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ROBOT LOCALIZATION

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Contents

Introduction

Mapping and Localization

Autonomous mobile robots are able to navigate through the environment.

In order to perform navigation, robots first need to answer two questions:

- Mapping - "How does the world look like?"
- Localization - "Where am I in this world?"

$\rightarrow$ Today's focus: Localization.

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What is Localization?

- Given: Map (model) of the environment.
- Task: Estimate the robot pose relative to the given map.

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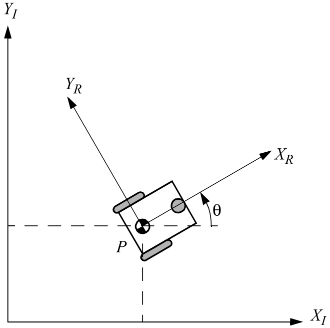
What is Localization?

- Given: Map (model) of the environment.
- Task: Estimate the robot pose relative to the given map.
- **Robot pose:**
  - position (x_R, y_R)
  - orientation θ.



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Why Do Robots Need Localization?

Autonomous mobile robots need to localize into the world in order to perform the following tasks:

- Map the environment.
- Plan a path to a goal position.
- Navigate autonomously.

Sensors for Localization

Sensors for Localization

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Proprioceptive Sensors

- Wheel encoder → Wheel odometry
- Inertial Measurement Unit (IMU) → Inertial odometry

Exteroceptive Sensors

- Camera → Visual odometry
- Laser scanner, sonar → Scan matching

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Proprioceptive Sensors

1. Wheel Odometry (Dead Reckoning)

- Wheel encoder: count the wheel rotations over time.

Pros:

- High frequency measurements.
- Cheap and lightweight sensor.

Cons:

- Drift due to wheel slippage.
- Only reliable on short term.

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Proprioceptive Sensors

2. Inertial Odometry

- Inertial Measurement Unit (IMU): integrate the linear acceleration and angular velocity measurements to obtain robot position and orientation.

Pros:

- High frequency measurements.
- Low processing time.

Cons:

- Drift due to time integration.
- Only reliable on short term.

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Exteroceptive Sensors

3. Visual Odometry

- Estimate robot pose use two (consecutive) camera images.
- Monocular / stereo camera.
- Direct / feature-based methods.

Pros:

- Provides rich information.
- Cheap and accessible sensor.

Cons:

- Sensitive to varying light conditions.
- Fails for fast camera motions.

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Exteroceptive Sensors

4. Lidar-based Localization

- Laser scanner: perform scan matching to find the transformation between two point clouds. $\rightarrow$ See lecture on Robot Mapping.

Pros:

- Provides depth information.
- Robust under various world conditions.

Cons:

- Reduced frequency.
- Limited range.

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External Sensors

5. Direct Localization

- Global Navigation Satellite System GNSS (e.g. GPS).
- Triangulation (camera motion tracking system).
- Trilateration (external beacons with known position).

Pros:

- Highly accurate measurements.
- Provide global localization.

Cons:

- GNSS signal obstructed by tall buildings or forests.
- Triangulation and trilateration require setup of the environment.

Algorithms for Probabilistic Localization

- Based on Bayesian statistics.
- Methods: Kalman filter, **particle filter (Monte Carlo Localization)**.
- Sensors measurements: wheel encoder, IMU, GPS, laser scanner, camera, etc.

Pros:

- Model sensor noise.
- Fuse multimodal sensor data.

Cons:

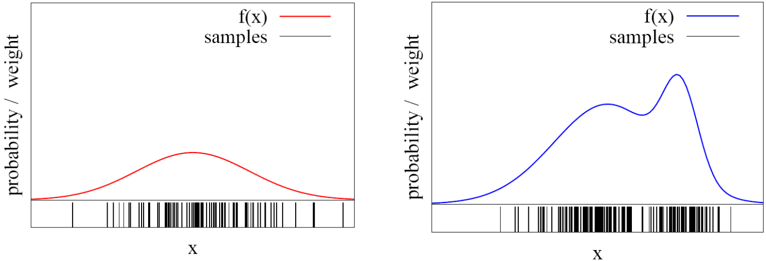
- Complex algorithms and models.
- Computationally expensive.

