

中心思想：当状态和量测不可导时，可以用差分代替微分

前向差分 $\delta_j^{(f)} f_i(\hat{X}_{k-1}) \square f_i(\hat{X}_{k-1} + e_j d_j) - f_i(\hat{X}_{k-1})$
 后向差分 $\delta_j^{(b)} f_i(\hat{X}_{k-1}) \square f_i(\hat{X}_{k-1}) - f_i(\hat{X}_{k-1} - e_j d_j)$

13 扩展卡尔曼滤波(EKF)

13.5 差商扩展卡尔曼滤波 (DQEKF)

中心差商
代替求导

$$\frac{\partial f_i(\hat{X}_{k-1})}{\partial x_j} \approx \frac{\delta_j f_i(\hat{X}_{k-1})}{\delta x_j} \square \frac{f_i(\hat{X}_{k-1} + e_j d_j / 2) - f_i(\hat{X}_{k-1} - e_j d_j / 2)}{d_j}$$

$X \sim N(\hat{X}_{k-1}, P_{k-1})$
 $d_j = \sqrt{P_{k-1, jj}}$

差分代替 Jacob

$$\Phi_{k|k-1} = \frac{\partial f(\hat{X}_{k-1})}{\partial X^{T-1}} \approx \frac{\partial f(\hat{X}_{k-1})}{\partial X^{T-1}} = \begin{bmatrix} \frac{\delta_1 f_1(\hat{X}_{k-1})}{\Delta x_1} & \frac{\delta_2 f_1(\hat{X}_{k-1})}{\Delta x_2} & \dots & \frac{\delta_n f_1(\hat{X}_{k-1})}{\Delta x_n} \\ \frac{\delta_1 f_2(\hat{X}_{k-1})}{\Delta x_1} & \frac{\delta_2 f_2(\hat{X}_{k-1})}{\Delta x_2} & \dots & \frac{\delta_n f_2(\hat{X}_{k-1})}{\Delta x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\delta_1 f_m(\hat{X}_{k-1})}{\Delta x_1} & \frac{\delta_2 f_m(\hat{X}_{k-1})}{\Delta x_2} & \dots & \frac{\delta_n f_m(\hat{X}_{k-1})}{\Delta x_n} \end{bmatrix}$$

$$H_k = \frac{\partial h(\hat{X}_{k-1})}{\partial X^{T-1}} \approx \frac{\partial h(\hat{X}_{k-1})}{\partial X^{T-1}} = \begin{bmatrix} \frac{\delta_1 h_1(\hat{X}_{k-1})}{\Delta x_1} & \frac{\delta_2 h_1(\hat{X}_{k-1})}{\Delta x_2} & \dots & \frac{\delta_n h_1(\hat{X}_{k-1})}{\Delta x_n} \\ \frac{\delta_1 h_2(\hat{X}_{k-1})}{\Delta x_1} & \frac{\delta_2 h_2(\hat{X}_{k-1})}{\Delta x_2} & \dots & \frac{\delta_n h_2(\hat{X}_{k-1})}{\Delta x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\delta_1 h_m(\hat{X}_{k-1})}{\Delta x_1} & \frac{\delta_2 h_m(\hat{X}_{k-1})}{\Delta x_2} & \dots & \frac{\delta_n h_m(\hat{X}_{k-1})}{\Delta x_n} \end{bmatrix}$$

$$\begin{cases} \hat{X}_{k|k-1} = f(\hat{X}_{k-1}) \\ P_{k|k-1} = \Phi_{k|k-1} P_{k-1} \Phi_{k|k-1}^T + \Gamma_{k-1} Q_{k-1} \Gamma_{k-1}^T \\ K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R_k)^{-1} \\ \hat{X}_k = \hat{X}_{k|k-1} + K_k [Z_k - h(\hat{X}_{k|k-1})] \\ P_k = (I - K_k H_k) P_{k|k-1} \end{cases}$$

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13 扩展卡尔曼滤波(EKF)

二阶差商

$$\frac{\partial^2 f_i(\hat{X}_{k-1})}{\partial x_j \partial x_l} \approx \frac{\delta_{jl}^2 f_i(\hat{X}_{k-1})}{\delta x_j \delta x_l} \square \frac{\delta_{jl} \left[\frac{f_i(\hat{X}_{k-1} + e_j d_j / 2) - f_i(\hat{X}_{k-1} - e_j d_j / 2)}{d_j} \right]}{\delta x_l}$$

$$= \frac{\delta_{jl} f_i(\hat{X}_{k-1} + e_j d_j / 2) / \delta x_l - \delta_{jl} f_i(\hat{X}_{k-1} - e_j d_j / 2) / \delta x_l}{d_j}$$

$$= \frac{1}{d_j d_l} \left\{ \left[f_i(\hat{X}_{k-1} + e_j d_j / 2 + e_l d_l / 2) - f_i(\hat{X}_{k-1} + e_j d_j / 2 - e_l d_l / 2) \right] - \left[f_i(\hat{X}_{k-1} - e_j d_j / 2 + e_l d_l / 2) - f_i(\hat{X}_{k-1} - e_j d_j / 2 - e_l d_l / 2) \right] \right\}$$

$$= \frac{1}{d_j d_l} \left[f_i(\hat{X}_{k-1} + e_j d_j / 2 + e_l d_l / 2) + f_i(\hat{X}_{k-1} - e_j d_j / 2 - e_l d_l / 2) - f_i(\hat{X}_{k-1} - e_j d_j / 2 + e_l d_l / 2) - f_i(\hat{X}_{k-1} + e_j d_j / 2 - e_l d_l / 2) \right]$$

特别的 $\frac{\partial^2 f_i(\hat{X}_{k-1})}{\partial x_j^2} \approx \frac{\delta_j^2 f_i(\hat{X}_{k-1})}{\delta x_j^2} = \frac{1}{d_j^2} \left[f_i(\hat{X}_{k-1} + e_j d_j) + f_i(\hat{X}_{k-1} - e_j d_j) - 2f_i(\hat{X}_{k-1}) \right]$

二阶差商卡尔曼滤波

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14 高斯分布采样非线性滤波

原函数积分 $\int_a^b f(x)dx = F(b) - F(a)$

14.1 高斯求积算法

积分中值定理 $\int_a^b f(x)dx = (b-a)f(\xi)$

经典矩形积分 $\int_a^b f(x)dx \approx (b-a)f\left(\frac{a+b}{2}\right)$ \square Rect

都只有1次代数精度!

