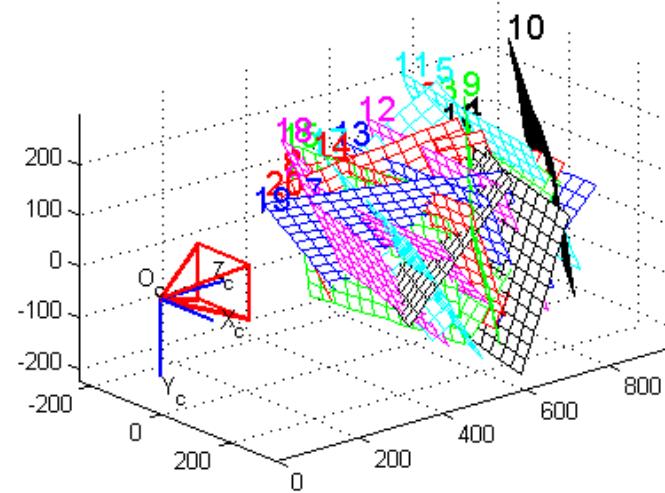
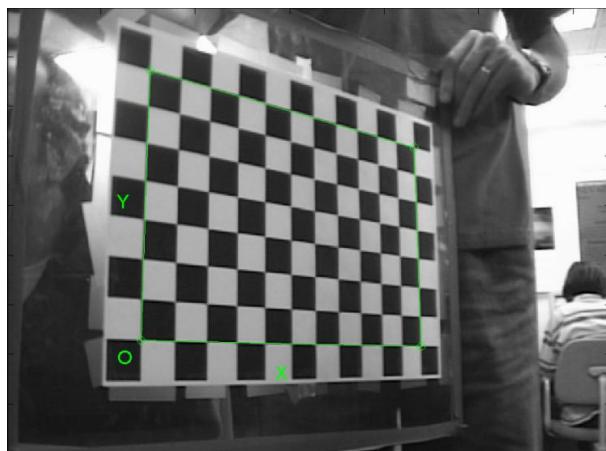


Camera Calibration

Kuan-Wen Chen
2022/3/17



Camera Types & Camera Models

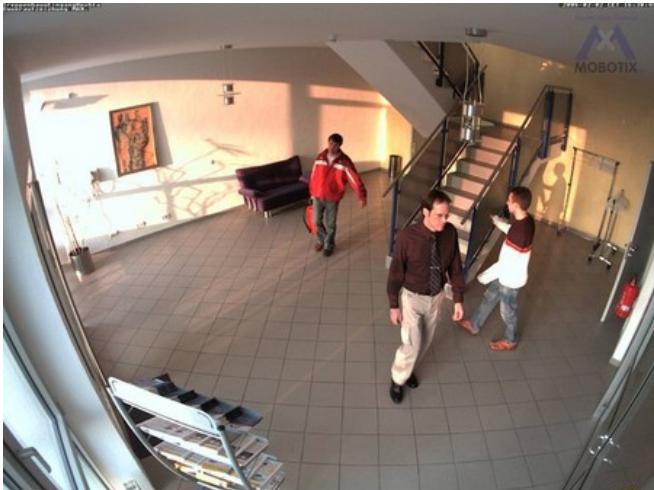
Camera Types

- Static/Fixed Camera



Camera Types

- Wide angle and Fish-eye camera



Camera Types

- Omni-directional camera



Camera Types

- Pan-Tilt-Zoom (PTZ) camera
- Speed-Dome Camera

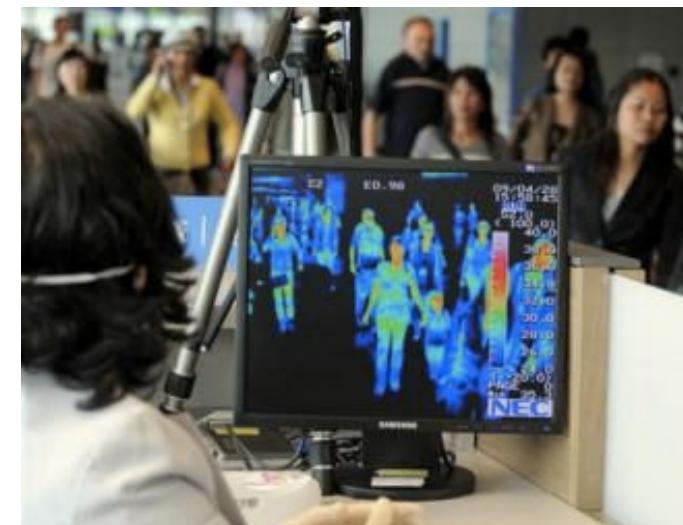
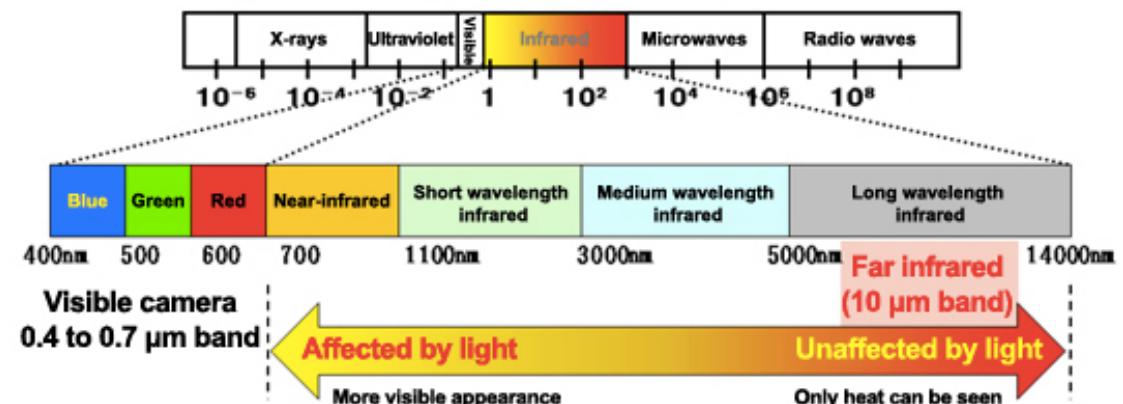


Camera Types

- Infrared (IR) Camera

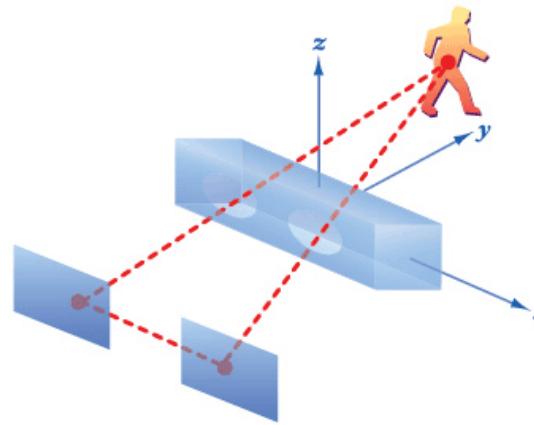


Generally, light known as infrared rays indicates electromagnetic waves on the optical wavelength with a longer wavelength of between $0.7 \mu\text{m}$ and 1 mm .



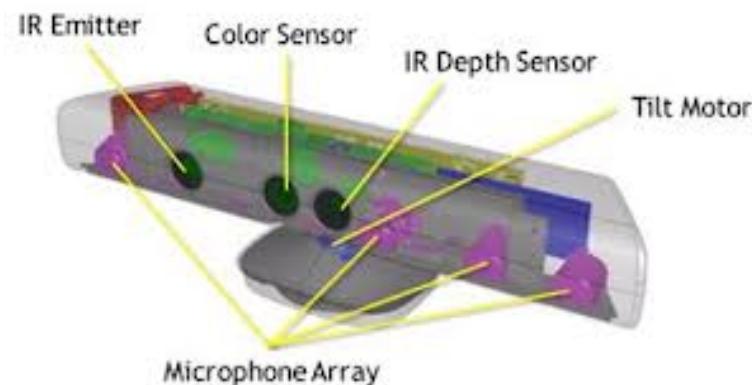
Camera Types

- Stereo camera



Camera Types

- Infrared-based depth camera



Motivation

- Getting more 3D information from images



Motivation

- Getting more 3D information from images

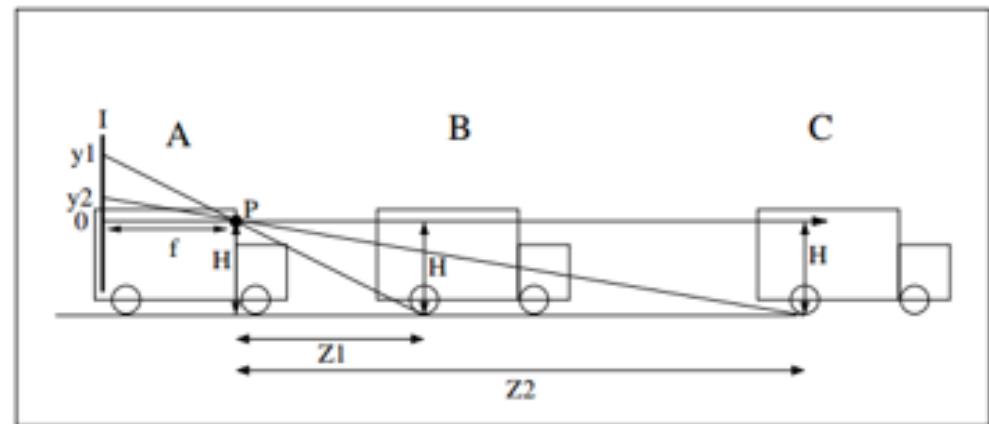
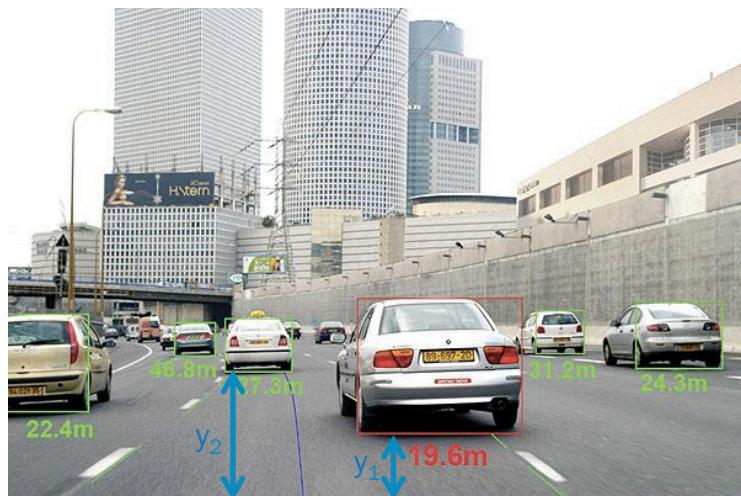
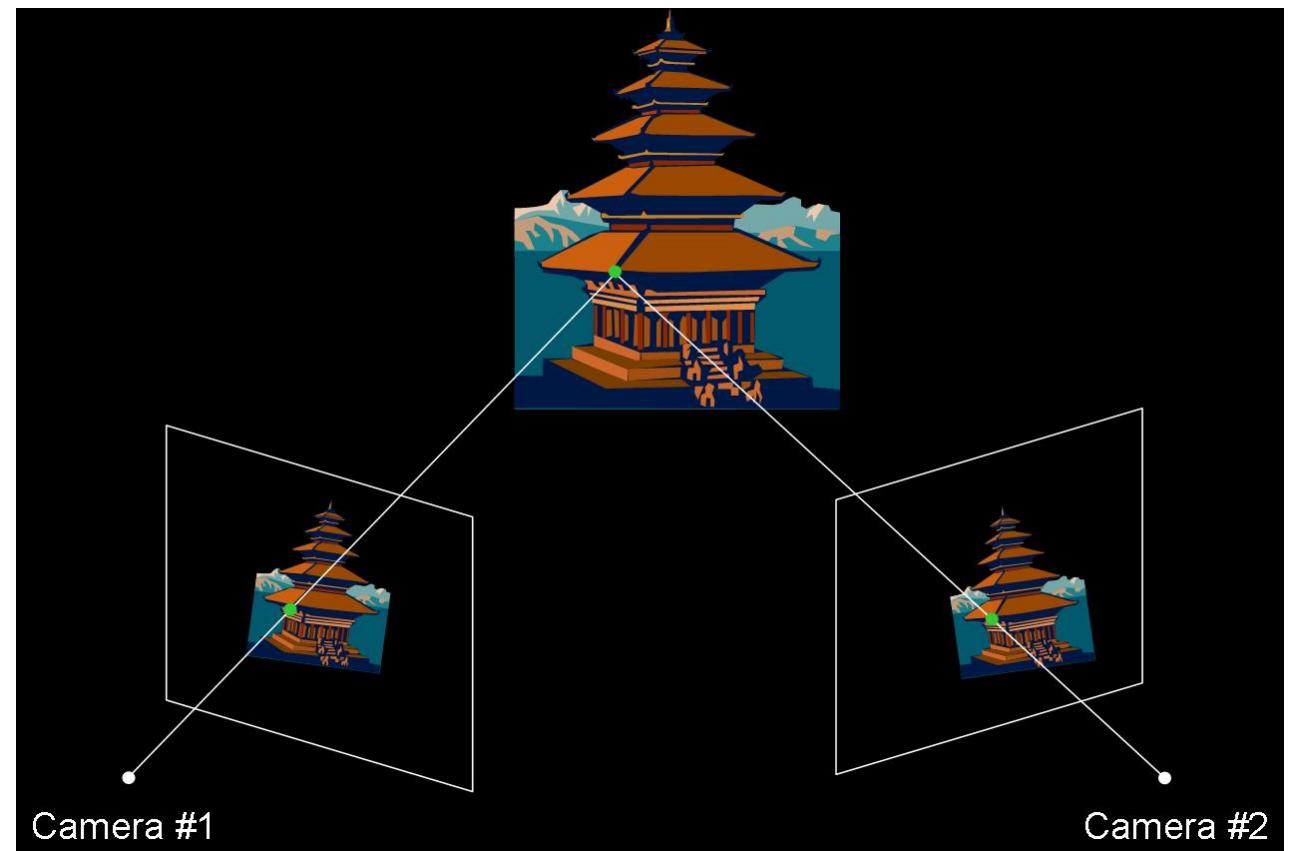
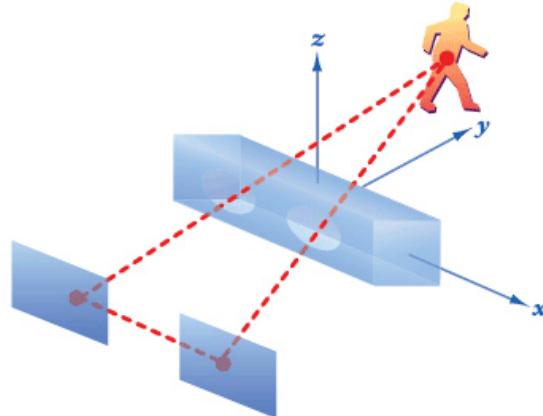


Figure 2: Schematic diagram of the imaging geometry (see text).

