

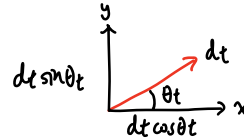
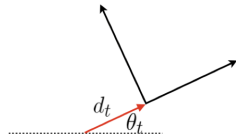
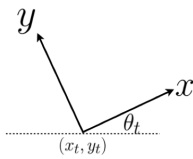
## 1 Theory

Given: 2D ground plane,  $t$

[move]  $d_t$  (meters in x-direction),  $\alpha_t$  (rotation in radian)

$p_t = [x_t \ y_t \ \theta_t]^T$ ,  $x_t + y_t$  2D coordinate of robot's position,  $\theta_t$  robot's orientation

1. Assume no noise or error, predict the next pose  $p_{t+1}$  ( $p_t, d_t, \alpha_t$ )



$$p_t = \begin{bmatrix} x_t \\ y_t \\ \theta_t \end{bmatrix} \xrightarrow{\text{[move]}} p_{t+1} = \begin{bmatrix} x_{t+1} \\ y_{t+1} \\ \theta_{t+1} \end{bmatrix} = \begin{bmatrix} x_t + d_t \cos(\theta_t) \\ y_t + d_t \sin(\theta_t) \\ \theta_t + \alpha_t \end{bmatrix}^*$$

2. Assume Gaussian errors ( $e_x \sim \mathcal{N}(0, \sigma_x^2)$ ,  $e_y \sim \mathcal{N}(0, \sigma_y^2)$ ,  $e_\alpha \sim \mathcal{N}(0, \sigma_\alpha^2)$ )

predict uncertainty of the robot at time  $t+1$  (Gaussian distribution with zero mean)

$$\Sigma_{t+1}^{\text{robot}} = G_t \Sigma_t G_t^T + R_t, \quad R_t = A_t \Sigma_t A_t^T \rightarrow \Sigma_{t+1}^{\text{robot}} = G_t \Sigma_t G_t^T + A_t \Sigma_t A_t^T$$

$$p_t = \begin{bmatrix} x_t \\ y_t \\ \theta_t \end{bmatrix}, \quad p_{t+1} = f(p_t, u_t, e) = \begin{bmatrix} x_t + (d_t + e_x) \cos(\theta_t) - e_y \sin(\theta_t) \\ y_t + (d_t + e_x) \sin(\theta_t) + e_y \cos(\theta_t) \\ \theta_t + \alpha_t + e_\alpha \end{bmatrix}, \quad \Sigma_t = \begin{bmatrix} \sigma_x^2 & 0 & 0 \\ 0 & \sigma_y^2 & 0 \\ 0 & 0 & \sigma_\alpha^2 \end{bmatrix}$$

$$G_t = \frac{\partial f}{\partial p_t} = \begin{bmatrix} 1 & 0 & -(d_t + e_x) \sin(\theta_t) - e_y \cos(\theta_t) \\ 0 & 1 & (d_t + e_x) \cos(\theta_t) - e_y \sin(\theta_t) \\ 0 & 0 & 1 \end{bmatrix}$$

$$G_t^T = \begin{bmatrix} 1 & 0 & -(d_t + e_x) \sin(\theta_t) - e_y \cos(\theta_t) \\ 0 & 1 & (d_t + e_x) \cos(\theta_t) - e_y \sin(\theta_t) \\ 0 & 0 & 1 \end{bmatrix}$$

$$A_t = \frac{\partial f}{\partial e} = \begin{bmatrix} \cos(\theta_t) & -\sin(\theta_t) & 0 \\ \sin(\theta_t) & \cos(\theta_t) & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad A_t^T = \begin{bmatrix} \cos(\theta_t) & \sin(\theta_t) & 0 \\ -\sin(\theta_t) & \cos(\theta_t) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

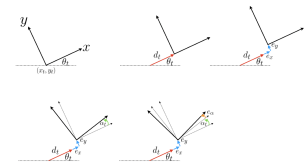


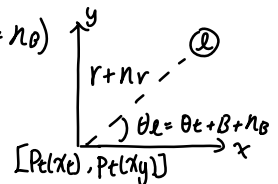
Figure 1: 0) Robot state; 1) robot moves  $d_t$  along its x-axis; 2) due to noise it shifted  $e_x$  and  $e_y$  along its x and y axes respectively; 3) robot rotates  $\alpha_t$  after shifting; 4) due to noise the rotation is disturbed by  $e_\alpha$ .

