

# MAEG 5720: Computer Vision in Practice

## Lecture 11: Camera Model and Calibration

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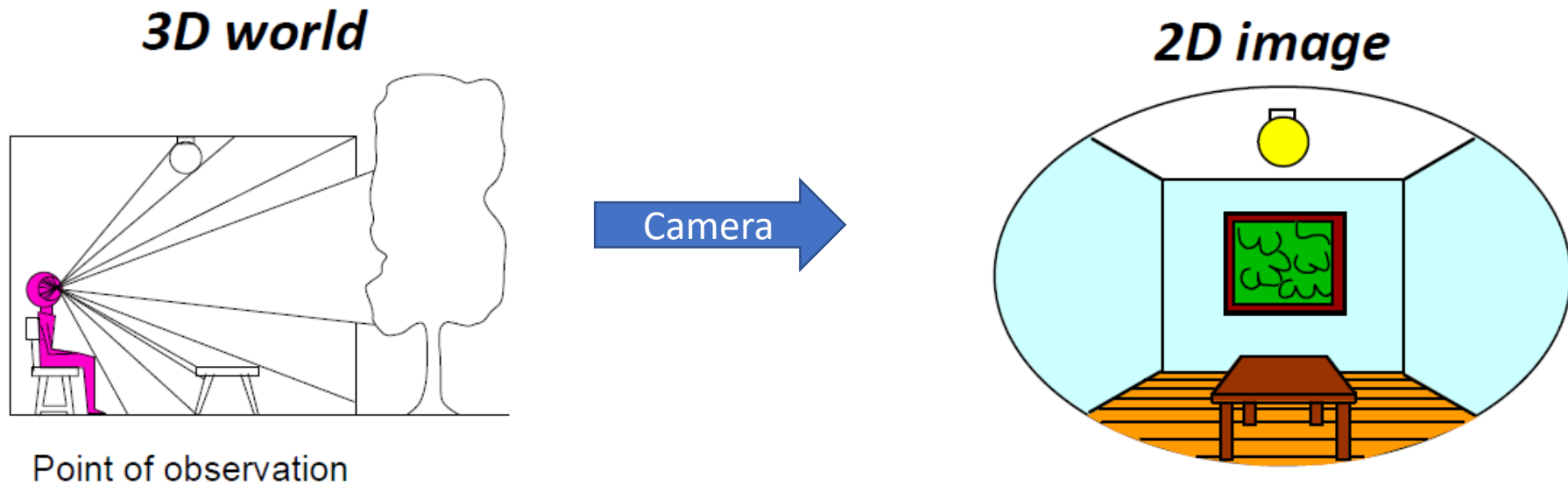
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# Content

- Camera models
  - Finite cameras
  - The projective cameras
  - The camera anatomy
- Camera Calibration
  - Direct Linear Transform
  - Zhang's methods

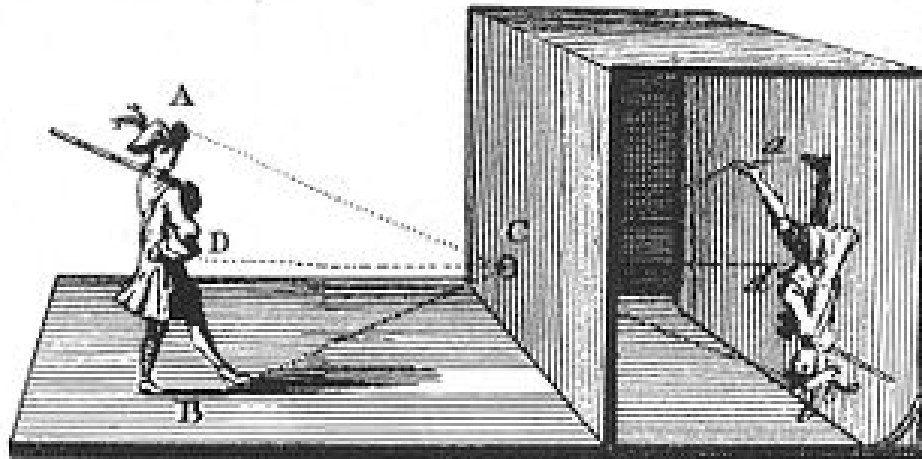
# Camera Models

- A camera is a mapping between the 3D world (object space) and a 2D image through the central projection.



# Finite Cameras

- We start with the most specialized and simplest camera model, which is the basic pinhole camera.
- Then progressively generalize this model through a series of gradations.



# Pinhole Camera Model

- The centre of project is **camera centre**, also known as the **optical centre**.
- The line from the camera centre **perpendicular** to the image plane is called the **principal axis** or **principal ray** of the camera
- The point where the principal axis meets the image plane is called **principal point**
- The plane through the camera centre parallel to the image plane is called **principal plane**

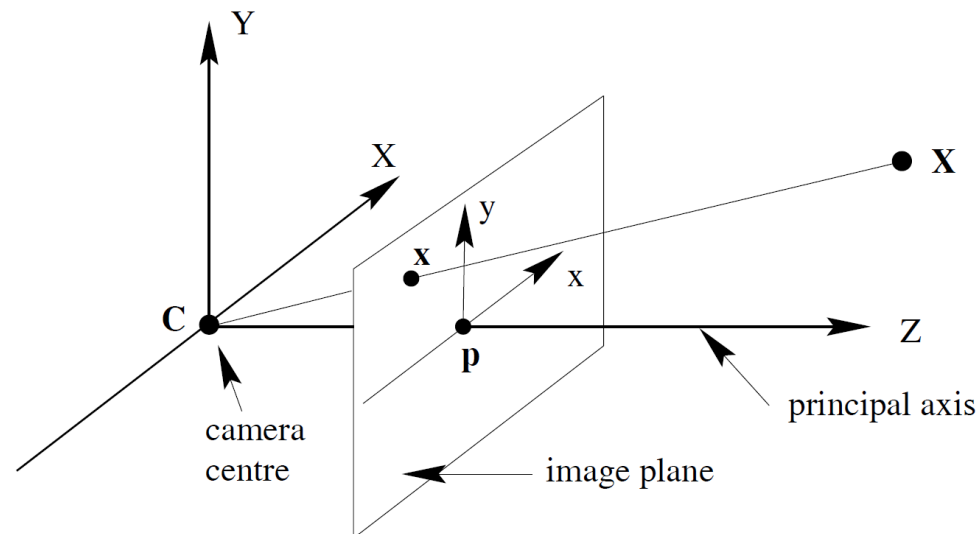


Image Credit: R. Hartley and A. Zisserman, "Multiple View Geometry in Computer Vision"

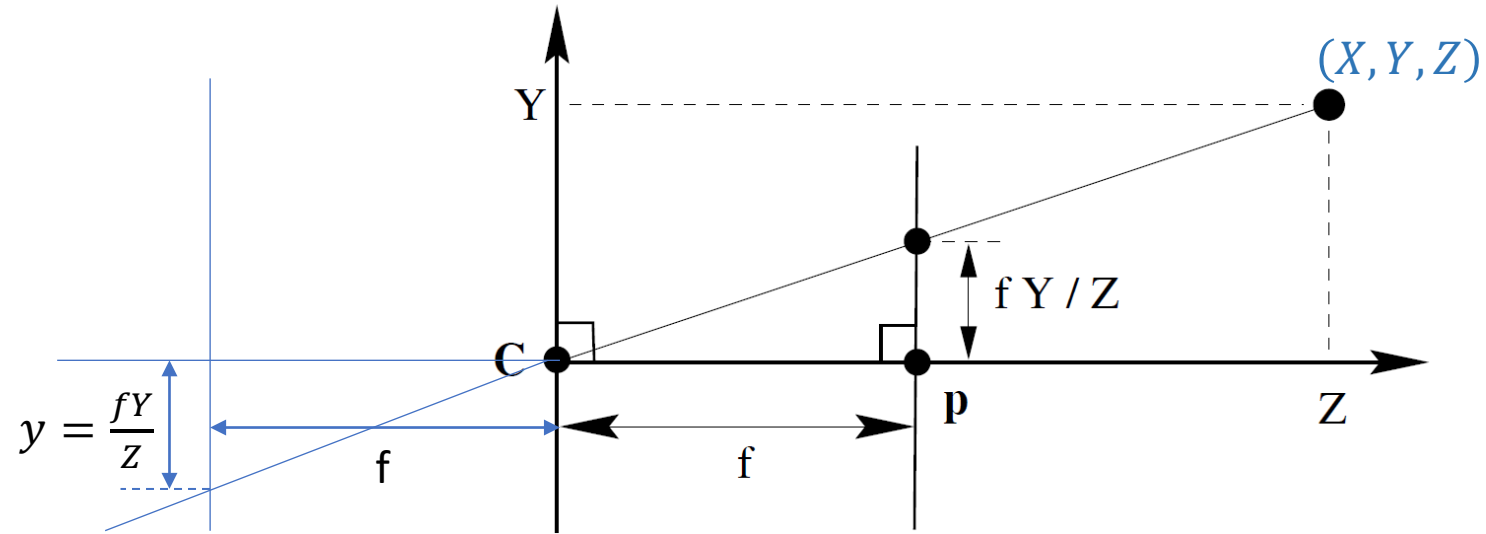
# Camera Models – Pinhole Camera

- *By Similar Triangle*

$$x = \frac{fX}{Z} \quad y = \frac{fY}{Z}$$

- One can quickly compute the point

$$(X, Y, Z)^T \rightarrow \left( \frac{fX}{Z}, \frac{fY}{Z}, f \right)^T$$



- Describes the **central projection** mapping from **world** to **image coordinates**

# Central projection using homogeneous coordinates

- Using homogenous coordinate representation, the central projection is very simply expressed as a linear mapping as follow:

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

The matrix can be written as  $\text{diag}(f, f, 1)[\mathbf{I} \mid \mathbf{0}]$  where

- $\text{diag}(f, f, 1)$  is **diagonal matrix** and
- $[\mathbf{I} \mid \mathbf{0}]$  represents a matrix divided up into a  $3 \times 3$  **identity matrix** plus a **column(Zero) vector**

# Central projection using homogeneous coordinates

- The notation
  - $X$  for the **world point** represented by a homogenous 4-vector  $(X, Y, Z, 1)^T$
  - $x$  for the **image point** represented by a homogenous 3-vector  $(x, y, 1)^T$
  - $P$  for **camera projection matrix** represented by a  $3 \times 4$  matrix.
- The mapping becomes
$$x = PX$$
- Which defines the camera matrix for pinhole model of central project as
$$P = \text{diag}(f, f, 1) [I \mid \mathbf{0}]$$



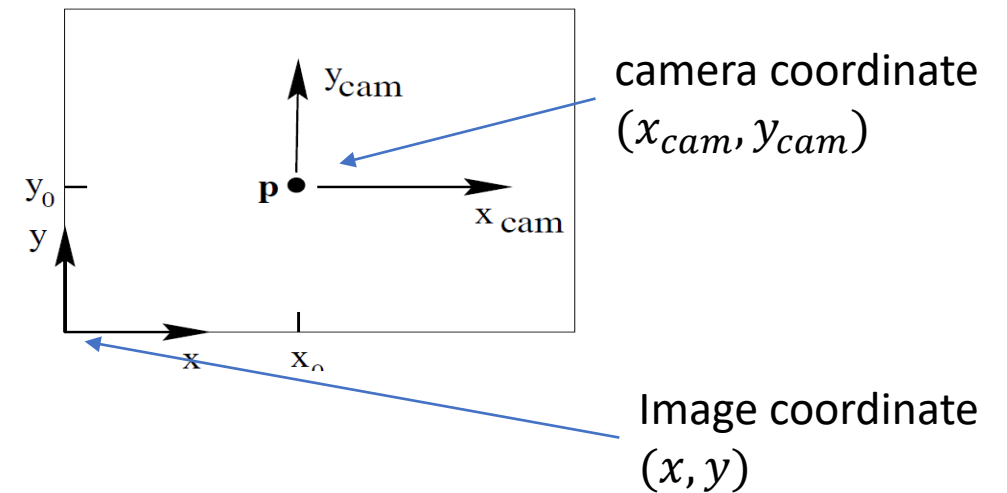
# The Principal point offset

- The **pinhole camera model** assumed that the origin of coordinates in the image plane is at the **principal point**. In practice, it may not be.

- In general, the mapping is

$$(X, Y, Z)^T \rightarrow \left( \frac{fX}{Z} + p_x, \frac{fY}{Z} + p_y \right)^T$$

where  $(p_x, p_y)^T$  are principal point



# The Principal point offset

- In homogenous coordinates, the mapping is expressed as follow:

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

- Writing the *camera calibration matrix*  $K$  is defined as follow

$$K = \begin{bmatrix} f & 0 & p_x \\ 0 & f & p_y \\ 0 & 0 & 1 \end{bmatrix}$$

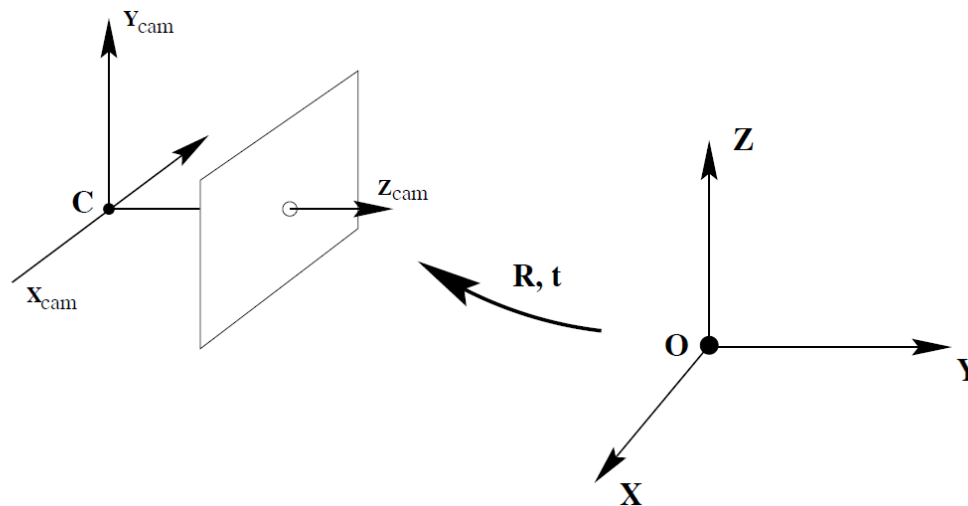
- Assuming the *camera* is located at the *origin* of a Euclidean coordinate system and *principal axis* of camera points *straight down the Z-axis*

$$x = K [I \mid \mathbf{0}] X_{\text{cam}}$$

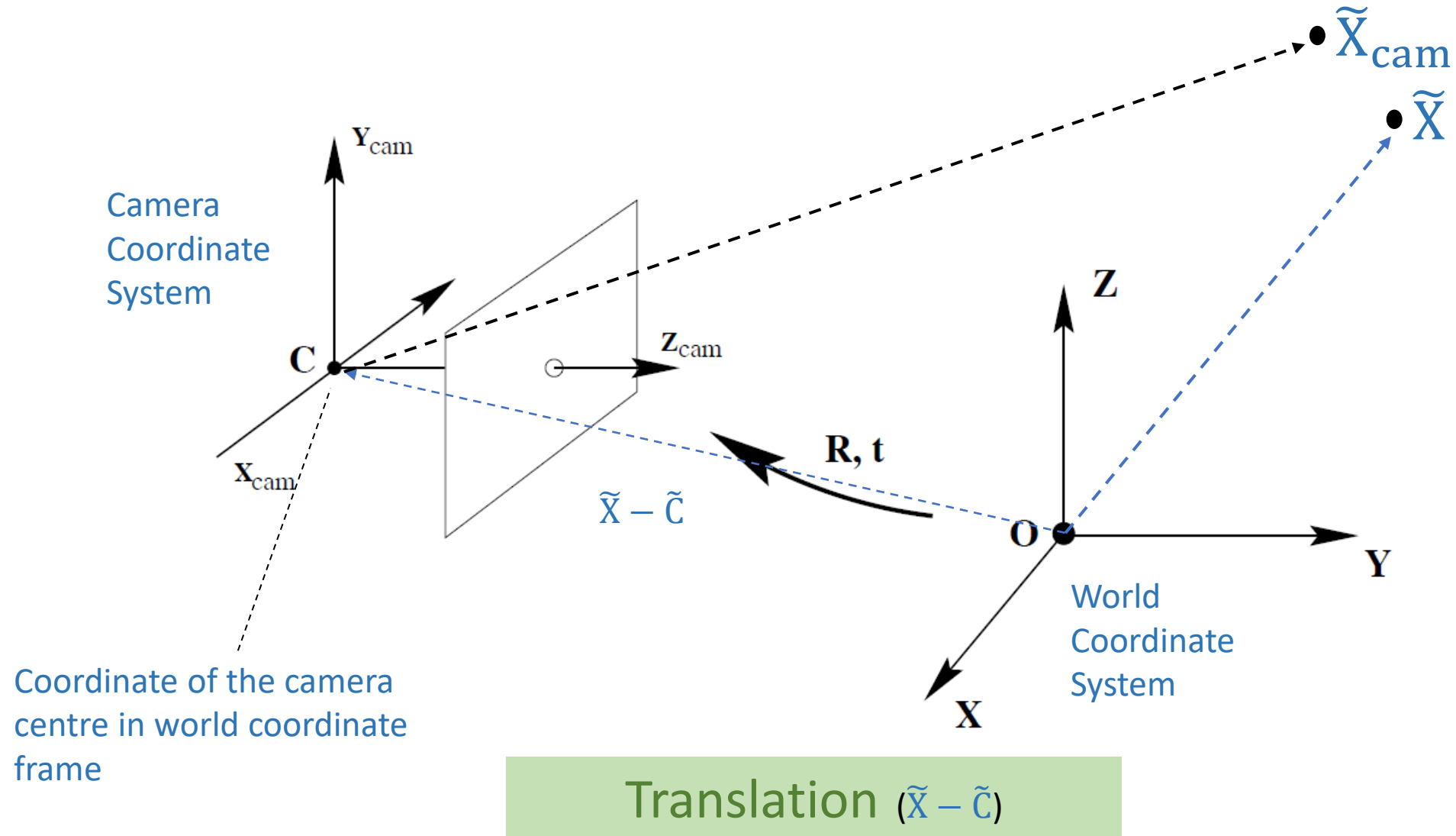
$X_{\text{cam}}$  is called *camera coordinate frame*

