

# SAIR

Spatial AI & Robotics Lab

# CSE 473/573

# L2: CAMERA MODEL

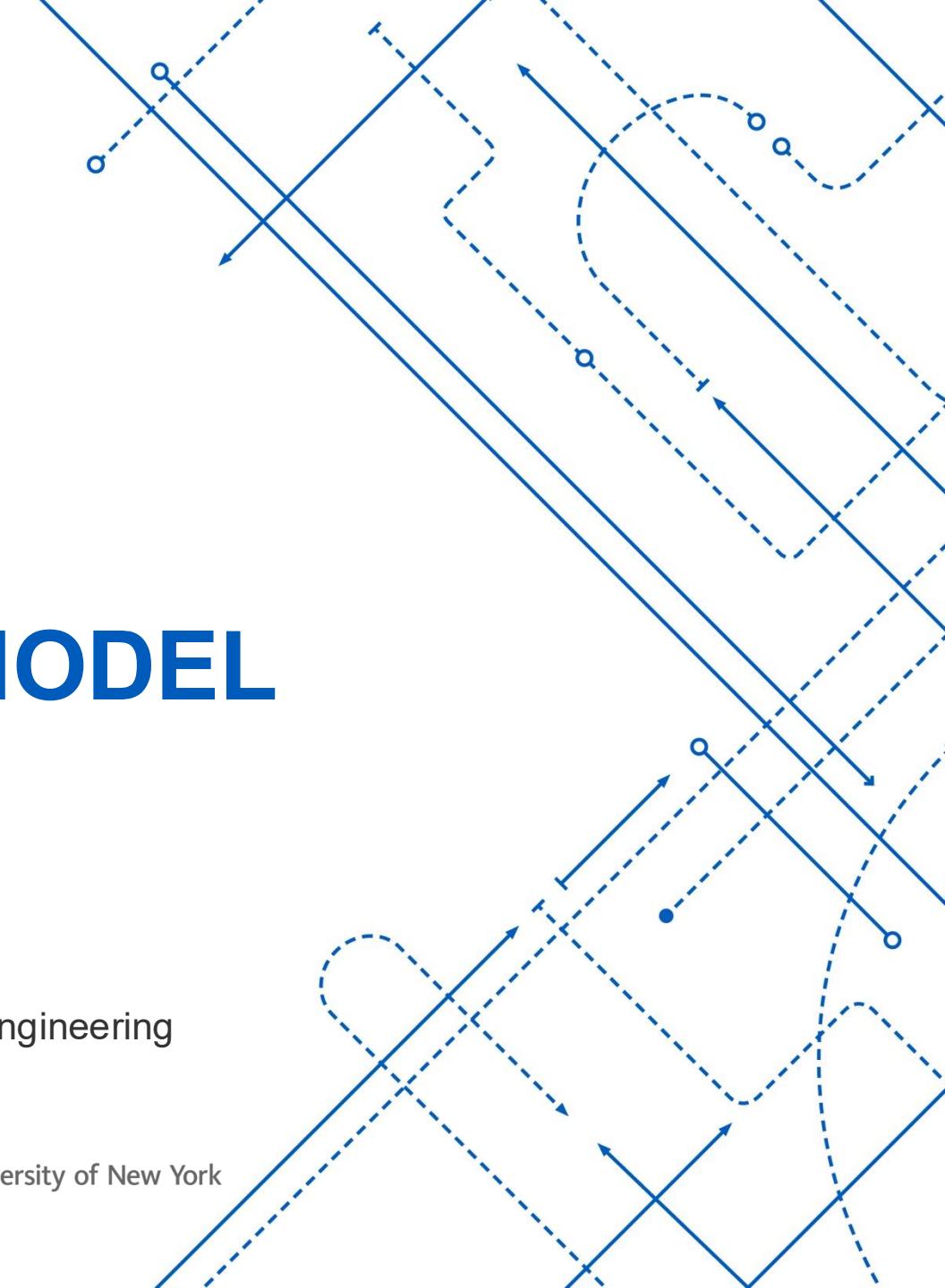
Chen Wang

Spatial AI & Robotics Lab

Department of Computer Science and Engineering



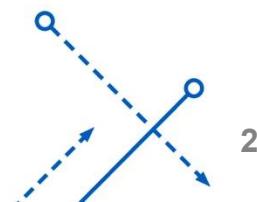
University at Buffalo The State University of New York



# Content

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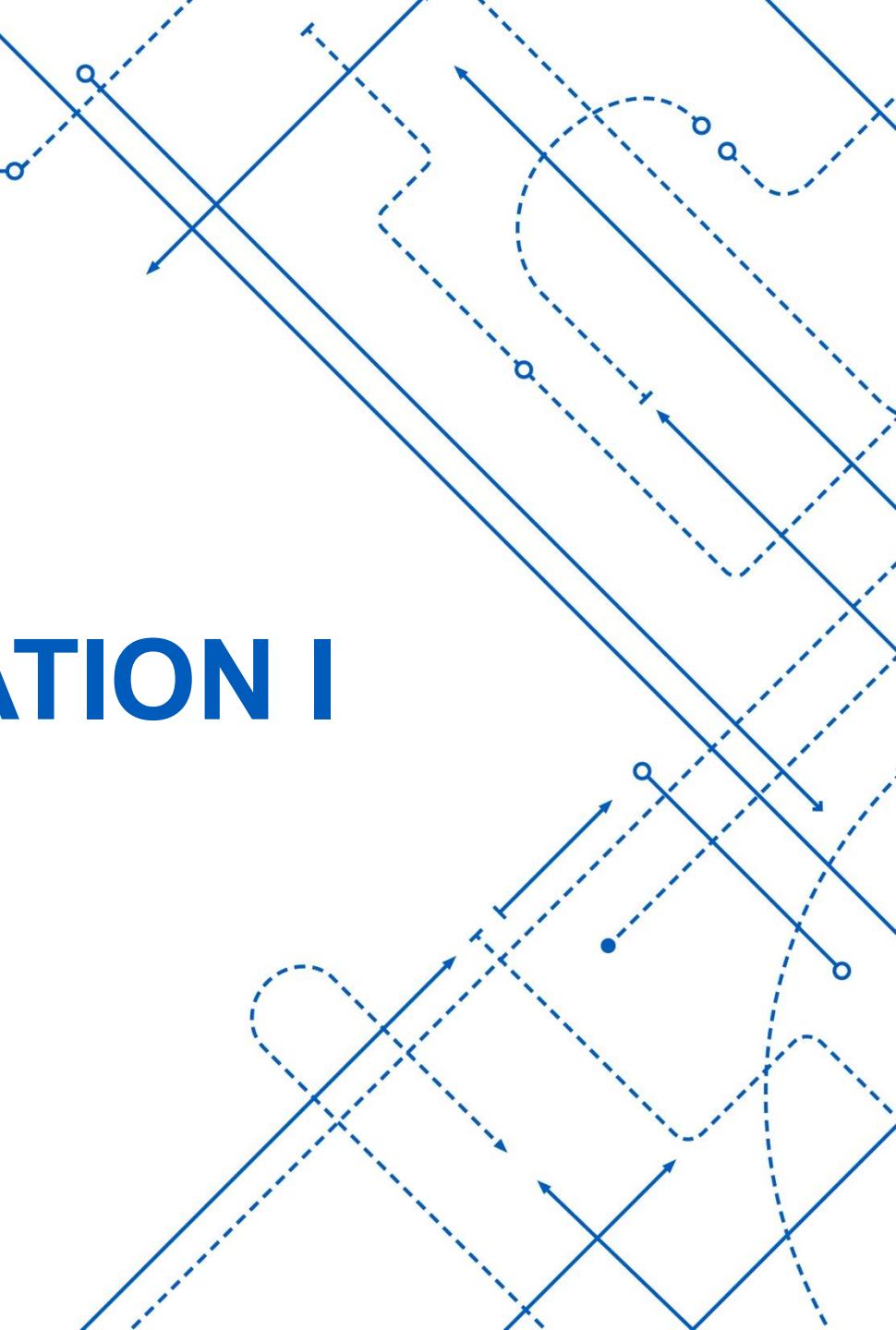
- Pinhole Camera
  - Perspective Projection
  - Projective Geometry
  - Vanishing Points and Lines
  - Homogeneous Coordinates
  - Matrix form of Perspective Projection
  - Intrinsic and Extrinsic Parameters
- Other type of projection
  - Weak Perspective Projection
  - Photo Finish Photography
  - 360 Imaging
  - Tilt-shift Imaging
- Camera Calibration





# IMAGE FORMATION I

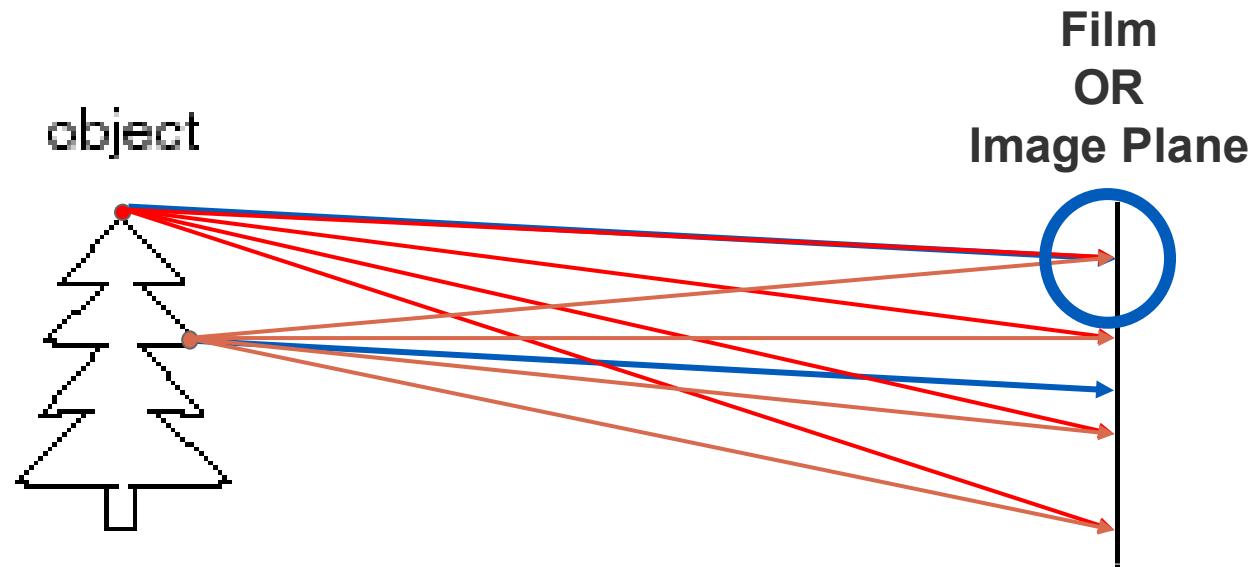
## Pinhole Camera



# Image formation

Let's design a camera

- Idea 1: put a piece of film in front of an object
- Do we get a reasonable image?



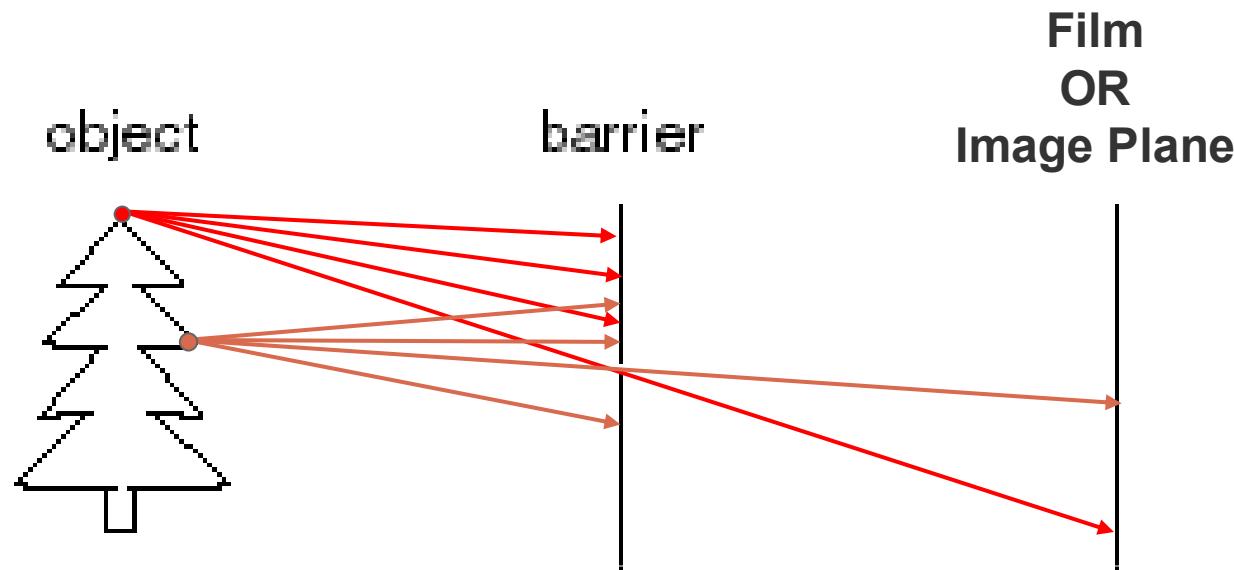
Answer is No....