经典梯形积分 $\int_a^b f(x)dx \approx \frac{b-a}{2}[f(a)+f(b)]$ \square Trap

数值积分形式 $\int_a^b f(x)dx \approx \sum_{k=1}^n w_k f(x_k)$ x_k 求积节点; w_k 求积系数

求积精度: 如果一个数值求积公式对于次数不大于m的多项式均能准确成立, 但对于m+1次多项式不成立, 则称之为具有m次代数精度。

$$\begin{cases} \sum_{k=1}^n w_k x_k^0 = \int_a^b 1 dx = b-a \\ \sum_{k=1}^n w_k x_k^1 = \int_a^b x dx = \frac{1}{2}(b^2 - a^2) \\ \vdots \\ \sum_{k=1}^n w_k x_k^m = \int_a^b x^m dx = \frac{1}{m+1}(b^{m+1} - a^{m+1}) \end{cases}$$

当积分节点等间隔选取即(b-a)/(n-1)时, n个节点的积分公式至少具有m=n-1次代数精度(当n为奇数时为n次代数精度)。

经典2点梯形公式、3点辛普森公式、5点科特斯公式都是等间隔的数值求积算法。

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14 高斯分布采样非线性滤波

14.1 高斯求积算法

$$\begin{cases} \sum_{k=1}^n w_k x_k^0 = \int_a^b 1 dx = b-a \\ \sum_{k=1}^n w_k x_k^1 = \int_a^b x dx = \frac{1}{2}(b^2 - a^2) \\ \vdots \\ \sum_{k=1}^n w_k x_k^m = \int_a^b x^m dx = \frac{1}{m+1}(b^{m+1} - a^{m+1}) \end{cases}$$

如果按不等间隔方式选取积分节点, 则有可能使求积公式具有m=2n-1次代数精度, 这类求积公式称为高斯求积公式, x_k 称为高斯节点。

比如[-1,1]上的n次勒让德多项式有n个零点, 它可作为n个高斯节点:

$P_0(x) = 1$

$P_1(x) = x$

$P_2(x) = (3x^2 - 1)/2 \rightarrow x_{1,2} = \pm 1/\sqrt{3}$

$P_3(x) = (5x^3 - 3x)/2$

...

$$\begin{cases} w_1 + w_2 = 1 - (-1) = 2 \\ w_1 \left(-\frac{1}{\sqrt{3}}\right) + w_2 \left(\frac{1}{\sqrt{3}}\right) = \frac{1}{2}[1^2 - (-1)^2] = 0 \\ \Rightarrow w_1 = w_2 = 1 \end{cases}$$

得2点高斯求积算法 $\int_{-1}^1 f(x)dx \approx f\left(-\frac{1}{\sqrt{3}}\right) + f\left(\frac{1}{\sqrt{3}}\right)$ 具有3次代数精度!

验证:

$\int_{-1}^1 x^0 dx = 2 = \left(-\frac{1}{\sqrt{3}}\right)^0 + \left(\frac{1}{\sqrt{3}}\right)^0$ $\int_{-1}^1 x^2 dx = \frac{2}{3} = \left(-\frac{1}{\sqrt{3}}\right)^2 + \left(\frac{1}{\sqrt{3}}\right)^2$ $\int_{-1}^1 x^4 dx = \frac{2}{5} = \left(-\frac{1}{\sqrt{3}}\right)^4 + \left(\frac{1}{\sqrt{3}}\right)^4 = \frac{2}{9}$

$\int_{-1}^1 x^1 dx = 0 = \left(-\frac{1}{\sqrt{3}}\right)^1 + \left(\frac{1}{\sqrt{3}}\right)^1$ $\int_{-1}^1 x^3 dx = 0 = \left(-\frac{1}{\sqrt{3}}\right)^3 + \left(\frac{1}{\sqrt{3}}\right)^3$

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14 高斯分布采样非线性滤波

14.1 高斯求积算法

带权重的高斯求积公式 $\int_a^b \rho(x)f(x)dx \approx \sum_{k=1}^n w_k f(x_k)$

$$\int_{-1}^1 \frac{1}{\sqrt{1-x^2}} f(x)dx = \sum_{k=1}^n w_k f(x_k) \quad \text{高斯-切比雪夫(Chebyshev)求积}$$

$$\int_0^\infty e^{-x} f(x)dx = \sum_{k=1}^n w_k f(x_k) \quad \text{高斯-拉盖尔(Laguerre)求积}$$

$$\int_0^\infty x^{\alpha/2-1} e^{-x} f(x)dx = \sum_{k=1}^n w_k f(x_k) \quad \text{高斯-广义拉盖尔求积}$$

$$\int_{-\infty}^\infty e^{-x^2/2} f(x)dx = \sum_{k=1}^n w_k f(x_k) \quad \text{高斯-埃尔米特(Hermite)求积} \quad x_{1,2} = \pm 1$$

勒让德多项式	切比雪夫多项式	广义拉盖尔多项式	埃尔米特多项式
$P_0(x)=1$	$T_0(x)=1$	$L_0^\alpha(x)=1$	$H_0(x)=1$
$P_1(x)=x$	$T_1(x)=x$	$L_1^\alpha(x)=-x+\alpha+1$	$H_1(x)=x$
$P_2(x)=(3x^2-1)/2$	$T_2(x)=2x^2-1$	$L_2^\alpha(x)=x^2-(2\alpha+4)x+(\alpha^2+2)$	$H_2(x)=x^2-1$
$P_3(x)=(5x^3-3x)/2$	$T_3(x)=4x^3-3x$	$L_3^\alpha(x)=$	$H_3(x)=x^3-3x$

14 高斯分布采样非线性滤波

14.2 高斯求积滤波

标量非线性概率函数 $Z = h(X)$ $p(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \square N(x|0,1)$ 标准高斯

$$E[Z] = \int_{-\infty}^\infty h(x) p(x) dx = \int_{-\infty}^\infty h(x) \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^\infty h(x) e^{-x^2/2} dx \approx \frac{1}{\sqrt{2\pi}} \sum_{k=1}^s w_k h(x_k)$$

$$\text{Var}[Z] = \int_{-\infty}^\infty (h(x) - E[Z])^2 p(x) dx = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^\infty (h(x) - E[Z])^2 e^{-x^2/2} dx \approx \frac{1}{\sqrt{2\pi}} \sum_{k=1}^s w_k (h(x_k) - E[Z])^2$$

若X高斯分布不标准 $X \sim N(\mu, \sigma^2)$ ，作变换 $x' = (x - \mu) / \sigma$ ，则有

$$E[Z] = \int_{-\infty}^\infty h(x) \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/(2\sigma^2)} dx = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^\infty h(\sigma x' + \mu) e^{-x'^2/2} dx'$$

$$\approx \frac{1}{\sqrt{2\pi}} \sum_{k=1}^s w_k h(\sigma x'_k + \mu) \square \frac{1}{\sqrt{2\pi}} \sum_{k=1}^s w_k h(\sigma x_k + \mu)$$

$$\text{Var}[Z] \approx \frac{1}{\sqrt{2\pi}} \sum_{k=1}^s w_k (h(\sigma x_k + \mu) - E[Z])^2$$