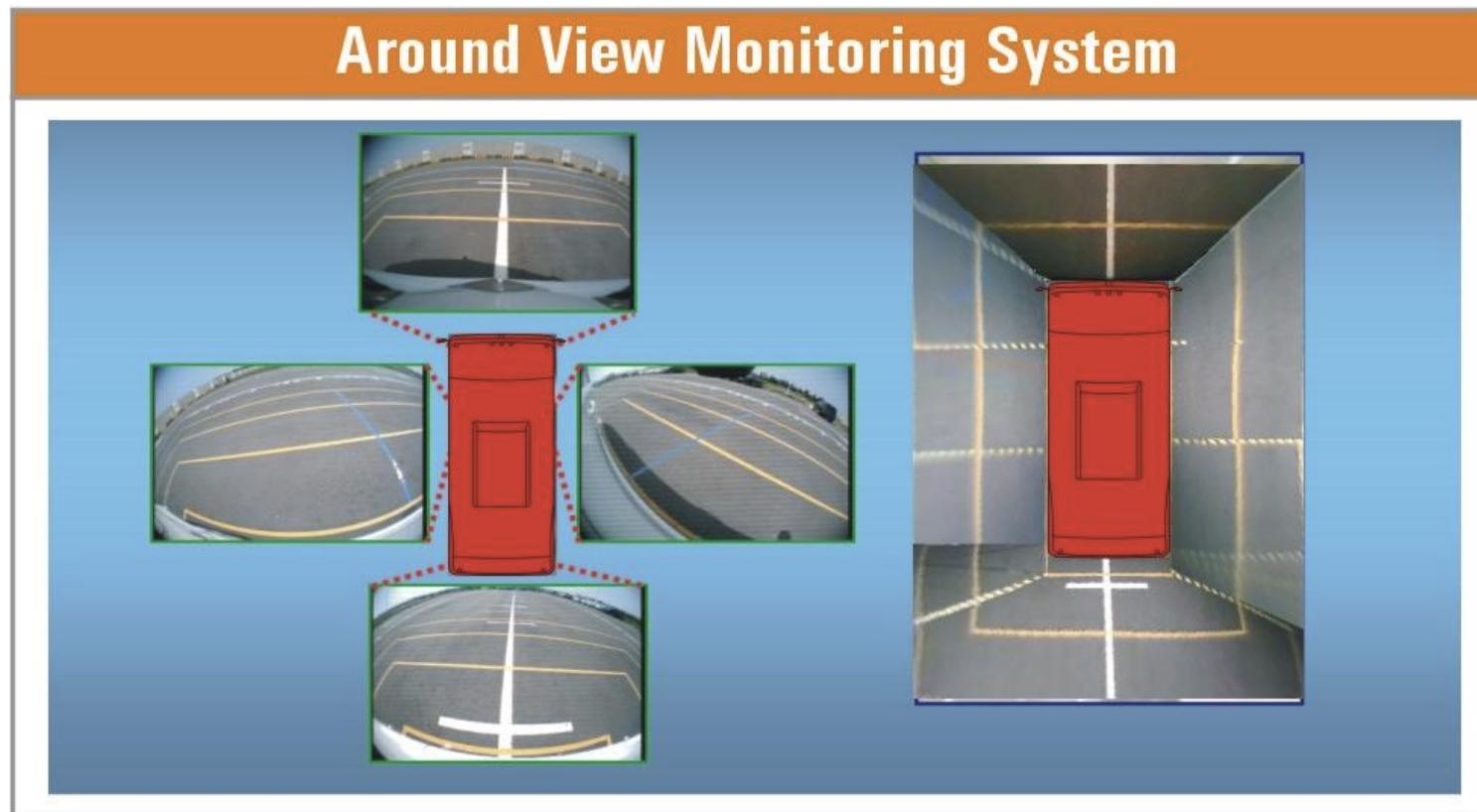
Motivation

- Getting more 3D information from images



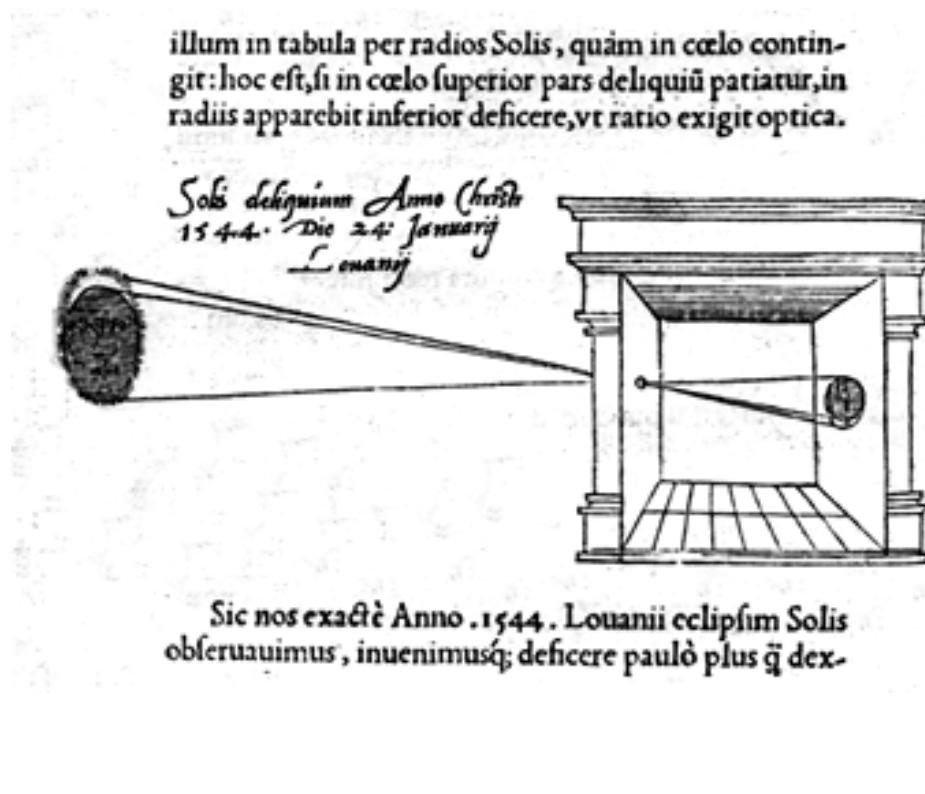
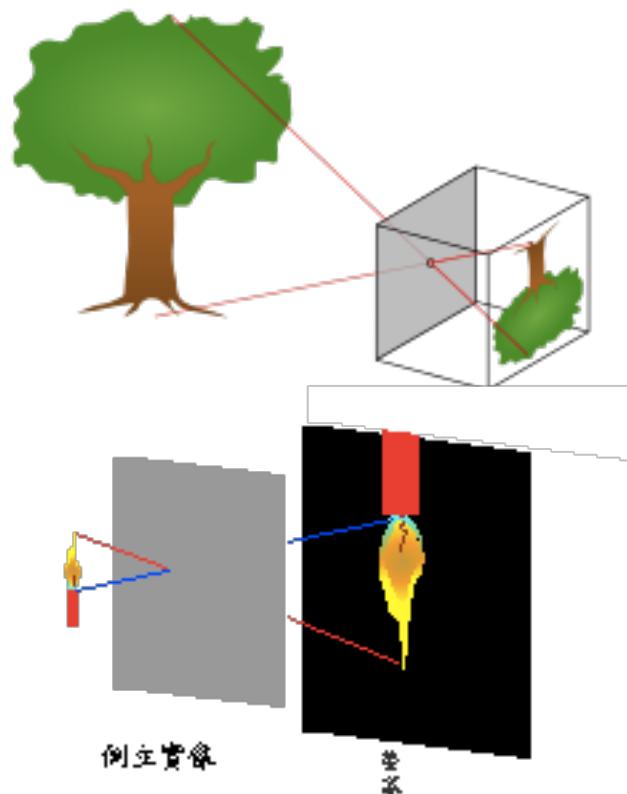
Motivation

- Integrate multiple views



Camera Projection Model

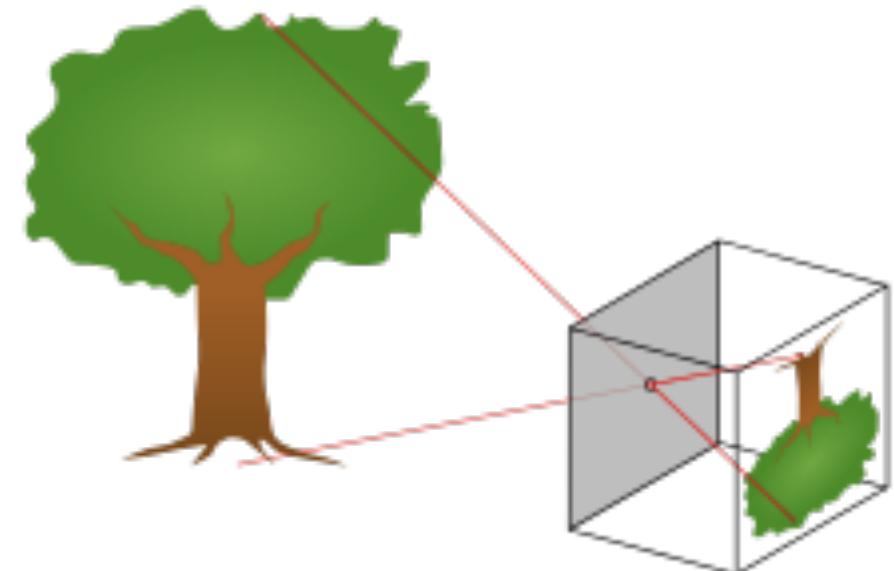
- **Pinhole camera** - also known as camera obscura, or "dark chamber", is a simple camera **without a lens** and **with a single small aperture**, a pinhole – effectively a light-proof box with a small hole in one side.



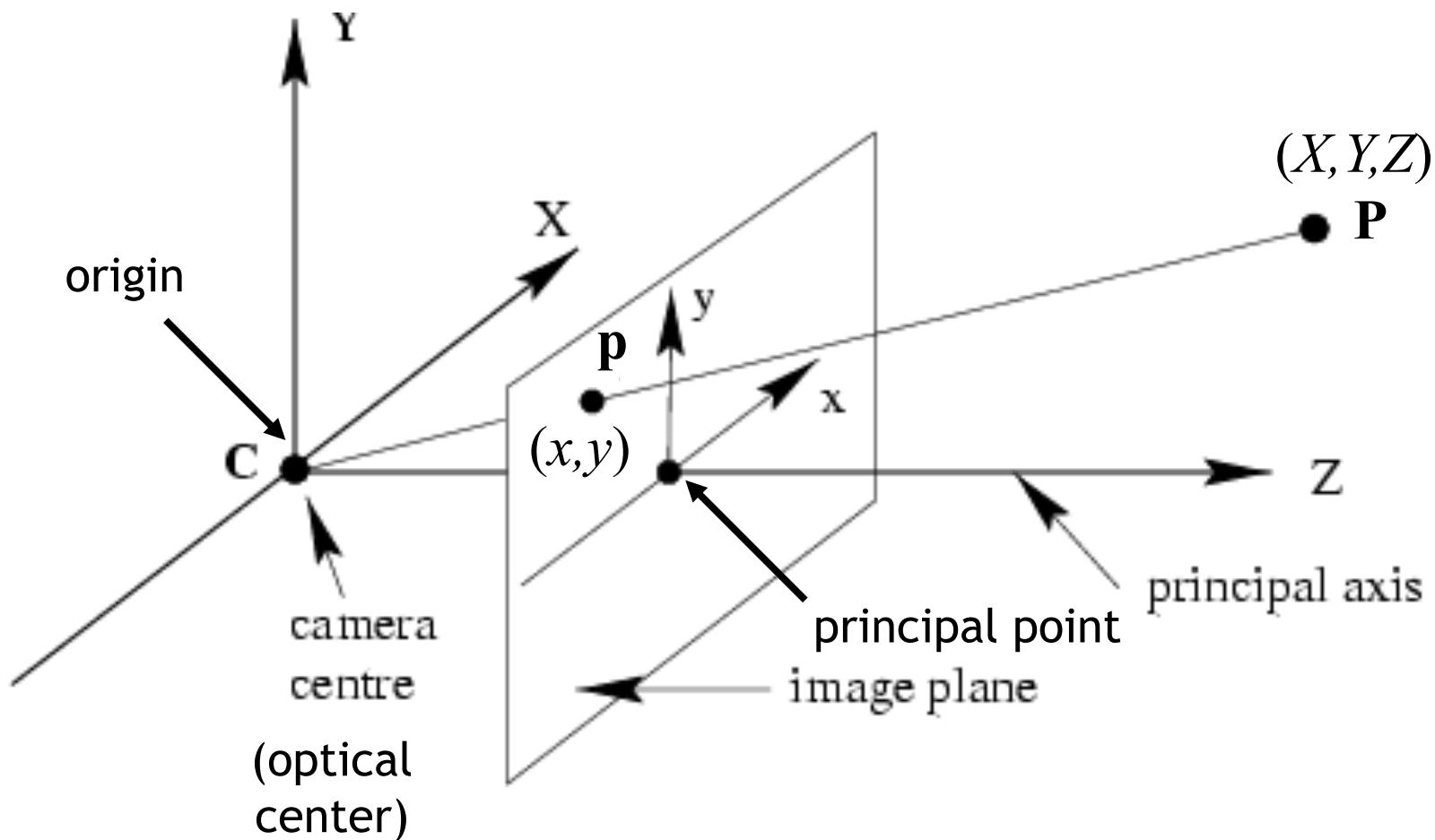
Camera Projection Model

- **Pinhole camera model** - describes the mathematical relationship between the coordinates of a 3D point and its projection onto the image plane of an ideal pinhole camera, where the camera aperture is described as a point and no lenses are used to focus light.

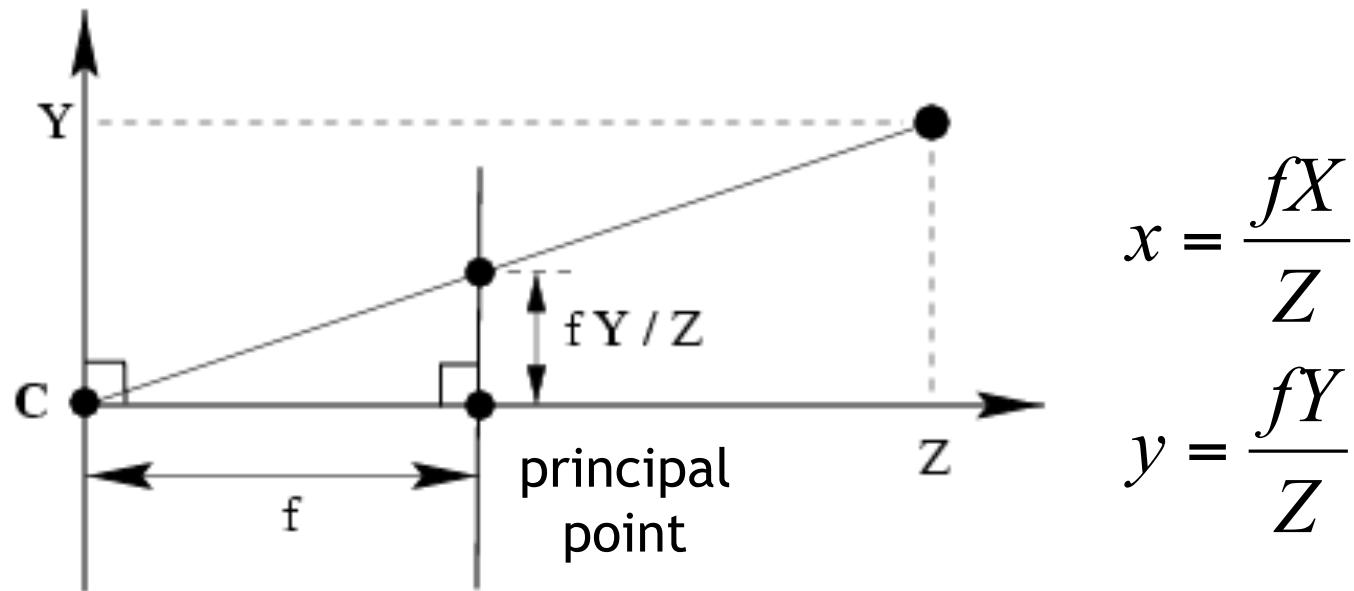
The model does not include geometric distortions or blurring of unfocused objects caused by lenses and finite sized apertures.



Pinhole Camera Model

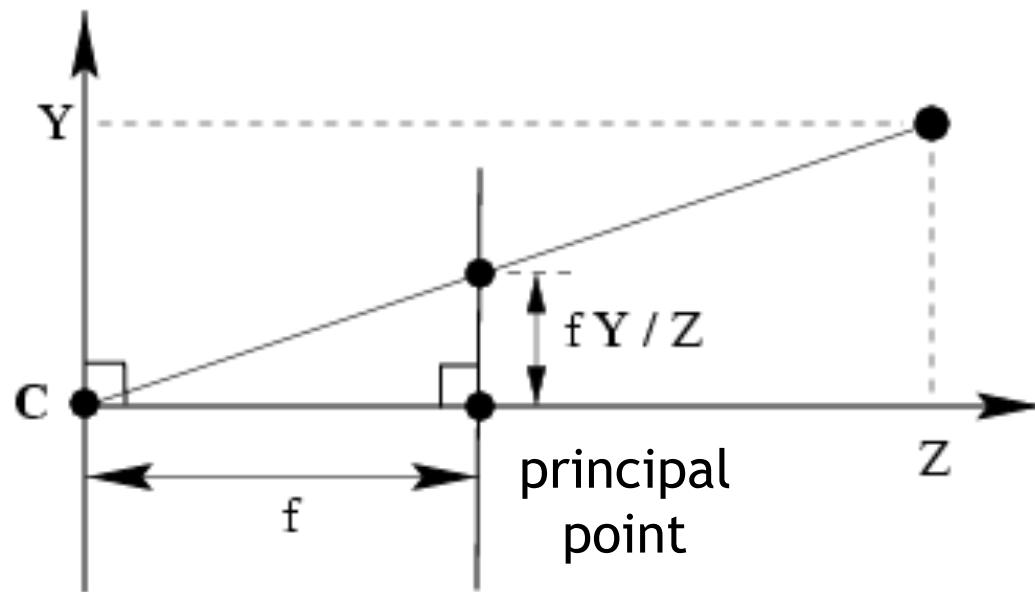


Pinhole Camera Model



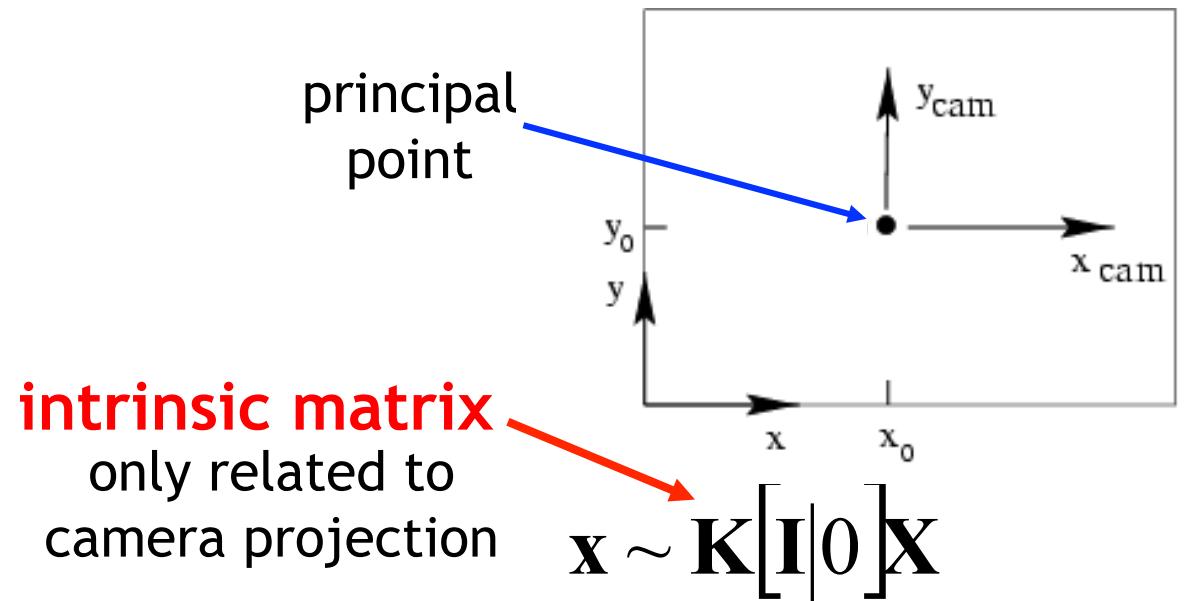
$$\begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \sim \begin{pmatrix} fX \\ fY \\ Z \end{pmatrix} = \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

