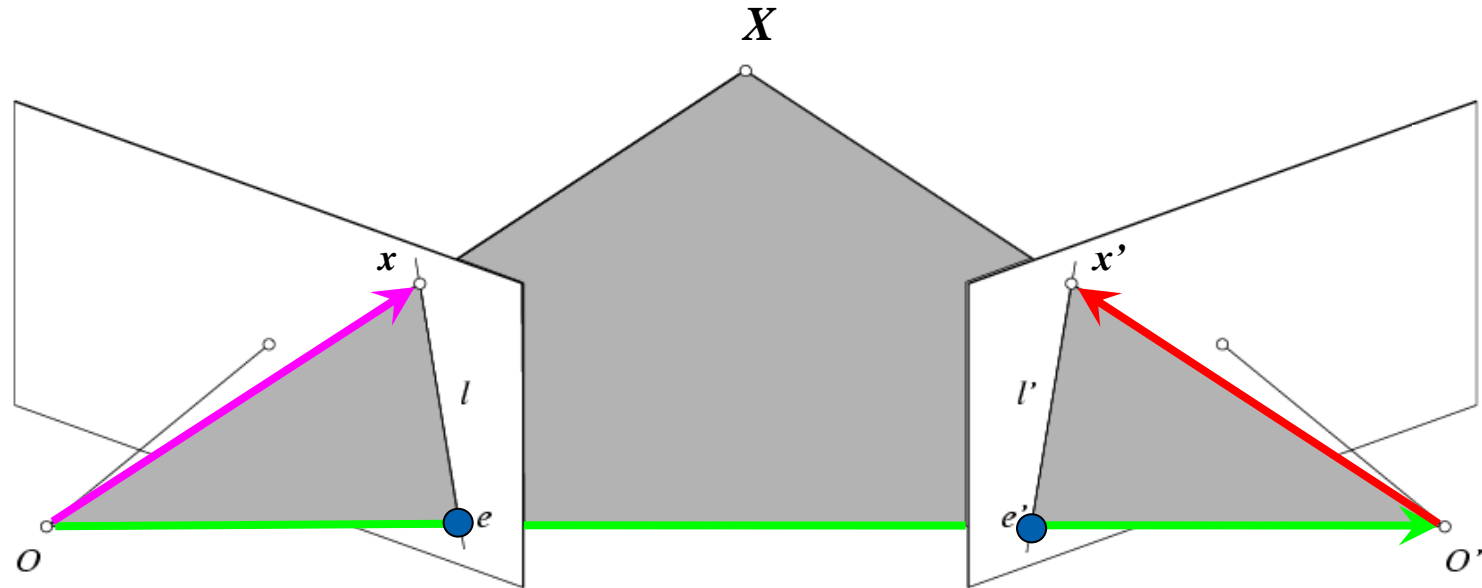
The calibration matrices  $K$  and  $K'$  of the two cameras are unknown

We can write the epipolar constraint in terms of unknown normalized coordinates:

