

四元数 (JPL)

1. 定义:

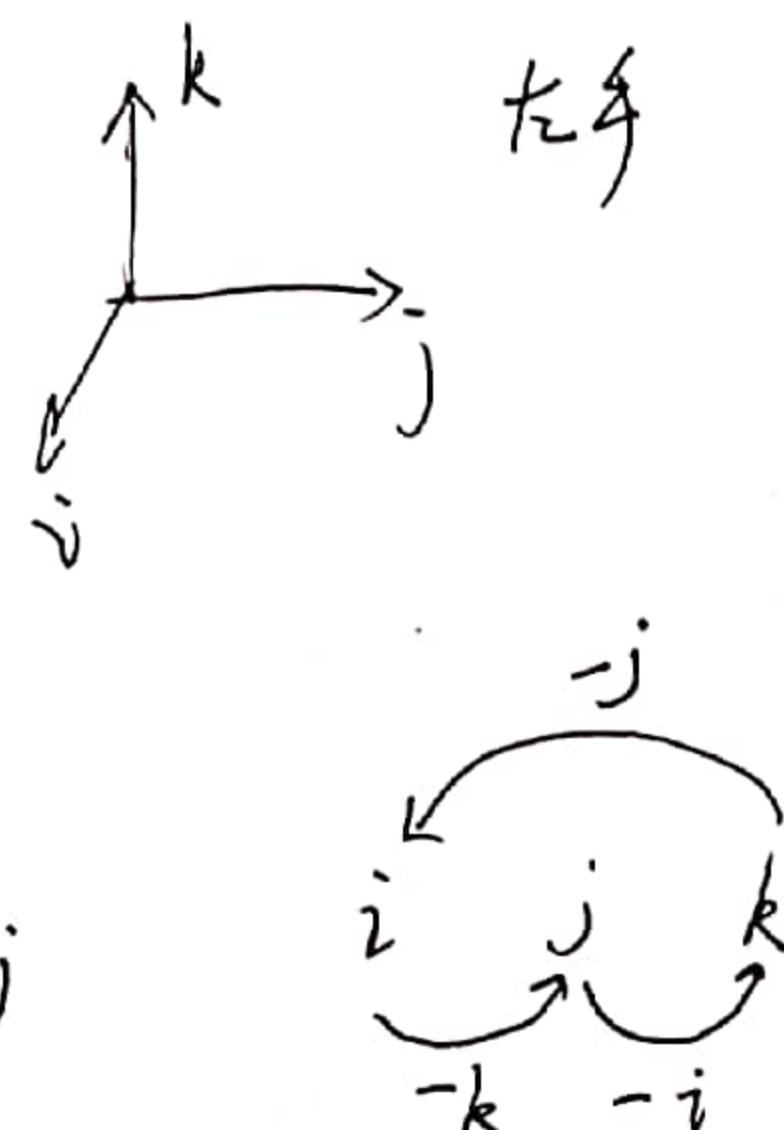
$$Q = q_w + q_x i + q_y j + q_z k \Leftrightarrow Q = q_w + q_v$$

其中 $q_v = q_x i + q_y j + q_z k = (q_x, q_y, q_z)^T$

$$q \triangleq \begin{bmatrix} q_v \\ q_w \end{bmatrix} = \begin{bmatrix} q_x \\ q_y \\ q_z \\ q_w \end{bmatrix}$$

另外: $i^2 = j^2 = k^2 = kji = -1$

$ij = -ji = -k, \quad jk = -kj = -i, \quad ki = -ik = -j$



2. 乘法:

$$q \otimes p = (q_w + q_x i + q_y j + q_z k)(p_w + p_x i + p_y j + p_z k)$$

$$\begin{aligned} &= q_w p_w - q_x p_x - q_y p_y - q_z p_z \\ &\quad + (q_w p_x + q_x p_w - q_y p_z + q_z p_y) i \\ &\quad + (q_w p_y + q_x p_z + q_y p_w - q_z p_x) j \\ &\quad + (q_w p_z - q_x p_y + q_y p_x + q_z p_w) k \end{aligned}$$

$$= \begin{bmatrix} p_w & -p_z & p_y & p_x \\ p_z & p_w & -p_x & p_y \\ -p_y & p_x & p_w & p_z \\ -p_x & -p_y & -p_z & p_w \end{bmatrix} \begin{pmatrix} q_x \\ q_y \\ q_z \\ q_w \end{pmatrix} = \begin{bmatrix} p_w I_3 + [p_v]_x & p_v \\ -p_v^T & p_w \end{bmatrix} q = [P]_R q$$

$\hat{L}[P]_R = [\Xi(p), P]$

$$= \begin{bmatrix} q_w & q_z & -q_y & q_x \\ -q_z & q_w & q_x & q_y \\ q_y & -q_x & q_w & q_z \\ -q_x & -q_y & -q_z & q_w \end{bmatrix} \begin{pmatrix} p_x \\ p_y \\ p_z \\ p_w \end{pmatrix} = \begin{bmatrix} q_w I_3 + [q_v]_x & q_v \\ -q_v^T & q_w \end{bmatrix} p = [q]_L p$$

