

# SISTEMAS ROBÓTICOS AUTÓNOMOS

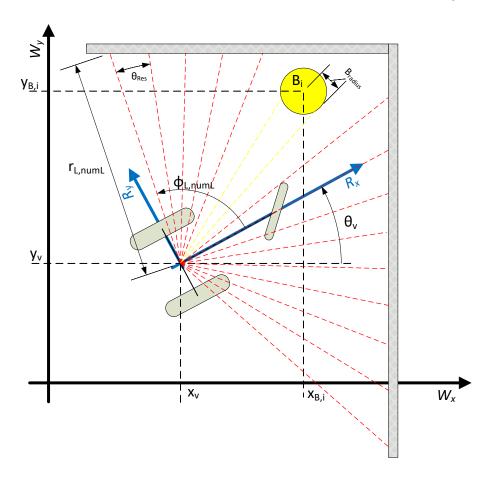
Mestrado em Engenharia Eletrotécnica e de Computadores de Faculdade de Engenharia da Universidade do Porto

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Observations – distance, angle and reflection rate in reflective beacons:

$$Z_{L}(k) = \left\{ Z_{L,i}(k) = \begin{bmatrix} r_{L,i}(k) & \phi_{L,i}(k) \end{bmatrix}^{T}, c_{L,i}(k) : i \in \begin{bmatrix} 1 & numL \end{bmatrix} \right\}$$



#### State transition model (motion model):

$$X_{v}(k+1) = \begin{bmatrix} x_{v}(k+1) \\ y_{v}(k+1) \\ \theta_{v}(k+1) \end{bmatrix} = f(X_{v}(k), u(k)) + N(0, Q(k))$$

#### with:

$$f\left(X_{v}(k), u(k)\right) = \begin{bmatrix} x_{v}(k) + \Delta d(k) \cos\left(\theta(k) + \frac{\Delta \theta(k)}{2}\right) \\ y_{v}(k) + \Delta d(k) \sin\left(\theta(k) + \frac{\Delta \theta(k)}{2}\right) \\ \theta(k) + \Delta \theta(k) \end{bmatrix}$$

The Jacobian matrix of f(.) with respect to the state, will be:

$$\nabla f_{x}\left(X_{v}(k), u(k)\right) = \begin{bmatrix} \frac{\partial x_{v}(k+1)}{\partial x_{v}(k)} & \frac{\partial x_{v}(k+1)}{\partial y_{v}(k)} & \frac{\partial x_{v}(k+1)}{\partial \theta_{v}(k)} \\ \frac{\partial y_{v}(k+1)}{\partial x_{v}(k)} & \frac{\partial y_{v}(k+1)}{\partial y_{v}(k)} & \frac{\partial y_{v}(k+1)}{\partial \theta_{v}(k)} \\ \frac{\partial \theta_{v}(k+|l)}{\partial x_{v}(k)} & \frac{\partial \theta_{v}(k+1)}{\partial y_{v}(k)} & \frac{\partial \theta_{v}(k+1)}{\partial \theta_{v}(k)} \end{bmatrix} = \begin{bmatrix} 1 & 0 & -\Delta d(k) \sin\left(\theta_{v}(k) + \frac{\Delta \theta(k)}{2}\right) \\ 0 & 1 & \Delta d(k) \cos\left(\theta_{v}(k) + \frac{\Delta \theta(k)}{2}\right) \\ 0 & 0 & 1 \end{bmatrix}$$

Assuming that the variances of the noise associated with the inputs of the state transition model:

$$u(k) = [\Delta d(k) \quad \Delta \theta(k)]^{T}$$

respectively are given by (there are other possibilities):

$$\left(\sigma_{\min,\Delta d} + \alpha_1 \Delta d(k) + \alpha_2 \Delta \theta(k)\right)^2$$

and

$$\left(\sigma_{\min,\Delta\theta} + \alpha_3 \Delta d(k) + \alpha_4 \Delta \theta(k)\right)^2$$



