

given a dynamic & measurement model :

$$x_{k+1} = f(x_k, u_k, w_k)$$

$$y_k = h(x_k, v_k)$$

Δ dynamic model remark: Note that all states are in the non-inertial frame

$x \in \mathbb{R}^6$

$$x = \begin{bmatrix} x \\ y \\ z \\ \dot{x} \\ \dot{y} \\ \dot{z} \end{bmatrix}, x_{k+1} = f(x_k) = \begin{bmatrix} x_k + \Delta t \dot{x}_k \\ y_k + \Delta t \dot{y}_k \\ z_k + \Delta t \dot{z}_k \\ \dot{x}_k + \Delta t \ddot{x}_k \\ \dot{y}_k + \Delta t \ddot{y}_k \\ \dot{z}_k + \Delta t \ddot{z}_k \end{bmatrix}, F = \dots$$

$$F = \begin{bmatrix} \frac{\partial x}{\partial x} & \frac{\partial x}{\partial \dot{x}} & \frac{\partial x}{\partial \ddot{x}} \\ \frac{\partial y}{\partial x} & \frac{\partial y}{\partial \dot{x}} & \frac{\partial y}{\partial \ddot{x}} \\ \frac{\partial z}{\partial x} & \frac{\partial z}{\partial \dot{x}} & \frac{\partial z}{\partial \ddot{x}} \\ \frac{\partial \dot{x}}{\partial x} & \frac{\partial \dot{x}}{\partial \dot{x}} & \frac{\partial \dot{x}}{\partial \ddot{x}} \\ \frac{\partial \dot{y}}{\partial x} & \frac{\partial \dot{y}}{\partial \dot{x}} & \frac{\partial \dot{y}}{\partial \ddot{x}} \\ \frac{\partial \dot{z}}{\partial x} & \frac{\partial \dot{z}}{\partial \dot{x}} & \frac{\partial \dot{z}}{\partial \ddot{x}} \end{bmatrix} = \begin{bmatrix} I_3 & 0 & \Delta t I_3 \\ 0 & I_3 & 0 \\ 0 & -R \dot{\theta} & I_3 \end{bmatrix}$$

$$J = \frac{\partial f(x)}{\partial x} = \lim_{\Delta t \rightarrow 0} \frac{f(x+\Delta x) - f(x)}{\Delta t} = \lim_{\Delta t \rightarrow 0} \frac{J \Delta x}{\Delta t} = J$$

$$\frac{\partial v_k}{\partial R} = \frac{R \dot{\theta}}{\partial R} = \lim_{\theta \rightarrow 0} \frac{(R \otimes I) \theta - R \cdot \theta}{\theta} = \lim_{\theta \rightarrow 0} \frac{R \cdot \theta - R \cdot \theta}{\theta} = -R \dot{\theta} = -R \dot{\theta} \cdot t$$

$$\frac{\partial v_k}{\partial R} = \frac{R \dot{\theta}}{\partial R} = \lim_{\theta \rightarrow 0} \frac{(R \otimes I) \theta - R \cdot \theta}{\theta} = \lim_{\theta \rightarrow 0} \frac{R \cdot \theta - R \cdot \theta}{\theta} = -R \dot{\theta} = -R \dot{\theta} \cdot t$$

Δ measurement model

$y_{k+1} = h(x_{k+1})$, let $(P, R) = \xi$

$$v = \begin{bmatrix} u \\ v \\ v \end{bmatrix} = \begin{bmatrix} f_1 \frac{x}{z} + c_x \\ f_2 \frac{y}{z} + c_y \\ d_{k+1} - d_k \end{bmatrix}$$

desired from $su = KTP$
 $\Rightarrow u = \frac{1}{2} KTP$

$$H = \frac{\partial h}{\partial x} = \begin{bmatrix} \frac{\partial h_1}{\partial x} & \frac{\partial h_1}{\partial \dot{x}} & \frac{\partial h_1}{\partial \ddot{x}} \\ \frac{\partial h_2}{\partial x} & \frac{\partial h_2}{\partial \dot{x}} & \frac{\partial h_2}{\partial \ddot{x}} \\ \frac{\partial h_3}{\partial x} & \frac{\partial h_3}{\partial \dot{x}} & \frac{\partial h_3}{\partial \ddot{x}} \end{bmatrix} = \begin{bmatrix} J_1 & 0 & 0 \\ J_2 & 0 & 0 \\ J_3 & 0 & I_3 \end{bmatrix}$$