Pinhole Camera Model



$$\begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \sim \begin{pmatrix} fX \\ fY \\ Z \end{pmatrix} = \begin{bmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

Principal point offset



$$\begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \sim \begin{pmatrix} fX \\ fY \\ Z \end{pmatrix} = \begin{bmatrix} f & 0 & x_0 \\ 0 & f & y_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

Intrinsic Matrix

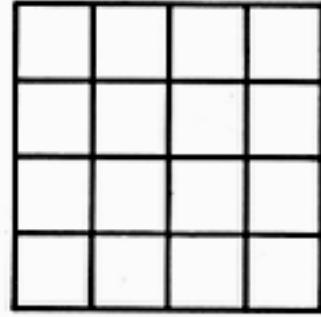
Is this form of \mathbf{K} good enough?

$$\mathbf{K} = \begin{bmatrix} f & 0 & x_0 \\ 0 & f & y_0 \\ 0 & 0 & 1 \end{bmatrix}$$

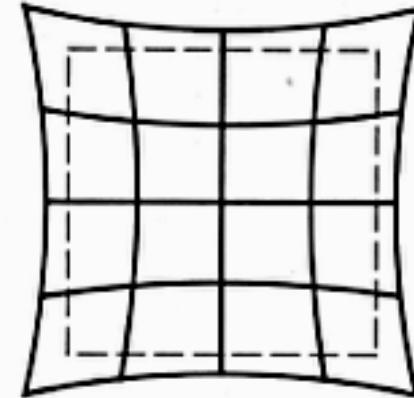
- non-square pixels (digital video)
- skew
- radial distortion

$$\mathbf{K} = \begin{bmatrix} fa & s & x_0 \\ 0 & f & y_0 \\ 0 & 0 & 1 \end{bmatrix}$$

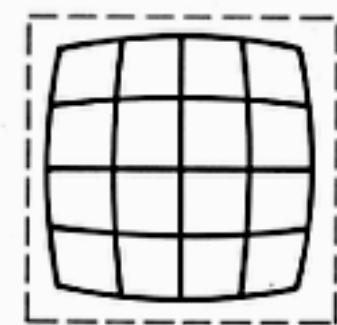
Distortion



No distortion



Pin cushion



Barrel

- Radial distortion of the image
 - Caused by imperfect lenses
 - Deviations are most noticeable for rays that pass through the edge of the lens

Distortion

$$x'' = x'^*(1 + k_1r^2 + k_2r^4) + 2*p_1x'^*y' + p_2(r^2+2*x'^2)$$
$$y'' = y'^*(1 + k_1r^2 + k_2r^4) + p_1(r^2+2*y'^2) + 2*p_2*x'^*y'$$

where $r^2 = x'^2+y'^2$

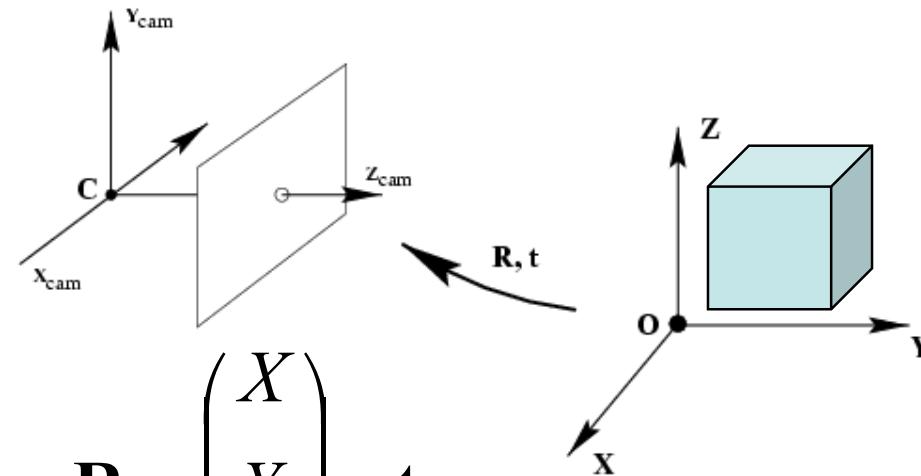


dewarp

→



Camera rotation and translation



$$\begin{pmatrix} X' \\ Y' \\ Z' \end{pmatrix} = \mathbf{R}_{3 \times 3} \begin{pmatrix} X \\ Y \\ Z \end{pmatrix} + \mathbf{t}$$

$$\begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \sim \begin{bmatrix} f & 0 & x_0 \\ 0 & f & y_0 \\ 0 & 0 & 1 \end{bmatrix} [\mathbf{R} | \mathbf{t}] \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

$\mathbf{x} \sim \mathbf{K}[\mathbf{R} | \mathbf{t}] \mathbf{X}$

extrinsic matrix

Two kinds of parameters

- internal or intrinsic parameters such as focal length, optical center, aspect ratio:
 - what kind of camera?
- external or extrinsic (pose) parameters including rotation and translation:
 - where is the camera?

Intrinsic parameters

$$x \sim K[R|t]x$$

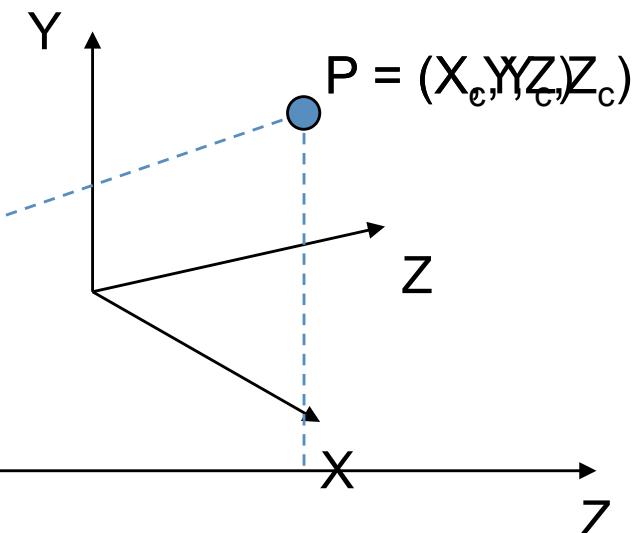
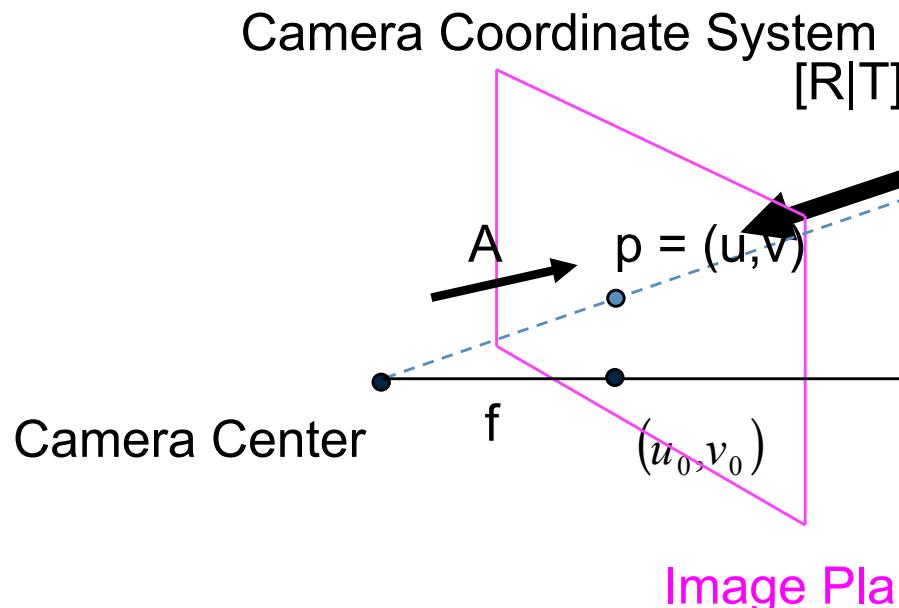


Extrinsic parameters

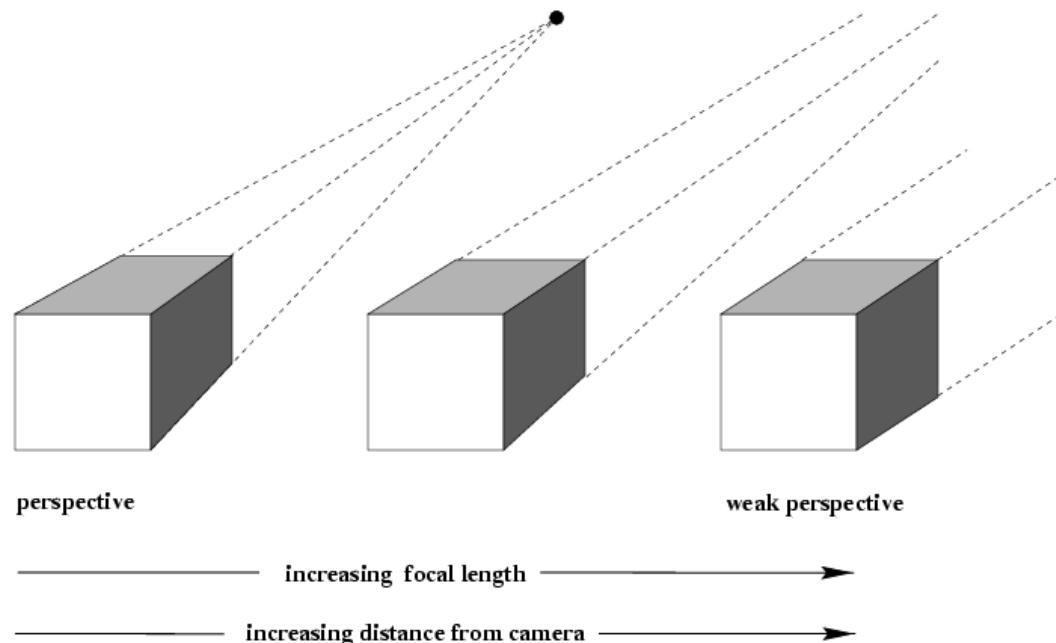
Camera Parameters

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f/d_u & \gamma & u_0 \\ 0 & f/d_v & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X_c \\ Y_c \\ Z_c \end{bmatrix}$$

Global Coordinate System



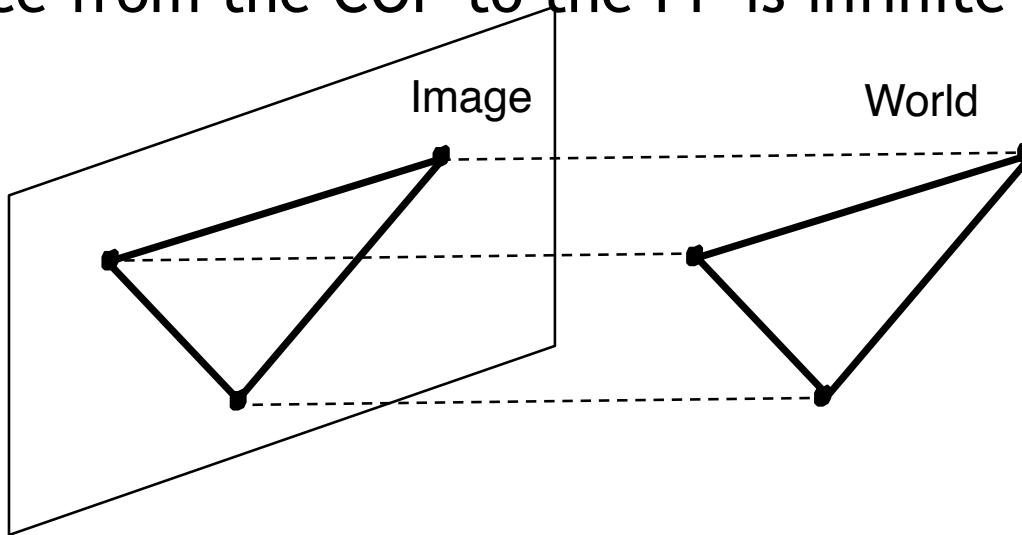
Other projection models



Slide credit: Yung-Yu Chuang

Orthographic projection

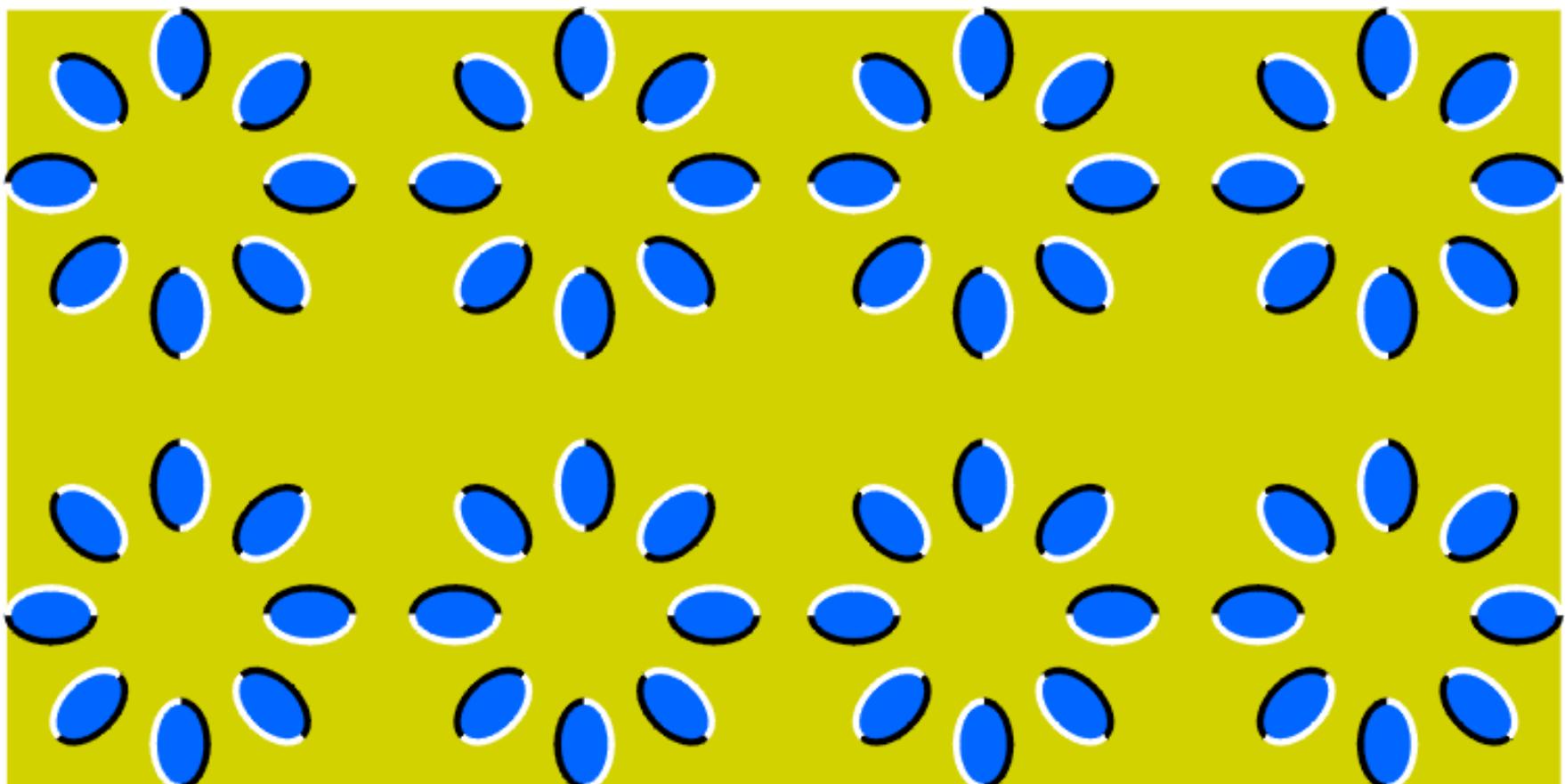
- Special case of perspective projection
 - Distance from the COP to the PP is infinite



