

Part I: We show that for x, z jointly Gaussian with mean and covariance

$$\begin{bmatrix} \mu_x \\ \mu_z \end{bmatrix} \quad \begin{bmatrix} \Sigma_x & \Sigma_{xz} \\ \Sigma_{zx} & \Sigma_z \end{bmatrix}$$

x conditioned on z is Gaussian, with conditional mean and conditional covariance

$$\mu_x^+ = \mu_x + \Sigma_{xz} \Sigma_z^{-1} (z - \mu_z) \quad \Sigma_x^+ = \Sigma_x + \Sigma_{xz} \Sigma_z^{-1} \Sigma_{zx}$$

Part II: We recall the update step for sequential Bayesian estimation

$$\underbrace{f(\mathbf{x}_n|\mathbf{y}_{1:n})}_{\text{Posterior pdf}} \propto \underbrace{f(\mathbf{y}_n|\mathbf{x}_n)}_{\text{Likelihood function}} \underbrace{f(\mathbf{x}_n|\mathbf{y}_{1:n-1})}_{\text{Predicted posterior pdf}}$$
$$= \frac{f(\mathbf{x}_n, \mathbf{y}_n|\mathbf{y}_{1:n-1})}{f(\mathbf{y}_n|\mathbf{y}_{1:n-1})}$$

and consider that conditioned on $\mathbf{y}_{1:n-1}$, \mathbf{x}_n and \mathbf{y}_n are jointly Gaussian with mean and covariance

$$\boldsymbol{\mu} = \begin{bmatrix} \boldsymbol{\mu}_x^- \\ \mathbf{H}_n \boldsymbol{\mu}_x^- \end{bmatrix} \quad \boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma}_{x_n}^- & \boldsymbol{\Sigma}_{x_n}^- \mathbf{H}_n^T \\ \mathbf{H}_n \boldsymbol{\Sigma}_{x_n}^- & \mathbf{H}_n \boldsymbol{\Sigma}_{x_n}^- \mathbf{H}_n^T + \boldsymbol{\Sigma}_{v_n} \end{bmatrix}$$

Now we directly obtain the expressions for the Kalman update step by using the result of Part I

$$\begin{bmatrix} I & -\Sigma_{xz}\Sigma_z^{-1} \\ 0 & I \end{bmatrix} \Sigma \begin{bmatrix} I & 0 \\ -\Sigma_z^{-1}\Sigma_{xz}^T & I \end{bmatrix} = \begin{bmatrix} \Sigma_x - \Sigma_{xz}\Sigma_z^{-1}\Sigma_{zx} & 0 \\ 0 & \Sigma_z \end{bmatrix}$$

$$\Sigma^{-1} = \begin{bmatrix} I & 0 \\ -\Sigma_z^{-1}\Sigma_{xz}^T & I \end{bmatrix} \begin{bmatrix} (\Sigma_x - \Sigma_{xz}\Sigma_z^{-1}\Sigma_{zx})^{-1} & 0 \\ 0 & \Sigma_z^{-1} \end{bmatrix} \begin{bmatrix} I & -\Sigma_{xz}\Sigma_z^{-1} \\ 0 & I \end{bmatrix}$$

$$\det \Sigma = \det(\Sigma_x - \Sigma_{xz}\Sigma_z^{-1}\Sigma_{zx}) \det \Sigma_z$$

$$\begin{aligned} & \begin{bmatrix} \boldsymbol{x}^T - \boldsymbol{\mu}_x^T & \boldsymbol{z}^T - \boldsymbol{\mu}_z^T \end{bmatrix} \boldsymbol{\Sigma}^{-1} \begin{bmatrix} \boldsymbol{x}^T - \boldsymbol{\mu}_x^T & \boldsymbol{z}^T - \boldsymbol{\mu}_z^T \end{bmatrix}^T \\ &= (\boldsymbol{x} - \boldsymbol{\mu}_x^+)^T (\boldsymbol{\Sigma}_x^+)^{-1} (\boldsymbol{x} - \boldsymbol{\mu}_x^+) + (\boldsymbol{z} - \boldsymbol{\mu}_z)^T \boldsymbol{\Sigma}_z^{-1} (\boldsymbol{z} - \boldsymbol{\mu}_z) \end{aligned}$$

$$\boldsymbol{\mu}_x^+ = \boldsymbol{\mu}_x + \boldsymbol{\Sigma}_{xz} \boldsymbol{\Sigma}_z^{-1} (\boldsymbol{z} - \boldsymbol{\mu}_z)$$

$$\boldsymbol{\Sigma}_x^+ = \boldsymbol{\Sigma}_x + \boldsymbol{\Sigma}_{xz} \boldsymbol{\Sigma}_z^{-1} \boldsymbol{\Sigma}_{zx}$$

$$\begin{aligned} f(\boldsymbol{x}|\boldsymbol{z}) &= \frac{f(\boldsymbol{x}, \boldsymbol{z})}{f(\boldsymbol{z})} \\ &= \frac{\sqrt{\det \boldsymbol{\Sigma}_z}}{\sqrt{(2\pi)^I \det \boldsymbol{\Sigma}}} \frac{\exp\left[-\frac{1}{2} \begin{bmatrix} \boldsymbol{x}^T - \boldsymbol{\mu}_x^T & \boldsymbol{z}^T - \boldsymbol{\mu}_z^T \end{bmatrix} \boldsymbol{\Sigma}^{-1} \begin{bmatrix} \boldsymbol{x}^T - \boldsymbol{\mu}_x^T & \boldsymbol{z}^T - \boldsymbol{\mu}_z^T \end{bmatrix}^T\right]}{\exp\left[-\frac{1}{2} (\boldsymbol{z} - \boldsymbol{\mu}_z)^T \boldsymbol{\Sigma}_z^{-1} (\boldsymbol{z} - \boldsymbol{\mu}_z)\right]} \\ &= \frac{1}{\sqrt{(2\pi)^I \det \boldsymbol{\Sigma}_x^+}} \exp\left[-\frac{1}{2} (\boldsymbol{x} - \boldsymbol{\mu}_x^+)^T (\boldsymbol{\Sigma}_x^+)^{-1} (\boldsymbol{x} - \boldsymbol{\mu}_x^+)\right] \end{aligned}$$