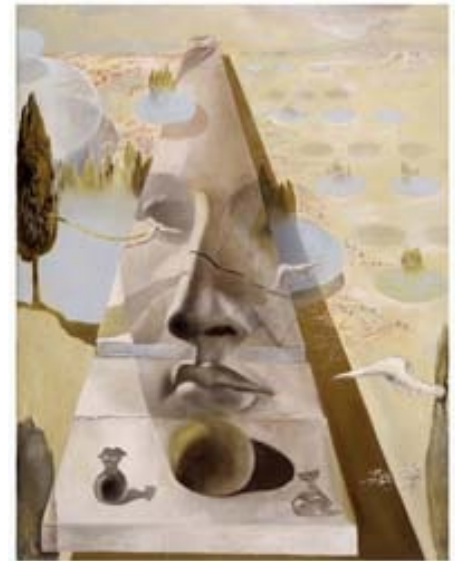


Lecture 3

Camera Models 2 & Camera Calibration

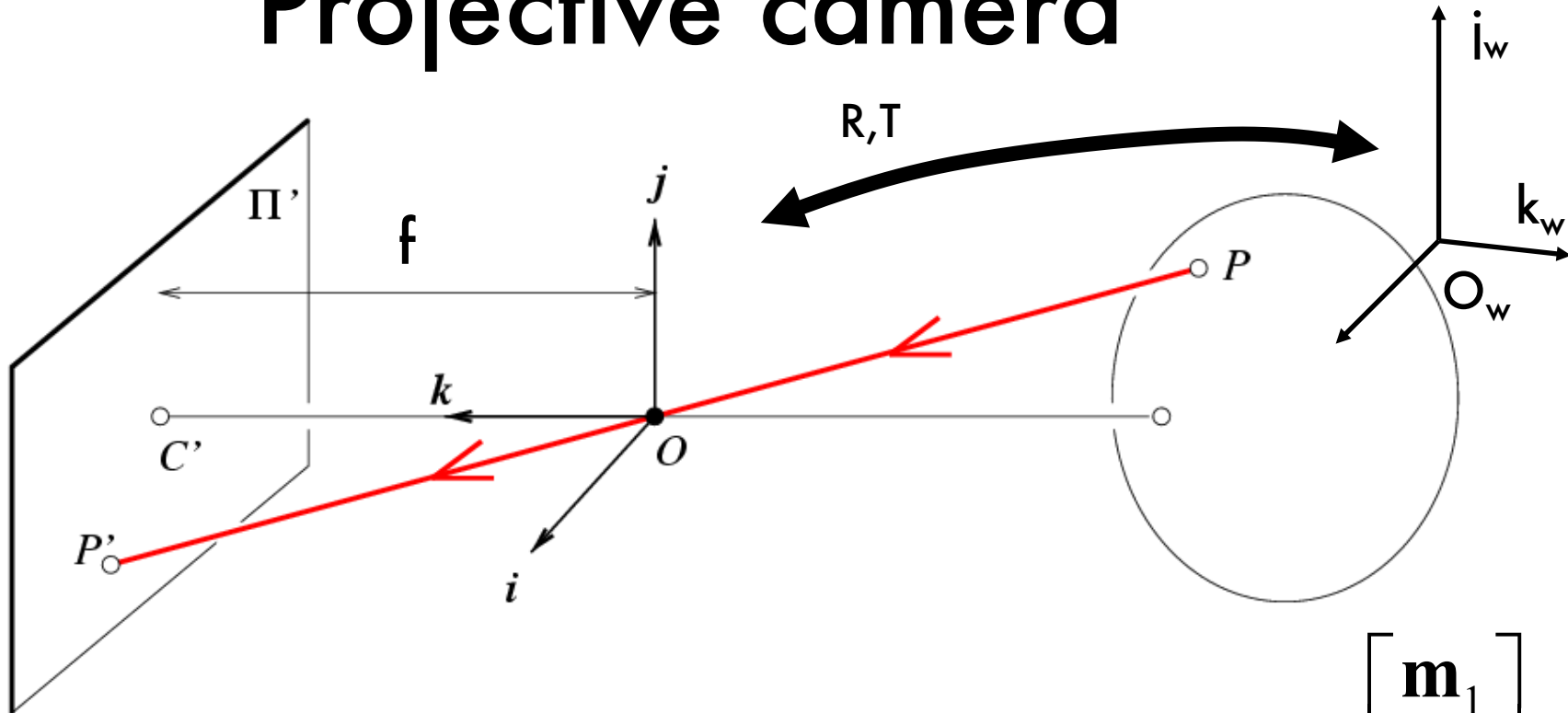
- Recap of camera models
- Camera calibration problem
- Camera calibration with radial distortion
- Example

Reading: [FP] Chapter 1 "Geometric Camera Calibration"
 [HZ] Chapter 7 "Computation of Camera Matrix P"



Some slides in this lecture are courtesy to Profs. J. Ponce, F-F Li

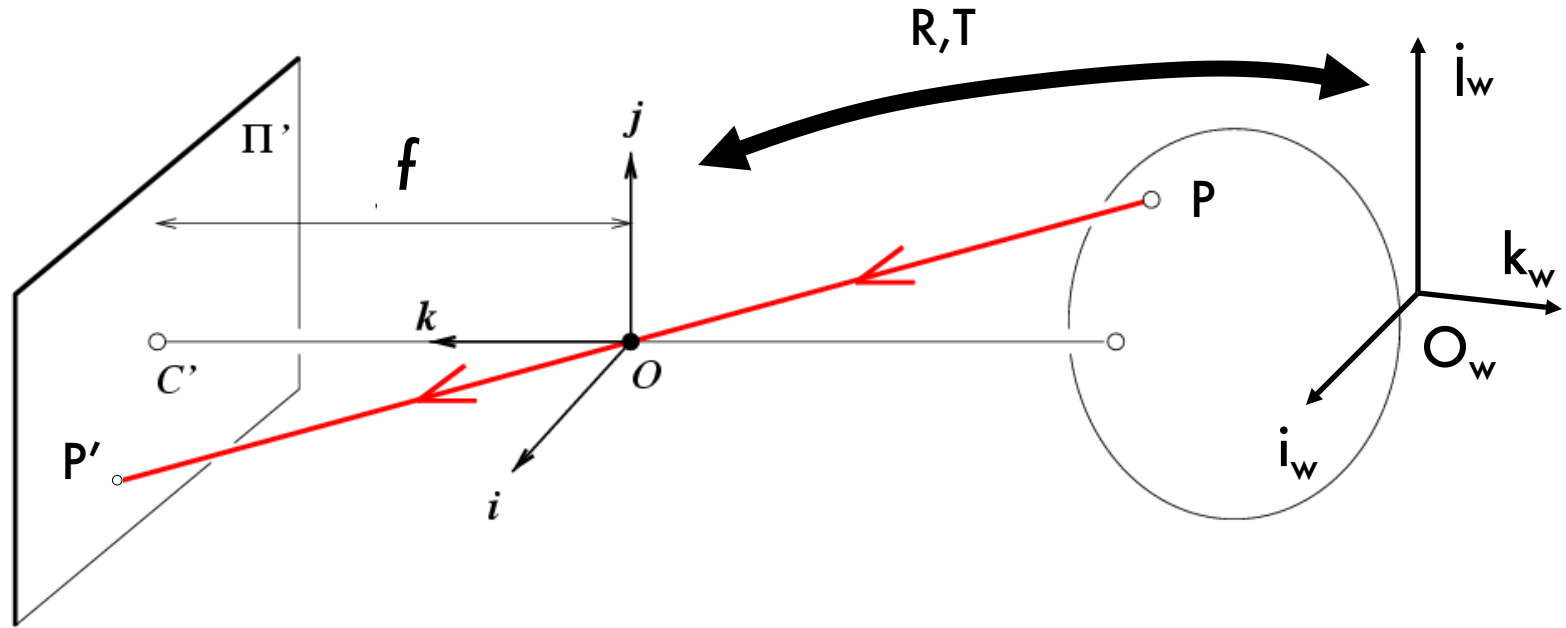
Projective camera



$$P'_{3 \times 1} = M P_w = K_{3 \times 3} \begin{bmatrix} R & T \end{bmatrix}_{3 \times 4} P_w_{4 \times 1} \quad M = \begin{bmatrix} \mathbf{m}_1 \\ \mathbf{m}_2 \\ \mathbf{m}_3 \end{bmatrix}$$

$$= \begin{bmatrix} \mathbf{m}_1 \\ \mathbf{m}_2 \\ \mathbf{m}_3 \end{bmatrix} P_w = \begin{bmatrix} \mathbf{m}_1 P_w \\ \mathbf{m}_2 P_w \\ \mathbf{m}_3 P_w \end{bmatrix} \quad \xrightarrow{\mathbf{E}} P'_E = \left(\frac{\mathbf{m}_1 P_w}{\mathbf{m}_3 P_w}, \frac{\mathbf{m}_2 P_w}{\mathbf{m}_3 P_w} \right)$$

Exercise!



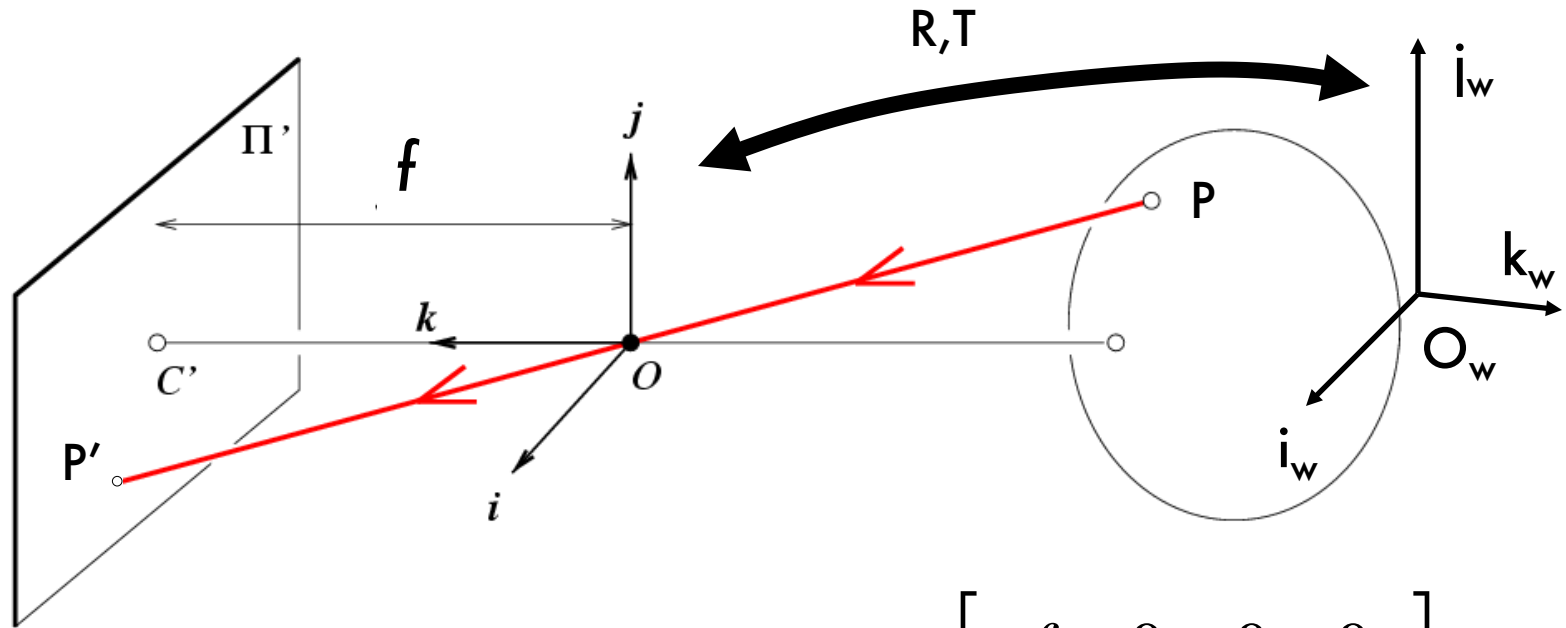
$$M = K \begin{bmatrix} R & T \end{bmatrix}$$

Suppose we have no rotation or translation
Zero skew, square pixels, no distortion, no off-set

$$\Rightarrow P'_E = \left(\frac{\mathbf{m}_1 P_w}{\mathbf{m}_3 P_w}, \frac{\mathbf{m}_2 P_w}{\mathbf{m}_3 P_w} \right)$$

$$P_w = \begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix}$$

Exercise!



$$M = K \begin{bmatrix} R & T \end{bmatrix} = K \begin{bmatrix} I & 0 \end{bmatrix} = \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$\Rightarrow P'_E = \left(\frac{\mathbf{m}_1 P_w}{\mathbf{m}_3 P_w}, \frac{\mathbf{m}_2 P_w}{\mathbf{m}_3 P_w} \right) = \left(f \frac{x_w}{z_w}, f \frac{y_w}{z_w} \right) \quad P_w = \begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix}$$