# Camera Rotation and Translation

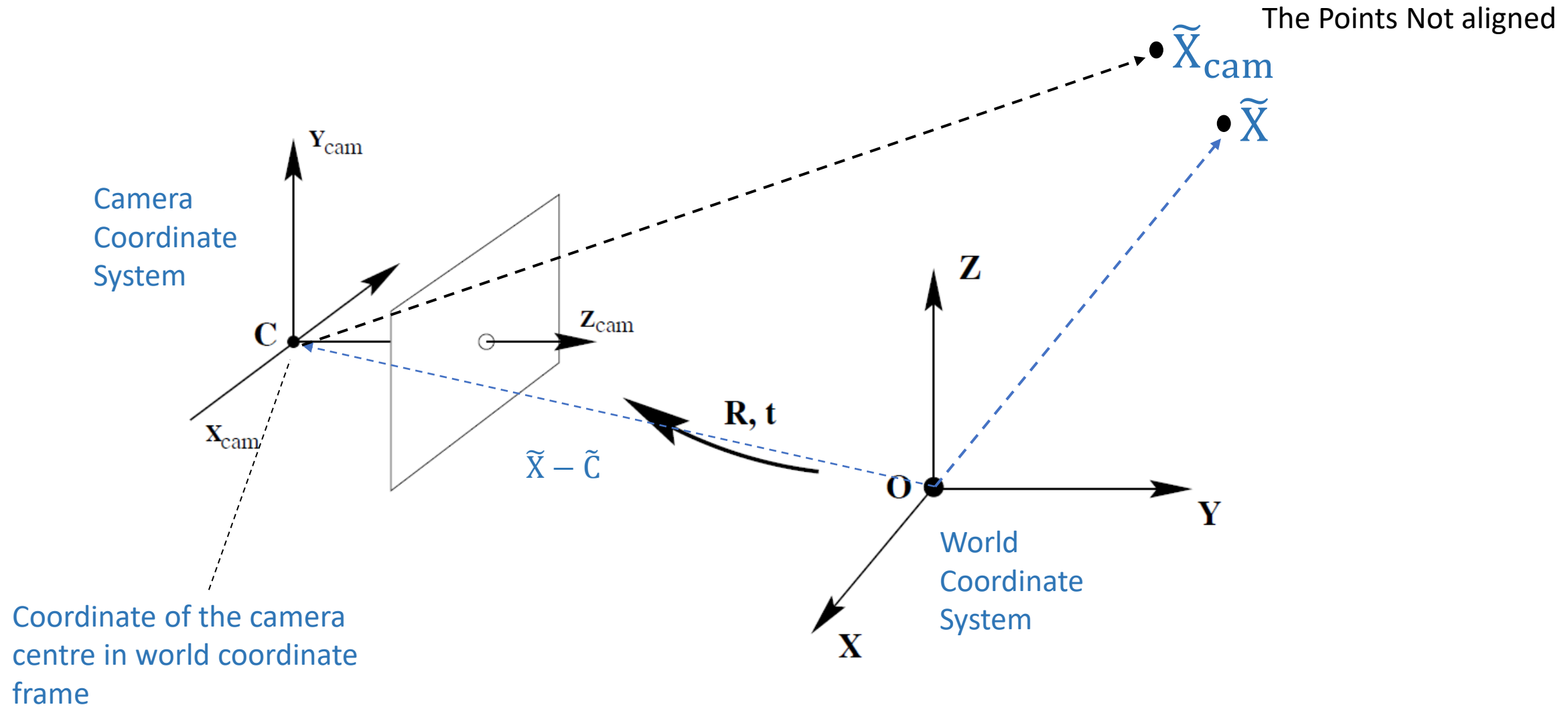
- In general, points in space will be expressed in different Euclidean coordinate frame, known as the *world coordinate frame*.
- The two coordinate frames are related via a *rotation* and a *translation*.
- Let  $\tilde{X}$  is an inhomogeneous 3-vector of a point in *world coordinate frame* and  $\tilde{X}_{cam}$  represent the same point in the *camera coordinate frame*,



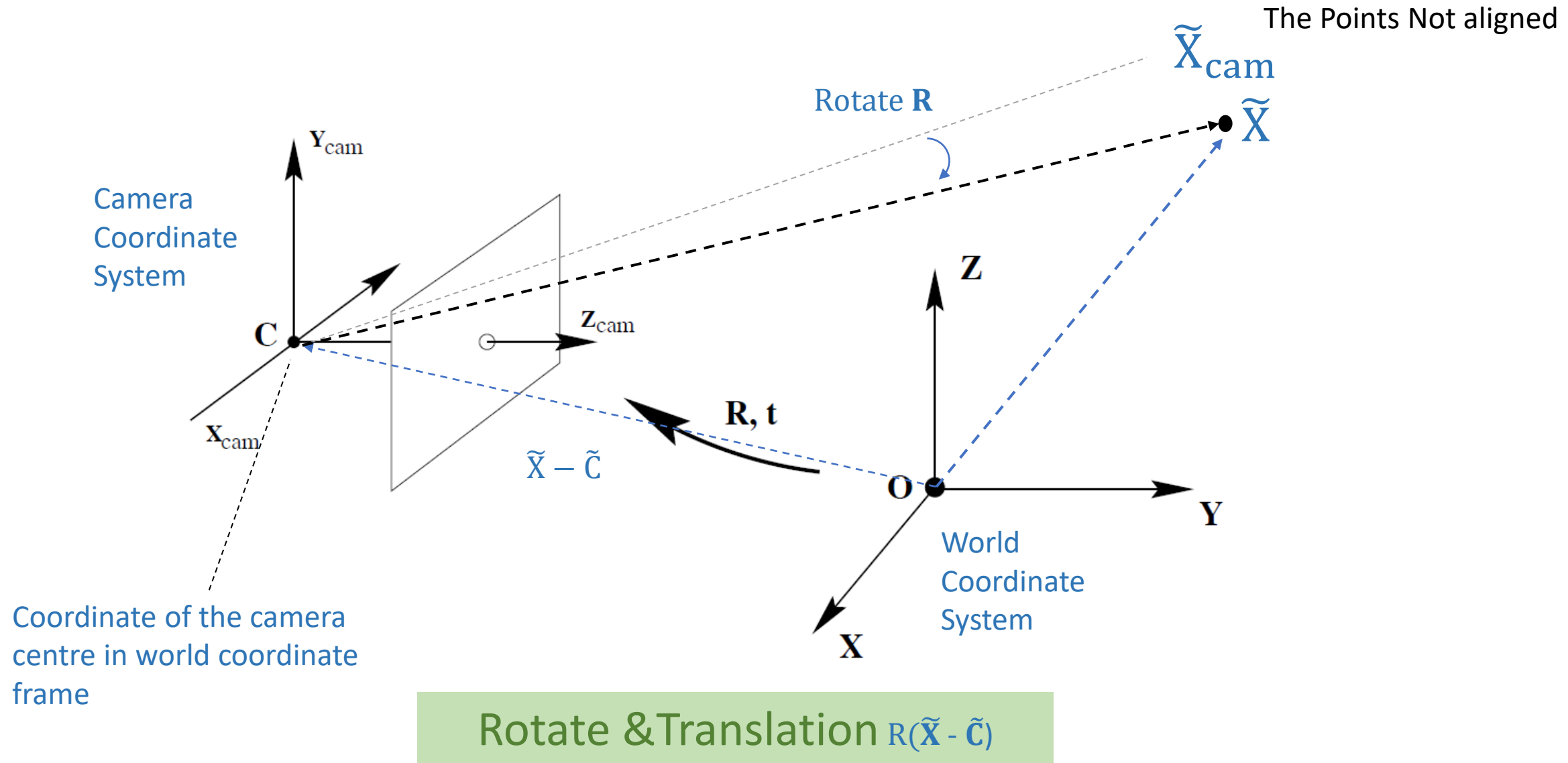
# Camera Rotation and Translation



# Camera Rotation and Translation



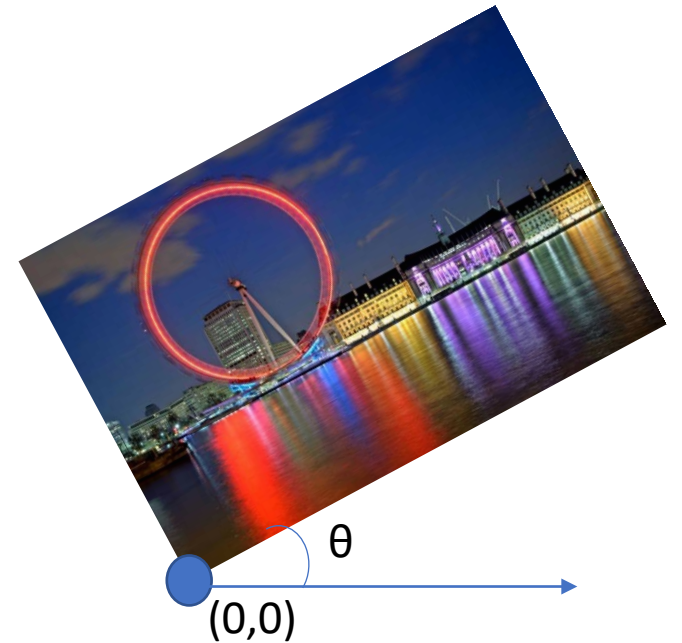
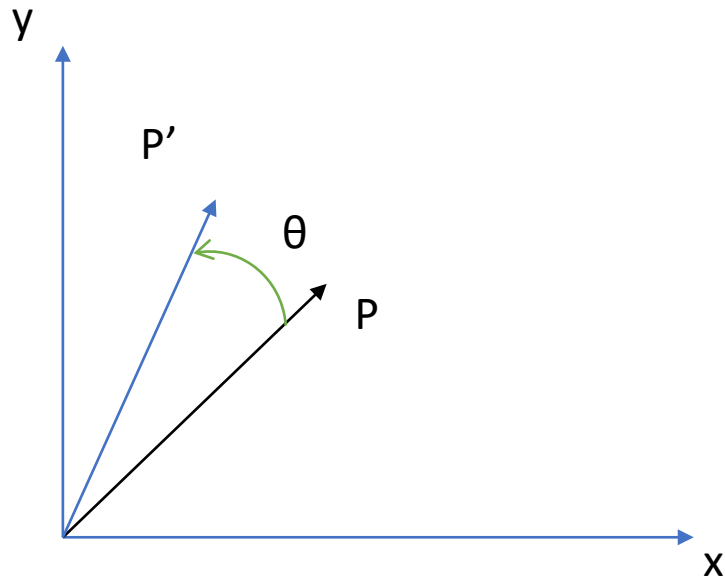
# Camera Rotation and Translation



# Recall – Rotation in 2D

- $\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$

- $R = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$



Degree of freedom = 1

# 3D Rotation Matrix

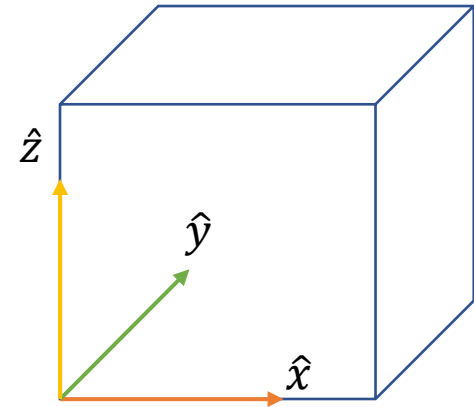
In 3D, we add a 3<sup>rd</sup> dimension to the rotation matrix

$$R = [\hat{x} \quad \hat{y} \quad \hat{z}] \in \mathbb{SO}(3)$$

Each column is a 3D unit vector

$$\begin{aligned} \hat{x}, \hat{y}, \hat{z} &\in \mathbb{R}^3 \\ \|\hat{x}\| &= \|\hat{y}\| = \|\hat{z}\| = 1 \end{aligned}$$

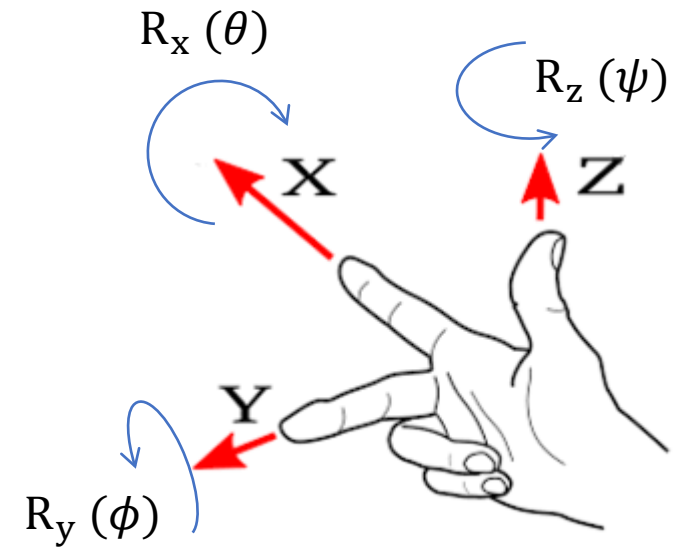
All columns are orthonormal





# Right Hand Rule

- X-axis is forward from the index finger
  - Y-axis is left from the middle finger
  - Z-axis is up from the thumb
- 
- Roll  $\theta$  about x-axis
  - Pitch  $\phi$  about y-axis
  - Yield  $\psi$  about z-axis

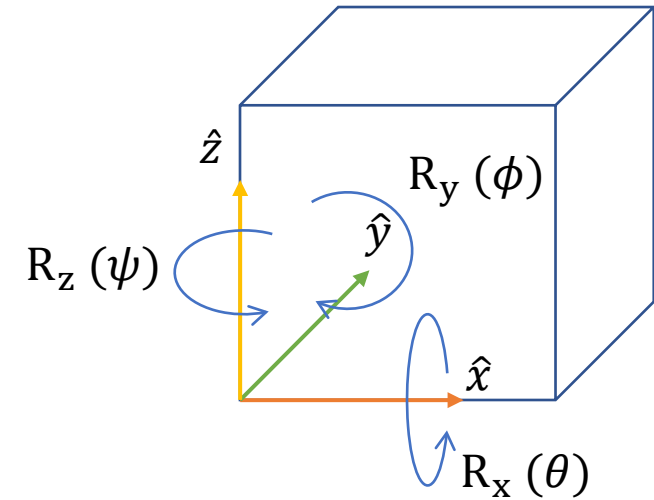


# Single Axis Rotations

- $R_x(\theta) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \theta & -\sin \theta \\ 0 & \sin \theta & \cos \theta \end{bmatrix}$

