

# 卡尔曼滤波与组合导航原理

西北工业大学自动化学院 严恭敏

2020-04

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## 14 UKF滤波(Unscented KF, 无迹/无味卡尔曼滤波)



**Simon J. Julier** (Member, IEEE) received the M.Eng. degree (first-class honors) in engineering, economics, and management and the D.Phil. degree in robotics from the University of Oxford, Oxford, U.K., in 1993 and 1997, respectively.

His principal research interests include distributed data fusion, vehicle localization and tracking, and user interfaces for mobile augmented reality systems.

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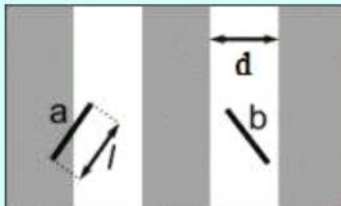
### 14.1 蒙特卡洛仿真

蒲丰投针问题（1777年,计算 $\pi$ 最稀奇的方法）

1) 取一张白纸，在上面画上许多条间距为 $d$ 的平行线；

2) 取一根长度为 $l$  ( $l < d$ ) 的针，随机地向画有平行直线的纸上掷 $n$ 次，观察针与直线相交的次数，记为 $m$ ；

3) 计算针与直线相交的概率： $p = \frac{2l}{\pi d} \approx \frac{m}{n}$



实验者	年份	投计次数	$\pi$ 的实验值
沃尔弗(Wolf)	1850	5000	3.1596
斯密思(Smith)	1855	3204	3.1553
福克斯(Fox)	1894	1120	3.1419
拉查里尼(Lazzarini)	1901	3408	3.1415929

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蒙特卡洛仿真名称来源(Monte Carlo)



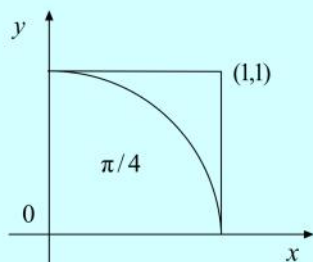
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蒙特卡洛仿真举例

【例1】我们都知道，单位圆围成的面积为 $\pi$ ，若以圆心为原点建立平面直角坐标系，则它在第一象限内的面积为 $\pi/4$ ，即有

$$\int_0^1 \int_0^{\sqrt{1-y^2}} 1 dx dy = \pi/4$$



Matlab编写的仿真语句和结果:

```
n = 1000000;  
p = unifrnd(0,1,2,n);  
PI = 4*sum(sum(p.^2)<1)/n
```

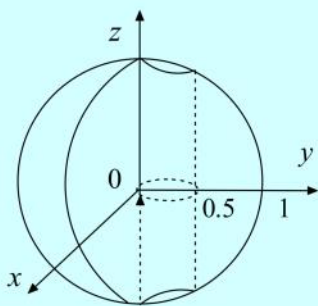
--> PI = 3.141092

收敛精度  $\varepsilon \propto \frac{1}{\sqrt{n}}$ ，收敛速度慢!

例子的  $\varepsilon \propto 10^5$ ，3位数字有效<sup>16</sup>

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【例2】在单位球体内偏离中心0.25的位置挖去一个半径为0.25的柱体（参见图），试求该球体剩余部分的体积。



Matlab编写的仿真语句和结果:

```
n = 100000;  
p = unifrnd(-1,1,3,n);  
V = 2^3*sum(sum(p.^2)<1&(p(1,:).^2+  
    (p(2,:)-0.25).^2)>0.25^2)/n
```

--> V = 3.812905

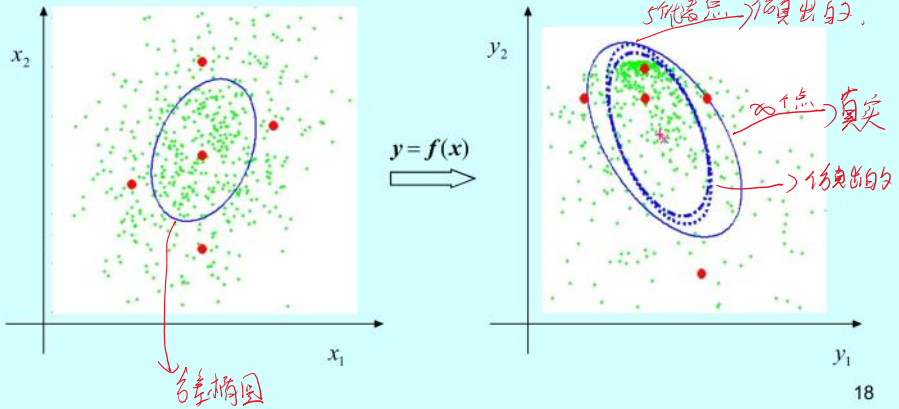
特点: 解决方法与维数无关, 只与边界有关, 看边界是否能描述

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【例3】二维随机向量的非线性变换/概率传播

$$\begin{cases} y_1 = (x_1 - 1) \cdot (x_2 - 0.2) \\ y_2 = -(x_1 - 1)^2 \end{cases}$$