$$H = \begin{bmatrix} J_1 & 0' \\ J_2 & 0' \\ J_3 & 0' \\ Q_{3 \times 6} & I_3 \end{bmatrix}, J_i = \begin{bmatrix} \frac{\partial f_1}{\partial x} & \frac{\partial f_1}{\partial \dot{x}} & \frac{\partial f_1}{\partial \ddot{x}} & -\frac{\partial f_1}{\partial z} & \frac{\partial f_1}{\partial \dot{z}} \\ \frac{\partial f_2}{\partial x} & \frac{\partial f_2}{\partial \dot{x}} & \frac{\partial f_2}{\partial \ddot{x}} & -\frac{\partial f_2}{\partial z} & \frac{\partial f_2}{\partial \dot{z}} \\ \frac{\partial f_3}{\partial x} & \frac{\partial f_3}{\partial \dot{x}} & \frac{\partial f_3}{\partial \ddot{x}} & -\frac{\partial f_3}{\partial z} & \frac{\partial f_3}{\partial \dot{z}} \end{bmatrix} \in \mathbb{R}^{2 \times 6}$$

$$O' \in \mathbb{R}^{2 \times 3}$$

Δ Jacobian for a pinhole model during bundle adjustment

Δ pinhole model :

$$s_i u_i = KTP_i \sim \mathbb{S}^2 \text{ points}$$

depth $\in \mathbb{R}^3$

Δ recall objective :

$$u_i = \frac{1}{s_i} KTP_i \text{ --- intermediate variable}$$

Δ let $P' \triangleq$ PCD in camera frame

$$P' = (TP)_{1:3} = [X', Y', Z']^T$$

$$\therefore su = KTP$$

$$\Rightarrow su = KP'$$

$$\Rightarrow \begin{bmatrix} su \\ sv \\ s \end{bmatrix} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X' \\ Y' \\ Z' \end{bmatrix}$$

$$\therefore u = f_x \frac{X'}{Z'} + c_x$$

$$v = f_y \frac{Y'}{Z'} + c_y$$

$\Delta e = u - \frac{1}{s} KTP$

$$\frac{\partial e}{\partial \xi} = \lim_{\delta \xi \rightarrow 0} \frac{e(\xi + \delta \xi) - e(\xi)}{\delta \xi} = \frac{\partial e}{\partial P'} \frac{\partial P'}{\partial \xi}$$

$$\Delta e = \begin{bmatrix} u - f_x \frac{X'}{Z'} + c_x \\ v - f_y \frac{Y'}{Z'} + c_y \end{bmatrix}$$

recall Jacobian:

$$J = \frac{\partial e}{\partial P'} = \begin{bmatrix} \frac{\partial e_1}{\partial X'} & \frac{\partial e_1}{\partial Y'} & \frac{\partial e_1}{\partial Z'} \\ \frac{\partial e_2}{\partial X'} & \frac{\partial e_2}{\partial Y'} & \frac{\partial e_2}{\partial Z'} \end{bmatrix} = \begin{bmatrix} -\frac{f_x X'}{Z'^2} & 0 & \frac{f_x X'}{Z'^3} \\ 0 & -\frac{f_y Y'}{Z'^2} & \frac{f_y Y'}{Z'^3} \end{bmatrix}$$

$$2 \frac{\partial P'}{\partial \xi} = \frac{\partial TP}{\partial \xi}$$

$$= \lim_{\delta \xi \rightarrow 0} \frac{\exp(\delta \xi) \exp(\xi) P - \exp(\xi) P}{\delta \xi} = \lim_{\delta \xi \rightarrow 0} \frac{[I + \delta \xi] \exp(\xi) P - \exp(\xi) P}{\delta \xi} = \lim_{\delta \xi \rightarrow 0} \frac{\delta \xi \exp(\xi) P}{\delta \xi} = \exp(\xi) P = TP = Rp + t$$

$$= \lim_{\delta \xi \rightarrow 0} \frac{[S \exp(\xi) P + S \delta \xi P]}{\delta \xi} = \begin{bmatrix} \frac{\partial}{\partial \xi} (S \exp(\xi) P) & \frac{\partial}{\partial \xi} (S \delta \xi P) \\ 0 & \frac{\partial}{\partial \xi} (S \exp(\xi) P) \end{bmatrix}$$

$$= \begin{bmatrix} I & -Rp + t \\ 0 & 0 \end{bmatrix}$$

• Here $P' = [X', Y', Z']$

$$\therefore \frac{\partial P'}{\partial \xi} = [I \quad -P'^A]$$

$$= \begin{bmatrix} 1 & 0 & 0 & 0 & X' & -Y' \\ 0 & 1 & 0 & 0 & Y' & -X' \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

$$\bullet \text{ as } \frac{\partial e}{\partial P'} = \begin{bmatrix} -\frac{f_x X'}{Z'^2} & 0 & \frac{f_x X'}{Z'^3} \\ 0 & -\frac{f_y Y'}{Z'^2} & \frac{f_y Y'}{Z'^3} \end{bmatrix}$$