$\hat{L}[q]_L = [\Psi(q), q]$

3. JPL 四元数表示旋转. (Rodrigues Rotation formula)

$$Lp = Lq \otimes p \otimes Lq^{-1}$$

$$= [q]_L p \otimes Lq^{-1}$$

$$= \begin{bmatrix} q_w I_3 - [q_v]_x & q_v \\ -q_v^T & q_w \end{bmatrix} \begin{bmatrix} p \\ 0 \end{bmatrix} \otimes Lq^{-1}$$

$$= \begin{bmatrix} q_w p - [q_v]_x p \\ -q_v^T p \end{bmatrix} \otimes Lq^{-1}$$

$$= \begin{bmatrix} q_w p - q_v \times p \\ -q_v^T p \end{bmatrix} \otimes \begin{bmatrix} -q_v \\ q_w \end{bmatrix} = [q]_R \begin{bmatrix} q_w p - q_v \times p \\ -q_v^T p \end{bmatrix}$$

$$= \begin{bmatrix} q_w I_3 - [q_v]_x & -q_v \\ q_v^T & q_w \end{bmatrix} \begin{bmatrix} q_w p - q_v \times p \\ -q_v^T p \end{bmatrix}$$

$$= \begin{bmatrix} q_w^2 p - q_w q_v \times p - q_w [q_v]_x p + [q_v]_x (q_v \times p) + q_v \cdot q_v^T p \\ -q_v^T (q_v \times p) \end{bmatrix}$$

$$= \begin{bmatrix} q_w^2 p - 2q_w q_v \times p + q_v \cdot q_v^T p - q_v \times p \times q_v \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} q_w^2 p - 2q_w [q_v]_x p + q_v \cdot q_v^T p + [q_v]_x^2 p \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} (2q_w^2 - 1)I_3 - 2q_w [q_v]_x + 2q_v \cdot q_v^T \\ 0 \end{bmatrix} \begin{bmatrix} q_p \\ 0 \end{bmatrix}$$

$$L C(Lq) = (2q_w^2 - 1)I_3 - 2q_w [q_v]_x + 2q_v \cdot q_v^T$$

$$= \Xi(q_v)^T \Psi(q_v)$$

※ $[q_v]_x^2 = q_v \cdot q_v^T - |q_v|^2 I_3$
 $= q_v \cdot q_v^T - (1 - q_w^2) I_3$

因此有四元数形式旋转 转为 旋转矩阵:

$${}^L C({}^L q) = (2q_w^2 - 1)I_3 - 2q_w[{}^L q_v]_x + 2{}^L q_v \cdot {}^L q_v^T$$

另外 四元数形式旋转 可以表示为欧拉公式 (Euler formula) 形式

$$q = \begin{bmatrix} u \sin(\phi/2) \\ \cos(\phi/2) \end{bmatrix} = \begin{bmatrix} q_v \\ q_w \end{bmatrix} \quad (\text{注意该处的 } u \text{ 为右手旋转轴})$$

可能是习惯表达式。

其中为什么是 $\phi/2$ 而不是 ϕ , 可参考 << Quaternion kinematics for the error-state

Kalman filter >> 中式 (54) 和 (109).

因此有.

$${}^L C({}^L q) = (2\cos^2(\phi/2) - 1)I_3 - 2\cos(\phi/2)\sin(\phi/2)[u]_x + 2\sin^2(\phi/2)uu^T$$

$$= \cos\phi \cdot I_3 - \sin\phi \cdot [u]_x + (1 - \cos\phi)uu^T$$

参考 << Quaternion kinematics ... >> 中式 (78) 可知

$${}^L C({}^L q) = \cos\phi \cdot I_3 + [-u]_x \sin\phi + (-u)(-u)^T (1 - \cos\phi)$$

$$= e^{-\phi[u]_x}$$

$$\approx I - \phi[u]_x$$

JPL 和 Hamilton 在该处有一个负号差别, 是由于 JPL 是左系, 而

Hamilton 是右系.

MSCKF 推导 (JPL)

1. 状态表示:

IMU state:

$$X_{IMU} = [{}^G p_I^T, {}^G v_I^T, {}^I \bar{q}^T, b_a^T, b_g^T]^T, \text{ 其中 } {}^I \bar{q}^T \text{ 为单位四元数, 从 } \{G\} \text{ 到 } \{I\}$$

IMU error-state:

$$\tilde{X}_{IMU} = [{}^G \tilde{p}_I^T, {}^G \tilde{v}_I^T, \delta \theta_I^T, \tilde{b}_a^T, \tilde{b}_g^T]^T$$

由《Quaternion kinematics for the error-state kalman filter》表3可知

true-state: x_t 表示带有噪声的运动学模型 (从测量中恢复)

nominal-state: \hat{x}_t 表示不带噪声的运动学模型 (求期望时消去了)

对于 error-state 的表示, 除了旋转, 其它状态量为

$$\tilde{x} = x_t - \hat{x}_t$$

假设 \hat{q} 为 \bar{q} 的估计值.

$$\bar{q} = \delta \bar{q} \otimes \hat{q}, \quad \delta \bar{q} \approx [\frac{1}{2} \delta \theta^T \quad 1]^T$$

假设有 N 帧相机 pose 也被包含在状态中

$$\hat{X}_k = [\hat{X}_{IMU_k}^T, {}^G \hat{q}^T, {}^G \hat{p}_{c_1}^T, \dots, {}^G \hat{p}_{c_N}^T]^T$$

error-state:

$$\tilde{X}_k = [\tilde{X}_{IMU_k}^T, \delta \theta_{c_1}^T, {}^G \tilde{p}_{c_1}^T, \dots, \delta \theta_{c_N}^T, {}^G \tilde{p}_{c_N}^T]^T$$

2. 连续形式 IMU 运动模型

true-state:

$${}^I \dot{\bar{q}}(t) = \frac{1}{2} \omega(t) \otimes {}^I \bar{q}(t) = \frac{1}{2} [{}^I \omega(t)]_L \cdot {}^I \bar{q}(t) = \frac{1}{2} \begin{bmatrix} -[\omega]_x & \omega \\ \omega^T & 0 \end{bmatrix} {}^I \bar{q}(t)$$

$${}^G \dot{v}_I(t) = {}^G a(t)$$

$$= \frac{1}{2} \Omega(\omega(t)) {}^I \bar{q}(t)$$

$${}^G \dot{p}_I(t) = {}^G v_I(t)$$

$$\dot{b}_a(t) = n_{wa}(t)$$

$$\dot{b}_g(t) = n_{wg}(t)$$

IMU 测量:

$$w_m = \omega + C({}^I \bar{q}) \omega_g + b_g + n_g$$

$$a_m = C({}^I \bar{q}) ({}^G a - {}^G g + 2[{}^G \omega_g]_x {}^G v_I + [{}^G \omega_g]_x^2 {}^G p_I) + b_a + n_a$$