$$E[\mathbf{xx}^T] = \begin{bmatrix} 1 & 0.42 \\ 0.42 & 2 \end{bmatrix}$$



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### 14.2 UT变换(Unscented Transformation)

(1) 线性函数的UT变换

假设随机向量的线性变换关系  $\mathbf{y} = \mathbf{F}\mathbf{x}$

$\rightarrow$  取类比为系统方程。

$$\begin{cases} \bar{\mathbf{x}} = E[\mathbf{x}] \\ \mathbf{P}_x = E[(\mathbf{x} - \bar{\mathbf{x}})(\mathbf{x} - \bar{\mathbf{x}})^T] \end{cases}$$

$\Rightarrow$

$$\begin{cases} \bar{\mathbf{y}} = \mathbf{F}\bar{\mathbf{x}} \\ \mathbf{P}_y = \mathbf{F}\mathbf{P}_x\mathbf{F}^T \\ \mathbf{P}_{xy} = \mathbf{P}_x\mathbf{F}^T \end{cases}$$

验证:

A) 矩阵的三角分解  $\mathbf{P}_x = \mathbf{A}\mathbf{A}^T$  记  $\sqrt{\mathbf{P}_x} = \mathbf{A}$

$$\mathbf{P}_x = \sqrt{\mathbf{P}_x} \sqrt{\mathbf{P}_x}^T = \sum_{i=1}^n (\sqrt{\mathbf{P}_x})_i (\sqrt{\mathbf{P}_x})_i^T$$

$$\begin{bmatrix} 1 & 2 \\ 2 & 13 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 2 & 3 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 0 & 3 \end{bmatrix} \\ = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \begin{bmatrix} 1 & 2 \end{bmatrix} + \begin{bmatrix} 0 \\ 3 \end{bmatrix} \begin{bmatrix} 0 & 3 \end{bmatrix}$$

每个向量即为新点

B) 输入近似成有限个 ( $n$ 个) Sigma点的估计形式

$$\begin{cases} \bar{\mathbf{x}} = \lim_{k \rightarrow \infty} \frac{1}{k} \sum_{i=1}^k \mathbf{x}_i \approx \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i \rightarrow \text{样本平均} \\ \mathbf{P}_x = \lim_{k \rightarrow \infty} \frac{1}{k} \sum_{i=1}^k (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^T \approx \frac{1}{n} \sum_{i=1}^n (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^T \end{cases}$$

方差定义

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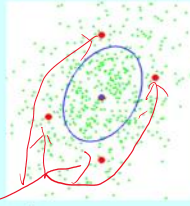
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采样点  $\leftarrow$

$$P_x = \sqrt{P_x} \sqrt{P_x}^T = \sum_{i=1}^n (\sqrt{P_x})_i (\sqrt{P_x})_i^T$$

均值存在意义  $\leftarrow$

$$\begin{cases} \bar{x} = \lim_{k \rightarrow \infty} \frac{1}{k} \sum_{i=1}^k x_i \approx \frac{1}{n} \sum_{i=1}^n x_i \\ P_x = \lim_{k \rightarrow \infty} \frac{1}{k} \sum_{i=1}^k (x_i - \bar{x})(x_i - \bar{x})^T \approx \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(x_i - \bar{x})^T \end{cases}$$



比较, 可得  $\frac{1}{\sqrt{n}}(x_i - \bar{x}) = \pm(\sqrt{P_x})_i$ , 即  $x_i = \bar{x} \pm (\sqrt{nP_x})_i$

C) 输入近似成有限个 ( $2n$ 个) Sigma点的估计形式

$$\begin{cases} \bar{x} = \frac{1}{2n} \sum_{i=1}^{2n} x_i \\ P_x = \frac{1}{2n} \sum_{i=1}^{2n} (x_i - \bar{x})(x_i - \bar{x})^T \end{cases}$$

