Trabalho #5

Simular os algoritmos apresentados no capítulo 7 do livro [THRUN ETAL:2006] .

Tabelas com os algoritmos:

m é a medida

Algorithm EKF_localization_known_correspondences($\mu_{t-1}, \Sigma_{t-1}, u_t, z_t, c_t, m$):

3 a 5 Jacobianos (modelo de velocidade)

c é a correspondência dos landmarks

$\theta = \mu_{t-1,\theta}$

$$G_t = \begin{pmatrix} 1 & 0 & -\frac{v_t}{\omega_t}\cos\theta + \frac{v_t}{\omega_t}\cos(\theta+\omega_t\Delta t) \\ 0 & 1 & -\frac{v_t}{\omega_t}\sin\theta + \frac{v_t}{\omega_t}\sin(\theta+\omega_t\Delta t) \\ 0 & 0 & 1 \end{pmatrix}$$

$$V_t = \begin{pmatrix} \frac{-\sin\theta+\sin(\theta+\omega_t\Delta t)}{\omega_t} & \frac{v_t(\sin\theta-\sin(\theta+\omega_t\Delta t))}{\omega_t^2} + \frac{v_t\cos(\theta+\omega_t\Delta t)\Delta t}{\omega_t} \\ \frac{\cos\theta-\cos(\theta+\omega_t\Delta t)}{\omega_t} & -\frac{v_t(\cos\theta-\cos(\theta+\omega_t\Delta t))}{\omega_t^2} + \frac{v_t\sin(\theta+\omega_t\Delta t)\Delta t}{\omega_t} \\ 0 & \Delta t \end{pmatrix}$$

$$M_t = \begin{pmatrix} \alpha_1 v_t^2 + \alpha_2\omega_t^2 & 0 \\ 0 & \alpha_3 v_t^2 + \alpha_4\omega_t^2 \end{pmatrix}$$

$$\bar\mu_t = \mu_{t-1} + \begin{pmatrix} -\frac{v_t}{\omega_t}\sin\theta + \frac{v_t}{\omega_t}\sin(\theta+\omega_t\Delta t) \\ \frac{v_t}{\omega_t}\cos\theta - \frac{v_t}{\omega_t}\cos(\theta+\omega_t\Delta t) \\ \omega_t\Delta t \end{pmatrix}$$

$\bar\Sigma_t = G_t\,\Sigma_{t-1}\,G_t^T + V_t\,M_t\,V_t^T$ Matriz de covariância

$$Q_t = \begin{pmatrix} \sigma_r^2 & 0 & 0 \\ 0 & \sigma_\phi^2 & 0 \\ 0 & 0 & \sigma_s^2 \end{pmatrix}$$ Ruídos de medição

for all observed features $z_t^i = (r_t^i\ \phi_t^i\ s_t^i)^T$ *do*

$j = c_t^i$

$q = (m_{j,x} - \bar\mu_{t,x})^2 + (m_{j,y} - \bar\mu_{t,y})^2$

$$\hat z_t^i = \begin{pmatrix} \sqrt{q} \\ \mathrm{atan2}(m_{j,y}-\bar\mu_{t,y}, m_{j,x}-\bar\mu_{t,x}) - \bar\mu_{t,\theta} \\ m_{j,s} \end{pmatrix}$$

$$H_t^i = \begin{pmatrix} -\frac{m_{j,x}-\bar\mu_{t,x}}{\sqrt{q}} & -\frac{m_{j,y}-\bar\mu_{t,y}}{\sqrt{q}} & 0 \\ \frac{m_{j,y}-\bar\mu_{t,y}}{q} & -\frac{m_{j,x}-\bar\mu_{t,x}}{q} & -1 \\ 0 & 0 & 0 \end{pmatrix}$$

$S_t^i = H_t^i\,\bar\Sigma_t\,[H_t^i]^T + Q_t$ Incerteza - H é o Jacobiano do modelo de medição

$K_t^i = \bar\Sigma_t\,[H_t^i]^T[S_t^i]^{-1}$

$\bar\mu_t = \bar\mu_t + K_t^i(z_t^i - \hat z_t^i)$

$\bar\Sigma_t = (I - K_t^i\,H_t^i)\,\bar\Sigma_t$

endfor

$\mu_t = \bar\mu_t$

$\Sigma_t = \bar\Sigma_t$

Considera as medidas independentes

$p_{z_t} = \prod_i \det(2\pi S_t^i)^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}(z_t^i - \hat z_t^i)^T[S_t^i]^{-1}(z_t^i - \hat z_t^i)\right\}$

return μ_t, Σ_t, p_{z_t}

não se sabe mais a correspondência c

Algorithm EKF_localization($\mu_{t-1}, \Sigma_{t-1}, u_t, z_t, m$):