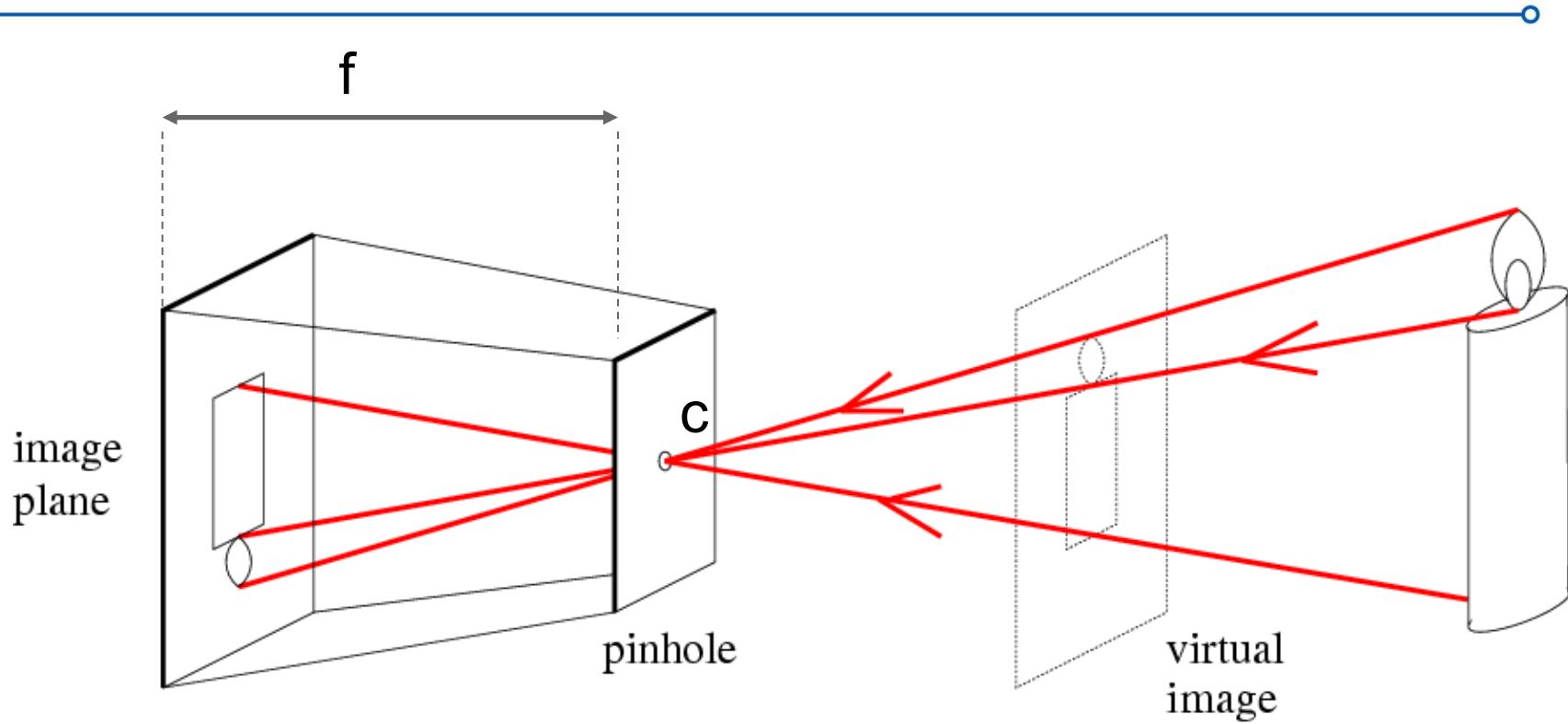
# Pinhole camera

Idea 2: add a barrier to block off most of the rays

- This reduces blurring
- The opening known as the **aperture**



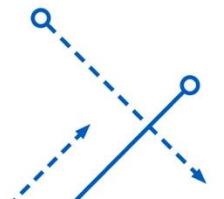
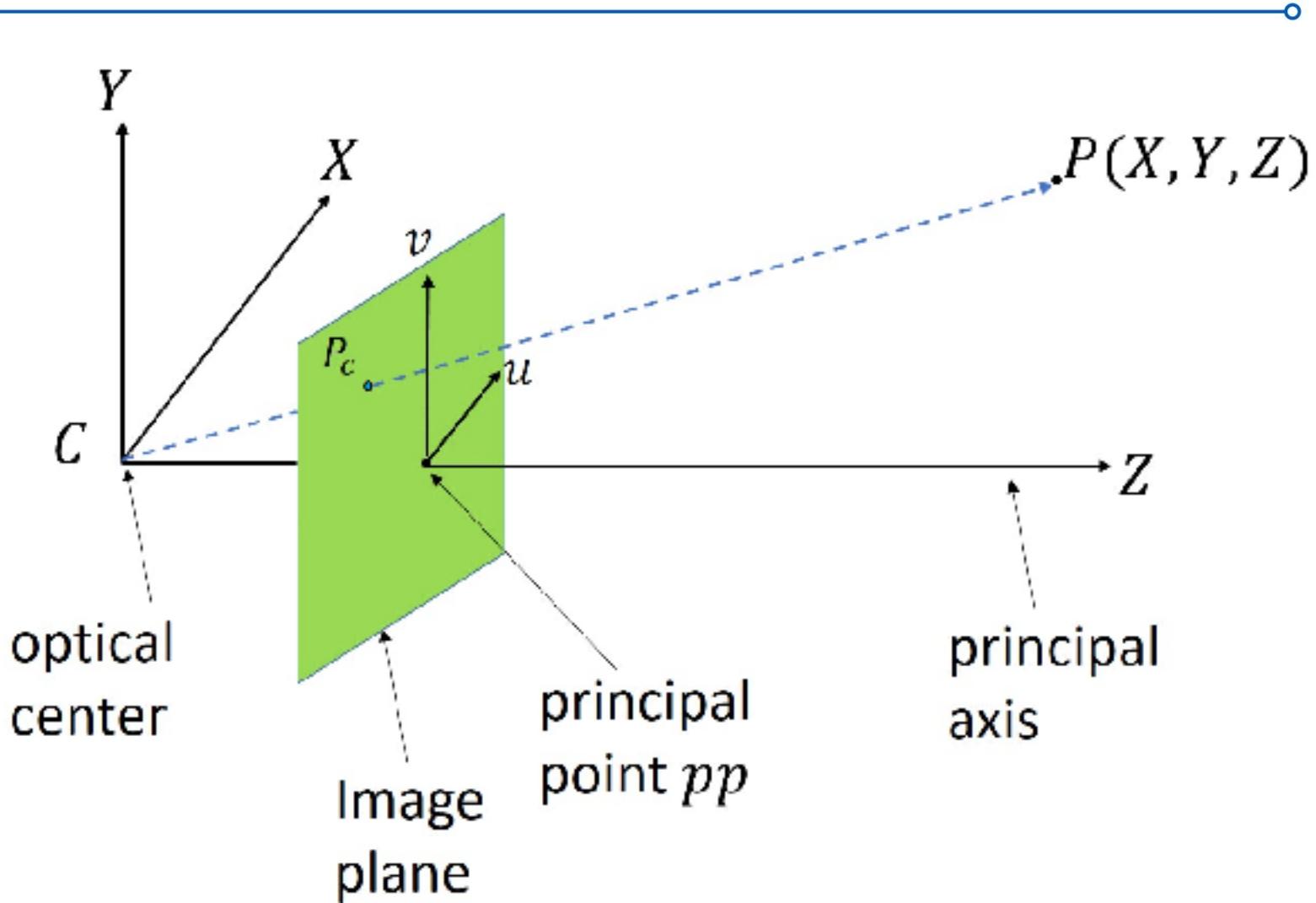
# Pinhole camera



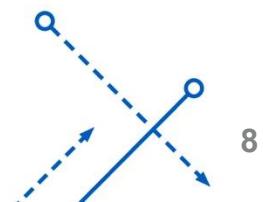
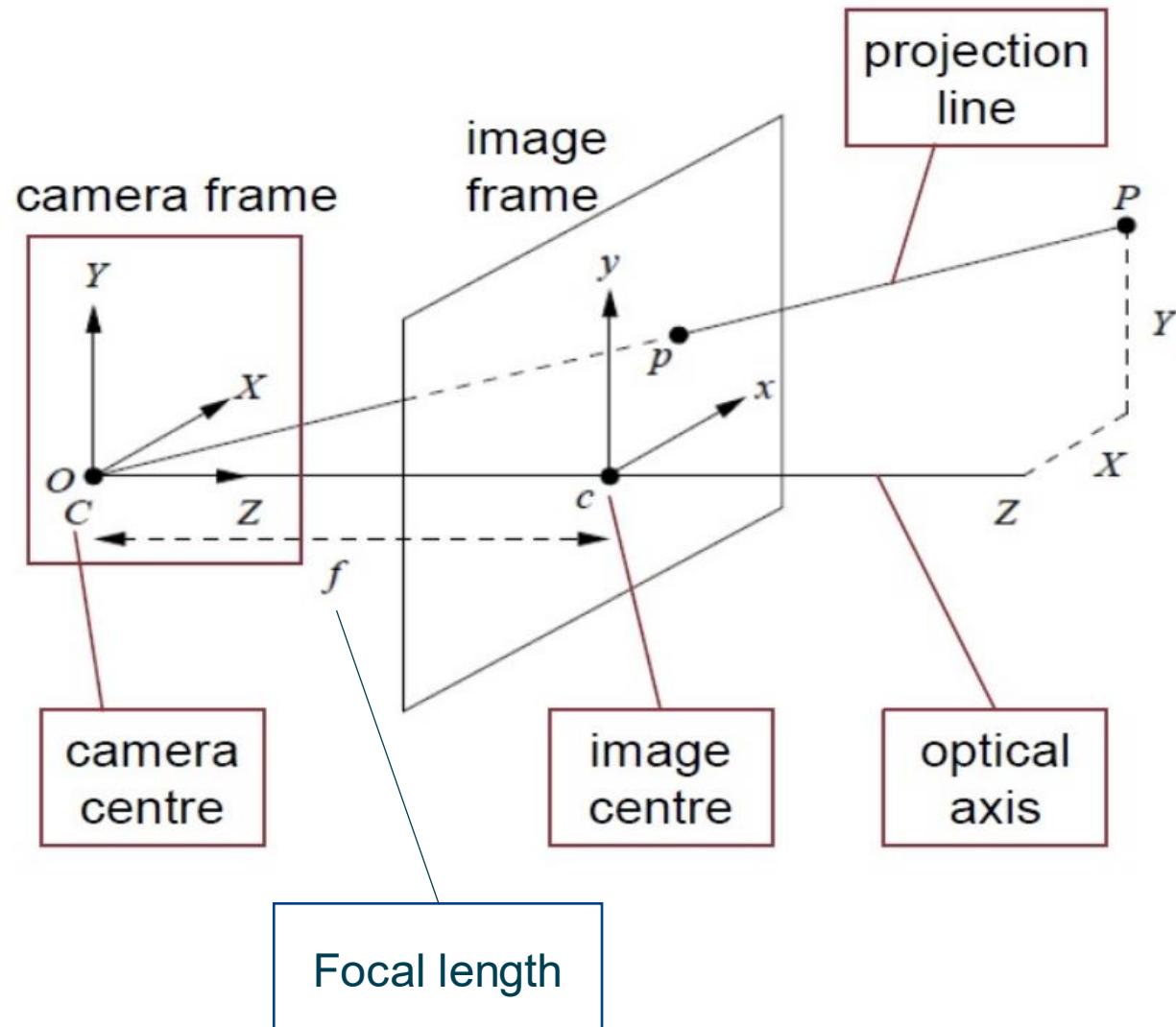
$f$  = focal length

c = center of the camera

# Perspective Projection

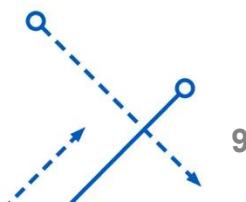
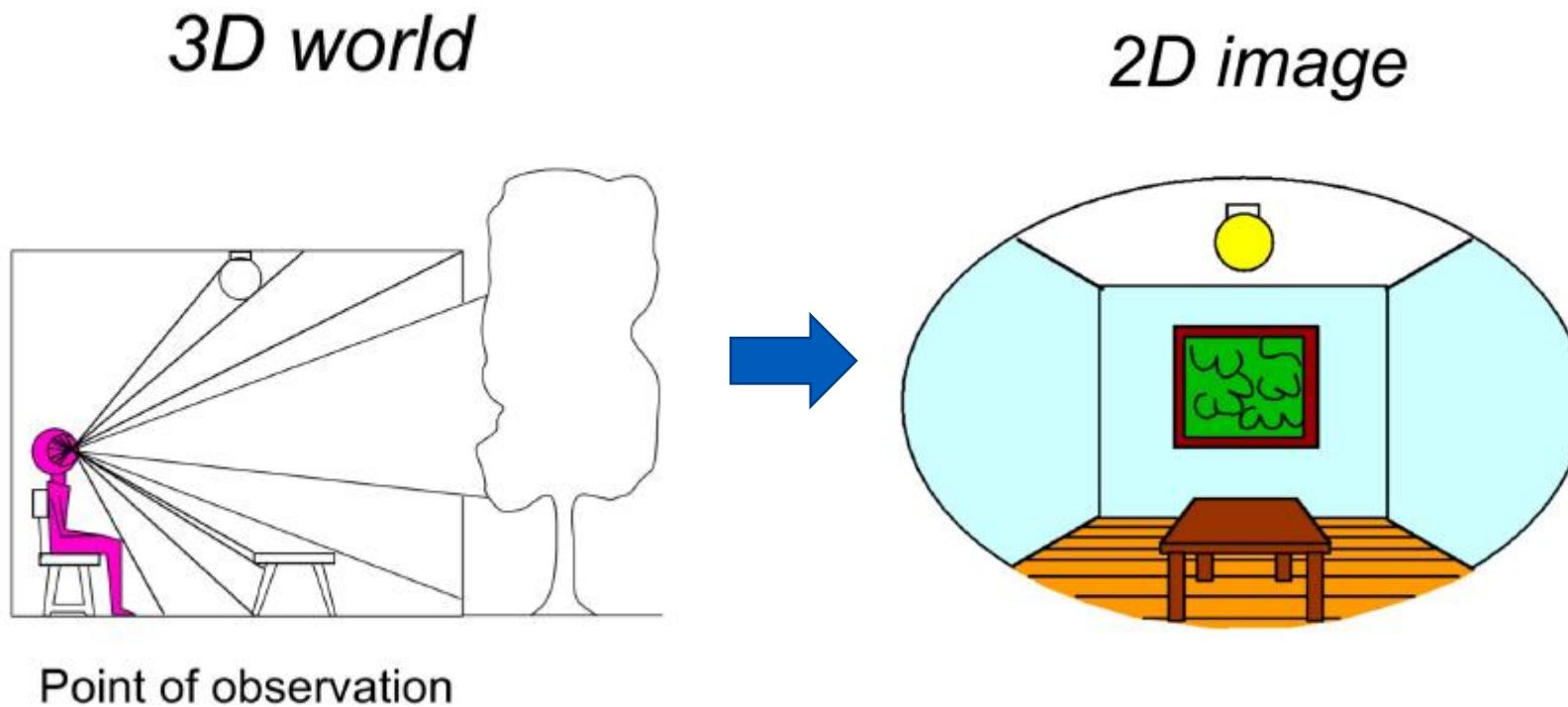


# Other names



# What do we lose?

- Projection from 3D world to 2D Image



# Long range objects appear to be small.

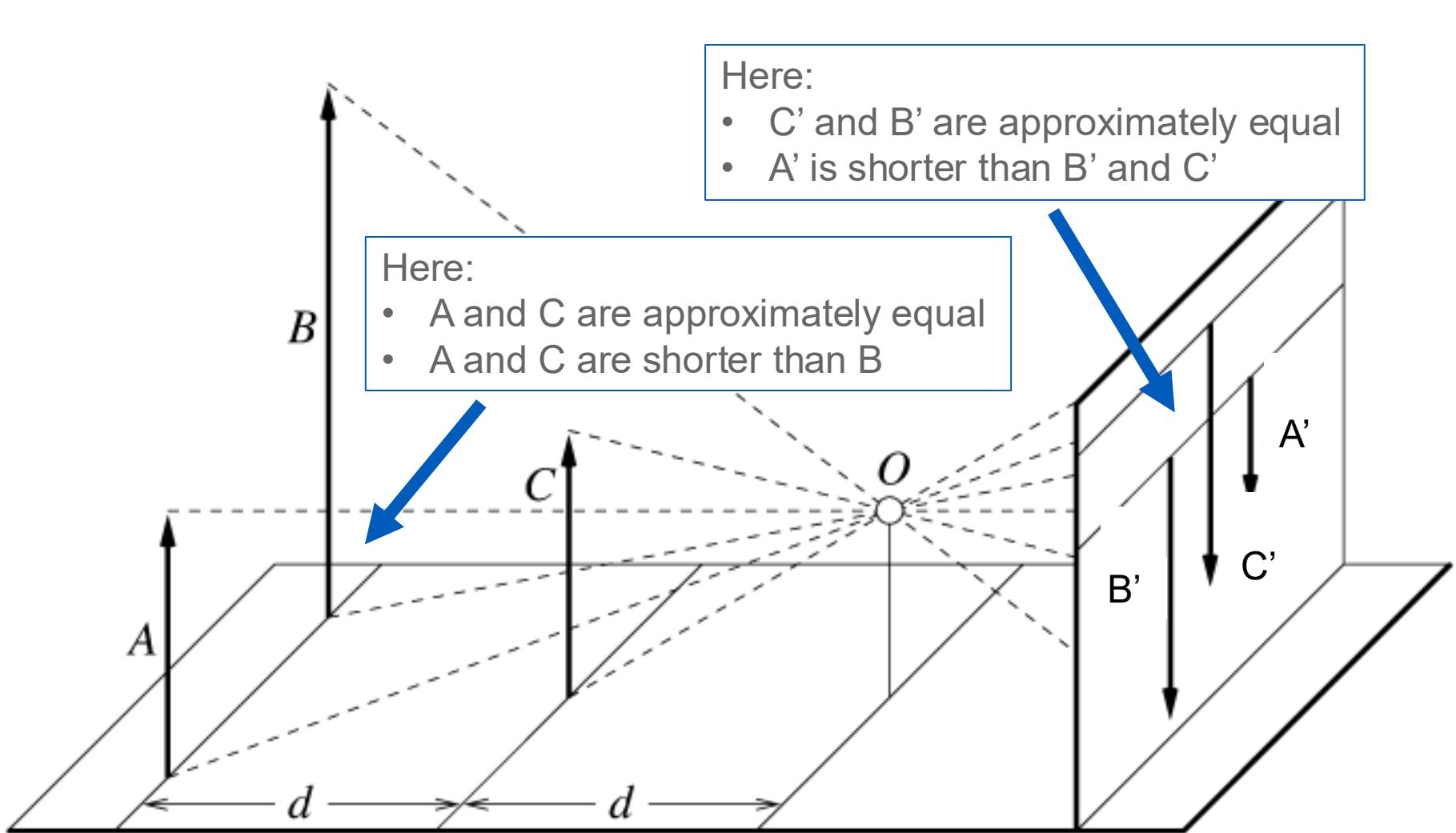


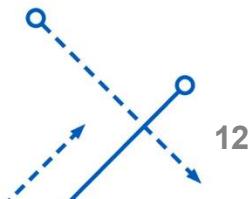
Figure by David Forsyth

# Perspective Projection - Example

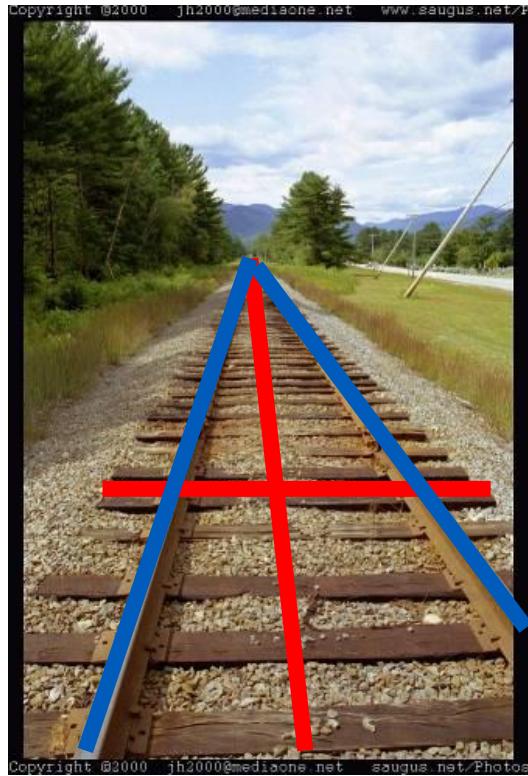


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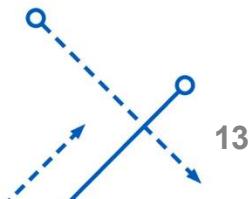
# Perspective Projection - Example



# What do we lose geometrically?



- Angles
- Distances
- and therefore Area



# Geometrical Properties

Many-to-one:

Points along same ray map to same point in image.