$$\Sigma_{t+1}^{mbot} = \begin{bmatrix} 1 & 0 & -(dx+lx)\sin(\theta_t) - ly\cos(\theta_t) \\ 0 & 1 & (dx+lx)\cos(\theta_t) - ly\sin(\theta_t) \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \sigma_x^2 & 0 & 0 \\ 0 & \sigma_y^2 & 0 \\ 0 & 0 & \sigma_a^2 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ -(dx+lx)\sin(\theta_t) - ly\cos(\theta_t) & (dx+lx)\cos(\theta_t) - ly\sin(\theta_t) & 1 \end{bmatrix} \\ + \begin{bmatrix} \cos(\theta_t) & -\sin(\theta_t) & 0 \\ \sin(\theta_t) & \cos(\theta_t) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \sigma_x^2 & 0 & 0 \\ 0 & \sigma_y^2 & 0 \\ 0 & 0 & \sigma_a^2 \end{bmatrix} \begin{bmatrix} \cos(\theta_t) & \sin(\theta_t) & 0 \\ -\sin(\theta_t) & \cos(\theta_t) & 0 \\ 0 & 0 & 1 \end{bmatrix}^{\#}$$

3. Consider landmarks  $l$  observed by laser sensor with measurement of bearing angle  $B \in [-\pi, \pi]$ , range  $r$ , with noise  $n_B \sim \mathcal{N}(0, \sigma_B^2)$  &  $n_r \sim \mathcal{N}(0, \sigma_r^2)$ .

Write down  $(l_x, l_y)$  in global coordinates as a function of  $P_t, B, r$ .

$$P_t = \begin{bmatrix} x_t \\ y_t \\ \theta_t \end{bmatrix}, \quad \begin{aligned} \theta_l &= P_t(\theta_t) + B + n_B \\ l_x &= P_t(x_t) + (r+n_r)\cos(\theta_l) \rightarrow l_x = P_t(x_t) + (r+n_r)\cos(P_t(\theta_t) + B + n_B) \\ l_y &= P_t(y_t) + (r+n_r)\sin(\theta_l) \rightarrow l_y = P_t(y_t) + (r+n_r)\sin(P_t(\theta_t) + B + n_B) \end{aligned}$$

$$\begin{bmatrix} l_x \\ l_y \end{bmatrix} = \begin{bmatrix} P_t(x_t) + (r+n_r)\cos(P_t(\theta_t) + B + n_B) \\ P_t(y_t) + (r+n_r)\sin(P_t(\theta_t) + B + n_B) \end{bmatrix}^{\#}$$


4. From 1.3, predict the measurement  $B$  &  $r$  based on  $l_x, l_y, P_t, n_r, n_B$

$$r+n_r = [(l_x - P_t(x_t))^2 + (l_y - P_t(y_t))^2]^{\frac{1}{2}} \rightarrow r = [(l_x - P_t(x_t))^2 + (l_y - P_t(y_t))^2]^{\frac{1}{2}} - n_r$$

$$B = \theta_l - P_t(\theta_t) - n_B, \quad \theta_l = \arctan\left(\frac{l_y - P_t(y_t)}{l_x - P_t(x_t)}\right), \quad B = \arctan\left(\frac{l_y - P_t(y_t)}{l_x - P_t(x_t)}\right) - P_t(\theta_t) - n_B$$

$$\begin{bmatrix} \hat{B} \\ \hat{r} \end{bmatrix} = \begin{bmatrix} \text{Warp2pi}(\text{np.arctan2}(l_y - P_t(y_t), l_x - P_t(x_t)) - P_t(\theta_t) - n_B) \\ [(l_x - P_t(x_t))^2 + (l_y - P_t(y_t))^2]^{\frac{1}{2}} - n_r \end{bmatrix}^{\#}$$