14 高斯分布采样非线性滤波

14.2 高斯求积滤波

向量非线性函数 $Z = h(X)$

$X \sim N(0, I)$

$$\{x_{k_1}\} = \left\{ \begin{bmatrix} 1 \\ \vdots \\ -1 \\ \vdots \\ 1 \end{bmatrix} \right\} \quad s=2, n=3$$

$$\{x_{k_1, k_2}\} = \left\{ \begin{bmatrix} 1 & 1 & 1 \\ -1 & 1 & -1 \\ 1 & -1 & 1 \\ -1 & -1 & -1 \end{bmatrix} \right\}$$

$$\{x_{k_1, k_2, k_3}\} = \left\{ \begin{bmatrix} 1 & 1 & 1 & 1 \\ -1 & 1 & -1 & 1 \\ 1 & -1 & 1 & -1 \\ -1 & -1 & -1 & 1 \\ 1 & 1 & 1 & -1 \\ -1 & 1 & -1 & -1 \\ 1 & -1 & 1 & -1 \\ -1 & -1 & -1 & -1 \end{bmatrix} \right\}$$

$$E[Z] = \int_{-\infty}^{\infty} h(x) p(x) dx = \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} h(x) p(x_1) p(x_2) \dots p(x_n) dx_1 dx_2 \dots dx_n$$

$$= \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} h(x) p(x_1) dx_1 p(x_2) dx_2 \dots p(x_n) dx_n \quad \hookrightarrow \text{相互独立}$$

$$\approx \frac{1}{(2\pi)^{n/2}} \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} \sum_{k_1=1}^s w_{k_1} h(x_{k_1}) p(x_2) dx_2 \dots p(x_n) dx_n$$

$$\approx \frac{1}{(2\pi)^{n/2}} \int_{-\infty}^{\infty} \dots \sum_{k_2=1}^s w_{k_2} \sum_{k_1=1}^s w_{k_1} h(x_{k_1, k_2}) \dots p(x_n) dx_n$$

$$\approx \frac{1}{(2\pi)^{n/2}} \sum_{k_n=1}^s w_{k_n} \dots \sum_{k_2=1}^s w_{k_2} \sum_{k_1=1}^s w_{k_1} h(x_{k_1, k_2, \dots, k_n}) \square \frac{1}{(2\pi)^{n/2}} \sum_{k_1, k_2, \dots, k_n=1}^s w_{k_1, k_2, \dots, k_n} h(x_{k_1, k_2, \dots, k_n})$$

高斯节点 $\{x_{k_1}\} = \left\{ \begin{bmatrix} x_{k_1} \\ \vdots \\ x_{k_n} \end{bmatrix}, \begin{bmatrix} x_{k_2} \\ \vdots \\ x_{k_n} \end{bmatrix}, \dots, \begin{bmatrix} x_{k_s} \\ \vdots \\ x_{k_n} \end{bmatrix} \right\}$

$$\{x_{k_1, k_2}\} = \left\{ \begin{bmatrix} x_{k_1} & x_{k_2} \\ \vdots & \vdots \\ x_{k_n} & x_{k_n} \end{bmatrix}, \begin{bmatrix} x_{k_1} & x_{k_2} \\ \vdots & \vdots \\ x_{k_n} & x_{k_n} \end{bmatrix}, \dots, \begin{bmatrix} x_{k_1} & x_{k_2} \\ \vdots & \vdots \\ x_{k_n} & x_{k_n} \end{bmatrix} \right\}$$

14 高斯分布采样非线性滤波

14.2 高斯求积滤波

若 X 非标准高斯分布 $X \sim N(\mu, P)$, 则有

$$E[Z] = \frac{1}{(2\pi)^{n/2}} \sum_{k_1, k_2, \dots, k_n=1}^s w_{k_1, k_2, \dots, k_n} h(\sqrt{P} x_{k_1, k_2, \dots, k_n} + \mu)$$

$$\begin{cases} X_k = f(X_{k-1}) + \Gamma_{k-1} W_{k-1} \\ Z_k = h(X_k) + V_k \end{cases}$$



$$\begin{cases} K_k = P_{ZZ, k/k-1} P_{ZZ, k/k-1}^{-1} \\ \hat{X}_k = \hat{X}_{k/k-1} + K_k (Z_k - \hat{Z}_{k/k-1}) \\ P_k = P_{k/k-1} - K_k P_{ZZ, k/k-1} K_k^T \end{cases}$$

滤波框架不变
如何求 K_k, \hat{X}_k, P_k 变了

GHQKF 滤波的求积计算过程: (特点: 精度高但计算量大!)

一步迭代
本须为均值

$$\hat{X}_{k/k-1} = \frac{1}{(2\pi)^{n/2}} \sum_{k_1, k_2, \dots, k_n=1}^s w_{k_1, k_2, \dots, k_n} f(\sqrt{P_{k/k-1}} x_{k_1, k_2, \dots, k_n} + \hat{X}_{k/k-1})$$

滤波一次精度提高, 一次过后不一定服从高斯分布了。

$$P_{k/k-1} = \frac{1}{(2\pi)^{n/2}} \sum_{k_1, k_2, \dots, k_n=1}^s w_{k_1, k_2, \dots, k_n} \langle f(\sqrt{P_{k/k-1}} x_{k_1, k_2, \dots, k_n} + \hat{X}_{k/k-1}) - \hat{X}_{k/k-1} \rangle^2 + \Gamma Q_{k-1} \Gamma^T$$

$$\hat{Z}_{k/k-1} = \frac{1}{(2\pi)^{n/2}} \sum_{k_1, k_2, \dots, k_n=1}^s w_{k_1, k_2, \dots, k_n} h(\sqrt{P_{k/k-1}} x_{k_1, k_2, \dots, k_n} + \hat{X}_{k/k-1}) \quad \langle M \rangle^2 \square MM^T$$

$$P_{ZZ, k/k-1} = \frac{1}{(2\pi)^{n/2}} \sum_{k_1, k_2, \dots, k_n=1}^s w_{k_1, k_2, \dots, k_n} \langle h(\sqrt{P_{k/k-1}} x_{k_1, k_2, \dots, k_n} + \hat{X}_{k/k-1}) - \hat{Z}_{k/k-1} \rangle^2 + R_k$$

$$P_{XZ, k/k-1} = \frac{1}{(2\pi)^{n/2}} \sum_{k_1, k_2, \dots, k_n=1}^s w_{k_1, k_2, \dots, k_n} (\sqrt{P_{k/k-1}} x_{k_1, k_2, \dots, k_n} + \hat{X}_{k/k-1}) (h(\sqrt{P_{k/k-1}} x_{k_1, k_2, \dots, k_n} + \hat{X}_{k/k-1}) - \hat{Z}_{k/k-1})^T$$