Points map to → ?

- points

Lines map to → ?

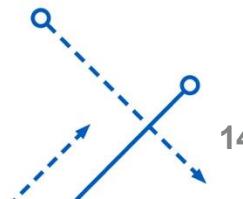
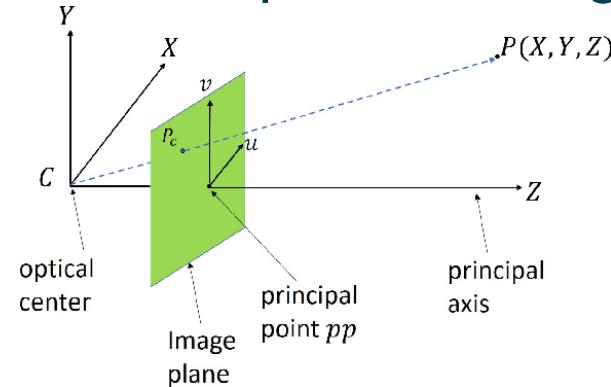
- lines

Distances and angles (are / are not ?) preserved

- are not

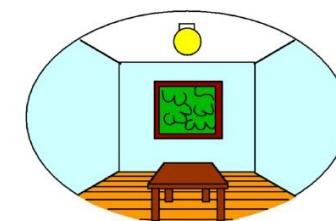
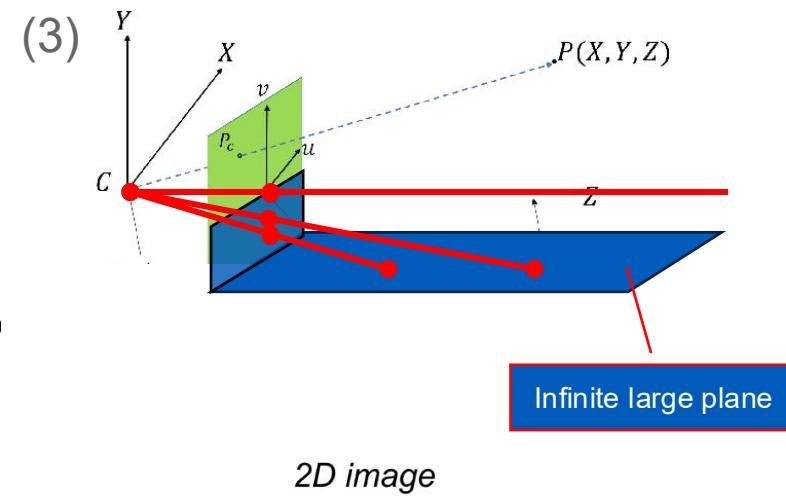
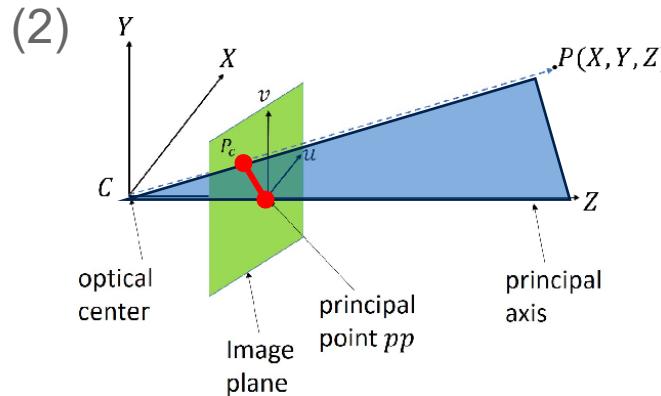
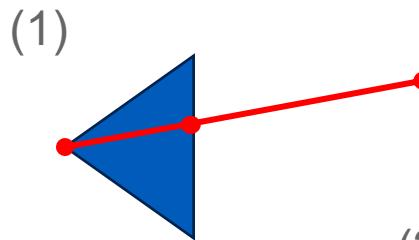
Degenerate cases:

- Line through focal point projects to a point.
- Plane through focal point projects to line
- Plane (not parallel to image plane) projects to part of the image.

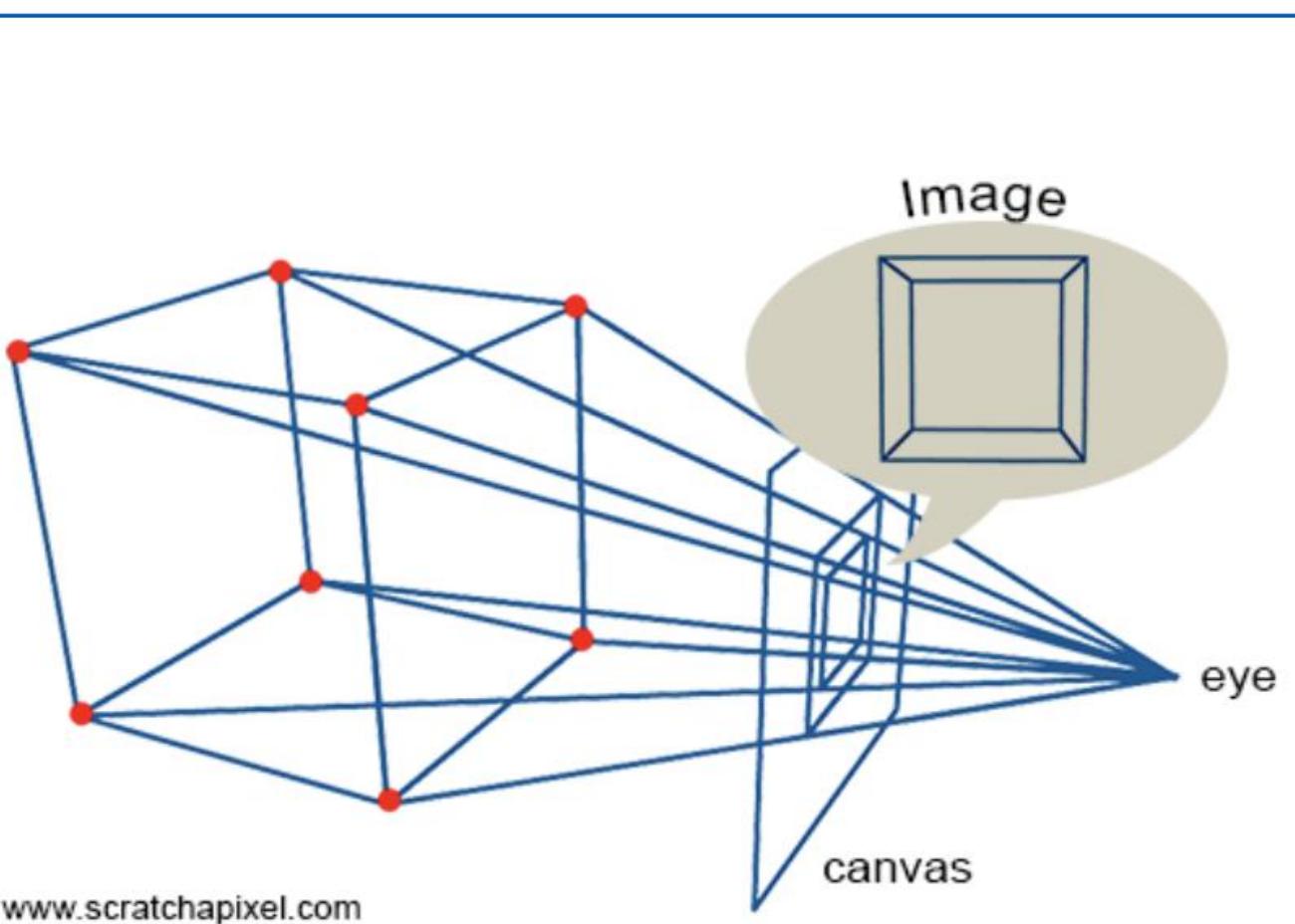


# Degenerate cases

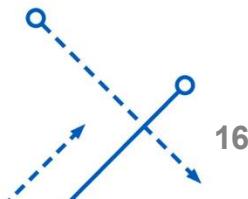
- (1) Line through focal point projects to a point.
- (2) Plane through focal point projects to line
- (3) Plane (not parallel to image plane) projects to part of the image.



# Perspective Projection - Example



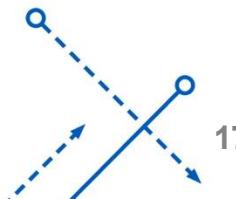
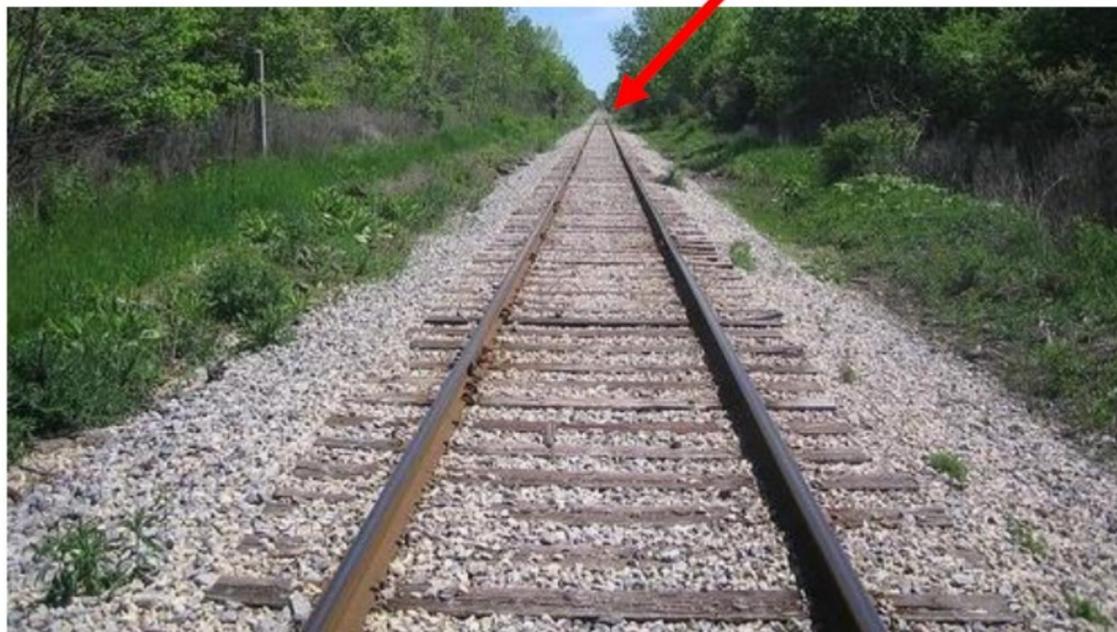
© www.scratchapixel.com



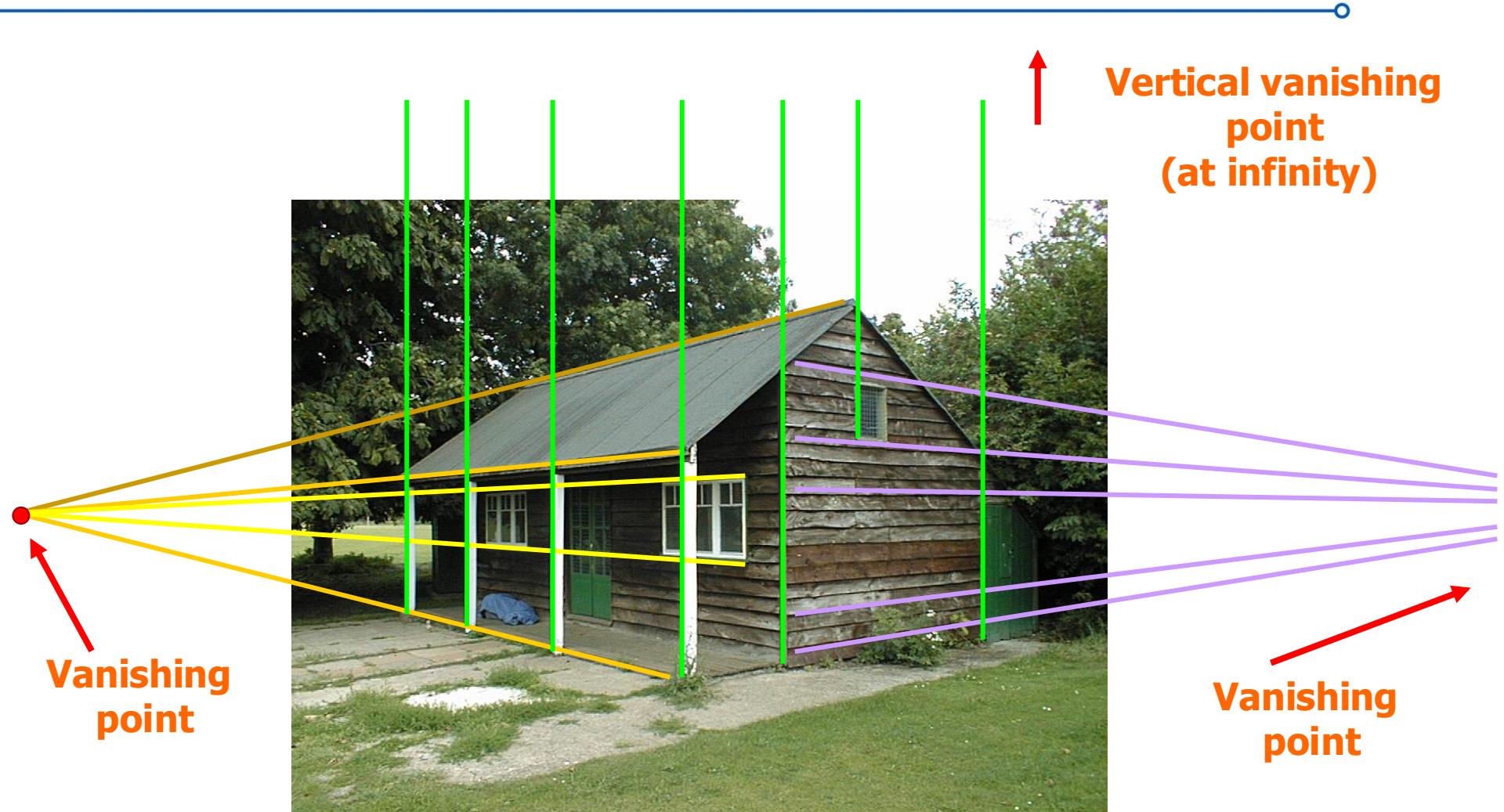
# Vanishing points and lines

Parallel lines in the world intersect in the image at a “vanishing point”

- Angles are not preserved
- Parallel lines meet!



