Distribution normale

$$\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

Fusion capteur

$$z_3 = (1-w)z_1 + wz_2$$

$$w = \frac{\sigma_1^2}{\sigma_1^2+\sigma_2^2}$$

Règles des dérivées

$$(f\cdot g)' = f'\cdot g + f\cdot g'$$

$$(x^n)' = nx^{n-1} \qquad (\sin(x))' = \cos(x)$$

$$(\sqrt{x})' = \frac{1}{2\sqrt{x}} \qquad (\cos(x))' = -\sin(x)$$

$$(\ln|x|)' = \frac{1}{x}$$

Règle de Bayes

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

$$P(A,B) = P(A|B)P(B)$$

Prob. totale $P(A) = \sum_n P(A,B_n) = \sum_n P(A|B_n)P(B_n)$

$$\sin\theta \approx \theta, \cos\theta \approx 1 \text{ si } \theta \ll 1 \text{ rad}$$

cinématique directe robot 2D

$$x(t) = \int_0^t V(t)\cos(\theta(t))dt$$

$$y(t) = \int_0^t V(t)\sin(\theta(t))dt$$

$$\theta(t) = \int_0^t \omega(t)dt$$

Conduite différentielle

$$R = \frac{l}{2}\frac{v_l+v_r}{v_r-v_l},\ \omega = \frac{v_r-v_l}{l},\ V = \frac{v_r+v_l}{2}$$

l: distance entre roues

v_l, v_r : vitesse linéare des roues

R : position ICC p/r milieu entre roues

V : vitesse linéaire du robot

ω: vitesse angulaire du robot

Jacobienne de $\begin{pmatrix} f_1(x_1,\ldots,x_n) \\ \vdots \\ f_m(x_1,\ldots,x_n)\end{pmatrix}$ est $J_F(P) = \begin{pmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1} & \cdots & \frac{\partial f_m}{\partial x_n}\end{pmatrix}$

$$T = \begin{pmatrix} 1 & 0 & 0 & T_x \\ 0 & 1 & 0 & T_y \\ 0 & 0 & 1 & T_z \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad R_x(\theta) = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos(\theta) & -\sin(\theta) & 0 \\ 0 & \sin(\theta) & \cos(\theta) & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad R_y(\theta) = \begin{pmatrix} \cos(\theta) & 0 & \sin(\theta) & 0 \\ 0 & 1 & 0 & 0 \\ -\sin(\theta) & 0 & \cos(\theta) & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

$$R_z(\theta) = \begin{pmatrix} \cos(\theta) & -\sin(\theta) & 0 & 0 \\ \sin(\theta) & \cos(\theta) & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad T = \begin{bmatrix} 1 & 0 & T_x \\ 0 & 1 & T_y \\ 0 & 0 & 1 \end{bmatrix} \quad R = \begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

cote(p) = p/(1-p) p = cote/(1+cote) $\text{cote}(c,t) = \frac{p(z|c)}{p(z|\bar{c})}\text{cote}(c,t-1)$

Statistiques :

$$\text{Var}(aX+bY) = a^2\text{Var}(X) + b^2\text{Var}(Y) + 2ab\,\text{Cov}(X,Y).$$

Filtre à particules : algorithme

```
while (explore)
  for i=1:C
      X_i(k+1) = f_X(X_i(k),u(k),σ_V)      Prédiction
  end
  z(k+1) = mesure();
  for i=1:C
      w_i(k+1) = p(z(k+1) | X_i(k+1)) w_i(k)      Mise-à-jour
  end
  for i=1:C
      w_i(k+1) = w_i(k+1) / Σ_j {w_j(k+1)}      Normalisation
  end
  if (Neff < Nseuil)
      X_i(k+1) = resample(X_i(k+1) , w_i(k+1));
      w_i(k+1) = 1/C
  end
  k=k+1
end
```

Prédiction: $X_i(k+1) = f_X(X_i(k), u(k), \sigma_V)$

Mise-à-jour: $w_i(k+1) = p(z(k+1) \mid X_i(k+1)) w_i(k)$

Normalisation: $w_i(k+1) = \dfrac{w_i(k+1)}{\sum_j \{w_j(k+1)\}}$

$$N_{eff} = \frac{1}{\sum_{i=1}^{N} w_i^2} < N_{seuil}$$

Ré-échantillonnage

EKF

(1) $\hat{X}(k+1 \mid k) = f_X(\hat{X}(k), u(k))$

(2) $\Phi = \left.\dfrac{df_X}{dX}\right|_{\hat{X}(k+1)} \quad G = \left.\dfrac{df_X}{du}\right|_{\hat{X}(k+1)}$

(3) $P(k+1 \mid k) = \Phi P(k) \Phi^T + G C_v G^T$

(4) $\hat{z}(k+1 \mid k) = h_z(\hat{X}(k+1 \mid k))$

(5) $r(k+1) = z(k+1) - \hat{z}(k+1 \mid k)$

(6) $\Lambda^T = \left.\dfrac{dh_z}{dX}\right|_{\hat{X}(k+1)}$

(7) $K(k+1) = P(k+1 \mid k) \Lambda^T \{\Lambda P(k+1 \mid k) \Lambda^T + C_w(k+1)\}^{-1}$

(8) $\hat{X}(k+1) = \hat{X}(k+1 \mid k) + K(k+1) r(k+1)$

(9) $P(k+1) = (I - K(k+1)\Lambda) P(k+1 \mid k)$

Filtre Kalman

(1) $\hat{x}(k+1 \mid k) = \Phi \hat{x}(k) + \Gamma u(k)$

(2) $P(k+1 \mid k) = \Phi P(k) \Phi^T + C_v$

(3) $\hat{z}(k+1 \mid k) = \Lambda \hat{x}(k+1 \mid k)$

(4) $r(k+1) = z(k+1) - \hat{z}(k+1 \mid k)$

(5) $K(k+1) = P(k+1 \mid k) \Lambda^T \{\Lambda P(k+1 \mid k) \Lambda^T + C_w(k+1)\}^{-1}$

(6) $\hat{x}(k+1) = \hat{x}(k+1 \mid k) + K(k+1) r(k+1)$

(7) $P(k+1) = (I - K(k+1)\Lambda) P(k+1 \mid k)$