Linearization for non-linear system

Nonlinear system

$$x_t = f(x_{t-1}, u_{t-1}, \omega_{t-1}), \omega_{t-1} \sim \mathcal{N}(0, Q)$$

$$z_t = h(x_t, v_t), v_t \sim \mathcal{N}(0, R)$$

$$f \text{ and } h \text{ are both nonlinear function}$$

Note

The nonlinear mapping of a Gaussian distribution is not Gaussian

Linearization

Taylor Series

$$f(x) = f(x_0) + \frac{\partial f}{\partial x}(x - x_0)$$

The best way to choose initial point is the real-value. However, we don't have this.

We linearize the system from the posterior estimation
$$\hat{x}_{t-1}$$
 of the last timestep.

$$x_t = f(\hat{x}_{t-1}, u_{t-1}, \omega_{t-1}) + A_t(x_t - \hat{x}_{t-1}) + W_t \omega_{t-1}$$

$$\text{Assuming } \omega_{t-1} = 0, \text{ we get } \tilde{x}_t = f(\hat{x}_{t-1}, u_{t-1}, 0)$$

$$A_t = \left(\frac{\partial f}{\partial x}\right)_{\hat{x}_{t-1}, u_{t-1}}$$

$$W_t = \left(\frac{\partial f}{\partial \omega}\right)_{\hat{x}_{t-1}, u_{t-1}}$$

$$z_t = h(\tilde{x}, v_t) + H_t(x_t - \tilde{x}_t) + V_t v_t$$

$$\text{Linearization at } \tilde{x}_t$$

$$\text{Assuming } v_t = 0, \text{ we get } \tilde{z}_t = h(\tilde{x}_t, 0)$$

$$H_t = \left(\frac{\partial h}{\partial x}\right)_{\tilde{x}_t}$$

$$V_t = \left(\frac{\partial h}{\partial v}\right)_{\tilde{x}_t}$$

$$\omega_t \sim \mathcal{N}(0, Q)$$

$$W_t \omega_t \sim \mathcal{N}(0, W_t Q W_t^\top)$$

E.g.
$$f_{1} := x_{1} \leftarrow x_{1} + \sin x_{2}$$

$$f_{2} := x_{2} \leftarrow x_{1}^{2}$$

$$A = \frac{\partial f}{\partial x} = \begin{bmatrix} \frac{\partial f_{1}}{\partial x_{1}} & \frac{\partial f_{1}}{\partial x_{2}} \\ \frac{\partial f_{2}}{\partial x_{1}} & \frac{\partial f_{2}}{\partial x_{2}} \end{bmatrix}$$

$$= \begin{bmatrix} 1 & \cos x_{2} \\ 2x_{1} & 0 \end{bmatrix}$$

Summary

 $V_t v_t \sim \mathcal{N}(0, V_t R V_t^{\mathsf{T}})$

propagation		correction	
prior	$\hat{x}_{t}^{-} = f(\tilde{x}_{t-1} + u_{t-1}, 0)$	Kalman gain	$K_t = (P_t^- H^\top) (H P_t^- H^\top + V_{t-1} R V_{t-1}^\top)^{-1}$
prior error covariance	$P_{t}^{-} = AP_{t-1}A^{T} + W_{t-1}QW_{t-1}^{T}$	posterior estimation	$\hat{x}_t = \hat{x}_t^- + K_t (z_t - h(\hat{x}_t^-))$
		update error covariance	$P_t = (I - K_t H) P_t^-$