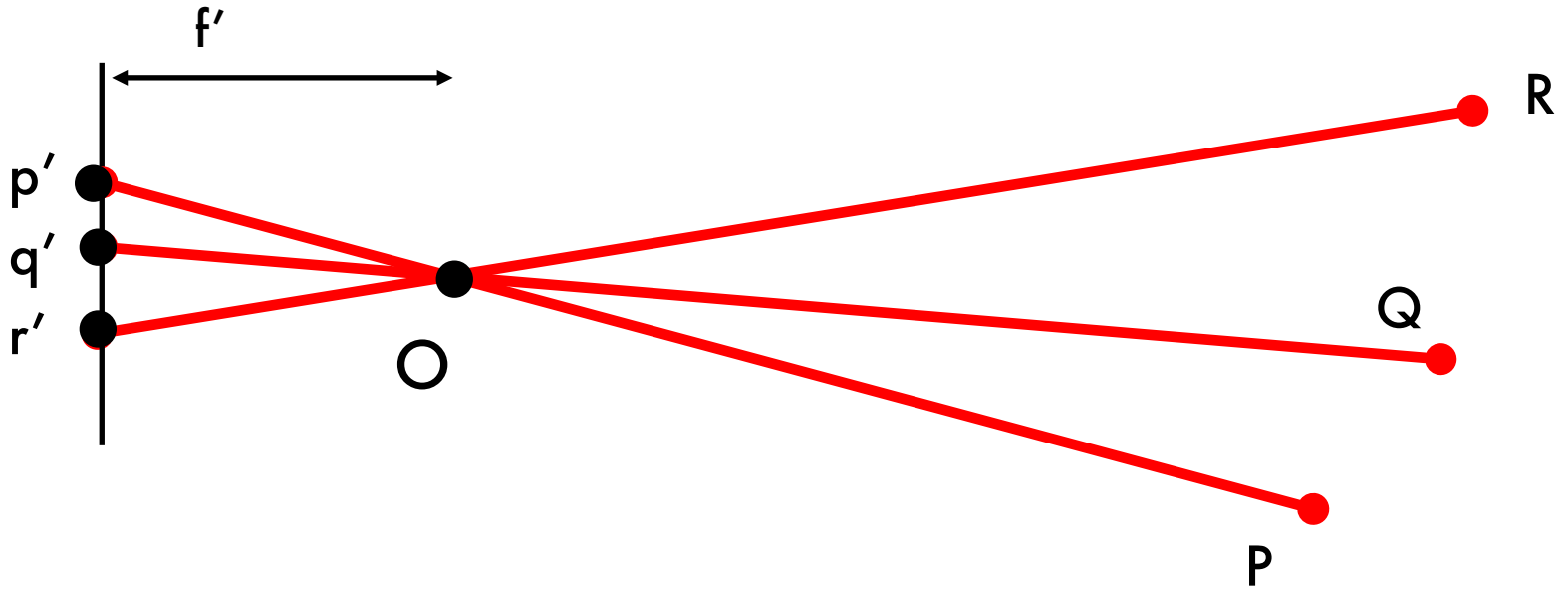
Canonical Projective Transformation

$$P' = \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}}_M \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

$$P' = M P$$
$$\mathfrak{R}^4 \xrightarrow{H} \mathfrak{R}^3$$

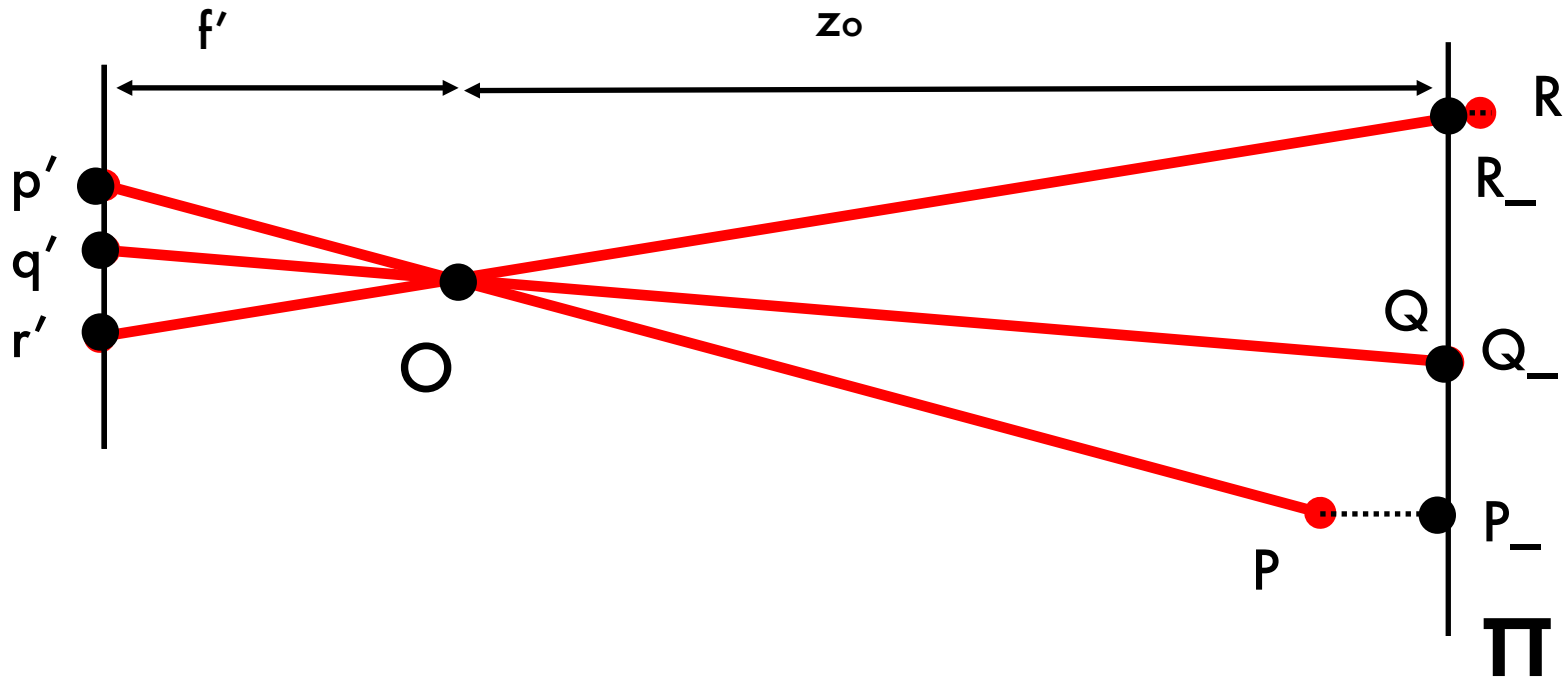
$$P'_i = \begin{bmatrix} \frac{x}{z} \\ \frac{y}{z} \end{bmatrix}$$

Projective camera

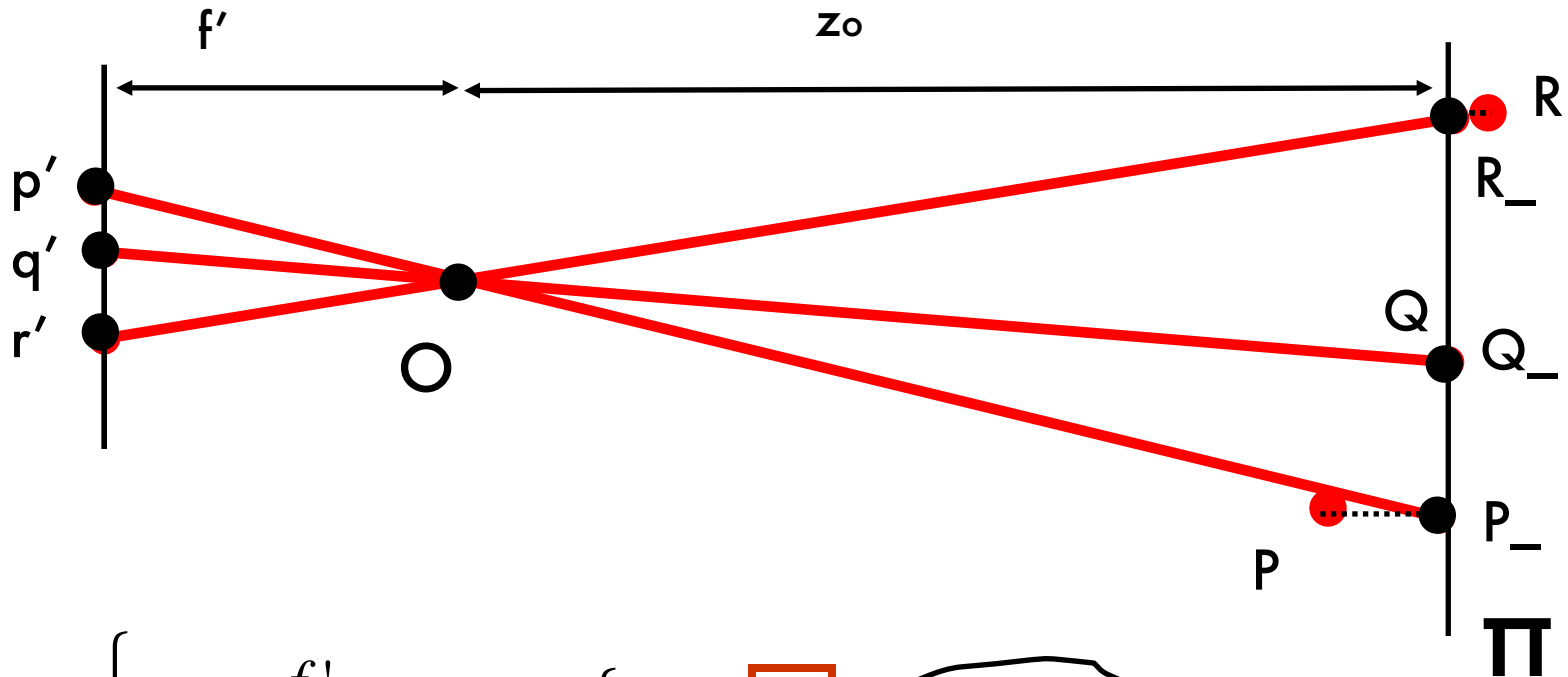


Weak perspective projection

When the relative scene depth is small compared to its distance from the camera



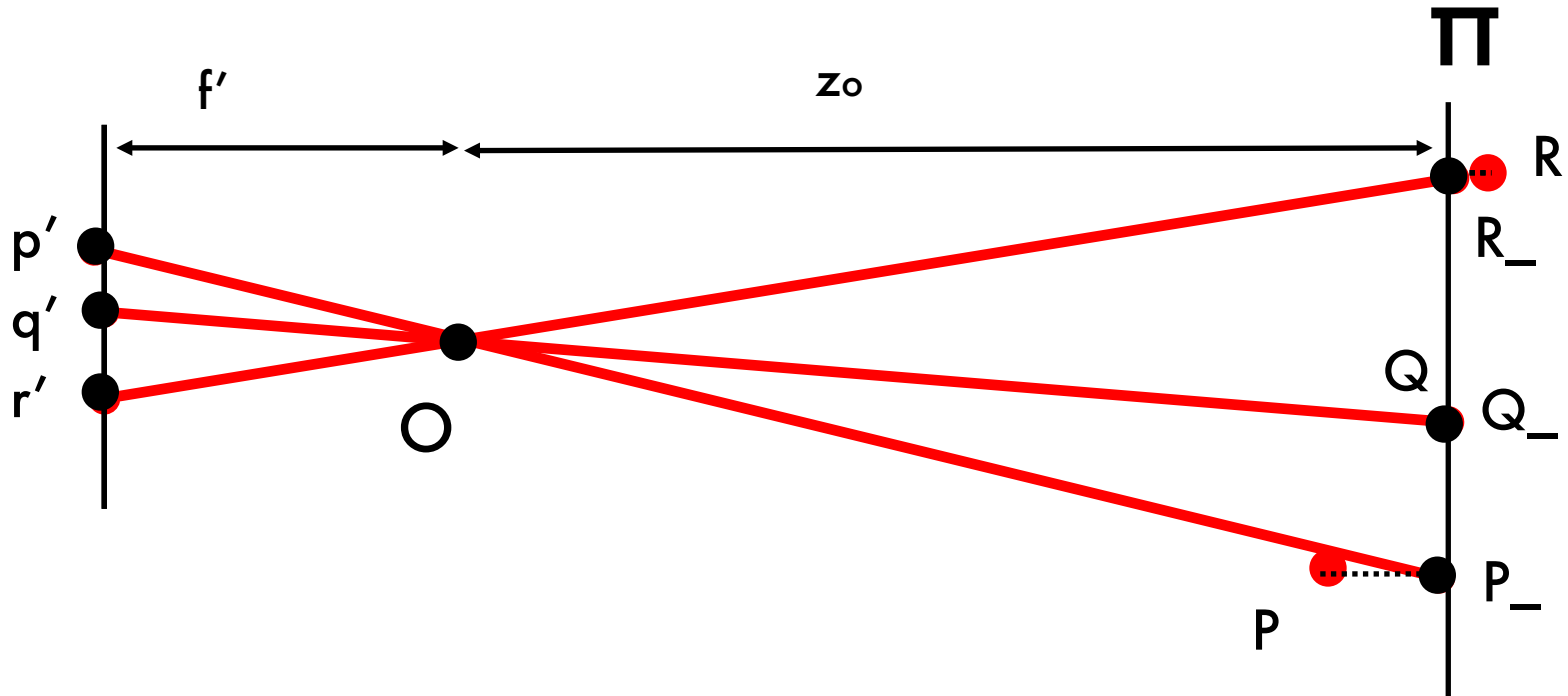
Weak perspective projection



$$\left\{ \begin{array}{l} x' = \frac{f'}{z} x \\ y' = \frac{f'}{z} y \end{array} \right. \rightarrow \left\{ \begin{array}{l} x' = \frac{f'}{z_0} x \\ y' = \frac{f'}{z_0} y \end{array} \right.$$

