

Real-Time 3D Rotation Smoothing for Video Stabilization

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Introduction

- Video recording by handheld cameras is growing exponentially due to:
 - *Compactness*
 - *Everywhere & Anytime*
 - *Easy Sharing*
 - *Good User Experience (touchscreen)*
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Common Problem: Unwanted inter-frame jitter ...

Introduction

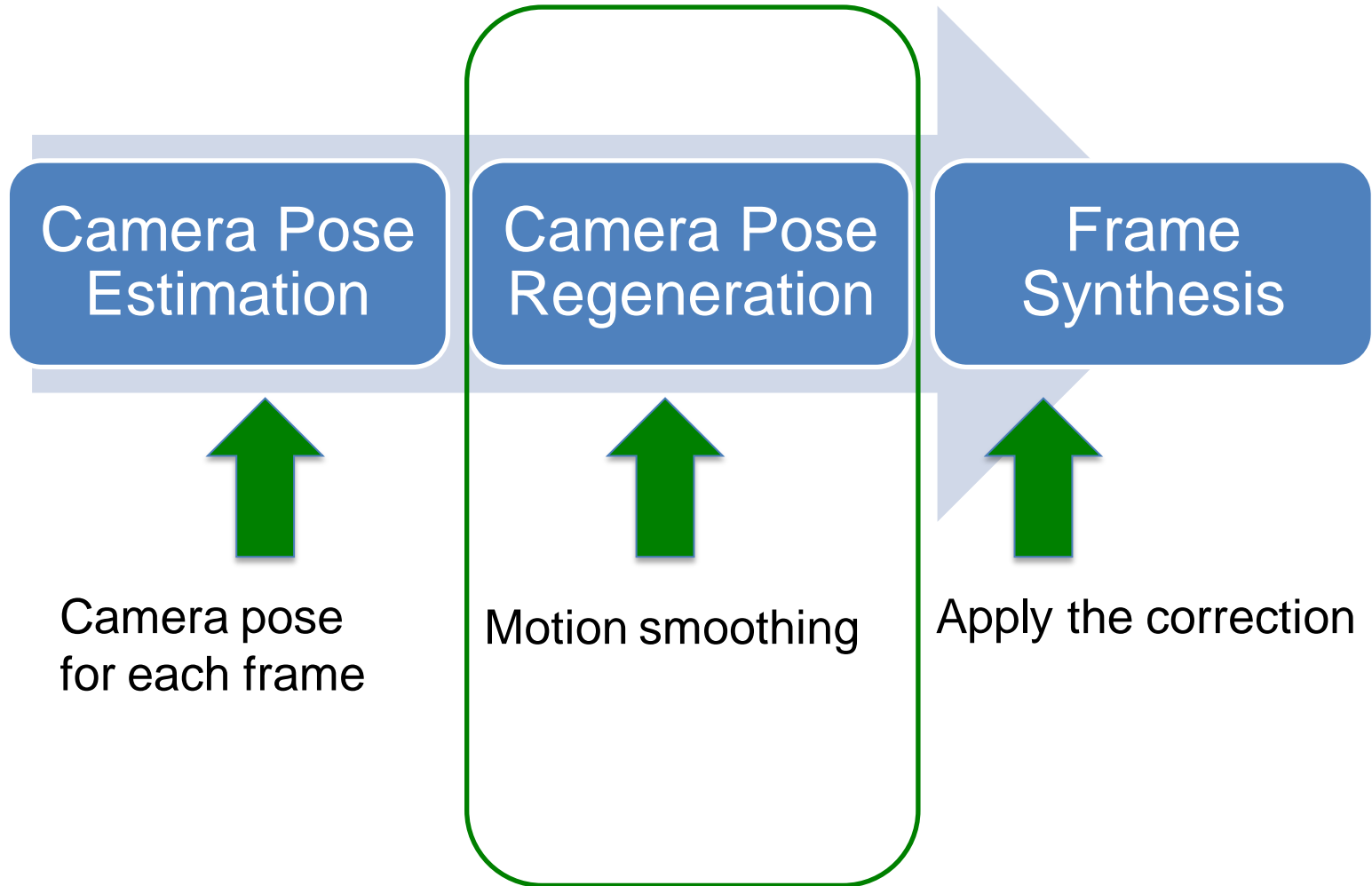
Why online video stabilization

- Real-time delivery: video conferencing, broadcasting, etc.
- Improved user experience: What You See is What You Get.
- More efficient compression



