

2. 群的性质

$\{\mathbb{Z}, +\}$ 是群, 满足群的四个性质:

- 1. 整数加整数仍然是整数
- 2. 加法结合律
- 3. 么元为0
- 4. 逆为本身取负

$\{\mathbb{N}, +\}$ 不是群, 对于正整数, 其逆不是自然数.

3. 向量叉乘的李代数性质

三维空间中的两个向量 \mathbf{a}, \mathbf{b} , 有:

$$\mathbf{a} \times \mathbf{b} = -\mathbf{b} \times \mathbf{a}$$
$$\mathbf{a} \times \mathbf{b} = \mathbf{a}^\wedge \mathbf{b} = \begin{bmatrix} 0 & -a_3 & a_2 \\ a_3 & 0 & -a_1 \\ -a_2 & a_1 & 0 \end{bmatrix} \mathbf{b} = - \begin{bmatrix} 0 & -b_3 & b_2 \\ b_3 & 0 & -b_1 \\ -b_2 & b_1 & 0 \end{bmatrix} \mathbf{a}$$

显然, $\mathfrak{g} = (\mathbb{R}^3, \mathbb{R}, \times)$

性质①显然满足, 叉乘的结果任然是三维向量.

将叉乘转换为矩阵相乘, 容易证明性质②也满足.

性质③, 根据叉乘的定义也可知满足.

性质④,

$$\begin{aligned} [X, [Y, Z]] + [Y, [Z, X]] + [Z, [X, Y]] &= X \times (Y \times Z) + Y \times (Z \times X) + Z \times (X \times Y) \\ &= X^\wedge Y^\wedge Z - Y^\wedge X^\wedge Z - X \times Y \times Z \\ &= (X^\wedge Y^\wedge - Y^\wedge X^\wedge)Z - (X^\wedge Y)^\wedge Z \\ &= (X^\wedge Y^\wedge - Y^\wedge X^\wedge - (X^\wedge Y)^\wedge)Z \end{aligned}$$

将括号内的矩阵展开:

$$\begin{aligned} X^\wedge Y^\wedge &= \begin{bmatrix} -x_3y_3 - x_2y_2 & x_2y_1 & x_3y_1 \\ x_1y_2 & -x_3y_3 - x_1y_1 & x_3y_2 \\ x_1y_3 & x_2y_3 & -x_2y_2 - x_1y_1 \end{bmatrix} \\ Y^\wedge X^\wedge &= \begin{bmatrix} -x_3y_3 - x_2y_2 & x_1y_2 & x_1y_3 \\ x_2y_1 & -x_3y_3 - x_1y_1 & x_2y_3 \\ x_3y_1 & x_3y_2 & -x_2y_2 - x_1y_1 \end{bmatrix} \\ (X^\wedge Y)^\wedge &= \begin{bmatrix} 0 & [x_2y_1 - x_1y_2] & [x_3y_1 - x_1y_3] \\ [x_1y_2 - x_2y_1] & 0 & [x_3y_2 - x_2y_3] \\ [x_1y_3 - x_3y_1] & [x_2y_3 - x_3y_2] & 0 \end{bmatrix} \end{aligned}$$

可得 $X^\wedge Y^\wedge - Y^\wedge X^\wedge - (X^\wedge Y)^\wedge = 0$, 性质④得证.

4. SE(3)指数映射推导

根据李代数se(3)的定义:

$$\mathfrak{se}(3) = \left\{ \boldsymbol{\xi} = \begin{bmatrix} \boldsymbol{\rho} \\ \phi \end{bmatrix} \in \mathbb{R}^6, \boldsymbol{\rho} \in \mathbb{R}^3, \phi \in \mathfrak{so}(3), \boldsymbol{\xi}^\wedge = \begin{bmatrix} \phi^\wedge & \boldsymbol{\rho} \\ \mathbf{0}^T & 0 \end{bmatrix} \in \mathbb{R}^{4 \times 4} \right\}$$

