

机器人学中的状态估计 - 作业 3

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May 21, 2020

1. $y_k|x_k \sim \mathcal{N}(\check{y}_k + G_k(x - \check{x}_k), R'_k)$, $x_k|\check{x}_0, v_{1:k}, y_{0:k} \sim \mathcal{N}(\check{x}_k, F_{k-1}\check{P}_{k-1}F_{k-1}^T + Q'_k)$. 将概率密度相乘得到:

$$\begin{aligned} p(\hat{x}_k|\check{x}_0, v_{1:k}, y_{0:k}) &= \eta p(y_k|x_k)p(x_k|\check{x}_0, v_{1:k}, y_{0:k}) \\ &= \eta \exp\left\{-\frac{1}{2}[y_k - (\check{y}_k + G_k(x - \check{x}_k))]^T R_k'^{-1}[y_k - (\check{y}_k + G_k(x - \check{x}_k))]\right\} \\ &\quad \times \exp\left\{-\frac{1}{2}(x_k - \check{x}_k)^T \check{P}_k^{-1}(x_k - \check{x}_k)\right\} \end{aligned} \quad (1)$$

显然后验 \hat{x}_k 仍然服从正态分布. 对于指数部分暂时忽略掉常数 $-\frac{1}{2}$, 相乘相当于在指数部分相加:

$$((y_k - \check{y}_k) - G_k(x - \check{x}_k))^T R_k'^{-1}((y_k - \check{y}_k) - G_k(x - \check{x}_k)) + (x_k - \check{x}_k)^T \check{P}_k^{-1}(x_k - \check{x}_k) \quad (2)$$

分离出包含 x 的项, 得到:

$$(x_k - \check{x}_k)^T G_k^T R_k'^{-1} G_k (x_k - \check{x}_k) - 2(x_k - \check{x}_k)^T G_k^T R_k'^{-1} (y_k - \check{y}_k) + (x_k - \check{x}_k)^T \check{P}_k^{-1} (x_k - \check{x}_k) \quad (3)$$

其中 x_k 的二次项对应 \hat{x}_k 的后验协方差:

$$\hat{P}_k^{-1} = G_k^T R_k'^{-1} G_k + \check{P}_k^{-1} \Rightarrow \hat{P}_k = (G_k^T R_k'^{-1} G_k + \check{P}_k^{-1})^{-1} \quad (4)$$

带入 SMW 公式得到:

$$\begin{aligned} \hat{P}_k &= (G_k^T R_k'^{-1} G_k + \check{P}_k^{-1})^{-1} \\ &= \check{P}_k - \check{P}_k G_k^T (R_k' + G_k \check{P}_k G_k^T)^{-1} G_k \check{P}_k \\ &= (I - \check{P}_k G_k^T (R_k' + G_k \check{P}_k G_k^T)^{-1} G_k) \check{P}_k \\ &= (I - K_k G_k) \check{P}_k \end{aligned} \quad (5)$$

其中 $K_k = \check{P}_k G_k^T (R_k' + G_k \check{P}_k G_k^T)^{-1}$

然后考虑 \hat{x}_k 的均值, 记为 μ , 有:

$$\begin{aligned} \hat{P}_k^{-1} \mu &= G_k^T R_k'^{-1} G_k \check{x}_k + G_k^T R_k'^{-1} (y_k - \check{y}_k) + \check{P}_k^{-1} \check{x}_k \\ &= (G_k^T R_k'^{-1} G_k + \check{P}_k^{-1}) \check{x}_k + R_k'^{-1} G_k (y_k - \check{y}_k) \end{aligned} \quad (6)$$

求解 μ 得到

$$\begin{aligned} \mu &= \hat{P}_k [(G_k^T R_k'^{-1} G_k + \check{P}_k^{-1}) \check{x}_k + G_k^T R_k'^{-1} (y_k - \check{y}_k)] \\ &= \hat{P}_k (G_k^T R_k'^{-1} G_k + \check{P}_k^{-1}) \check{x}_k + \hat{P}_k G_k^T R_k'^{-1} (y_k - \check{y}_k) \\ &= \check{x}_k + (G_k^T R_k'^{-1} G_k + \check{P}_k^{-1})^{-1} G_k^T R_k'^{-1} (y_k - \check{y}_k) \\ &= \check{x}_k + \check{P}_k G_k^T (R_k' + G_k \check{P}_k G_k^T)^{-1} (y_k - \check{y}_k) \\ &= \check{x}_k + K_k (y_k - \check{y}_k) \end{aligned} \quad (7)$$