# Vanishing points and lines



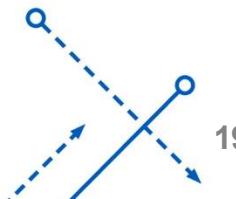
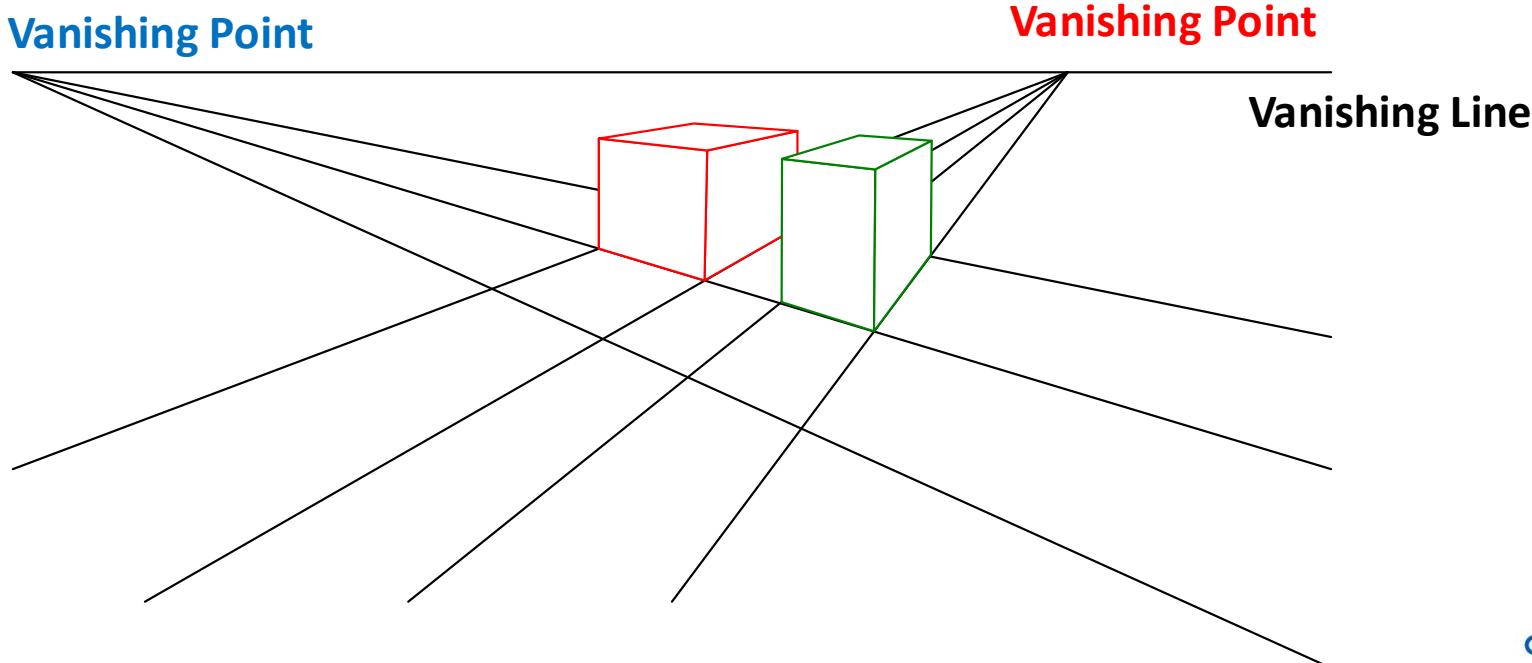
Vertical vanishing point (at infinity)

Vanishing point

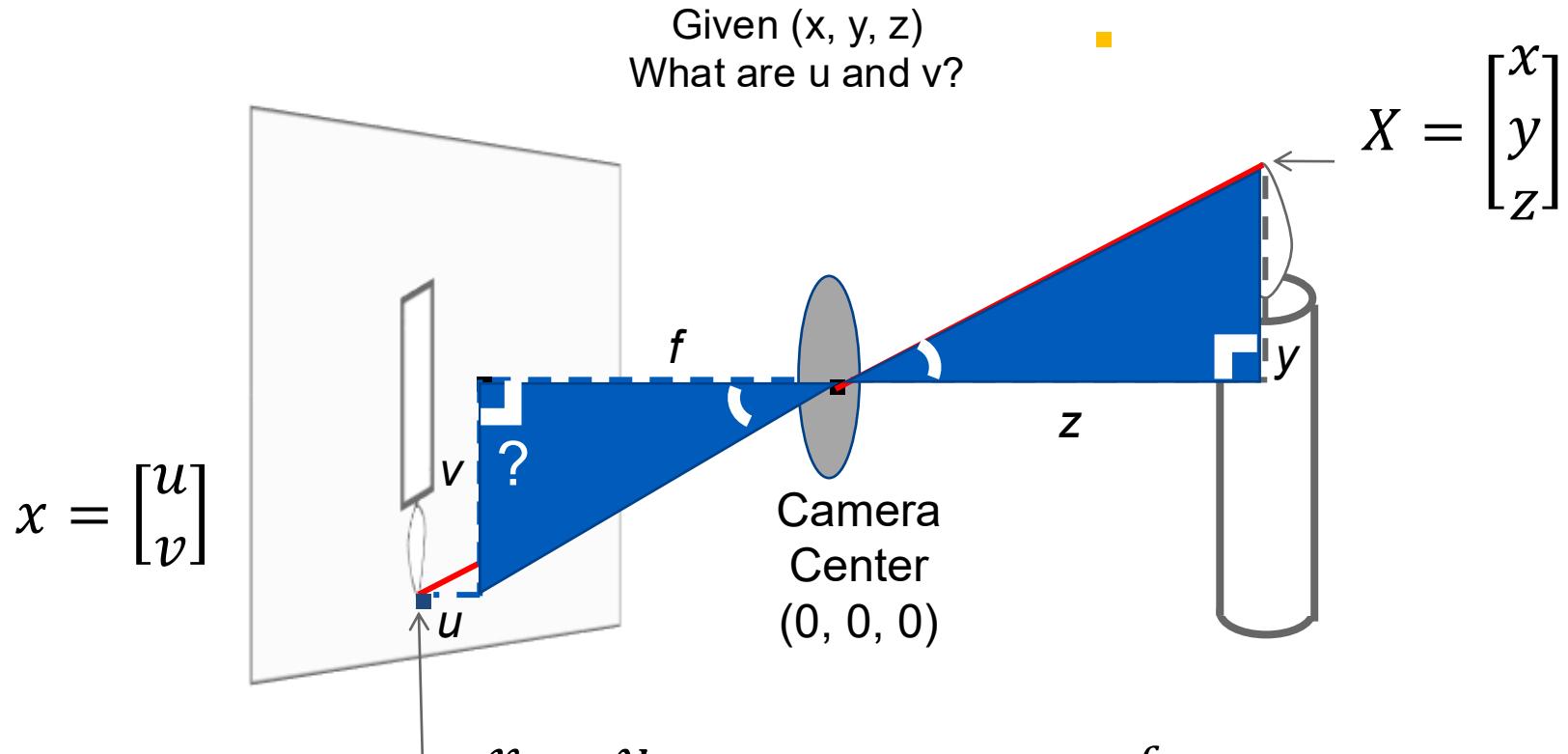
Vanishing point

# Vanishing points and lines

- Any two lines, parallel in 3D will meet at a unique vanishing point in image plane.
- All pairs of parallel lines on the same plane in 3D will have vanishing points on a unique vanishing line.



# Perspective Projection

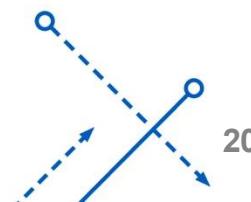


$$\frac{v}{-f} = \frac{y}{z}$$

$$v = -y * \frac{f}{z}$$

$$\frac{u}{-f} = \frac{x}{z}$$

$$u = -x * \frac{f}{z}$$



# Perspective Projection Equations

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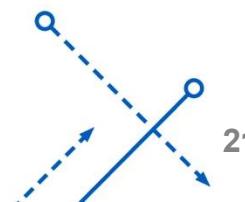
- ◎ 3D point  $\mathbf{P} = (X, Y, Z)^\top$  projects to 2D image point  $\mathbf{p} = (x, y)^\top$ .
- ◎ By symmetry,

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

i.e.,

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

- ◎ Simplest form of perspective projection.



# Preliminary: Homogeneous coordinates

Converting to *homogeneous* coordinates

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

homogeneous image  
coordinates

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

homogeneous scene  
coordinates

Converting *from* homogeneous coordinates

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

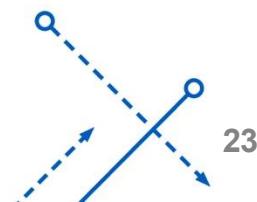
$$\begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} \Rightarrow (x/w, y/w, z/w)$$

- A way of representing N-dimensional coordinates with N+1 numbers.
- It allows perspective projection representing as matrix-vector multiplication.

# Perspective Projection

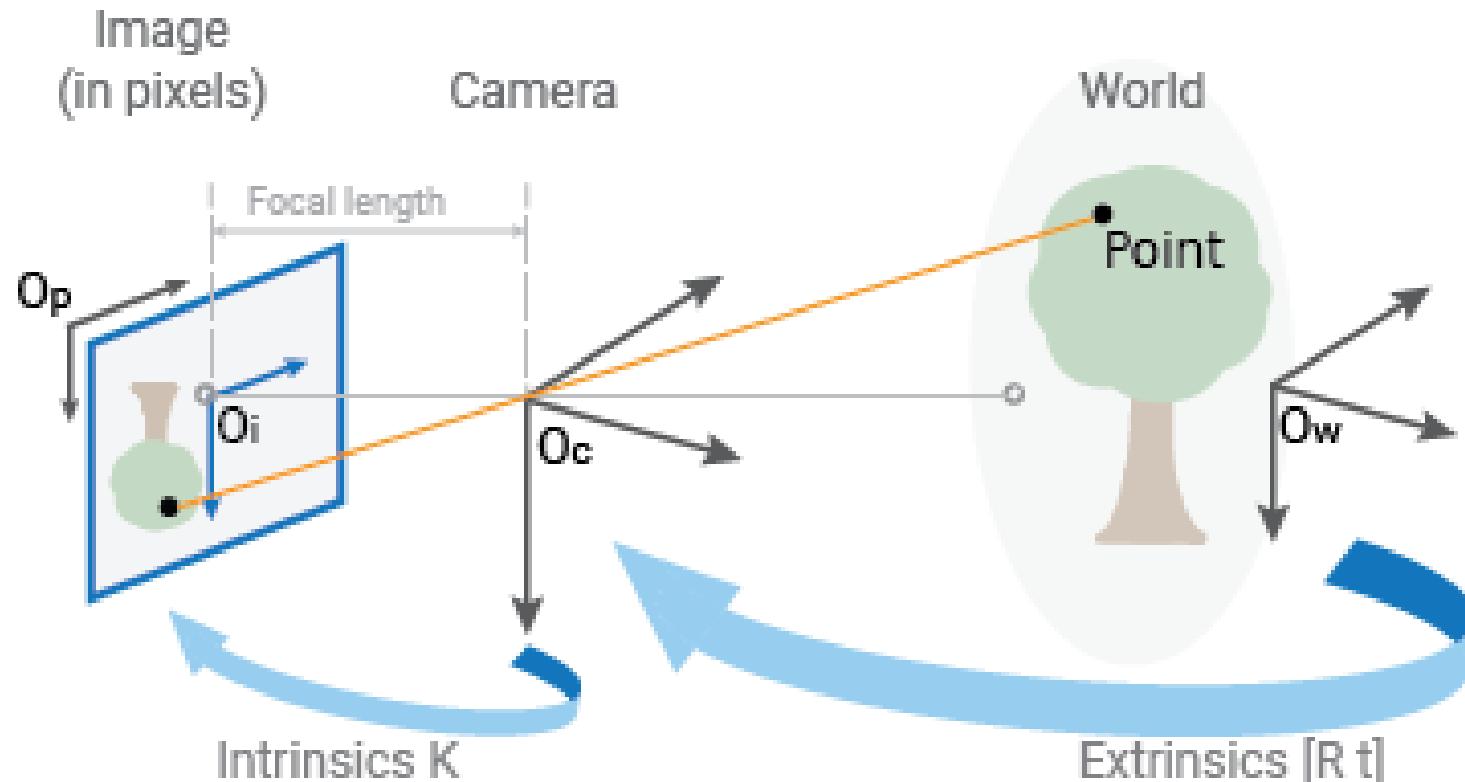
- Matrix Form

$$w \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$



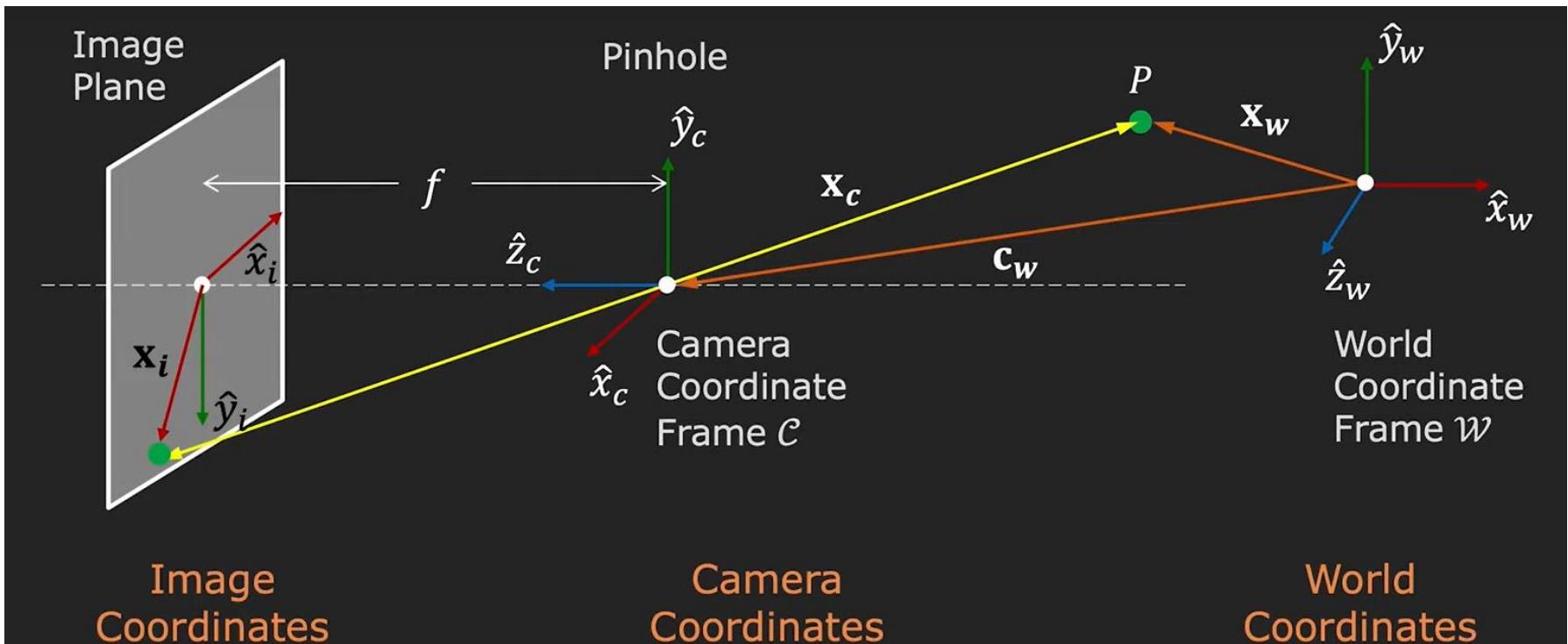
# Intrinsic and Extrinsic Parameters

- Perspective equations so far in terms of camera's frame.
- Camera's *intrinsic* (Camera) and *extrinsic* (World) parameters needed to calibrate geometry.