5. From 1.4, derive the analytical form of the measurement Jacobian  $H_p$  ( $2 \times 3$  matrix)

$$H_p = \frac{\partial h(\bar{u}_p)}{\partial \bar{x}_p} \rightarrow H_p = \begin{bmatrix} \frac{\partial h(B)}{\partial P_t(x_t)} & \frac{\partial h(B)}{\partial P_t(y_t)} & \frac{\partial h(B)}{\partial P_t(\theta_t)} \\ \frac{\partial h(r)}{\partial P_t(x_t)} & \frac{\partial h(r)}{\partial P_t(y_t)} & \frac{\partial h(r)}{\partial P_t(\theta_t)} \end{bmatrix},$$

$$B = \text{Warp2pi}(\text{np.arctan2}(l_y - P_t(y_t), l_x - P_t(x_t)) - P_t(\theta_t) - n_B) = \arctan\left(\frac{l_y - P_t(y_t)}{l_x - P_t(x_t)}\right) - P_t(\theta_t) - n_B$$

$$r = [(l_x - P_t(x_t))^2 + (l_y - P_t(y_t))^2]^{\frac{1}{2}} - n_r$$

$$H_p = \begin{bmatrix} \frac{-l_y + P_t(y_t)}{(l_x - P_t(x_t))^2 + (l_y - P_t(y_t))^2} & \frac{l_x - P_t(x_t)}{(l_x - P_t(x_t))^2 + (l_y - P_t(y_t))^2} & -1 \\ \frac{-l_x + P_t(x_t)}{\sqrt{(l_x - P_t(x_t))^2 + (l_y - P_t(y_t))^2}} & \frac{-l_y + P_t(y_t)}{\sqrt{(l_x - P_t(x_t))^2 + (l_y - P_t(y_t))^2}} & 0 \end{bmatrix}^{\#}$$

$\frac{d}{dx}(\arctan(\frac{y}{x})) = -\frac{y}{y^2+x^2}$   
 $\frac{d}{dy}(\arctan(\frac{y}{x})) = \frac{x}{y^2+x^2}$

$l_x - P_t(x_t) \cdot (-1)$   
 $l_y - P_t(y_t) \cdot (-1)$

6. Derive the analytical form of the measurement Jacobian  $H_e$  ( $2 \times 2$  matrix)

$$H_e = \begin{bmatrix} \frac{\partial h(B)}{\partial l_x} & \frac{\partial h(B)}{\partial l_y} \\ \frac{\partial h(r)}{\partial l_x} & \frac{\partial h(r)}{\partial l_y} \end{bmatrix}, \quad \begin{aligned} B &= \arctan\left(\frac{l_y - p_t(y_t)}{l_x - p_t(x_t)}\right) - p_t(\theta_t) - n_B \\ r &= [(l_x - p_t(x_t))^2 + (l_y - p_t(y_t))^2]^{\frac{1}{2}} - n_r \end{aligned}$$

$$H_e = \begin{bmatrix} \frac{-l_y + p_t(y_t)}{(l_x - p_t(x_t))^2 + (l_y - p_t(y_t))^2} & \frac{l_x - p_t(x_t)}{(l_x - p_t(x_t))^2 + (l_y - p_t(y_t))^2} \\ \frac{-l_x + p_t(x_t)}{\sqrt{(l_x - p_t(x_t))^2 + (l_y - p_t(y_t))^2}} & \frac{-l_y + p_t(y_t)}{\sqrt{(l_x - p_t(x_t))^2 + (l_y - p_t(y_t))^2}} \end{bmatrix} \#$$

$\frac{d}{dx}(\arctan(\frac{y}{x})) = -\frac{y}{y^2 + x^2}$   
 $\frac{d}{dy}(\arctan(\frac{y}{x})) = \frac{x}{y^2 + x^2}$   
 $l_x - p_t(x_t) \cdot (-1)$   
 $l_y - p_t(y_t) \cdot (-1)$

Due to the independence assumption in EKF-SLAM, we do not need to calculate the measurement Jacobian with respect to other landmarks except for itself. Measurements from different landmarks are conditionally independent from each other.