

$$1. \quad z = Ax + By + c$$

$$A + B$$

$$E[z] = \bar{z} = E[Ax + By + c]$$

$$= E[Ax] + E[By] + E[c]$$

$$\bar{z} = A\bar{x} + B\bar{y} + c$$

$$\begin{aligned} & (\Gamma x)^T \\ & = x^T \Gamma^T \end{aligned}$$

$$\text{Cov}(z) = E[(z - \bar{z})(z - \bar{z})^T]$$

$$= E[(Ax + By + c - A\bar{x} - B\bar{y} - c)(Ax + By + c - A\bar{x} - B\bar{y} - c)^T]$$

$$= E[(A(x - \bar{x}) + B(y - \bar{y})) (A(x - \bar{x}) + B(y - \bar{y}))^T]$$

$$= E[(A(x - \bar{x}) + B(y - \bar{y})) ((x - \bar{x})^T A^T + (y - \bar{y})^T B^T)]$$

$$= E[A(x - \bar{x})(x - \bar{x})^T A^T + A(x - \bar{x})(y - \bar{y})^T B^T + B(y - \bar{y})(x - \bar{x})^T A^T + B(y - \bar{y})(y - \bar{y})^T B^T]$$

$$= E[A(x - \bar{x})(x - \bar{x})^T A^T] + E[A(x - \bar{x})(y - \bar{y})^T B^T] + E[B(y - \bar{y})(x - \bar{x})^T A^T] + E[B(y - \bar{y})(y - \bar{y})^T B^T]$$

$$= AE[(x - \bar{x})(x - \bar{x})^T]A^T + AE[(x - \bar{x})(y - \bar{y})^T]B^T + BE[(y - \bar{y})(x - \bar{x})^T]A^T + BE[(y - \bar{y})(y - \bar{y})^T]B^T$$

$$\text{Cov}(z) = AP_{xx}A^T + AP_{xy}B^T + BP_{yx}A^T + BP_{yy}B^T$$

2.) Dimension of A, B, c

$$A : n_z \times n_x$$

$$B : n_z \times n_y$$

$$c : n_z \times 1$$

$$\begin{aligned} & \underline{n_z \times n_z} \times \underline{n_x \times 1} \\ & \underline{n_z \times n_x} \times \underline{n_y \times 1} \\ & z = Ax + By + c \end{aligned}$$

$$n_z \times 1$$

$$n_x \times 1$$

## Exercise 2.

$$x_{k+1} = x_k + v_k \Delta t_k \cos(\theta_k) \leftarrow$$

$$y_{k+1} = y_k + v_k \Delta t_k \sin(\theta_k) \leftarrow$$

$$\theta_{k+1} = \theta_k + \frac{\Delta t_k v_k}{L} \tan(\phi_k)$$

$$v_{k+1} = v_k$$

$$\phi_{k+1} = \phi_k$$

$$x_k = \begin{bmatrix} x_k \\ y_k \\ \theta_k \\ v_k \\ \phi_k \end{bmatrix}$$

$$x_{k+1} = f(x_k, t_k)$$

$f$  is a vector valued function.

$$\frac{\partial f}{\partial x} \Big|_{x=x_k} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \frac{\partial f_1}{\partial x_3} & \frac{\partial f_1}{\partial x_4} & \frac{\partial f_1}{\partial x_5} \\ \frac{\partial f_2}{\partial x_1} & \dots & \dots & \dots & \dots \\ \vdots & & & & \\ \frac{\partial f_5}{\partial x_1} & \frac{\partial f_5}{\partial x_2} & \dots & \dots & \dots \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 0 & -v_k \Delta t_k \sin(\theta_k) & \Delta t_k \cos(\theta_k) & 0 \\ 0 & 1 & v_k \Delta t_k \cos(\theta_k) & \Delta t_k \sin(\theta_k) & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$f \quad \bar{x}_k = E[x_k]$$

Extended Kalman Filter.

$$f(x_k, \dots) = f(\bar{x}_k, \dots) + \frac{\partial f}{\partial x} \Big|_{x=\bar{x}_k} (x_k - \bar{x}_k) +$$

$$x_{k+1} = f(x_k, \dots) = f(\bar{x}_k) + J (x_k - \bar{x}_k)$$

$$\text{cov}(x_{k+1})$$

$$x_{k+1} = f(\bar{x}_k) + J x_k - J \bar{x}_k$$

$$\text{cov}(x_k) = P_{x_k x_k}$$

$$x_{k+1} = c + J x_k$$

$$\text{cov}(x_{k+1}) = J P_{x_k x_k} J^T$$

$$\int p(x_k | x_{k-1}) p(x_{k-1} | x_{k-2}) dx_{k-1} = p(x_k | x_{k-2})$$

$$p(x_k, x_{k-1}, x_{k-2}) = \underbrace{p(x_k | x_{k-1}, x_{k-2})}_{\downarrow} p(x_{k-1}, x_{k-2})$$

$$= p(x_k | x_{k-1}) p(x_{k-1}, x_{k-2})$$

$$p(x_k, x_{k-1}, x_{k-2}) = p(x_k | x_{k-1}) p(x_{k-1} | x_{k-2}) p(x_{k-2})$$

$$\int \underbrace{p(x_k, x_{k-1}, x_{k-2})}_{\downarrow} dx_{k-1} = \int p(x_k | x_{k-1}) p(x_{k-1} | x_{k-2}) p(x_{k-2}) dx_{k-1}$$

$$\underbrace{p(x_k, x_{k-2})}_{\downarrow} = \int p(x_k | x_{k-1}) p(x_{k-1} | x_{k-2}) p(x_{k-2}) dx_{k-1}$$

so yes:

$$p(x_k | x_{k-2}) p(x_{k-2}) = \int p(x_k | x_{k-1}) p(x_{k-1} | x_{k-2}) p(x_{k-2}) dx_{k-1}$$

$$p(x_k | x_{k-2}) \cancel{p(x_{k-2})} = \cancel{p(x_{k-2})} \int p(x_k | x_{k-1}) p(x_{k-1} | x_{k-2}) dx_{k-1}$$

$$\rho_{xy} = \frac{\text{cov}(x, y)}{\sigma_x \sigma_y}$$

$$= \frac{-3}{2 \times 3} = -0.5$$

$$\Rightarrow \rho_{xy} = 1$$

$$x = \alpha + \beta y$$

$\sigma_x$ : standard deviation.

$$\sigma_x = \sqrt{\text{variance}_x}$$