分析乘积:

$$\begin{aligned} \left(\begin{bmatrix} \boldsymbol{\rho} \\ \phi \end{bmatrix}^\wedge \right)^2 &= \begin{bmatrix} \phi^\wedge & \boldsymbol{\rho} \\ \mathbf{0}^T & 0 \end{bmatrix} \begin{bmatrix} \phi^\wedge & \boldsymbol{\rho} \\ \mathbf{0}^T & 0 \end{bmatrix} = \begin{bmatrix} (\phi^\wedge)^2 & \phi^\wedge \boldsymbol{\rho} \\ \mathbf{0}^T & 0 \end{bmatrix} \\ \Rightarrow \left(\begin{bmatrix} \boldsymbol{\rho} \\ \phi \end{bmatrix}^\wedge \right)^n &= \begin{bmatrix} (\phi^\wedge)^n & (\phi^\wedge)^{n-1} \boldsymbol{\rho} \\ \mathbf{0}^T & 0 \end{bmatrix} \end{aligned}$$

指数Taylor展开:

$$\begin{aligned}\exp\left(\begin{bmatrix} \rho \\ \phi \end{bmatrix}^\wedge\right) &= \sum_{n=0}^{\infty} \frac{1}{n!} \left(\begin{bmatrix} \rho \\ \phi \end{bmatrix}^\wedge\right)^n = \frac{1}{0!} \left(\begin{bmatrix} \rho \\ \phi \end{bmatrix}^\wedge\right)^0 + \sum_{n=1}^{\infty} \frac{1}{n!} \left(\begin{bmatrix} (\phi^\wedge)^n & (\phi^\wedge)^{n-1}\rho \\ \mathbf{0}^T & 0 \end{bmatrix}\right) \\ &= \mathbf{I} + \begin{bmatrix} \sum_{n=1}^{\infty} \frac{1}{n!} (\phi^\wedge)^n & \sum_{n=1}^{\infty} \frac{1}{n!} (\phi^\wedge)^{n-1}\rho \\ \mathbf{0}^T & 0 \end{bmatrix} \\ &= \begin{bmatrix} \sum_{n=0}^{\infty} \frac{1}{n!} (\phi^\wedge)^n & \sum_{n=0}^{\infty} \frac{1}{(n+1)!} (\phi^\wedge)^n \rho \\ \mathbf{0}^T & 1 \end{bmatrix}\end{aligned}$$

由此, 得到Jacobian矩阵. 这里, 利用了矩阵的0次幂是 \mathbf{I} . 参考SO(3)指数映射的推导, 对Jacobian矩阵做进一步化简:

$$\begin{aligned}\mathbf{J} &= \sum_{n=0}^{\infty} \frac{1}{(n+1)!} (\phi^\wedge)^n = \sum_{n=0}^{\infty} \frac{1}{(n+1)!} (\theta \mathbf{a}^\wedge)^n \\ &= \mathbf{I} + \frac{1}{2!} \theta \mathbf{a}^\wedge + \frac{1}{3!} \theta^2 \mathbf{a}^\wedge \mathbf{a}^\wedge + \frac{1}{4!} \theta^3 \mathbf{a}^\wedge \mathbf{a}^\wedge \mathbf{a}^\wedge + \dots \\ \Rightarrow \theta \mathbf{J} &= \left(\theta + \frac{1}{2!} \theta^2 \mathbf{a}^\wedge + \frac{1}{3!} \theta^3 \mathbf{a}^\wedge \mathbf{a}^\wedge + \frac{1}{4!} \theta^4 \mathbf{a}^\wedge \mathbf{a}^\wedge \mathbf{a}^\wedge + \dots\right) \\ &= -\left(\theta - \frac{1}{3!} \theta^3 + \frac{1}{5!} \theta^5 - \dots\right) \mathbf{a}^\wedge \mathbf{a}^\wedge - \left(1 - \frac{1}{2!} \theta^2 + \frac{1}{4!} \theta^4 - \dots\right) \mathbf{a}^\wedge + \theta + \theta \mathbf{a}^\wedge \mathbf{a}^\wedge + \mathbf{a}^\wedge \\ \Rightarrow J &= \frac{\sin \theta}{\theta} I + \left(1 - \frac{\sin \theta}{\theta}\right) \mathbf{a} \mathbf{a}^T + \frac{1 - \cos \theta}{\theta} \mathbf{a}^\wedge\end{aligned}$$