The Jacobian matrix of f(.) with respect to the inputs, will be:

$$\nabla f_{u}\left(X_{v}(k), u(k)\right) = \begin{bmatrix} \frac{\partial x_{v}(k+1)}{\partial \Delta d(k)} & \frac{\partial x_{v}(k+1)}{\partial \Delta \theta(k)} \\ \frac{\partial y_{v}(k+1)}{\partial \Delta d(k)} & \frac{\partial y_{v}(k+1)}{\partial \Delta \theta(k)} \\ \frac{\partial \theta_{v}(k+1)}{\partial \Delta d(k)} & \frac{\partial \theta_{v}(k+1)}{\partial \Delta \theta(k)} \end{bmatrix} = \begin{bmatrix} \cos\left(\theta_{v}(k) + \frac{\Delta \theta(k)}{2}\right) & -\frac{1}{2}\Delta d(k)\sin\left(\theta_{v}(k) + \frac{\Delta \theta(k)}{2}\right) \\ \sin\left(\theta_{v}(k) + \frac{\Delta \theta(k)}{2}\right) & \frac{1}{2}\Delta d(k)\cos\left(\theta_{v}(k) + \frac{\Delta \theta(k)}{2}\right) \\ 0 & 1 \end{bmatrix}$$

### And the covariance matrix Q(k):

$$Q(k) = \nabla f_{u} \left( X_{v}(k), u(k) \right) * \begin{bmatrix} \left( \sigma_{\text{min}, \Delta d} + \alpha_{1} \Delta d(k) + \alpha_{2} \Delta \theta(k) \right)^{2} & 0 \\ 0 & \left( \sigma_{\text{min}, \Delta \theta} + \alpha_{3} \Delta d(k) + \alpha_{4} \Delta \theta(k) \right)^{2} \end{bmatrix} * \nabla f_{u}^{T} \left( X_{v}(k), u(k) \right)$$

The prediction of the next state given the current estimate of the state and the values for the model inputs, will be:

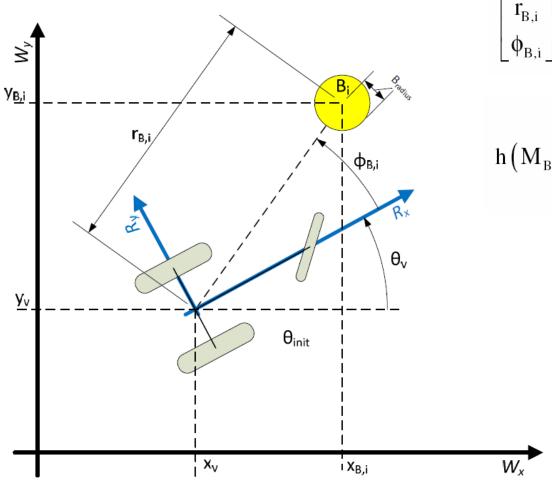
$$\widehat{X}(k+1|k) = f(\widehat{X}(k|k), u(k))$$

And the uncertainty of this estimate given by the covariance matrix:

$$P(k+1|k) = \nabla f_{X}(\widehat{X}(k|k), u(k)) * P(k|k) * \nabla f_{X}^{T}(\widehat{X}(k|k), u(k)) + Q(k)$$

The Jacobians are calculated on present estimates of the state and present values of inputs.

#### Observation model:



$$\begin{bmatrix} r_{B,i} \\ \phi_{B,i} \end{bmatrix} = h(M_{B,i}, X_v(k)) + N(0,R)$$

$$h(M_{B,i}, X_{v}(k)) = \begin{bmatrix} \sqrt{(x_{B,i} - x_{v})^{2} + (y_{B,i} - y_{v})^{2}} \\ a \tan 2(y_{B,i} - y_{v}, x_{B,i} - x_{v}) - \theta_{v}(k) \end{bmatrix}$$

Measurements noise covariance:

$$R = \begin{bmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_\phi^2 \end{bmatrix}$$