其中 ω_g 是考虑地球自转的影响

nominal-state (estimate-state):

$${}^I \dot{\hat{q}} = \frac{1}{2} \hat{\omega}(t) \otimes {}^I \hat{q}(t) = \frac{1}{2} \Omega(\hat{\omega}(t)) {}^I \hat{q}(t)$$

$${}^G \dot{\hat{v}}_I = E[{}^G \dot{v}_I] = E[{}^G a(t)]$$

$$= E[C({}^I \hat{q}) (a_m - b_a - n_a) + {}^G g - 2[{}^G \omega_g]_x {}^G v_I - [{}^G \omega_g]_x^2 {}^G p_I]$$

$$= C({}^I \hat{q}) (a_m - \hat{b}_a) + {}^G g - 2[{}^G \omega_g]_x {}^G \hat{v}_I - [{}^G \omega_g]_x^2 {}^G \hat{p}_I$$

$${}^G \dot{\hat{p}}_I = {}^G \hat{v}_I$$

$$\dot{\hat{b}}_a = 0_{3 \times 1}$$

$$\dot{\hat{b}}_g = 0_{3 \times 1}$$

The linearized continuous-time model for IMU error-state

$$\dot{\tilde{x}}_{IMU} = F \tilde{x}_{IMU} + G n_{IMU}$$

其中 $n_{IMU} = [n_g^T \ n_{wg}^T \ n_a^T \ n_{wa}^T]^T$

首先给出 F 和 G 的形式，再作推导：

~~$$F = \begin{bmatrix} 0_{3 \times 3} & 0_{3 \times 3} & I_3 & 0_{3 \times 3} & 0_{3 \times 3} \\ -C_g^T [\hat{a}]_x & 0_{3 \times 3} & -2[W_g]_x & -C_g^T & -[W_g]_x^2 \\ -[\hat{\omega}]_x & -I_3 & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} \end{bmatrix}$$

$$G = \begin{bmatrix} 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & -C_g^T & 0_{3 \times 3} \\ -I_3 & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & I_3 \\ 0_{3 \times 3} & I_3 & 0_{3 \times 3} & 0_{3 \times 3} \end{bmatrix}$$

错误!!!
在后面补充.

其中 $C_g = C(\frac{1}{g}\hat{g})$
 $\hat{a} = a_m - \hat{b}_a$
 $\hat{\omega} = \omega_m - \hat{b}_g - C_g W_g$~~

$$g \dot{\tilde{p}}_1^* = g \dot{p}_1 - g \dot{\hat{p}}_1 = g v_1 - g \hat{v}_1 = g \tilde{v}_1$$

$$\dot{\tilde{b}}_a = \dot{b}_a - \dot{\hat{b}}_a = n_{wa}$$

$$\dot{\tilde{b}}_g = \dot{b}_g - \dot{\hat{b}}_g = n_{wg}$$

下面推导 $g \dot{\tilde{v}}_1$ 和 $\dot{\theta}_1$

$$\frac{1}{g} \dot{\hat{g}} = \frac{1}{2} \omega \otimes \frac{1}{g} \hat{g}$$

$$(\partial \hat{g} \otimes \frac{1}{g} \hat{g}) = \frac{1}{g} \dot{\hat{g}} = \frac{1}{2} \omega \otimes \frac{1}{g} \hat{g}$$

$$\partial \hat{g} \otimes \frac{1}{g} \hat{g} + \partial \hat{g} \otimes \frac{1}{g} \hat{g} = \frac{1}{g} \dot{\hat{g}} = \frac{1}{2} \omega \otimes \partial \hat{g} \otimes \frac{1}{g} \hat{g}$$

$$\partial \hat{g} \otimes \frac{1}{g} \hat{g} + \partial \hat{g} \otimes \frac{1}{2} \hat{\omega} \otimes \frac{1}{g} \hat{g} = \frac{1}{g} \dot{\hat{g}} = \frac{1}{2} \omega \otimes \partial \hat{g} \otimes \frac{1}{g} \hat{g}$$

$$\partial \hat{g} \otimes \frac{1}{g} \hat{g} = \frac{1}{2} \omega \otimes \partial \hat{g} \otimes \frac{1}{g} \hat{g} - \frac{1}{2} \partial \hat{g} \otimes \hat{\omega} \otimes \frac{1}{g} \hat{g}$$

$$\partial \hat{g} = \frac{1}{2} (\omega \otimes \partial \hat{g} - \partial \hat{g} \otimes \hat{\omega})$$

$$\begin{bmatrix} \frac{\partial \theta}{\partial t} \\ 0 \end{bmatrix} = \frac{1}{2} ([\omega]_L - [\hat{\omega}]_R) \partial \hat{g}$$

$$= \frac{1}{2} \left(\begin{bmatrix} -[\omega]_x & \omega \\ -\omega^T & 0 \end{bmatrix} - \begin{bmatrix} [\hat{\omega}]_x & \hat{\omega} \\ -\hat{\omega}^T & 0 \end{bmatrix} \right) \partial \hat{g}$$

$$= \frac{1}{2} \begin{bmatrix} -[\omega + \hat{\omega}]_x & \omega - \hat{\omega} \\ -(\omega - \hat{\omega})^T & 0 \end{bmatrix} \partial \hat{g}$$

$$= \frac{1}{2} \begin{bmatrix} -[\omega + \hat{\omega}]_x & \omega - \hat{\omega} \\ -(\omega - \hat{\omega})^T & 0 \end{bmatrix} \begin{bmatrix} \frac{\partial \theta}{\partial t} \\ 1 \end{bmatrix}$$

$$\Rightarrow \dot{\theta} = -[\omega + \hat{\omega}]_x \frac{\partial \theta}{\partial t} + \omega - \hat{\omega}$$