Magnification m

Weak perspective projection



Projective (perspective)

Weak perspective

$$M = K \begin{bmatrix} R & T \end{bmatrix} = \begin{bmatrix} \mathbf{A} & \mathbf{b} \\ \mathbf{v} & \mathbf{1} \end{bmatrix} \rightarrow M = \begin{bmatrix} \mathbf{A} & \mathbf{b} \\ \mathbf{0} & \mathbf{1} \end{bmatrix}$$

$$P' = M P_w = \begin{bmatrix} \mathbf{m}_1 \\ \mathbf{m}_2 \\ \mathbf{m}_3 \end{bmatrix} P_w = \begin{bmatrix} \mathbf{m}_1 P_w \\ \mathbf{m}_2 P_w \\ \mathbf{m}_3 P_w \end{bmatrix}$$

$$M = \begin{bmatrix} \mathbf{A} & \mathbf{b} \\ \mathbf{v} & \mathbf{1} \end{bmatrix} = \begin{bmatrix} \mathbf{m}_1 \\ \mathbf{m}_2 \\ \mathbf{m}_3 \end{bmatrix}$$

$$\mathbf{E} \rightarrow \left(\frac{\mathbf{m}_1 P_w}{\mathbf{m}_3 P_w}, \frac{\mathbf{m}_2 P_w}{\mathbf{m}_3 P_w} \right)$$

Perspective

$$P' = M P_w = \begin{bmatrix} \mathbf{m}_1 \\ \mathbf{m}_2 \\ \mathbf{m}_3 \end{bmatrix} P_w = \begin{bmatrix} \mathbf{m}_1 P_w \\ \mathbf{m}_2 P_w \\ 1 \end{bmatrix}$$

$$M = \begin{bmatrix} \mathbf{A} & \mathbf{b} \\ \mathbf{0} & \mathbf{1} \end{bmatrix} = \begin{bmatrix} \mathbf{m}_1 \\ \mathbf{m}_2 \\ \mathbf{m}_3 \end{bmatrix} = \begin{bmatrix} \mathbf{m}_1 \\ \mathbf{m}_2 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

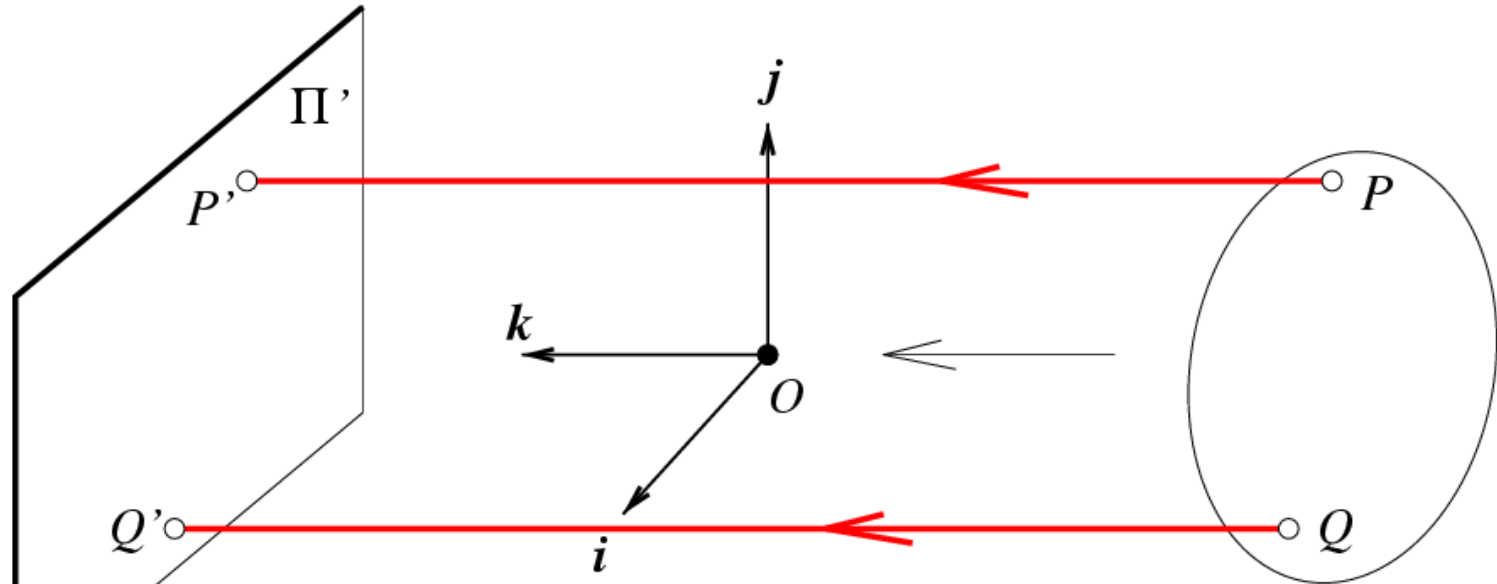
$$\mathbf{E} \rightarrow (\mathbf{m}_1 P_w, \mathbf{m}_2 P_w)$$

↑ ↑
magnification

Weak perspective

Orthographic (affine) projection

Distance from center of projection to image plane is infinite



$$\left\{ \begin{array}{l} x' = \frac{f'}{z} x \\ y' = \frac{f'}{z} y \end{array} \right. \rightarrow \left\{ \begin{array}{l} x' = x \\ y' = y \end{array} \right.$$

Orthographic Projection

Suppose $d \rightarrow \infty$ in perspective projection model:

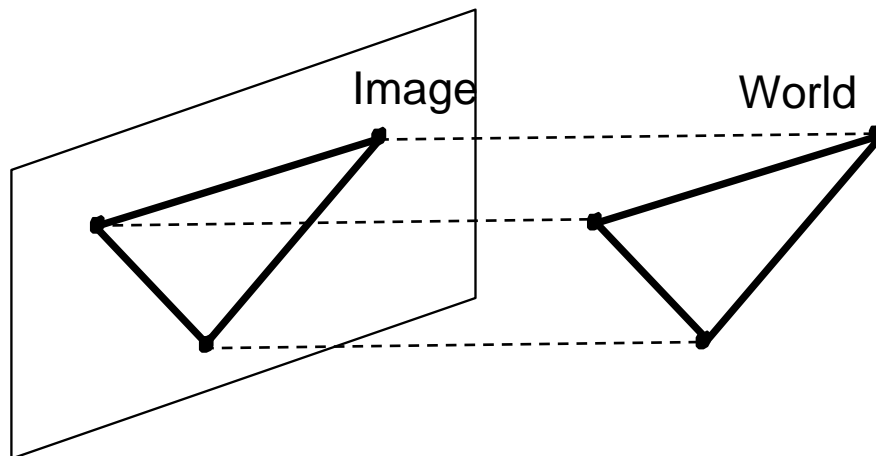
$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & -1/d & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} = \begin{bmatrix} x \\ y \\ -z/d \end{bmatrix} \Rightarrow \left(-d\frac{x}{z}, -d\frac{y}{z}\right)$$

Then, we have $z \rightarrow -\infty$ so that $-d/z \rightarrow 1$

Therefore: $(x, y, z) \rightarrow (x, y)$

This is called orthographic or “parallel projection

Good approximation for telephoto optics



Pros and Cons of These Models

- Weak perspective results in much simpler math.
 - Accurate when object is small and distant.
 - Most useful for recognition.
- Pinhole perspective is much more accurate for modeling the 3D-to-2D mapping.
 - Used in structure from motion or SLAM.

Lecture 3

Camera Calibration



- Recap of camera models
- Camera calibration problem
- Camera calibration with radial distortion
- Example

Reading: [FP] Chapter 1 "Geometric Camera Calibration"
[HZ] Chapter 7 "Computation of Camera Matrix P"

Some slides in this lecture are courtesy to Profs. J. Ponce, F-F Li

Why is this important?

Estimate camera parameters such pose or focal length from images!



Projective camera

$$P' = M P_w = \boxed{K} \boxed{[R \quad T]} P_w$$

Internal parameters

External parameters

$$M = \begin{pmatrix} \alpha \mathbf{r}_1^T - \alpha \cot \theta \mathbf{r}_2^T + u_0 \mathbf{r}_3^T & \alpha t_x - \alpha \cot \theta t_y + u_0 t_z \\ \frac{\beta}{\sin \theta} \mathbf{r}_2^T + v_0 \mathbf{r}_3^T & \frac{\beta}{\sin \theta} t_y + v_0 t_z \\ \mathbf{r}_3^T & t_z \end{pmatrix}_{3 \times 4}$$

$$K = \begin{bmatrix} \alpha & -\alpha \cot \theta & u_0 \\ 0 & \frac{\beta}{\sin \theta} & v_0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$R = \begin{bmatrix} \mathbf{r}_1^T \\ \mathbf{r}_2^T \\ \mathbf{r}_3^T \end{bmatrix}$$

$$T = \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix}$$

Goal of calibration

$$P' = M P_w = \underbrace{K}_{\text{Internal parameters}} \underbrace{[R \quad T]}_{\text{External parameters}} P_w$$

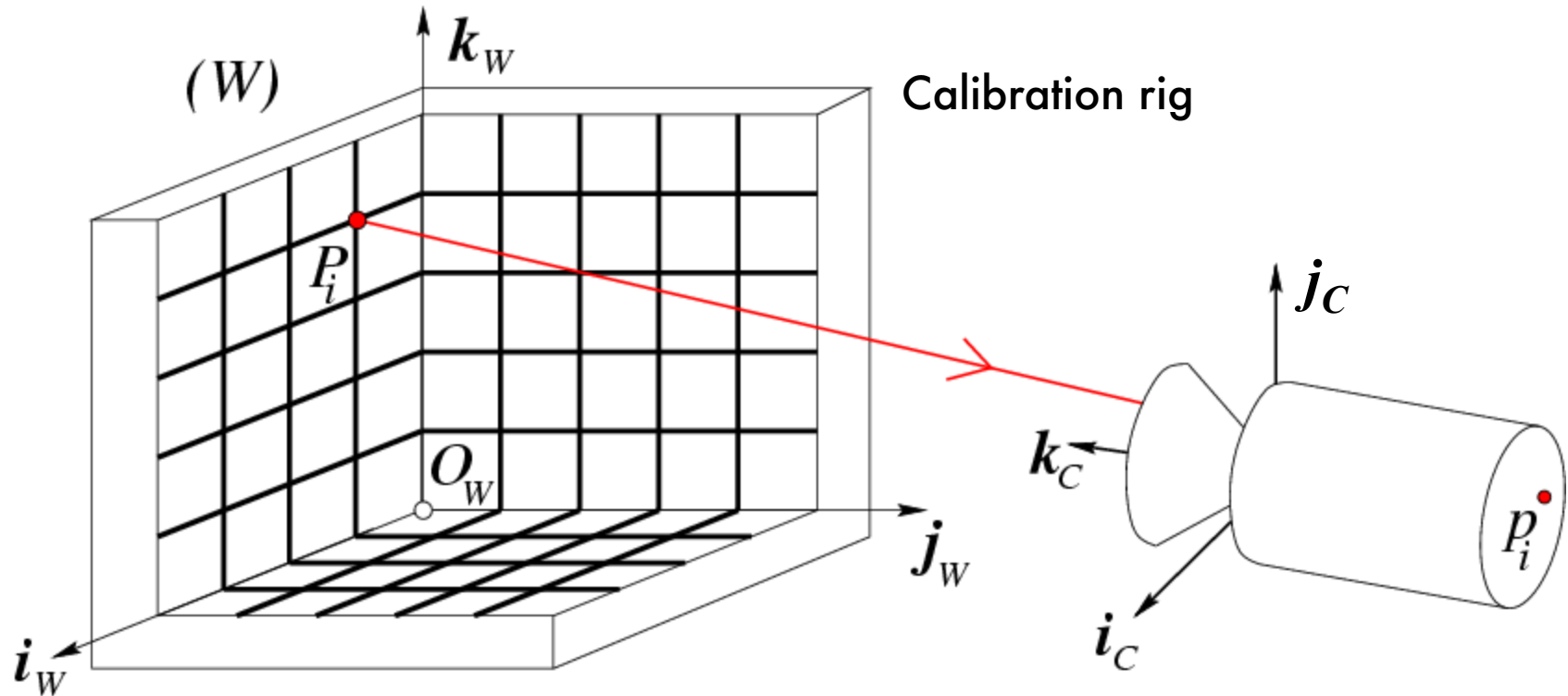
Estimate intrinsic and extrinsic parameters from 1 or multiple images