Online Video Stabilization

- Removing unwanted jitter (**inter**-frame correction)



Motion Model Selection

- 2D motion: apparent pixel displacements

Translation Similarity Euclidean Affine Projective
→ Degrees of Freedom

- 3D real camera motion

Rotation Full (Rotation + Translation)

Motion Model	Estimation Complexity	Smoothing Effectiveness	Correction Complexity
2D	high	low	low
3D Full	high	high	high
3D Rotation	low (using gyro)	high	low (projective transform)

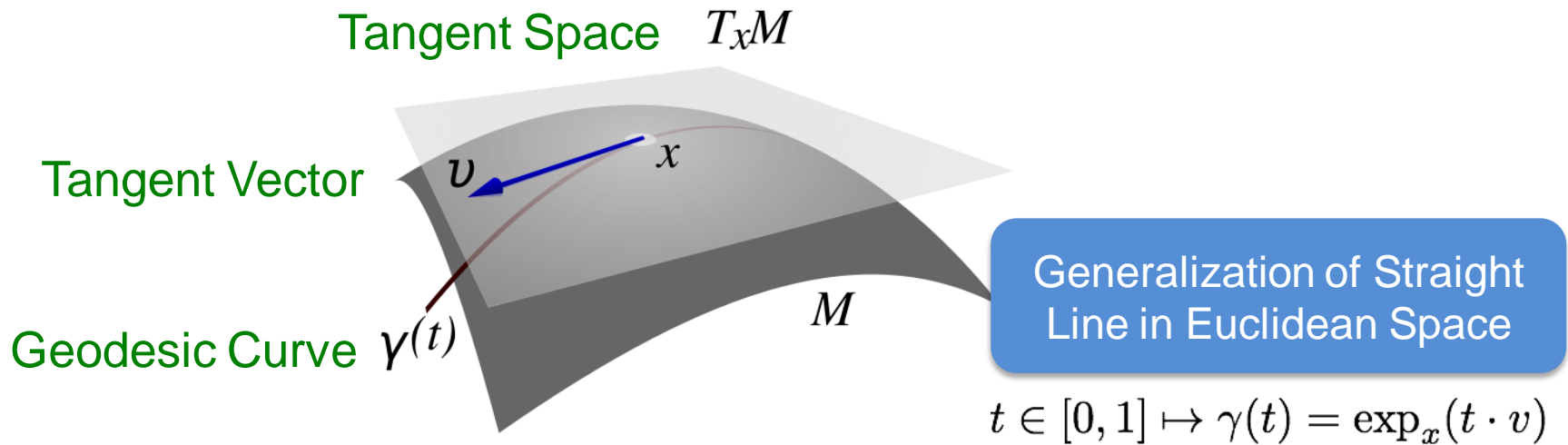
- No approximation in 3D rotational stabilization (proposed method)
 - We are not assuming pure camera rotation
 - Translation is kept as is, and not smoothed

Online 3D Rotation Smoothing

- Classical approaches for 2D motion models
 - (1st order low-pass) IIR filtering
 - Kalman filtering with constant-velocity (CV) model
- Extension to 3D rotation smoothing
 - Euclidean space \rightarrow SO(3) manifold
 - Ad-hoc projection for black-border constraint

3D Rotation Matrix

- Manifold of 3D Rotation Matrices
 - Special Orthogonal Group $\mathbf{SO}(3)$ $\mathbf{R}\mathbf{R}^T = \mathbf{I}$
 - An embedded submanifold in \mathbb{R}^9 (dimension = 3)