记Sigma点组成的输入矩阵  $\chi = [\bar{x}]_n + \sqrt{nP_x} \quad [\bar{x}]_n - \sqrt{nP_x}$

得Sigma点组成的输出矩阵  $\eta = [F\bar{x}]_n + F\sqrt{nP_x} \quad [F\bar{x}]_n - F\sqrt{nP_x}$

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$y = f(x)$

## 14 UKF滤波

$$\chi = [\bar{x}]_n + \sqrt{nP_x} \quad [\bar{x}]_n - \sqrt{nP_x}$$

$$\eta = [F\bar{x}]_n + F\sqrt{nP_x} \quad [F\bar{x}]_n - F\sqrt{nP_x}$$

由输入输出Sigma点计算传播统计特征

$$\begin{cases} \bar{y} = \frac{1}{2n} \sum_{i=1}^{2n} \eta_i = \frac{1}{2n} \sum_{i=1}^{2n} Fx_i = F\bar{x} \\ P_y = \frac{1}{2n} \sum_{i=1}^{2n} (\eta_i - \bar{y})(\eta_i - \bar{y})^T = \frac{1}{2n} \sum_{i=1}^{2n} (F\sqrt{nP_x})(F\sqrt{nP_x})^T = FP_xF^T \\ P_{xy} = \frac{1}{2n} \sum_{i=1}^{2n} (x_i - \bar{x})(\eta_i - \bar{y})^T = \frac{1}{2n} \sum_{i=1}^{2n} (\sqrt{nP_x})(F\sqrt{nP_x})^T = P_xF^T \end{cases}$$

这与理论结果完全一致, 精确地捕获了输出的一、二阶矩!

线性的思路移植到非线性

(2) 非线性函数的UT变换

非线性函数  
 $y = f(x)$

UT变换

$$\begin{cases} \chi = [\bar{x}]_n + \sqrt{nP_x} \quad [\bar{x}]_n - \sqrt{nP_x} \\ \eta_i = f(x_i) \\ \bar{y} \approx 1/(2n) \cdot \sum_{i=1}^{2n} \eta_i \\ P_y \approx 1/(2n) \cdot \sum_{i=1}^{2n} (\eta_i - \bar{y})(\eta_i - \bar{y})^T \\ P_{xy} \approx 1/(2n) \cdot \sum_{i=1}^{2n} (x_i - \bar{x})(\eta_i - \bar{y})^T \end{cases}$$

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非线性函数UT变换的一般形式

$$\left\{ \begin{aligned} \chi &= [\bar{x}]_n + \sqrt{n\mathbf{P}_x} \quad [\bar{x}]_n - \sqrt{n\mathbf{P}_x} \\ \eta_i &= f(\chi_i) \\ \bar{y} &\approx 1/(2n) \cdot \sum_{i=1}^{2n} \eta_i \\ \mathbf{P}_y &\approx 1/(2n) \cdot \sum_{i=1}^{2n} (\eta_i - \bar{y})(\eta_i - \bar{y})^T \\ \mathbf{P}_{xy} &\approx 1/(2n) \cdot \sum_{i=1}^{2n} (\chi_i - \bar{x})(\eta_i - \bar{y})^T \end{aligned} \right. \Rightarrow \left\{ \begin{aligned} \chi &= [\bar{x} \quad [\bar{x}]_n + \gamma\sqrt{\mathbf{P}_x} \quad [\bar{x}]_n - \gamma\sqrt{\mathbf{P}_x}] \\ \eta_i &= f(\chi_i) \\ \bar{y} &= \sum_{i=0}^{2n} W_i^m \eta_i \\ \mathbf{P}_y &= \sum_{i=0}^{2n} W_i^c (\eta_i - \bar{y})(\eta_i - \bar{y})^T \\ \mathbf{P}_{xy} &= \sum_{i=0}^{2n} W_i^c (\chi_i - \bar{x})(\eta_i - \bar{y})^T \end{aligned} \right.$$

其中

$$\left\{ \begin{aligned} \lambda &= \alpha^2(n + \kappa) - n \\ \gamma &= \sqrt{n + \lambda} \\ W_0^m &= \lambda / \gamma^2 \quad W_0^c = \lambda / \gamma^2 + (1 - \alpha^2 + \beta) \\ W_i^m &= W_i^c = 1 / (2\gamma^2) \quad (i = 1, 2, \dots, 2n) \end{aligned} \right.$$