- $R_y(\phi) = \begin{bmatrix} \cos \phi & 0 & \sin \phi \\ 0 & 1 & 0 \\ -\sin \phi & 0 & \cos \phi \end{bmatrix}$

- $R_z(\psi) = \begin{bmatrix} \cos \psi & -\sin \psi & 0 \\ \sin \psi & \cos \psi & 0 \\ 0 & 0 & 1 \end{bmatrix}$



# Combinations of single axis rotations

- A rotation matrix can be formed by 3 sequential rotation about the primary axes represented by

$$R(\theta, \phi, \psi)$$

- The sequence can be arbitrary chosen but not the repeated axis in succession since

$$R_x(\theta)R_x(\theta) = R_x(2\theta)$$

In total, there are  $3 \times 2 \times 2 = 12$  combinations

# Combination of Elementary Rotations

## Euler Angles:

- Same Axis twice      ( $3 \times 2 \times 1 = 6$  combinations)

XYX    XZX

YXY    YZY

ZXZ    ZYZ

## Cardan Angles:

- All three axes      ( $3 \times 2 \times 1 = 6$  combinations)

XYZ    XZY

YXZ    YZX

ZXY    ZYX

# Roll, Pitch and Yaw to Rotation Matrix

$$\begin{aligned}
& R_X R_Y R_Z \\
&= \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos A & -\sin A \\ 0 & \sin A & \cos A \end{pmatrix} \begin{pmatrix} \cos B & 0 & \sin B \\ 0 & 1 & 0 \\ -\sin B & 0 & \cos B \end{pmatrix} \begin{pmatrix} \cos C & -\sin C & 0 \\ \sin C & \cos C & 0 \\ 0 & 0 & 1 \end{pmatrix} \\
&= \begin{pmatrix} \cos B & 0 & \sin B \\ \sin A \sin B & \cos A & -\sin A \cos B \\ -\cos A \sin B & \sin A & \cos A \cos B \end{pmatrix} \begin{pmatrix} \cos C & -\sin C & 0 \\ \sin C & \cos C & 0 \\ 0 & 0 & 1 \end{pmatrix} \\
&= \begin{pmatrix} \cos B \cos C & -\cos B \sin C & \sin B \\ \sin A \sin B \cos C + \cos A \sin C & -\sin A \sin B \sin C + \cos A \cos C & -\sin A \cos B \\ -\cos A \sin B \cos C + \sin A \sin C & \cos A \sin B \sin C + \sin A \cos C & \cos A \cos B \end{pmatrix}
\end{aligned}$$

$$\begin{aligned}
 R_Y R_X R_Z &= \begin{pmatrix} \cos B & 0 & \sin B \\ 0 & 1 & 0 \\ -\sin B & 0 & \cos B \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos A & -\sin A \\ 0 & \sin A & \cos A \end{pmatrix} \begin{pmatrix} \cos C & -\sin C & 0 \\ \sin C & \cos C & 0 \\ 0 & 0 & 1 \end{pmatrix} \\
 &= \begin{pmatrix} \cos B & \sin B \sin A & \sin B \cos A \\ 0 & \cos A & -\sin A \\ -\sin B & \cos B \sin A & \cos B \cos A \end{pmatrix} \begin{pmatrix} \cos C & -\sin C & 0 \\ \sin C & \cos C & 0 \\ 0 & 0 & 1 \end{pmatrix} \\
 &= \begin{pmatrix} \textcolor{red}{\cos B \cos C + \sin B \sin A \sin C} & \textcolor{green}{-\cos B \sin C + \sin B \sin A \cos C} & \textcolor{blue}{\sin B \cos A} \\ \textcolor{red}{\cos A \sin C} & \textcolor{green}{\cos A \cos C} & \textcolor{blue}{-\sin A} \\ \textcolor{red}{-\sin B \cos C + \cos B \sin A \sin C} & \textcolor{green}{\sin B \sin C + \cos B \sin A \cos C} & \textcolor{blue}{\cos B \cos A} \end{pmatrix}
 \end{aligned}$$

$$\begin{aligned}
R_Z R_X R_Y &= \begin{pmatrix} \cos C & -\sin C & 0 \\ \sin C & \cos C & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos A & -\sin A \\ 0 & \sin A & \cos A \end{pmatrix} \begin{pmatrix} \cos B & 0 & \sin B \\ 0 & 1 & 0 \\ -\sin B & 0 & \cos B \end{pmatrix} \\
&= \begin{pmatrix} \cos C & -\sin C \cos A & \sin C \sin A \\ \sin C & \cos C \cos A & -\cos C \sin A \\ 0 & \sin A & \cos A \end{pmatrix} \begin{pmatrix} \cos B & 0 & \sin B \\ 0 & 1 & 0 \\ -\sin B & 0 & \cos B \end{pmatrix} \\
&= \begin{pmatrix} \cos C \cos B - \sin C \sin A \sin B & -\sin C \cos A & \cos C \sin B + \sin C \sin A \cos B \\ \sin C \cos B + \cos C \sin A \sin B & \cos C \cos A & \sin C \sin B - \cos C \sin A \cos B \\ -\cos A \sin B & \sin A & \cos A \cos B \end{pmatrix}
\end{aligned}$$

$$\begin{aligned}
 R_X R_Z R_Y &= \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos A & -\sin A \\ 0 & \sin A & \cos A \end{pmatrix} \begin{pmatrix} \cos C & -\sin C & 0 \\ \sin C & \cos C & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \cos B & 0 & \sin B \\ 0 & 1 & 0 \\ -\sin B & 0 & \cos B \end{pmatrix} \\
 &= \begin{pmatrix} \cos C & -\sin C & 0 \\ \cos A \sin C & \cos A \cos C & -\sin A \\ \sin A \sin C & \sin A \cos C & \cos A \end{pmatrix} \begin{pmatrix} \cos B & 0 & \sin B \\ 0 & 1 & 0 \\ -\sin B & 0 & \cos B \end{pmatrix} \\
 &= \begin{pmatrix} \cos C \cos B & -\sin C & \cos C \sin B \\ \cos A \sin C \cos B + \sin A \sin B & \cos A \cos C & \cos A \sin C \sin B - \sin A \cos B \\ \sin A \sin C \cos B - \cos A \sin B & \sin A \cos C & \sin A \sin C \sin B + \cos A \cos B \end{pmatrix}
 \end{aligned}$$

$$\begin{aligned}
& R_Y R_Z R_X \\
&= \begin{pmatrix} \cos B & 0 & \sin B \\ 0 & 1 & 0 \\ -\sin B & 0 & \cos B \end{pmatrix} \begin{pmatrix} \cos C & -\sin C & 0 \\ \sin C & \cos C & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos A & -\sin A \\ 0 & \sin A & \cos A \end{pmatrix} \\
&= \begin{pmatrix} \cos B \cos C & -\cos B \sin C & \sin B \\ \sin C & \cos C & 0 \\ -\sin B \cos C & \sin B \sin C & \cos B \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos A & -\sin A \\ 0 & \sin A & \cos A \end{pmatrix} \\
&= \begin{pmatrix} \cos B \cos C & -\cos B \sin C \cos A + \sin B \sin A & \cos B \sin C \sin A + \sin B \cos A \\ \sin C & \cos C \cos A & -\cos C \sin A \\ -\sin B \cos C & \sin B \sin C \cos A + \cos B \sin A & -\sin B \sin C \sin A + \cos B \cos A \end{pmatrix}
\end{aligned}$$

$$\begin{aligned}
R_Z R_Y R_X &= \begin{pmatrix} \cos C & -\sin C & 0 \\ \sin C & \cos C & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \cos B & 0 & \sin B \\ 0 & 1 & 0 \\ -\sin B & 0 & \cos B \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos A & -\sin A \\ 0 & \sin A & \cos A \end{pmatrix} \\
&= \begin{pmatrix} \cos C \cos B & -\sin C & \cos C \sin B \\ \sin C \cos B & \cos C & \sin C \sin B \\ -\sin B & 0 & \cos B \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos A & -\sin A \\ 0 & \sin A & \cos A \end{pmatrix} \\
&= \begin{pmatrix} \color{red}{\cos C \cos B} & \color{green}{-\sin C \cos A + \cos C \sin B \sin A} & \color{blue}{\sin C \sin A + \cos C \sin B \cos A} \\ \color{red}{\sin C \cos B} & \color{green}{\cos C \cos A + \sin C \sin B \sin A} & \color{blue}{-\cos C \sin A + \sin C \sin B \cos A} \\ \color{red}{-\sin B} & \color{green}{\cos B \sin A} & \color{blue}{\cos B \cos A} \end{pmatrix}
\end{aligned}$$

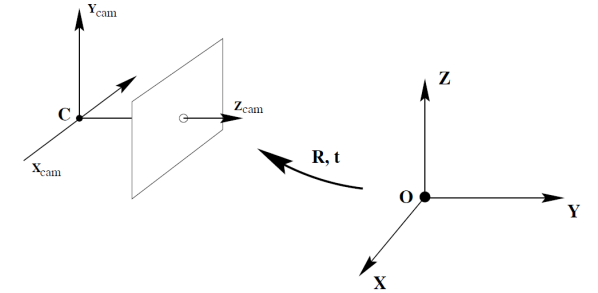
# Camera Rotation and Translation

- We can write

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

- Where

- $\tilde{\mathbf{C}}$  represents the coordinate of the camera in the world coordinate frame
- $\mathbf{R}$  is a  $3 \times 3$  rotation matrix representing the orientation of the camera coordinate frame.



- In homogenous coordinate, the equation becomes

$$\mathbf{X}_{\text{cam}} = \begin{bmatrix} \mathbf{R} & -\mathbf{R}\tilde{\mathbf{C}} \\ 0 & 1 \end{bmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix} = \begin{bmatrix} \mathbf{R} & -\mathbf{R}\tilde{\mathbf{C}} \\ 0 & 1 \end{bmatrix} \mathbf{X}$$

# General Mapping of Pinhole Camera

- Since

$$\mathbf{x} = K [I \mid \mathbf{0}] \mathbf{X}_{\text{cam}} \text{ and } \mathbf{X}_{\text{cam}} = \begin{bmatrix} R & -R\tilde{C} \\ 0 & 1 \end{bmatrix} \mathbf{x}$$

- We have

$$\mathbf{x} = K \begin{bmatrix} R & -R\tilde{C} \\ 0 & 1 \end{bmatrix} \mathbf{x}$$

- This becomes the general mapping of a pinhole camera

$$\mathbf{x} = K R [I \mid -\tilde{C}] \mathbf{x}$$

# General Mapping of a Pinhole camera

- The general mapping of a pinhole camera

$$\mathbf{x} = \mathbf{K} \mathbf{R} [\mathbf{I} \mid -\tilde{\mathbf{C}}] \mathbf{X}$$

- The camera matrix  $\mathbf{P} = \mathbf{K} \mathbf{R} [\mathbf{I} \mid -\tilde{\mathbf{C}}]$  has 9 degrees of freedom
  - 3 for  $\mathbf{K}$  (the elements  $f, p_x, p_y$ ) called internal or intrinsic parameters
  - 3 for  $\mathbf{R}$  and 3 for  $\tilde{\mathbf{C}}$  called external or extrinsic parameters
- It is convenient to express the camera centre as

$$\begin{aligned}\tilde{\mathbf{X}}_{\text{cam}} &= \mathbf{R}(\tilde{\mathbf{X}} - \tilde{\mathbf{C}}) \\ &= \mathbf{R}\tilde{\mathbf{X}} + \mathbf{t} \text{ where } \mathbf{t} = -\mathbf{R}\tilde{\mathbf{C}}\end{aligned}$$

- The camera matrix is simply

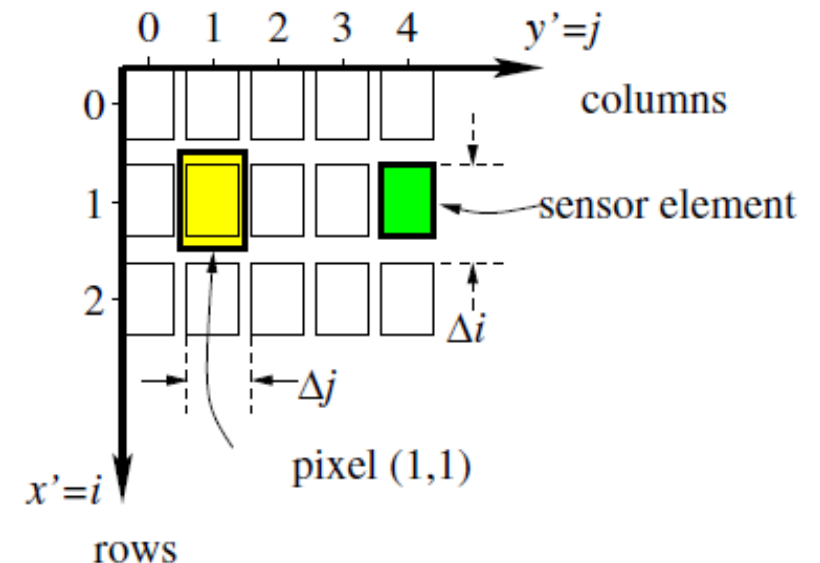
$$\mathbf{P} = \mathbf{K} \mathbf{R} [\mathbf{I} \mid \mathbf{t}]$$



# From pinhole to CCD cameras

- The pin hole camera model assumes image coordinates having equal scales in both axial direction
- CCD cameras has non-square pixels, unequal scale factors in each direction is required
- Let  $m_x, m_y$  be pixel per unit distance in the  $x$  and  $y$  direction. We have to multiple extra factor  $diag(m_x, m_y, 1)$  to the transform
- The general form of calibration matrix of CCD

$$K = \begin{bmatrix} m_x f & p_x & 0 \\ 0 & m_y f & p_y \\ 0 & 0 & 1 \end{bmatrix}$$

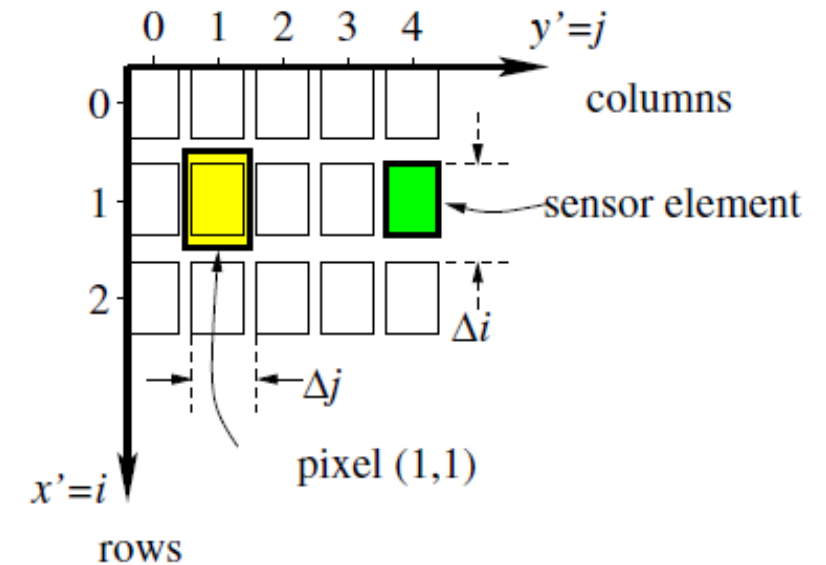


# From pinhole to CCD cameras (alternative representation)

- Correction of the scale factor by
- Let  $\alpha_x = fm_x$ ,  $\alpha_y = fm_y$  be the focal length in  $x$  and  $y$  direction

$$K = \begin{bmatrix} \alpha_x & p_x \\ & \alpha_y & p_y \\ & & 1 \end{bmatrix}$$

- A CCD camera thus has 10 degree of freedom.