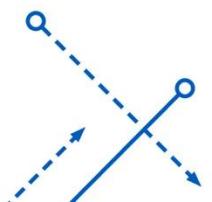


K. Grauman  
24

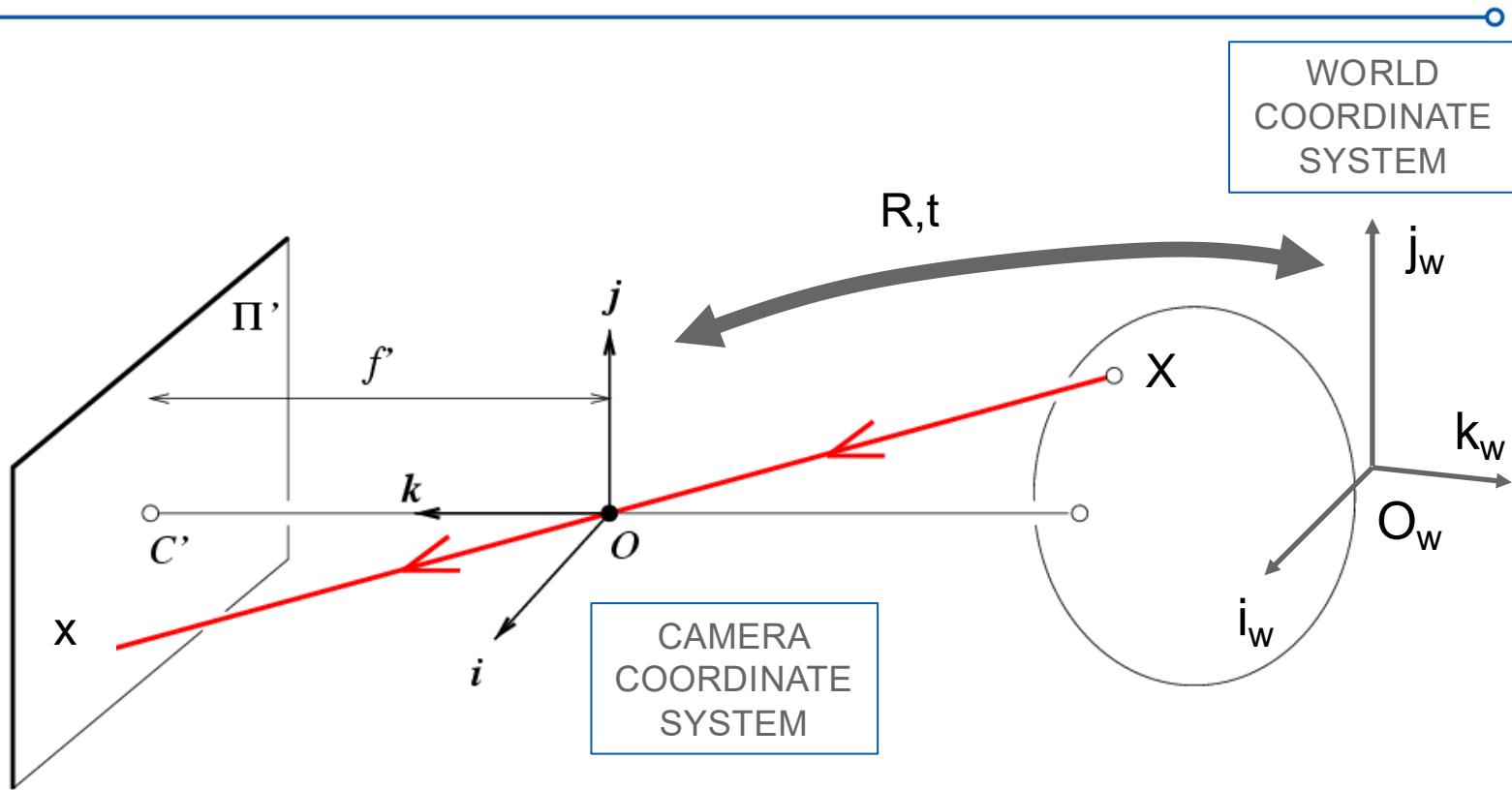
# Three different coordinate systems



$\mathbf{x}_i$  is the projection of point  $P$  in the world



# Projection Matrix



$$\mathbf{x} = \mathbf{K} [\mathbf{R} \quad \mathbf{t}] \mathbf{X}$$

Extrinsic Matrix

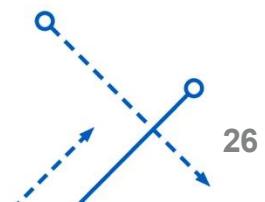
$\mathbf{x}$ : Image Coordinates:  $(u, v, 1)$

$\mathbf{K}$ : Intrinsic Matrix (3x3)

$\mathbf{R}$ : Rotation (3x3)

$\mathbf{t}$ : Translation (3x1)

$\mathbf{X}$ : World Coordinates:  $(X, Y, Z, 1)$



# Intrinsic and Extrinsic Parameters

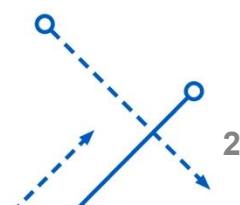
$$s \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_1 \\ r_{21} & r_{22} & r_{23} & t_2 \\ r_{31} & r_{32} & r_{33} & t_3 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

2D Image  
Coordinates

Intrinsic properties  
(Optical Centre, scaling)

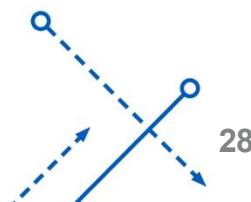
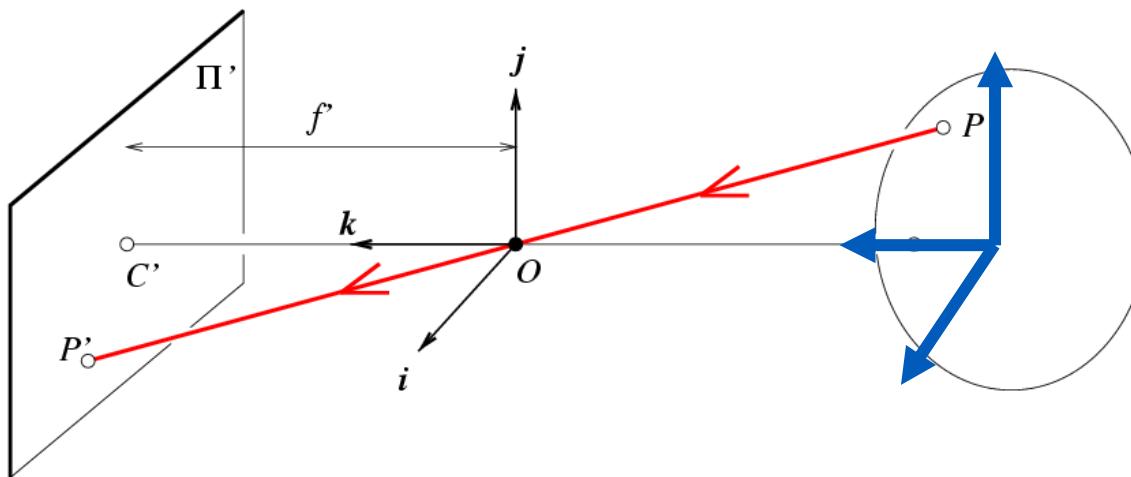
Extrinsic properties  
(Camera Rotation  
and translation)

3D World  
Coordinates

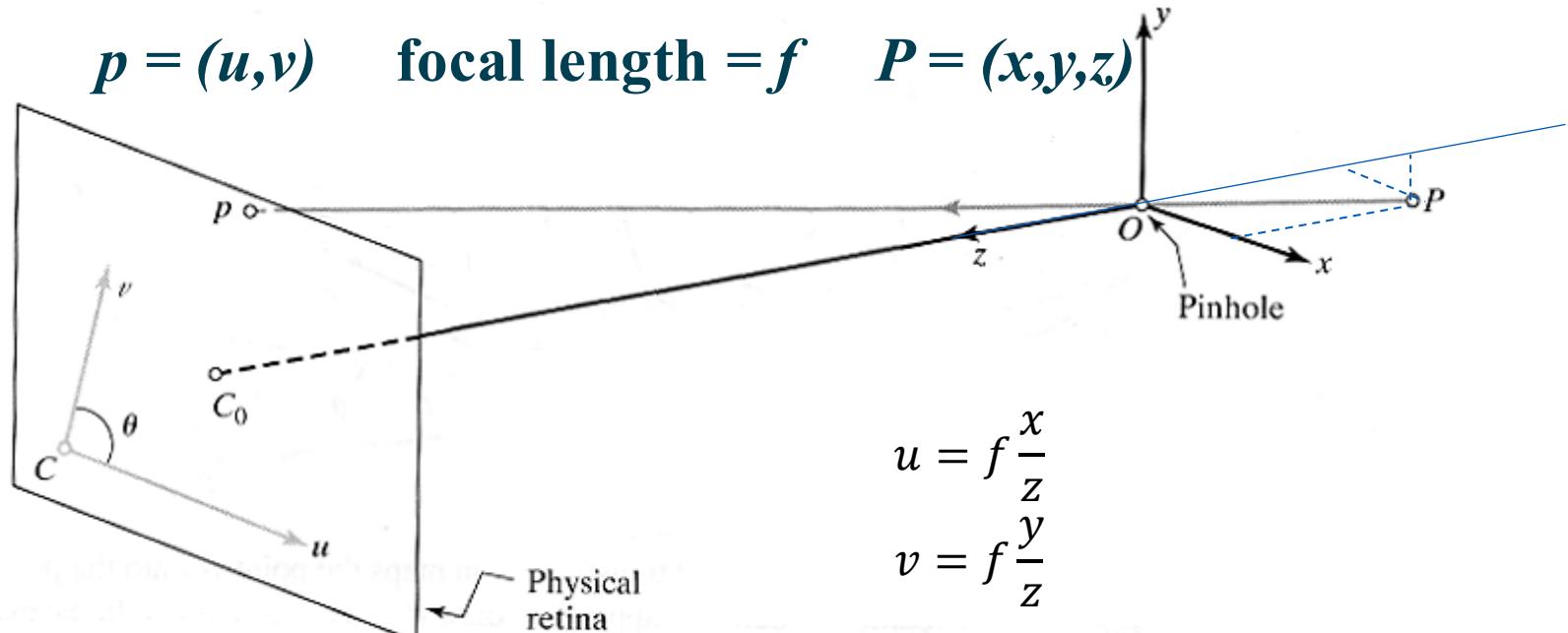


# Idealized (Pinhole) Assumptions

- Everything is a unit length
  - Focal Length is 1 unit, pixels are 1 unit
- The camera and the world coordinate systems are aligned with the image plane.
  - No Rotation or Translation



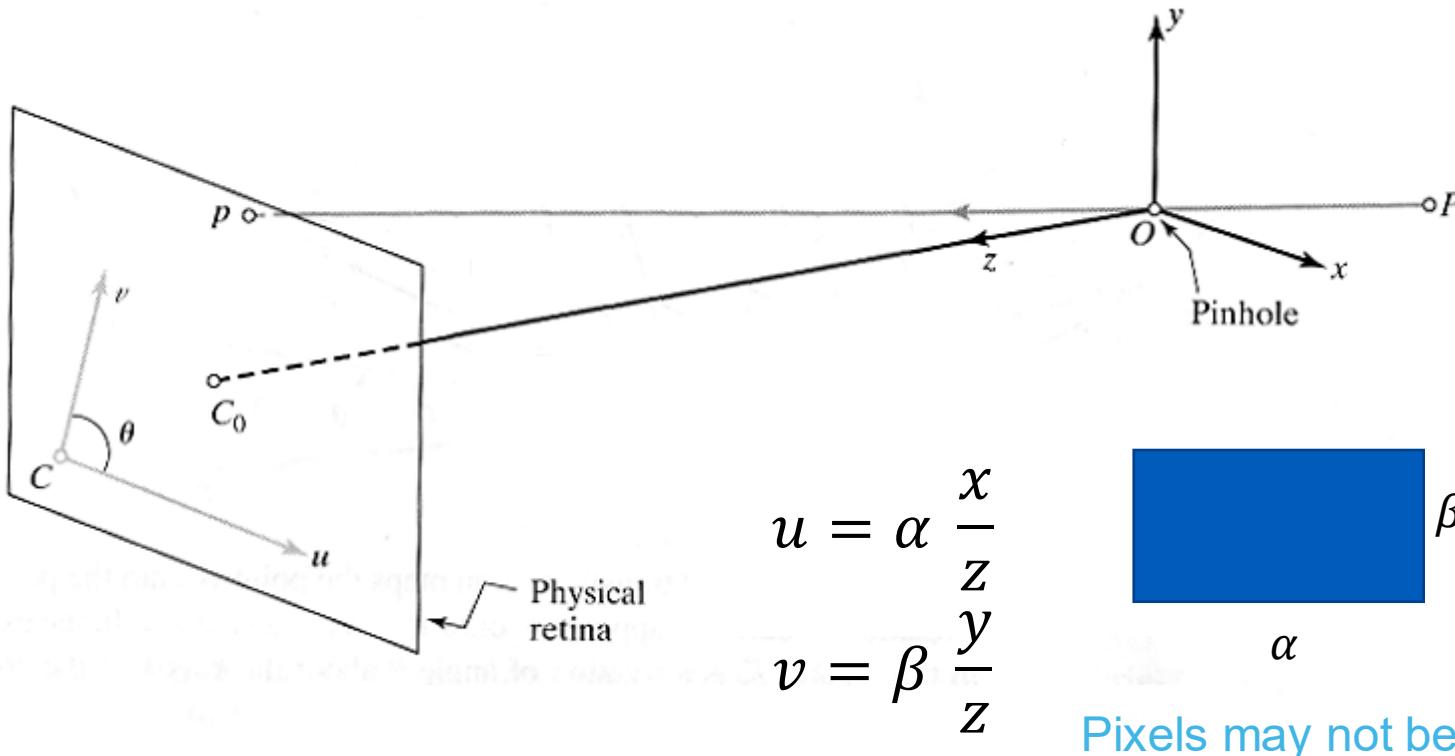
# Intrinsic parameters: from World to Pixel



Perspective projection

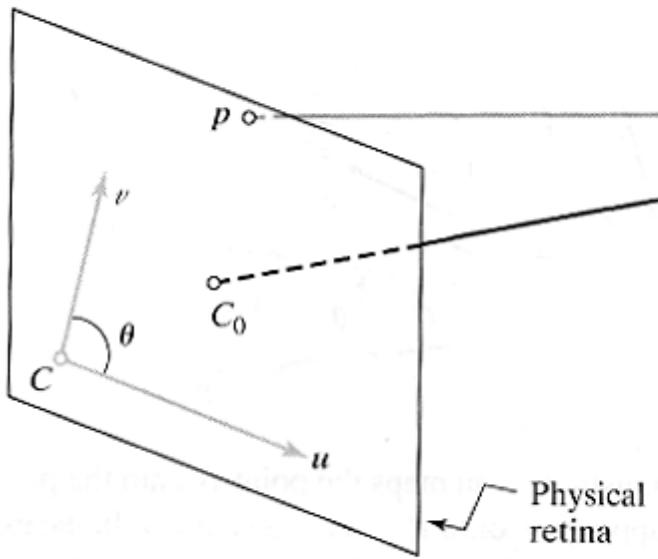
Forsyth&Ponce

# Intrinsic parameters: Relax pixels aspect



30  
W. Freeman

# Intrinsic parameters: Relax image center



The diagram shows a 3D coordinate system with axes  $x$ ,  $y$ , and  $z$ . A point  $P$  is located in the  $xy$ -plane. A point  $C$  is located on the  $z$ -axis at a distance  $z$  from the origin  $O$ . The camera coordinate system is centered at the pinhole, with axes  $u$  and  $v$  defining the image plane. The equations for mapping from 3D coordinates to camera coordinates are:

$$u = \alpha \frac{x}{z} + u_0$$
$$v = \beta \frac{y}{z} + v_0$$

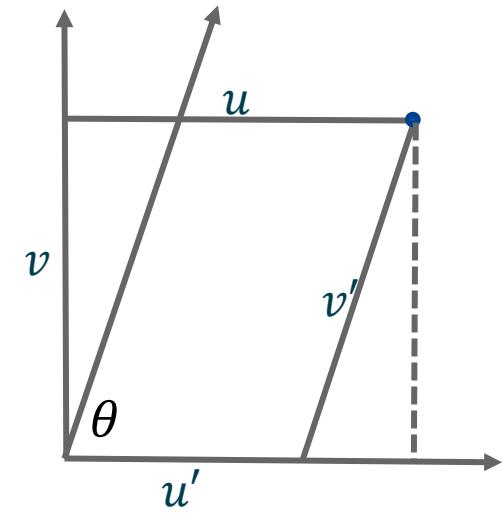
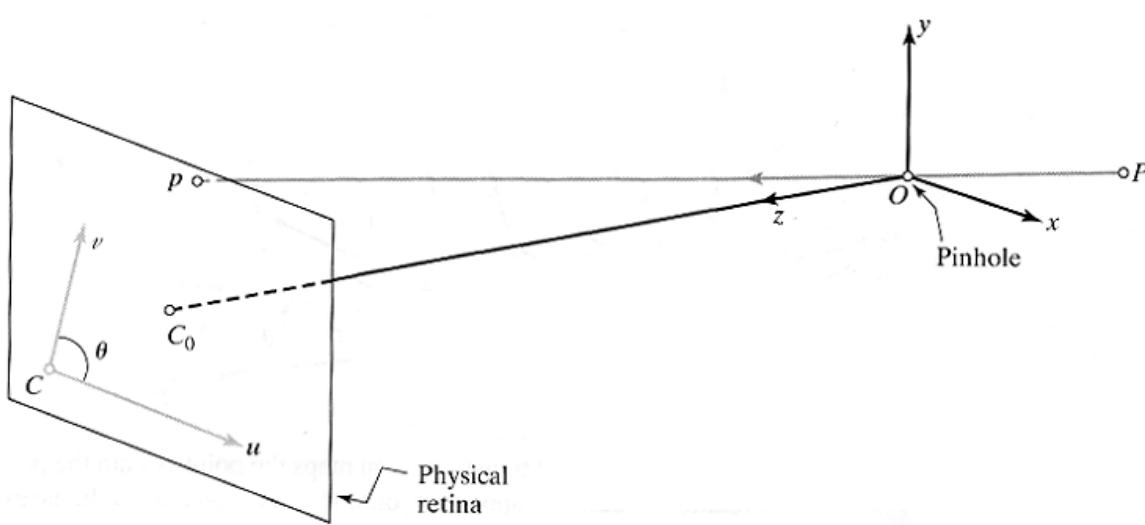
Origin of our camera pixel  
coordinates is offset



