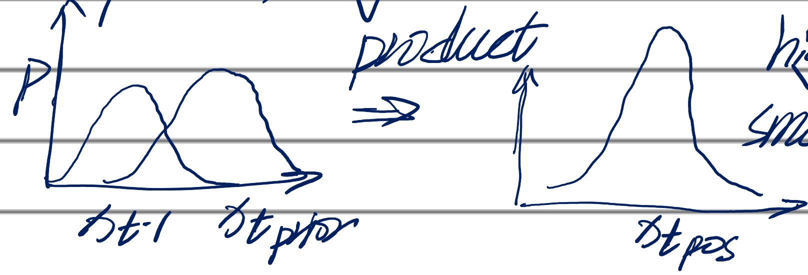
Kalman Filter summary.

Gaussian Assumption, Bayes Filter

1D Example:



higher center.
smaller variance

1. initialize state x_0. Process covariance matrix
2. predict the state. P.
3. calculate the difference measurement − Prediction.
4. caculate the kalman Gain.
5. update the state and P

back 1.

non-lin process

predict state noise

1: x_{k-1}, P_{k-1}

2: $x = Ax + Bu + w_k$, $P = APA^T + Q$

process noise

3.4: $K = \dfrac{PH}{HPH^T + R}$, $x_k = x + K[Y - Hx]$

sensor noise

might from different space.

5: $P = P + [I - KH]P_k$, x_p

Y. x different space, Example $Y \rightarrow \begin{bmatrix} \rho \\ \phi \\ \dot{\rho} \end{bmatrix}$ $x \rightarrow \begin{bmatrix} x \\ y \\ \dot{x} \\ \dot{y} \end{bmatrix}$ diff $= Y - h(x')$

non linear.

1. Extended kalman: linearization. Taylor Expansion.

$h(x)|_{\mu} = h(\mu) + h'(x)[x - \mu]$

Jacobian. matrix.

$$H_j = \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} & \frac{\partial f}{\partial \dot{x}} & \frac{\partial f}{\partial \dot{y}} \\ \frac{\partial \psi}{\partial x} & \cdots & & \\ \cdots & & & \frac{\partial f}{\partial \dot{y}} \end{bmatrix}$$

2. Uncentered kalman Filter: sample points. refit a Gaussian.

Generate sigma points (subsample points]

1. state of dimension
2. number of the sigma points

$x = \left[x_{center} \quad x_{center} \pm \boxed{(\lambda + n_x) P} \right]$ with different weight.

design params scalar Process covariance

$\lambda = 3 - n_x$ (emperical).

$$w_i = \begin{cases} \frac{\lambda}{\lambda + n_\sigma} & i = 0 \\ \frac{1}{2(\lambda + n_\sigma)} & i = 1 \ldots n_\sigma \end{cases}$$

UKF Augmentation ← Process noise. $\nu_k = \begin{bmatrix} \nu_{k_1} \\ \nu_{k_2} \end{bmatrix}$

$x_a = \begin{bmatrix} \bar{x} \\ \bar{\nu} \end{bmatrix}$ $P = \begin{bmatrix} \bar{P} & 0 \\ 0 & \bar{Q} \end{bmatrix}$ $\bar{Q} = \nu_k \cdot \nu^T$.

prediction: x_k, $f(x)$, process.

reuse the sigma points for prediction / resample sigma points

skip augmentation in $H(x)$ process