# Alternative representation of the scale

## Alternative Representation:

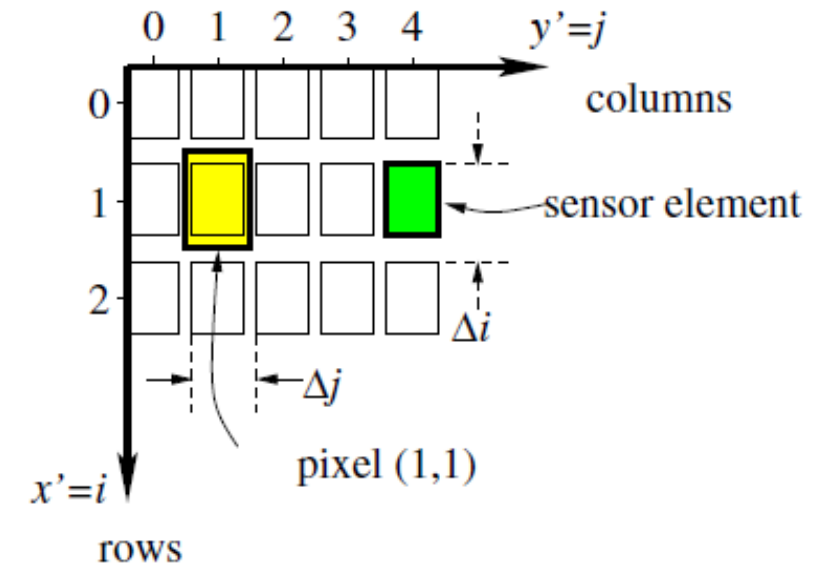
- Correction of scale factor by

$$1 + m = \Delta j / \Delta i$$

- The calibration matrix becomes

$$K = \begin{bmatrix} f & & p_x \\ & f(1 + m) & p_y \\ & & 1 \end{bmatrix}$$

- A CCD camera thus has 10 degree of freedom.

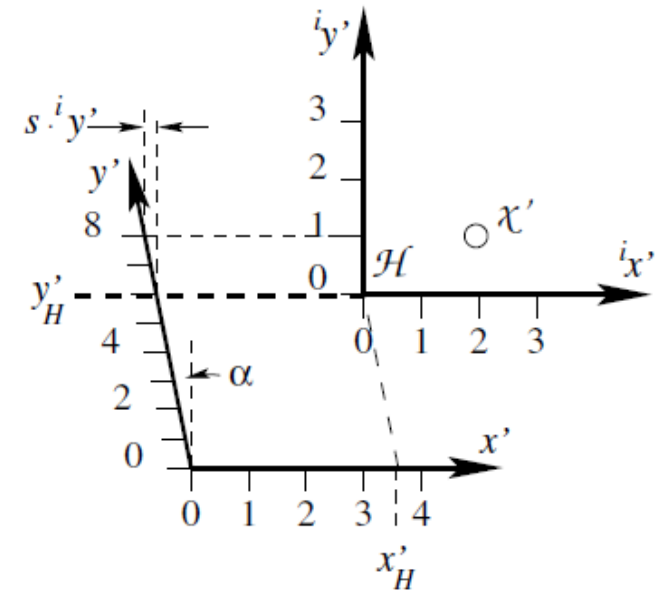


# Adding Skew to the calibration matrix

- For added generality, we consider the calibration matrix of the form

$$K = \begin{bmatrix} \alpha_x & s & p_x \\ & \alpha_y & p_y \\ & & 1 \end{bmatrix}$$

- The parameter  $s$  is referred to the skew parameters
- The camera with calibration matrix  $K$  above is called a **finite projective camera** which has **11 degree of freedom**



$$\begin{aligned} s x &= i_x + s i_y + x_H \\ s y &= i_y + m i_y + y_H \end{aligned}$$

where  $s = \tan \alpha$

# The Finite Projective Camera

- A camera below is called a finite projective camera

$$\mathbf{x} = \mathbf{P}\mathbf{X} \quad \text{where } \mathbf{P} = \mathbf{K}\mathbf{R}[\mathbf{I} \mid -\tilde{\mathbf{C}}]$$

- The projective matrix  $\mathbf{P}$  is a  $3 \times 4$  matrix defined by to an *arbitrary scale* with *11 degrees of freedom*.
- We can write  $\mathbf{P} = [\mathbf{p}_1 \mathbf{p}_2 \mathbf{p}_3 \mathbf{p}_4]$  and let  $\mathbf{M} = [\mathbf{p}_1 \mathbf{p}_2 \mathbf{p}_3]$  be the left  $3 \times 3$  submatrix of  $\mathbf{P}$ , then we have:

$$\mathbf{P} = \mathbf{M}[\mathbf{I} \mid \mathbf{M}^{-1}\mathbf{p}_4] = \mathbf{K}\mathbf{R}[\mathbf{I} \mid -\tilde{\mathbf{C}}]$$

- The set of camera matrices of finite projective cameras is identical with the set of homogeneous  $3 \times 4$  matrix for which the left hand  $3 \times 3$  submatrix is *non-singular*

# Projective Finite Camera - The Camera Anatomy

## The Camera Centre:

- The matrix  $P$  is *rank 3* but it has *4 columns*, therefore it has *1-dimensional right null-space*. Suppose it is generated by the 4-vector  $C$ , i.e.

$$PC = 0$$

- $C$  is the homogenous 4-vector representing the *camera centre*
- $PC$  is the image point  $(0,0,0)^T$  is *undefined*.

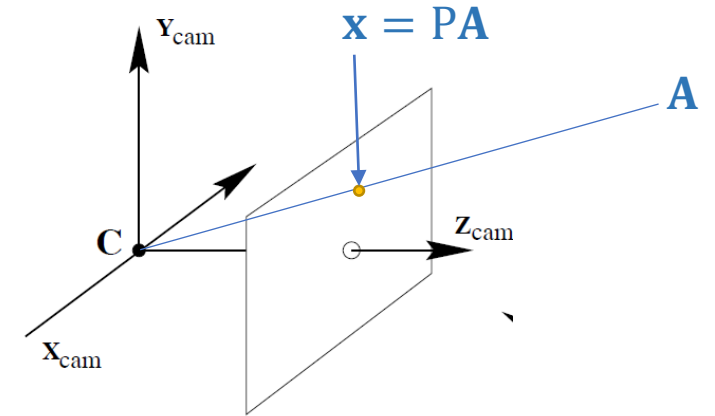
# Projective Finite Camera - The Camera Centre

- **Proof:**
- Consider the line containing **C** and any point **A** in 3-space. Points on this line may be represented:

$$\mathbf{X}(\lambda) = \lambda \mathbf{A} + (1 - \lambda) \mathbf{C}$$

- Under the mapping  $\mathbf{x} = \mathbf{P}\mathbf{X}$ , we have

$$\mathbf{x} = \mathbf{P}\mathbf{X}(\lambda) = \lambda \mathbf{P}\mathbf{A} + (1 - \lambda) \mathbf{P}\mathbf{C} = \lambda \mathbf{P}\mathbf{A}$$



- Therefore  $\mathbf{P}\mathbf{C} = \mathbf{0}$  and all points on the line are mapped to the same point  $\mathbf{P}\mathbf{A}$ , the line must through the camera centre **C**

# Projective Finite Camera - The Camera Anatomy

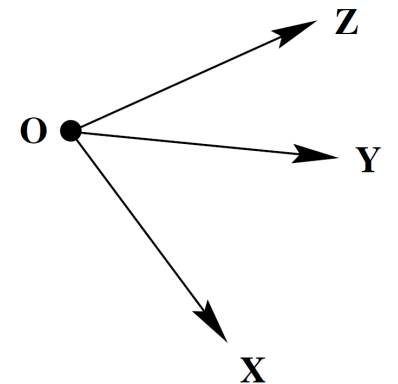
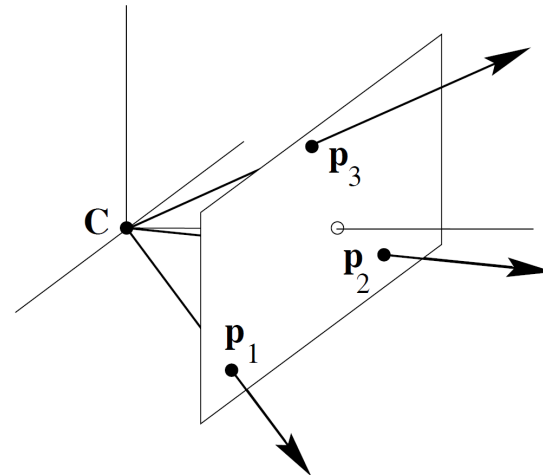
## Column vectors:

- The columns of the projective camera are 3-vectors which has a geometric meaning as particular image points.
- With the notation that the columns of  $\mathbf{P}$  are  $\mathbf{p}_i, i = 1, \dots, 4$ . (i.e.)  $\mathbf{P} = [\mathbf{p}_1 | \mathbf{p}_2 | \mathbf{p}_3 | \mathbf{p}_4]$ .
- Then  $\mathbf{p}_1, \mathbf{p}_2$  and  $\mathbf{p}_3$  are the vanishing point of the world coordinate  $X, Y, Z$  axes respectively

## For example:

$x$ -axis has direction  $\mathbf{D} = (1,0,0,0)^T$

$$\mathbf{p}_1 = \mathbf{P}\mathbf{D} = [\mathbf{p}_1 | \mathbf{p}_2 | \mathbf{p}_3 | \mathbf{p}_4] \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$





# Projective Finite Camera - The Camera Anatomy

## Row Vectors:

- The **rows** of the projective camera are 4-vectors which may be interpreted geometrically as **particular world planes**

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{41} \\ p_{21} & p_{22} & p_{23} & p_{42} \\ p_{31} & p_{23} & p_{33} & p_{43} \end{bmatrix} = \begin{bmatrix} \mathbf{p}^{1T} \\ \mathbf{p}^{2T} \\ \mathbf{p}^{3T} \end{bmatrix}$$

# Projective Finite Camera - The Camera Anatomy

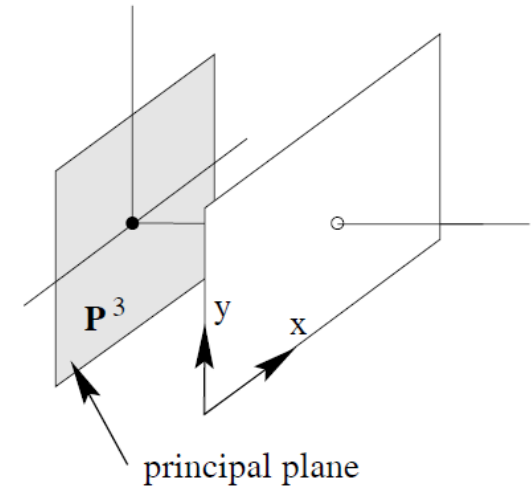
## The principal plane:

- The plane through the **camera centre** *parallel* to the **image plane**
- It consists the set of points **X** which are imaged on **the line at infinity** explicitly  $\mathbf{P}\mathbf{X} = (x, y, 0)^T$
- $\mathbf{p}^{3T}$  represents the principal plane of the camera

- **Proof:**

$$\begin{pmatrix} x \\ y \\ 0 \end{pmatrix} = \begin{bmatrix} \mathbf{p}^{1T} \\ \mathbf{p}^{2T} \\ \mathbf{p}^{3T} \end{bmatrix} \mathbf{X}, \text{ therefore } \mathbf{p}^{3T} \mathbf{X} = 0$$

- Since  $\mathbf{P}\mathbf{C} = 0 \Rightarrow \mathbf{C}$  lies on the principal plane.



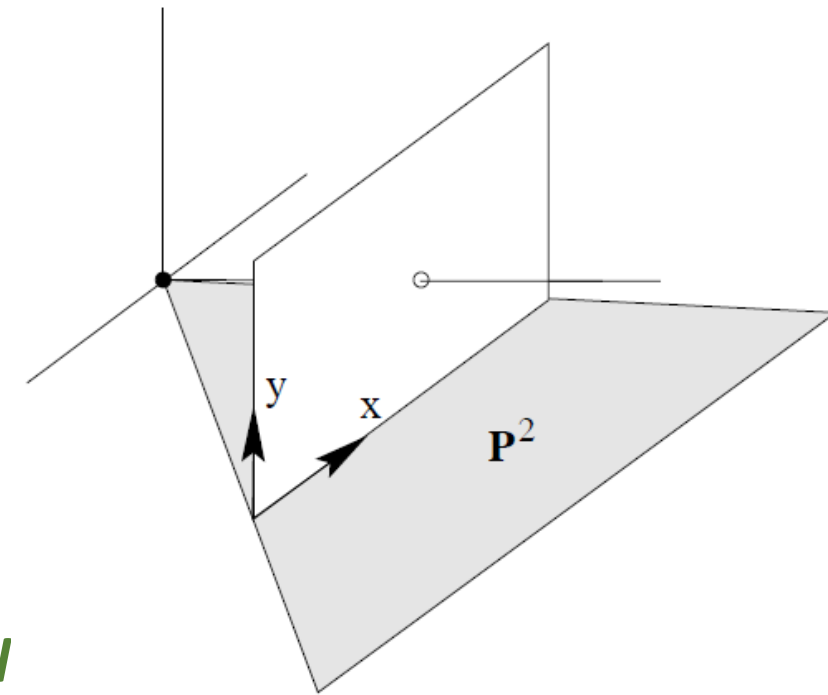
# Projective Finite Camera - The Camera Anatomy

## Axis planes

- Consider the set of points on  $\mathbf{p}^1$  satisfies  $\mathbf{p}^{1T}\mathbf{X}=0$  and imaged at  $\mathbf{PX} = (0, y, w)^T$ , which are points on the y-axis.

$$\text{i.e. } \mathbf{x} = \begin{bmatrix} \mathbf{p}^{1T} \\ \mathbf{p}^{2T} \\ \mathbf{p}^{3T} \end{bmatrix} \mathbf{X} \quad \mathbf{p}^{1T}\mathbf{X}=0 \Rightarrow \mathbf{x} = \begin{pmatrix} 0 \\ y \\ w \end{pmatrix}$$

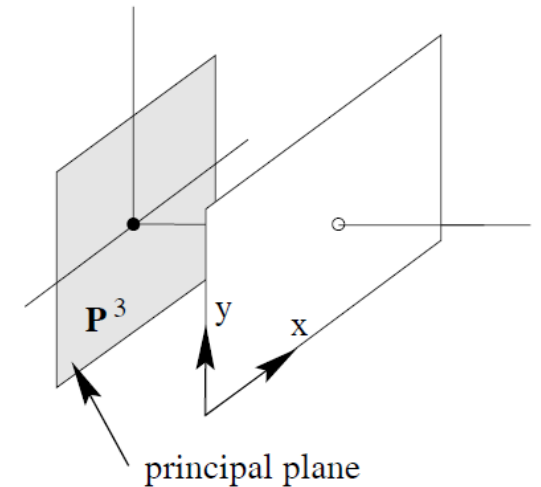
- It follows  $\mathbf{p}^{1T}\mathbf{X} = 0$  and  $\mathbf{PC} = 0$  and so  $\mathbf{C}$  also lies on  $\mathbf{p}^1$
- Similarly for the case of  $\mathbf{p}^2$  imaged at  $\mathbf{PX} = (x, 0, w)^T$
- The **Camera Centre  $\mathbf{C}$**  lies on the intersection all three  $\mathbf{p}^i$



# Projective Finite Camera - The Camera Anatomy

## The principal point:

- The principal axis is the line passing through the camera centre  $\mathbf{C}$ , with direction perpendicular to the principal plane.
- The principal axis intercepts the image plane at the principal point.
- A plane  $\pi = (\pi_1, \pi_2, \pi_3, \pi_4)^T$  has normal vector  $(\pi_1, \pi_2, \pi_3)^T$  which may be represented by a point  $(\pi_1, \pi_2, \pi_3, 0)^T$  on the plane at infinity.