Particle Filter

Function Approximation

- Probabilistic method used for non-parametric **function approximation**.
- An arbitrary function can be described by a set of M **particles** at time t:

$$\mathcal{X}_t := \left\{ x_t^{(1)}, x_t^{(2)}, \ldots, x_t^{(M)} \right\}$$



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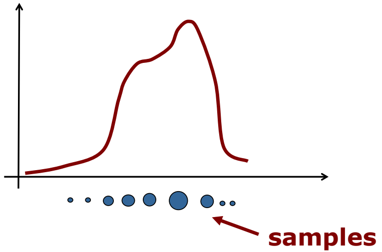
Particle Filter for Localization

- Definition: non-parametric, **recursive Bayes filter** that estimates a posterior distribution based on noisy measurements.
- In robot localization, every sample (particle) in the particle filter represents a hypothesis of the **robot position**.
- The more samples, the better the robot position estimate.



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Monte Carlo Localization

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Introduction

- Localization method using **particle filter** to represent the posterior distribution. (Fox et al., 1999)
- One of the most popular localization algorithms.
- Applicable to both local and global localization problems.
- Various extensions exist to address shortcomings.

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Prerequisites

- **Occupancy grid map** of the environment.
- **Wheel odometry** to estimate the robot motion model.
- **Laser scanner** sensor measurements.

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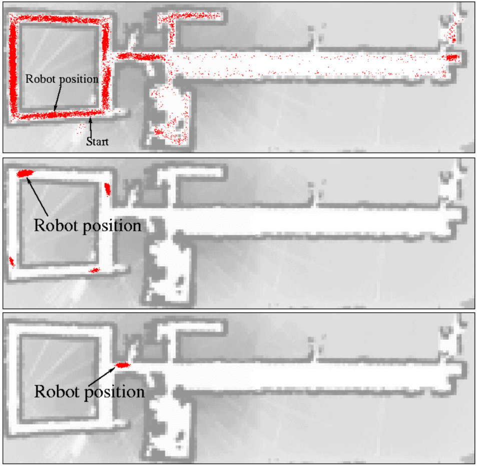

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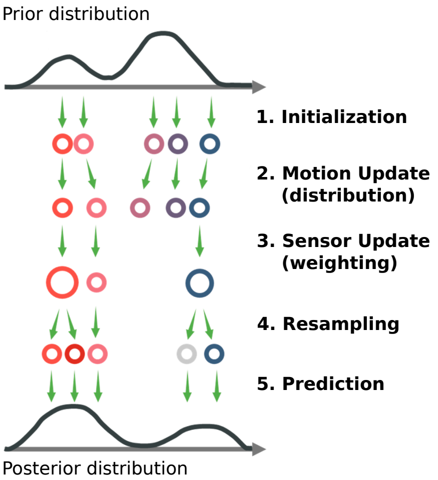
Monte Carlo Localization

Particle Filter Steps

1. Initialization: draw samples from prior distribution.
2. Motion Update: distribute samples according to the **motion model**.
3. Sensor Update: assign weights to particles based on **sensor model**.
4. Resampling: draw particles according to their weights.
5. Prediction: output the estimated posterior distribution.



Monte Carlo Localization

Parameters

$\mathcal{X}_{t-1}$ = set of particles at time $t-1$

u_t = wheel odometry at time t

z_t = laser scan at time t

m = occupancy grid map

M = number of particles

$x_t^{[m]}$ = particle m at time t

$w_t^{[m]}$ = weight of particle m at time t

Algorithm MCL$(\mathcal{X}_{t-1}, u_t, z_t, m)$**:**
$\quad \bar{\mathcal{X}}_t = \mathcal{X}_t = \emptyset$
$\quad$ for $m = 1$ to M do
$\quad\quad x_t^{[m]} =$ **sample_motion_model**$(u_t, x_{t-1}^{[m]})$
$\quad\quad w_t^{[m]} =$ **measurement_model**$(z_t, x_t^{[m]}, m)$
$\quad\quad \bar{\mathcal{X}}_t = \bar{\mathcal{X}}_t + \langle x_t^{[m]}, w_t^{[m]} \rangle$
$\quad$ endfor
$\quad$ for $m = 1$ to M do
$\quad\quad$ draw i with probability $\propto w_t^{[i]}$
$\quad\quad$ add $x_t^{[i]}$ to $\mathcal{X}_t$
$\quad$ endfor
$\quad$ return $\mathcal{X}_t$

resampling

Pseudocode of MCL algorithm.