2.

$$\begin{aligned}
\sum_{i=0}^{2L} \alpha_i x_i &= \alpha_0 x_0 + \sum_{i=1}^{2L} \alpha_i x_i \\
&= \frac{\kappa}{\kappa + L} \mu_x + \frac{1}{2} \frac{1}{\kappa + L} \sum_{i=1}^L x_i \\
&= \frac{\kappa}{\kappa + L} \mu_x + \frac{1}{2} \frac{1}{\kappa + L} 2\mu_x \\
&= \frac{\kappa + L}{\kappa + L} \mu_x \\
&= \mu_x
\end{aligned} \tag{8}$$

$$\begin{aligned}
\sum_{i=0}^{2L} \alpha_i (x_i - \mu_x)(x_i - \mu_x)^T &= \sum_{i=1}^{2L} \alpha_i (x_i - \mu_x)(x_i - \mu_x)^T \\
&= \frac{1}{2} \frac{1}{\kappa + L} \sum_{i=1}^{2L} (\kappa + L) L_i L_i^T \\
&= \frac{1}{2} \sum_{i=1}^{2L} L_i L_i^T \\
&= \sum_{i=1}^L L_i L_i^T \\
&= [L_1 \quad L_2 \quad \dots \quad L_L] \begin{bmatrix} L_1^T \\ L_2^T \\ \vdots \\ L_L^T \end{bmatrix} \\
&= \mathbf{L} \mathbf{L}^T \\
&= \Sigma_{xx}
\end{aligned} \tag{9}$$

3.

$$\begin{aligned}\mathbf{F}_{k-1} &= \left. \frac{\partial f(\mathbf{x}_{k-1}, \mathbf{v}_k, \mathbf{w}_k)}{\partial \mathbf{x}_{k-1}} \right|_{\hat{\mathbf{x}}_{k-1}, \mathbf{v}_k, 0} \\ &= \begin{bmatrix} 1 & 0 & -T \sin \theta_{k-1} v_k \\ 0 & 1 & T \cos \theta_{k-1} v_k \\ 0 & 0 & 1 \end{bmatrix}\end{aligned}\quad (10)$$

$$\begin{aligned}\mathbf{G}_{k-1} &= \left. \frac{\partial g(\mathbf{x}_k, \mathbf{n}_k)}{\partial \mathbf{x}_k} \right|_{\check{\mathbf{x}}_k, 0} \\ &= \begin{bmatrix} \frac{x_k}{\sqrt{x_k^2 + y_k^2}} & \frac{y_k}{\sqrt{x_k^2 + y_k^2}} & 0 \\ -\frac{y_k}{x_k^2 + y_k^2} & \frac{x_k}{x_k^2 + y_k^2} & -1 \end{bmatrix}\end{aligned}\quad (11)$$

$$\begin{aligned}\mathbf{w}'_k &= \left. \frac{\partial f(\mathbf{x}_{k-1}, \mathbf{v}_k, \mathbf{w}_k)}{\partial \mathbf{w}_k} \right|_{\hat{\mathbf{x}}_{k-1}, \mathbf{v}_k, 0} \mathbf{w}_k \\ &= \begin{bmatrix} T \cos \theta_{k-1} & 0 \\ T \sin \theta_{k-1} & 0 \\ 0 & T \end{bmatrix} \mathbf{w}_k\end{aligned}\quad (12)$$

$$\begin{aligned}\mathbf{n}'_k &= \left. \frac{\partial g(\mathbf{x}_k, \mathbf{n}_k)}{\partial \mathbf{n}_k} \right|_{\check{\mathbf{x}}_k, 0} \mathbf{n}_k \\ &= \mathbf{n}_k\end{aligned}\quad (13)$$

因此线性化后的协方差矩阵为:

$$\begin{aligned}\mathbf{Q}'_k &= \mathbb{E}[\mathbf{w}'_k \mathbf{w}'_k{}^T] \\ &= \begin{bmatrix} T \cos \theta_{k-1} & 0 \\ T \sin \theta_{k-1} & 0 \\ 0 & T \end{bmatrix} \mathbf{Q} \begin{bmatrix} T \cos \theta_{k-1} & 0 \\ T \sin \theta_{k-1} & 0 \\ 0 & T \end{bmatrix}^T\end{aligned}\quad (14)$$

$$\mathbf{R}'_k = \mathbb{E}[\mathbf{n}'_k \mathbf{n}'_k{}^T] = \mathbf{R}\quad (15)$$

将以上式子带入 EKF 迭代公式即可.