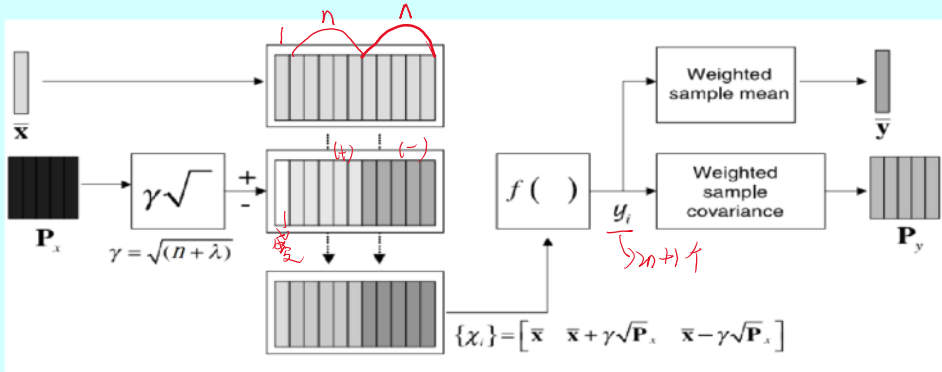
$\alpha$  控制Sigma点分布, 0~1;  
 $\kappa$  一比例因子, 常为0;  
 $\beta \geq 0$  另一比例因子, 常为2

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将Sigma点加权系数  
 控制点离均值的远近, 非线性越强, 应越小

## 14 UKF滤波

UT变换的直观图示:



非线性函数的一阶近似, 二阶近似的概率传播

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# 14 UKF滤波

## 14.3 UKF滤波

系统模型  $\begin{cases} \mathbf{x}_k = \mathbf{f}(\mathbf{x}_{k-1}) + \mathbf{B}_{k-1} \mathbf{w}_{k-1} \\ \mathbf{y}_k = \mathbf{h}(\mathbf{x}_k) + \mathbf{v}_k \end{cases}$  滤波框架  $\begin{cases} \mathbf{K}_k = \mathbf{P}_{xy,k/k-1} \mathbf{P}_{y,k/k-1}^{-1} \\ \hat{\mathbf{x}}_k = \hat{\mathbf{x}}_{k/k-1} + \mathbf{K}_k (\mathbf{y}_k - \hat{\mathbf{y}}_{k/k-1}) \\ \mathbf{P}_{x,k} = \mathbf{P}_{x,k/k-1} - \mathbf{K}_k \mathbf{P}_{y,k/k-1} \mathbf{K}_k^T \end{cases}$

本矩阵不变  
= 阶在矩阵怎么算变了。

状态预测 UT变换  $\begin{cases} \mathcal{X}_{k-1} = [\hat{\mathbf{x}}_{k-1} \quad [\hat{\mathbf{x}}_{k-1}]_n + \gamma \sqrt{\mathbf{P}_{x,k-1}} \quad [\hat{\mathbf{x}}_{k-1}]_n - \gamma \sqrt{\mathbf{P}_{x,k-1}}] \rightarrow \text{先用上一时刻的估计值和方差生成 sigma 点 } (\mathcal{X}) \\ \mathcal{X}_{i,k/k-1}^* = \mathbf{f}(\mathcal{X}_{i,k-1}) \\ \hat{\mathbf{x}}_{k/k-1} = \sum_{i=0}^{2n} W_i^m \mathcal{X}_{i,k/k-1}^* \rightarrow \text{均值} \\ \mathbf{P}_{x,k/k-1} = \sum_{i=0}^{2n} W_i^c (\mathcal{X}_{i,k/k-1}^* - \hat{\mathbf{x}}_{k/k-1})(\mathcal{X}_{i,k/k-1}^* - \hat{\mathbf{x}}_{k/k-1})^T + \mathbf{B}_{k-1} \mathbf{Q}_{k-1} \mathbf{B}_{k-1}^T \rightarrow \text{方差} \end{cases}$