中心思想: 泰勒展开后的微分量用差分代替

14 高斯分布采样非线性滤波 $Y = \tilde{f}(Z) = \tilde{f}(\hat{Z}) + \sum_{i=1}^m \frac{1}{i!} D'_{\Delta z} \tilde{f}$ ✓
 14.3 差分Kalman滤波 $D_{\Delta z} \tilde{f} = \left(\sum_{j=1}^n \frac{\partial}{\partial z_j} \Delta z_j \right) \tilde{f}(\hat{Z}) = \sum_{j=1}^m e_j \left(\sum_{i=1}^n \frac{\partial}{\partial z_i} \Delta z_i \right) \tilde{f}_j(\hat{Z})$

$D_{\Delta z} \tilde{f} \approx \tilde{D}_{\Delta z} \tilde{f} \stackrel{\Delta}{=} \sum_{j=1}^m e_j \left(\sum_{i=1}^n \frac{\delta_i}{2\delta z_i} \Delta z_i \right) \tilde{f}_j(\hat{Z}) = \sum_{j=1}^m e_j \left(\sum_{i=1}^n \frac{\delta_i \tilde{f}_j(\hat{Z})}{2d_i} \Delta z_i \right)$ 差分代替微分

✓ $Y = \tilde{f}(\hat{Z}) + \tilde{D}_{\Delta z} \tilde{f}$ $\delta_i \tilde{f}_j(\hat{Z}) = \tilde{f}_j(\hat{Z} + e_i d) - \tilde{f}_j(\hat{Z} - e_i d)$

假设标准正态分布 $\Delta Z \sim N(0, I)$ ，则输出的统计特性：

$\bar{Y} = E[\tilde{f}(\hat{Z}) + \tilde{D}_{\Delta z} \tilde{f}] = \tilde{f}(\hat{Z})$

$P_Y = E[(Y - \bar{Y})(Y - \bar{Y})^T] = E[(\tilde{D}_{\Delta z} \tilde{f})(\tilde{D}_{\Delta z} \tilde{f})^T] = E \left\{ \sum_{j=1}^m e_j \left(\sum_{i=1}^n \frac{\delta_i \tilde{f}_j(\hat{Z})}{2d_i} \Delta z_i \right) \left[\sum_{k=1}^m e_k \left(\sum_{i=1}^n \frac{\delta_i \tilde{f}_k(\hat{Z})}{2d_k} \Delta z_k \right) \right]^T \right\}$
 $= \sum_{j=1}^m \sum_{k=1}^m e_j e_k^T E \left[\left(\sum_{i=1}^n \frac{\delta_i \tilde{f}_j(\hat{Z})}{2d_i} \Delta z_i \right) \left(\sum_{k=1}^n \frac{\delta_k \tilde{f}_k(\hat{Z})}{2d_k} \Delta z_k \right) \right] \square \sum_{j=1}^m \sum_{i=1}^n e_j P_{Y,j,i}$

$P_{Y,j,i} = E \left[\left(\sum_{i=1}^n \frac{\delta_i \tilde{f}_j(\hat{Z})}{2d_i} \Delta z_i \right) \left(\sum_{k=1}^n \frac{\delta_k \tilde{f}_i(\hat{Z})}{2d_k} \Delta z_k \right) \right] = \sum_{i=1}^n \frac{\delta_i \tilde{f}_j(\hat{Z}) \cdot \delta_i \tilde{f}_i(\hat{Z})}{2d \cdot 2d} E[\Delta z_i \Delta z_i]$
 $= \frac{1}{4d^2} \sum_{i=1}^n [\tilde{f}_j(\hat{Z} + e_i d) - \tilde{f}_j(\hat{Z} - e_i d)] [\tilde{f}_i(\hat{Z} + e_i d) - \tilde{f}_i(\hat{Z} - e_i d)]$ 8

$P_{Y,j,i} = \frac{1}{4d^2} \sum_{i=1}^n [\tilde{f}_j(\hat{Z} + e_i d) - \tilde{f}_j(\hat{Z} - e_i d)] [\tilde{f}_i(\hat{Z} + e_i d) - \tilde{f}_i(\hat{Z} - e_i d)]$

14 高斯分布采样非线性滤波

14.3 差分Kalman滤波

若分布不标准 $\Delta X \sim N(0, P_{\Delta X})$ 记 $P_{\Delta X} = SS^T$ $\tilde{f}_j(Z) = f_j(SZ) = f_j(X)$

则有 $\tilde{f}_j(\hat{Z} \pm e_i d) = f_j(S(\hat{Z} \pm e_i d)) = f_j(\hat{X} \pm S_i d)$

$P_{Y,j,i} = \frac{1}{4d^2} \sum_{i=1}^n [f_j(\hat{X} + S_i d) - f_j(\hat{X} - S_i d)] [f_i(\hat{X} + S_i d) - f_i(\hat{X} - S_i d)]$

$P_Y = \frac{1}{4d^2} \sum_{i=1}^n [f(\hat{X} + S_i d) - f(\hat{X} - S_i d)] [f(\hat{X} + S_i d) - f(\hat{X} - S_i d)]^T$

$P_{XY} = E[(X - \bar{X})(Y - \bar{Y})^T] = E[(\Delta X)(\tilde{D}_{\Delta z} \tilde{f})^T]$

$= \frac{1}{4d^2} \sum_{i=1}^n [(\hat{X} + S_i d) - (\hat{X} - S_i d)] [f(\hat{X} + S_i d) - f(\hat{X} - S_i d)]^T$

$= \frac{1}{2d} \sum_{i=1}^n S_i [f(\hat{X} + S_i d) - f(\hat{X} - S_i d)]^T$

14 高斯分布采样非线性滤波

14.3 差分Kalman滤波

(1) 一阶差分CDKF

$$\hat{X}_{k/k-1} = f(\hat{X}_{k-1})$$

$$P_{k/k-1} = \frac{1}{4d^2} \sum_{i=1}^n \langle f(\hat{X}_{k-1} + S_{k-1,i}d) - f(\hat{X}_{k-1} - S_{k-1,i}d) \rangle^2 + \Gamma_{k-1} Q_{k-1} \Gamma_{k-1}^T$$

$$\hat{Z}_{k/k-1} = h(\hat{X}_{k/k-1})$$

$$P_{ZZ,k/k-1} = \frac{1}{4d^2} \sum_{i=1}^n \langle h(\hat{X}_{k/k-1} + S_{k/k-1,i}d) - h(\hat{X}_{k/k-1} - S_{k/k-1,i}d) \rangle^2 + R_k$$

$$P_{XZ,k/k-1} = \frac{1}{2d} \sum_{i=1}^n S_{k/k-1,i} [h(\hat{X}_{k/k-1} + S_{k/k-1,i}d) - h(\hat{X}_{k/k-1} - S_{k/k-1,i}d)]^T$$

$$\begin{cases} X_k = f(X_{k-1}) + \Gamma_{k-1} W_{k-1} \\ Z_k = h(X_k) + V_k \end{cases}$$