# Projective Finite Camera - The Camera Anatomy

## The principal point:

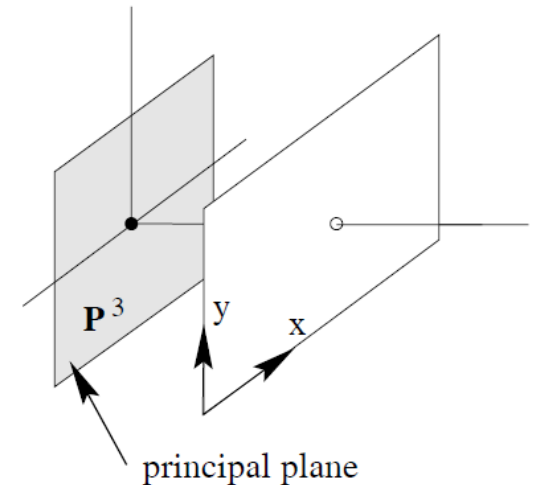
- In the case of  $\mathbf{p}^3$ , the point at plane at infinity is  $\hat{\mathbf{p}}^3 = (p_{11}, p_{12}, p_{13}, 0)^T$
- Projecting  $\hat{\mathbf{p}}^3$  using the camera matrix  $\mathbf{P}$  gives the principal point of the camera,

$$\mathbf{x}_0 = \mathbf{P}\hat{\mathbf{p}}^3$$

- As only the left  $3 \times 3$  part of  $\mathbf{P} = [\mathbf{M} \mid \mathbf{p}_4]$  is involved,

- The principal point is computed as

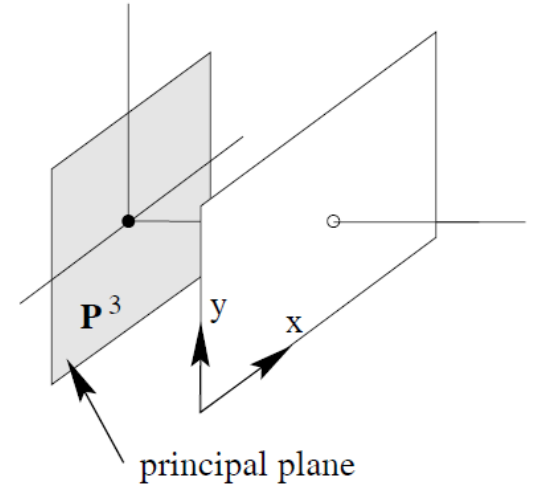
$$\mathbf{x}_0 = \mathbf{M}\mathbf{m}^3 \quad \text{where } \mathbf{m}^{3T} \text{ is third row of } \mathbf{M}$$



# Projective Finite Camera - The Camera Anatomy

## The principal axis vector:

- Although any point  $\mathbf{X}$  not on the principal plane may be mapped to an image point according to  $\mathbf{x} = \mathbf{P}\mathbf{X}$
- In reality only half the points in space, in front of the camera, may be seen in an image.
- Let  $\mathbf{P} = [\mathbf{M} \mid \mathbf{p}_4]$ , it is shown the vector  $\mathbf{m}^3$  points in the direction of principal axis
- However  $\mathbf{P}$  is only defined up to a sign, we need to determine if  $\mathbf{m}^3$  or  $-\mathbf{m}^3$  points in the positive direction.



# Projective Finite Camera - The Camera Anatomy

## The principal axis vector:

- The equation for projection of a 3D point to image is given by

$$\mathbf{x} = P_{\text{cam}} \mathbf{X}_{\text{cam}} = K[I \mid 0] \mathbf{X}_{\text{cam}} \text{ where } \mathbf{X}_{\text{cam}} \text{ is 3D points in camera coordinate.}$$

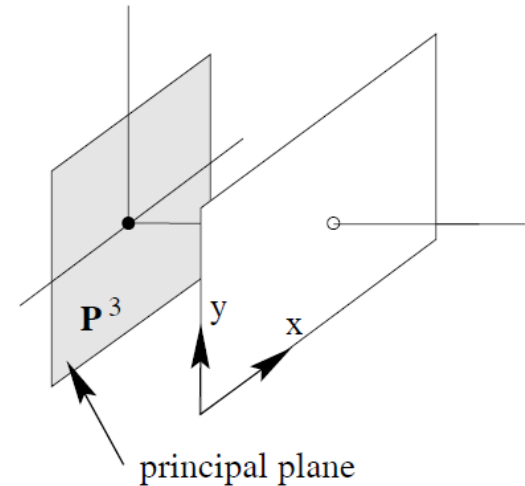
- The vector  $\mathbf{v} = \det(M) \mathbf{m}^3 = (0,0,1)^T$  points to the front of camera irrespective of the scaling of  $P_{\text{cam}}$

- In world coordinate, we have

$$P = kK[R \mid -R\tilde{C}] = [M \mid \mathbf{p}_4], \text{ where } M=kKR$$

- Since  $\det(R) > 0$ ,  $\mathbf{v} = \det(M) \mathbf{m}^3$  is also unaffected by scale.

- In summary,  $\mathbf{v} = \det(M) \mathbf{m}^3$  is a vector in the direction of the principal axis, directed toward the front of camera



# Summary of the Properties of a Projective Camera

**Camera centre.** The camera centre is the 1-dimensional right null-space  $\mathbf{C}$  of  $\mathbf{P}$ , i.e.  $\mathbf{P}\mathbf{C} = \mathbf{0}$ .

- ◇ **Finite camera** ( $\mathbf{M}$  is not singular)  $\mathbf{C} = \begin{pmatrix} -\mathbf{M}^{-1}\mathbf{p}_4 \\ 1 \end{pmatrix}$
- ◇ **Camera at infinity** ( $\mathbf{M}$  is singular)  $\mathbf{C} = \begin{pmatrix} \mathbf{d} \\ 0 \end{pmatrix}$  where  $\mathbf{d}$  is the null 3-vector of  $\mathbf{M}$ , i.e.  $\mathbf{M}\mathbf{d} = \mathbf{0}$ .

**Column points.** For  $i = 1, \dots, 3$ , the column vectors  $\mathbf{p}_i$  are vanishing points in the image corresponding to the X, Y and Z axes respectively. Column  $\mathbf{p}_4$  is the image of the coordinate origin.

**Principal plane.** The principal plane of the camera is  $\mathbf{P}^3$ , the last row of  $\mathbf{P}$ .

**Axis planes.** The planes  $\mathbf{P}^1$  and  $\mathbf{P}^2$  (the first and second rows of  $\mathbf{P}$ ) represent planes in space through the camera centre, corresponding to points that map to the image lines  $x = 0$  and  $y = 0$  respectively.

**Principal point.** The image point  $\mathbf{x}_0 = \mathbf{M}\mathbf{m}^3$  is the principal point of the camera, where  $\mathbf{m}^{3\top}$  is the third row of  $\mathbf{M}$ .

**Principal ray.** The principal ray (axis) of the camera is the ray passing through the camera centre  $\mathbf{C}$  with direction vector  $\mathbf{m}^{3\top}$ . The principal axis vector  $\mathbf{v} = \det(\mathbf{M})\mathbf{m}^3$  is directed towards the front of the camera.



# Action of a Projective Camera on Points

## Forward Projection:

- A general projective camera maps a point in space  $\mathbf{X}$  to an image point through  $\mathbf{x} = \mathbf{P}\mathbf{X}$ .
- Points  $\mathbf{D} = (\mathbf{d}^T, 0)^T$  on the plane at infinity represent *vanishing points*. Such points map to

$$\mathbf{x} = \mathbf{P}\mathbf{D} = [\mathbf{M} \mid \mathbf{p}_4]\mathbf{D} = \mathbf{M}\mathbf{d}$$

- $\mathbf{x}$  is *only affected* by  $\mathbf{M}$ , the first  $3 \times 3$  submatrix of  $\mathbf{P}$

# Action of a Projective Camera on Points

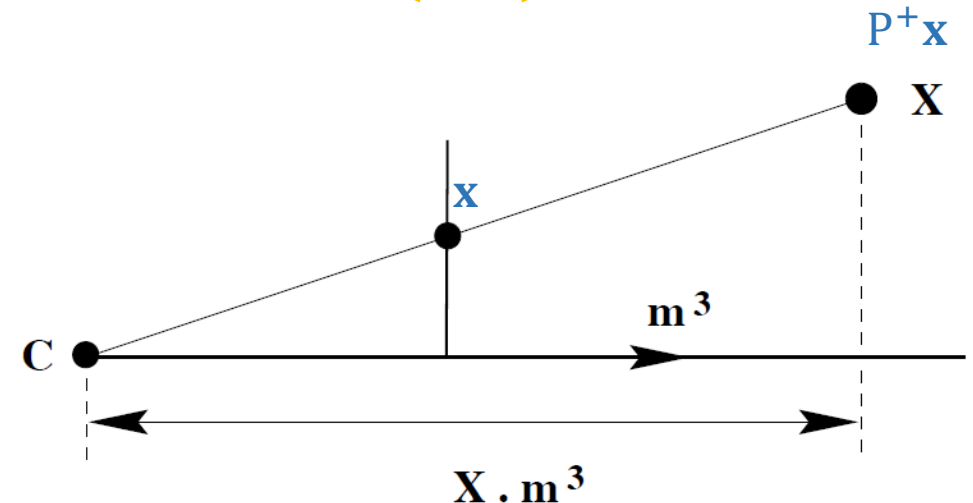
## Back-projection of points to rays:

- Given a point  $\mathbf{x}$  in an image, we wish to determine the set of points in space map to this point.
- We know two points on the ray.
  - The **camera centre**  $\mathbf{C}$  where  $\mathbf{P}\mathbf{C} = \mathbf{0}$
  - The point  $\mathbf{P}^+\mathbf{x}$  where  $\mathbf{P}^+$  is **pseudo-inverse** of  $\mathbf{P}$  where  $\mathbf{P}^+ = \mathbf{P}^T(\mathbf{P}\mathbf{P}^T)^{-1}$
- The point  $\mathbf{P}^+\mathbf{x}$  lies on the ray because

$$\mathbf{P}(\mathbf{P}^+\mathbf{x}) = \mathbf{I}\mathbf{x} = \mathbf{x}$$

- Hence the ray is a line

$$\mathbf{X}(\lambda) = \mathbf{P}^+\mathbf{x} + \lambda\mathbf{C}$$

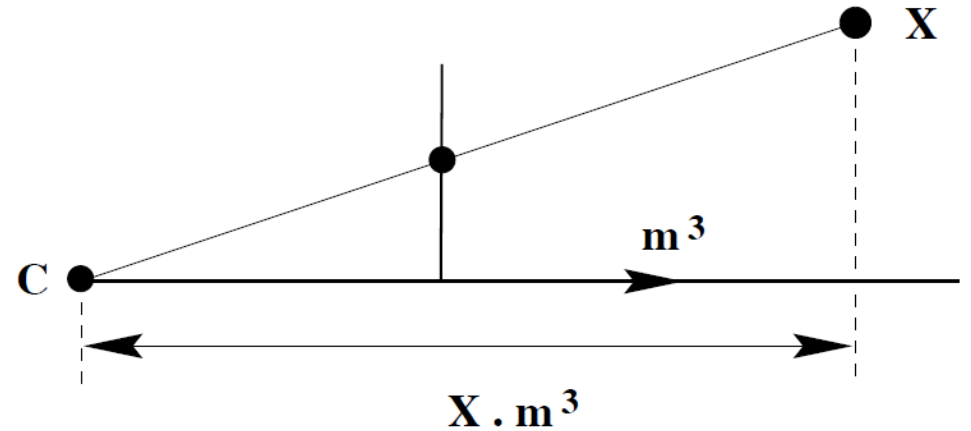


# Action of a Projective Camera on Points

- In the case of finite camera  $\mathbf{M}^{-1}$ , we can write  $\mathbf{P} = [\mathbf{M} \mid \mathbf{p}_4]$ 
  - The *camera centre* is  $\tilde{\mathbf{C}} = -\mathbf{M}^{-1}\mathbf{p}_4$
  - An image point  $\mathbf{x}$  back-projects to a ray intersecting the plane at infinity  $\pi_\infty$  at the *ideal point*  
 $\mathbf{D} = \left( (\mathbf{M}^{-1}\mathbf{x})^T, 0 \right)^T$

- The line joining two points

$$\begin{aligned} X(\mu) &= \mu \begin{pmatrix} \mathbf{M}^{-1}\mathbf{x} \\ 0 \end{pmatrix} + \begin{pmatrix} -\mathbf{M}^{-1}\mathbf{p}_4 \\ 1 \end{pmatrix} \\ &= \begin{pmatrix} -\mathbf{M}^{-1}(\mu\mathbf{x} - \mathbf{p}_4) \\ 1 \end{pmatrix} \end{aligned}$$



# Action of a Projective Camera on Points

## Depth of points:

- Consider a camera matrix  $P = [M \mid \mathbf{p}_4]$ , projecting a point  $\mathbf{X} = (X, Y, Z, 1)^T = (\tilde{\mathbf{X}}^T, 1)^T$  to the image point  $\mathbf{x} = w(x, y, 1)^T = P\mathbf{X}$

- We have

$$\mathbf{x} = \begin{pmatrix} wx \\ wy \\ w \end{pmatrix} = \begin{bmatrix} \mathbf{p}^{1T} \\ \mathbf{p}^{2T} \\ \mathbf{p}^{3T} \end{bmatrix} \mathbf{X}$$

- hence  $w = \mathbf{p}^{3T}\mathbf{X} = \mathbf{p}^{3T}(\mathbf{X} - \mathbf{C})$  since  $P\mathbf{C}=0$
- $w = \mathbf{p}^{3T}(\mathbf{X} - \mathbf{C}) = \mathbf{m}^{3T}(\tilde{\mathbf{X}} - \tilde{\mathbf{C}})$  where  $\mathbf{m}^3$  is the principal ray direction

Inhomogeneous  
coordinates



# Action of a Projective Camera on Points

- Therefore
- $w = \mathbf{m}^{3T}(\tilde{\mathbf{X}} - \tilde{\mathbf{C}})$  can be written as dot product of ray from camera centre to the point  $\mathbf{X}$  and principal ray direction
- Dot product can be written as  $\|\mathbf{m}^3\| \|\tilde{\mathbf{X}} - \tilde{\mathbf{C}}\| \cos \theta = \text{sign}(\det M)w$
- The camera matrix can be normalized  $\det(M) > 0$  and  $\|\mathbf{m}^3\| = 1$ ,

## Example:

- $\mathbf{X} = (X, Y, Z, T)^T$ ,  $P\mathbf{X} = w(x, y, 1)^T$

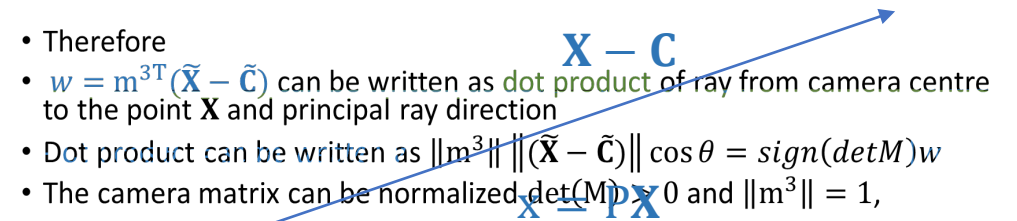
$$\text{depth}(\mathbf{X}; P) = \frac{\text{sign}(\det M)w}{T\|\mathbf{m}^3\|}$$

- Therefore
- $w = \mathbf{m}^{3T}(\tilde{\mathbf{X}} - \tilde{\mathbf{C}})$  can be written as dot product of ray from camera centre to the point  $\mathbf{X}$  and principal ray direction
- Dot product can be written as  $\|\mathbf{m}^3\| \|\tilde{\mathbf{X}} - \tilde{\mathbf{C}}\| \cos \theta = \text{sign}(\det M)w$
- The camera matrix can be normalized  $\det(M) > 0$  and  $\|\mathbf{m}^3\| = 1$ ,

## Example:

- $\mathbf{X} = (X, Y, Z, T)^T$ ,  $P\mathbf{X} = w(x, y, 1)^T$

$$\text{depth}(\mathbf{X}; P) = \frac{\text{sign}(\det M)w}{T\|\mathbf{m}^3\|}$$



# Decomposition of the Camera Matrix

## Decomposition of the camera matrix:

Let  $P$  be a camera representing a general projective camera.

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{41} \\ p_{21} & p_{22} & p_{23} & p_{42} \\ p_{31} & p_{23} & p_{33} & p_{43} \end{bmatrix}$$

We wish to find *camera centre, orientation of the camera* and the *internal parameters* of the camera from  $P$

# Decomposition of the Camera Matrix

## Finding the camera centre:

- The camera centre **C** is the point for which  $\mathbf{PC}=0$ .