因为 $\omega = \omega_m - \hat{b}_g - n_g - C(\frac{1}{g}\hat{g})W_g$ 其中 $C(\frac{1}{g}\hat{g}) = e^{[\partial \theta]_x} C(\frac{1}{g}\hat{g})$
 $\hat{\omega} = \omega_m - \hat{b}_g - C(\frac{1}{g}\hat{g})W_g$
 $\approx (1 + [\partial \theta]_x) C(\frac{1}{g}\hat{g})$
 $= C(\frac{1}{g}\hat{g}) + [\partial \theta]_x C(\frac{1}{g}\hat{g})$

$$\begin{aligned} \omega + \hat{\omega} &= 2\omega_m - \hat{b}_g - \hat{b}_g - n_g - 2C(\frac{1}{g}\hat{g})W_g + [\partial \theta]_x C(\frac{1}{g}\hat{g})W_g \\ &= 2\omega_m - (\hat{b}_g + \tilde{b}_g) - \hat{b}_g - n_g - 2C(\frac{1}{g}\hat{g})W_g + [\partial \theta]_x C(\frac{1}{g}\hat{g})W_g \\ &= 2\omega_m - 2\hat{b}_g - 2C(\frac{1}{g}\hat{g})W_g - \tilde{b}_g - n_g + [\partial \theta]_x C(\frac{1}{g}\hat{g})W_g \end{aligned}$$

$$[\omega + \hat{\omega}]_x \frac{\partial \theta}{2} = [2\omega_m - 2\hat{b}_g - 2C(\frac{1}{4}\hat{g})]_x \frac{\partial \theta}{2} - \underbrace{[\tilde{b}_g - n_g + [\partial\theta]_x C(\frac{1}{4}\hat{g})]_x \frac{\partial \theta}{2}}_{\text{忽略高阶小项}}$$

$$= [\omega_m - \hat{b}_g - C(\frac{1}{4}\hat{g})]_x \partial\theta$$

$$= [\hat{\omega}]_x \partial\theta$$

$$\omega - \hat{\omega} = (\omega_m - \hat{b}_g - n_g - C(\frac{1}{4}\hat{g})\omega_g + [\partial\theta]_x C(\frac{1}{4}\hat{g})\omega_g) - (\omega_m - \hat{b}_g - C(\frac{1}{4}\hat{g})\omega_g)$$

$$= -(b_g - \hat{b}_g) - n_g + \underbrace{[\partial\theta]_x C(\frac{1}{4}\hat{g})\omega_g}_{\text{忽略小项}}$$

$$= -\tilde{b}_g - n_g$$

$$\Rightarrow \dot{\partial\theta} = -[\hat{\omega}]_x \partial\theta - \tilde{b}_g - n_g$$

$${}^G \dot{V}_1(t) = {}^G a(t)$$

$$= C^T(\frac{1}{4}\hat{g})(a_m - b_a - n_a) + g - 2[\omega_g]_x {}^G \tilde{V}_1 - [\omega_g]_x^2 {}^G \tilde{P}_1$$

$${}^G \dot{\tilde{V}}_1 = C^T(\frac{1}{4}\hat{g})(a_m - \hat{b}_a) + g - 2[\omega_g]_x {}^G \tilde{V}_1 - [\omega_g]_x^2 {}^G \tilde{P}_1$$

$${}^G \dot{\tilde{V}}_1 = {}^G \dot{V}_1(t) - {}^G \dot{\tilde{V}}_1$$

$$= C^T(\frac{1}{4}\hat{g})(a_m - b_a - n_a) - C^T(\frac{1}{4}\hat{g})(a_m - \hat{b}_a) - 2[\omega_g]_x {}^G \tilde{V}_1 - [\omega_g]_x^2 {}^G \tilde{P}_1$$

$$= (C(\partial\theta)C(\frac{1}{4}\hat{g}))^T (a_m - b_a - n_a) - C^T(\frac{1}{4}\hat{g})(a_m - \hat{b}_a) - 2[\omega_g]_x {}^G \tilde{V}_1 - [\omega_g]_x^2 {}^G \tilde{P}_1$$

$$\approx ((1 - [\partial\theta]_x)C(\frac{1}{4}\hat{g}))^T (a_m - b_a - n_a) - C^T(\frac{1}{4}\hat{g})(a_m - \hat{b}_a) - X$$

$$= C^T(\frac{1}{4}\hat{g})(1 - [\partial\theta]_x^T)(a_m - b_a - n_a) - C^T(\frac{1}{4}\hat{g})(a_m - \hat{b}_a) - X$$

$$= C^T(\frac{1}{4}\hat{g})(a_m - b_a - n_a) + C^T(\frac{1}{4}\hat{g})[\partial\theta]_x(a_m - b_a - n_a) - C^T(\frac{1}{4}\hat{g})(a_m - \hat{b}_a) - X$$

$$= C^T(\frac{1}{4}\hat{g})(-\tilde{b}_a - n_a) + C^T(\frac{1}{4}\hat{g})[\partial\theta]_x(a_m - \hat{b}_a - \tilde{b}_a - n_a) - X$$

$$= C^T(\frac{1}{4}\hat{g})(-\tilde{b}_a - n_a) + C^T(\frac{1}{4}\hat{g})[\partial\theta]_x(a_m - \hat{b}_a) + \underbrace{C^T(\frac{1}{4}\hat{g})[\partial\theta]_x(-\tilde{b}_a - n_a)}_{\text{高阶小量}} - X$$

$$= -C^T(\frac{1}{4}\hat{g})\tilde{b}_a - C^T(\frac{1}{4}\hat{g})n_a - C^T(\frac{1}{4}\hat{g})[a_m - \hat{b}_a]_x \partial\theta - 2[\omega_g]_x {}^G \tilde{V}_1 - [\omega_g]_x^2 {}^G \tilde{P}_1$$