$\theta = \mu_{t-1,\theta}$

$$G_t = \begin{pmatrix} 1 & 0 & -\frac{v_t}{\omega_t}\cos\theta + \frac{v_t}{\omega_t}\cos(\theta+\omega_t\Delta t) \\ 0 & 1 & -\frac{v_t}{\omega_t}\sin\theta + \frac{v_t}{\omega_t}\sin(\theta+\omega_t\Delta t) \\ 0 & 0 & 1 \end{pmatrix}$$

$$V_t = \begin{pmatrix} \frac{-\sin\theta+\sin(\theta+\omega_t\Delta t)}{\omega_t} & \frac{v_t(\sin\theta-\sin(\theta+\omega_t\Delta t))}{\omega_t^2} + \frac{v_t\cos(\theta+\omega_t\Delta t)\Delta t}{\omega_t} \\ \frac{\cos\theta-\cos(\theta+\omega_t\Delta t)}{\omega_t} & -\frac{v_t(\cos\theta-\cos(\theta+\omega_t\Delta t))}{\omega_t^2} + \frac{v_t\sin(\theta+\omega_t\Delta t)\Delta t}{\omega_t} \\ 0 & \Delta t \end{pmatrix}$$

$$M_t = \begin{pmatrix} \alpha_1 v_t^2 + \alpha_2\omega_t^2 & 0 \\ 0 & \alpha_3 v_t^2 + \alpha_4\omega_t^2 \end{pmatrix}$$

$$\bar\mu_t = \mu_{t-1} + \begin{pmatrix} -\frac{v_t}{\omega_t}\sin\theta + \frac{v_t}{\omega_t}\sin(\theta+\omega_t\Delta t) \\ \frac{v_t}{\omega_t}\cos\theta - \frac{v_t}{\omega_t}\cos(\theta+\omega_t\Delta t) \\ \omega_t\Delta t \end{pmatrix}$$

$\bar\Sigma_t = G_t\,\Sigma_{t-1}\,G_t^T + V_t\,M_t\,V_t^T$

$$Q_t = \begin{pmatrix} \sigma_r^2 & 0 & 0 \\ 0 & \sigma_\phi^2 & 0 \\ 0 & 0 & \sigma_s^2 \end{pmatrix}$$

for all observed features $z_t^i = (r_t^i\ \phi_t^i\ s_t^i)^T$ *do*

for all landmarks k *in the map* m *do*

$q = (m_{k,x} - \bar\mu_{t,x})^2 + (m_{k,y} - \bar\mu_{t,y})^2$

$$\hat z_t^k = \begin{pmatrix} \sqrt{q} \\ \mathrm{atan2}(m_{k,y}-\bar\mu_{t,y}, m_{k,x}-\bar\mu_{t,x}) - \bar\mu_{t,\theta} \\ m_{k,s} \end{pmatrix}$$

$$H_t^k = \begin{pmatrix} -\frac{m_{k,x}-\bar\mu_{t,x}}{\sqrt{q}} & -\frac{m_{k,y}-\bar\mu_{t,y}}{\sqrt{q}} & 0 \\ \frac{m_{k,y}-\bar\mu_{t,y}}{q} & -\frac{m_{k,x}-\bar\mu_{t,x}}{q} & -1 \\ 0 & 0 & 0 \end{pmatrix}$$

$S_t^k = H_t^k\,\bar\Sigma_t\,[H_t^k]^T + Q_t$

endfor

$j(i) = \operatorname{argmax}_k\ \det(2\pi S_t^k)^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}(z_t^i - \hat z_t^k)^T[S_t^k]^{-1}(z_t^i - \hat z_t^k)\right\}$

$K_t^i = \bar\Sigma_t\,[H_t^{j(i)}]^T[S_t^{j(i)}]^{-1}$

$\bar\mu_t = \bar\mu_t + K_t^i(z_t^i - \hat z_t^{j(i)})$

$\bar\Sigma_t = (I - K_t^i\,H_t^{j(i)})\,\bar\Sigma_t$

endfor

$\mu_t = \bar\mu_t$

$\Sigma_t = \bar\Sigma_t$

return μ_t, Σ_t

Algorithm UKF_localization($\mu_{t-1}, \Sigma_{t-1}, u_t, z_t, m$):