量测预测 UT变换  $\begin{cases} \mathcal{X}_{k/k-1} = [\hat{\mathbf{x}}_{k/k-1} \quad [\hat{\mathbf{x}}_{k/k-1}]_n + \gamma \sqrt{\mathbf{P}_{x,k/k-1}} \quad [\hat{\mathbf{x}}_{k/k-1}]_n - \gamma \sqrt{\mathbf{P}_{x,k/k-1}}] \rightarrow \text{再生成 sigma 点 } (\mathcal{Y}) \\ \boldsymbol{\eta}_{i,k/k-1} = \mathbf{h}(\mathcal{X}_{i,k/k-1}) \\ \hat{\mathbf{y}}_{k/k-1} = \sum_{i=0}^{2n} W_i^m \boldsymbol{\eta}_{i,k/k-1} \\ \mathbf{P}_{y,k/k-1} = \sum_{i=0}^{2n} W_i^c (\boldsymbol{\eta}_{i,k/k-1} - \hat{\mathbf{y}}_{k/k-1})(\boldsymbol{\eta}_{i,k/k-1} - \hat{\mathbf{y}}_{k/k-1})^T + \mathbf{R}_k \\ \mathbf{P}_{xy,k/k-1} = \sum_{i=0}^{2n} W_i^c (\mathcal{X}_{i,k/k-1} - \hat{\mathbf{x}}_{k/k-1})(\boldsymbol{\eta}_{i,k/k-1} - \hat{\mathbf{y}}_{k/k-1})^T \end{cases}$

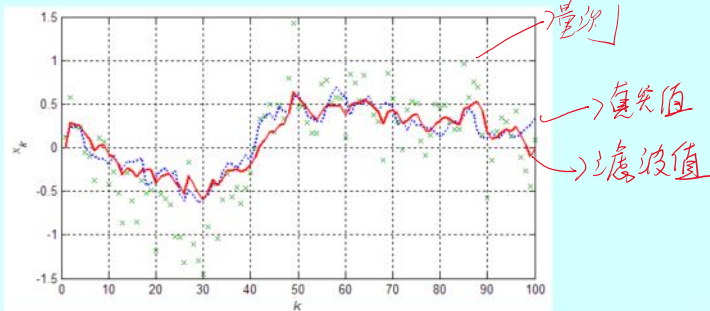
# 14 UKF滤波

## 【例1】一维非线性随机系统

$$\begin{cases} x_k = \sin(x_{k-1}) + w_{k-1} \\ y_k = \begin{cases} x_k + v_k & x_k > 0 \\ 2x_k + v_k & x_k \leq 0 \end{cases} \quad w_k \sim WN(0, 0.1^2) \quad v_k \sim WN(0, 0.3^2) \end{cases}$$

↪ 此处不可导，EKF就不行了

仿真结果



非线性系统UKF滤波仿真

## 14 UKF滤波

【例2】针对非常复杂的非线性系统模型，近似非线性概率传播比近似非线性函数（泰勒展开线性化）更简单，此时UKF滤波比EKF滤波更具优势。

非线性方程有输入和输出  
就可以用UKF, 不必考虑副的

(EKF的展开和Jacob矩阵)

$$\begin{cases} \dot{\mathbf{a}} = \mathbf{C}_\omega^{-1} \dot{\boldsymbol{\delta}} - \mathbf{C}_n^{n'} \boldsymbol{\omega}_{in}^n - \boldsymbol{\varepsilon}^{n'} \\ \delta \mathbf{v}^n = \dot{\boldsymbol{\delta}} - (\mathbf{C}_n^{n'})^T \tilde{\mathbf{f}}_{sf}^{n'} + (\mathbf{C}_n^{n'})^T \boldsymbol{\omega}^{n'} \end{cases}$$

其中

$$\mathbf{C}_\omega^{-1} = \frac{1}{c\alpha_x} \begin{bmatrix} c\alpha_y c\alpha_x & 0 & s\alpha_y c\alpha_x \\ s\alpha_y s\alpha_x & c\alpha_x & -c\alpha_y s\alpha_x \\ -s\alpha_y & 0 & c\alpha_y \end{bmatrix} \leftarrow \begin{cases} c - \cos \\ s - \sin \end{cases}$$

$$\mathbf{C}_n^{n'} = \begin{bmatrix} c\alpha_y c\alpha_z - s\alpha_y s\alpha_x s\alpha_z & c\alpha_y s\alpha_z + s\alpha_y s\alpha_x c\alpha_z & -s\alpha_y c\alpha_x \\ -c\alpha_x s\alpha_z & c\alpha_x c\alpha_z & s\alpha_x \\ s\alpha_y c\alpha_z + c\alpha_y s\alpha_x s\alpha_z & s\alpha_y s\alpha_z - c\alpha_y s\alpha_x c\alpha_z & c\alpha_y c\alpha_x \end{bmatrix}$$

摘自：基于欧拉平台误差角的SINS非线性误差模型研究，西北工业大学学报，2008.