綜上可得

$${}^G \dot{\tilde{P}}_1 = {}^G \tilde{V}_1$$

$${}^G \dot{\tilde{V}}_1 = -[\omega_g]_x^2 {}^G \tilde{P}_1 - 2[\omega_g]_x {}^G \tilde{V}_1 - C^T(\frac{1}{4}\hat{g})[a_m - \hat{b}_a]_x \partial\theta - C^T(\frac{1}{4}\hat{g})\tilde{b}_a - C^T(\frac{1}{4}\hat{g})n_a$$

$$\dot{\partial\theta} = -[\hat{\omega}]_x \partial\theta - \tilde{b}_g - n_g$$

$$\dot{\tilde{b}}_a = n_{wa}$$

$$\dot{\tilde{b}}_g = n_{wg}$$

$$F = \begin{bmatrix} 0_{3 \times 3} & I_3 & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} \\ -[\omega_g]_x^2 & -2[\omega_g]_x & -C^T(\frac{1}{4}\hat{g})[a_m - \hat{b}_a]_x & -C^T(\frac{1}{4}\hat{g})\tilde{b}_a & -C^T(\frac{1}{4}\hat{g})n_a \\ 0_{3 \times 3} & 0_{3 \times 3} & -[\hat{\omega}]_x & 0_{3 \times 3} & -I_3 \\ 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} \end{bmatrix}$$

$$G = \begin{bmatrix} 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & -C^T(\frac{1}{4}\hat{g}) & 0_{3 \times 3} \\ -I_3 & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & I_3 \\ 0_{3 \times 3} & I_3 & 0_{3 \times 3} & 0_{3 \times 3} \end{bmatrix}$$

3. 离散形式 IMU 运动学模型

从连续形式的运动学模型 得到 离散形式. 分为两部分:

- ① IMU 状态的估计状态离散化 (nominal 或 estimate state)
- ② IMU 状态对应的协方差离散化, 该协方差离散化主要从连续形式的 error-state 运动模型得到.

首先讨论 IMU 估计状态的离散化.

对于运动学模型:

$$\dot{\hat{g}}_b = \frac{1}{2} \Omega(\hat{\omega}(t)) \hat{g}_b(t)$$

$$\dot{\hat{v}}_b = C^T(\hat{g}_b)(a_m - \hat{b}_a) + g - 2[W_G]_x \hat{v}_b - [W_G]_x^2 \hat{p}_b^1$$

$$\dot{\hat{p}}_b^1 = \hat{v}_b$$

$$\dot{\hat{b}}_a = 0_{3 \times 1}$$

$$\dot{\hat{b}}_g = 0_{3 \times 1}$$

利用 四阶 Runge-Kutta 数值积分 (4th-order Runge-Kutta numerical integration), 得到 每个时刻 离散的 IMU 估计状态. 其中 RK 积分

可参考 «Quaternion kinematics...» 公式 (334)

接下来讨论 IMU 状态的协方差离散化.

对于连续 error-state 模型

$$\dot{\tilde{X}}_{IMU} = F \tilde{X}_{IMU} + G \tilde{N}_{IMU}$$

该一阶微分方程 解的形式为

$$\tilde{X}_{t_{k+dt}} = \Phi(t_{k+dt}, t_k) \tilde{X}_{t_k} + \int_{t_k}^{t_{k+dt}} \Phi(t_{k+dt}, \tau) G \tilde{N}_{IMU} d\tau$$

其中状态传递矩阵 $\Phi(t_{k+dt}, t_k)$

$$\dot{\Phi}(t_{k+dt}, t_k) = F(t) \Phi(t_{k+dt}, t_k) \quad \text{其中 } \Phi(t_k, t_k) = I$$

$$\Rightarrow \Phi(t_{k+dt}, t_k) = \exp\left(\int_{t_k}^{t_{k+dt}} F(t) dt\right) = \bar{\Phi}_k \approx e^{F \Delta t} \approx I + F \Delta t$$

另外 error-state 的噪声协方差为

$$Q_{t_k} = \int_{t_k}^{t_{k+dt}} \Phi(t_{k+dt}, \tau) G Q G^T \Phi(t_{k+dt}, \tau)^T d\tau = Q_k$$

则 IMU 状态的协方差离散传递形式为:

$$P_{I|k+1|k} = \bar{\Phi}_k P_{I|k|k} \bar{\Phi}_k^T + Q_k$$

若包含 IMU 和 Camera 的全状态协方差为

$$P_{k|k} = \begin{pmatrix} P_{I|k|k} & P_{IC|k|k} \\ P_{IC|k|k}^T & P_{CC|k|k} \end{pmatrix}$$

则传递协方差为

$$P_{k+1|k} = \begin{pmatrix} P_{I|k+1|k} & \bar{\Phi}_k P_{IC|k|k} \\ P_{IC|k+1|k}^T \bar{\Phi}_k^T & P_{CC|k+1|k} \end{pmatrix}$$

接下来讨论状态扩展 (state Augmentation):

当有一帧新图像被处理时, 相机位姿可通过 IMU 位姿得到:

$$\hat{g}_b = \hat{g}_b \otimes \hat{g}_b$$

$$\hat{p}_c = \hat{p}_b^1 + C^T(\hat{g}_b) p_c$$

其中 \hat{g}_b 为相机与 IMU 之间旋转, p_c 为相机在 IMU 系下坐标

最新相机位姿的协方差可通过下式扩展

$$P_{klk} \leftarrow \begin{bmatrix} I_{6N+15} \\ J_z^c \end{bmatrix} P_{klk} \begin{bmatrix} I_{6N+15} \\ J_z^c \end{bmatrix}^T$$