$$\bullet \frac{\partial e}{\partial \xi} = \begin{bmatrix} 1 & 0 & 0 & 0 & X' & -Y' \\ 0 & 1 & 0 & 0 & Y' & -X' \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} -\frac{f_x X'}{Z'^2} & 0 & \frac{f_x X'}{Z'^3} \\ 0 & -\frac{f_y Y'}{Z'^2} & \frac{f_y Y'}{Z'^3} \\ 0 & 0 & 0 \end{bmatrix}$$

$$\bullet \frac{\partial e}{\partial \xi} = \begin{bmatrix} -\frac{f_x X'}{Z'^2} & 0 & \frac{f_x X'}{Z'^3} & 0 & 0 & 0 \\ 0 & -\frac{f_y Y'}{Z'^2} & \frac{f_y Y'}{Z'^3} & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} -\frac{f_x X'}{Z'^2} & 0 & \frac{f_x X'}{Z'^3} & -\frac{f_x X'}{Z'^2} & \frac{f_x X'}{Z'^3} \\ 0 & -\frac{f_y Y'}{Z'^2} & \frac{f_y Y'}{Z'^3} & -\frac{f_y Y'}{Z'^2} & \frac{f_y Y'}{Z'^3} \\ 0 & 0 & 0 & -\frac{f_x X'}{Z'^2} & \frac{f_x X'}{Z'^3} \\ 0 & 0 & 0 & -\frac{f_y Y'}{Z'^2} & \frac{f_y Y'}{Z'^3} \end{bmatrix}$$

Iterated Extended Kalman filter

Δ prediction same as EKF

Δ correction different :

- after receive \hat{x}_{k+1}
- $\hat{x}_k = \hat{x}_{k+1}$ & start loop
- $H_k = \frac{\partial h(x)}{\partial x} |_{x=\hat{x}_k}$
- $K_k = P_k H_k^T (H_k P_k H_k^T + R_k)^{-1}$
- $\hat{x}_k = K_k (\bar{z}_k - h(\hat{x}_k))$
- $\hat{x}_k^{i+1} = \hat{x}_k^i + \hat{x}_k$
- break when $\| \hat{x}_k^i \| < \epsilon$

in our case, we have additional points, thus residual slightly different

- embed Q, R into one residual form

$$\lambda = \begin{bmatrix} \alpha & \beta \\ \beta & \lambda \end{bmatrix} = \begin{bmatrix} \alpha & 0 \\ 0 & \beta \end{bmatrix} \begin{bmatrix} P_k^{-1} & -H_k^T \hat{x}_k \\ H_k \hat{x}_k - H^T \hat{x}_k \end{bmatrix}$$

$$\alpha = \frac{1}{\text{tr}(R)} \quad \beta = \frac{1}{\text{tr}(Q)}$$

$$-\frac{\partial \lambda}{\partial x} = J \quad \Delta x = -[JJ^T]^{-1} J^T \lambda(x)$$

Summary for ALAN-RPE

• $\hat{x}_{k+1} = \hat{x}_k \otimes \Delta x$

• $\hat{x}_{k+1} = R_k(x_k, f(x_k))$ (euler's method)

• $\hat{x}_{k+1} = F_k \hat{x}_k + \Delta$

• $F_k = \frac{\partial f}{\partial x} |_{x=\hat{x}_k}$

• for correction (IEKF)

→ $\hat{x}_k = \hat{x}_k$

→ $s_k = \inf$

→ $i := 0$

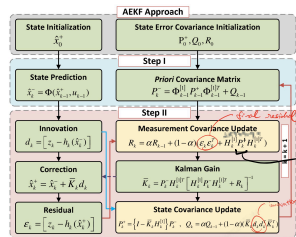
→ while $s_k > \epsilon$

• $\lambda = \begin{bmatrix} \alpha & \beta \\ \beta & \lambda \end{bmatrix} = \begin{bmatrix} \alpha & 0 \\ 0 & \beta \end{bmatrix} \begin{bmatrix} P_k^{-1} & -H_k^T \hat{x}_k \\ H_k \hat{x}_k - H^T \hat{x}_k \end{bmatrix}$

• $\alpha = \frac{1}{\text{tr}(R)} \quad \beta = \frac{1}{\text{tr}(Q)}$

• $\frac{\partial \lambda}{\partial x} = J \quad \Delta x = -[JJ^T]^{-1} J^T \lambda(x)$

• $\hat{x}_k^{i+1} = \hat{x}_k^i \otimes \Delta x$



$$P_k = \begin{bmatrix} \delta \mathbb{E}(3) \\ v \end{bmatrix} \quad [R_{2 \times 2}] \quad [R_{3 \times 3}]$$

Summary: after optimization: use that for HSE

$$\begin{bmatrix} 6 \times 6 \\ 3 \times 3 \end{bmatrix}$$