## Numerically:

- it is the right null-vector obtained by SVD of **P**

$\text{SVD}(\mathbf{P}) = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T$  where **C** is last column of **V** corresponding to the least singular value  $\sigma$

## Algebraically:

**C** can be obtained by the null-space of **P**

$$\mathbf{X} = \det([\mathbf{p}_2, \mathbf{p}_3, \mathbf{p}_4])$$

$$\mathbf{Z} = \det([\mathbf{p}_1, \mathbf{p}_2, \mathbf{p}_4])$$

$$\mathbf{Y} = \det([\mathbf{p}_1, \mathbf{p}_3, \mathbf{p}_4])$$

$$\mathbf{T} = \det([\mathbf{p}_1, \mathbf{p}_2, \mathbf{p}_3])$$

# Decomposition of the Camera Matrix

## Finding the camera orientation and internal parameters

- In the case of finite camera, we have

$$P = [M \mid -M\tilde{C}] = K[R \mid -R\tilde{C}]$$

- Recall that  $K = \begin{bmatrix} \alpha_x & s & p_x \\ 0 & \alpha_y & p_y \\ 0 & 0 & 1 \end{bmatrix}$  which is an *upper-triangular matrix*
- $R$  is the rotation matrix which is *orthogonal matrix*
- $K$  and  $R$  can be found easily by *RQ-Decomposition* of  $M$  as  $M = KR$
- The ambiguity in the decomposition is removed by requiring that  $K$  have *positive diagonal entries*



# QR Decomposition

**Finding the camera orientation and internal parameters:**

- The matrix  $K$  has the form:

$$K = \begin{bmatrix} \alpha_x & s & x_0 \\ 0 & \alpha_y & y_0 \\ 0 & 0 & 1 \end{bmatrix}$$

Where

- $\alpha_x$  is the scale factor in the  $x$ -coordinate direction
- $\alpha_y$  is the scale factor in the  $y$ -coordinate direction
- $s$  is the skew
- $(x_0, y_0)^T$  are the coordinates of the principal point
- The aspect ratio is  $\alpha_x/\alpha_y$

# QR Decomposition

- Given a matrix  $A$ , we can decompose it into

$$A = QR$$

Where  $Q$  is an orthogonal matrix (i.e.  $Q^T Q = I$ ) and  $R$  is an upper triangular matrix. We can solve by Gram-Schmidt process.

$$A = [a_1 \quad | \quad a_2 \quad | \quad \dots \quad | \quad a_n]$$

# QR Decomposition

By Gram-Schmidt

$$u_1 = a_1, \quad q_1 = \frac{u_1}{\|u_1\|},$$

$$u_2 = a_2 - (a_2 \cdot q_1)q_1, \quad q_2 = \frac{u_2}{\|u_2\|},$$

$$u_{k+1} = a_{k+1} - (a_{k+1} \cdot q_1)q_1 - \cdots - ((a_{k+1} \cdot q_k)q_k, \quad q_{k+1} = \frac{u_{k+1}}{\|u_{k+1}\|},$$

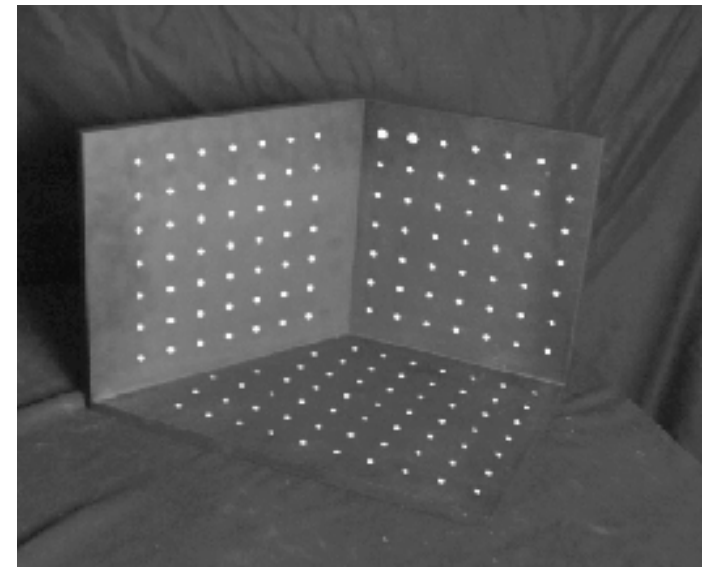
$$\begin{aligned} \bullet \quad A &= [a_1 \mid a_2 \mid \cdots \mid a_n] \\ &= [q_1 \mid q_2 \mid \cdots \mid q_n] \begin{bmatrix} a_1 \cdot q_1 & a_2 \cdot q_1 & \cdots & a_n \cdot q_1 \\ 0 & a_2 \cdot q_2 & \cdots & a_n \cdot q_2 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & a_n \cdot q_n \end{bmatrix} = QR \end{aligned}$$

# Camera Calibration

- Mapping from World Coord to image

$$\mathbf{x} = \mathbf{P}\mathbf{X} = \mathbf{K}[\mathbf{R} \mid -\mathbf{R}\tilde{\mathbf{C}}]\mathbf{X}$$

- Goal: To estimate the intrinsic and extrinsic parameters of the camera
- Given: Known 3D points
- Observation: corresponding 2d points



# Camera Calibration

We have

$$\mathbf{x} = \mathbf{P}\mathbf{X} = \mathbf{K}[\mathbf{R} \mid -\mathbf{R}\tilde{\mathbf{C}}]\mathbf{X}$$

3 rotations

5 intrinsic paras

3 translations

- Total: 11 parameters, 6 extrinsic, 5 intrinsic
- How many points to we need?
  - Six points, each point gives two equations

# Direct Linear Transform (DLT)

**Mapping from World Coordinate to image:**

$$\mathbf{x} = \mathbf{P}\mathbf{X}$$

- where

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{41} \\ p_{21} & p_{22} & p_{23} & p_{42} \\ p_{31} & p_{23} & p_{33} & p_{43} \end{bmatrix}$$

# Direct Linear Transform

For every data point  $i$ , we have

$$\mathbf{x}_i = \begin{bmatrix} u_i \\ v_i \\ w_i \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \end{bmatrix} \begin{bmatrix} X_i \\ Y_i \\ Z_i \\ 1 \end{bmatrix}$$

- Collinear equations

$$x_i = \frac{u_i}{w_i} = \frac{p_{11}X_i + p_{12}Y_i + p_{13}Z_i + p_{14}}{p_{31}X_i + p_{32}Y_i + p_{33}Z_i + p_{34}}$$

$$y_i = \frac{v_i}{w_i} = \frac{p_{21}X_i + p_{22}Y_i + p_{23}Z_i + p_{24}}{p_{31}X_i + p_{32}Y_i + p_{33}Z_i + p_{34}}$$

# Direct Linear Transform

$$x_i = \frac{u_i}{w_i} = \frac{p_{11}X_i + p_{12}Y_i + p_{13}Z_i + p_{14}}{p_{31}X_i + p_{32}Y_i + p_{33}Z_i + p_{34}} \quad y_i = \frac{v_i}{w_i} = \frac{p_{21}X_i + p_{22}Y_i + p_{23}Z_i + p_{24}}{p_{31}X_i + p_{32}Y_i + p_{33}Z_i + p_{34}}$$

- Rearranging the equation, we have

$$x_i (p_{31}X_i + p_{32}Y_i + p_{33}Z_i + p_{34}) - (p_{11}X_i + p_{12}Y_i + p_{13}Z_i + p_{14}) = 0$$

$$y_i (p_{31}X_i + p_{32}Y_i + p_{33}Z_i + p_{34}) - (p_{21}X_i + p_{22}Y_i + p_{23}Z_i + p_{24}) = 0$$

- Rewrite as

$$\begin{array}{llll} -(p_{11}X_i + p_{12}Y_i + p_{13}Z_i + p_{14}) & +x_i (p_{31}X_i + p_{32}Y_i + p_{33}Z_i + p_{34}) & =0 \\ -(p_{21}X_i + p_{22}Y_i + p_{23}Z_i + p_{24}) & +x_i (p_{31}X_i + p_{32}Y_i + p_{33}Z_i + p_{34}) & =0 \end{array}$$



# Direct Linear Transform

- For every point  $i$ , we have

$$(-X_i, -Y_i, -Z_i, -1, 0, 0, 0, 0, x_i X_i, x_i Y_i, x_i Z_i, x_i) \begin{bmatrix} p_{11} \\ p_{12} \\ p_{13} \\ p_{14} \\ p_{21} \\ p_{22} \\ p_{23} \\ p_{24} \\ p_{31} \\ p_{32} \\ p_{33} \\ p_{34} \end{bmatrix} = 0$$

# Direct Linear Transform

$$(0, \quad 0, \quad 0, \quad 0, \quad -X_i, \quad -Y_i, \quad -Z_i, \quad -1, \quad y_i X_i, \quad y_i Y_i, \quad y_i Z_i, \quad y_i) \begin{bmatrix} p_{11} \\ p_{12} \\ p_{13} \\ p_{14} \\ p_{21} \\ p_{22} \\ p_{23} \\ p_{24} \\ p_{31} \\ p_{32} \\ p_{33} \\ p_{34} \end{bmatrix} = 0$$

# Combining the equations

$$2Xn \text{ equations} \begin{bmatrix} -X_i, & -Y_i, & -Z_i, & -1, & 0, & 0, & 0, & 0, & x_i X_i, & x_i Y_i, & x_i Z_i, & x_i \\ 0, & 0, & 0, & 0, & -X_i, & -Y_i, & -Z_i, & -1, & y_i X_i, & y_i Y_i, & y_i Z_i, & y_i \\ \vdots & & & & & & & & & & & \vdots \\ \vdots & & & & & & & & & & & \vdots \end{bmatrix} \begin{bmatrix} p_{11} \\ p_{12} \\ p_{13} \\ p_{14} \\ p_{21} \\ p_{22} \\ p_{23} \\ p_{24} \\ p_{31} \\ p_{32} \\ p_{33} \\ p_{34} \end{bmatrix} = 0$$

Rewrite as:

$$A_{2n \times 12} P_{12 \times 1} = 0$$

# Singular Value Decomposition (SVD)

Given the linear system

$$AP = 0$$

By SVD,

$$A_{2n \times 12} = U_{2n \times 12} \Sigma_{12 \times 12} V^T_{12 \times 12} = \sum_{i=1}^{12} u_i \sigma_i v_i^T$$

For A has rank 11 (for  $n > 6$ ), the system has a nontrivial solution  $p$  which is proportional to the column of  $V$  corresponding to the smaller singular value  $\sigma$  which is  $\sigma_{12}$

# Singular Value Decomposition (SVD)

- Therefore the estimated  $p$  is

$$\hat{p} = v_{12} = \begin{bmatrix} \widehat{p}_1 & \widehat{p}_2 & \widehat{p}_3 & \widehat{p}_4 \\ \widehat{p}_5 & \widehat{p}_6 & \widehat{p}_7 & \widehat{p}_8 \\ \widehat{p}_9 & \widehat{p}_{10} & \widehat{p}_{11} & \widehat{p}_{12} \end{bmatrix}$$

# Note for the DLT solution of Camera Calibration

- A is of rank 11, we need
  - number of points  $n > 6$
  - No error measurement
- Pay attention to the sample points
  - No solution if all points  $X_i$  are on a plane

$$A = \begin{bmatrix} -X_i & -Y_i & -Z_i & -1 & 0 & 0 & 0 & 0 & x_i X_i & x_i Y_i & x_i Z_i & x_i \\ 0 & 0 & 0 & 0 & -X_i & -Y_i & -Z_i & -1 & y_i X_i & y_i Y_i & y_i Z_i & y_i \\ \vdots & & & & & & & & & & & \vdots \\ \vdots & & & & & & & & & & & \vdots \end{bmatrix}$$

- If all  $X_i$  on a plane (say  $Z=0$ ), we have

$$A = \begin{bmatrix} -X_i & -Y_i & 0 & -1 & 0 & 0 & 0 & 0 & x_i X_i & x_i Y_i & 0 & x_i \\ 0 & 0 & 0 & 0 & -X_i & -Y_i & 0 & -1 & y_i X_i & y_i Y_i & 0 & y_i \\ \vdots & & & & & & & & & & & \vdots \\ \vdots & & & & & & & & & & & \vdots \end{bmatrix} \text{ reduced rank and no – solution!}$$

# Decomposition of P

- Now we have

$$\hat{P} = \begin{bmatrix} \hat{p}_1 & \hat{p}_2 & \hat{p}_3 & \hat{p}_4 \\ \hat{p}_5 & \hat{p}_6 & \hat{p}_7 & \hat{p}_8 \\ \hat{p}_9 & \hat{p}_{10} & \hat{p}_{11} & \hat{p}_{12} \end{bmatrix}$$

- But we are interested in projection

$$\hat{P} = \hat{K} \hat{R} [I_3 | -\hat{C}]$$

We need to compute

$$\hat{K}, \hat{R}, \hat{C} \text{ from } \hat{p}$$

# Decomposition of P

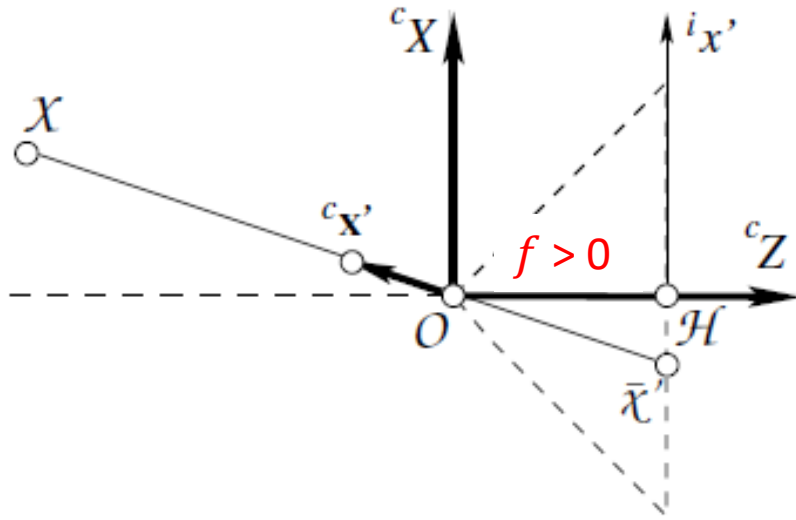
The intrinsic parameters  $K = \begin{bmatrix} \alpha_x & s & x_0 \\ 0 & \alpha_y & y_0 \\ 0 & 0 & 1 \end{bmatrix}$

- If  $\hat{K}$  diagonal element is position,  $\alpha_x$  and is  $\alpha_y$  positive and also  $f$ .
- To get negative camera constant  $f$ , apply another rotation

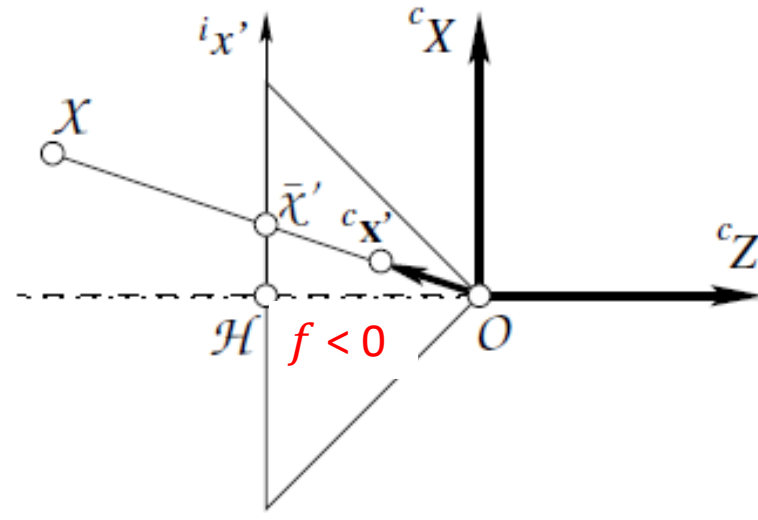
$$R = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$



# Image plane in the front



$f > 0$ , image behind the origin  
Image upside down



$f < 0$ , image in front of the origin,  
Image orientation maintained

# Summary of DLT steps

1. Vectorize the P:  $\mathbf{p} = (p_k)$
2. Construct the Linear System

$$\begin{bmatrix} -X_i & -Y_i & -Z_i & -1 & 0 & 0 & 0 & 0 & x_i X_i & x_i Y_i & x_i Z_i & x_i \\ 0 & 0 & 0 & 0 & -X_i & -Y_i & -Z_i & -1 & y_i X_i & y_i Y_i & y_i Z_i & y_i \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix} \mathbf{p} = 0$$