$$\hat{x}^T E \hat{x}' = 0$$

$$x = K \hat{x}, \quad x' = K' \hat{x}'$$

# Epipolar constraint: Uncalibrated case



$\Rightarrow x^T F x' = 0$  with  $F = K^{-T} E K'^{-1}$



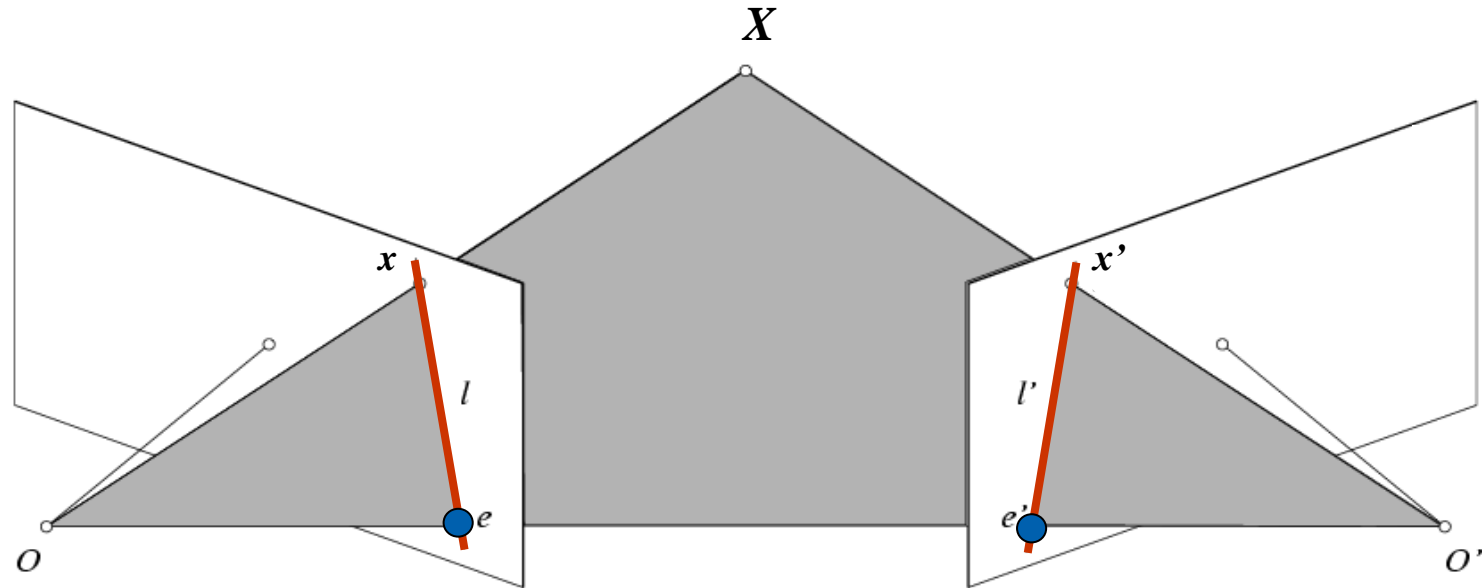
$$\hat{x} = K^{-1} x$$

$$\hat{x}' = K'^{-1} x'$$

**Fundamental Matrix**  
 (Faugeras and Luong, 1992)



# Epipolar constraint: Uncalibrated case



$$x^T F x' = 0 \quad \text{with} \quad F = K^{-T} E K'^{-1}$$

- $F x'$  is the epipolar line associated with  $x'$  ( $l = F x'$ )
- $F^T x$  is the epipolar line associated with  $x$  ( $l' = F^T x$ )
- $F e' = 0$  and  $F^T e = 0$
- $F$  is singular (rank two)
- $F$  has seven degrees of freedom

# The eight-point algorithm

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

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

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

Minimize:

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

under the constraint

$$F_{33} = 1$$

# The eight-point algorithm

- Meaning of error  $\sum_{i=1}^N (x_i^T F x'_i)^2 :$

sum of Euclidean distances between points  $x_i$  and epipolar lines  $Fx'_i$  (or points  $x'_i$  and epipolar lines  $F^T x_i$ ) multiplied by a scale factor

- Nonlinear approach: minimize

$$\sum_{i=1}^N \left[ d^2(x_i, F x'_i) + d^2(x'_i, F^T x_i) \right]$$

# Problem with eight-point algorithm

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

# 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
135384.58	75411.13	198.72	411350.03	229127.78	603.79	681.28	379.48

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

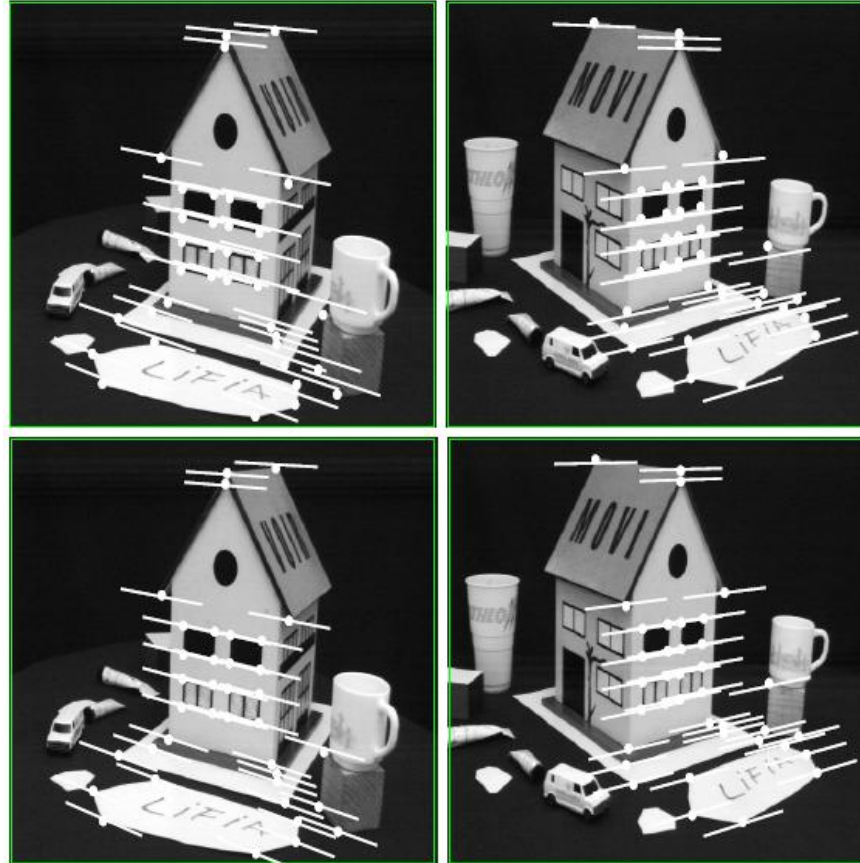
- Poor numerical conditioning
- Can be fixed by rescaling the data

# The normalized eight-point algorithm

(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
- 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  $T^T F T'$

# Comparison of estimation algorithms



	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

- 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:  $E = K^T F K'$
- The essential matrix gives us the relative rotation and translation between the cameras, or their extrinsic parameters



The logo of the University of Bonn, featuring a blue square with a white curved line and a grey square.

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