### Jacobian matrix of funtion h(.):

$$\nabla h\left(M_{B,i}, X_{v}(k)\right) = \begin{bmatrix} \frac{\partial r_{i}}{\partial x_{v}(k)} & \frac{\partial r_{i}}{\partial y_{v}(k)} & \frac{\partial r_{i}}{\partial \theta_{v}(k)} \\ \frac{\partial \phi}{\partial x_{v}(k)} & \frac{\partial \phi}{\partial y_{v}(k)} & \frac{\partial \phi}{\partial \theta_{v}(k)} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{x_{B,i} - x_{v}(k)}{\sqrt{\left(x_{B,i} - x_{v}(k)\right)^{2} + \left(y_{B,i} - y_{v}(k)\right)^{2}}} & -\frac{y_{B,i} - y_{v}(k)}{\sqrt{\left(x_{B,i} - x_{v}(k)\right)^{2} + \left(y_{B,i} - y_{v}(k)\right)^{2}}} \\ \frac{y_{B,i} - y_{v}(k)}{\left(x_{B,i} - x_{v}(k)\right)^{2} + \left(y_{B,i} - y_{v}(k)\right)^{2}} & -\frac{x_{B,i} - x_{v}(k)}{\left(x_{B,i} - x_{v}(k)\right)^{2} + \left(y_{B,i} - y_{v}(k)\right)^{2}} \end{bmatrix}$$

## Correction phase taking into account the observations

Estimation of measurements taking into account the current estimation of the state and the detected beacon:

$$\hat{Z}_{B,i}(k) = h(M_{B,i}, \hat{X}(k+1|k))$$

with covariance:

$$S_{i}(k) = \nabla h \left( M_{B,i}, \hat{X}(k+1|k) \right) * P(k+1|k) * \left[ \nabla h \left( M_{B,i}, \hat{X}(k+1|k) \right) \right]^{T} + R$$



## Correction phase taking into account the observations

### Kalman Filter gain:

$$K_{i}(k) = P(k+1|k) * \left[ \nabla h \left( M_{B,i}, \hat{X}(k+1|k) \right) \right]^{T} * \left[ S_{i}(k) \right]^{-1}$$

#### State correction:

$$\widehat{X}(k+1|k+1) = \widehat{X}(k+1|k) + K_{i}(k) * \left[ Z_{B,i}(k) - \widehat{Z}_{B,i}(k) \right]$$

Update of the covariance of the estimated state:

$$P(k+1|k+1) = \left[ I - K_i(k) * \nabla h \left( M_{B,i}, \hat{X}(k+1|k) \right) \right] * P(k+1|k)$$



### Correction step (update) with variable number of observations

The state estimation and its covariance are updated in the prediction step:

$$\hat{X}(k+1|k+1) = \hat{X}(k+1|k)$$
 e  $P(k+1|k+1) = P(k+1|k)$ 

For each observation the estimation of the state and its covariance are updated repeatedly in accordance with the following equations:

$$S_{i}(k) = \nabla h \left( M_{B,i}, \hat{X}(k+1|k+1) \right) * P(k+1|k+1) * \left[ \nabla h \left( M_{B,i}, \hat{X}(k+1|k+1) \right) \right]^{T} + R$$

$$K_{i}(k) = P(k+1|k+1)* \left[\nabla h(M_{B,i}, \hat{X}(k+1|k+1))\right]^{T}* \left[S_{i}(k)\right]^{-1}$$

$$\widehat{X}(k+1|k+1) = \widehat{X}(k+1|k+1) + K_{i}(k) * \left[ Z_{B,i} - \widehat{Z}_{B,i}(k) \right]$$

$$P(k+1|k+1) = \left[I - K_{i}(k) * \nabla h \left(B_{j=C_{B,i}(k)}, \widehat{X}(k+1|k+1)\right)\right] * P(k+1|k+1)$$



#### **VIDEOS:**

PRODUTECH project demonstration at ADIRA:

https://youtu.be/aUM5B6sZQVk

https://youtu.be/oNGMu-gQqeA

