

# Coordinate Transformation & Image Formation

Ziheng  
2017/09/28

## Coordinate Transformation

- Rigid-body motion
  - Rotation
  - Translation
  - Homogenous Representation

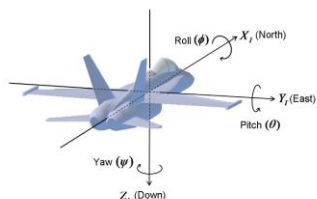
**Transform coordinate in world frame to cam frame**

**How to parameterize rigid-body motion?**

# Coordinate Transformation

Computer Vision I  
Recitation – 3

- Rotation – Euler angles (e.g. IMU)



$$\mathbf{R} = \mathbf{R}_x \mathbf{R}_y \mathbf{R}_z$$

$$\mathbf{R}_x(\theta_x) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \theta_x & -\sin \theta_x \\ 0 & \sin \theta_x & \cos \theta_x \end{bmatrix}$$

$$\mathbf{R}_y(\theta_y) = \begin{bmatrix} \cos \theta_y & 0 & \sin \theta_y \\ 0 & 1 & 0 \\ -\sin \theta_y & 0 & \cos \theta_y \end{bmatrix}$$

$$\mathbf{R}_z(\theta_z) = \begin{bmatrix} \cos \theta_z & -\sin \theta_z & 0 \\ \sin \theta_z & \cos \theta_z & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

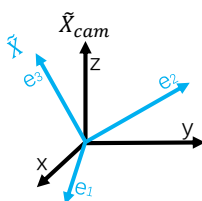
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# Coordinate Transformation

Computer Vision I  
Recitation – 3

- Rotation – Basis Transformation (e.g. Compass, Encoder)



$$\begin{aligned} \mathbf{R} &= [\mathbf{e}_{wc} \quad \mathbf{e}_{wc} \quad \mathbf{e}_{wc}] \\ &= [\mathbf{e}_{cw} \quad \mathbf{e}_{cw} \quad \mathbf{e}_{cw}]^T \end{aligned}$$

Where  $\mathbf{e}_{wc} \mathbf{e}_{wc} \mathbf{e}_{wc}$  is basis of world frame,  
represented in cam coordinate

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# Coordinate Transformation

Computer Vision I  
Recitation – 3

- Rotation group  $SO(n)$  – DoF:  $\frac{n(n-1)}{2}$

The set of  $n \times n$  orthogonal matrices forms a group  $O(n)$ , known as the orthogonal group. The subgroup  $SO(n)$  consisting of orthogonal matrices with determinant **+1** is called the special orthogonal group, and each of its elements is a **special orthogonal matrix**. As a linear transformation, **every special orthogonal matrix acts as a rotation**.

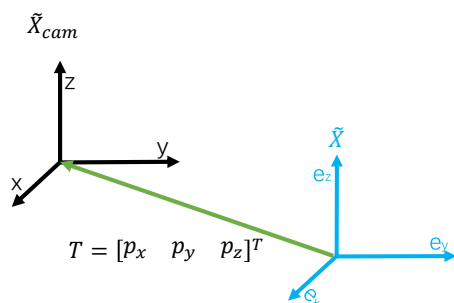
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# Coordinate Transformation

Computer Vision I  
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- Translation



$$[x \ y \ z]^T \Rightarrow [x \ y \ z]^T + T$$

Where  $p_x \ p_y \ p_z$  is translation **along cam coordinate**

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# Altogether

## Computer Vision I Recitation – 3

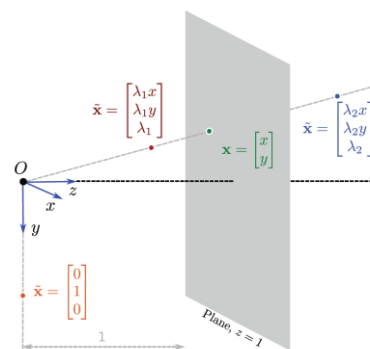
### • Homogeneous Coordinates

Mapping to homogeneous coordinates

$$\begin{cases} 2D: & (x,y)^T \rightarrow (x,y,1)^T \\ 3D: & (x,y,z)^T \rightarrow (x,y,z,1)^T \end{cases}$$

Mapping back from homogeneous coordinates

$$\begin{cases} 2D: & (x,y,w)^T \rightarrow (\frac{x}{w}, \frac{y}{w})^T \\ 3D: & (x,y,z,w)^T \rightarrow (\frac{x}{w}, \frac{y}{w}, \frac{z}{w})^T \end{cases}$$



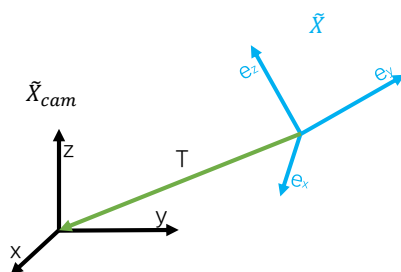
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# Altogether