- Minimizing Geodesic & Geodesic Distance

$$d_g(\mathbf{R}, \mathbf{R}') = \|\log_m(\mathbf{R}^{-1}\mathbf{R}')\|_F$$

Constrained Motion Smoothing

- Inevitably some pixels are not visible after view change



$$\begin{bmatrix} \tilde{u}_{ij} \\ \tilde{v}_{ij} \end{bmatrix} = g \left(\mathbf{K} \tilde{\mathbf{R}}_i \mathbf{R}_i^T \mathbf{K}^{-1} \begin{bmatrix} u_{ij} \\ v_{ij} \\ 1 \end{bmatrix} \right)$$

Correction by
image warping

$$\begin{cases} 0 \leq \tilde{u}_{ij} \leq w \\ 0 \leq \tilde{v}_{ij} \leq h \end{cases}, \forall \begin{bmatrix} u_{ij} \\ v_{ij} \end{bmatrix} \text{ s.t. } \begin{cases} c_1 \leq u_{ij} \leq c_2 \\ d_1 \leq v_{ij} \leq d_2 \end{cases}$$

Hard Constraint: All of the pixels in the cropped new frame should be visible in the original frame.

IIR-like 3D Rotation Smoothing

- First-Order IIR filtering

$$\hat{\boldsymbol{\theta}}_k = \alpha \hat{\boldsymbol{\theta}}_{k-1} + (1 - \alpha) \boldsymbol{\theta}_k \quad \text{SO(3) } \times$$



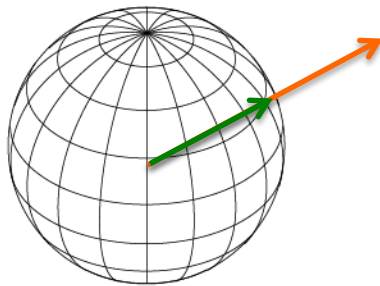
$$\hat{\boldsymbol{\theta}}_k = \operatorname{argmin}_{\boldsymbol{\theta}} \alpha \|\boldsymbol{\theta} - \hat{\boldsymbol{\theta}}_{k-1}\|^2 + (1 - \alpha) \|\boldsymbol{\theta} - \boldsymbol{\theta}_k\|^2 \quad \text{SO(3) } \checkmark$$



Euclidean distance \rightarrow Geodesic distance

$$\hat{\mathbf{R}}_k = \operatorname{argmin}_{\mathbf{R}} \alpha d_g(\mathbf{R}, \hat{\mathbf{R}}_{k-1})^2 + (1 - \alpha) d_g(\mathbf{R}, \mathbf{R}_k)^2 \quad \begin{array}{l} \text{spherical} \\ \text{linear} \\ \text{interpolation} \\ \text{(SLERP)} \end{array}$$