5.伴随

首先, 证明 $\mathbf{R} \mathbf{a}^\wedge \mathbf{R}^T = (\mathbf{R} \mathbf{a})^\wedge$:
直观理解为, 对于任意向量 \mathbf{v} , $\mathbf{R} \mathbf{a}^\wedge \mathbf{R}^T \mathbf{v}$ 可以解释为, 先根据 \mathbf{R} 做一个逆旋转, 然后与 \mathbf{a} 做叉乘, 再根据 \mathbf{R} 旋转回来. 这个等价于对 \mathbf{a} 做完旋转后再叉乘. 又可理解为, 向量先旋转到一个局部坐标系中做叉乘再旋转回全局坐标系, 与先旋转到全局坐标系, 再叉乘等价.

$$(\mathbf{R} \mathbf{a}) \times \mathbf{v} = (\mathbf{R} \mathbf{a}) \times (\mathbf{R} \mathbf{R}^T \mathbf{v}) = \mathbf{R} [\mathbf{a} \times (\mathbf{R}^T \mathbf{v})]$$

对任意向量 \mathbf{v} 均成立, 故而 $\mathbf{R} \mathbf{a}^\wedge \mathbf{R}^T = (\mathbf{R} \mathbf{a})^\wedge$.

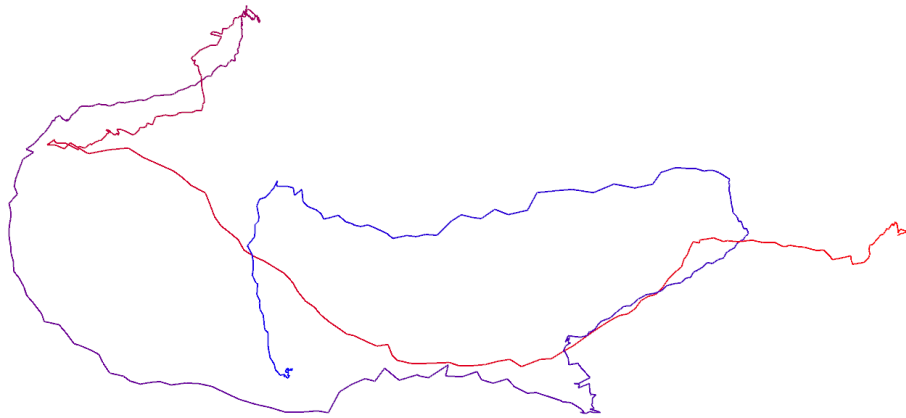
接下来证明 $\mathbf{R} \cdot \mathbf{q}^\wedge \cdot \mathbf{R}^T = (\mathbf{R} \cdot \mathbf{q})^\wedge \Rightarrow \mathbf{R} \exp(\mathbf{p}^\wedge) \mathbf{R}^T = \exp((\mathbf{R} \mathbf{p})^\wedge)$

令 $\mathbf{p} = t \cdot \mathbf{q}, t \in \mathbb{R}$, 在 $t = 0$ 处对 t 求导,有

$$\begin{aligned}\frac{d}{dt} \Big|_{t=0} \left[\mathbf{R} \cdot \exp(t \cdot \mathbf{q}) \cdot \mathbf{R}^T \right] &= \frac{d}{dt} \Big|_{t=0} \exp((\mathbf{R} \cdot t \cdot \mathbf{q})_\times) \\ \mathbf{R} \cdot \frac{d}{dt} \Big|_{t=0} \left[\mathbf{I} + (t \cdot \mathbf{q})_\times + O(t^2) \right] \cdot \mathbf{R}^T &= \frac{d}{dt} \Big|_{t=0} \left[\mathbf{I} + (\mathbf{R} \cdot t \cdot \mathbf{q})_\times + O(t^2) \right] \\ \mathbf{R} \cdot (t \cdot \mathbf{q})_\times \cdot \mathbf{R}^T &= (\mathbf{R} \cdot t \cdot \mathbf{q})_\times \\ \mathbf{R} \cdot \mathbf{q}^\wedge \cdot \mathbf{R}^T &= (\mathbf{R} \cdot \mathbf{q})^\wedge\end{aligned}$$

6. 轨迹的描绘

- 1. \mathbf{T}_{WC} 的平移部分, 物理意义是机器人在世界坐标系中的位置, 因此, 画出平移部分就画出了机器人运动的轨迹.
- 2. 结果如下图, 代码见附件.



7. 轨迹的误差

我的运算结果答案为: 2.20548 与参考答案 2.207 有些相差, 若有错误, 望指正, 代码见附件.