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

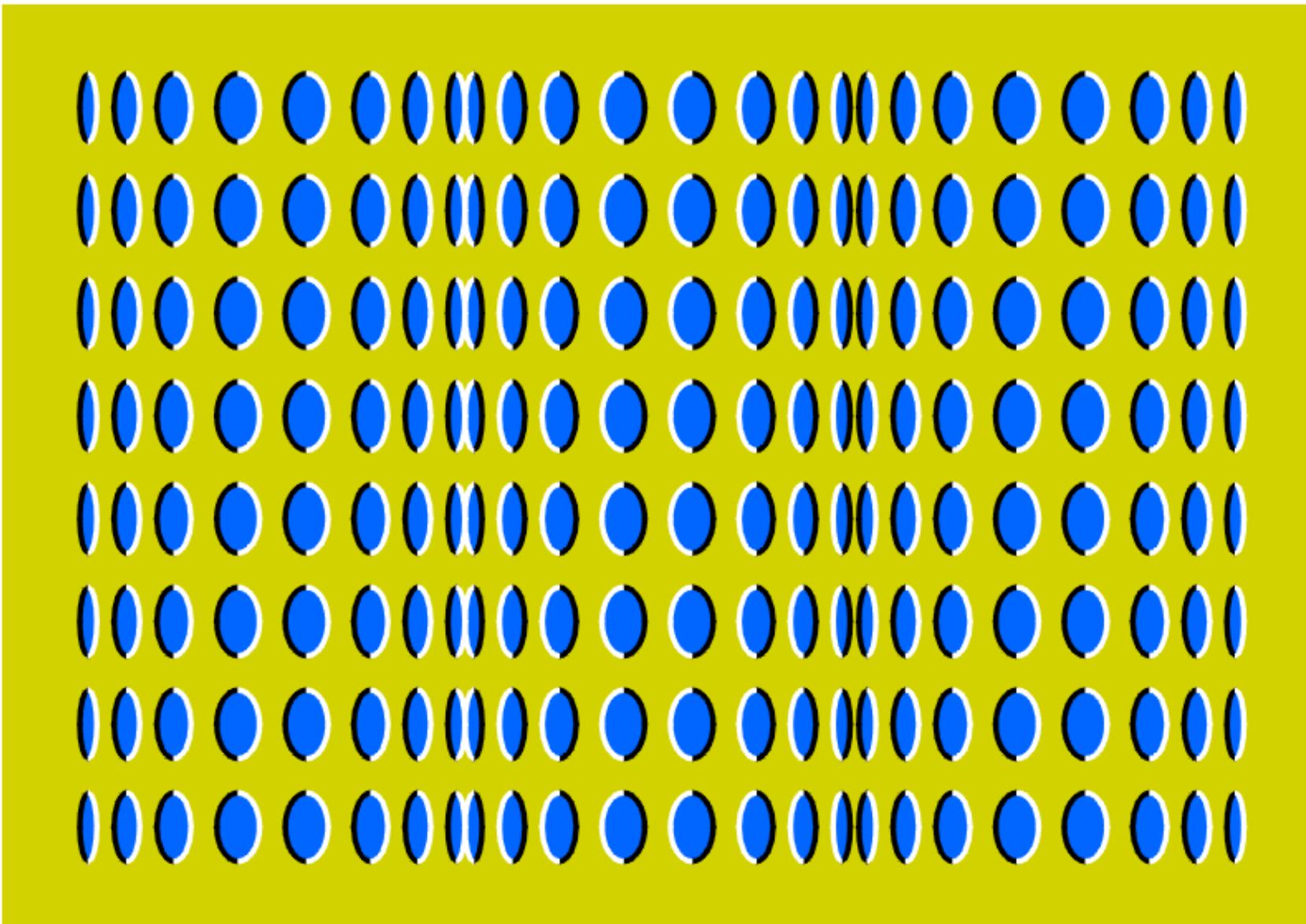
- Also called “parallel projection”: $(x, y, z) \rightarrow (x, y)$

Illusion



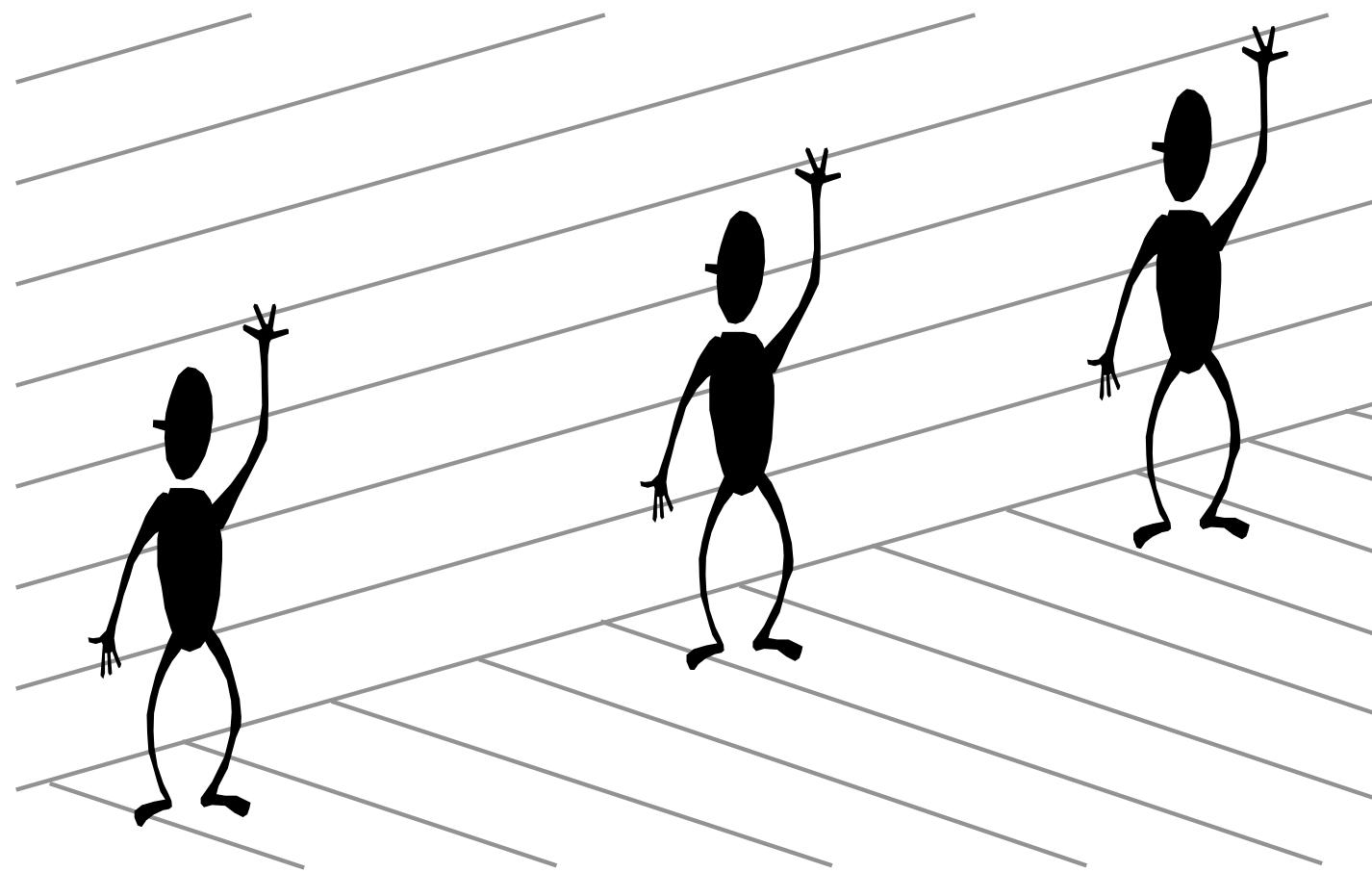
Slide credit: Yung-Yu Chuang

Illusion



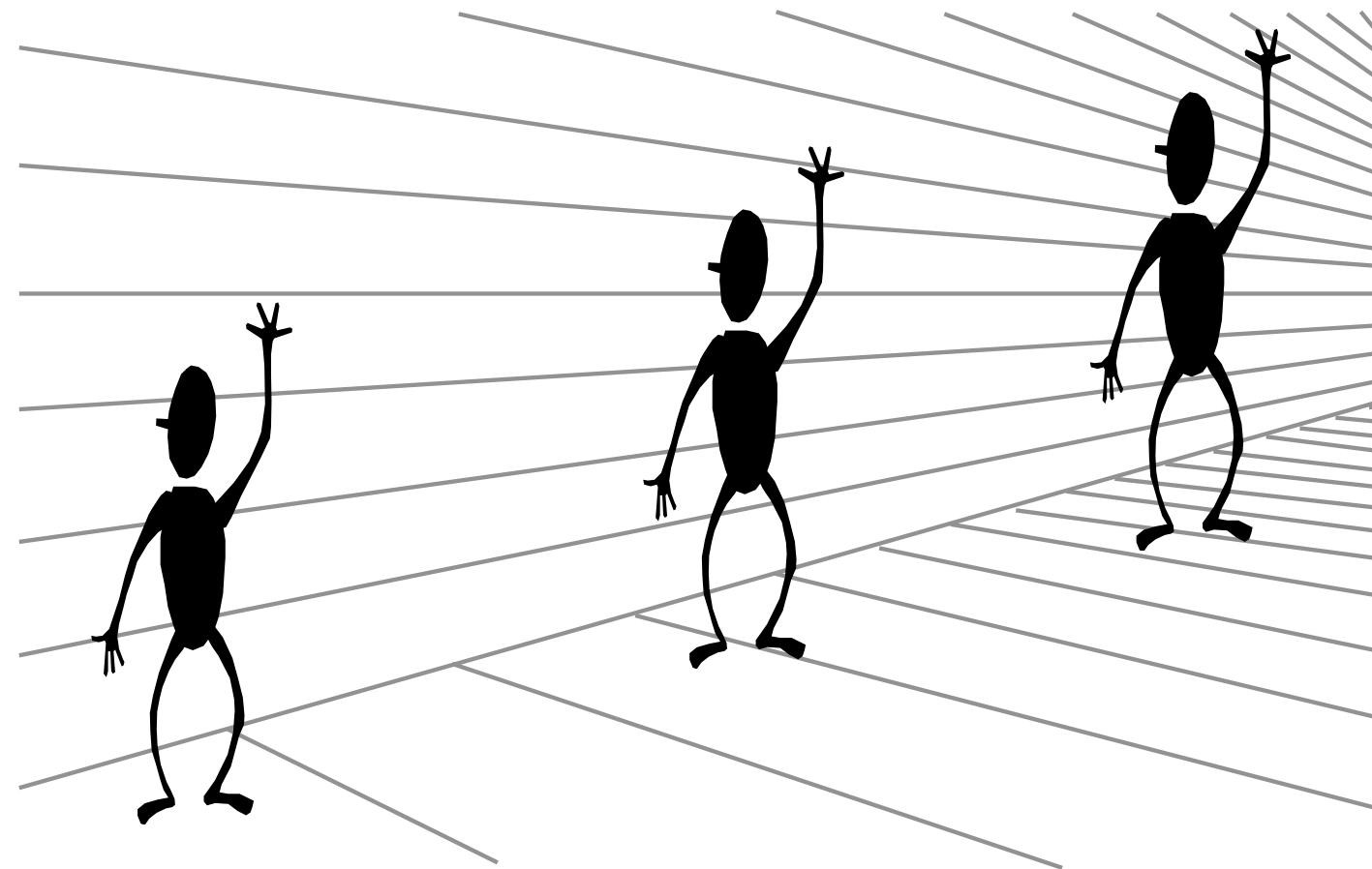
Slide credit: Yung-Yu Chuang

Fun with perspective



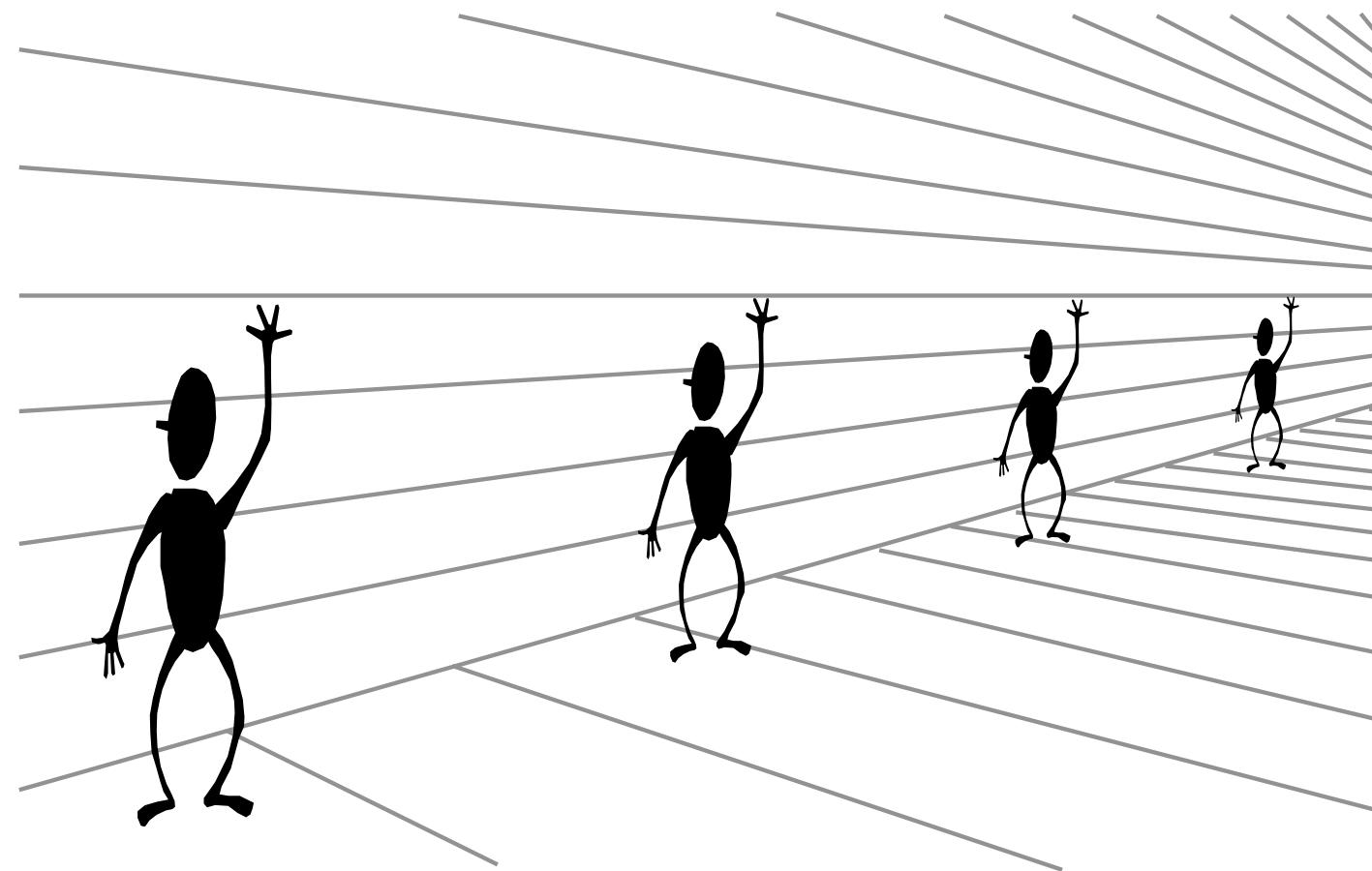
Slide credit: Yung-Yu Chuang

Fun with perspective



Slide credit: Yung-Yu Chuang

Fun with perspective

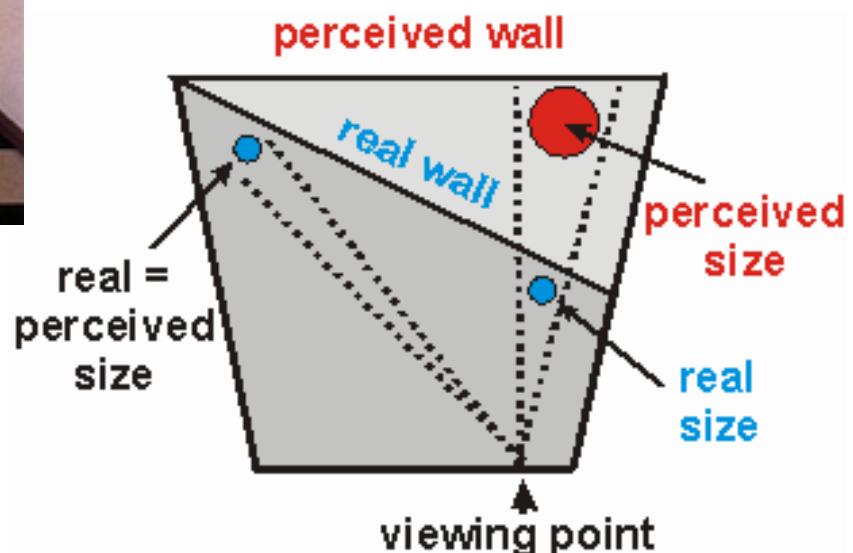
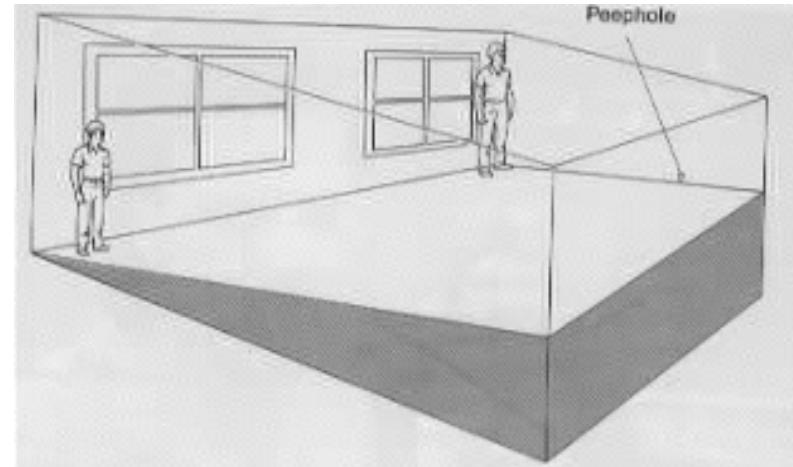