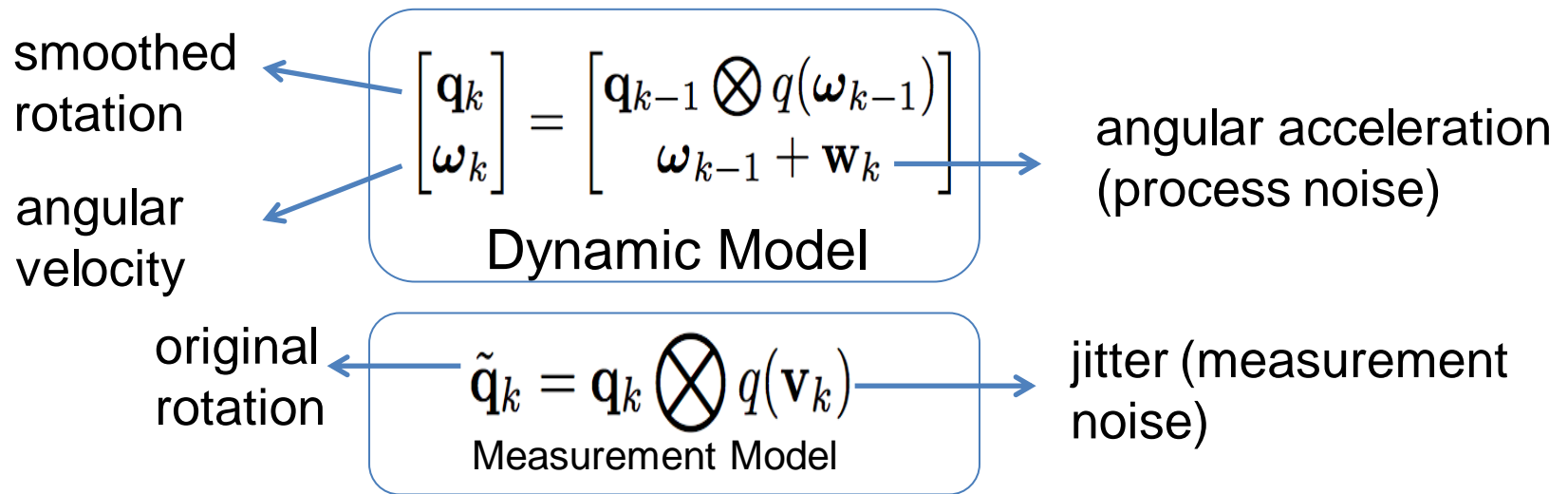
- Ad-hoc projection $\hat{\mathbf{R}} = \mathbb{P}(\hat{\mathbf{R}}^*) = \mathbf{R} \expm(\beta^* \logm(\mathbf{R}^{-1} \hat{\mathbf{R}}^*))$



Move closer to the original rotation if necessary for black-border constraint

UKF-based 3D Rotation Smoothing

- Constant-Velocity Model (widely used in target tracking)



- Hard to solve on $SO(3)$
- Nonlinear on Euclidean space
- Solved approximately by unscented Kalman filter (UKF)

Proposed Algorithms

Algorithm - IIR-like 3D Rotation Smoothing

- 1: **Input:** $\mathbf{q}_1, \dots, \mathbf{q}_K$ (original rotations)
- 2: **Output:** $\hat{\mathbf{q}}_1, \dots, \hat{\mathbf{q}}_K$ (smoothed rotations)
- 3: $\hat{\mathbf{q}}_1 = \mathbf{q}_1$
- 4: **for** $k = 2$ **to** K **do**
- 5: $\hat{\mathbf{q}}_k = \text{slerp}(\mathbf{q}_k, \hat{\mathbf{q}}_{k-1}, \alpha)$
- 6: $\hat{\mathbf{q}}_k \leftarrow \mathbb{P}(\hat{\mathbf{q}}_k)$
- 7: **end for**

1.54ms/frame

Algorithm - UKF-based 3D Rotation Smoothing

- 1: **Input:** $\mathbf{q}_1, \dots, \mathbf{q}_K$ (original rotations)
- 2: **Output:** $\hat{\mathbf{q}}_1, \dots, \hat{\mathbf{q}}_K$ (smoothed rotations)
- 3: **Parameters:** \mathbf{Q}, \mathbf{R} (process and measurement noise variance)
- 4: **for** $k = 1$ **to** K **do**
- 5: Obtain unconstrained UKF estimate $\hat{\mathbf{q}}_k^*, \hat{\omega}_k^*, \mathbf{P}_k$
- 6: $\hat{\mathbf{q}}_k^* = \hat{\mathbf{q}}_k^* / \|\hat{\mathbf{q}}_k^*\|_2$ (normalization)
- 7: $\hat{\mathbf{q}}_k \leftarrow \mathbb{P}(\hat{\mathbf{q}}_k^*)$
- 8: (Mean and covariance estimate to pass to the next stage are $\hat{\mathbf{q}}_k, \hat{\omega}_k, \mathbf{P}_k$)
- 9: **end for**