Change notation:

$$P = P_w$$

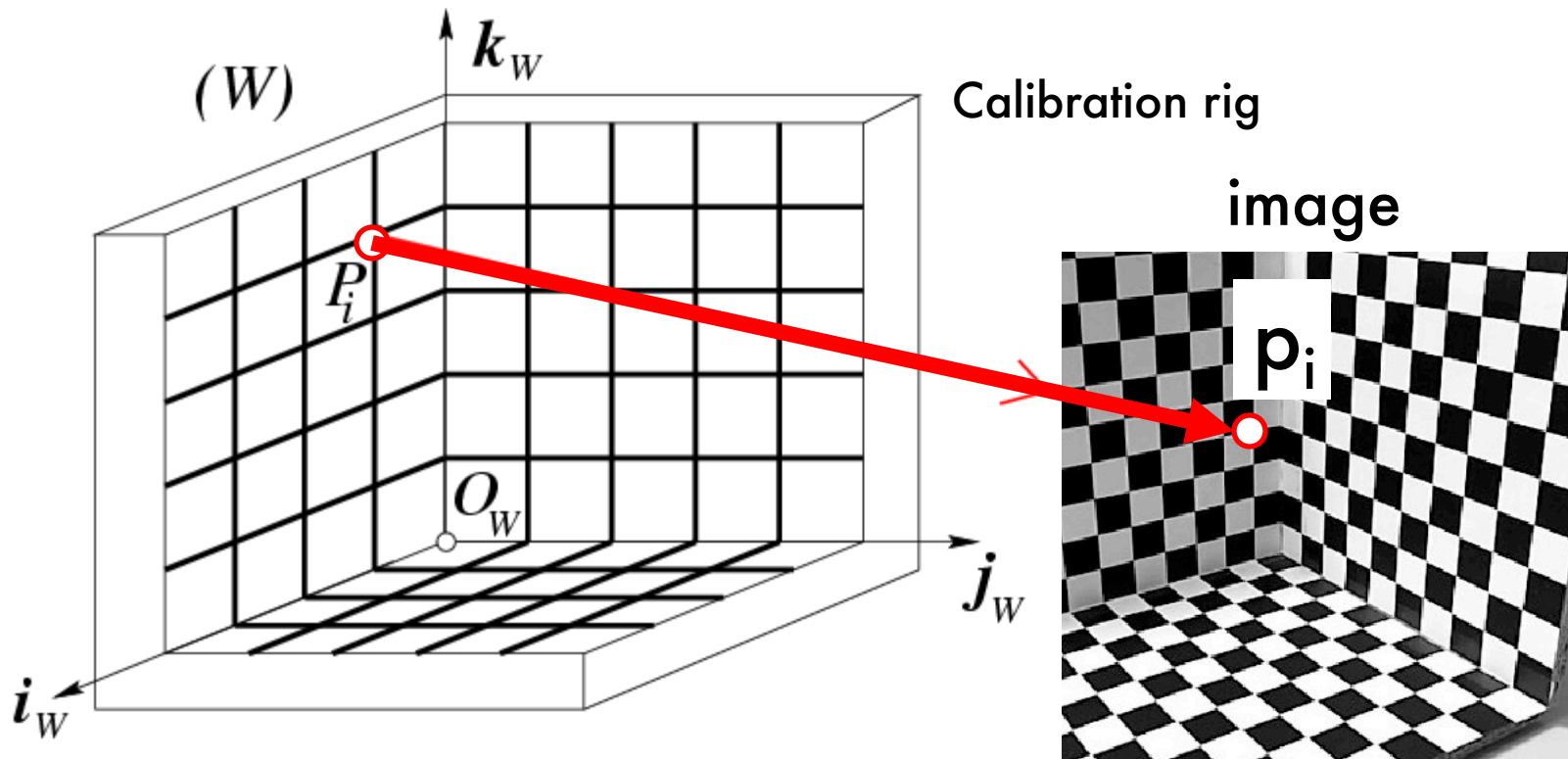
$$p = P'$$

Calibration Problem



- $P_1 \dots P_n$ with **known** positions in $[O_W, i_W, j_W, k_W]$

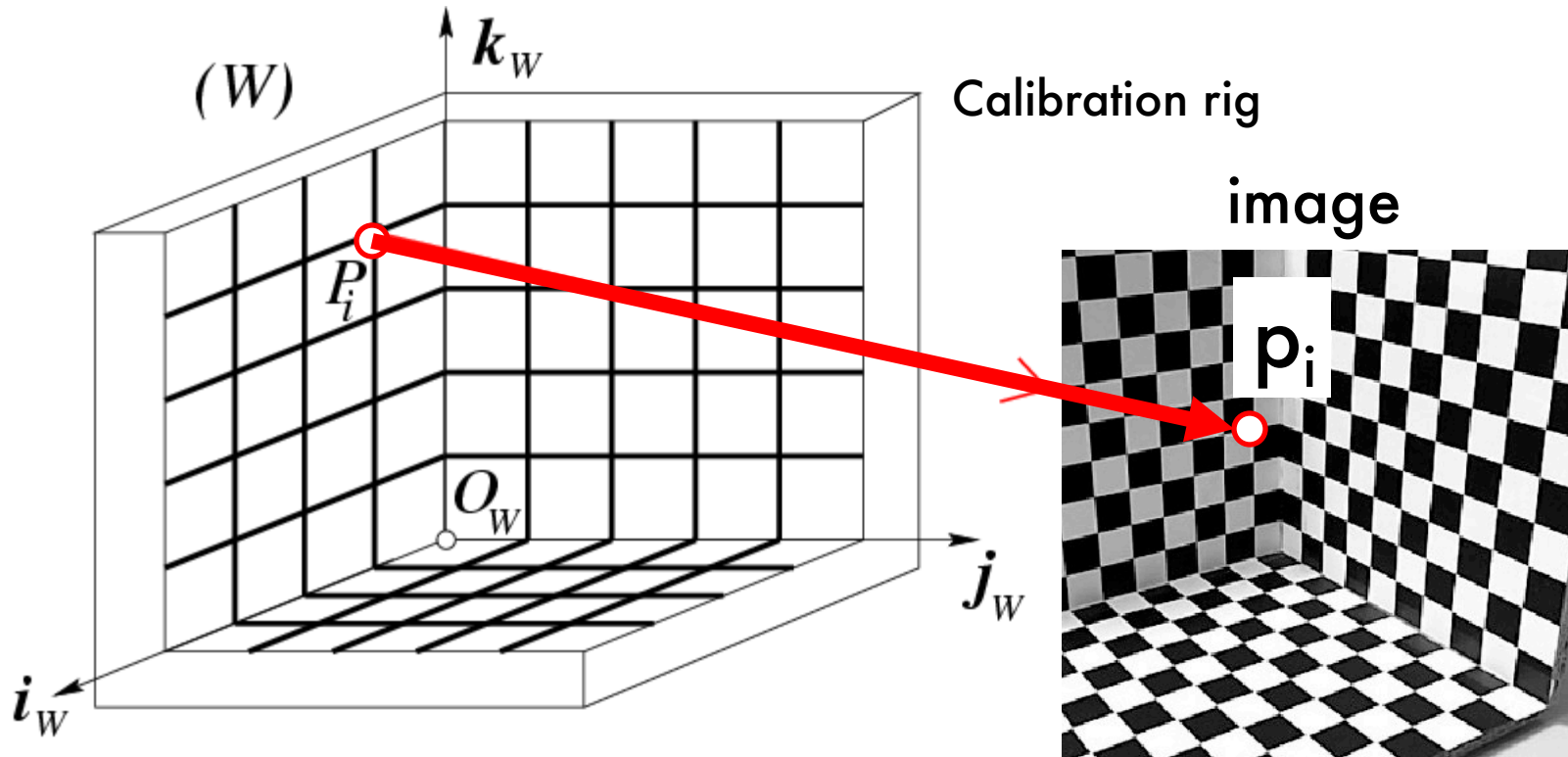
Calibration Problem



- $P_1 \dots P_n$ with **known** positions in $[O_w, i_w, j_w, k_w]$
- p_1, \dots, p_n **known** positions in the image

Goal: compute intrinsic and extrinsic parameters

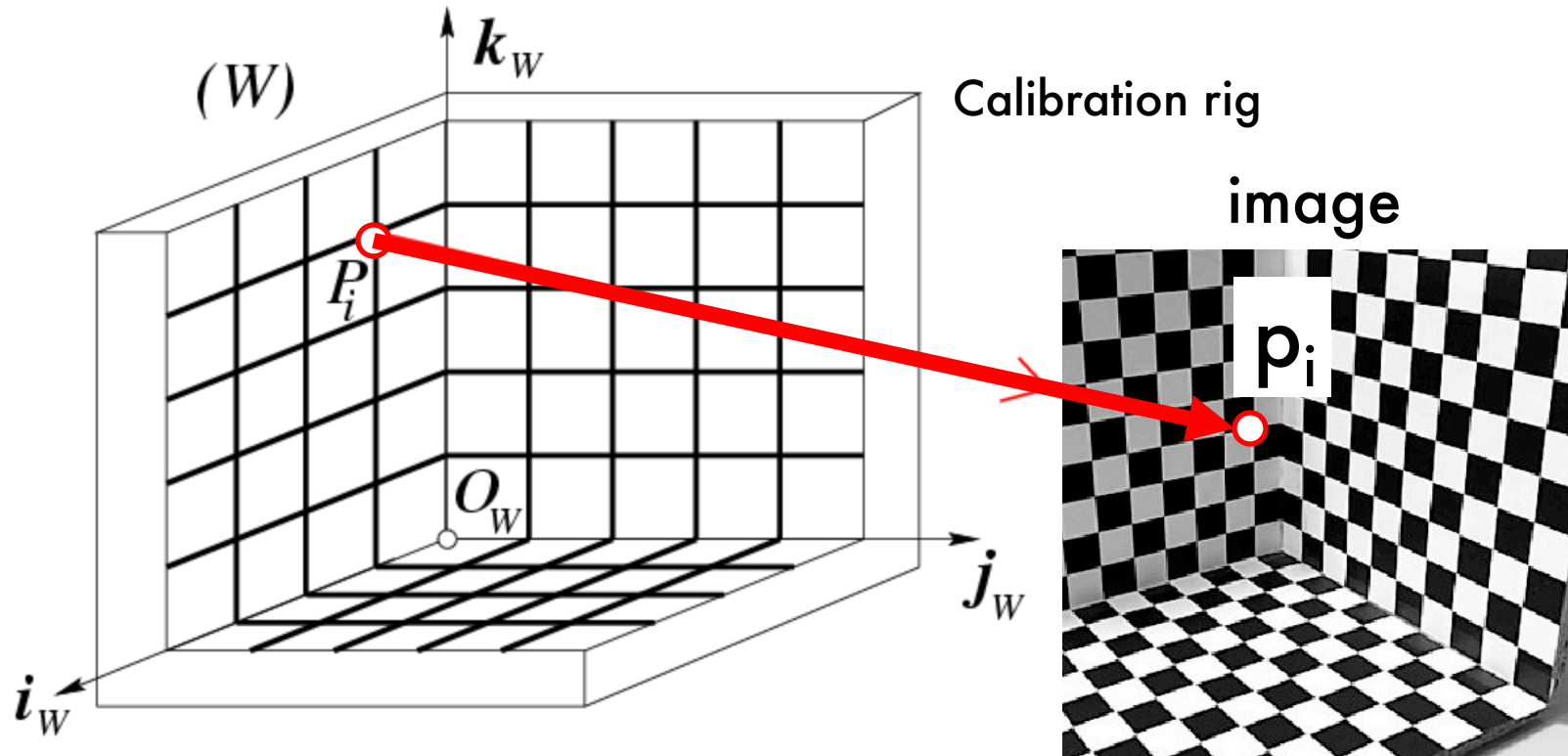
Calibration Problem



How many correspondences do we need?

