Particle Localization

→ don't use known locations

Scenario

Observations $\begin{cases} \Delta\rho \\ \Delta\theta \end{cases}$

2D landmarks ⌣ We will also perform the data association!

Map → 2D points

Domains

- state space: $X_t = [R_t \mid t_t] \in SE(3)$ → $X_t = \begin{pmatrix} x_t \\ y_t \\ \theta_t \end{pmatrix} \in \mathbb{R}^3$ integrated motion in time
  - ↑ in PF, not actually necessary to be $\mathbb{R}^3$ → unlike Gaussian that we begin a vector for μ and a matrix for covariance
- space controls:

$$u_t = \begin{pmatrix} \Delta t\, v_t \\ \Delta\, w_t \end{pmatrix} = \begin{bmatrix} u_t^1 \\ u_t^2 \end{bmatrix} \in \mathbb{R}^2$$

- observation space:

$$z_t^{[i]} = \begin{pmatrix} x_t^{[i]} \\ y_t^{[i]} \end{pmatrix} \in \mathbb{R}^2$$

transition ⊕ observation models → stay the same

Control Noise → different than before

$$m_{u,t} \sim \begin{pmatrix} a_1 \|u_t^2\| \cdot U(-0.5, 0.5) \\ a_2 \|u_t^2\| \cdot U(-0.5, 0.5) \end{pmatrix}$$

$p(z_t^{[i]} \mid x_t) \propto \exp$

↑

ONLY TO SIMPLIFY

(but we can put any distribution / "piece of code")

PROJECT ⟶ particles die time due to speed our error

↙

NOT NECESSARILY A BAD THING

↳ we calculate then may of multi-hypotheses of where the robot may be!

example → only applied it GATTING (take closest landmark if distance lower than certain measurement)

ℓ miss ≈ regularization term

NOTE: in this specific problem, we will start from uniform belief and then converge to Gaussians

indices sampled = # indices from the previous step!