6.97ms/frame



Experimental Results – 2D vs. 3D KF

Original Video



2D Affine KF



3D Rotational UKF



Experimental Results– 2D vs. 3D KF

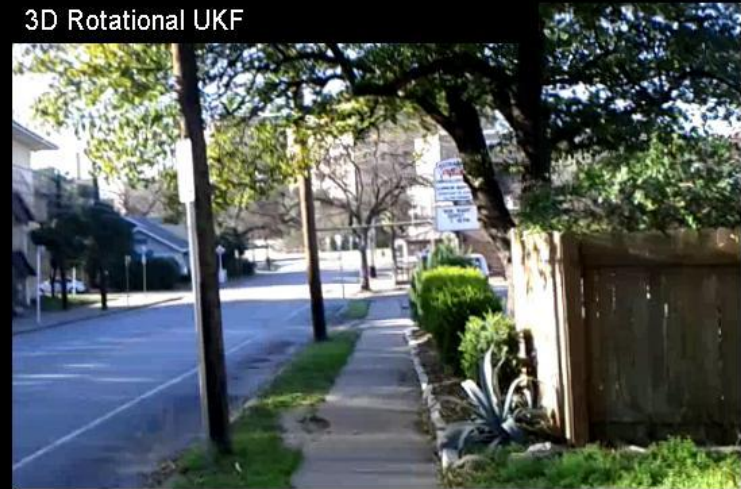
Original Video



2D Affine KF



3D Rotational UKF