$$\begin{cases} K_k = P_{XZ,k/k-1} P_{ZZ,k/k-1}^{-1} \\ \hat{X}_k = \hat{X}_{k/k-1} + K_k (Z_k - \hat{Z}_{k/k-1}) \\ P_k = P_{k/k-1} - K_k P_{ZZ,k/k-1} K_k^T \end{cases}$$

$$S_{k-1} = \sqrt{P_{k-1}}$$

$$S_{k/k-1} = \sqrt{P_{k/k-1}}$$

相较于DQEKF, CDKF非线性函数计算次数少, 但需chol分解。

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14 高斯分布采样非线性滤波

14.3 差分Kalman滤波

(2) 二阶差分CDKF

$$\hat{X}_{k/k-1} = \frac{d^2-n}{d^2} f(\hat{X}_{k-1}) + \frac{1}{2d^2} \sum_{i=1}^n [f(\hat{X}_{k-1} + S_{k-1,i}d) + f(\hat{X}_{k-1} - S_{k-1,i}d)]$$

$$P_{k/k-1} = \frac{1}{4d^2} \sum_{i=1}^n \langle f(\hat{X}_{k-1} + S_{k-1,i}d) - f(\hat{X}_{k-1} - S_{k-1,i}d) \rangle^2 + \frac{d^2-1}{4d^2} \sum_{i=1}^n \langle f(\hat{X}_{k-1} + S_{k-1,i}d) + f(\hat{X}_{k-1} - S_{k-1,i}d) - 2f(\hat{X}_{k-1}) \rangle^2 + \Gamma_{k-1} Q_{k-1} \Gamma_{k-1}^T$$

$$\hat{Z}_{k/k-1} = \frac{d^2-n}{d^2} h(\hat{X}_{k/k-1}) + \frac{1}{2d^2} \sum_{i=1}^n [h(\hat{X}_{k/k-1} + S_{k/k-1,i}d) + h(\hat{X}_{k/k-1} - S_{k/k-1,i}d)]$$

$$P_{ZZ,k/k-1} = \frac{1}{4d^2} \sum_{i=1}^n \langle h(\hat{X}_{k/k-1} + S_{k/k-1,i}d) - h(\hat{X}_{k/k-1} - S_{k/k-1,i}d) \rangle^2 + \frac{d^2-1}{4d^2} \sum_{i=1}^n \langle h(\hat{X}_{k/k-1} + S_{k/k-1,i}d) + h(\hat{X}_{k/k-1} - S_{k/k-1,i}d) - 2h(\hat{X}_{k/k-1}) \rangle^2 + R_k$$

$$P_{XZ,k/k-1} = \frac{1}{2d} \sum_{i=1}^n S_{k/k-1,i} [h(\hat{X}_{k/k-1} + S_{k/k-1,i}d) - h(\hat{X}_{k/k-1} - S_{k/k-1,i}d)]^T$$

$$\begin{cases} X_k = f(X_{k-1}) + \Gamma_{k-1} W_{k-1} \\ Z_k = h(X_k) + V_k \end{cases}$$



$$\begin{cases} K_k = P_{XZ,k/k-1} P_{ZZ,k/k-1}^{-1} \\ \hat{X}_k = \hat{X}_{k/k-1} + K_k (Z_k - \hat{Z}_{k/k-1}) \\ P_k = P_{k/k-1} - K_k P_{ZZ,k/k-1} K_k^T \end{cases}$$

与二阶EKF相比, 计算量大幅减小。

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14 高斯分布采样非线性滤波

14.4 容积卡尔曼滤波 (CKF)

(1) 球面—径向积分准则

$$\begin{aligned} \iiint_{\mathbb{R}^n} f(x, y, z) dx dy dz &= \int_0^\infty \int_0^{2\pi} \int_0^\pi f(rs) r^2 \sin \phi d\phi d\theta dr \\ &= \int_0^\infty r^2 \int_{U_n} f(rs) d\sigma(s) dr \end{aligned}$$

所谓容积就是高维空间求导

针对高斯加权积分 $I(f) = \int_{\mathbb{R}^n} f(x) \exp(-x^T x) dx$, 令 $x = rs$, $s^T s = 1$, $r = \sqrt{x^T x}$

可转换为球面—径向坐标积分:

$$I(f) = \int_0^\infty \int_{U_n} f(rs) r^{n-1} e^{-r^2} d\sigma(s) dr = \int_0^\infty r^{n-1} e^{-r^2} \int_{U_n} f(rs) d\sigma(s) dr$$

$$S(r) = \int_{U_n} f(rs) d\sigma(s) = \sum_{i=1}^{n_s} w_{s,i} f(rs_i)$$

$$I(f) = \int_0^\infty S(r) r^{n-1} e^{-r^2} dr = \sum_{j=1}^{n_r} w_{r,j} S(r_j)$$

$$= \sum_{j=1}^{n_r} w_{r,j} \sum_{i=1}^{n_s} w_{s,i} f(r_j s_i) = \sum_{j=1}^{n_r} \sum_{i=1}^{n_s} w_{r,j} w_{s,i} f(r_j s_i)$$

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14 高斯分布采样非线性滤波

14.4 容积卡尔曼滤波 (CKF)

A) 球面积分准则

单位半径球面上的单项式积分公式:

$$S(r) = \int_{U_n} f(rs) d\sigma(s)$$

$$\begin{cases} \Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt \quad (x > 0) \\ \Gamma(x+1) = x\Gamma(x), \Gamma(1/2) = \sqrt{\pi} \end{cases}$$

$$S_d = \int_{U_n} s_1^{d_1} s_2^{d_2} \dots s_n^{d_n} d\sigma(s) = 2 \frac{\prod_{i=1}^n \Gamma((d_i+1)/2)}{\Gamma((d+n)/2)} \quad \checkmark \quad d = \sum_{i=1}^n d_i$$

当 $d = \text{odd}$ (奇数) 时, 单项式 $s_1^{d_1} s_2^{d_2} \dots s_n^{d_n}$ 在单位球面上正负对称, 总有 $S_{\text{odd}} = 0$

当总阶次 $d=0$ 时有任意 $d_i=0$, 有

$$S_0 = \int_{U_n} 1 d\sigma(s) = 2 \frac{\prod_{i=1}^n \Gamma(1/2)}{\Gamma((0+n)/2)} = \frac{2\pi^{n/2}}{\Gamma(n/2)} \stackrel{\Delta}{=} A_n$$

特例

$$A_1 = 2\pi^{1/2} / \Gamma(1/2) = 2\pi^{1/2} / \pi^{1/2} = 2$$

$$A_2 = 2\pi^{2/2} / \Gamma(2/2) = 2\pi / 1 = 2\pi$$

$$A_3 = 2\pi^{3/2} / \Gamma(3/2) = 2\pi^{3/2} / (\pi^{1/2} / 2) = 4\pi$$

→ 直径 (一维空间)
→ 周长 (二维)
→ 表面积 (三维)