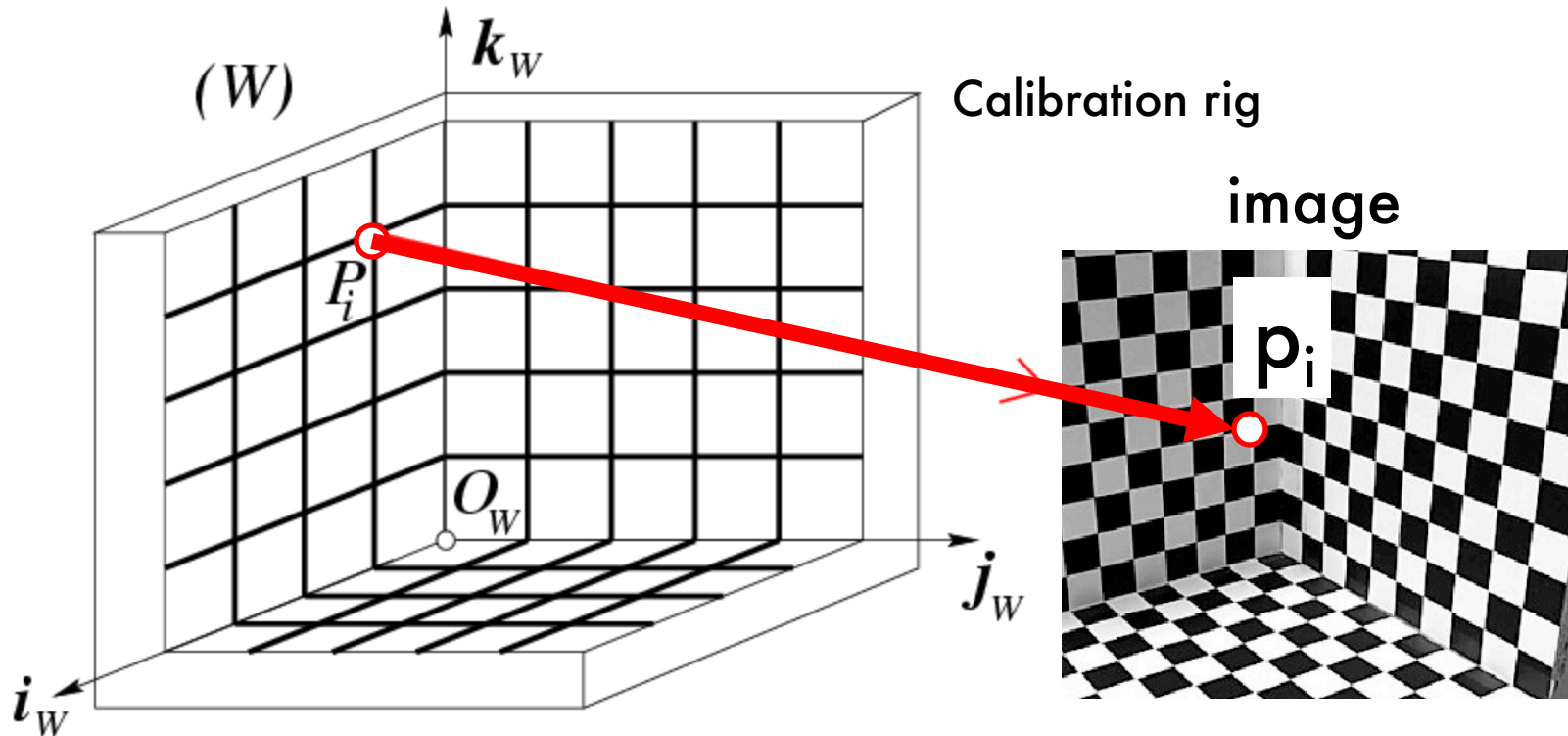
- M has 11 unknowns
- We need 11 equations
- 6 correspondences would do it

Calibration Problem



In practice, using more than 6 correspondences enables more robust results

Calibration Problem



$$\begin{aligned}
 p_i &= \begin{bmatrix} u_i \\ v_i \end{bmatrix} = \begin{bmatrix} \frac{\mathbf{m}_1 P_i}{\mathbf{m}_3 P_i} \\ \frac{\mathbf{m}_2 P_i}{\mathbf{m}_3 P_i} \end{bmatrix} = M P_i \quad \text{[Eq. 1]} \quad M = \begin{bmatrix} \mathbf{m}_1 \\ \mathbf{m}_2 \\ \mathbf{m}_3 \end{bmatrix}
 \end{aligned}$$

in pixels

Calibration Problem

$$\text{[Eq. 1]} \quad \begin{bmatrix} u_i \\ v_i \end{bmatrix} = \begin{bmatrix} \frac{\mathbf{m}_1 P_i}{\mathbf{m}_3 P_i} \\ \frac{\mathbf{m}_2 P_i}{\mathbf{m}_3 P_i} \end{bmatrix}$$

$$u_i = \frac{\mathbf{m}_1 P_i}{\mathbf{m}_3 P_i} \rightarrow u_i(\mathbf{m}_3 P_i) = \mathbf{m}_1 P_i \rightarrow u_i(\mathbf{m}_3 P_i) - \mathbf{m}_1 P_i = 0$$

$$v_i = \frac{\mathbf{m}_2 P_i}{\mathbf{m}_3 P_i} \rightarrow v_i(\mathbf{m}_3 P_i) = \mathbf{m}_2 P_i \rightarrow v_i(\mathbf{m}_3 P_i) - \mathbf{m}_2 P_i = 0$$

[Eqs. 2]

Calibration Problem

$$\left\{ \begin{array}{l} u_1(\mathbf{m}_3 P_1) - \mathbf{m}_1 P_1 = 0 \\ v_1(\mathbf{m}_3 P_1) - \mathbf{m}_2 P_1 = 0 \\ \vdots \\ u_i(\mathbf{m}_3 P_i) - \mathbf{m}_1 P_i = 0 \\ v_i(\mathbf{m}_3 P_i) - \mathbf{m}_2 P_i = 0 \\ \vdots \\ u_n(\mathbf{m}_3 P_n) - \mathbf{m}_1 P_n = 0 \\ v_n(\mathbf{m}_3 P_n) - \mathbf{m}_2 P_n = 0 \end{array} \right. \quad [\text{Eqs. 3}]$$

Block Matrix Multiplication

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_{11} & \mathbf{A}_{12} \\ \mathbf{A}_{21} & \mathbf{A}_{22} \end{bmatrix} \quad \mathbf{B} = \begin{bmatrix} \mathbf{B}_{11} & \mathbf{B}_{12} \\ \mathbf{B}_{21} & \mathbf{B}_{22} \end{bmatrix}$$

What is \mathbf{AB} ?

$$\mathbf{AB} = \begin{bmatrix} \mathbf{A}_{11}\mathbf{B}_{11} + \mathbf{A}_{12}\mathbf{B}_{21} & \mathbf{A}_{11}\mathbf{B}_{12} + \mathbf{A}_{12}\mathbf{B}_{22} \\ \mathbf{A}_{21}\mathbf{B}_{11} + \mathbf{A}_{22}\mathbf{B}_{21} & \mathbf{A}_{21}\mathbf{B}_{12} + \mathbf{A}_{22}\mathbf{B}_{22} \end{bmatrix}$$

Calibration Problem

$$\left\{ \begin{array}{l} -u_1(\mathbf{m}_3 P_1) + \mathbf{m}_1 P_1 = 0 \\ -v_1(\mathbf{m}_3 P_1) + \mathbf{m}_2 P_1 = 0 \\ \vdots \\ -u_n(\mathbf{m}_3 P_n) + \mathbf{m}_1 P_n = 0 \\ -v_n(\mathbf{m}_3 P_n) + \mathbf{m}_2 P_n = 0 \end{array} \right.$$

\longrightarrow

Homogenous linear system

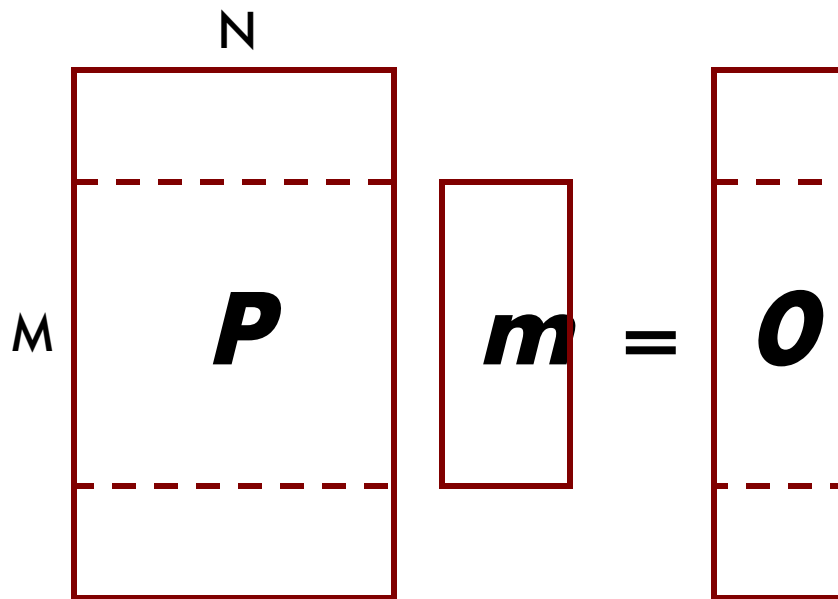
$$\mathbf{P} \stackrel{\text{def}}{=} \begin{pmatrix} \mathbf{P}_1^T & \mathbf{0}^T & -u_1 \mathbf{P}_1^T \\ \mathbf{0}^T & \mathbf{P}_1^T & -v_1 \mathbf{P}_1^T \\ \vdots & \vdots & \vdots \\ \mathbf{P}_n^T & \mathbf{0}^T & -u_n \mathbf{P}_n^T \\ \mathbf{0}^T & \mathbf{P}_n^T & -v_n \mathbf{P}_n^T \end{pmatrix} \begin{matrix} 1 \times 4 \\ \\ \\ 2n \times 12 \end{matrix}$$

$$\mathbf{m} \stackrel{\text{def}}{=} \begin{pmatrix} \mathbf{m}_1^T \\ \mathbf{m}_2^T \\ \mathbf{m}_3^T \end{pmatrix} \begin{matrix} 4 \times 1 \\ \\ \\ 12 \times 1 \end{matrix}$$

Homogeneous $M \times N$ Linear Systems

M =number of equations = $2n$

N =number of unknown = 11



Rectangular system ($M > N$)

- 0 is always a solution
- To find non-zero solution

Minimize $|\mathbf{P}\mathbf{m}|^2$

under the constraint $|\mathbf{m}|^2 = 1$

Calibration Problem

$$\mathbf{P} \mathbf{m} = 0$$

- How do we solve this homogenous linear system?
- Via SVD decomposition!

Calibration Problem

$$\mathbf{P} \mathbf{m} = 0$$

SVD decomposition of \mathbf{P}

$$\mathbf{U}_{2n \times 12} \mathbf{D}_{12 \times 12} \mathbf{V}^T_{12 \times 12}$$

Last column of \mathbf{V} gives \mathbf{m}

Why? See pag 592 of HZ

$$\mathbf{m} \stackrel{\text{def}}{=} \begin{pmatrix} \mathbf{m}_1^T \\ \mathbf{m}_2^T \\ \mathbf{m}_3^T \end{pmatrix}$$

\mathbf{M}

Extracting camera parameters

$$M = \begin{pmatrix} \alpha \mathbf{r}_1^T - \alpha \cot \theta \mathbf{r}_2^T + u_0 \mathbf{r}_3^T & \alpha t_x - \alpha \cot \theta t_y + u_0 t_z \\ \frac{\beta}{\sin \theta} \mathbf{r}_2^T + v_0 \mathbf{r}_3^T & \frac{\beta}{\sin \theta} t_y + v_0 t_z \\ \mathbf{r}_3^T & t_z \end{pmatrix} \rho$$

Extracting camera parameters

See [FP],
Sec. 1.3.1

$$\frac{M}{\rho} = \begin{pmatrix} \alpha \mathbf{r}_1^T - \alpha \cot \theta \mathbf{r}_2^T + u_0 \mathbf{r}_3^T & \alpha t_x - \alpha \cot \theta t_y + u_0 t_z \\ \frac{\beta}{\sin \theta} \mathbf{r}_2^T + v_0 \mathbf{r}_3^T & \frac{\beta}{\sin \theta} t_y + v_0 t_z \\ \mathbf{r}_3^T & t_z \end{pmatrix} = \mathbf{K} \begin{bmatrix} \mathbf{R} & \mathbf{T} \end{bmatrix}$$

A

\mathbf{b}

$\mathbf{K} = \begin{bmatrix} \alpha & -\alpha \cot \theta & u_0 \\ 0 & \frac{\beta}{\sin \theta} & v_0 \\ 0 & 0 & 1 \end{bmatrix}$

Box 1

$$A = \begin{bmatrix} \mathbf{a}_1^T \\ \mathbf{a}_2^T \\ \mathbf{a}_3^T \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

Estimated values

Intrinsic

$$\rho = \frac{\pm 1}{|\mathbf{a}_3|} \quad \begin{aligned} u_0 &= \rho^2 (\mathbf{a}_1 \cdot \mathbf{a}_3) \\ v_0 &= \rho^2 (\mathbf{a}_2 \cdot \mathbf{a}_3) \end{aligned}$$

$$\cos \theta = \frac{(\mathbf{a}_1 \times \mathbf{a}_3) \cdot (\mathbf{a}_2 \times \mathbf{a}_3)}{|\mathbf{a}_1 \times \mathbf{a}_3| \cdot |\mathbf{a}_2 \times \mathbf{a}_3|}$$

Extracting camera parameters

See [FP],
Sec. 1.3.1

$$\frac{M}{\rho} = \begin{pmatrix} \alpha \mathbf{r}_1^T - \alpha \cot \theta \mathbf{r}_2^T + u_0 \mathbf{r}_3^T & \alpha t_x - \alpha \cot \theta t_y + u_0 t_z \\ \frac{\beta}{\sin \theta} \mathbf{r}_2^T + v_0 \mathbf{r}_3^T & \frac{\beta}{\sin \theta} t_y + v_0 t_z \\ \mathbf{r}_3^T & t_z \end{pmatrix} = \mathbf{K} \begin{bmatrix} \mathbf{R} & \mathbf{T} \end{bmatrix}$$

A

\mathbf{b}

$$\mathbf{K} = \begin{bmatrix} \alpha & -\alpha \cot \theta & u_0 \\ 0 & \frac{\beta}{\sin \theta} & v_0 \\ 0 & 0 & 1 \end{bmatrix}$$

Box 1

$$A = \begin{bmatrix} \mathbf{a}_1^T \\ \mathbf{a}_2^T \\ \mathbf{a}_3^T \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

Estimated values

Intrinsic

$$\alpha = \rho^2 |\mathbf{a}_1 \times \mathbf{a}_3| \sin \theta$$

$$\beta = \rho^2 |\mathbf{a}_2 \times \mathbf{a}_3| \sin \theta$$

Theorem (Faugeras, 1993)

Let $\mathcal{M} = (\mathcal{A} \ \mathbf{b})$ be a 3×4 matrix and let \mathbf{a}_i^T ($i = 1, 2, 3$) denote the rows of the matrix \mathcal{A} formed by the three leftmost columns of \mathcal{M} .