Generate augmented mean and covariance

$$M_t = \begin{pmatrix} \alpha_1 v_t^2 + \alpha_2\omega_t^2 & 0 \\ 0 & \alpha_3 v_t^2 + \alpha_4\omega_t^2 \end{pmatrix}$$

$$Q_t = \begin{pmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_\phi^2 \end{pmatrix}$$

$\mu_{t-1}^a = (\mu_{t-1}^T\ \ (0\ 0)^T\ \ (0\ 0)^T)^T$

$$\Sigma_{t-1}^a = \begin{pmatrix} \Sigma_{t-1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & M_t & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & Q_t \end{pmatrix}$$ Estado aumentado (7 dim.)

Generate sigma points

$\mathcal{X}_{t-1}^a = (\mu_{t-1}^a\ \ \ \mu_{t-1}^a + \gamma\sqrt{\Sigma_{t-1}^a}\ \ \ \mu_{t-1}^a - \gamma\sqrt{\Sigma_{t-1}^a})$

Pass sigma points through motion model and compute Gaussian statistics

$\bar{\mathcal{X}}_t^x = g(u_t + \mathcal{X}_t^u, \mathcal{X}_{t-1}^x)$

$\bar\mu_t = \sum_{i=0}^{2L} w_i^{(m)}\,\bar{\mathcal{X}}_{i,t}^x$

$\bar\Sigma_t = \sum_{i=0}^{2L} w_i^{(c)}(\bar{\mathcal{X}}_{i,t}^x - \bar\mu_t)(\bar{\mathcal{X}}_{i,t}^x - \bar\mu_t)^T$

Na aplicação do movimento não se usa o aumentado, se aplica os passos individualmente

Predict observations at sigma points and compute Gaussian statistics

$\bar{\mathcal{Z}}_t = h(\bar{\mathcal{X}}_t^x) + \mathcal{X}_t^z$

$\hat z_t = \sum_{i=0}^{2L} w_i^{(m)}\,\bar{\mathcal{Z}}_{i,t}$

$S_t = \sum_{i=0}^{2L} w_i^{(c)}(\bar{\mathcal{Z}}_{i,t} - \hat z_t)(\bar{\mathcal{Z}}_{i,t} - \hat z_t)^T$

$\bar\Sigma_t^{x,z} = \sum_{i=0}^{2L} w_i^{(c)}(\bar{\mathcal{X}}_{i,t}^x - \bar\mu_t)(\bar{\mathcal{Z}}_{i,t} - \hat z_t)^T$

Update mean and covariance

$K_t = \bar\Sigma_t^{x,z}\,S_t^{-1}$

$\mu_t = \bar\mu_t + K_t(z_t - \hat z_t)$

$\Sigma_t = \bar\Sigma_t - K_t\,S_t\,K_t^T$

$p_{z_t} = \det(2\pi S_t)^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}(z_t - \hat z_t)^T S_t^{-1}(z_t - \hat z_t)\right\}$

return μ_t, Σ_t, p_{z_t}

Material disponível no Moodle

- Notas de aula.

Referências

[1] SEBASTIAN THRUN, WOLFRAM BURGARD & DIETER FOX
Probabilistic robotics.
MIT Press, **2006**.
Link: http://probabilistic-robotics.informatik.uni-freiburg.de/

[2] HOWIE CHOSET, KEVIN LYNCH, SETH HUTCHINSON, GEORGE KANTOR, WOLFRAM BURGARD, LYDIA KAVRAKI & SEBASTIAN THRUN

Principles of Robot Motion. Theory, Algorithms, and Implementations.
MIT Press, **2005**.
Link: http://biorobotics.ri.cmu.edu/book/

Contém uma descrição detalhada do filtro de Kalman e do EKF.

[3] Gregor Klancar, Andrej Zdešar, Sašo Blažic & Igor Škrjanc
Wheeled Mobile Robotics. From Fundamentals Towards Autonomous Systems.
Butterworth-Heinemann, **2017**.
Link: http://booksite.elsevier.com/9780128042045/manuscript.php

Contém códigos em Matlab.

Apresentações

- Os grupos terão cerca de 20 minutos para fazer as apresentações.
- As apresentações serão realizadas na seguinte data:

ND

Avaliação do trabalho

Preparar e enviar por email:

1. Relatório contendo a descrição dos algoritmos, resultados das simulações e discussão dos resultados.
2. Códigos dos programas utilizados nas simulações.
3. Slides preparados para a apresentação do trabalho.

Grupos

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