当总阶次 $d=2$ 时

$$\text{若 } d_i = d_j = 1, \text{ 有 } S_{2(i \neq j)} = \int_{U_n} s_i s_j d\sigma(s) = 0$$

若 $d_i = 2$, 有

$$S_2 = S_{2(i=j)} = \int_{U_n} s_i^2 d\sigma(s) = 2 \frac{\Gamma(3/2) \cdot \prod_{j=1, j \neq i}^n \Gamma(1/2)}{\Gamma((2+n)/2)} = 2 \frac{\sqrt{\pi}/2 \times \sqrt{\pi}^{n-1}}{\Gamma(n/2) \times n/2} = \frac{A_n}{n} \quad 13$$

14 高斯分布采样非线性滤波

14.4 容积卡尔曼滤波 (CKF)

$$S = \int_{U_n} f(s) d\sigma(s) \approx w_s \sum_{i=1}^{2n} f(s_i) \\ \approx \frac{A_n}{2n} \sum_{i=1}^n [f(e_i) + f(-e_i)]$$

令 $f(s) = 1$, 得 $S_0 = A_n \approx w_s \sum_{i=1}^{2n} 1 = 2nw_s$
 $f(s) = s_i^2 = f(\pm s_i)$ $S_2 = A_n / n \approx w_s [f(s_i) + f(-s_i)] = 2w_s s_i^2$

$$\implies w_s = \frac{A_n}{2n} = \frac{\pi^{n/2}}{n\Gamma(n/2)} \quad s_i^2 = 1$$

球面积分方法与球面半径无关 $f(s) \rightarrow f(rs)$

$$S_0(r) = \int_{U_n} r d\sigma(s) = rA_n \approx w_s \sum_{i=1}^{2n} r = 2nrw_s$$

$$S_2(r) = \int_{U_n} r^2 s_i^2 d\sigma(s) = r^2 A_n / n \approx w_s [f(rs_i) + f(-rs_i)] = 2w_s r^2 s_i^2$$

$$\implies S(r) = \int_{U_n} f(rs) d\sigma(s) \approx \frac{A_n}{2n} \sum_{i=1}^n [f(re_i) + f(-re_i)] \quad \rightarrow \text{高斯积分转到球面上后, 高斯节点为 } 2n \text{, 运算减少}$$

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14 高斯分布采样非线性滤波

14.4 容积卡尔曼滤波 (CKF)

B) 径向积分准则

$$I(f) = \int_0^\infty S(r) r^{n-1} e^{-r^2} dr = \int_0^\infty S(\sqrt{t}) t^{n/2-1} e^{-t} dt \quad t = r^2 \\ \approx \Gamma(n/2) S(\sqrt{n/2}) \square w_{r,1} S(r_1) \quad \text{1点 } \Gamma \text{ 义高斯-拉盖尔求积, 具有1次代数精度 (对于 } r \text{ 为2次)}$$

C) 3阶球面—径向积分准则 (具有3次代数精度)

$$I(f) = \int_{\mathbb{R}^n} f(x) \exp(-x^T x) dx \approx \sum_{j=1}^{n_1} \sum_{i=1}^{n_2} w_{r,j} w_{s,i} f(r_j s_i) = w_{r,1} \sum_{i=1}^{2n} w_s f(r_1 s_i) \\ = \Gamma(n/2) \frac{\pi^{n/2}}{n\Gamma(n/2)} \sum_{i=1}^{2n} f\left(\frac{\sqrt{n}}{2} s_i\right) = \frac{\pi^{n/2}}{n} \sum_{i=1}^n \left[f\left(\frac{\sqrt{n}}{2} e_i\right) + f\left(-\frac{\sqrt{n}}{2} e_i\right) \right]$$

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14 高斯分布采样非线性滤波

14.4 容积卡尔曼滤波 (CKF)

对于非标准高斯分布 $N(\mathbf{x}; \hat{\mathbf{X}}, \mathbf{P})$, 作变换 $\mathbf{x} = (2\mathbf{P})^{1/2} \mathbf{y} + \hat{\mathbf{X}}$, 则有

$$\begin{aligned} \int_{\mathbb{R}^n} f(\mathbf{x}) N(\mathbf{x}; \hat{\mathbf{X}}, \mathbf{P}) d\mathbf{x} &= \int_{\mathbb{R}^n} f\left((2\mathbf{P})^{1/2} \mathbf{y} + \hat{\mathbf{X}}\right) \frac{1}{(2\pi)^{n/2} |\mathbf{P}|^{1/2}} \exp(-\mathbf{y}^T \mathbf{y}) 2|\mathbf{P}|^{1/2} d\mathbf{y} \\ &= \frac{\sqrt{2}}{(2\pi)^{n/2}} \int_{\mathbb{R}^n} f\left((2\mathbf{P})^{1/2} \mathbf{y} + \hat{\mathbf{X}}\right) \exp(-\mathbf{y}^T \mathbf{y}) d\mathbf{y} \\ &= \frac{\sqrt{2}}{(2\pi)^{n/2}} \int_{\mathbb{R}^n} f\left((2\mathbf{P})^{1/2} \mathbf{x} + \hat{\mathbf{X}}\right) \exp(-\mathbf{x}^T \mathbf{x}) d\mathbf{x} \\ &\approx \frac{\sqrt{2}}{(2\pi)^{n/2}} \frac{\pi^{n/2}}{n} \sum_{i=1}^n \left[f\left(\sqrt{\frac{n}{2}}(2\mathbf{P})^{1/2} \mathbf{e}_i + \hat{\mathbf{X}}\right) + f\left(-\sqrt{\frac{n}{2}}(2\mathbf{P})^{1/2} \mathbf{e}_i + \hat{\mathbf{X}}\right) \right] \\ &= \frac{1}{2n} \sum_{i=1}^n \left[f\left(\sqrt{n\mathbf{P}} \mathbf{e}_i + \hat{\mathbf{X}}\right) + f\left(-\sqrt{n\mathbf{P}} \mathbf{e}_i + \hat{\mathbf{X}}\right) \right] \checkmark \\ &\quad \begin{cases} w_i = 1/(2n) \\ \{\xi_i\} = \left\{ \sqrt{n\mathbf{P}} + [\hat{\mathbf{X}}]_n, -\sqrt{n\mathbf{P}} + [\hat{\mathbf{X}}]_n \right\} \end{cases} \end{aligned}$$

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14 高斯分布采样非线性滤波

14.4 容积卡尔曼滤波 (CKF)