Monte Carlo Localization

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sensor model

Pseudocode of MCL algorithm.

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Sensor Model

In order to use the laser scans for localization, we have to define the sensor model and take the possible measurement errors into account:

- z_hit: Beams reflected by obstacles.
- z_short: Beams reflected by persons / caused by crosstalk.
- z_rand: Random measurements.
- z_max: Maximum range measurements.

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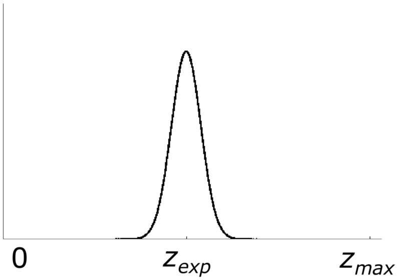
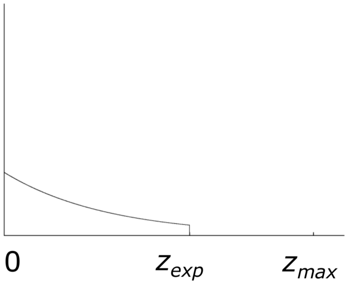
Measurement noise



$$P_{hit}(z \mid x, m) = \eta \frac{1}{\sqrt{2\pi b}} e^{-\frac{1}{2}\frac{(z - z_{exp})^2}{b}}$$

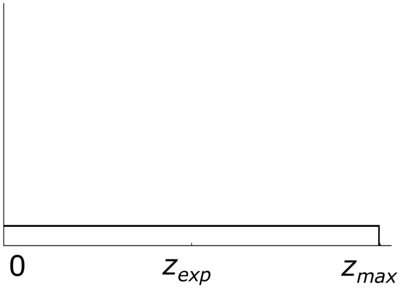
Unexpected obstacles



$$P_{unexp}(z \mid x, m) = \begin{Bmatrix} \eta \ \lambda \ e^{-\lambda z} & z < z_{exp} \\ 0 & otherwise \end{Bmatrix}$$

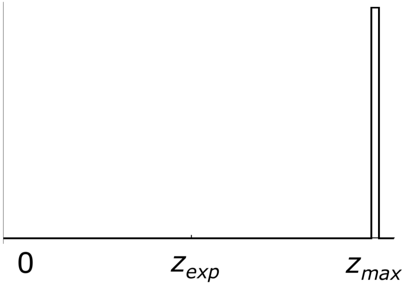
Monte Carlo Localization

Random measurement



$$P_{rand}(z \mid x, m) = \eta \frac{1}{z_{\max}}$$

Max range



$$P_{\max}(z|x,m) = \begin{cases} 1 & z = z_{\max} \\ 0 & \text{otherwise} \end{cases}$$

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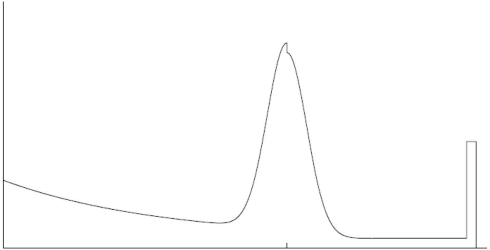
Sensor Model

- The overall probability is given by the sum of the 4 probabilities.
- The parameters α are scaling factors which sum up to 1.



$$P(z \mid x, m) = \begin{pmatrix} \alpha_{\text{hit}} \\ \alpha_{\text{unexp}} \\ \alpha_{\text{max}} \\ \alpha_{\text{rand}} \end{pmatrix}^T \cdot \begin{pmatrix} P_{\text{hit}}(z \mid x, m) \\ P_{\text{unexp}}(z \mid x, m) \\ P_{\text{max}}(z \mid x, m) \\ P_{\text{rand}}(z \mid x, m) \end{pmatrix}$$

Sensor model after including all 4 types of measurement errors.