3. Apply SVD on A and select the last column of V as the solution to compute a solution  $\hat{\mathbf{P}}$
4. To calculate the extrinsic and intrinsic parameters, decompose  $\hat{\mathbf{P}}$

$$\hat{\mathbf{P}} = [\hat{\mathbf{P}}_1 \mid \hat{\mathbf{P}}_2] = \hat{\mathbf{K}}\hat{\mathbf{R}}[\mathbf{I}_3 \mid -\hat{\mathbf{C}}]$$

$$\hat{\mathbf{X}}_0 = -(\hat{\mathbf{P}}_1)^{-1} \hat{\mathbf{P}}_2$$

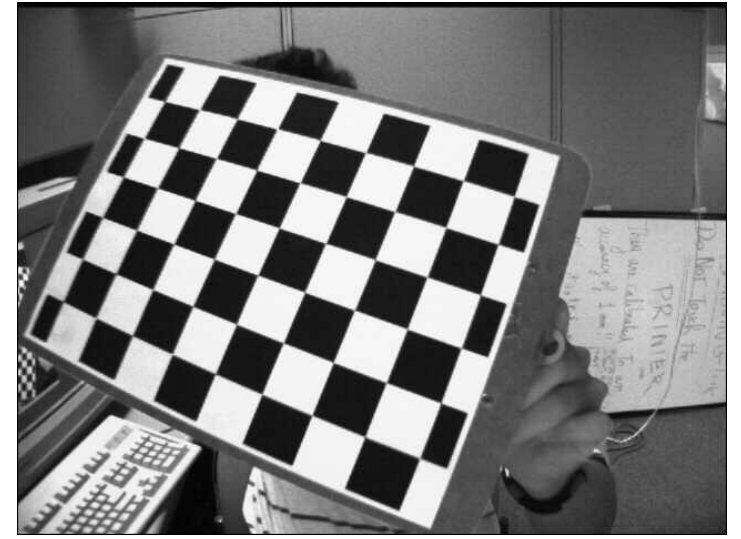
$$\hat{\mathbf{P}}_1 = \hat{\mathbf{K}}\hat{\mathbf{R}} \text{ computed by } \textit{QR decomposition}$$

# Summary of DLT

- For un-calibrated camera, we need at least 6 points
- Advantages:
  - Very simple to formulate and solve
- Disadvantages
  - You need to 3D co-ordinates of the control points.
  - Solution non-stable if control points lie on a plane.
  - Doesn't model radial distortion.

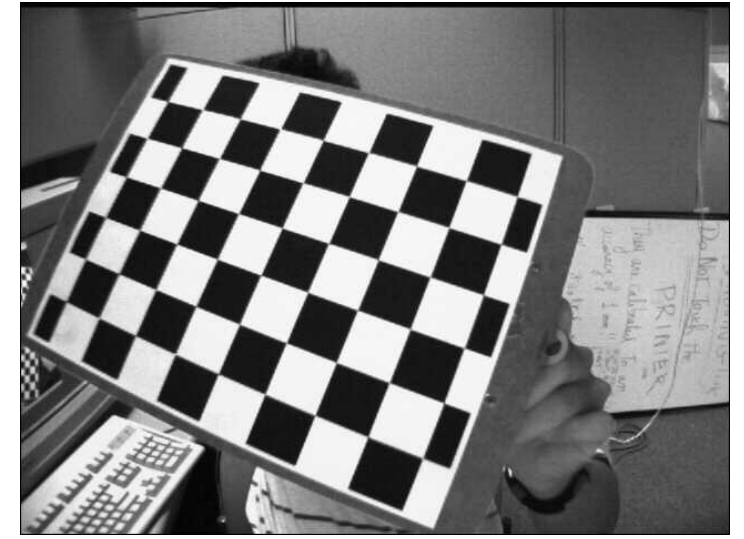
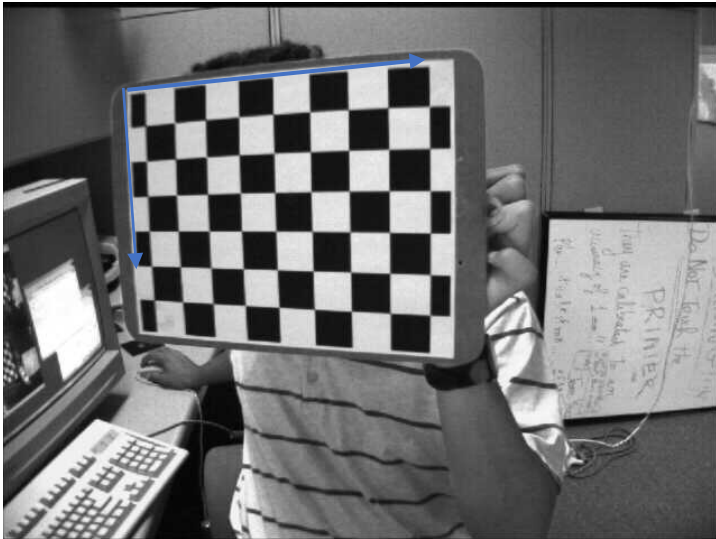
# Multi-Plane Camera Calibration(Zhang 2000)

- Use a 2D known pattern (checkerboard) for calibration



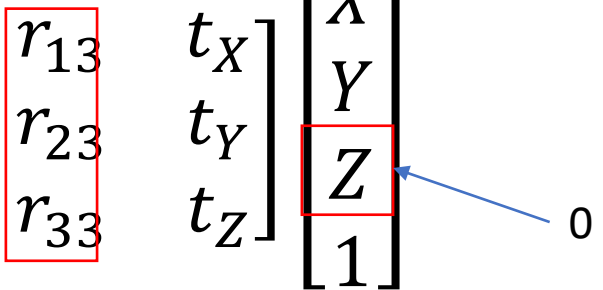
# Checkerboard Calibration

- Set the world coordinate on the checkerboard with X-Y plane ( $Z=0$ ) lies on the checkerboard



# The mapping Function

- As all points lie on the checkerboard and therefore have  $Z=0$
- The mapping function

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \mathbf{K} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$


- We can take away 3<sup>rd</sup> Column of the extrinsic matrix, and the mapping function becomes

# Simplified Mapping Function

- The Z-Coordinate of all points on checkerboard is zero
- The 3<sup>rd</sup> column of the extrinsic matrix is deleted

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} \alpha_x & s & x_0 \\ 0 & \alpha_y & y_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & t_x \\ r_{21} & r_{22} & t_y \\ r_{31} & r_{32} & t_z \end{bmatrix} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}$$

We can rewrite as:

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = K_{3 \times 3} \begin{bmatrix} r_1 & r_2 & t \end{bmatrix}_{3 \times 3} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} = H \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}$$

Where H is a homography between the transformation

$$H = \begin{bmatrix} h_1 & h_2 & h_3 \end{bmatrix} = K \begin{bmatrix} r_1 & r_2 & t \end{bmatrix}$$

# Setting up the Equations

- For all the point  $X_i$ , we have

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = [h_1, \quad h_2, \quad h_3] \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} \quad i = 1 \dots n \text{ for } n \text{ points}$$

- We perform similar steps in DLT with 3 columns taken away

$$\begin{bmatrix} -X_i, & -Y_i, & -Z_i, & -1, & 0, & 0, & 0, & 0, & x_i X_i, & x_i Y_i, & x_i Z_i, & x_i \\ 0, & 0, & 0, & 0, & -X_i, & -Y_i, & -Z_i, & -1, & y_i X_i, & y_i Y_i, & y_i Z_i, & y_i \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ h_3 \end{bmatrix} = 0$$



# Setting up Equations

- Solving the system of linear equations will give you H
- H has DoF of 8, each point gives you two equations, therefore you need at least 4 points

$$\begin{bmatrix} -X_i & -Y_i & -1 & 0 & 0 & 0 & x_i X_i & x_i Y_i & x_i \\ 0 & 0 & 0 & -X_i & -Y_i & -1 & y_i X_i & y_i Y_i & y_i \\ \vdots & & & & & & & & \vdots \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ h_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

**A**

2n x 9

**h**

9 x 1

**0**

2n

How to solve?

SVD

# Estimation of Calibration matrix from H

- $H = [h_1, \quad h_2, \quad h_3] = \begin{bmatrix} \alpha_x & s & x_0 \\ 0 & \alpha_y & y_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & t_X \\ r_{21} & r_{22} & t_Y \\ r_{31} & r_{32} & t_Z \end{bmatrix}$

- How can we can K and R and  $X_0$ ? Can we use QR decomposition again?
- No!

$$\begin{bmatrix} r_{11} & r_{12} & t_X \\ r_{21} & r_{22} & t_Y \\ r_{31} & r_{32} & t_Z \end{bmatrix} \text{ not a rotation matrix anymore.}$$

# Estimation of Calibration matrix from H

$$H = [h_1, \quad h_2, \quad h_3] = \begin{bmatrix} \alpha_x & s & x_0 \\ 0 & \alpha_y & y_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & t_X \\ r_{21} & r_{22} & t_Y \\ r_{31} & r_{32} & t_Z \end{bmatrix}$$

As

$$H = [h_1, \quad h_2, \quad h_3] = K [r_1, \quad r_2, \quad t]$$

we have

$$r_1 = K^{-1} h_1 \text{ -----eq(1)}$$

$$r_2 = K^{-1} h_2 \text{ -----eq(2)}$$

# Other Constraints

Any rotation matrix is an orthonormal matrix

$$r_1 = K^{-1}h_1 \text{ -----eq(1)}$$

$$r_2 = K^{-1}h_2 \text{ -----eq(2)}$$

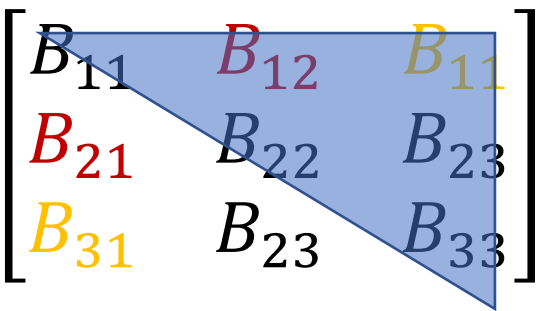
i.e  $r_i \cdot r_j = \begin{cases} 0 & \text{when } i \neq j \\ 1 & \text{when } i = j \end{cases}$

$$r_1^T r_2 = h_1^T K^{-T} K^{-1} h_2 = 0 \text{ -----eq(3)}$$

$$r_1^T r_1 = r_2^T r_2 = h_1^T K^{-T} K^{-1} h_1 - h_2^T K^{-T} K^{-1} h_2 = 0 \text{ -----eq(4)}$$

# Other Constraints

Let B be a symmetric and positive definite matrix such that

$$B = K^{-T}K^{-1} = \begin{bmatrix} B_{11} & B_{12} & B_{13} \\ B_{21} & B_{22} & B_{23} \\ B_{31} & B_{23} & B_{33} \end{bmatrix} \text{ where } B_{13} = B_{31}, B_{23} = B_{32}$$


Since B is symmetric matrix, B is defined by 6D vector

$$B = [B_{11}, B_{12}, B_{13}, B_{22}, B_{23}, B_{33}]^T$$

# Other Constraints

Let B be a symmetric and positive definite matrix such that

$$B = K^{-T}K^{-1} = \begin{bmatrix} B_{11} & B_{12} & B_{13} \\ B_{12} & B_{22} & B_{23} \\ B_{13} & B_{23} & B_{33} \end{bmatrix}$$

We have

$$h_1^T B h_2 = 0 \text{ - (eq. 5)}$$

$$h_1^T B h_1 - h_2^T B h_2 = 0 \text{ - (eq. 6)}$$

Note: One image gives two linear equation in elements of B, how many images we need?

Ans: 3 images

# Solving K from B

$$\bullet \begin{bmatrix} B_{11} & \textcolor{red}{B}_{12} & \textcolor{brown}{B}_{11} \\ \textcolor{red}{B}_{12} & B_{22} & B_{23} \\ \textcolor{brown}{B}_{13} & B_{23} & B_{33} \end{bmatrix} = \begin{bmatrix} c & s & x_H \\ 0 & c(1+m) & y_H \\ 0 & 0 & 1 \end{bmatrix}^{-T} \begin{bmatrix} c & s & x_H \\ 0 & c(1+m) & y_H \\ 0 & 0 & 1 \end{bmatrix}^{-1}$$

$$c = \sqrt{\frac{\lambda}{B_{11}}}$$

$$s = -\frac{B_{12}c^3(1+m)}{\lambda}$$

$$\lambda = B_{33} - \frac{B_{33}^2 + u_y(B_{12}B_{13} - B_{11}B_{23})}{B_{11}}$$

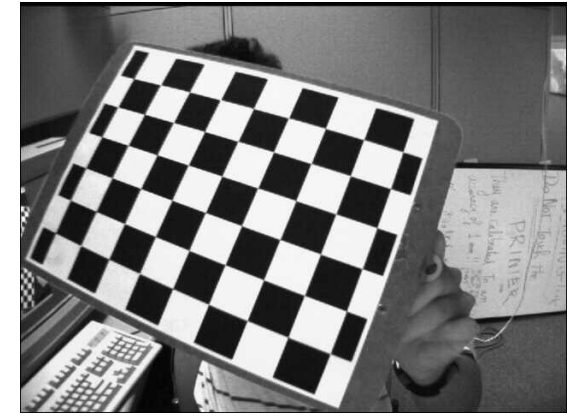
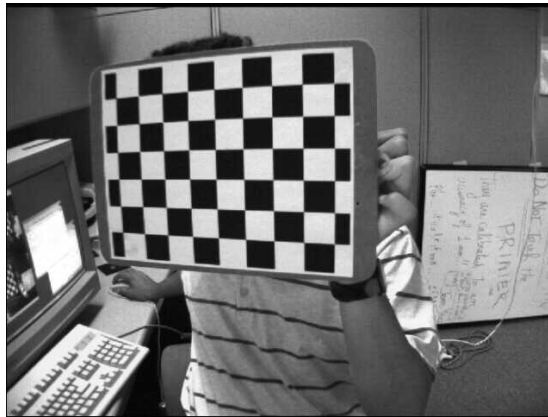
$$m = \frac{1}{c} \sqrt{\frac{\lambda B_{11}}{B_{11}B_{22} - B_{12}^2} - 1}$$

$$u_y = \frac{B_{12}B_{13} - B_{13}B_{23}}{B_{11}B_{22} - B_{12}^2}$$

$$u_x = \frac{su_y}{c} - B_{13} \frac{c^2}{\lambda}$$

# What do we need?

- Each Plane gives **2** equations
- Since B has **6 degree of freedom**, we need at least **3 different views** of a plane



- We need at least **4 points** per plane to compute the Homography
- Solve B and then you can compute K by Cholesky decomposition



# Solving for Extrinsic Parameters

- Once  $K$  is known, the extrinsic parameters

$$r_1 = \lambda K^{-1} h_1$$

$$r_2 = \lambda K^{-1} h_2$$

where

$$\lambda = \frac{1}{\|K^{-1} h_1\|}$$

$r_3$  can be retrieved by cross-production of

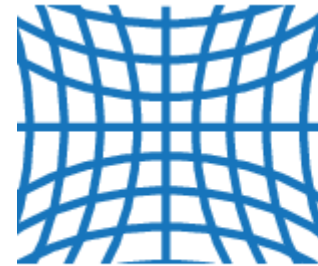
$$r_3 = r_1 \times r_2$$

Translation  $t$  can be found by

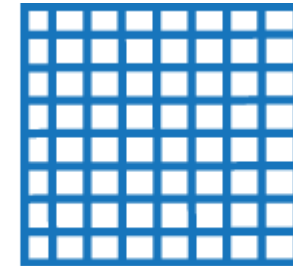
$$t = \lambda K^{-1} h_3$$

# Non-linear Error

- Non-linear Effect
  - Radial Distortion
  - Tangential Distortion
- Radial Distortion
  - $x_{distorted} = x(1 + k_1r^2 + k_2r^4 + k_3r^6)$
  - $y_{distorted} = y(1 + k_1r^2 + k_2r^4 + k_3r^6)$
- Tangential Distortion
  - $x_{distorted} = x + [2p_1xy + p_2(r^2 + 2x^2)]$
  - $y_{distorted} = y + [p_1(r^2 + 2x^2) + 2p_2xy]$