Extracting camera parameters

See [FP],
Sec. 1.3.1

$$\frac{M}{\rho} = \begin{pmatrix} \alpha \mathbf{r}_1^T - \alpha \cot \theta \mathbf{r}_2^T + u_0 \mathbf{r}_3^T & \alpha t_x - \alpha \cot \theta t_y + u_0 t_z \\ \frac{\beta}{\sin \theta} \mathbf{r}_2^T + v_0 \mathbf{r}_3^T & \frac{\beta}{\sin \theta} t_y + v_0 t_z \\ \mathbf{r}_3^T & t_z \end{pmatrix} = \mathbf{K} \begin{bmatrix} \mathbf{R} & \mathbf{T} \end{bmatrix}$$

$$\mathbf{A}$$

$$\mathbf{b}$$

$$\mathbf{K} = \begin{bmatrix} \alpha & -\alpha \cot \theta & u_0 \\ 0 & \frac{\beta}{\sin \theta} & v_0 \\ 0 & 0 & 1 \end{bmatrix}$$

Box 1

$$\mathbf{A} = \begin{bmatrix} \mathbf{a}_1^T \\ \mathbf{a}_2^T \\ \mathbf{a}_3^T \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

Estimated values

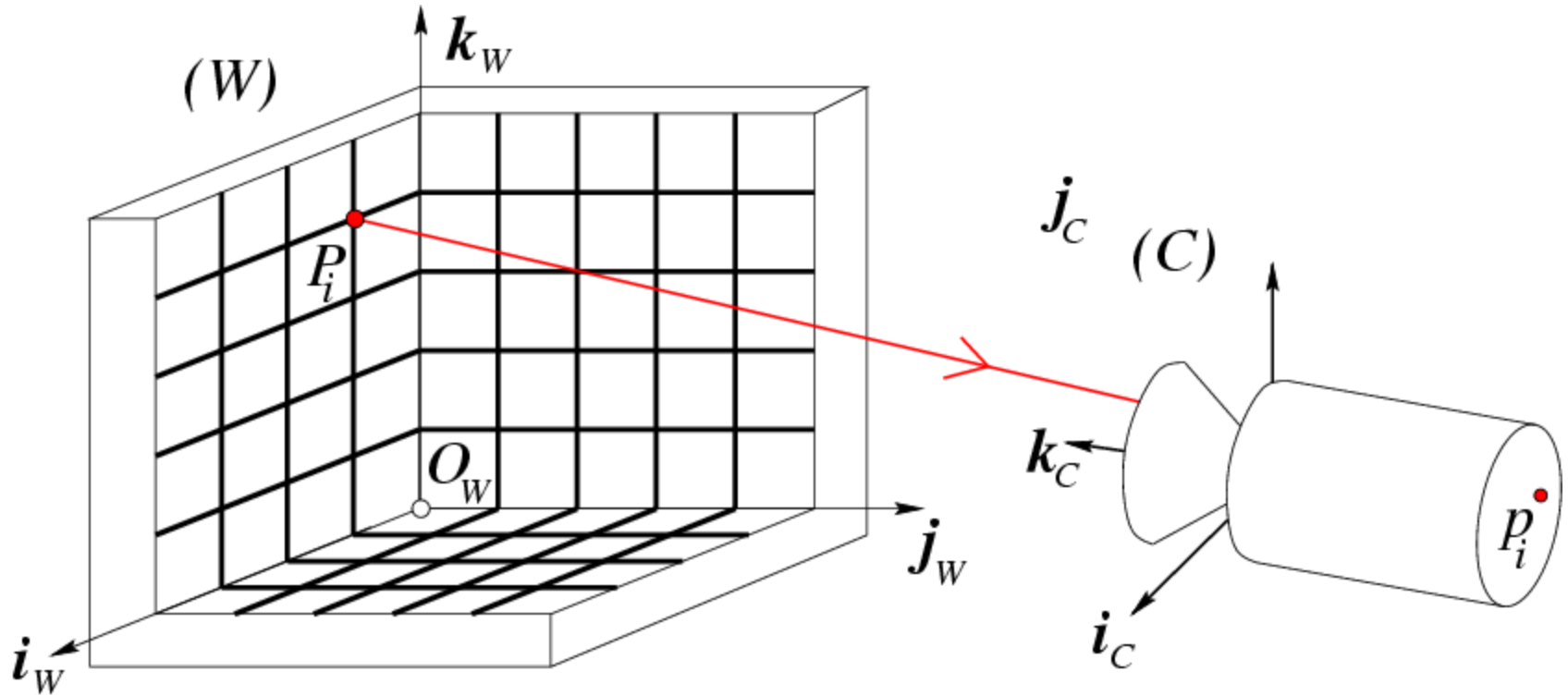
Extrinsic

$$\mathbf{r}_1 = \frac{(\mathbf{a}_2 \times \mathbf{a}_3)}{|\mathbf{a}_2 \times \mathbf{a}_3|} \quad \mathbf{r}_3 = \frac{\pm \mathbf{a}_3}{|\mathbf{a}_3|}$$

$$\mathbf{r}_2 = \mathbf{r}_3 \times \mathbf{r}_1$$

$$\mathbf{T} = \rho \mathbf{K}^{-1} \mathbf{b}$$

Degenerate cases



- P_i 's cannot lie on the same plane!
- Points cannot lie on the intersection curve of two quadric surfaces [FP] section 1.3

Lecture 3

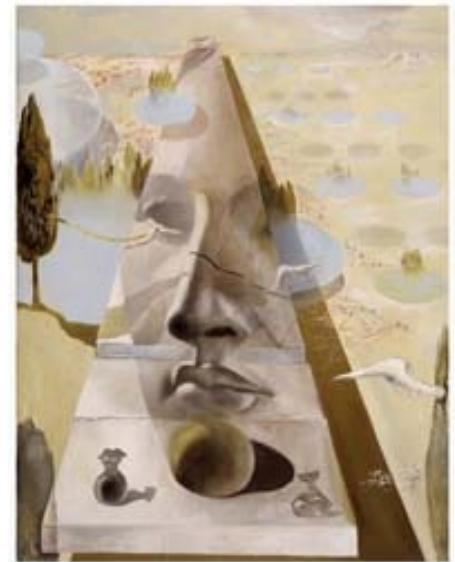
Camera Calibration

- Recap of projective cameras
- Camera calibration problem
- Camera calibration with radial distortion
- Example

Reading:

[FP] Chapter 1 "Geometric Camera Calibration"

[HZ] Chapter 7 "Computation of Camera Matrix P"



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Lecture 3

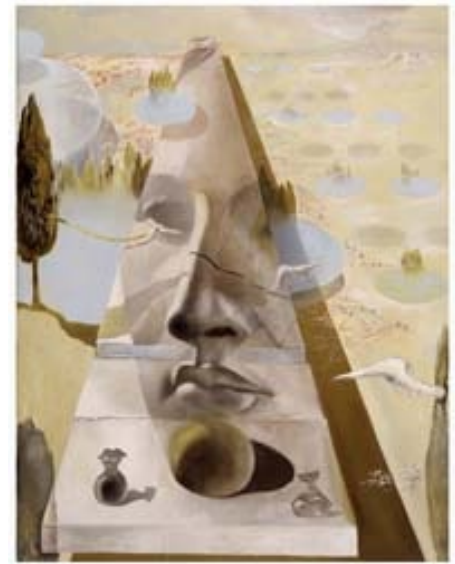
Camera Calibration

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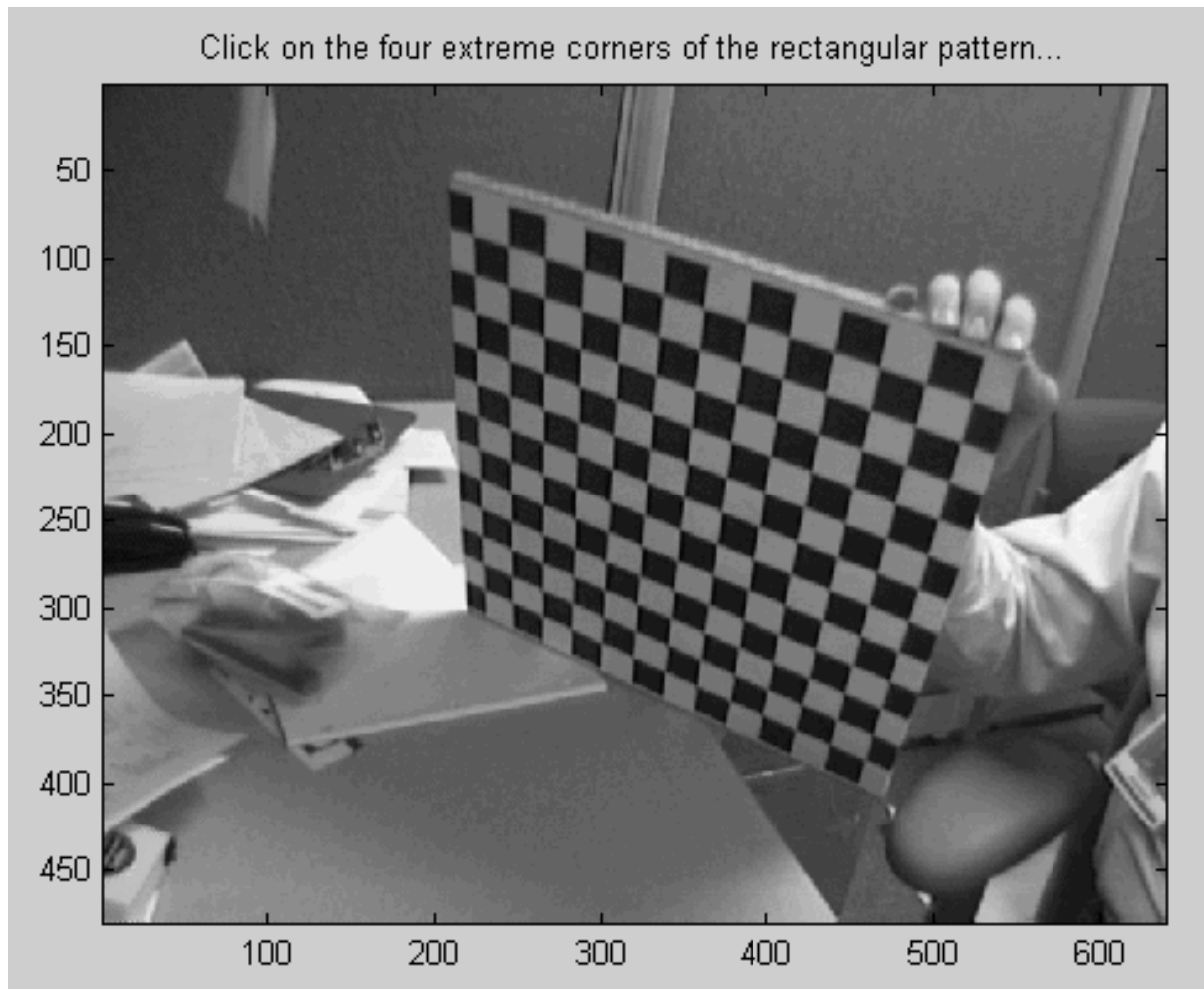
Camera Calibration video from Matlab