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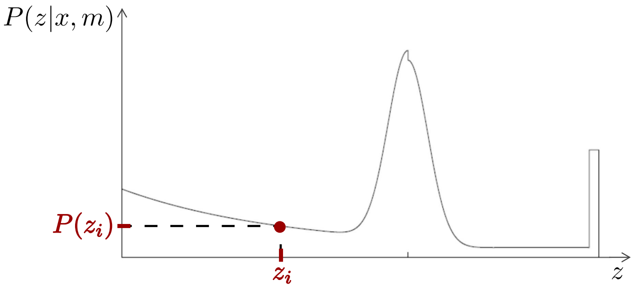
Sensor Model

- For every laser beam measurement z_i, look up its probability $P(z_i|x, m)$.
- The probability distribution of the measurement z is the product of all individual laser beam probabilities: $P(z|x, m) = \prod_i P(z_i|x, m)$.



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Monte Carlo Localization

Algorithm MCL$(\mathcal{X}_{t-1}, u_t, z_t, m)$**:**

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$w_t^{[m]} =$ **measurement_model**$(z_t, x_t^{[m]}, m)$ sensor model

$\bar{\mathcal{X}}_t = \bar{\mathcal{X}}_t + \langle x_t^{[m]}, w_t^{[m]} \rangle$

endfor

for $m = 1$ to M do

draw i with probability $\propto w_t^{[i]}$ resampling

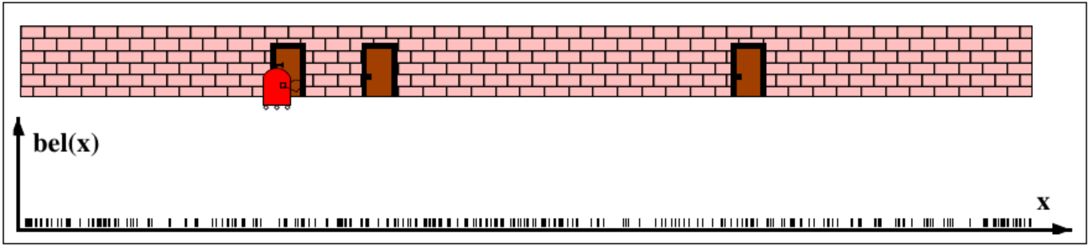
add $x_t^{[i]}$ to $\mathcal{X}_t$

endfor

return $\mathcal{X}_t$

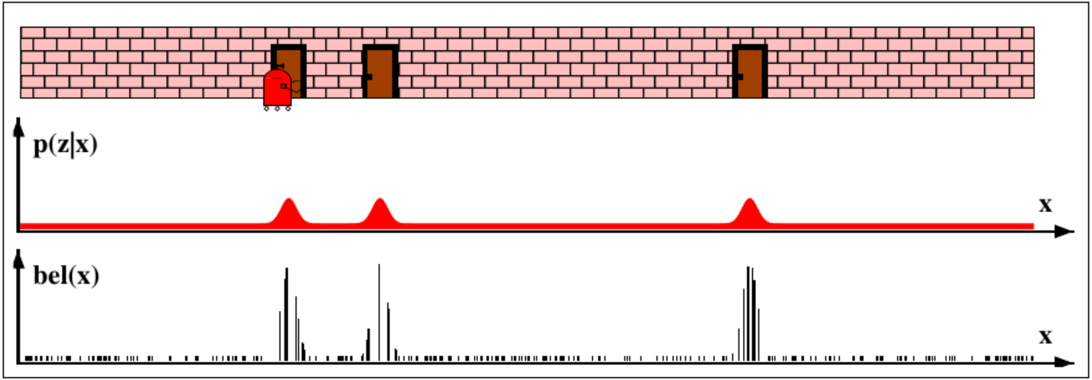
Pseudocode of MCL algorithm.

MCL Example (1)



Initialize by sampling poses from uniform distribution.

MCL Example (2)



Sensor update: assign importance weights to each particle.