Slide credit: Yung-Yu Chuang

Fun with perspective

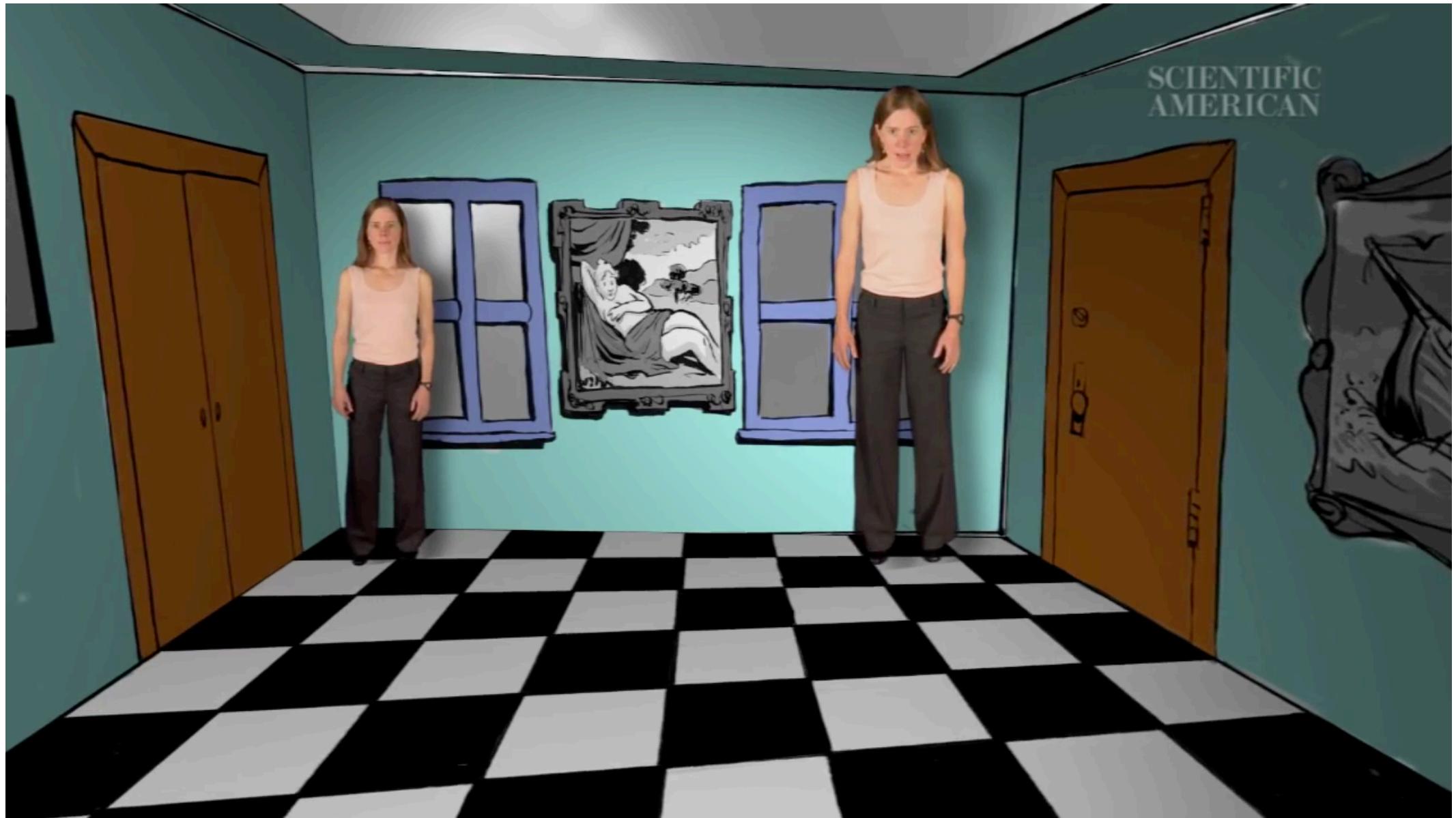


Ames room



Slide credit: Yung-Yu Chuang

Ames room



Forced perspective in LOTR



Two kinds of parameters

- internal or intrinsic parameters such as focal length, optical center, aspect ratio:
 - what kind of camera?
- external or extrinsic (pose) parameters including rotation and translation:
 - where is the camera?

Intrinsic parameters

$$x \sim K[R|t]x$$



Extrinsic parameters

Camera Calibration

Camera Calibration

- Estimate both intrinsic and extrinsic parameters.
- Two main categories:
 - **Photometric calibration:** uses reference objects (3D, 2D, 1D, 0D) with known geometry
 - **Self calibration:** only assumes static scene, e.g. structure from motion

Intrinsic parameters

$$\mathbf{x} \sim \mathbf{K}[\mathbf{R}|\mathbf{t}] \mathbf{x}$$



Extrinsic parameters

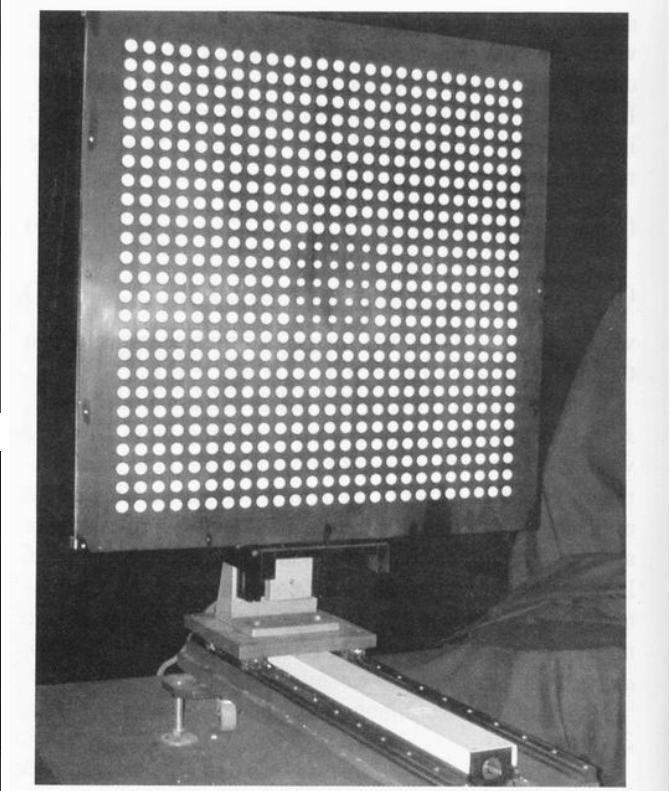
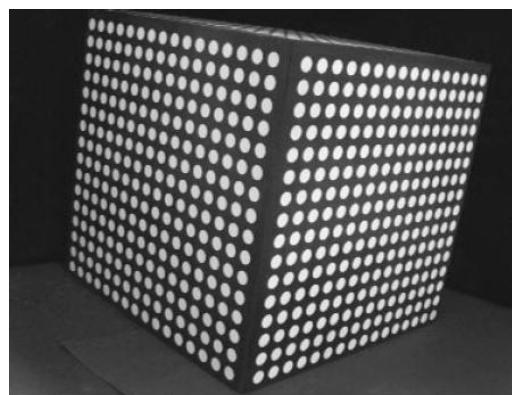
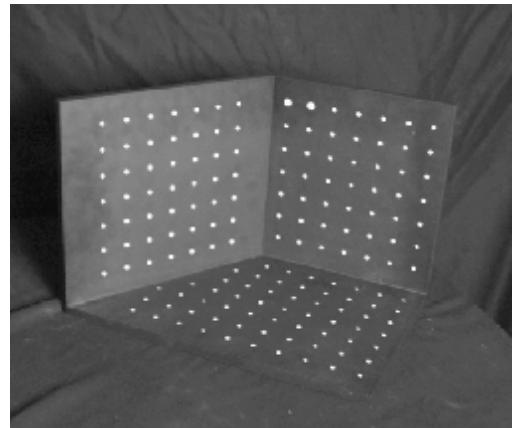
Camera Calibration

- Known 2D coordinates in the image and their corresponding 3D coordinates in the world, then we can solve the parameters by
 - linear regression (least squares)
 - nonlinear optimization

Intrinsic parameters

$$\mathbf{x} \sim \mathbf{K} \underbrace{[\mathbf{R} | \mathbf{t}]}_{\text{Extrinsic parameters}} \mathbf{x}$$

Extrinsic parameters



Camera Calibration

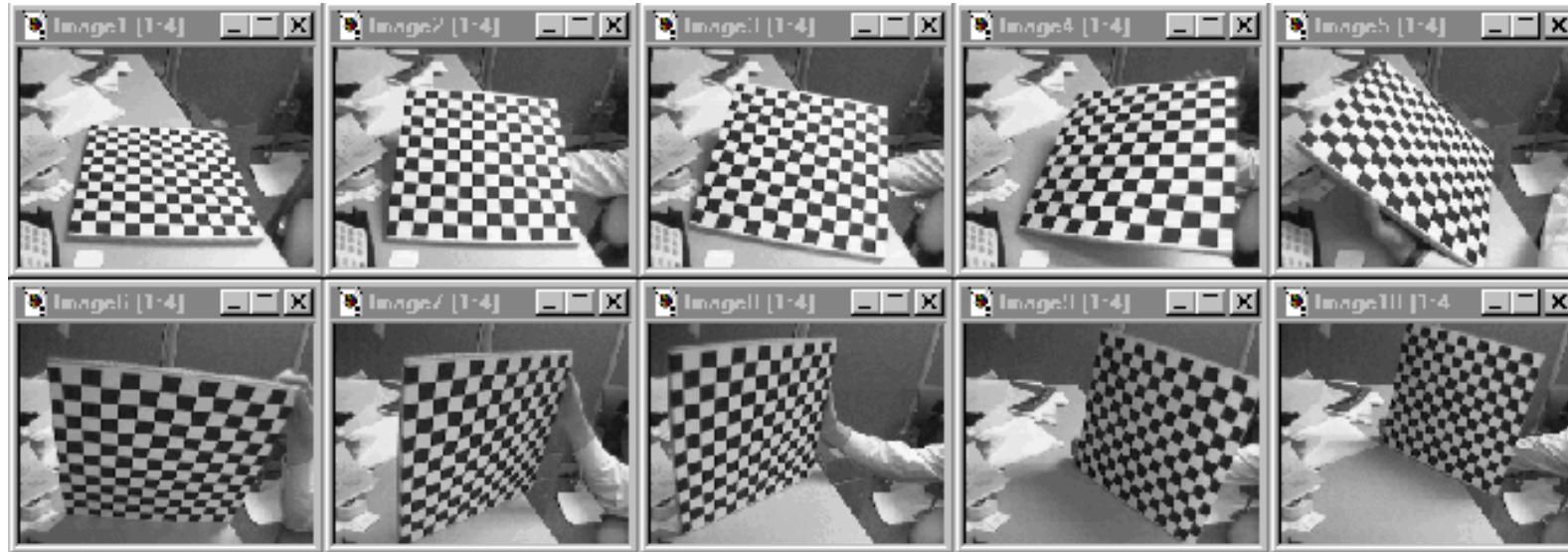
Z. Zhang, “Flexible Camera Calibration by Viewing a Plane from Unknown Orientations,” *International Conference on Computer Vision (ICCV)*, 1999.

(cited number: [3422](#) from Google)

Z. Zhang, “A flexible new technique for camera calibration,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2000.

(cited number: [16672](#) from Google)

Multi-plane calibration



Images courtesy Jean-Yves Bouguet, Intel Corp.

Advantage

- Only requires a plane
- Don't have to know positions/orientations
- Good code available online!
 - Intel's OpenCV library: <http://www.intel.com/research/mrl/research/opencv/>
 - Matlab version by Jean-Yves Bouguet:
http://www.vision.caltech.edu/bouguetj/calib_doc/index.html
 - Zhengyou Zhang's web site: <http://research.microsoft.com/~zhang/Calib/>

Notation

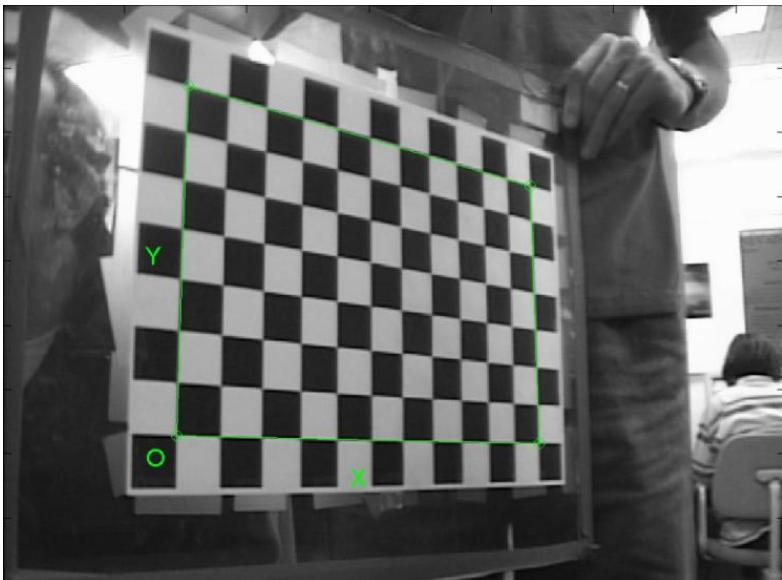
$$\mathbf{x} \sim \mathbf{K}[\mathbf{R}|\mathbf{t}]\mathbf{x}$$

- ◆ 2D point : $m = [u, v]^T \implies \tilde{m} = [u, v, 1]^T$
- ◆ 3D point : $M = [X, Y, Z]^T \implies \tilde{M} = [X, Y, Z, 1]^T$
- ◆ The usual pinhole :

$$s\tilde{m} = A[R | t]\tilde{M} \quad , \text{ with } \quad A = \begin{bmatrix} \alpha & \gamma & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix}$$

- ◆ Using the abbreviation A^{-T} for $(A^{-1})^T$ or $(A^T)^{-1}$

Estimating Homography



?

Homography

- Projective transformation
- Defined in 2D space as a mapping between a point on a ground plane as seen from one camera, to the same point on the ground plane as seen from a second camera

$$s \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

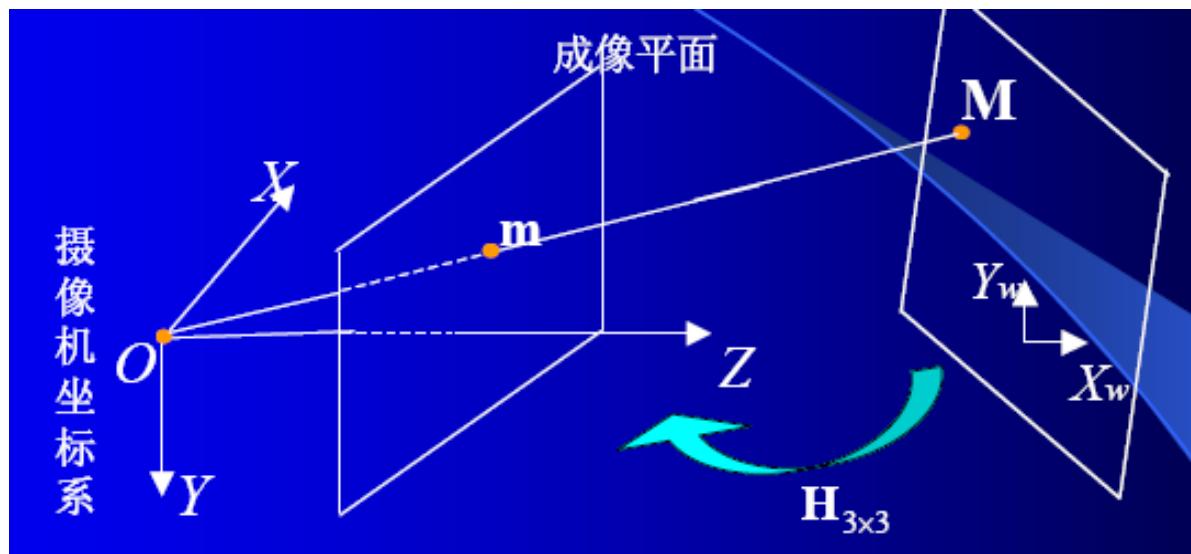
8 unknowns
- at least 4 points
are needed