(2) CKF滤波 *→ 精度*

$$\hat{\mathbf{X}}_{k/k-1} = \sum_{i=1}^L w_i f(\xi_{i,k-1})$$

$$\mathbf{P}_{k/k-1} = \sum_{i=1}^L w_i \left[f(\xi_{i,k-1}) - \hat{\mathbf{X}}_{k/k-1} \right] \left[f(\xi_{i,k-1}) - \hat{\mathbf{X}}_{k/k-1} \right]^T + \mathbf{\Gamma}_{k-1} \mathbf{Q}_{k-1} \mathbf{\Gamma}_{k-1}^T$$

$$\hat{\mathbf{Z}}_{k/k-1} = \sum_{i=1}^L w_i h(\xi_{i,k-1})$$

$$\mathbf{P}_{ZZ,k/k-1} = \sum_{i=1}^L w_i \left[h(\xi_{i,k-1}) - \hat{\mathbf{Z}}_{k/k-1} \right] \left[h(\xi_{i,k-1}) - \hat{\mathbf{Z}}_{k/k-1} \right]^T + \mathbf{R}_k$$

$$\mathbf{P}_{XZ,k/k-1} = \sum_{i=1}^L w_i \left(\xi_{i,k-1} - \hat{\mathbf{X}}_{k/k-1} \right) \left[h(\xi_{i,k-1}) - \hat{\mathbf{Z}}_{k/k-1} \right]^T$$

$$L = 2n \quad w_i = 1/(2n) \quad \{\xi_{i,k}\} = \left\{ \sqrt{n\mathbf{P}_k} + [\hat{\mathbf{X}}_k]_n, -\sqrt{n\mathbf{P}_k} + [\hat{\mathbf{X}}_k]_n \right\} \quad K \square k-1, k/k-1$$

$$\begin{cases} \hat{\mathbf{X}}_k = f(\hat{\mathbf{X}}_{k-1}) + \mathbf{\Gamma}_{k-1} \mathbf{W}_{k-1} \\ \mathbf{Z}_k = h(\hat{\mathbf{X}}_k) + \mathbf{V}_k \end{cases}$$



$$\begin{cases} \mathbf{K}_k = \mathbf{P}_{XZ,k/k-1} \mathbf{P}_{ZZ,k/k-1}^{-1} \\ \hat{\mathbf{X}}_k = \hat{\mathbf{X}}_{k/k-1} + \mathbf{K}_k (\mathbf{Z}_k - \hat{\mathbf{Z}}_{k/k-1}) \\ \mathbf{P}_k = \mathbf{P}_{k/k-1} - \mathbf{K}_k \mathbf{P}_{ZZ,k/k-1} \mathbf{K}_k^T \end{cases}$$

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14.4 容积卡尔曼滤波 (CKF)

(3) 5阶球面—径向容积准则CKF滤波

$$\hat{X}_{k/k-1} = \sum_{i=1}^L w_i f(\xi_{i,k-1})$$

$$P_{k/k-1} = \sum_{i=1}^L w_i \left[f(\xi_{i,k-1}) - \hat{X}_{k/k-1} \right] \left[f(\xi_{i,k-1}) - \hat{X}_{k/k-1} \right]^T + \Gamma_{k-1} Q_{k-1} \Gamma_{k-1}^T$$

$$\hat{Z}_{k/k-1} = \sum_{i=1}^L w_i h(\xi_{i,k/k-1})$$

$$P_{ZZ,k/k-1} = \sum_{i=1}^L w_i \left[h(\xi_{i,k/k-1}) - \hat{Z}_{k/k-1} \right] \left[h(\xi_{i,k/k-1}) - \hat{Z}_{k/k-1} \right]^T + R_k$$

$$P_{XZ,k/k-1} = \sum_{i=1}^L w_i \left(\xi_{i,k/k-1} - \hat{X}_{k/k-1} \right) \left[h(\xi_{i,k/k-1}) - \hat{Z}_{k/k-1} \right]^T$$

$$L = 2n^2 + 1 \quad \{w_i\} = \left\{ \frac{4-n}{2(n+2)^2} \right\}_{2n} \left\{ \frac{1}{(n+2)^2} \right\}_{2n(n-1)} \left\{ \frac{2}{n+2} \right\} \quad e_i^+ = (e_j + e_k) / \sqrt{2}, e_i^- = (e_j - e_k) / \sqrt{2}$$

$$\{\xi_{i,k}\} = \left\{ \left[\hat{X}_k \right]_{2n^2+1} + \sqrt{(n+2)P_k} \left[\begin{matrix} e_i \\ -e_i \\ e_i^+ \\ -e_i^+ \\ e_i^- \\ -e_i^- \\ 0 \end{matrix} \right] \right\} \quad K \square k-1, k/k-1$$

$$\begin{cases} X_k = f(X_{k-1}) + \Gamma_{k-1} W_{k-1} \\ Z_k = h(X_k) + V_k \end{cases}$$



$$\begin{cases} K_k = P_{XZ,k/k-1} P_{ZZ,k/k-1}^{-1} \\ \hat{X}_k = \hat{X}_{k/k-1} + K_k (Z_k - \hat{Z}_{k/k-1}) \\ P_k = P_{k/k-1} - K_k P_{ZZ,k/k-1} K_k^T \end{cases}$$

14 高斯分布采样非线性滤波

14.5 UKF滤波

$$\hat{X}_{k/k-1} = \sum_{i=1}^L w_i^m f(\xi_{i,k-1})$$

$$P_{k/k-1} = \sum_{i=1}^L w_i^c \left[f(\xi_{i,k-1}) - \hat{X}_{k/k-1} \right] \left[f(\xi_{i,k-1}) - \hat{X}_{k/k-1} \right]^T + \Gamma_{k-1} Q_{k-1} \Gamma_{k-1}^T$$

$$\hat{Z}_{k/k-1} = \sum_{i=1}^L w_i^m h(\xi_{i,k/k-1})$$

$$P_{ZZ,k/k-1} = \sum_{i=1}^L w_i^c \left[h(\xi_{i,k/k-1}) - \hat{Z}_{k/k-1} \right] \left[h(\xi_{i,k/k-1}) - \hat{Z}_{k/k-1} \right]^T + R_k$$

$$P_{XZ,k/k-1} = \sum_{i=1}^L w_i^c \left(\xi_{i,k/k-1} - \hat{X}_{k/k-1} \right) \left[h(\xi_{i,k/k-1}) - \hat{Z}_{k/k-1} \right]^T$$

$$\{\xi_{i,k}\} = \left\{ \gamma \sqrt{P_x} + \left[\hat{X}_k \right]_n, -\gamma \sqrt{P_x} + \left[\hat{X}_k \right]_n, \hat{X}_k \right\} \quad K \square k-1, k/k-1$$

$$\{w_i^m\} = \left\{ \left[1/(2\gamma^2) \right]_{2n}, \lambda/\gamma^2 \right\} \quad \{w_i^c\} = \left\{ \left[1/(2\gamma^2) \right]_{2n}, \lambda/\gamma^2 + (1-\alpha^2 + \beta) \right\}$$