<https://www.mathworks.com/videos/camera-calibration-with-matlab-81233.html>

Calibration Procedure

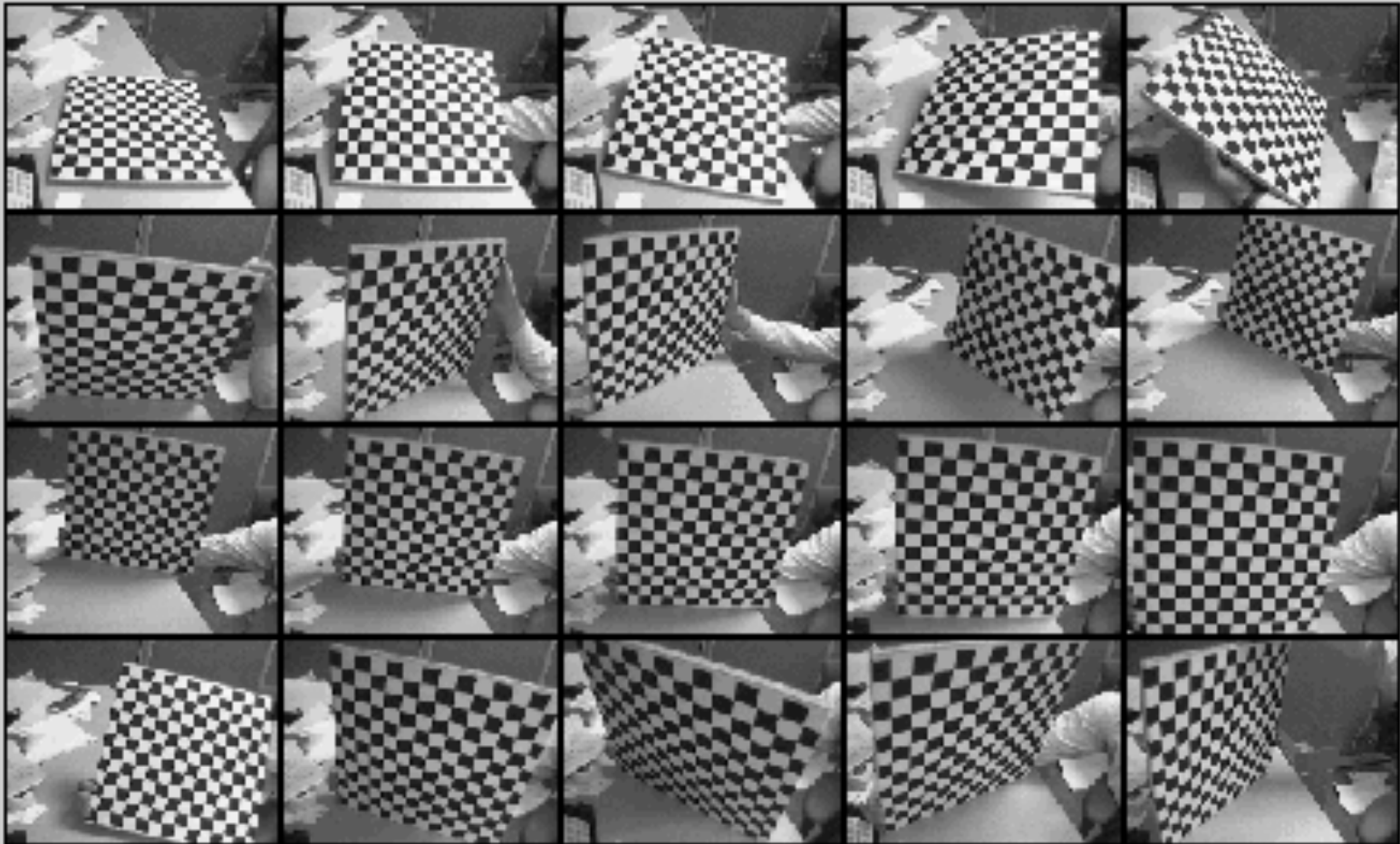
Camera Calibration Toolbox for Matlab
J. Bouguet – [1998-2000]

http://www.vision.caltech.edu/bouguetj/calib_doc/index.html#examples



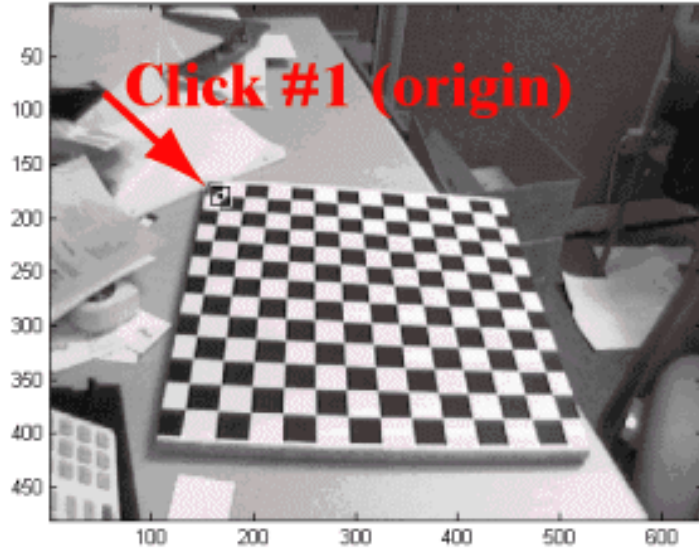
Calibration Procedure

Calibration images

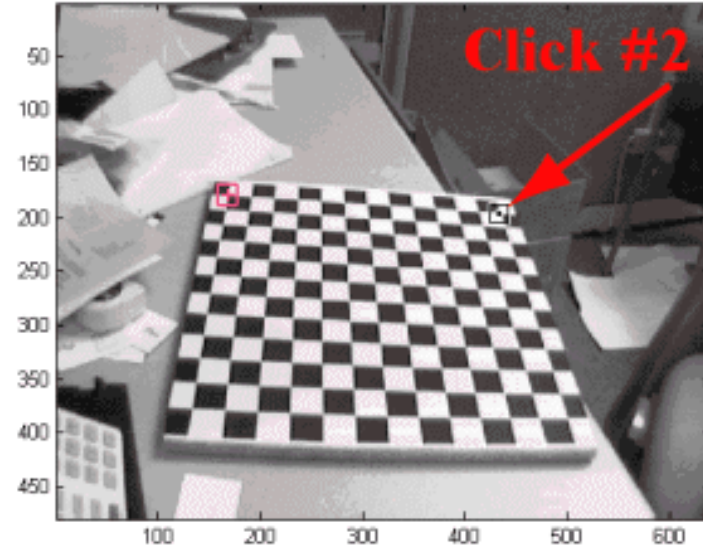


Calibration Procedure

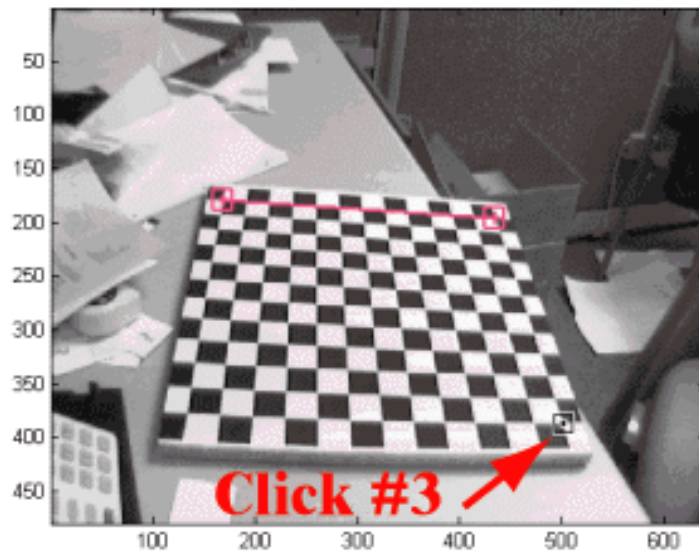
Click on the four extreme corners of the rectangular pattern (first corner = origin)... Image 1



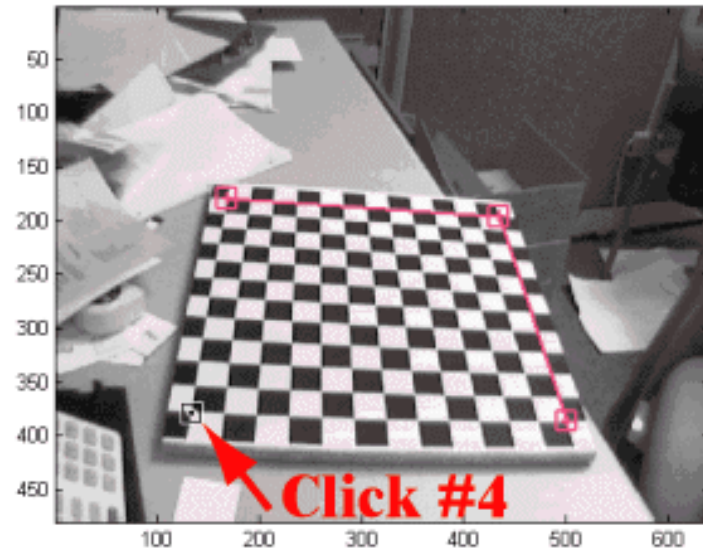
Click on the four extreme corners of the rectangular pattern (first corner = origin)... Image 1



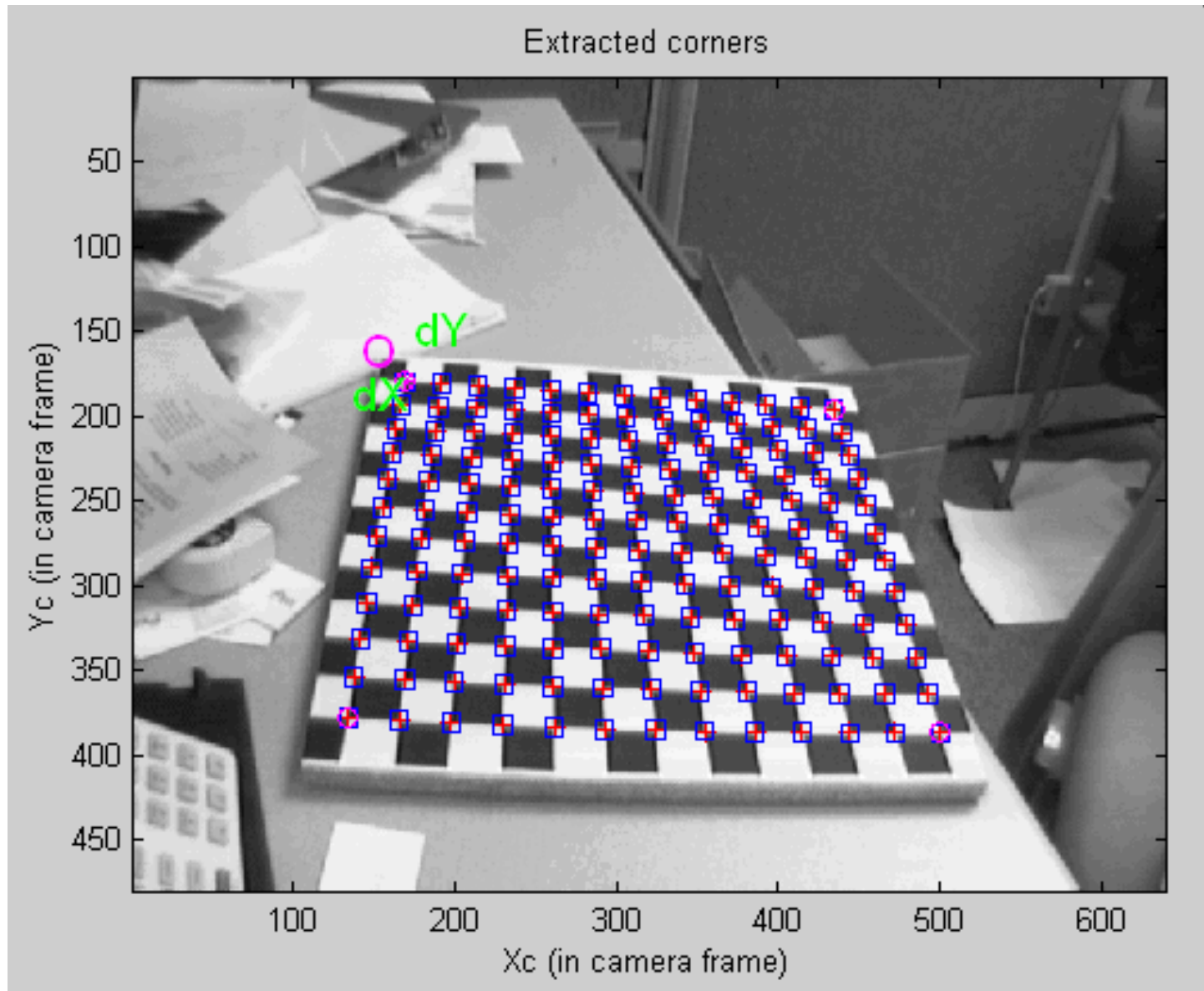
Click on the four extreme corners of the rectangular pattern (first corner = origin)... Image 1