Experimental Results– 2D vs. 3D IIR

Original Video



2D affine IIR



3D Rotational IIR



Experimental Results – 2D vs. 3D IIR

Original Video



2D Affine IIR

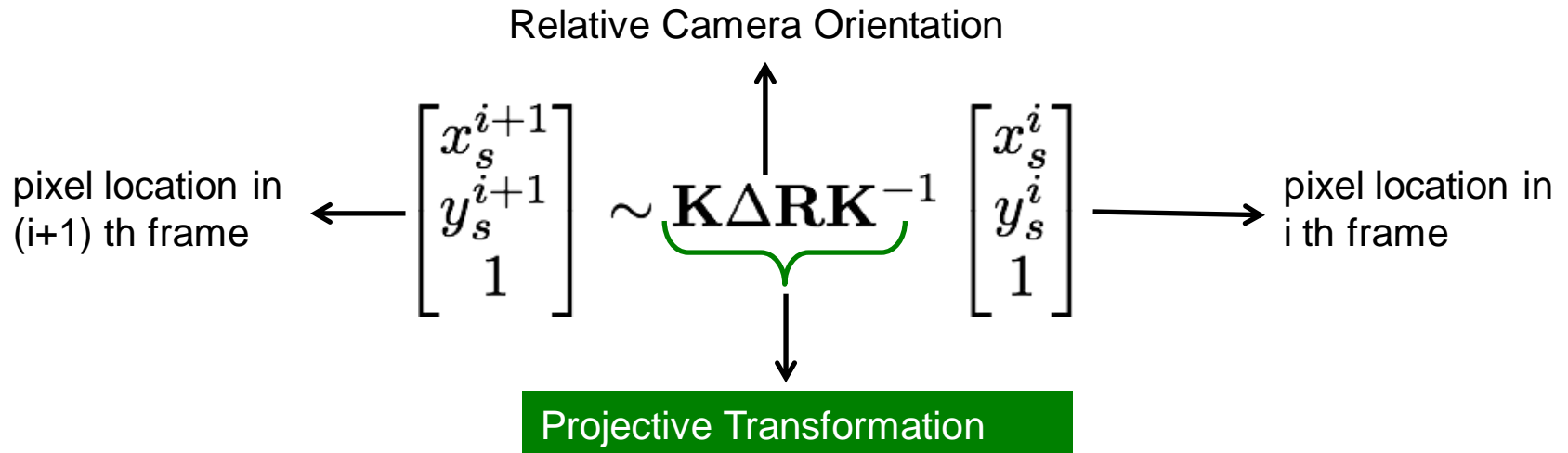
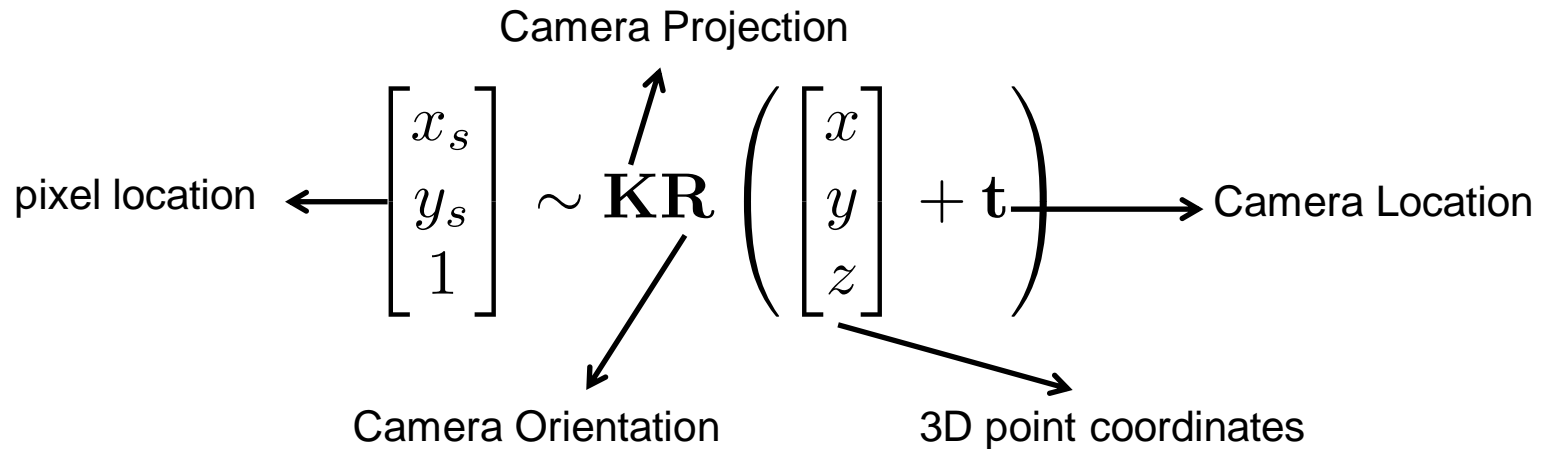


