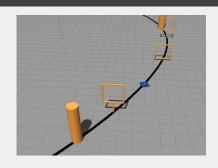
## **AUTONOMOUS MOBILE ROBOTICS**

**ROBOT LOCALIZATION** 

GEESARA KULATHUNGA

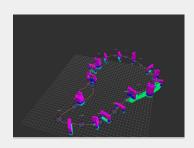
**OCTOBER 5, 2022** 



# **ROBOT LOCALIZATION**

### **CONTENTS**

- A Taxonomy of Localization Problems
- Markov localization
  - ► Environment Sensing
  - ► Motion in the Environment
  - ► Localization in the Environment
- EKF localization with known correspondence
- Particle filter localization with known correspondence



### A TAXONOMY OF LOCALIZATION PROBLEMS

- Local Versus Global
  - Position tracking where initial position is known (local tracking)
  - Robot position is unknown, initially has to assume that pose of robot is uniform in the most of the cases (global)
  - Kidnapped robot problem; anytime robot can be moved to different location without prior knowledge (global)
- Static Versus Dynamic Environments
  - In static environment, robot's pose is only the variable quantity
  - Dynamics environment, whole configuration can be changed over the time
- Passive Versus Active Approaches
  - ► In passive, robot is controlled through some other means, robot motion is not aiming at facilitating localization

### MARKOV LOCALIZATION

# Algorithm Markov\_localization( $bel(x_{t-1}), u_t, z_t, m$ ): for all $x_t$ do $\overline{bel}(x_t) = \int p(x_t \mid u_t, x_{t-1}, m) \ bel(x_{t-1}) \ dx$ $bel(x_t) = \eta \ p(z_t \mid x_t, m) \ \overline{bel}(x_t)$ endfor $return \ bel(x_t)$

- Markov localization is derived from the algorithm Bayes filter
- However, it requires information about the map to estimate the measurement model  $p(z_t|x_t, m)$
- Markov localization addresses the global localization, the position tracking, and the kidnapped robot problem in static environment

### MARKOV LOCALIZATION

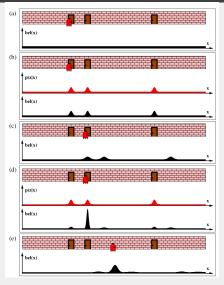


Illustration of the Markov localization algorithm, Thrun, Sebastian. "Probabilistic robotics." Communications of the ACM 45.3 (2002): 52-57.

### **GRID-BASED LOCALIZATION**



.02	.05	.05	.05
.02	.05	.18	.05
.05	.05	.18	.05
.05	.05	.05	.05

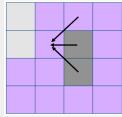
robot initial belief

- The map is discretized into 16 cells, each of which has an area of 1m²
- Consider the initial belief of the robot position is given
- If control command to the robot is given by  $\delta x$ ,  $\delta y$  = -1.0 cells, 0.0 cells, what is the probability that robot be in the position (2,3)
- The following outcomes are possible when the control command is being applied

.00	.00	.00	<u>(Δx,Δy)</u>	.00	.20	.00
.00	.00	1.0		.00	.50	.10
.00	.00	.00		.00	.20	.00

### **GRID-BASED LOCALIZATION**

■ How many possible ways to get to (2,3)?



Prediction step

$$p(x_k|z_{1:k-1},u_{1:k-1}) = \sum_{x_{k-1}\in X} p(x_k|x_{k-1},u_{k-1})p(x_{k-1}|z_{1:k-1},u_{0:k-1})$$
(1)

Correction step

$$p(x_k|z_{1:k},u_{0:k-1}) = \frac{p(z_k|x_k)p(x_k|z_{1:k-1},u_{0:k-1})}{p(z_k|z_{1:k-1},u_{0:k-1})}$$
(2)

, where

$$p(z_k|z_{1:k-1},u_{0:k-1}) = \sum_{x_k \in X} p(z_k|x_k)p(x_k|z_{1:k-1},u_{0:k-1})$$

### **GRID-BASED LOCALIZATION**

■ How many possible ways to get to (2,3)?



► Prediction step

$$p(x_{i,t}|u_t) = \sum_{j=1}^{n} p(x_{i,t}|x_{j,t-1}, u_t) p(x_{j,t-1})$$

$$= p(x_{i,t} = (2,3)|x_{j,t-1} = (3,3), u_t = (-1,0)) p(x_{j,t-1} = (3,3))$$

$$+ p(x_{i,t} = (2,3)|x_{j,t-1} = (2,3), u_t = (-1,0)) p(x_{j,t-1} = (2,3))$$

$$+ p(x_{i,t} = (2,3)|x_{j,t-1} = (3,2), u_t = (-1,0)) p(x_{j,t-1} = (3,2))$$

$$+ p(x_{i,t} = (2,3)|x_{j,t-1} = (3,4), u_t = (-1,0)) p(x_{j,t-1} = (3,4))$$

$$= 0.5 \cdot 0.18 + 0.1 \cdot 0.05 + 0.18 \cdot 0.2 + 0.05 \cdot 0.2$$

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