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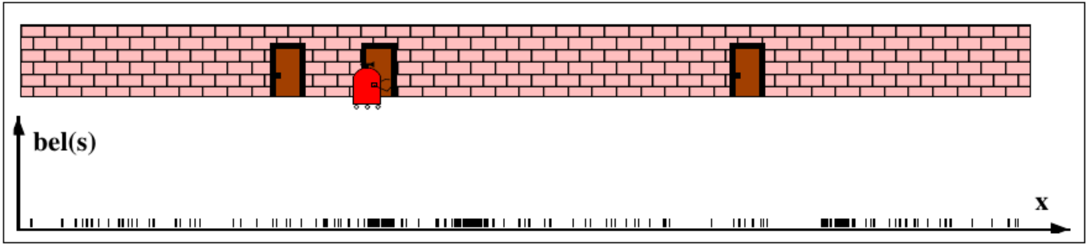
MCL Example (3)



Resample the particle set based on weights, then **motion update** (apply noisy motion transformation to each particle).

MCL Example (4)

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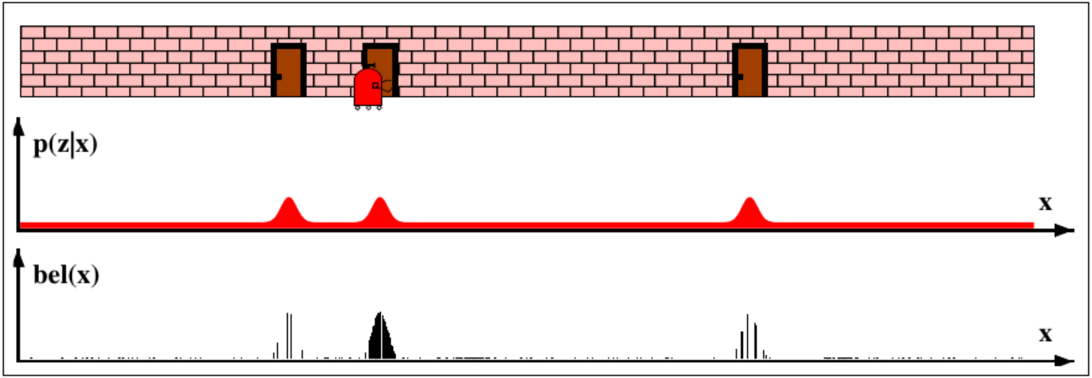

Next **sensor update**.

MCL Example (5)

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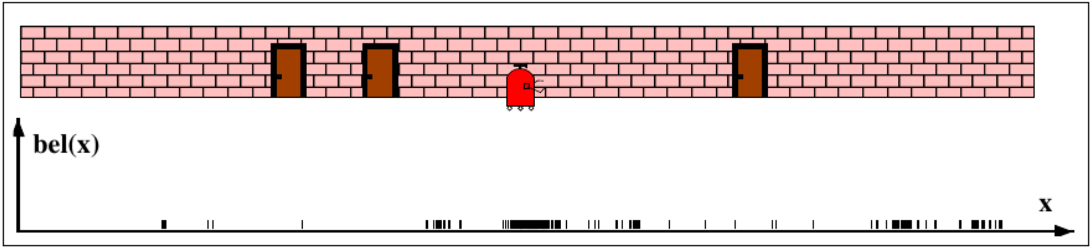

Resample and **motion update**.

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Monte Carlo Localization

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Pros

- Estimates any posterior distribution (i.e. not limited to Gaussian distribution).
- Able to cope with noisy sensor data and inaccurate odometry.
- Easy to implement.

Cons

- Large number of particles slows down localization.
- Requires large storage space.
- High computational resources.

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Further Problems

- We need to keep a random distribution throughout the state space by using a sufficient amount of particles.
- Without **addition of random particles**, MCL can fail if the particles converge to an incorrect pose.
- After all particles converged to the robot location they become redundant.
- Problematic for **high-dimensional spaces**, many particles slow down localization.

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Further Problems

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- Problematic for **high-dimensional spaces**, many particles slow down localization.