Homography

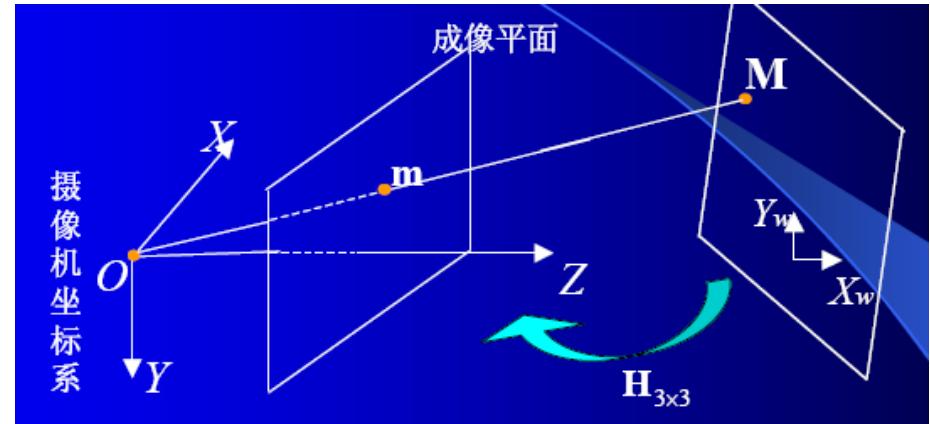
Homography - Case 1

- Case 1: a mapping between image coordinates and ground plane coordinates



Proof – Case 1

$$s\tilde{\mathbf{m}} = A[R \mid t]\tilde{\mathbf{M}}$$



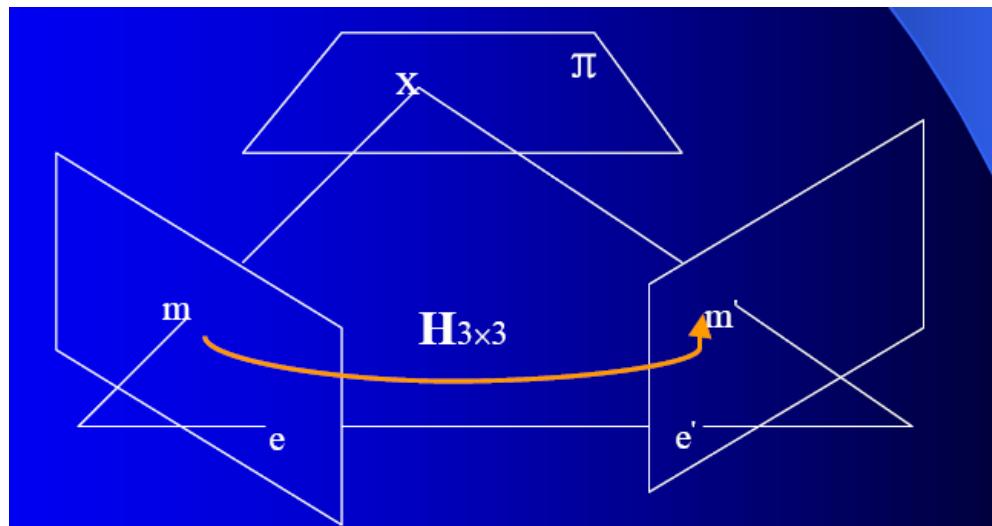
- We assume the model plane is on $Z = 0$, then

$$s \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = A[\mathbf{r}_1 \quad \mathbf{r}_2 \quad \mathbf{r}_3 \quad \mathbf{t}] \begin{bmatrix} \mathbf{X} \\ \mathbf{Y} \\ 0 \\ 1 \end{bmatrix} = A[\mathbf{r}_1 \quad \mathbf{r}_2 \quad \mathbf{t}] \begin{bmatrix} \mathbf{X} \\ \mathbf{Y} \\ 1 \end{bmatrix}$$

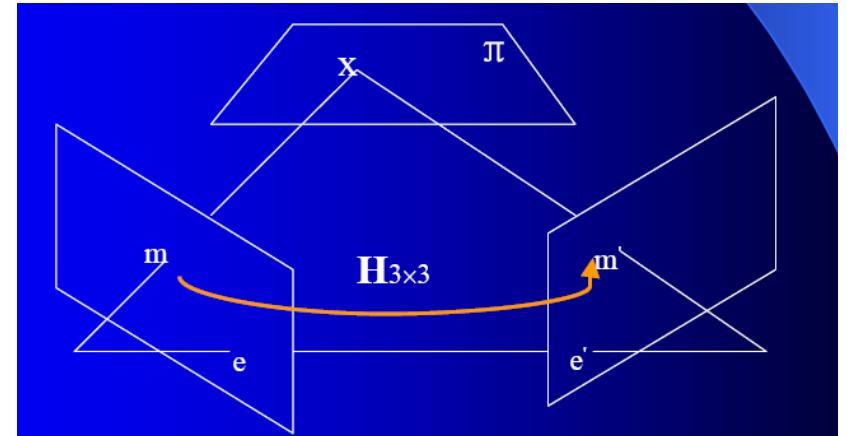
$$s\tilde{\mathbf{m}} = \mathbf{H}\tilde{\mathbf{M}}, \text{ with } \mathbf{H} = A[\mathbf{r}_1 \quad \mathbf{r}_2 \quad \mathbf{t}]$$

Homography - Case 2

- Case 1: a mapping between a point on a ground plane as seen from one camera, to the same point on the ground plane as seen from a second camera



Proof – Case 2



- ❖ m_1 is the image coordinate of Camera 1
- ❖ m_2 is the image coordinate of Camera 2
- ❖ M is the coordinate on the ground plane
- ❖ From Case 1:

$$s_1 \tilde{m}_1 = H_1 \tilde{M}$$

$$s_2 \tilde{m}_2 = H_2 \tilde{M}$$



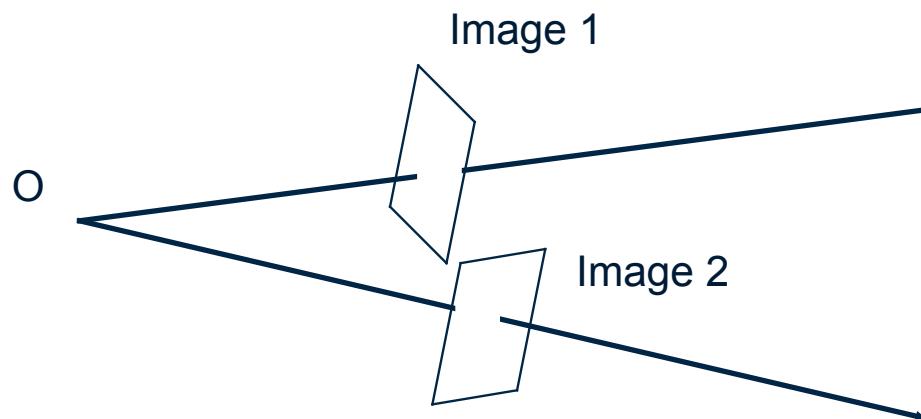
$$s \tilde{m}_2 = H_2 H_1^{-1} \tilde{m}_1$$



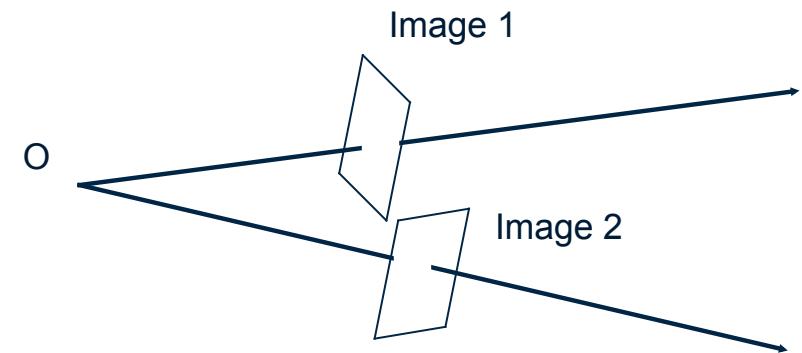
$$s \tilde{m}_2 = H \tilde{m}_1$$

Homography - Case 3

- Case 1: a mapping between image coordinates of Camera 1 and image coordinates of Camera 2, where Camera 1 and Camera 2 is located in the same position



Proof – Case 3

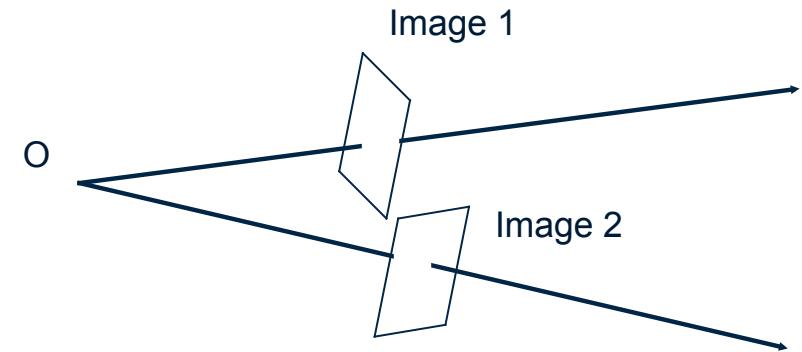


$$s\tilde{m} = A[R \mid t]\tilde{M}$$

- Let the position of camera is $(0, 0, 0)$ in the global coordinate system, then

$$s \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \mathbf{A} \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{r}_3 & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} = \mathbf{A} \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{r}_3 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \mathbf{A}R \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

Proof – Case 3



$$S_1 \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \mathbf{A}R \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \quad \dots \dots \dots \quad (1)$$

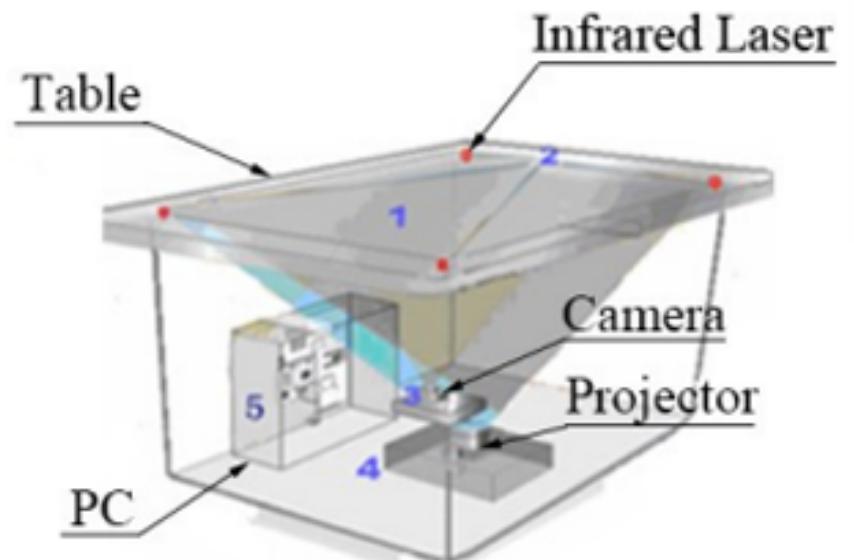
$$S_2 \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \mathbf{A}R' \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \quad \dots \dots \dots \quad (2)$$

From (1), (2) :

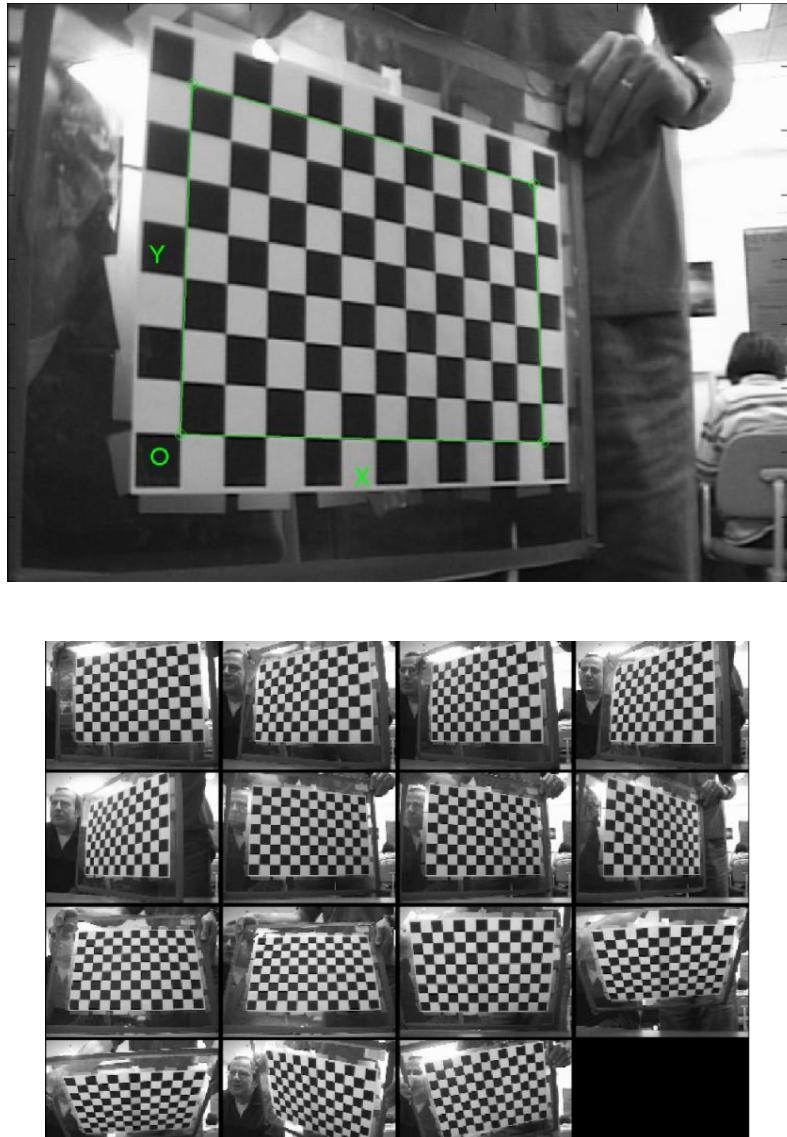
$$S \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \mathbf{A}R'R\mathbf{A}^{-1} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = H \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Application of Homography

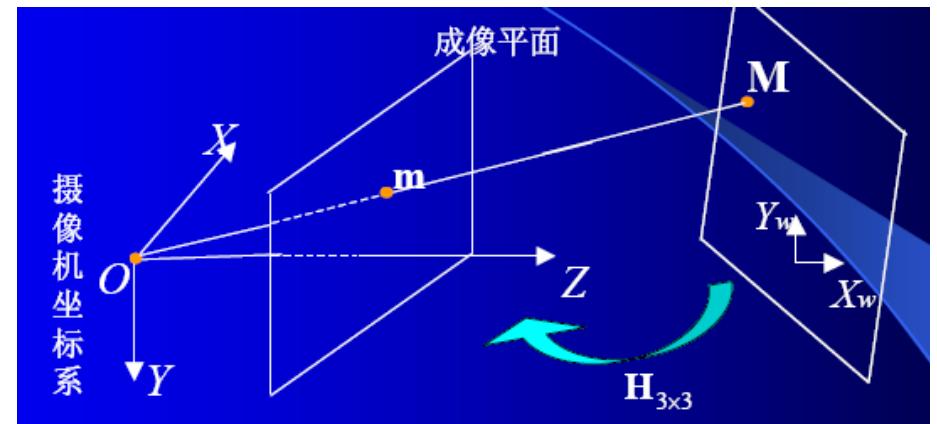
- Projector-Camera System



Estimating Homography



- Case 1: a mapping between image coordinates and ground plane coordinates



$$s \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Estimating Homography

- Without loss of generality, we assume the model plane is on $Z = 0$

$$s \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = A \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{r}_3 & \mathbf{t} \end{bmatrix} \begin{bmatrix} \mathbf{X} \\ \mathbf{Y} \\ 0 \\ 1 \end{bmatrix} = A \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{t} \end{bmatrix} \begin{bmatrix} \mathbf{X} \\ \mathbf{Y} \\ 1 \end{bmatrix}$$

$$s \tilde{\mathbf{m}} = \tilde{\mathbf{H}} \tilde{\mathbf{M}}, \text{ with } \mathbf{H} = A \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{t} \end{bmatrix}$$

Constraints on Intrinsic Parameters

$$\mathbf{H} = \mathbf{A} [\mathbf{r}_1 \quad \mathbf{r}_2 \quad \mathbf{t}]$$

◆ Denote $\mathbf{H} = [\mathbf{h}_1 \quad \mathbf{h}_2 \quad \mathbf{h}_3]$
then $[\mathbf{h}_1 \quad \mathbf{h}_2 \quad \mathbf{h}_3] = \lambda \mathbf{A} [\mathbf{r}_1 \quad \mathbf{r}_2 \quad \mathbf{t}] \rightarrow \begin{aligned} \mathbf{r}_1 &= \mathbf{A}^{-1} \mathbf{h}_1 \\ \mathbf{r}_2 &= \mathbf{A}^{-1} \mathbf{h}_2 \end{aligned}$

◆ Since \mathbf{r}_1 and \mathbf{r}_2 are orthonormal

$$\begin{cases} \|\mathbf{r}_1\| = \|\mathbf{r}_2\| \\ \mathbf{r}_1 \cdot \mathbf{r}_2 = 0 \end{cases} \implies \begin{cases} \mathbf{h}_1^T \mathbf{A}^{-T} \mathbf{A}^{-1} \mathbf{h}_1 = \mathbf{h}_2^T \mathbf{A}^{-T} \mathbf{A}^{-1} \mathbf{h}_2 \\ \mathbf{h}_1^T \mathbf{A}^{-T} \mathbf{A}^{-1} \mathbf{h}_2 = 0 \end{cases}$$

Closed-Form Solution

◆ Let

$$\mathbf{B} = \mathbf{A}^{-T} \mathbf{A}^{-1}$$

$$A = \begin{bmatrix} \alpha & \gamma & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} B_{11} & B_{21} & B_{31} \\ B_{12} & B_{22} & B_{32} \\ B_{13} & B_{23} & B_{33} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{1}{\alpha^2} & -\frac{\gamma}{\alpha^2 \beta} & \frac{v_0 \gamma - u_0 \beta}{\alpha^2 \beta} \\ -\frac{\gamma}{\alpha^2 \beta} & \frac{\gamma^2}{\alpha^2 \beta^2} + \frac{1}{\beta^2} & -\frac{\gamma(v_0 \gamma - u_0 \beta)}{\alpha^2 \beta^2} - \frac{v_0}{\beta^2} \\ \frac{v_0 \gamma - u_0 \beta}{\alpha^2 \beta} & -\frac{\gamma(v_0 \gamma - u_0 \beta)}{\alpha^2 \beta^2} - \frac{v_0}{\beta^2} & \frac{(v_0 \gamma - u_0 \beta)^2}{\alpha^2 \beta^2} + \frac{v_0^2}{\beta^2} + 1 \end{bmatrix}$$