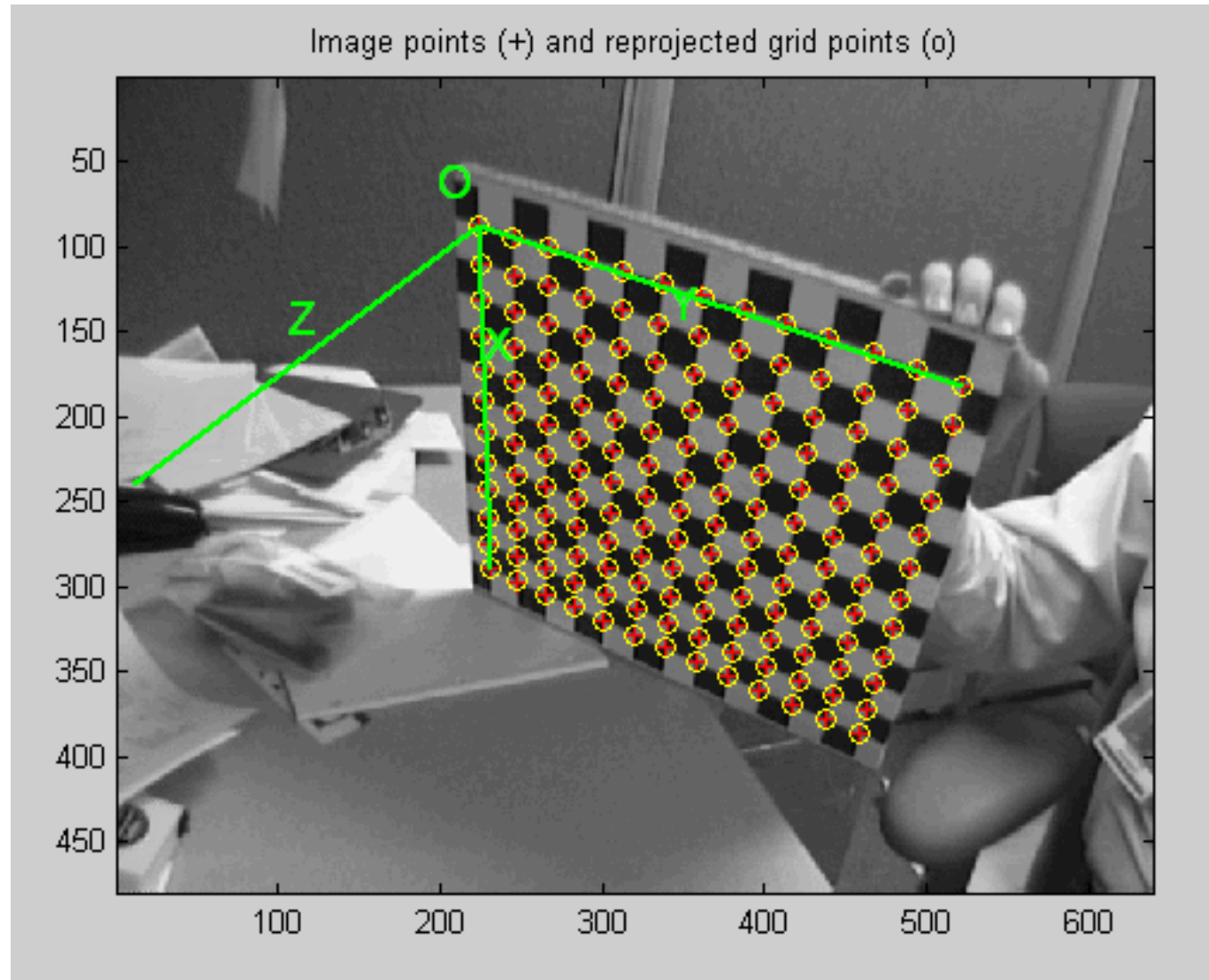
Click on the four extreme corners of the rectangular pattern (first corner = origin)... Image 1



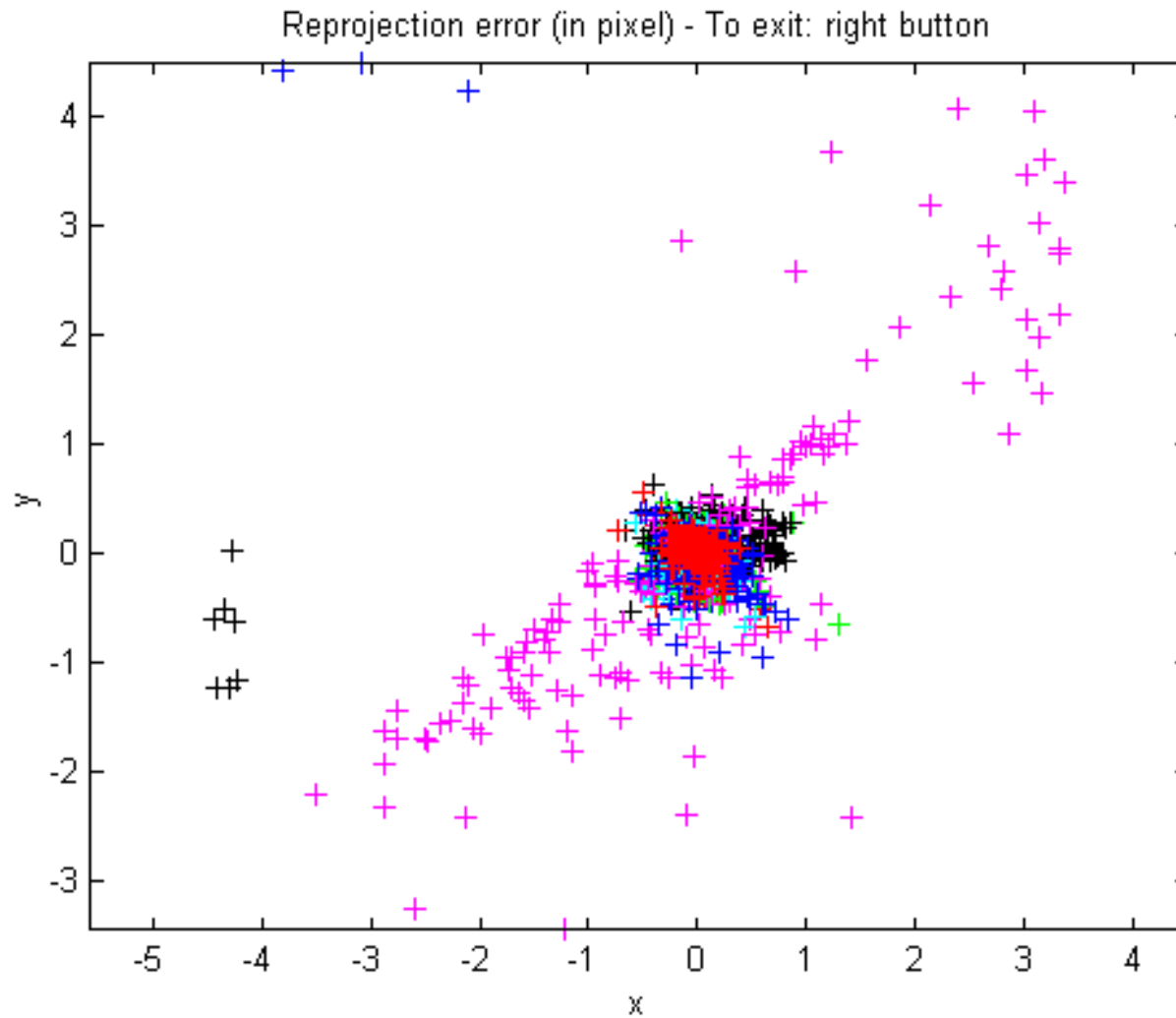
Calibration Procedure



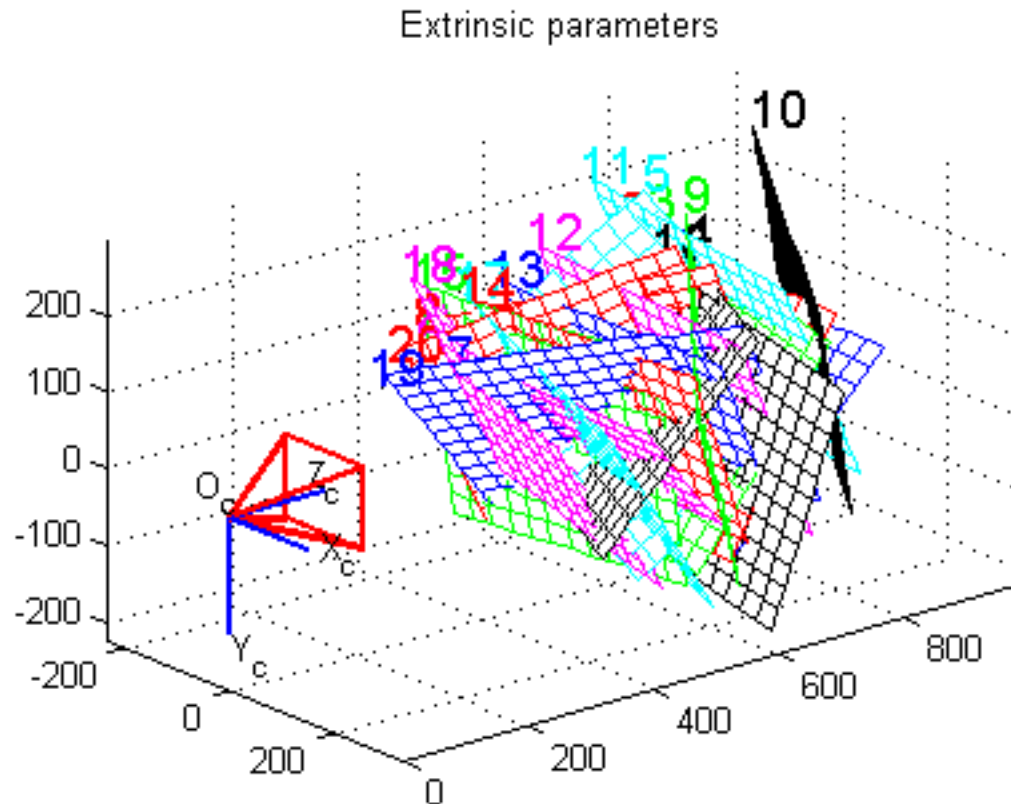
Calibration Procedure



Calibration Procedure

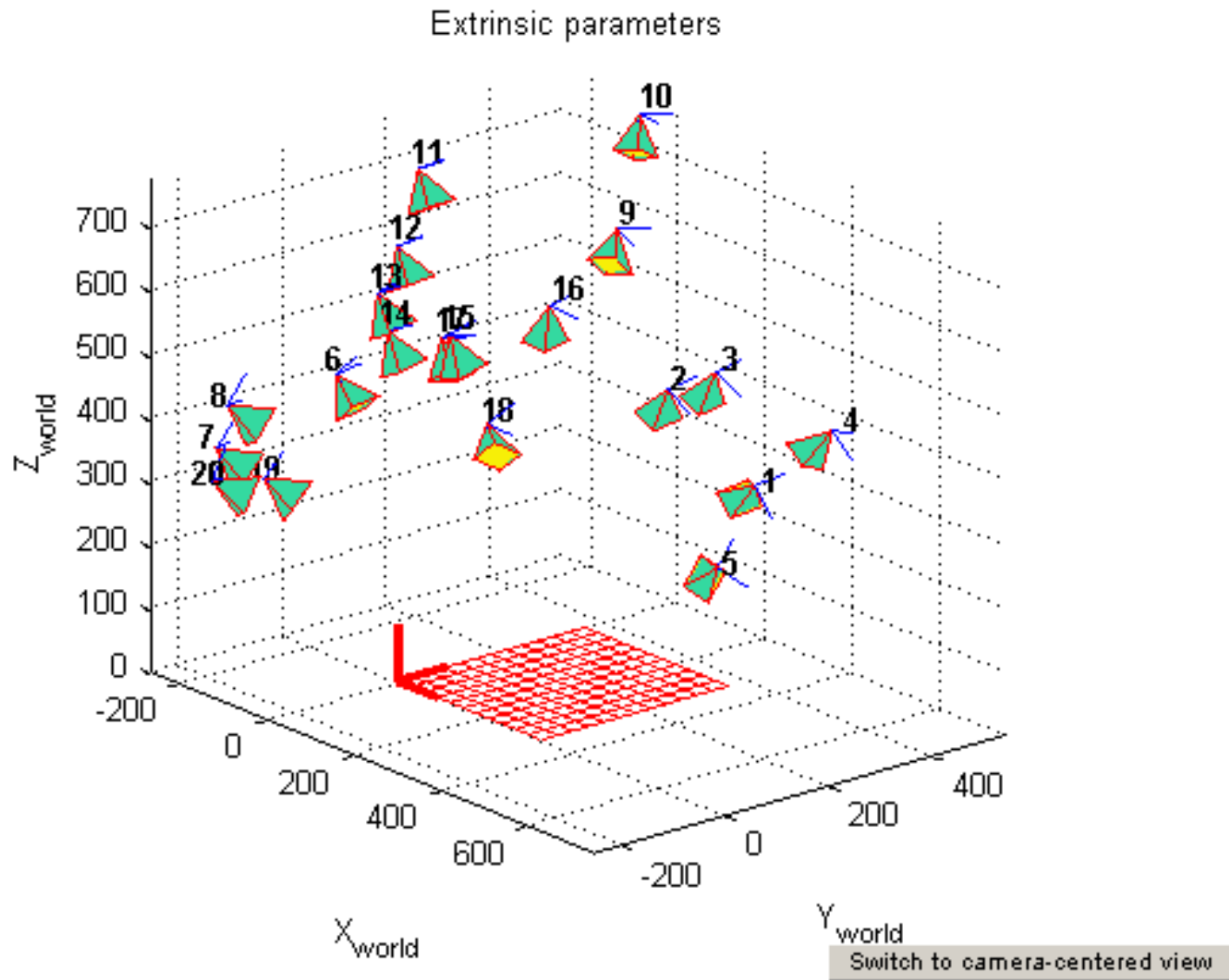


Calibration Procedure



Switch to world-centered view

Calibration Procedure



Next lecture

- **Single view reconstruction**

Eigenvalues and Eigenvectors

Eigendecomposition

$$A = S \Lambda S^{-1} = S \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \cdot & \\ & & & \lambda_N \end{bmatrix} S^{-1}$$

Eigenvectors of A are
columns of S

$$S = [\mathbf{v}_1 \quad \mathbf{v}_N]$$

Singular Value decomposition

$$A = U \Sigma V^{-1} \quad \Sigma = \begin{bmatrix} \sigma_1 & & & \\ & \sigma_2 & & \\ & & \cdot & \\ & & & \sigma_N \end{bmatrix}$$

$U, V =$ orthogonal matrix

$$\sigma_i = \sqrt{\lambda_i}$$

$\sigma =$ singular value

$\lambda =$ eigenvalue of $A^\dagger A$