其中 J_z^c 为协方差从 IMU 转到 Camera 的雅克比, 推导如下

$$\hat{g}_b^c = \hat{g}_b \otimes \hat{g}_b^c$$

$$C(\hat{g}_b^c) = C(\hat{g}_b) C(\hat{g}_b^c)$$

$$C(\delta g^c) C(\hat{g}_b^c) = C(\hat{g}_b) C(\delta g^c) C(\hat{g}_b^c)$$

$$(1 - [\delta \theta^c]_x) C(\hat{g}_b^c) = C(\hat{g}_b) (1 - [\delta \theta^c]_x) C(\hat{g}_b^c)$$

$$C(\hat{g}_b^c) - [\delta \theta^c]_x C(\hat{g}_b^c) = C(\hat{g}_b) C(\hat{g}_b^c) - C(\hat{g}_b) [\delta \theta^c]_x C(\hat{g}_b^c)$$

$$[\delta \theta^c]_x C(\hat{g}_b^c) = C(\hat{g}_b) [\delta \theta^c]_x C(\hat{g}_b^c)$$

$$[\delta \theta^c]_x = C(\hat{g}_b) [\delta \theta^c]_x C(\hat{g}_b^c) C^T(\hat{g}_b^c)$$

$$= C(\hat{g}_b) [\delta \theta^c]_x C(\hat{g}_b^c) C^T(\hat{g}_b^c) C^T(\hat{g}_b)$$

$$= C(\hat{g}_b) [\delta \theta^c]_x C^T(\hat{g}_b)$$

$$[\delta \theta^c]_x = [C(\hat{g}_b) \delta \theta^c]_x$$

$$\delta \theta^c = C(\hat{g}_b) \delta \theta^c$$

$$\Rightarrow \frac{\partial \delta \theta^c}{\partial \delta \theta^c} = C(\hat{g}_b)$$

以上推导假设相机与 IMU 之间外参 $C(\hat{g}_b)$ 为常数, 若需标定该外参

$$C(\hat{g}_b^c) = C(\hat{g}_b) C(\hat{g}_b^c)$$

$$C(\delta g^c) C(\hat{g}_b^c) = C(\delta g^c) C(\hat{g}_b) C(\hat{g}_b^c)$$

$$(1 - [\delta \theta^c]_x) C(\hat{g}_b^c) = (1 - [\delta \theta^c]_x) C(\hat{g}_b) C(\hat{g}_b^c)$$

$$\delta \theta^c = \delta \theta^c$$

$$\Rightarrow \frac{\partial \delta \theta^c}{\partial \delta \theta^c} = I_3$$

$$g_{P_c}^{\hat{}} = g_{P_z}^{\hat{}} + C^T(\hat{g}_b^c) {}^z P_c$$

$$g_{P_c}^{\hat{}} + g_{P_c}^{\sim} = g_{P_z}^{\hat{}} + g_{P_z}^{\sim} + C^T(\hat{g}_b^c) {}^z P_c$$

$$\Rightarrow \frac{\partial g_{P_c}^{\sim}}{\partial g_{P_z}^{\sim}} = I_3$$

$$g_{P_c}^{\hat{}} + g_{P_c}^{\sim} = g_{P_z}^{\hat{}} + (C(\delta g^c) C(\hat{g}_b^c))^T {}^z P_c$$

$$= g_{P_z}^{\hat{}} + (1 - [\delta \theta^c]_x) C(\hat{g}_b^c) {}^T {}^z P_c$$

$$= g_{P_z}^{\hat{}} + C^T(\hat{g}_b^c) (1 - [\delta \theta^c]_x) {}^T {}^z P_c$$

$$= g_{P_z}^{\hat{}} + C^T(\hat{g}_b^c) (1 + [\delta \theta^c]_x) {}^T {}^z P_c$$

$$= g_{P_z}^{\hat{}} + C^T(\hat{g}_b^c) {}^T {}^z P_c + C^T(\hat{g}_b^c) [\delta \theta^c]_x {}^T {}^z P_c$$

$$g_{P_c}^{\sim} = C^T(\hat{g}_b^c) [\delta \theta^c]_x {}^T {}^z P_c$$

$$= -C^T(\hat{g}_b^c) [{}^z P_c]_x \delta \theta^c$$

$$\Rightarrow \frac{\partial g_{P_c}^{\sim}}{\partial \delta \theta^c} = -C^T(\hat{g}_b^c) [{}^z P_c]_x$$

若需标定相机和 IMU 外参

$$g_{P_c}^{\hat{}} + g_{P_c}^{\sim} = g_{P_z}^{\hat{}} + C^T(\hat{g}_b^c) ({}^z P_c + {}^z \tilde{P}_c)$$

$$= g_{P_z}^{\hat{}} + C^T(\hat{g}_b^c) {}^z P_c + C^T(\hat{g}_b^c) {}^z \tilde{P}_c$$

$$g_{P_c}^{\sim} = C^T(\hat{g}_b^c) {}^z \tilde{P}_c$$

$$\Rightarrow \frac{\partial g_{P_c}^{\sim}}{\partial {}^z \tilde{P}_c} = C^T(\hat{g}_b^c)$$

至此, 联立比 J_1^c 可得

$$J_1^c = \begin{bmatrix} \frac{\partial \theta^c}{\partial \hat{p}_x} & \frac{\partial \theta^c}{\partial \hat{p}_y} & \frac{\partial \theta^c}{\partial \theta_z} & \frac{\partial \theta^c}{\partial \hat{b}_a} & \frac{\partial \theta^c}{\partial \hat{b}_g} \\ \frac{\partial \tilde{p}_c}{\partial \hat{p}_x} & \frac{\partial \tilde{p}_c}{\partial \hat{p}_y} & \frac{\partial \tilde{p}_c}{\partial \theta_z} & \frac{\partial \tilde{p}_c}{\partial \hat{b}_a} & \frac{\partial \tilde{p}_c}{\partial \hat{b}_g} \end{bmatrix} \begin{bmatrix} O_{3 \times N} \\ O_{3 \times N} \end{bmatrix}$$

$$= \begin{bmatrix} O_{3 \times 3} & O_{3 \times 3} & C(\hat{g}) & O_{3 \times 3} & O_{3 \times 3} \\ I_3 & O_{3 \times 3} & -C(\hat{g})[{}^I p_c]_x & O_{3 \times 3} & O_{3 \times 3} \end{bmatrix} \begin{bmatrix} O_{3 \times N} \\ O_{3 \times N} \end{bmatrix}$$