Closed-Form Solution

- ◆ B is symmetric, defined by a 6D vector

$$\mathbf{b} = [B_{11} \quad B_{12} \quad B_{22} \quad B_{13} \quad B_{23} \quad B_{33}]^T$$

- ◆ Let i th column vector of H be $\mathbf{h}_i = [h_{i1} \quad h_{i2} \quad h_{i3}]^T$

$$\mathbf{h}_i^T \mathbf{B} \mathbf{h}_j = \mathbf{v}_{ij}^T \mathbf{b}$$

with $\mathbf{v}_{ij} = [h_{i1}h_{j1} \quad h_{i1}h_{j2} + h_{i2}h_{j1} \quad h_{i2}h_{j2} \quad h_{i3}h_{j1} + h_{i1}h_{j3} \quad h_{i3}h_{j2} + h_{i2}h_{j3} \quad h_{i3}h_{j3}]$

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

Closed-Form Solution

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

- Therefore, two constraints can be written as

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

- If n images of the model plane are observed

$$\mathbf{V}\mathbf{b} = 0$$

where \mathbf{V} is a $2n \times 6$ matrix

Closed-Form Solution

- ❖ If $n \geq 3$, we will have in general a unique solution b defined up to a scale factor
- ❖ The solution is well-known as the eigenvector of $V^T V$ associated with the smallest eigenvalue

Closed-Form Solution

- Once b is estimated, then

$$\nu_0 = (B_{12}B_{13} - B_{11}B_{23}) / (B_{11}B_{22} - B_{12}^2)$$

$$\lambda = B_{33} - [B_{13}^2 + \nu_0(B_{12}B_{13} - B_{11}B_{23})] / B_{11}$$

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

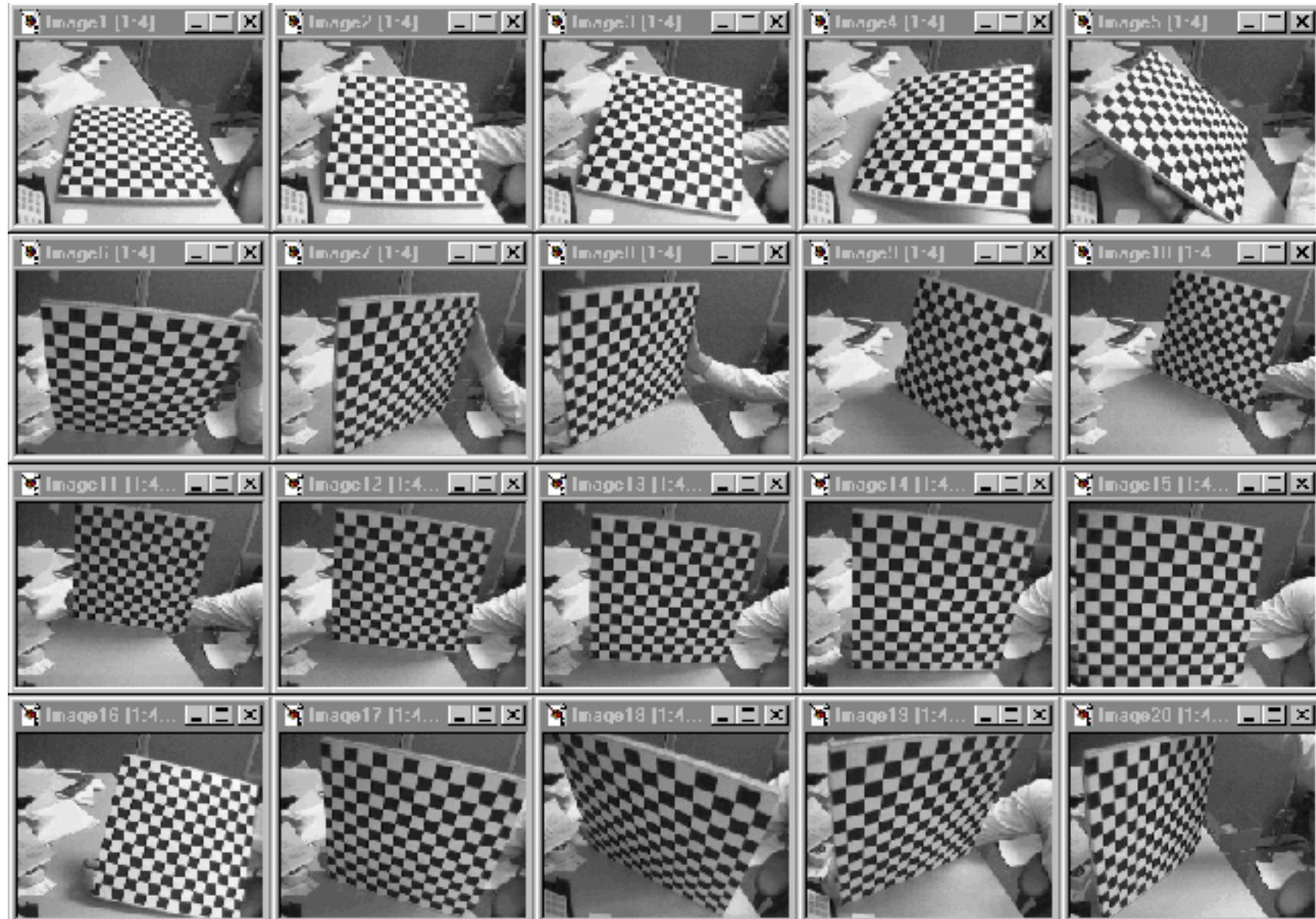
$$\beta = \sqrt{\lambda B_{11} / (B_{11}B_{22} - B_{12}^2)}$$

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

$$u_0 = \nu_0 / \beta - B_{13}\alpha^2 / \gamma$$

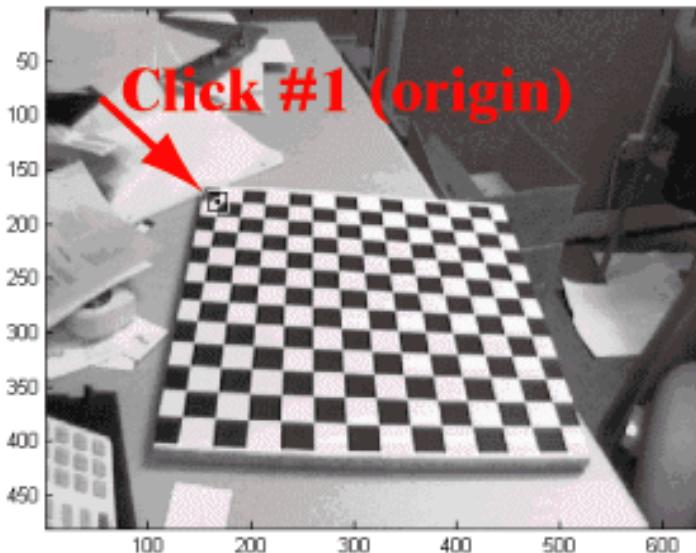
$$A = \begin{bmatrix} \alpha & \gamma & u_0 \\ 0 & \beta & \nu_0 \\ 0 & 0 & 1 \end{bmatrix}$$

Step 1: data acquisition

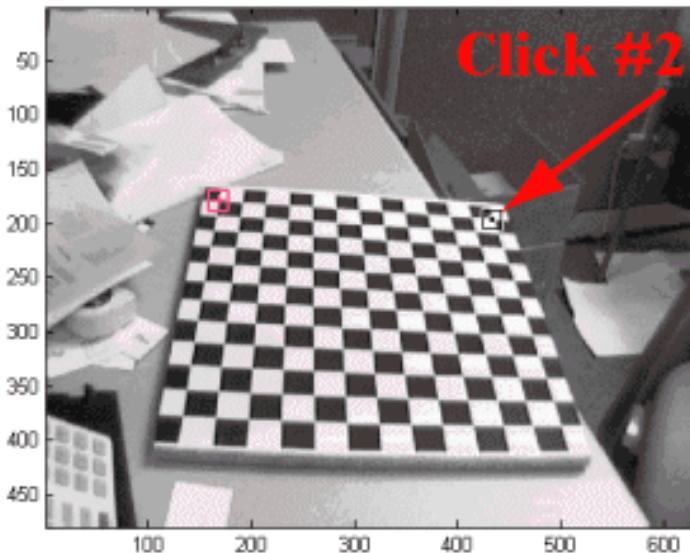


Step 2: specify corner order

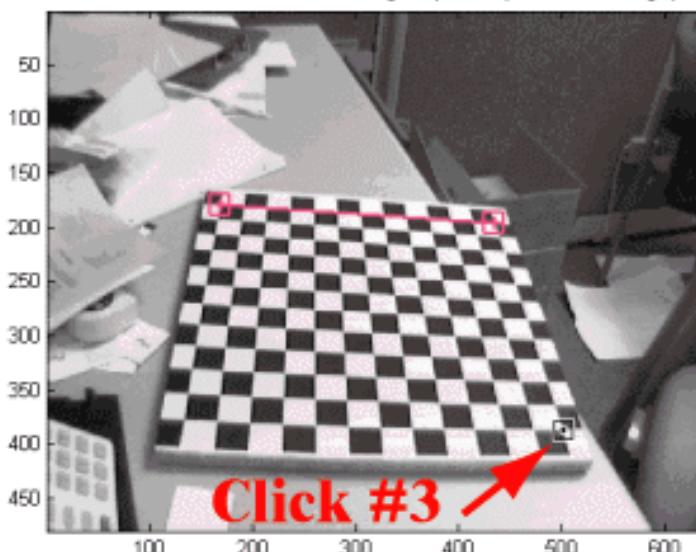
Click on the four extreme corners of the rectangular pattern (first corner = origin)... Image 1



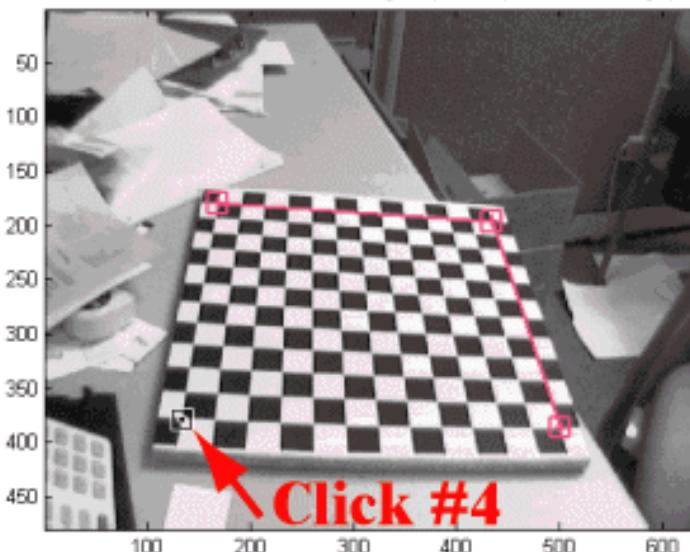
Click on the four extreme corners of the rectangular pattern (first corner = origin)... Image 1



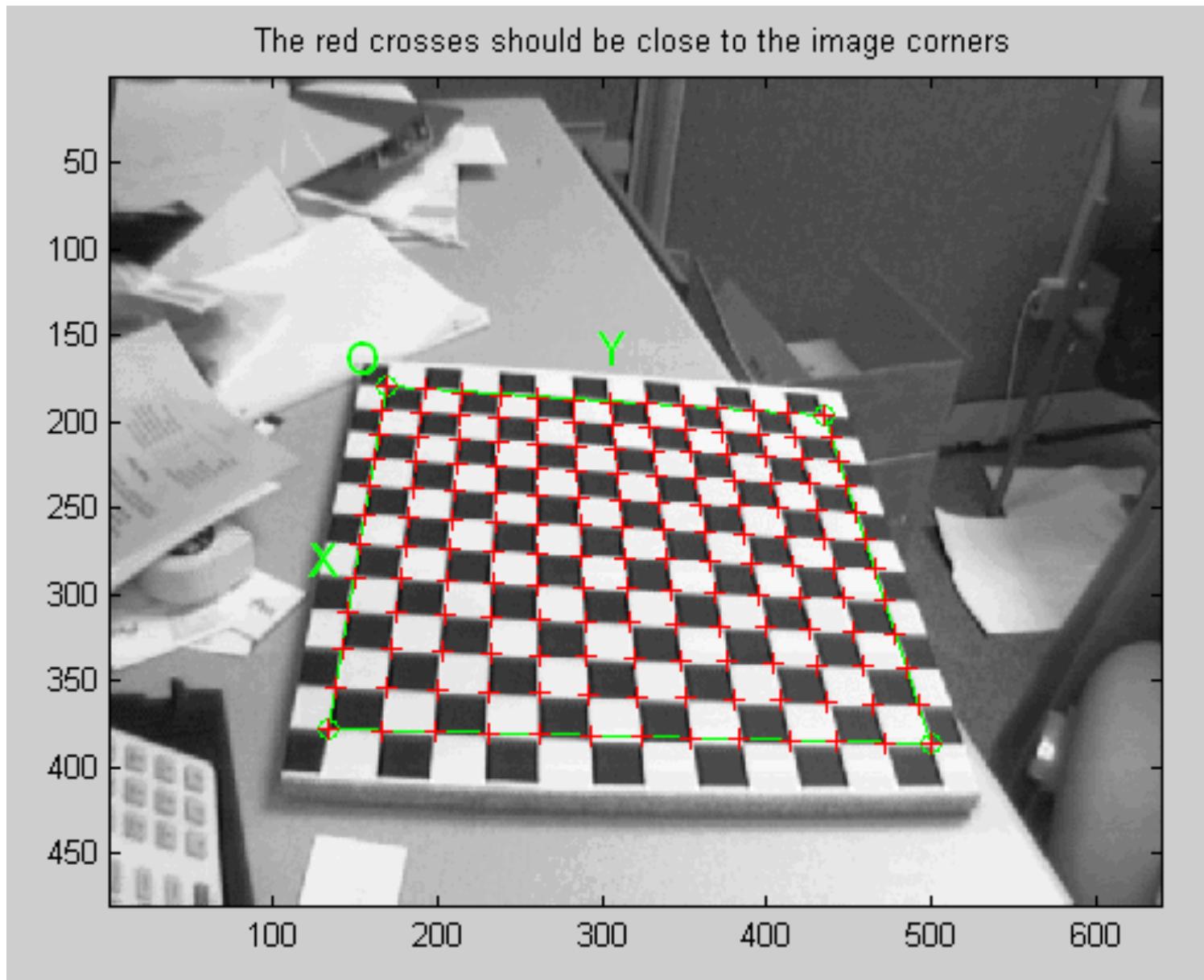
Click on the four extreme corners of the rectangular pattern (first corner = origin)... Image 1



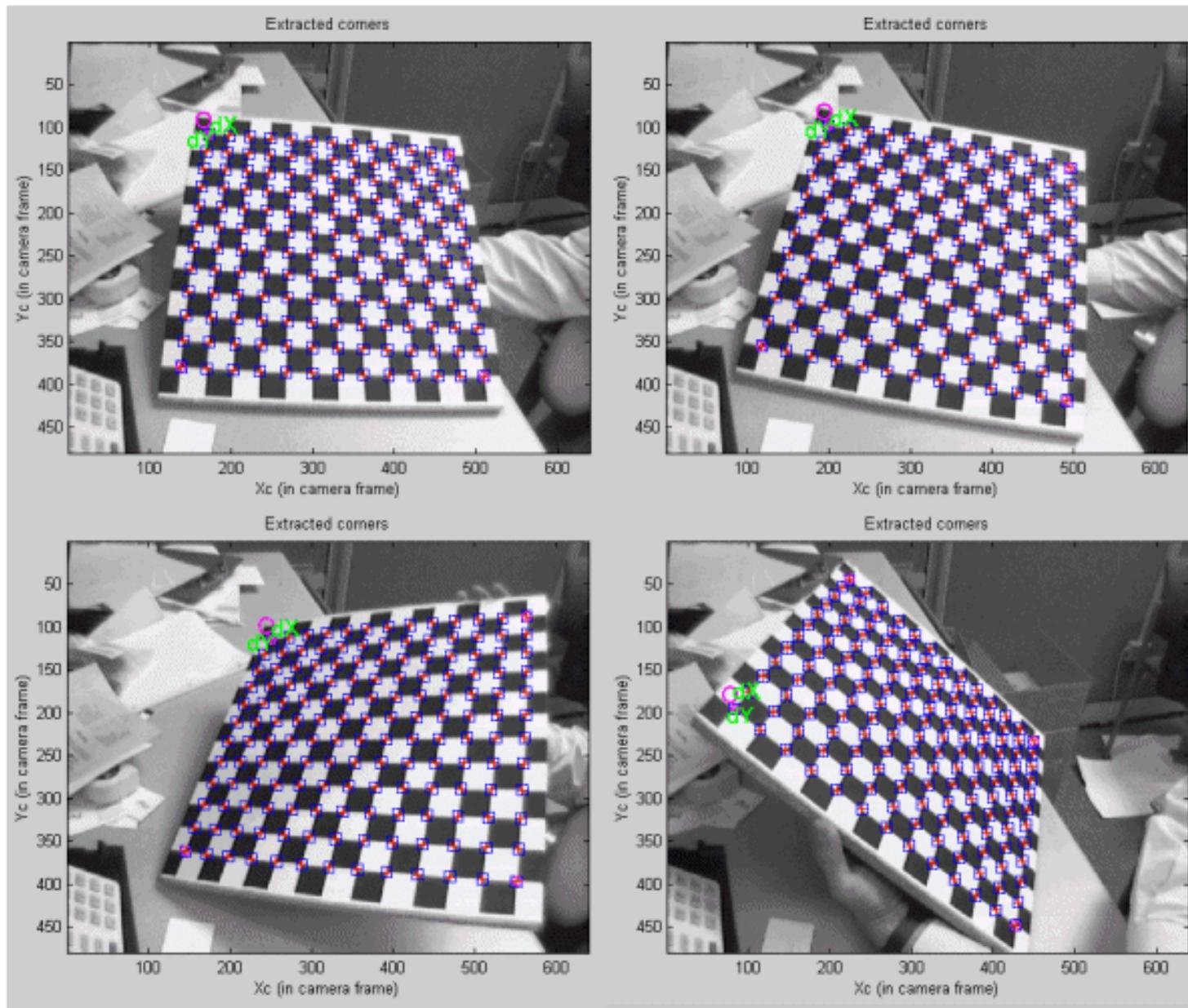
Click on the four extreme corners of the rectangular pattern (first corner = origin)... Image 1



