

1. Consider the noiseless, scalar, continuous-time dynamical system

$$\dot{x}(t) = 0$$

that is accompanied by scalar, discrete-time measurements of the form

$$z_k = x_k + v_k,$$

where v_k is a zero-mean measurement noise with constant variance P_{vv} . If the initial mean and variance of the state are known to be $m_{x,0}$ and $P_{xx,0}$, respectively, derive closed-form expressions for the Kalman gain and posterior variance at the ℓ^{th} update time, where $k = 1, 2, \dots, \ell$. Your results should be expressed entirely in terms of $P_{xx,0}$, P_{vv} , and ℓ .

Given :

- $\rightarrow \mathbb{E} \left\{ \underline{v}_k \right\} = 0$
- $\rightarrow p_{v,k} = p_w \quad \forall k$
- $\rightarrow \mathbb{E} \left\{ \underline{x}(t_0) \right\} = \underline{m}_x, 0$

Thus, $x_k = \alpha \quad \forall k$

Starting with the definition of the Kalman gain, given on page 205 of the notes:

$$K_K = (P_{\tilde{z}z, K}) (P_{\tilde{z}z, K})^{-1}$$

$$p_{xz, k}^- = p_{xx, k}^- H_{x, k}^+$$

$$P_{22, \kappa} = H_{x, \kappa} P_{xx, \kappa} H_{x, \kappa} + H_{y, \kappa} P_{yy, \kappa} H_{y, \kappa}$$

where $\underline{z}_k = H_{x,k} \underline{x}_k + H_{v,k} \underline{v}_k$

Need to find $\rho_{xx}, \bar{\kappa} \dots$

P_{x,k^-} is found by propagating the covariance forward, under the propagation model described by:

$$\dot{P}_{xx}(t) = F_x(t) P_{xx}(t) + P_{xx}(t) F_x^T(t) + \cancel{F_w(t) Q_{ww}(t) F_w^T(t)} \quad \begin{matrix} 0 \text{ (no modelled} \\ \text{process noise)} \end{matrix}$$

Since $\dot{x}(t) = 0$, $F_x(t) = 0$, $\therefore \dot{p}_{xx}(t) = 0$

To find the results at an arbitrary update time, I let's find the pattern by starting with $K=1$...

For $k=1$, $P_{xx,1}^- = P_{xx,0}$ because $\dot{P}_{xx}(t) = 0$

$$\left. \begin{aligned} P_{xz,1}^- &= P_{xx,0} \\ P_{zz,1}^- &= P_{xx,0} + P_{vv} \end{aligned} \right\} k_1 = (P_{xx,0})(P_{xx,0} + P_{vv})^{-1}$$

The state covariance is then updated according to the equation given on page 228 of the notes, which is valid for this case since we have linear measurements:

$$\begin{aligned} P_{xx,1}^+ &= [I_2 - K_1 H] P_{xx,1}^- \\ &= [I_2 - (P_{xx,0})(P_{xx,0} + P_{vv})^{-1}] P_{xx,0} \\ &= \left[I - \frac{P_{xx,0}}{P_{xx,0} + P_{vv}} \right] P_{xx,0} \\ &= \left[\frac{\cancel{P_{xx,0}} + P_{vv}}{P_{xx,0} + P_{vv}} - \frac{\cancel{P_{xx,0}}}{P_{xx,0} + P_{vv}} \right] P_{xx,0} \\ P_{xx,1}^+ &= \frac{P_{vv} P_{xx,0}}{P_{xx,0} + P_{vv}} \end{aligned}$$

The same procedure can be done with $k=2$, using $P_{xx,1}^+$ as $P_{xx,2}^-$

$$P_{xz,2}^- = P_{xx,2}^-$$

$$P_{zz,2}^- = P_{xx,2}^- + P_{vv}$$

$$\begin{aligned} \text{Thus, } k_2 &= (P_{xx,2}^-)(P_{xx,2}^- + P_{vv})^{-1} = \left(\frac{P_{vv} P_{xx,0}}{P_{xx,0} + P_{vv}} \right) \left(\frac{P_{vv} P_{xx,0}}{P_{xx,0} + P_{vv}} + P_{vv} \right)^{-1} \\ &= \left(\frac{P_{vv} P_{xx,0}}{P_{xx,0} + P_{vv}} \right) \left(\frac{P_{vv} P_{xx,0}}{P_{xx,0} + P_{vv}} + \frac{P_{vv}(P_{xx,0} + P_{vv})}{P_{xx,0} + P_{vv}} \right)^{-1} \\ &= \left(\frac{P_{vv} P_{xx,0}}{P_{xx,0} + P_{vv}} \right) \left(\frac{P_{vv} P_{xx,0} + P_{vv}(P_{xx,0} + P_{vv})}{P_{xx,0} + P_{vv}} \right)^{-1} \end{aligned}$$

$$\begin{aligned}
&= \left(\frac{P_{VV} P_{XX,0}}{P_{XX,0} + P_{VV}} \right) \left(\frac{P_{XX,0} + P_{VV}}{P_{VV} P_{XX,0} + P_{VV} (P_{XX,0} + P_{VV})} \right) \\
&= \frac{P_{VV} P_{XX,0}}{2 P_{XX,0} P_{VV} + P_{VV}^2} \\
K_2 &= \frac{P_{XX,0}}{2 P_{XX,0} + P_{VV}}
\end{aligned}$$

And again, we can solve for $P_{XX,2}^+$ which will be $P_{XX,3}^-$ in the next iteration using

$$\begin{aligned}
P_{XX,2}^+ &= [I_2 - K_2 H] P_{XX,2}^- \\
&= \left[\frac{2 P_{XX,0} + P_{VV} - P_{XX,0}}{2 P_{XX,0} + P_{VV}} \right] \left[\frac{P_{VV} P_{XX,0}}{P_{XX,0} + P_{VV}} \right] \\
&= \left[\frac{P_{XX,0} + P_{VV}}{2 P_{XX,0} + P_{VV}} \right] \left[\frac{P_{VV} P_{XX,0}}{P_{XX,0} + P_{VV}} \right] \\
P_{XX,2}^+ &= \left[\frac{P_{VV} P_{XX,0}}{2 P_{XX,0} + P_{VV}} \right]
\end{aligned}$$

Doing the same for $K=3$ will result in $K_3 = \frac{P_{XX,0}}{3 P_{XX,0} + P_{VV}}$, & $P_{XX,3}^+ = \frac{P_{VV} P_{XX,0}}{3 P_{XX,0} + P_{VV}}$

This pattern holds for all $k=1, 2, 3, \dots$ and so for an arbitrary $k=l$ the Kalman gain, and the posterior variance will be:

$$\boxed{K_l = \frac{P_{XX,0}}{l P_{XX,0} + P_{VV}}} \quad \text{and} \quad \boxed{P_{XX,l}^+ = \frac{P_{VV} P_{XX,0}}{l P_{XX,0} + P_{VV}}}$$