$\rightarrow$ Solution: **Adaptive** Monte Carlo Localization

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Concept

- The Adaptive MCL is a variant of the standard MCL algorithm. (Fox, 2002)
- It **dynamically adjusts the number of particles** in the filter based on the certainty of the robot localization.
- The number of particles is decreased when the position estimate has higher certainty (when particles converge to robot pose).
- Allows a trade-off between processing speed and localization accuracy.

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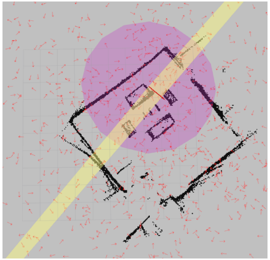
AMCL ROS Package

- We will use the amcl package from the ROS2 Navigation Stack.
- Parameters that can be configured:
  - Minimum and maximum number of particles.
  - Initial robot pose and covariance.
  - Laser scanner model parameters:
    - min/max range.
    - sensor model: z_hit, z_short, z_rand, z_max.
- Link: `https://navigation.ros.org/configuration/packages/configuring-amcl.html`

Particle Convergence

- Particles are initially spread out randomly over the entire map.
- Particles converge over time to the true robot location.
- The ellipses represent the uncertainty of the position and orientation estimates.



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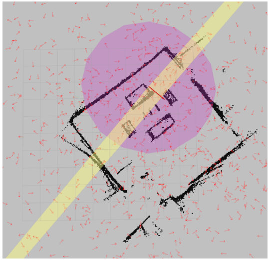

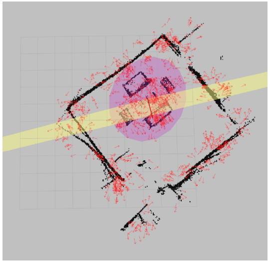

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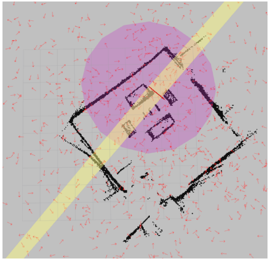

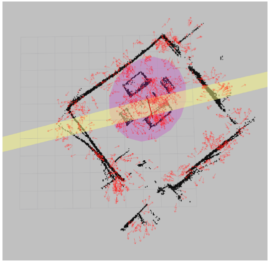

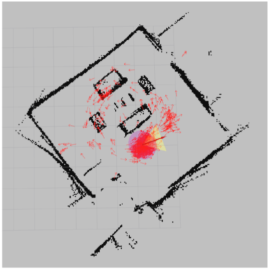

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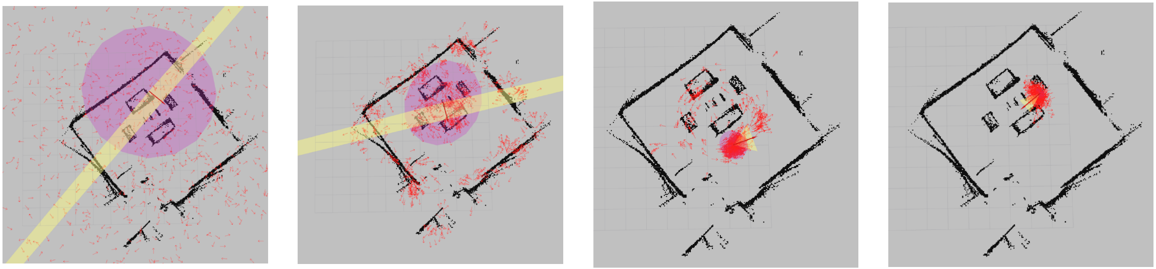

Challenges

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Sensor Errors

- All sensors have errors (noise, bias, limited resolution/range).
- Sensor models are not perfect.
- Constraints:
  - Cost.
  - Size/Weight/Power.
  - Measurement frequency.
  - Usability of sensors depends on environment.

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Global Localization

- Goal: estimate absolute robot position in the entire working space.
- Initial pose unknown (i.e. equally distributed over the map).
  $\rightarrow$ Determine robot pose under global uncertainty.
- Use sensor measurements to generate clusters of possible robot poses.
  $\rightarrow$ Hypotheses where the robot can be.
- Implement a strategy by which the robot can correctly eliminate all hypotheses except the right location (e.g. particle filter).