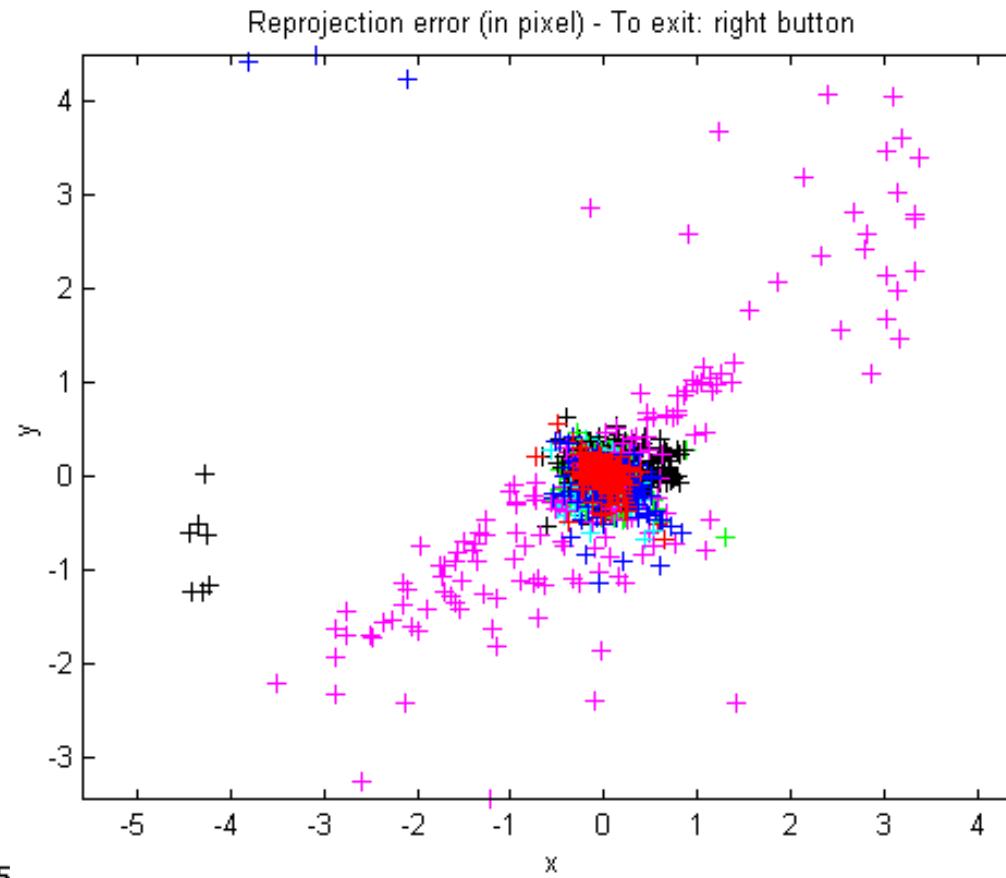
Step 3: corner extraction



Step 3: corner extraction

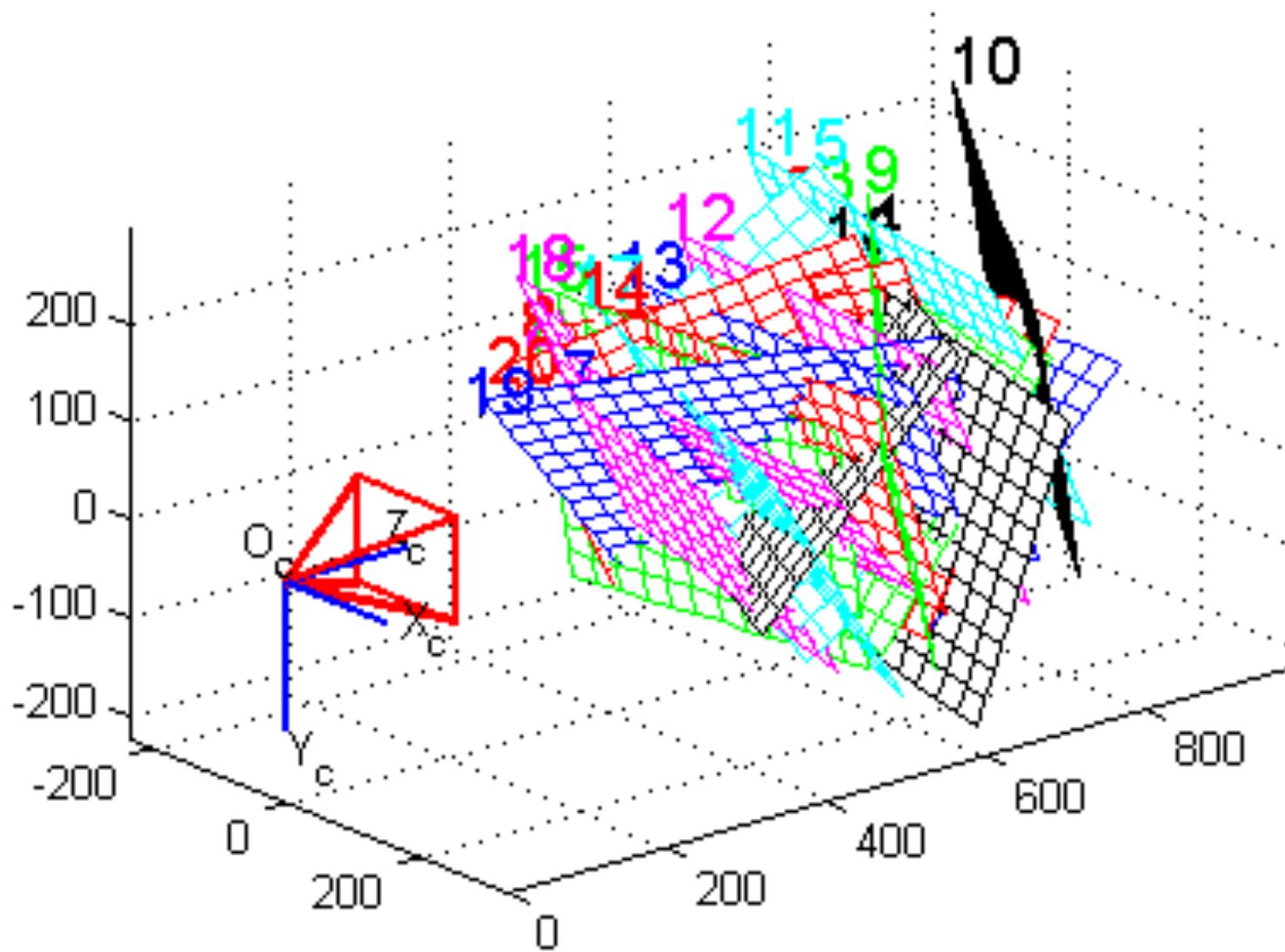


Step 4: minimize projection error

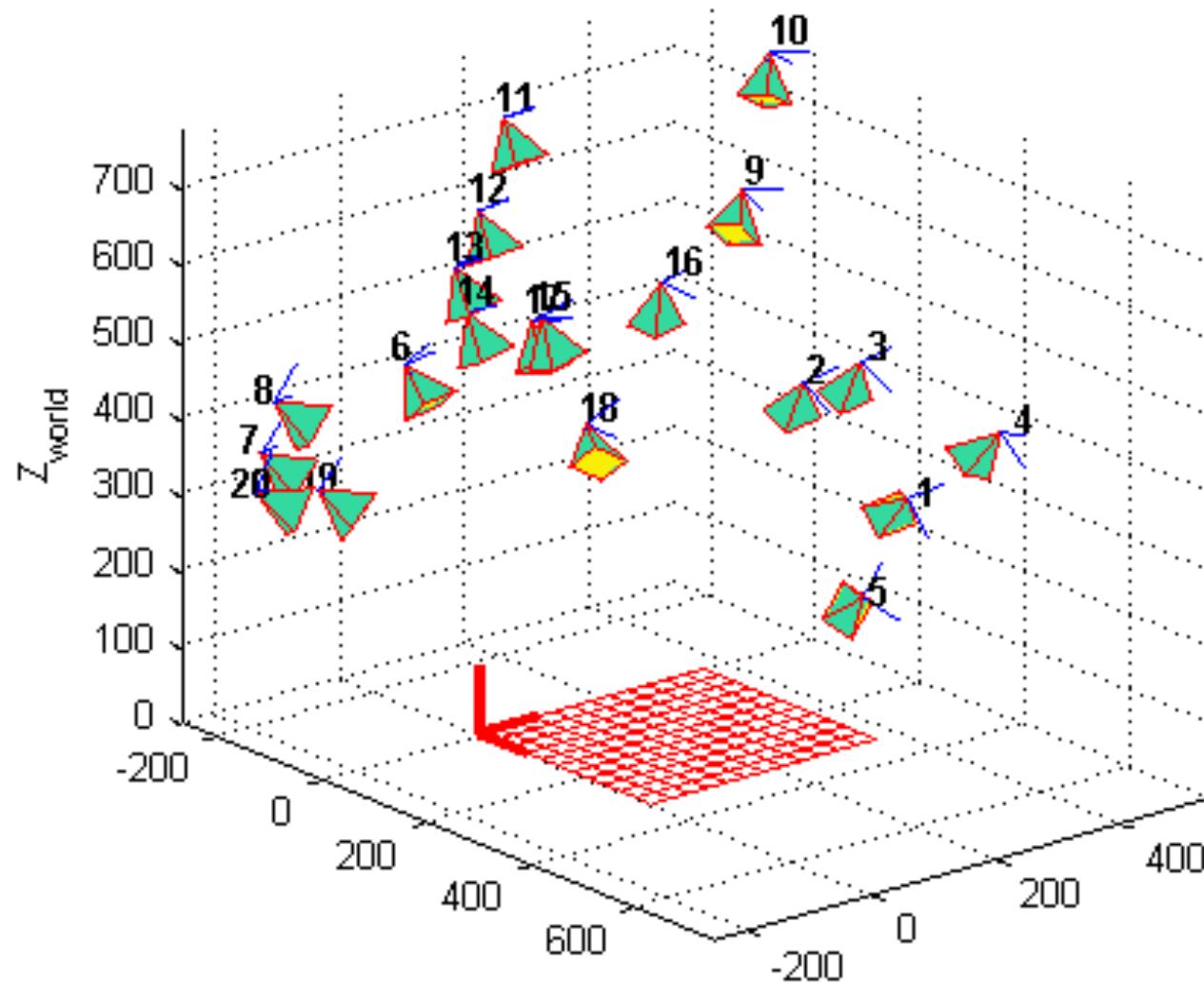


Focal Length: $fc = [657.46290 \quad 657.94673] \pm [0.31819 \quad 0.34046]$
Principal point: $cc = [303.13665 \quad 242.56935] \pm [0.64682 \quad 0.59218]$
Skew: $\alpha_c = [0.00000] \pm [0.00000] \Rightarrow \text{angle of pixel axes} =$
Distortion: $k_c = [-0.25403 \quad 0.12143 \quad -0.00021 \quad 0.00002 \quad 0.00000]$
Pixel error: $err = [0.11689 \quad 0.11500]$

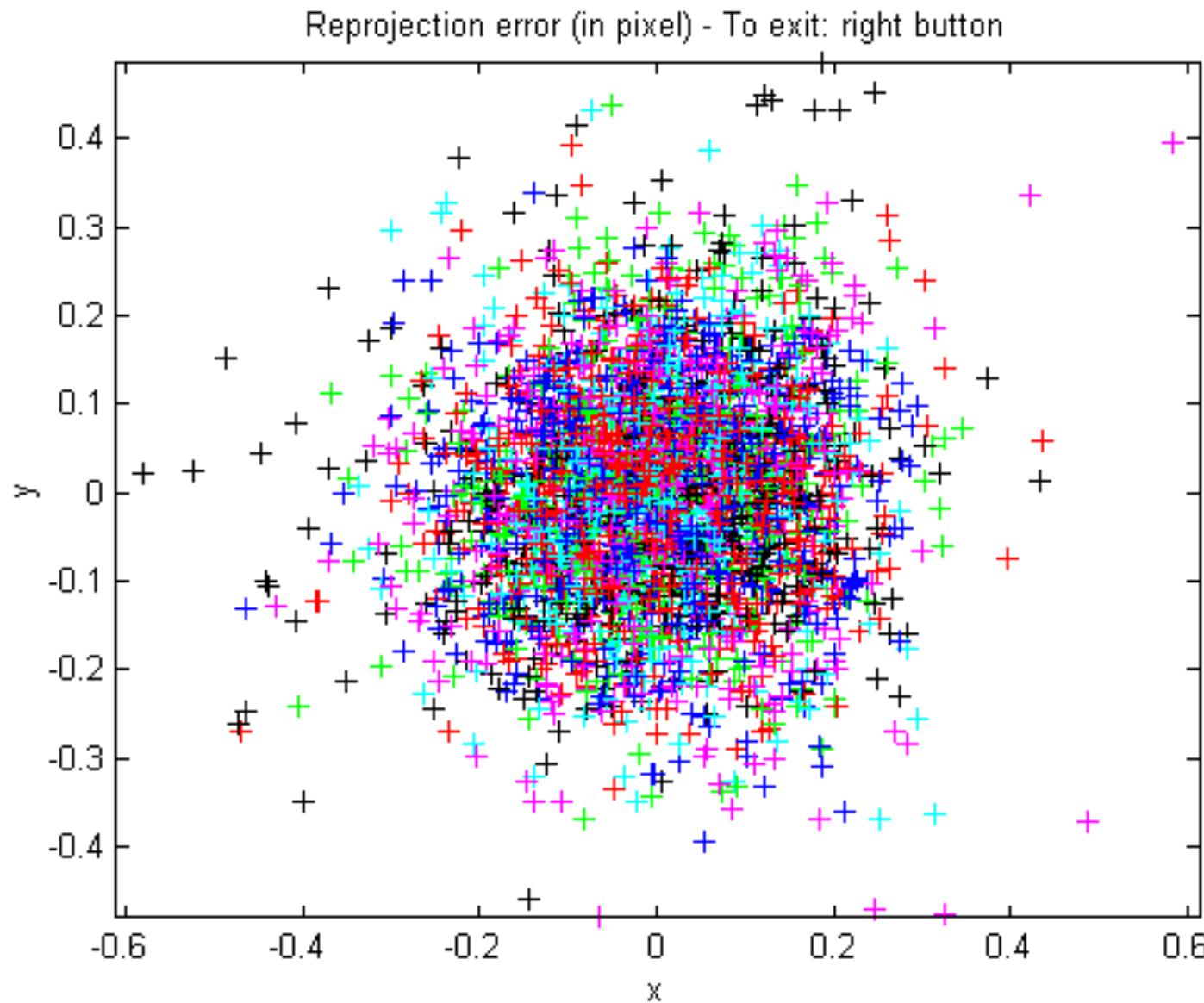
Step 4: camera calibration



Step 4: camera calibration



Step 5: refinement



Optimized parameters

```
Aspect ratio optimized (est_aspect_ratio = 1) -> both components of fc are estimated (DEFAULT).
Principal point optimized (center_optim=1) - (DEFAULT). To reject principal point, set center_optim=0
Skew not optimized (est_alpha=0) - (DEFAULT)
Distortion not fully estimated (defined by the variable est_dist):
    Sixth order distortion not estimated (est_dist(5)=0) - (DEFAULT) .
```

```
Main calibration optimization procedure - Number of images: 20
Gradient descent iterations: 1...2...3...4...5...done
Estimation of uncertainties...done
```

Calibration results after optimization (with uncertainties):

```
Focal Length:      fc = [ 657.46290   657.94673 ] ± [  0.31819   0.34046 ]
Principal point:  cc = [ 303.13665   242.56935 ] ± [  0.64682   0.59218 ]
Skew:             alpha_c = [ 0.00000 ] ± [ 0.00000 ] => angle of pixel axes = 90.00000 ± 0.00000 degrees
Distortion:        kc = [ -0.25403   0.12143   -0.00021   0.00002   0.00000 ] ± [  0.00248   0.00986   0.00000
Pixel error:       err = [ 0.11689   0.11500 ]
```

Note: The numerical errors are approximately three times the standard deviations (for reference).

Camera Calibration

Kuan-Wen Chen
2022/3/17