# Intrinsic parameters

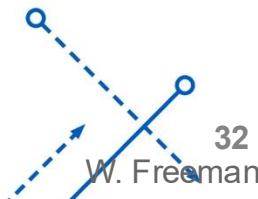
Relax the image plane is orthogonal to the camera axis:

May be skew between camera pixel axes



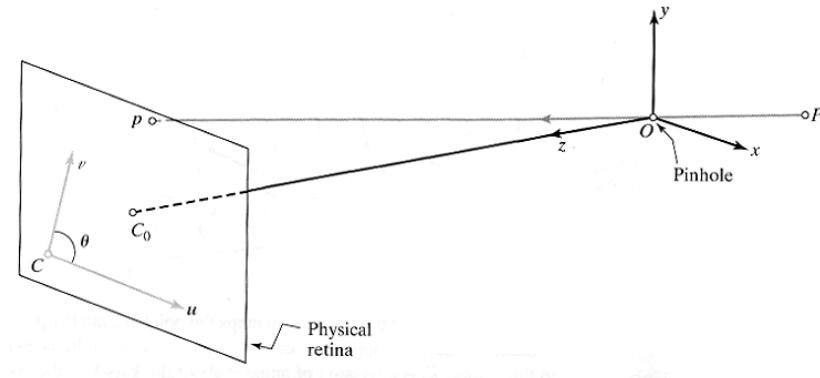
$$v' \sin(\theta) = v$$
$$u' = u - \cos(\theta)v' = u - \cot(\theta)v$$

$$u = \alpha \frac{x}{z} - \alpha \cot(\theta) \frac{y}{z} + u_0$$
$$v = \frac{\beta}{\sin(\theta)} \frac{y}{z} + v_0$$



# Intrinsic parameters: Matrix form

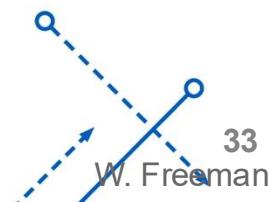
- Using homogenous coordinates



$$u = \alpha \frac{x}{z} - \alpha \cot(\theta) \frac{y}{z} + u_0$$

$$v = \frac{\beta}{\sin(\theta)} \frac{y}{z} + v_0$$

$$\begin{pmatrix} u \\ v \\ 1 \end{pmatrix} = \begin{pmatrix} \alpha & -\alpha \cot(\theta) & u_0 \\ 0 & \frac{\beta}{\sin(\theta)} & v_0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ z \\ 1 \end{pmatrix}$$



# Projection matrix

$$\mathbf{x} = \mathbf{K}[\mathbf{R} \quad \mathbf{t}] \mathbf{X}$$

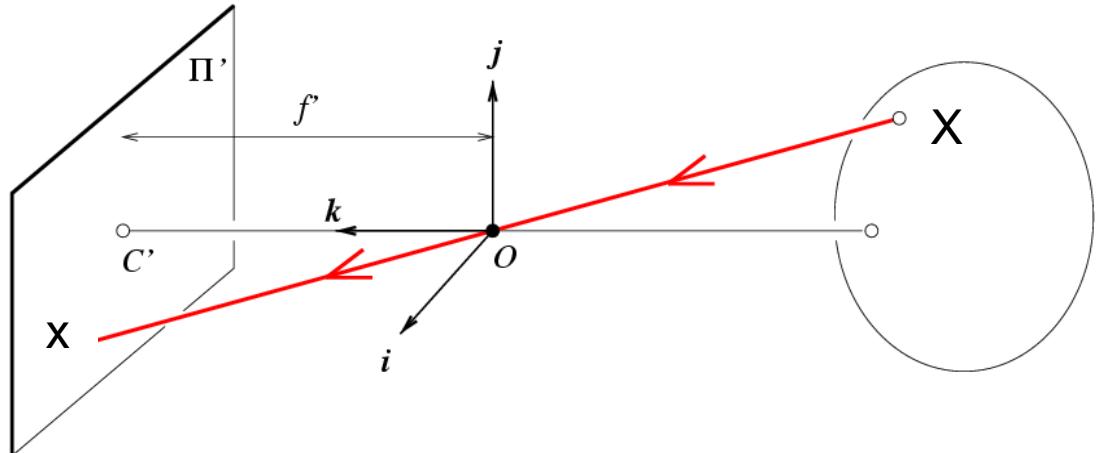
$\mathbf{x}$ : Image Coordinates:  $(u, v, 1)$   
 $\mathbf{K}$ : Intrinsic Matrix (3x3)  
 $\mathbf{R}$ : Rotation (3x3)  
 $\mathbf{t}$ : Translation (3x1)  
 $\mathbf{X}$ : World Coordinates:  $(X, Y, Z, 1)$

## Extrinsic Assumptions

- No rotation
- Camera at  $(0,0,0)$

## Intrinsic Assumptions

- Optical center at  $(0,0)$
- Unit aspect ratio
- No skew



$$\mathbf{x} = \mathbf{K}[\mathbf{I} \quad \mathbf{0}] \mathbf{X} \rightarrow w \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

Slide Credit: Savarese

# Remove assumption: known optical center

$$\mathbf{x} = \mathbf{K}[\mathbf{R} \quad \mathbf{t}] \mathbf{X}$$

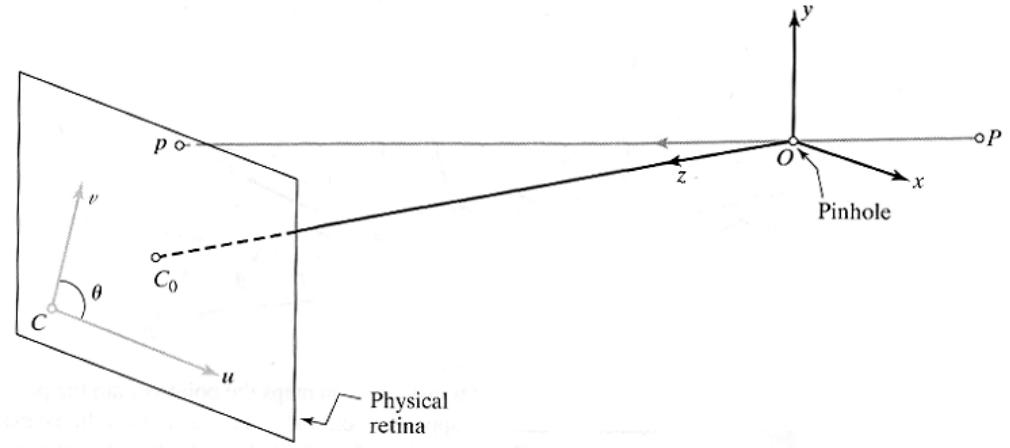
$\mathbf{x}$ : Image Coordinates:  $(u, v, 1)$   
 $\mathbf{K}$ : Intrinsic Matrix (3x3)  
 $\mathbf{R}$ : Rotation (3x3)  
 $\mathbf{t}$ : Translation (3x1)  
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## Extrinsic Assumptions

- No rotation
- Camera at  $(0,0,0)$

## Intrinsic Assumptions

- Optical center at  $(0,0)$
- Unit aspect ratio
- No skew



$$\mathbf{x} = \mathbf{K}[\mathbf{I} \quad \mathbf{0}] \mathbf{X}$$



$$w \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f & 0 & u_0 \\ 0 & f & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

# Remove assumption: square pixels

$$\mathbf{x} = \mathbf{K}[\mathbf{R} \quad \mathbf{t}] \mathbf{X}$$

x: Image Coordinates: (u,v,1)  
K: Intrinsic Matrix (3x3)  
R: Rotation (3x3)  
t: Translation (3x1)  
X: World Coordinates: (X,Y,Z,1)

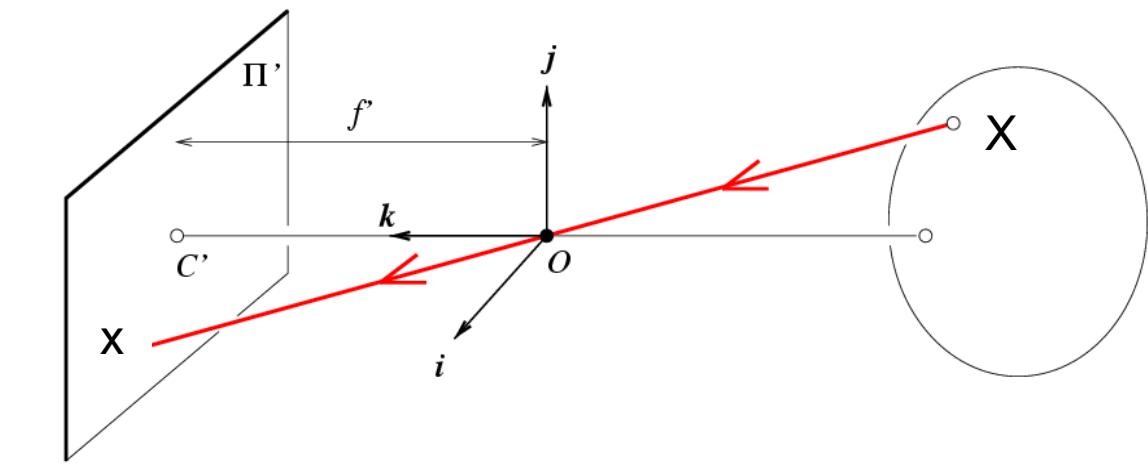
## Extrinsic Assumptions

- No rotation
- Camera at (0,0,0)

## Intrinsic Assumptions

- Optical center at (0,0)
- Unit aspect ratio
- No skew

$$\mathbf{x} = \mathbf{K}[\mathbf{I} \quad \mathbf{0}] \mathbf{X}$$



$$w \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \alpha & 0 & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

# Remove assumption: non-skewed pixels

$$\mathbf{x} = \mathbf{K}[\mathbf{R} \quad \mathbf{t}] \mathbf{X}$$

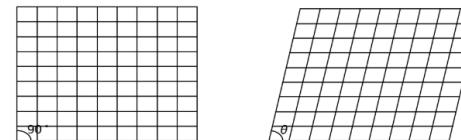
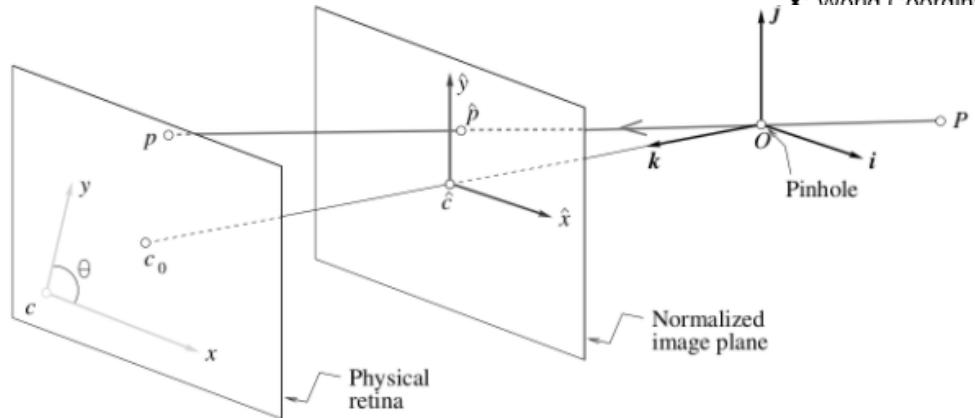
$\mathbf{x}$ : Image Coordinates:  $(u, v, 1)$   
 $\mathbf{K}$ : Intrinsic Matrix (3x3)  
 $\mathbf{R}$ : Rotation (3x3)  
 $\mathbf{t}$ : Translation (3x1)  
 $\mathbf{X}$ : World Coordinates:  $(X, Y, Z, 1)$

## Extrinsic Assumptions

- No rotation
- Camera at  $(0,0,0)$

## Intrinsic Assumptions

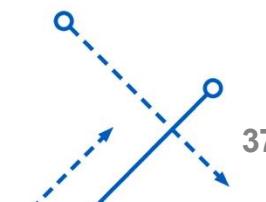
- Optical center at  $(0,0)$
- Unit aspect ratio
- No skew



$$\mathbf{x} = \mathbf{K}[\mathbf{I} \quad \mathbf{0}] \mathbf{X}$$



$$w \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \alpha & s & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$



Note: different books use different notation for parameters

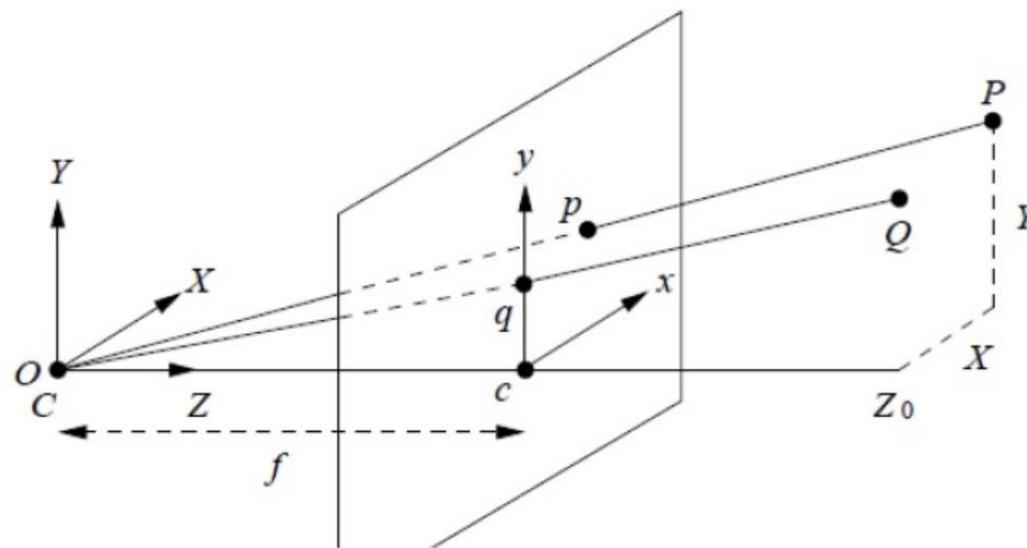


# IMAGE FORMATION I

## Other types of projection

# Weak Perspective Projection

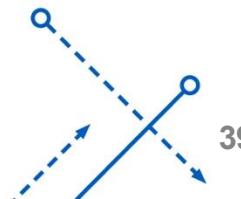
- When you zoom your camera very far, the depth changes in the scene are negligible when compared to the distance from camera