Negative radial distortion  
"pincushion"



No distortion



Positive radial distortion  
"barrel"

# Error Minimization

- Lens distortion can be calculated by minimizing a non-linear error function

- $$\min_{(K, \mathbf{q}, R_i, \mathbf{t}_i)} \sum_i \sum_j \|\mathbf{X}_{ij} - \hat{\mathbf{x}}(K, \mathbf{q}, R_i, \mathbf{t}_i, \mathbf{X}_{ij})\|^2$$

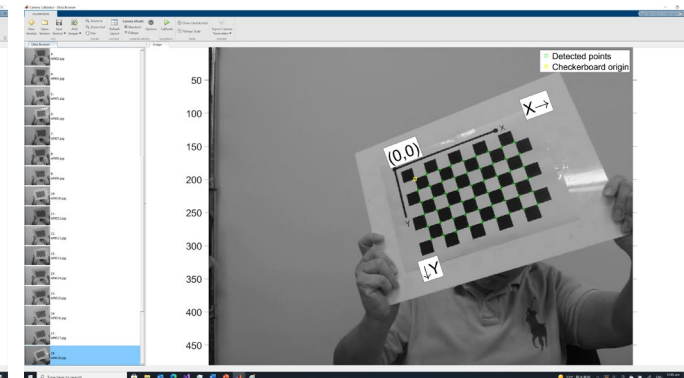
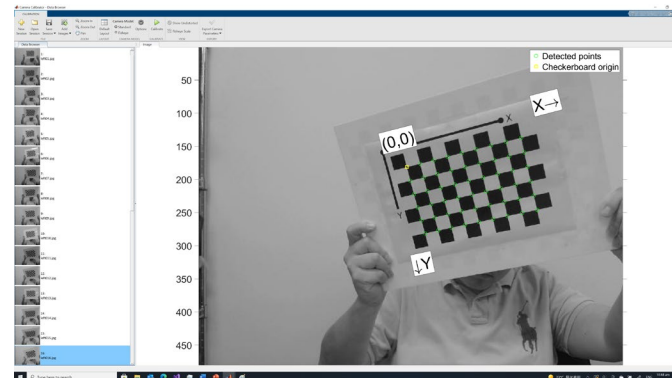
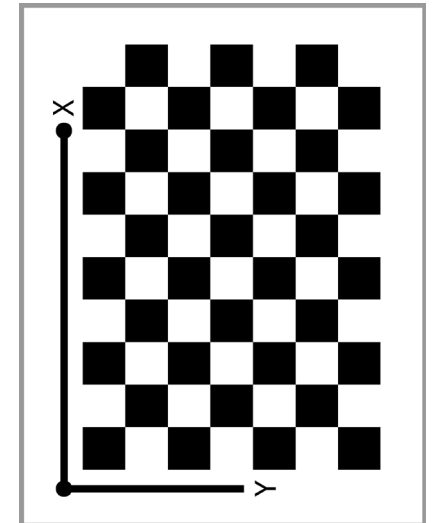
- Solved by using Levenberg-Marquardt
  - [Levenberg–Marquardt algorithm - Wikipedia](#)

# Summary of Steps for Checkboard calibration

1. Print a *pattern* and attach it to a *planar* surface
2. Take a few images of the model plane under *different orientations* by moving either the plane or the camera
3. Detect the feature points in the images
4. Estimate the *five intrinsic parameters* and all the extrinsic parameters using the closed-form solution
5. Estimate the coefficient of the *radial distortion* by solving the *linear least-squares*
6. Refine all parameters, including lens distortion parameters by minimizing

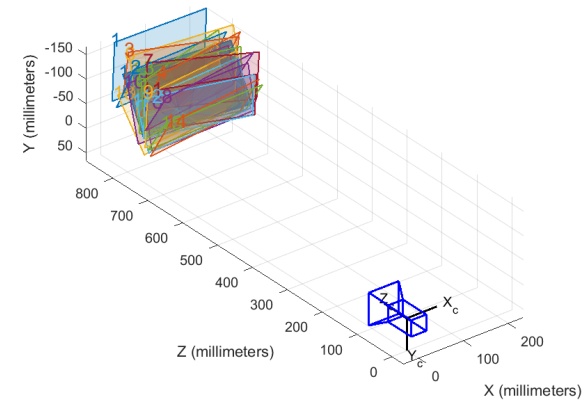
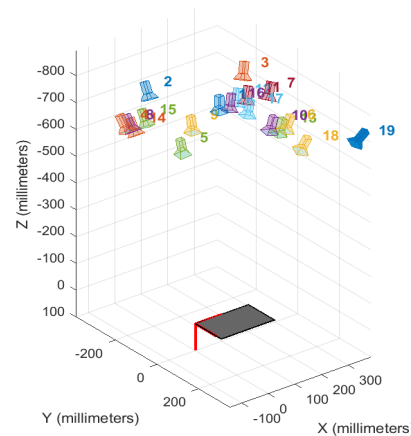
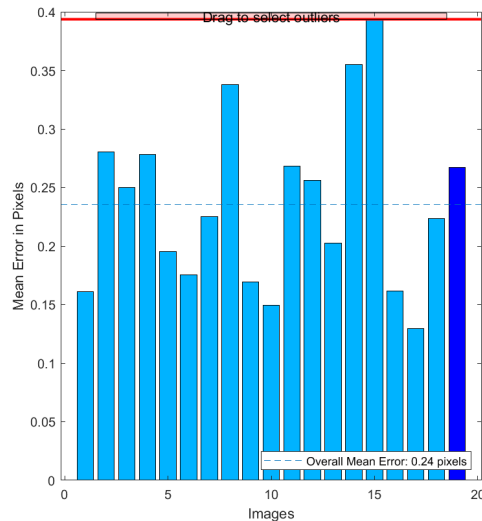
# MATLAB Camera Calibration Toolbox

- MATLAB provides the toolbox for camera calibration
- You will need a checkerboard.  
Type “[open checkerboardPattern.pdf](#)”
- Measure the checkerboard sizes and take 15+ pictures of the checkerboard pattern with different angles.



# MATLAB Camera Calibration Toolbox

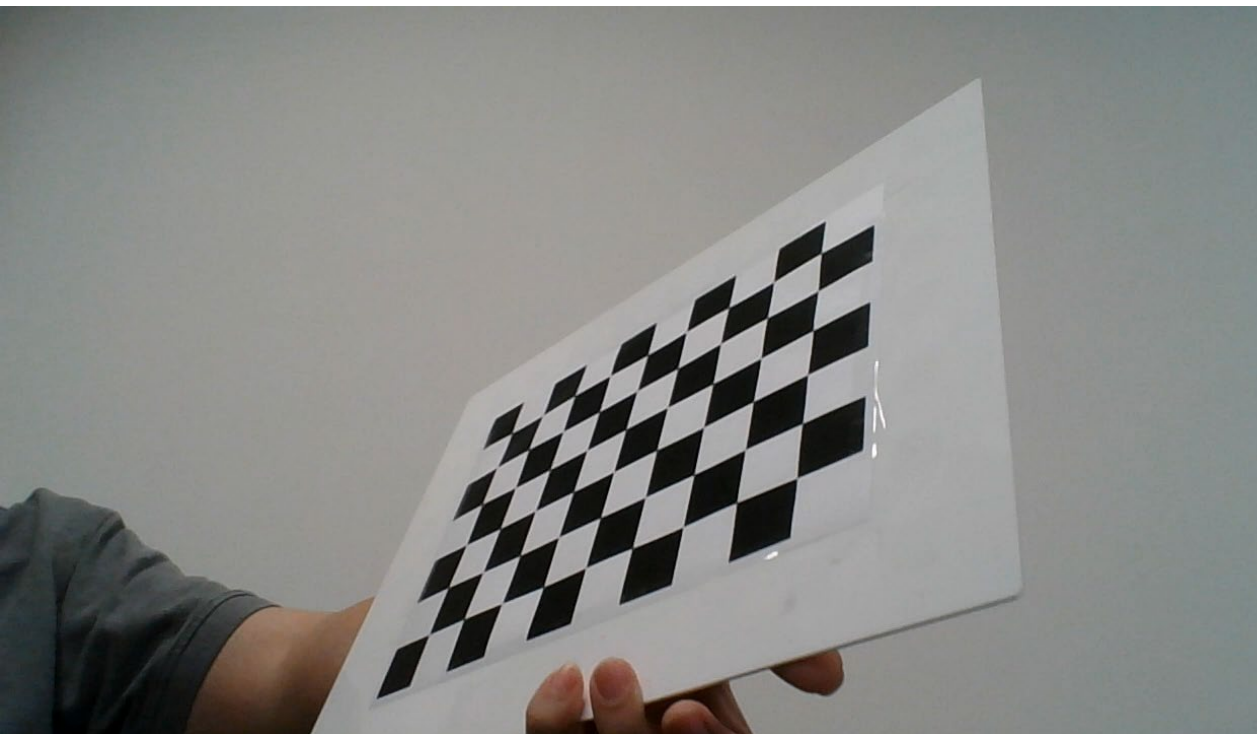
- Open the camera calibrator in MATLAB
- Add all the images and calibrate



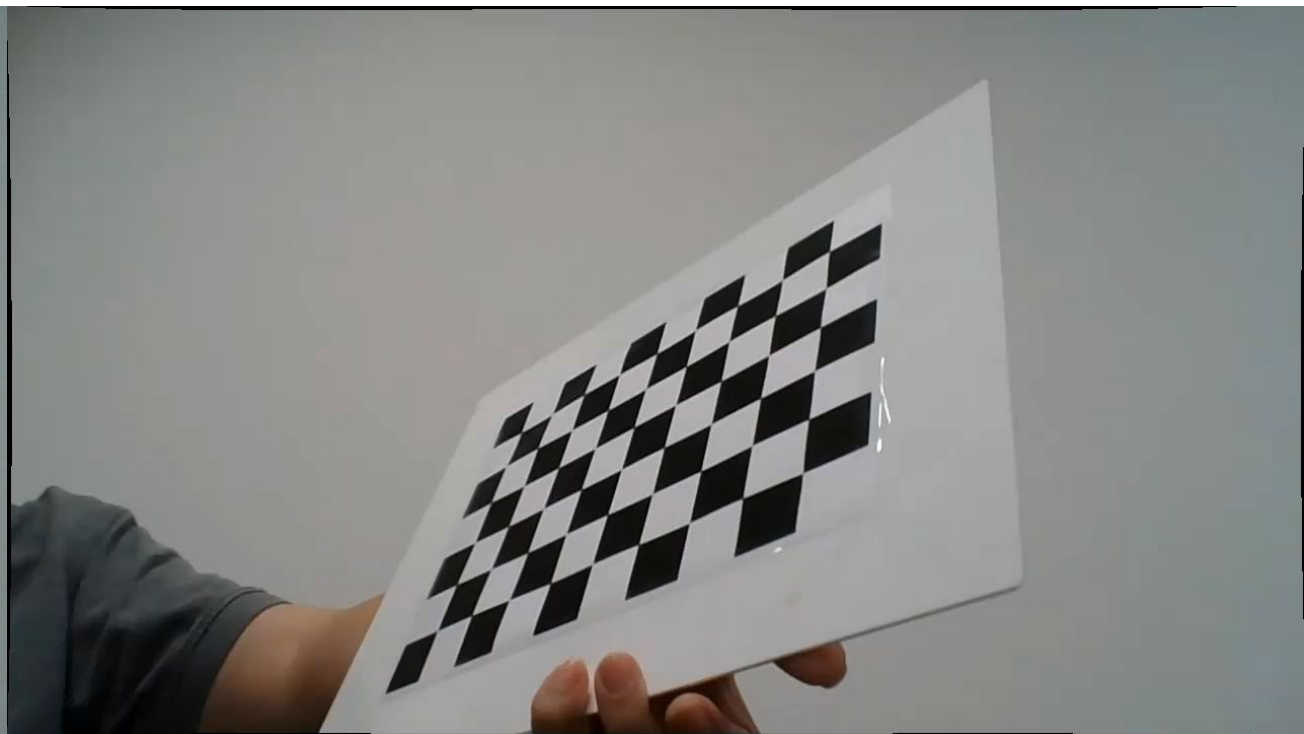
☐ FocalLength  
☐ PrincipalPoint  
☐ ImageSize  
☐ RadialDistortion  
☐ TangentialDistortion  
☐ Skew  
☐ IntrinsicMatrix

[650.0602,650.1585]  
[305.5123,253.3729]  
[480,640]  
[-0.0018,0.0326]  
[0,0]  
0  
[650.0602,0,0;0,650.1585,0;305.5123,253.3729,1]

# Applications: Calibrate distorted video

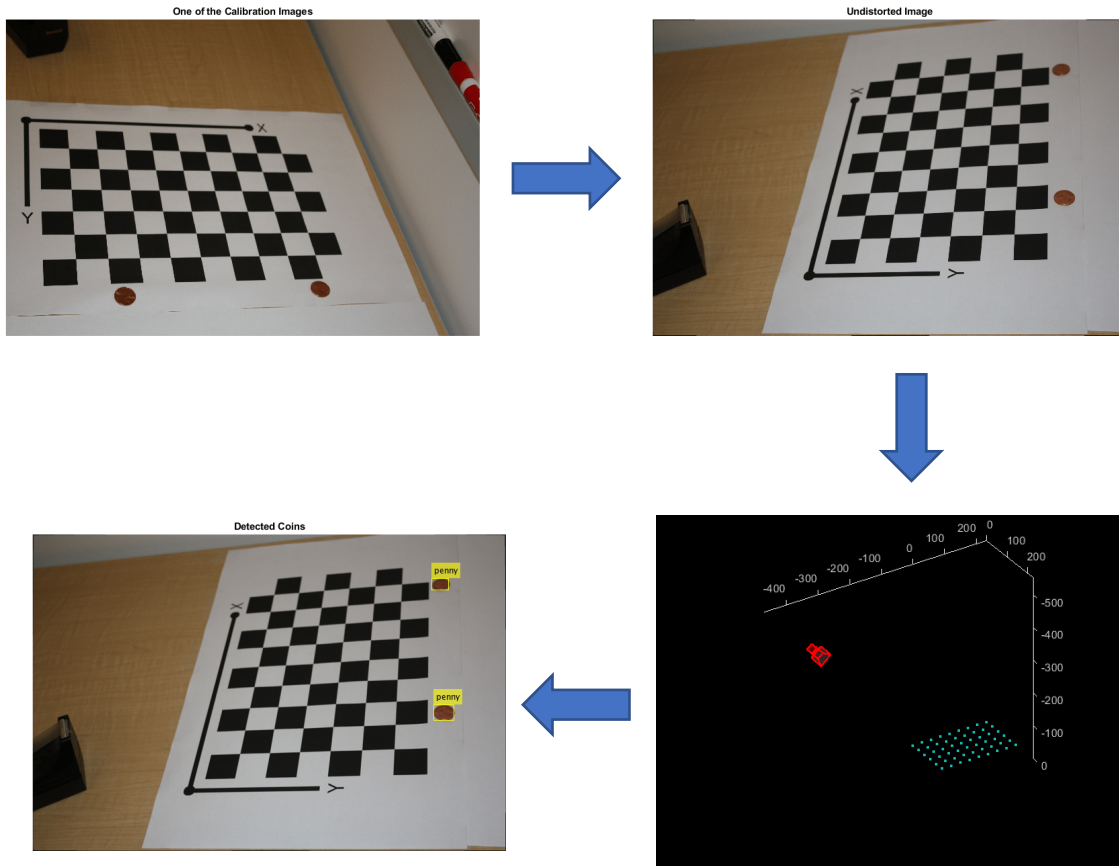


Original Video



Undistorted Video

# Applications: Measurement of Planar Objects



1. Calibrate the camera
2. Take the images and undistort them.
3. Detect the coins (blob analysis or Hough transform)
4. Estimate the camera extrinsic parameters  $R$ ,  $T$  using “**extrinsic**” function by MATLAB
5. Get world coordinate of the coins



# Reading

- Wolfgang Forstner, Bernhard P. Wrobel (2016), Photogrammetric Computer Vision, Statistic, Geometry, Orientation and Reconstruction, Springer. Chapter 12
- Zhang, Z. (2000). A flexible new technique for camera calibration. IEEE Transactions on Pattern Analysis and Machine Intelligence, 22(11):1330–1334.