## Computer Vision I Recitation – 3

### • Rotation & Translation (Extrinsic Parameters)



$$\begin{aligned} \tilde{X} = RX + T &= \begin{bmatrix} I & T \\ 0 & 1 \end{bmatrix} \begin{bmatrix} R & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \\ &= \begin{bmatrix} R & T \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \end{aligned}$$

$$R = [e_x \quad e_y \quad e_z]^T$$

DoF: 3+3=6

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# Altogether

## Computer Vision I Recitation – 3

- Rigid motion group  $SE(n)$ – DoF:  $\frac{n(n-1)}{2} + n \rightarrow \frac{n(n+1)}{2}$

The Euclidean group  $E(n)$  is the symmetry group including the **orientation-reversing isometries** (like reflections, glide reflections and improper rotations) . There is a subgroup of the direct isometries, i.e., isometries preserving orientation also called **rigid motions**. These include the translations, and the rotations, which together generate a **special Euclidean group**, and denoted  $SE(n)$ .

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# Image Formation

## Computer Vision I Recitation – 3

- Camera Models
  - Ideal Perspective Camera
  - Intrinsic Parameters
  - General Perspective Camera
  - (Thin) Lens Camera
  - Camera with Distortion

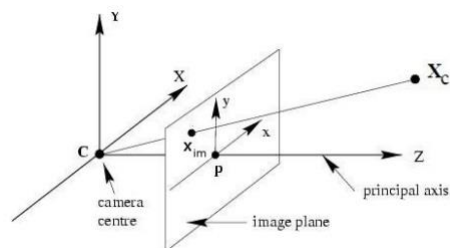
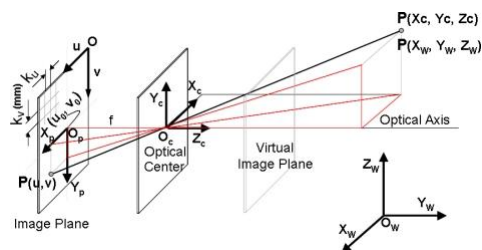
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# Image Formation

## Computer Vision I Recitation – 3

- Ideal Perspective Camera



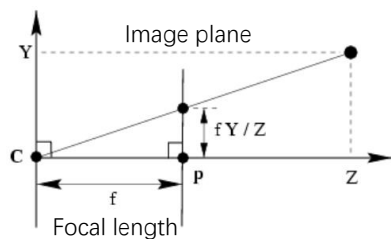
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# Image Formation

## Computer Vision I Recitation – 3

- Ideal Perspective Camera



By similar triangles

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} fX_0/Z_0 \\ fY_0/Z_0 \\ f \end{bmatrix}$$

Dropping third coordinate

$$\begin{bmatrix} X \\ Y \end{bmatrix} = \begin{bmatrix} fX_0/Z_0 \\ fY_0/Z_0 \end{bmatrix}$$

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# Image Formation

## Computer Vision I Recitation – 3

- Ideal Perspective Camera

$$\lambda \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X_0 \\ Y_0 \\ Z_0 \\ 1 \end{bmatrix} = \begin{bmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} X_0 \\ Y_0 \\ Z_0 \\ 1 \end{bmatrix} = K_f [I_{3 \times 3} \quad \mathbf{0}_{3 \times 1}] \begin{bmatrix} X_0 \\ Y_0 \\ Z_0 \\ 1 \end{bmatrix}$$

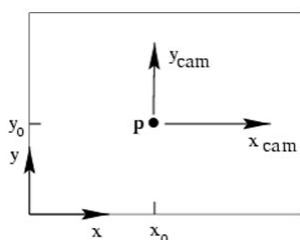
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# Image Formation

## Computer Vision I Recitation – 3

- Intrinsic Parameters (from cam coordinate to image coordinate)



$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} X_0 + p_x \\ Y_0 + p_y \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & p_x \\ 0 & 1 & p_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

$P = [p_x, p_y]$  Principal-point offset in **image coordinate**

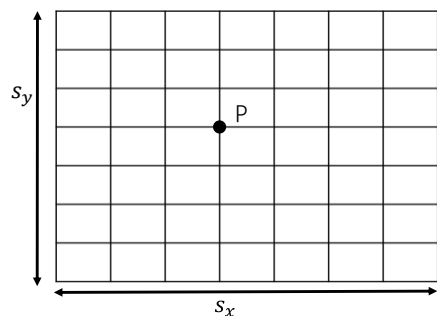
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# Image Formation

Computer Vision I  
Recitation – 3

- Intrinsic Parameters (from cam coordinate to image coordinate)



