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State: Time Step:

Process Noise:

Measurement Noise:

Linear Kalman Filter

y(k) = H(k)x(k) + w(k)

x(k+1) = F(k)x(k) + G(k)u(k) + v(k)

prediction:

Input: Output:

$$\hat{x}(k+1|k) = F(k)\hat{x}(k|k) + G(k)u(k)$$

 $P(k+1|k) = F(k)P(k|k)F(k)^T + V(k)$

update:

$$\begin{array}{lcl} \hat{x}(k+1|k+1) & = & \hat{x}(k+1|k) + R\nu \\ P(k+1|k+1) & = & P(k+1|k) - RH(k+1)P(k+1|k) \end{array}$$

where

$$\begin{array}{rcl} \nu & = & y(k+1) - H(k+1)x(k+1|k)) \\ S & = & H(k+1)P(k+1|k)H(k+1)^T + W(k+1) \\ R & = & P(k+1|k)H(k+1)^T S^{-1}. \end{array}$$

Extended Kalman Filter

Kalman Filter for nonlinear systems where F and H are linearized about the current state estimate

$$F(k) = \frac{\partial f}{\partial x}\Big|_{x=\hat{x}(k|k)}$$
 $H(k+1) = \frac{\partial h}{\partial x}\Big|_{x=\hat{x}(k+1|k)}$

Kalman Filter SLAM

Simultaneous Localization and Mapping

Use Kalman Filter to simultaneously estimate position of robot and landmarks in environment

$$x = \begin{bmatrix} x_r & y_r & x_{\ell 1} & y_{\ell 1} & x_{\ell 2} & y_{\ell 2} & \dots & x_{\ell n_{\ell}} & y_{\ell n_{\ell}} \end{bmatrix}^T$$

Linear Relative Position Output:

$$y_i(k) = \begin{bmatrix} x_{\ell i}(k) - x_r(k) \\ y_{\ell i}(k) - y_r(k) \end{bmatrix} + w_i(k)$$

Nonlinear Range and Bearing Output:

$$\begin{array}{lll}
\nu & = & y(k+1) - H(k+1)x(k+1|k)) \\
S & = & H(k+1)P(k+1|k)H(k+1)^T + W(k+1)
\end{array}$$

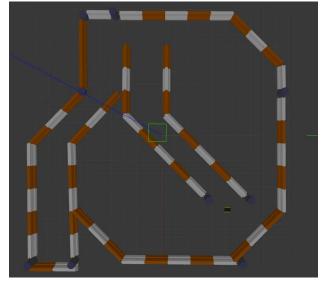
$$\begin{array}{lll}
y_i(k) = \begin{bmatrix} \sqrt{(x_{\ell i}(k) - x_r(k))^2 + (y_{\ell i}(k) - y_r(k))^2} \\
\text{atan2}((y_{\ell i}(k) - y_r(k)), (x_{\ell i}(k) - x_r(k)) - \theta_r(k) \end{bmatrix} + w_i(k)
\end{array}$$

Data Association

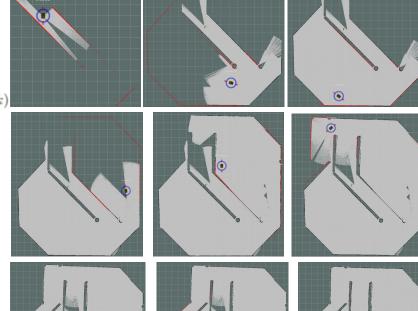
Which landmark is each measurement associated with?

Use Mahalanobis Distance

$$\chi_{ij}^2 = (y(k)_i - h(k)_j)^T S_{ij} (y(k)_i - h(k)_j)$$



ROS gmapping in Jackal Simulator



Source: Principles of Robot Motion: Theory, Algorithms, and Implementations Ch. 8 – Choset et. al.

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