超参数 $\gamma = \sqrt{n + \lambda}, \lambda = \alpha^2(n + \kappa) - n \quad 10^{-4} \leq \alpha \leq 1, \kappa = 0, \beta \geq 0 (= 2)$

特例 $\alpha = 1, \kappa = \beta = 0 \Rightarrow \{w_i^c\} = \left\{ \left[1/(2n) \right]_{2n}, 0 \right\} \Leftrightarrow \text{CKF}$ 19

$$\begin{cases} X_k = f(X_{k-1}) + \Gamma_{k-1} W_{k-1} \\ Z_k = h(X_k) + V_k \end{cases}$$



$$\begin{cases} K_k = P_{XZ,k/k-1} P_{ZZ,k/k-1}^{-1} \\ \hat{X}_k = \hat{X}_{k/k-1} + K_k (Z_k - \hat{Z}_{k/k-1}) \\ P_k = P_{k/k-1} - K_k P_{ZZ,k/k-1} K_k^T \end{cases}$$

14 高斯分布采样非线性滤波

$$\begin{cases} X_k = f(X_{k-1}) + \Gamma_{k-1}W_{k-1} \\ Z_k = h(X_k) + V_k \end{cases}$$

14.6 SR-UKF滤波 (平方根UKF)

$$P_{k|k-1} = \sum_{i=1}^L w_i^c [f(\xi_{i,k-1}) - \hat{X}_{k|k-1}][f(\xi_{i,k-1}) - \hat{X}_{k|k-1}]^T + \Gamma_{k-1}Q_{k-1}\Gamma_{k-1}^T$$

$$P_{ZZ,k|k-1} = \sum_{i=1}^L w_i^c [h(\xi_{i,k|k-1}) - \hat{Z}_{k|k-1}][h(\xi_{i,k|k-1}) - \hat{Z}_{k|k-1}]^T + R_k$$

$$\{w_i^c\} = \left\{ \left[\frac{1}{2\gamma^2} \right]_{2n} \right\} \quad \lambda/\gamma^2 + (1-\alpha^2 + \beta) \quad \gamma = \sqrt{n + \lambda}, \lambda = \alpha^2(n + \kappa) - n \quad 10^{-4} \leq \alpha \leq 1, \kappa = 0, \beta \geq 0 (\Rightarrow 2)$$

$$P_{k|k-1} = \left[\sqrt{w_1^c} \Delta \hat{X}_{1,2n} \right] \left[\sqrt{w_1^c} \Delta \hat{X}_{1,2n} \right]^T + \Gamma_{k-1} \sqrt{Q_{k-1}} (\Gamma_{k-1} \sqrt{Q_{k-1}})^T + w_{2n+1}^c \Delta \hat{X}_{2n+1} \Delta \hat{X}_{2n+1}^T$$

$$= \left[\sqrt{w_1^c} \Delta \hat{X}_{1,2n} \quad \Gamma_{k-1} \sqrt{Q_{k-1}} \right] \left[\sqrt{w_1^c} \Delta \hat{X}_{1,2n} \quad \Gamma_{k-1} \sqrt{Q_{k-1}} \right]^T \oplus \left[\sqrt{w_{2n+1}^c} \Delta \hat{X}_{2n+1} \right] \left[\sqrt{w_{2n+1}^c} \Delta \hat{X}_{2n+1} \right]^T$$

$$= R^T R \oplus \left[\sqrt{w_{2n+1}^c} \Delta \hat{X}_{2n+1} \right] \left[\sqrt{w_{2n+1}^c} \Delta \hat{X}_{2n+1} \right]^T \quad \text{QR分解}$$

$$\sqrt{P_{k|k-1}} = \text{cholupdate}(R, \sqrt{w_{2n+1}^c} \Delta \hat{X}_{2n+1}, '-')^T \quad \text{cholupdate: } R^T R - VV^T \rightarrow R_1^T R_1$$

$$\sqrt{P_{ZZ,k|k-1}} = \text{cholupdate}(\sqrt{w_1^c} \Delta \hat{Z}_{1,2n} \quad \sqrt{R_k})^T \rightarrow R, \sqrt{w_{2n+1}^c} \Delta \hat{Z}_{2n+1}, '-')^T$$

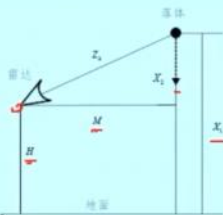
$$\sqrt{P_0} = \sqrt{P_{k|k-1}}; \quad \text{for } i=1:m \quad \sqrt{P_i} = \text{cholupdate}(\sqrt{P_{i-1}}^T, (K_k \sqrt{P_{ZZ,k|k-1}})_i, '-')^T; \quad P_k = \sqrt{P_m}^{20}$$

14 高斯分布采样非线性滤波

14.7 非线性滤波举例

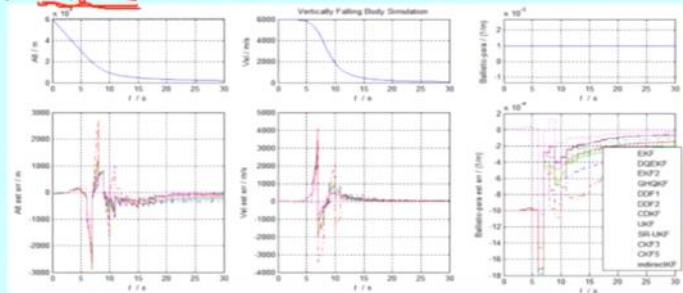
运动学方程 $\begin{cases} \dot{X}_1 = -X_2 \\ \dot{X}_2 = -\frac{C\rho A}{2m} X_2^2 \\ \dot{X}_3 = 0 \end{cases}$

$f(X): \begin{cases} \dot{X}_1 = -X_2 \\ \dot{X}_2 = -e^{-\gamma X_1} X_2^2 X_3 \\ \dot{X}_3 = 0 \end{cases}$



$h(X_k): Z_k = \sqrt{M^2 + (X_{1,k} - H)^2} + V_k$ VFB(Vertically Falling Body)

C, ρ, A, m 空气阻力系数、空气密度、迎风面积、落体质量
 波尔兹曼公式 $\rho = \rho_0 e^{-\gamma X_1}$ ρ_0 海平面大气密度, 参数 $\gamma \approx 1.7 \times 10^{-4} (1/m)$
 $X_3 = C\rho_0 A / (2m)$ 定义为弹道系数 (单位1/m)



$M = H = 30\text{km}$
 $R_k = (100\text{m})^2$
 $f_{\text{update}} = 1\text{Hz}$

知道了, 状态方程迭代
 → 构造出量测, 再滤波估计出状态量

在高精度惯性组合导航中
 非线性滤波方法基本上没用!!!

→ 将轻用不同的算法比做诈骗



→ 将工程用不同的算法比做诈骗骗
逆天

总结：这一节只听个大概思路 和 思想，具体教学推导一知半解。