$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & p_x \\ 0 & 1 & p_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Number of pixels along cam coordinate

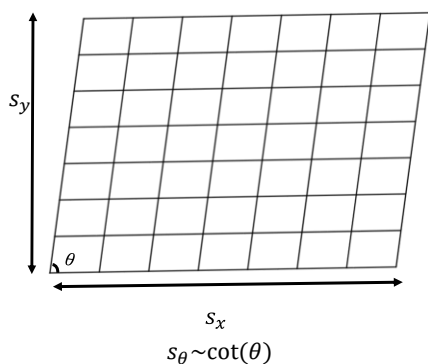
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# Image Formation

Computer Vision I  
Recitation – 3

- Intrinsic Parameters (from cam coordinate to image coordinate)



$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & p_x \\ 0 & 1 & p_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} s_x & s_\theta & 0 \\ 0 & s_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = K_s \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

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# Image Formation

## Computer Vision I Recitation – 3

- General Perspective Camera (from cam coordinate to image coordinate)

$$K \doteq K_s K_f = \begin{bmatrix} s_x & s_\theta & p_x \\ 0 & s_y & p_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} f s_x & s_\theta & p_x \\ 0 & f s_y & p_y \\ 0 & 0 & 1 \end{bmatrix}$$

Calibration Matrix (Intrinsic Parameters)

$$\Pi_0 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

Standard Projection Matrix

$$\lambda \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = K \Pi_0 X = \begin{bmatrix} f s_x & s_\theta & p_x \\ 0 & f s_y & p_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} = \lambda \begin{bmatrix} f s_x & s_\theta & p_x \\ 0 & f s_y & p_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

$$\lambda \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \lambda K^{-1} \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix}$$

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# Image Formation

## Computer Vision I Recitation – 3

- General Perspective Camera (from world coordinate to image coordinate)

$$g = \begin{bmatrix} R & T \\ 0 & 1 \end{bmatrix} \quad \text{Extrinsic Parameters}$$

$$\lambda \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = K \Pi_0 g X_0 = \begin{bmatrix} f s_x & s_\theta & p_x \\ 0 & f s_y & p_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} R & T \\ 0 & 1 \end{bmatrix} X_0 = K [R \ T] X_0 \quad \text{DoF: } 5+6=11$$

Intrinsic Parameters
Extrinsic Parameters

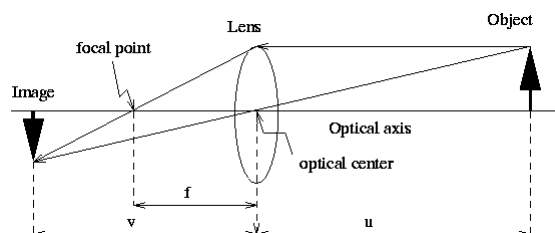
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# Image Formation

Computer Vision I  
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- (Thin) Lens Camera



$$\frac{1}{u} + \frac{1}{v} = \frac{1}{f}$$

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# Image Formation

Computer Vision I  
Recitation – 3

- (Thin) Lens Camera

Thin Lens => Paraxial Refraction Model

For the angle  $\theta$  that incoming light rays make with the optical axis of the lens, the paraxial assumption substitutes  $\theta$  for any place  $\sin \theta$  is used. This approximation of  $\theta$  for  $\sin \theta$  holds as  $\theta$  approaches 0.

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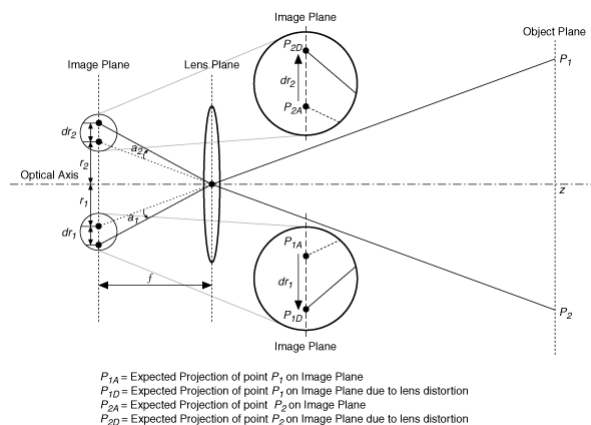
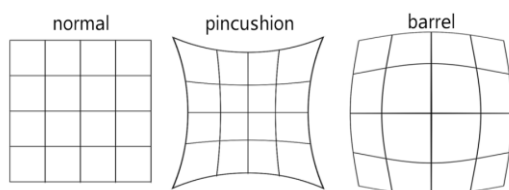
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# Image Formation