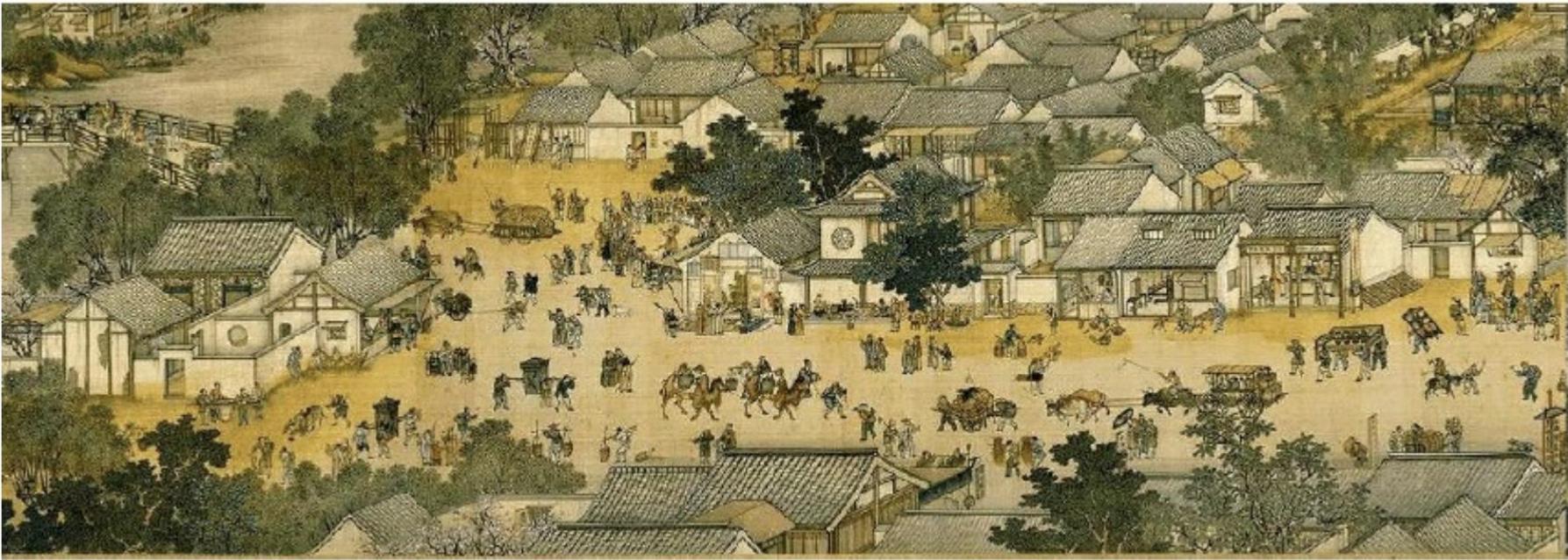
$$u = f \frac{x}{z}$$
$$v = f \frac{y}{z}$$

- Scene depth  $\ll$  distance to camera.
- $Z$  is the same for all scene points, say  $Z_0$

$$x = sX, \quad y = sY, \quad s = \frac{f}{Z_0} \text{ for all scene points.}$$

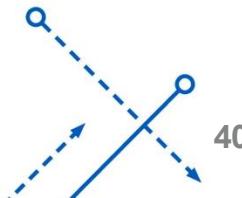


# Weak Perspective Projection - Example



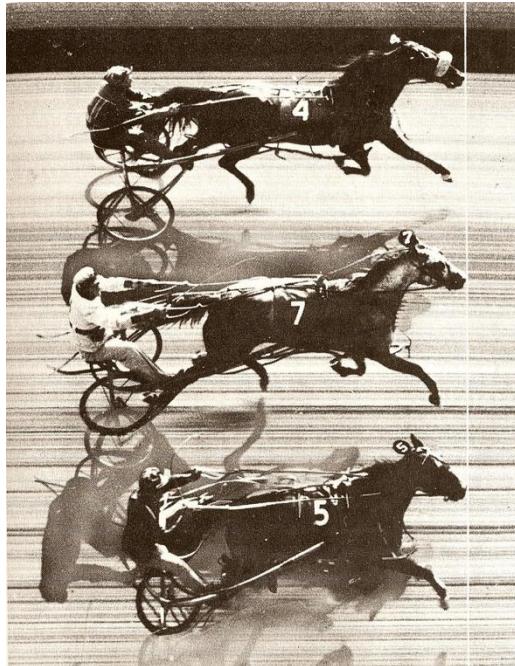
*Qingming Festival by the Riverside* Zhang Zeduan ~900 AD

As a comparison



# Photo Finish Photography (strip photography)

- A photo-finish image is made by a camera with an extremely thin, vertical slit.
- A photo-finish camera records an object moving past its exposure slit over time. 1D array



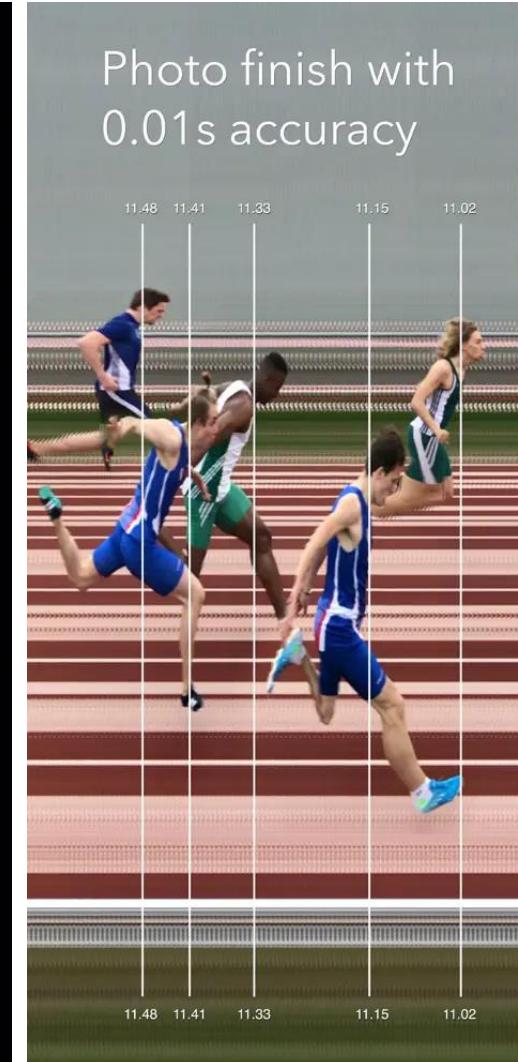
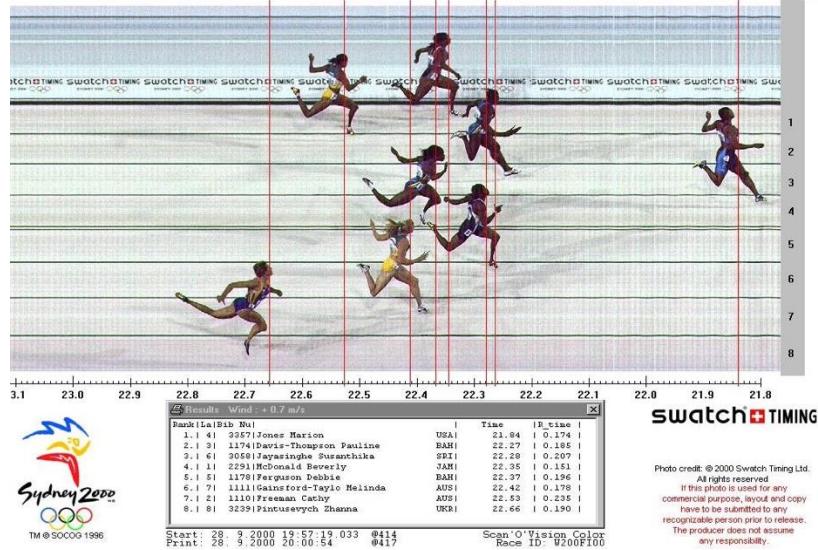
1960 Olympic tryouts at Palo Alto, CA

# Photo Finish Example



**SprintTimer - Photo Finish** 4+  
Professional Sports Timer  
Sten Kaiser  
2,490.00₺ · Offers In-App Purchases

The 2000 Sydney Olympic Games - 200m Women Final

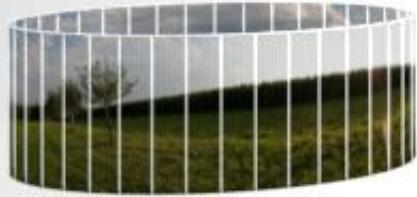


# 360 Imaging



# 360 Camera and Projection Mode

CYLINDRICAL



SKYDOME



FULL SPHERE



QTVR CUBE



# Tilt-shift Imaging

Note how the focus plane is along the train, and how the blurring of the background proceeds from left to right.



Often used to simulate a miniature scene

# Tilt-shift perspective correction



*Three photos of the 1858 Robert M. Bashford House Madison, Dane County, Wisconsin, placed on the National Register of Historic Places in 1973.*

*In the first photo, the camera has been leveled, but no shift lens was used. The top of the house isn't in the picture at all.*

*The second shows what results when the same camera without a shift lens is tilted to get the whole house. The house looks like it is falling over backwards.*

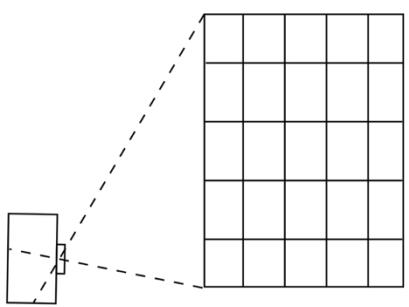
*The third view, from the same angle, but this time with a shift, or PC, lens gives the results wanted.*

# Tilt-shift Camera

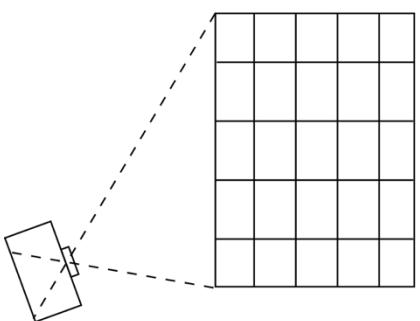


[http://en.wikipedia.org/wiki/Tilt-shift\\_photography](http://en.wikipedia.org/wiki/Tilt-shift_photography)

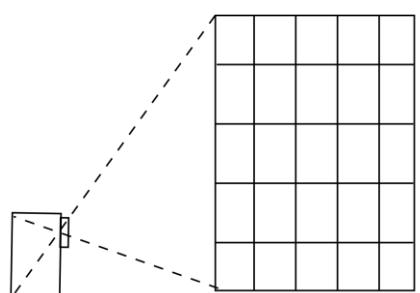
# Tilt-shift Correction



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



Tilting the camera upwards results in perspective distortion.



Shifting the lens upwards results in a picture of the entire subject without perspective distortion.

# Tilt-shift Software Correction

Normal Camera



Tilt-shift Camera

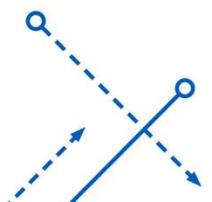
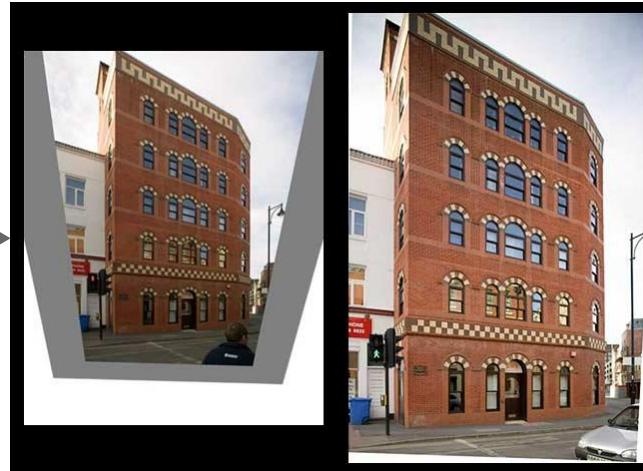
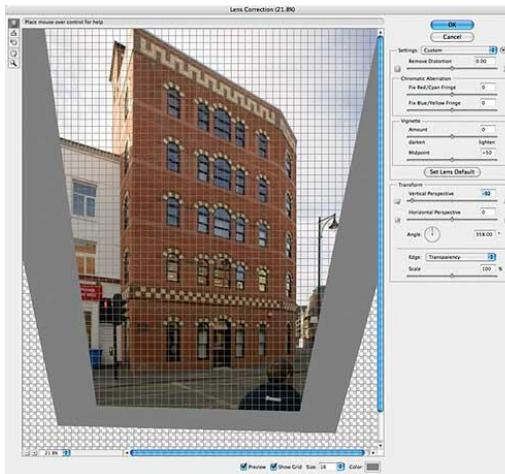


Image transformation is in the next lecture.



# IMAGE FORMATION

## Camera Calibration



# Camera Calibration (Simplest form)

- Intrinsic + Extrinsic combined

Camera to Pixel

$$\begin{bmatrix} \tilde{u} \\ \tilde{v} \\ \tilde{w} \end{bmatrix} = \begin{bmatrix} f_x & 0 & o_x & 0 \\ 0 & f_y & o_y & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x_c \\ y_c \\ z_c \\ 1 \end{bmatrix}$$

World to Camera

$$\begin{bmatrix} x_c \\ y_c \\ z_c \\ 1 \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix}$$

$$\tilde{\mathbf{u}} = M_{int} \tilde{\mathbf{x}}_c$$

$$\tilde{\mathbf{x}}_c = M_{ext} \tilde{\mathbf{x}}_w$$

Combining the above two equations, we get the full projection matrix  $P$ :

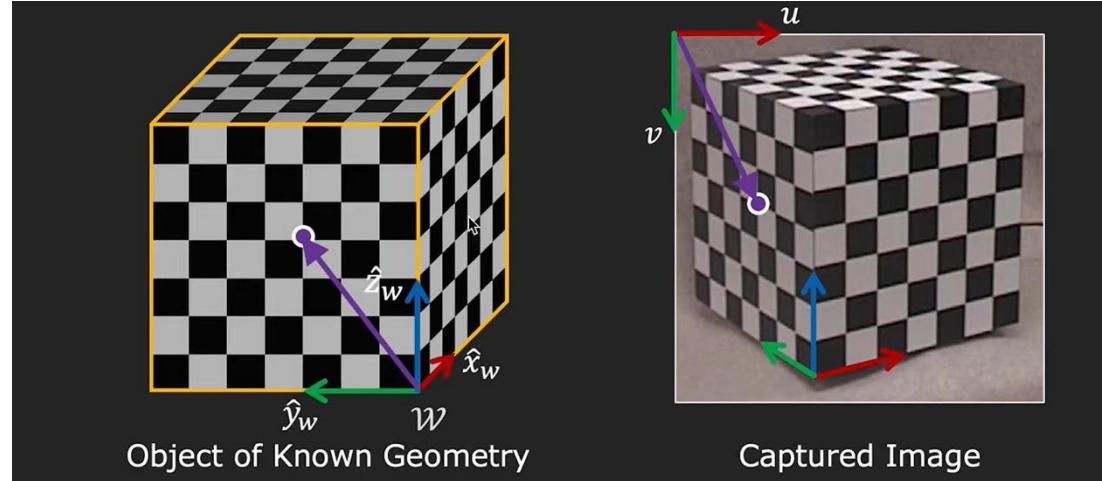
$$\tilde{\mathbf{u}} = M_{int} M_{ext} \tilde{\mathbf{x}}_w = P \tilde{\mathbf{x}}_w$$

$$\begin{bmatrix} \tilde{u} \\ \tilde{v} \\ \tilde{w} \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \end{bmatrix} \begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix}$$

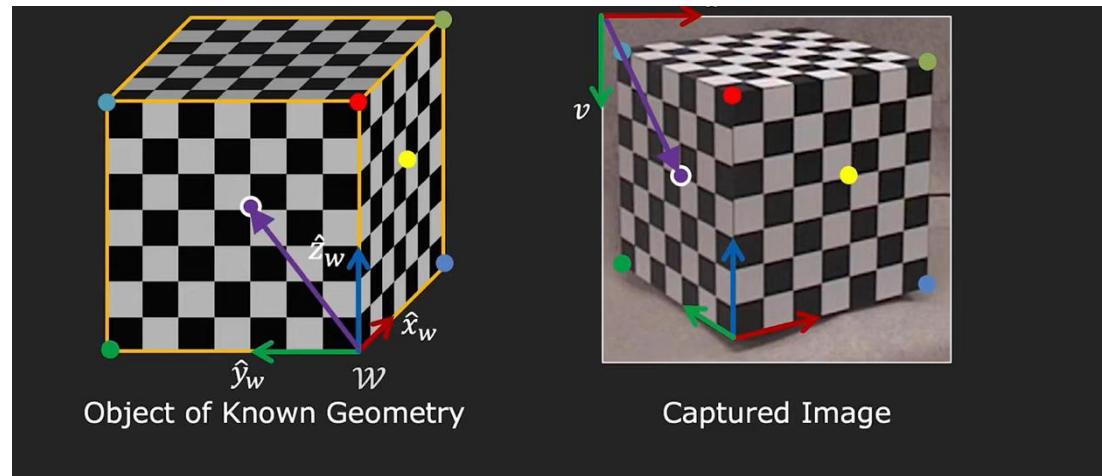
# Point Correspondence

- Get correspondence of world points and image points

$$\bullet \mathbf{u} = \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 56 \\ 115 \end{bmatrix} \text{ (pixels)}$$



$$\bullet \mathbf{x}_w = \begin{bmatrix} x_w \\ y_w \\ z_w \end{bmatrix} = \begin{bmatrix} 0 \\ 3 \\ 4 \end{bmatrix} \text{ (inches)}$$