其中 $\frac{\partial \tilde{p}_c}{\partial \theta_z} = -C(\hat{g})[{}^I p_c]_x$ 与原始论文《A multi-state constraint

Kalman filter for vision-aided inertial navigation》

$\frac{\partial \tilde{p}_c}{\partial \theta_z} = [C^T(\hat{g})^T p_c]_x$ 不同, 若旋转采用左扰动,

$$\begin{aligned} {}^G \hat{p}_c + {}^G \tilde{p}_c &= {}^G \hat{p}_c + (C(\hat{g})({}^G \delta \theta^G))^T {}^I p_c \\ &= {}^G \hat{p}_c + (C(\hat{g})(1 - [{}^G \delta \theta^G]_x))^T {}^I p_c \\ &= {}^G \hat{p}_c + (1 - [{}^G \delta \theta^G]_x)^T C^T(\hat{g}) {}^I p_c \\ &= {}^G \hat{p}_c + C^T(\hat{g}) {}^I p_c - [{}^G \delta \theta^G]_x^T C^T(\hat{g}) {}^I p_c \end{aligned}$$

$$\begin{aligned} {}^G \tilde{p}_c &= [{}^G \delta \theta^G]_x^T C^T(\hat{g}) {}^I p_c \\ &= -[C^T(\hat{g}) {}^I p_c]_x \delta \theta^G \end{aligned}$$

$$\Rightarrow \frac{\partial \tilde{p}_c}{\partial \theta^G} = -[C^T(\hat{g}) {}^I p_c]_x$$

与原文仍然相差一个负号, 可能是原文书写有误。

另外 $\frac{\partial \theta^c}{\partial \theta_z} = C(\hat{g})$ 与论文《Robust stereo visual inertial odometry for fast autonomous flight》 $\Rightarrow \frac{\partial \theta^c}{\partial \theta_z} = C(\hat{g})$, ~~是原文~~

该处确认为原文书写有误, 因为在其开源代码中为 $C(\hat{g})$

下面讨论视觉观测模型

假设在第 i 个相机的归一化平面上, 第 j 个地图点的观测为 $z_i^{(j)}$,

则

$$z_i^{(j)} = \frac{1}{c_i z_j} \begin{bmatrix} c_i x_j \\ c_i y_j \end{bmatrix} + n_i^{(j)}$$

其中 $n_i^{(j)}$ 为 2×1 图像噪声, 方差为 $R_i^{(j)} = \sigma_{im}^2 I_2$

另外, 地图点 p_j 在第 i 个相机下坐标为 ${}^G p_{fj}$

$${}^G p_{fj} = \begin{bmatrix} c_i x_j \\ c_i y_j \\ c_i z_j \end{bmatrix} = C(\hat{g})({}^G p_j - {}^G p_{ci})$$

其中 ${}^G p_j$ 是地图点在世界坐标系下位置, ${}^G p_{ci}$ 是相机在 G 系下位置。

则第 j 个地图点在第 i 个相机观测残差

$$r_i^{(j)} = z_i^{(j)} - \hat{z}_i^{(j)}$$

$$\text{其中 } \hat{z}_i^{(j)} = \frac{1}{c_i \hat{z}_j} \begin{bmatrix} c_i \hat{x}_j \\ c_i \hat{y}_j \end{bmatrix}, \quad {}^G \hat{p}_{fj} = \begin{bmatrix} c_i \hat{x}_j \\ c_i \hat{y}_j \\ c_i \hat{z}_j \end{bmatrix} = C(\hat{g})({}^G \hat{p}_j - {}^G \hat{p}_{ci})$$

由于视觉观测 $z_i^{(j)}$ 相对于状态 $a\bar{q}$, $a p_{ci}$, $a p_{fi}$ 是非线性的, 利用 EKF 估计器则需要线性化, 接下来讨论线性化过程.

假设 $z_i^{(j)} = h(X_{ci}, p_{fi}) = h(a\bar{q}, a p_{ci}, a p_{fi})$, 则

$$\text{又因为 } z_i^{(j)} = \frac{1}{a z_j} \begin{bmatrix} a x_j \\ a y_j \end{bmatrix} = \begin{bmatrix} u \\ v \end{bmatrix} \quad c p_{fj} = \begin{bmatrix} a x_j \\ a y_j \\ a z_j \end{bmatrix} = c(a\bar{q})(a p_{fj} - a p_{ci})$$

根据链式求导可知

$$H_{x_i}^{(j)} = \frac{\partial z_i^{(j)}}{\partial X_{ci}} = \frac{\partial z_i^{(j)}}{\partial a p_{fj}} \cdot \frac{\partial a p_{fj}}{\partial X_{ci}}, \quad H_{p_j}^{(j)} = \frac{\partial z_i^{(j)}}{\partial a p_{fj}} = \frac{\partial z_i^{(j)}}{\partial a p_{fj}} \cdot \frac{\partial a p_{fj}}{\partial a p_{fj}}$$

$$\frac{\partial z_i^{(j)}}{\partial a p_{fj}} = \begin{bmatrix} \frac{\partial u}{\partial a x_j} & \frac{\partial u}{\partial a y_j} & \frac{\partial u}{\partial a z_j} \\ \frac{\partial v}{\partial a x_j} & \frac{\partial v}{\partial a y_j} & \frac{\partial v}{\partial a z_j} \end{bmatrix} = \begin{bmatrix} \frac{1}{a z_j} & 0 & -\frac{a x_j}{a z_j^2} \\ 0 & \frac{1}{a z_j} & -\frac{a y_j}{a z_j^2} \end{bmatrix}$$