## Computer Vision I Recitation – 3

### • Camera with Distortion

Practical Lens Camera => Radial Distortion



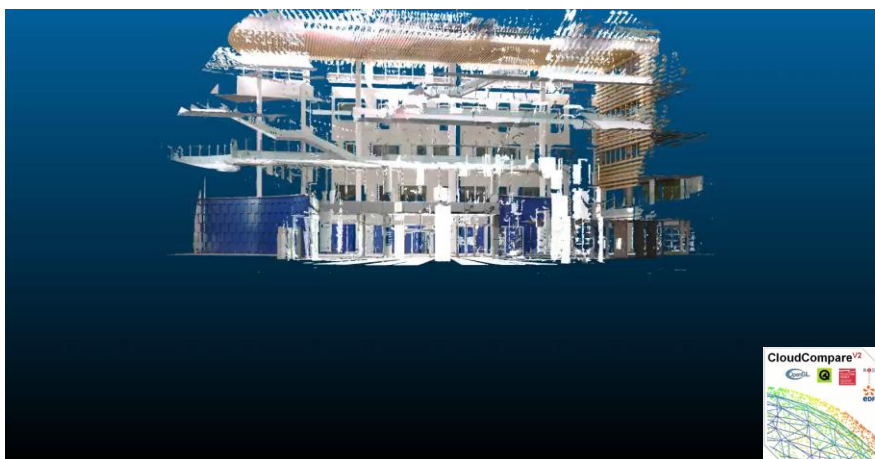
$$\lambda \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = K[R \ T]X_0 \mapsto \lambda \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = K \begin{bmatrix} f(r) & 0 & 0 \\ 0 & f(r) & 0 \\ 0 & 0 & 1 \end{bmatrix} [R \ T]X_0 \text{ where } f(r) = 1 + a_1(x^2 + y^2) + a_2(x^2 + y^2)^2 + \dots$$

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# Walk Around SIST-Building!

## Computer Vision I Recitation – 3



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# Coding Exercises

## Computer Vision I Recitation – 3

- Photo Competition
  - Design your own virtual camera with different intrinsic parameters
  - Choose appropriate viewpoint
  - Take photos to test your cameras
  - And hand in your favorite picture to us
- Video Advertisement Competition
  - Design scenic route as well as camera poses, and use your own virtual camera to make promotional video for SIST building

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# Coding Exercises

## Computer Vision I Recitation – 3

- XYZ File – ASCII point cloud.

	X	Y	Z	R	G	B
5292 1491	-7.7413	-28.9407	-1.553	255	255	255
5292 1441	-7.2838	-29.0514	-1.554	255	255	255
5292 1480	-7.6417	-28.9667	-1.553	255	255	255
5292 1474	-7.5868	-28.9808	-1.553	255	255	255
5292 1461	-7.4682	-29.0099	-1.554	255	255	255
5292 1456	-7.4212	-29.0143	-1.554	255	255	255
5292 1451	-7.3757	-29.0264	-1.554	255	255	255
5292 1453	-7.3811	-28.9716	-1.551	255	255	255
5292 1446	-7.3239	-29.018	-1.5534	254	254	254
5292 1440	-7.2686	-29.0297	-1.553	255	255	255
5292 1449	-7.3487	-28.9993	-1.552	255	255	255
5293 1444	-7.2651	-28.8619	-1.554	255	255	255
5292 1435	-7.2288	-29.0669	-1.555	255	255	255
5292 1429	-7.1762	-29.0856	-1.555	254	254	254
5292 1437	-7.2397	-29.0336	-1.553	255	255	255
5293 1439	-7.2164	-28.8619	-1.553	255	255	255
5293 1434	-7.1736	-28.8838	-1.554	255	255	255

```
from tqdm import tqdm

# line count
num_points = sum(1 for line in open('abc.xyz'))
fp = open('abc.xyz')
keys = ['x', 'y', 'z', 'r', 'g', 'b']
# load .xyz pointcloud with progress bar
points = []
for line in tqdm(fp, total=num_points, desc='loading pointcloud'):
    # ignore empty lines
    if not line:
        continue
    row_list = line.split()
    elements = list(map(float, row_list[2:5])) + list(map(int, row_list[5:]))
    points.append(dict(zip(keys, elements)))
```

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# Coding Exercises




## Computer Vision I Recitation – 3

- Due: 21:00(GMT+8) 28, Oct

- Optional Exercises
- No restrictions on languages & using of existing libraries
- Extra bonus for excellent works
- Exhibition for all submissions
- Generous Extra bonus for winners

Download Point Cloud:

<http://10.19.124.26:8000/d/c7a4b04f231d412db46c/>

	<a href="#">SIST_000_oct0_01.bin</a>	Binary point cloud (downsampled)
	<a href="#">SIST_000_oct0_01.xyz</a>	ASCII point cloud (downsampled)
	<a href="#">SIST_scan_000.xyz</a>	ASCII point cloud (raw)