# Expanding Projection Matrix

$$\mathbf{w} \begin{bmatrix} u^{(i)} \\ v^{(i)} \\ 1 \end{bmatrix} \equiv \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \end{bmatrix} \begin{bmatrix} x_w^{(i)} \\ y_w^{(i)} \\ z_w^{(i)} \\ 1 \end{bmatrix}$$

Known                          Unknown                          Known

Expanding the matrix as linear equations:

$$u^{(i)} = \frac{p_{11}x_w^{(i)} + p_{12}y_w^{(i)} + p_{13}z_w^{(i)} + p_{14}}{p_{31}x_w^{(i)} + p_{32}y_w^{(i)} + p_{33}z_w^{(i)} + p_{34}}$$

$$v^{(i)} = \frac{p_{21}x_w^{(i)} + p_{22}y_w^{(i)} + p_{23}z_w^{(i)} + p_{24}}{p_{31}x_w^{(i)} + p_{32}y_w^{(i)} + p_{33}z_w^{(i)} + p_{34}}$$

# Expanded Projection matrix

$$\begin{bmatrix}
 x_w^{(1)} & y_w^{(1)} & z_w^{(1)} & 1 & 0 & 0 & 0 & 0 & -u_1 x_w^{(1)} & -u_1 y_w^{(1)} & -u_1 z_w^{(1)} & -u_1 \\
 0 & 0 & 0 & 0 & x_w^{(1)} & y_w^{(1)} & z_w^{(1)} & 1 & -v_1 x_w^{(1)} & -v_1 y_w^{(1)} & -v_1 z_w^{(1)} & -v_1 \\
 \vdots & \vdots \\
 x_w^{(i)} & y_w^{(i)} & z_w^{(i)} & 1 & 0 & 0 & 0 & 0 & -u_i x_w^{(i)} & -u_i y_w^{(i)} & -u_i z_w^{(i)} & -u_i \\
 0 & 0 & 0 & 0 & x_w^{(i)} & y_w^{(i)} & z_w^{(i)} & 1 & -v_i x_w^{(i)} & -v_i y_w^{(i)} & -v_i z_w^{(i)} & -v_i \\
 \vdots & \vdots \\
 x_w^{(n)} & y_w^{(n)} & z_w^{(n)} & 1 & 0 & 0 & 0 & 0 & -u_n x_w^{(n)} & -u_n y_w^{(n)} & -u_n z_w^{(n)} & -u_n \\
 0 & 0 & 0 & 0 & x_w^{(n)} & y_w^{(n)} & z_w^{(n)} & 1 & -v_n x_w^{(n)} & -v_n y_w^{(n)} & -v_n z_w^{(n)} & -v_n
 \end{bmatrix} = \begin{bmatrix} p_{11} \\ p_{12} \\ p_{13} \\ p_{14} \\ p_{21} \\ p_{22} \\ p_{23} \\ p_{24} \\ p_{31} \\ p_{32} \\ p_{33} \\ p_{34} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

# Solution space is scale-invariant

$$\boxed{\begin{bmatrix} x_w^{(1)} & y_w^{(1)} & z_w^{(1)} & 1 & 0 & 0 & 0 & 0 & -u_1 x_w^{(1)} & -u_1 y_w^{(1)} & -u_1 z_w^{(1)} & -u_1 \\ 0 & 0 & 0 & 0 & x_w^{(1)} & y_w^{(1)} & z_w^{(1)} & 1 & -v_1 x_w^{(1)} & -v_1 y_w^{(1)} & -v_1 z_w^{(1)} & -v_1 \\ \vdots & \vdots \\ x_w^{(i)} & y_w^{(i)} & z_w^{(i)} & 1 & 0 & 0 & 0 & 0 & -u_i x_w^{(i)} & -u_i y_w^{(i)} & -u_i z_w^{(i)} & -u_i \\ 0 & 0 & 0 & 0 & x_w^{(i)} & y_w^{(i)} & z_w^{(i)} & 1 & -v_i x_w^{(i)} & -v_i y_w^{(i)} & -v_i z_w^{(i)} & -v_i \\ \vdots & \vdots \\ x_w^{(n)} & y_w^{(n)} & z_w^{(n)} & 1 & 0 & 0 & 0 & 0 & -u_n x_w^{(n)} & -u_n y_w^{(n)} & -u_n z_w^{(n)} & -u_n \\ 0 & 0 & 0 & 0 & x_w^{(n)} & y_w^{(n)} & z_w^{(n)} & 1 & -v_n x_w^{(n)} & -v_n y_w^{(n)} & -v_n z_w^{(n)} & -v_n \end{bmatrix}} = \begin{bmatrix} p_{11} \\ p_{12} \\ p_{13} \\ p_{14} \\ p_{21} \\ p_{22} \\ p_{23} \\ p_{24} \\ p_{31} \\ p_{32} \\ p_{33} \\ p_{34} \end{bmatrix}$$

A

Known

p

Unknown

Solve for p

$$A \mathbf{p} = \mathbf{0}$$

# Objective/Loss Function

We want  $Ap$  as close to 0 as possible and  $\|\mathbf{p}\|^2 = 1$ :

$$\min_{\mathbf{p}} \|A\mathbf{p}\|^2 \text{ such that } \|\mathbf{p}\|^2 = 1$$

$$\min_{\mathbf{p}} (\mathbf{p}^T A^T A \mathbf{p}) \text{ such that } \mathbf{p}^T \mathbf{p} = 1$$

Loss function  $L(\mathbf{p}, \lambda)$ :

$$L(\mathbf{p}, \lambda) = \mathbf{p}^T A^T A \mathbf{p} - \lambda(\mathbf{p}^T \mathbf{p} - 1)$$

# Solve Objective Function

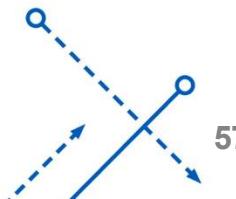
Taking derivatives of  $L(\mathbf{p}, \lambda)$  w.r.t  $\mathbf{p}$ :  $2A^T A \mathbf{p} - 2\lambda \mathbf{p} = \mathbf{0}$

$$A^T A \mathbf{p} = \lambda \mathbf{p}$$

Eigenvalue Problem

Eigenvector  $\mathbf{p}$  with **smallest eigenvalue**  $\lambda$  of matrix  $A^T A$  minimizes the loss function  $L(\mathbf{p})$ .

- An explanation



# Estimation K, R

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \end{bmatrix} = \begin{bmatrix} f_x & 0 & o_x & 0 \\ 0 & f_y & o_y & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$M_{int}$      $\nwarrow$      $M_{ext}$

$$\begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix} = \begin{bmatrix} f_x & 0 & o_x \\ 0 & f_y & o_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix} = KR$$

Given that  $K$  is an **Upper Right Triangular** matrix and  $R$  is an **Orthonormal** matrix, it is possible to uniquely “decouple”  $K$  and  $R$  from their product using “**QR factorization**”.

# Estimating Translation

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \end{bmatrix} = \begin{bmatrix} f_x & 0 & o_x & 0 \\ 0 & f_y & o_y & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

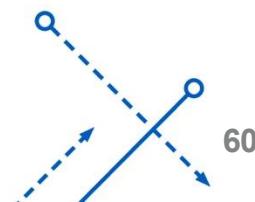
$M_{int}$      $\rightarrow$      $M_{ext}$

That is:

$$\begin{bmatrix} p_{14} \\ p_{24} \\ p_{34} \end{bmatrix} = \begin{bmatrix} f_x & 0 & o_x \\ 0 & f_y & o_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix} = K\mathbf{t}$$

Therefore:

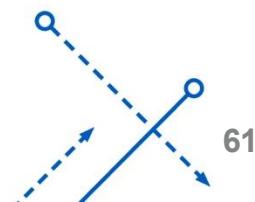
$$\mathbf{t} = K^{-1} \begin{bmatrix} p_{14} \\ p_{24} \\ p_{34} \end{bmatrix}$$



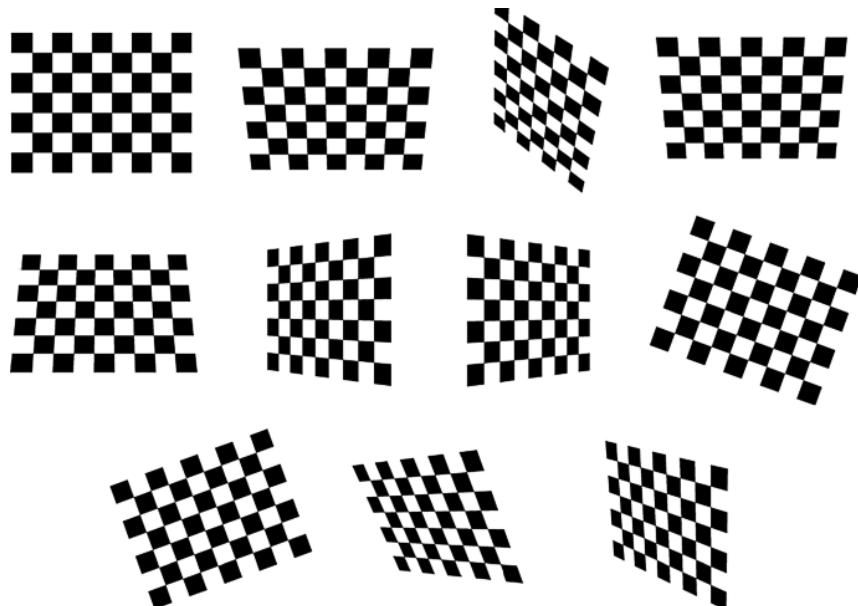
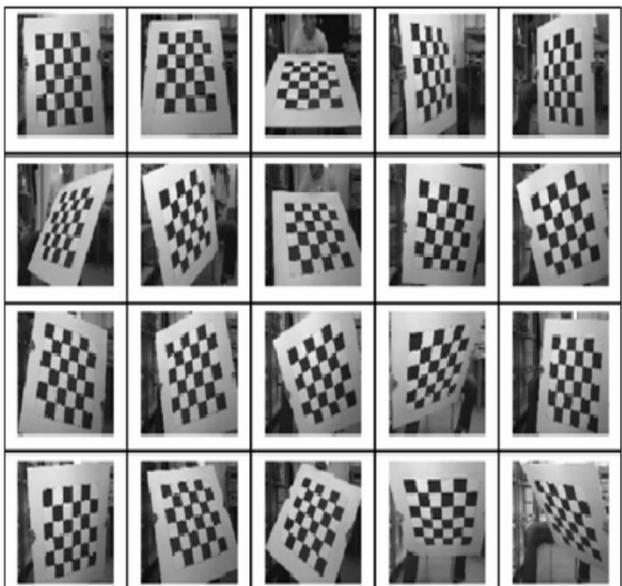
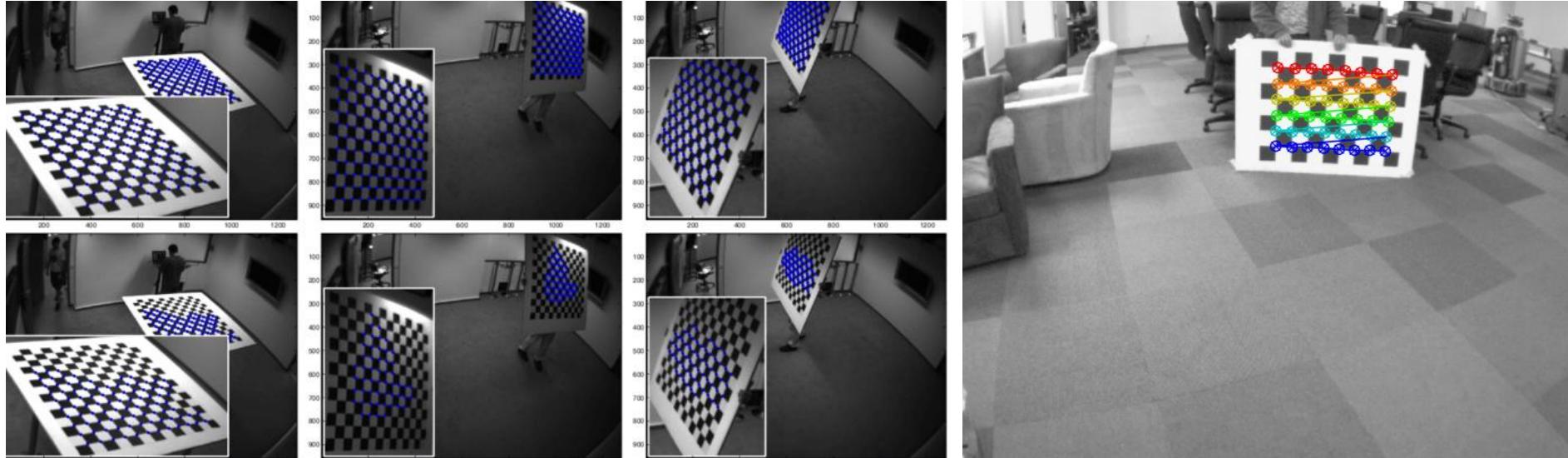
# Steps of Camera Calibration

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- From a set of corresponding points build A
- Compute the eigenvector  $\mathbf{p}$  of  $\mathbf{A}^T \mathbf{A}$  for the smallest eigenvalue.
- Rearrange  $\mathbf{p}$  as  $\mathbf{P}$  as a  $3 \times 4$  matrix
- Take the  $3 \times 3$  matrix and compute the QR decomposition
  - Q is K (Calibration matrix)
  - R is rotation matrix
- Compute  $\mathbf{T} = \mathbf{K}^{-1} \mathbf{P}_{i4}$



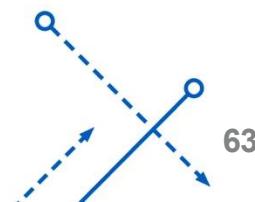
# Cover more poses



# Why rotation matrix is orthogonal

---

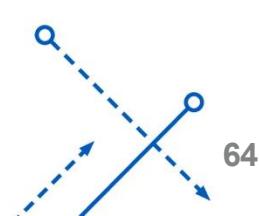
- Assume a point  $x$ , a rotation matrix  $R$ ;
- A rotated point  $Rx$  has the same length with  $x$ ;
  - So  $\|Rx\|^2 = \|x\|^2$
  - $(Rx)^T(Rx) = x^T R^T Rx = x^T (R^T R)x = x^T Ix$
  - So  $R^T R = I$
- A rotated point  $Rx$  can be rotated back to the original point  $x$  with the “reversed rotation”  $R^{-1}$ .
  - So,  $R^{-1}(Rx) = x$ , then  $R^{-1} = R^T$ .



# How many degrees of freedom?

---

- Extrinsic Parameters
  - $6 = 3 \text{ translation} + 3 \text{ rotation}$
- Intrinsic Parameters
  - $5 = 2 \text{ focal length}, 2 \text{ image center}, 1 \text{ skew}$
  - $= 6 \text{ (3D transform)} - 1 \text{ depth losing}$
- Camera Calibration
  - $11 = 6 \text{ Extrinsic} + 5 \text{ Intrinsic}$
  - $= 12 \text{ (3x4 Projection matrix)} - 1 \text{ scale factor}$



# Project 1: Camera Calibration

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- The only **algorithm libraries** that are allowed to use.
  - PyTorch: Tensor operations.
    - Ready for modern deep learning frameworks
    - Solution can be a little different from slides.
  - Find the project access link in Piazza.