3D Rotational IIR

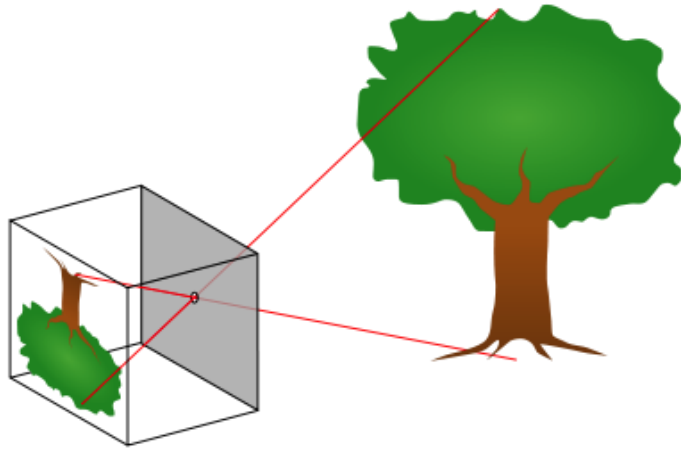


Thanks!

Backup – Pure Rotation



Backup - Pinhole Camera Model

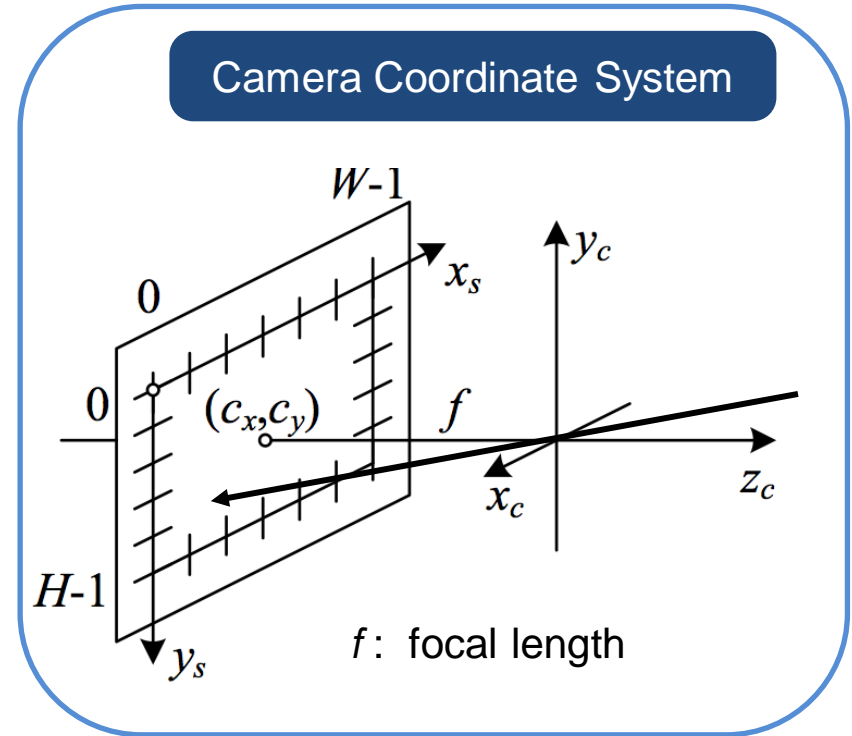


Camera Intrinsic Matrix K

$$\begin{bmatrix} x_s \\ y_s \\ 1 \end{bmatrix} \sim \begin{bmatrix} f & 0 & c_x \\ 0 & f & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix}$$

2D Coordinates in Image Plane

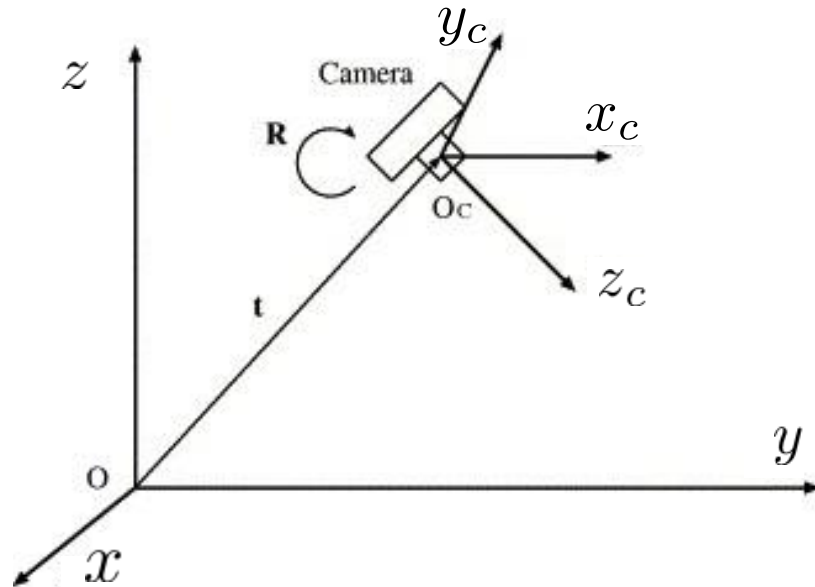
3D Coordinates in Camera Coordinate System



$$x_s = x_c \frac{f}{z_c} + c_x$$

$$y_s = y_c \frac{f}{z_c} + c_y$$

Backup - Camera Model & Camera Motion



World Coordinates \rightarrow Camera Coordinates

$$\begin{bmatrix} x_s \\ y_s \\ 1 \end{bmatrix} \sim \begin{bmatrix} f & 0 & c_x \\ 0 & f & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix} \rightarrow \begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix} = \mathbf{R} \left(\begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix} \right)$$