$$a p_{fj} = c(a\bar{q})(a p_{fj} - a p_{ci})$$

$$a p_{fj} + a \tilde{p}_{fj} = c(\partial \theta^a) c(a\bar{q})(a p_{fj} - a p_{ci}) \\ = (1 - [\partial \theta^a]_x) c(a\bar{q})(a p_{fj} - a p_{ci})$$

$$a \tilde{p}_{fj} = -[\partial \theta^a]_x c(a\bar{q})(a p_{fj} - a p_{ci}) \\ = [c(a\bar{q})(a p_{fj} - a p_{ci})]_x \partial \theta^a$$

$$\frac{\partial a p_{fj}}{\partial a \bar{q}} = \frac{\partial a \tilde{p}_{fj}}{\partial \partial \theta^a} = [c(a\bar{q})(a p_{fj} - a p_{ci})]_x = [a p_{fj}]_x$$

$$a p_{fj} + a \tilde{p}_{fj} = c(a\bar{q})(a p_{fj} - (a p_{ci} + a \tilde{p}_{ci})) \\ = c(a\bar{q})(a p_{fj} - a p_{ci}) - c(a\bar{q}) a \tilde{p}_{ci}$$

$$a \tilde{p}_{fj} = -c(a\bar{q}) a \tilde{p}_{ci}$$

$$\frac{\partial a p_{fj}}{\partial a p_{ci}} = \frac{\partial a \tilde{p}_{fj}}{\partial a \tilde{p}_{ci}} = -c(a\bar{q})$$

$$a p_{fj} + a \tilde{p}_{fj} = c(a\bar{q})(a p_{fj} + a \tilde{p}_{fj} - a p_{ci}) \\ = c(a\bar{q}) a \tilde{p}_{fj} + c(a\bar{q})(a p_{fj} - a p_{ci})$$

$$a \tilde{p}_{fj} = c(a\bar{q}) a \tilde{p}_{fj}$$

$$\frac{\partial a p_{fj}}{\partial a p_{fj}} = \frac{\partial a \tilde{p}_{fj}}{\partial a \tilde{p}_{fj}} = c(a\bar{q})$$

因此有

$$\frac{\partial a p_{fj}}{\partial X_{ci}} = \begin{bmatrix} \frac{\partial a p_{fj}}{\partial a \bar{q}} & \frac{\partial a p_{fj}}{\partial a p_{ci}} \end{bmatrix} = \begin{bmatrix} [a p_{fj}]_x & -c(a\bar{q}) \end{bmatrix}$$

$$\frac{\partial a p_{fj}}{\partial a p_{fj}} = c(a\bar{q})$$

则有测量残差

$$r_i^{(j)} = z_i^{(j)} - \hat{z}_i^{(j)} \approx H_{x_i}^{(j)} \tilde{x} + H_{p_j}^{(j)} a \tilde{p}_{fj} + n_i^{(j)}$$

将同一地图点 j 在所有相机下的观测堆放一起

$$r^{(j)} = H_x^{(j)} \tilde{x} + H_{p_j}^{(j)} a \tilde{p}_{fj} + n^{(j)} \quad (\text{噪声 } n^{(j)} \text{ 方差为 } R^{(j)} = \sigma^2 I)$$

由于地图点 q_{f_j} 的计算会有状态量 X 的参与, 因此 \tilde{x} 与 q_{f_j} 相关. 测量残差 $r^{(j)}$ 没法直接用在 EKF 中, 因此将残差 $r^{(j)}$ 投影到 $H_{f_j}^{(j)}$ 的左零空间 (left nullspace), $A^T H_{f_j}^{(j)} q_{f_j} = 0$. 则

$$r_0^{(j)} = A^T (z^{(j)} - \hat{z}^{(j)}) \approx A^T H_{f_j}^{(j)} \tilde{x} + A^T n^{(j)} = H_0^{(j)} \tilde{x}^{(j)} + n_0^{(j)}$$

其中矩阵 A 不用显式计算出来, 可利用 Givens rotations 将 $r^{(j)}$ 和 $H_{f_j}^{(j)}$ 投影到 $H_{f_j}^{(j)}$ 的左零空间. 另外 $E[n_0^{(j)} n_0^{(j)T}] = \sigma^2 A^T A = \sigma^2 I$

将多个地图点的观测堆放到一起:

$$r_0 = H_x \tilde{x} + n_0$$

为减少计算量, 对雅克比矩阵 QK 分解:

$$H_x = [Q_1 \ Q_2] \begin{bmatrix} T_H \\ 0 \end{bmatrix}$$

则

$$r_0 = [Q_1 \ Q_2] \begin{bmatrix} T_H \\ 0 \end{bmatrix} \tilde{x} + n_0$$

$$\Rightarrow \begin{bmatrix} Q_1^T r_0 \\ Q_2^T r_0 \end{bmatrix} = \begin{bmatrix} T_H \\ 0 \end{bmatrix} \tilde{x} + \begin{bmatrix} Q_1^T n_0 \\ Q_2^T n_0 \end{bmatrix}$$

$$\Rightarrow r_n = Q^T r_0 = T_H \tilde{x} + n_n$$

其中测量噪声 $n_n = Q_1^T n_0$ 方差为 $R_n = Q_1^T R_0 Q_1 = \sigma^2 I$

最后 EKF 状态更新有:

$$\text{Kalman 增益: } K = P T_H^T (T_H P T_H^T + R_n)^{-1}$$

$$\text{状态更新: } X_{k+1|k+1} = X_{k+1|k} + K \cdot r_n$$

$$\text{协方差更新: } P_{k+1|k+1} = (I - K T_H) P_{k+1|k} (I - K T_H)^T + K R_n K^T$$

其中 Q_1 不用显式计算出来, r_n 和 T_H 可利用 Givens rotations 获取.