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Position Tracking

- Assume initially known starting position.
- Update the current pose based on the previous pose.
- Errors add up over multiple iterations.
- Can lead to localization drifts.

Kidnapped Robot Problem

- It occurs when the robot is displaced to an unknown location in the map.
- Localization sensors (eg. wheel encoder, laser scanner) not aware of kidnapping. $\rightarrow$ Localization fails.
- This problem needs to be first recognized and then handled.
- Solution: add a few random uniformly distributed samples in the particle filter to recover, otherwise the robot will keep resampling from the wrong distribution.

Conclusion

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Collaborative Localization

- In a multiagent system, robots can cooperate to improve their localization.
- Algorithm proposed by the Ben Gurion University of the Negev (Israel) in 2019:
  - Robots use **particle filter** for localization and **Extended Kalman Filter (EKF)** to track the other robots.
  - When two or more robots are in each others' field of view, they fuse their particle filters with a method called **Particles Intersection**. (Tslil and Carmi, 2018)
  - Localization package available in ROS: `http://wiki.ros.org/mcl_pi`.

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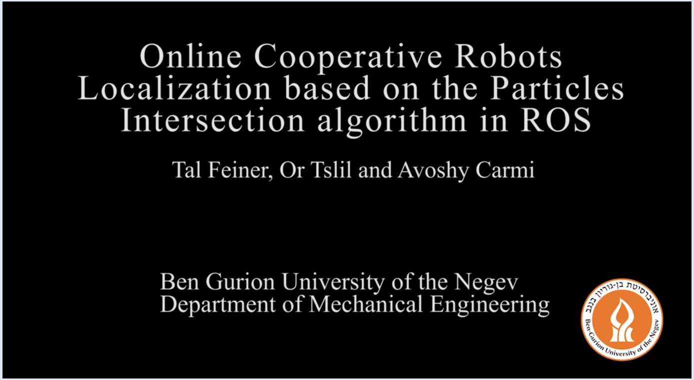
Collaborative Localization



Online Cooperative Robots Localization in ROS.
Source: `http://wiki.ros.org/mcl_pi`

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Summary

- Introduction to robot localization.
- Proprioceptive and exteroceptive sensors for localization.
- Particle filter for function approximation.
- Monte Carlo Localization & Adaptive MCL.
- Challenges (global localization, kidnapped robot problem).
- Collaborative localization.

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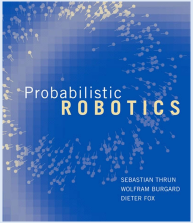
Additional Literature

Probabilistic Robotics, Thrun et al.

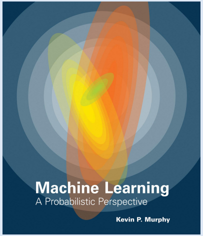
- Chapter 4.2: The Particle Filter.
- Chapter 8.3: MCL.



Source: `https://docs.ufpr.br/~danielsantos/ProbabilisticRobotics.pdf`

Machine Learning: A Probabilistic Perspective, Kevin P. Murphy

- Chapter 23.5: Particle filtering.



Source: `http://noiselab.ucsd.edu/ECE228/Murphy_Machine_Learning.pdf`

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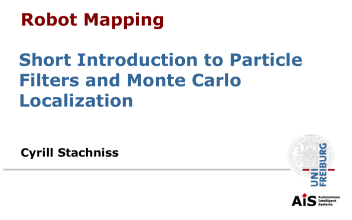
Additional Literature

Robot Mapping Course, Uni Freiburg

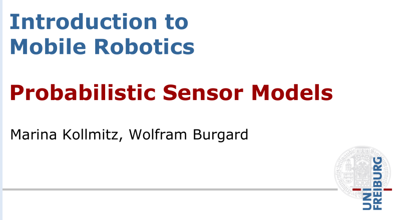
- Particle Filter and MCL.



Source: http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam09-particle-filter.pdf

Introduction to Mobile Robotics

- Probabilistic Sensor Models.



Source: http://ais.informatik.uni-freiburg.de/teaching/ss19/robotics/slides/07-sensor-models.pdf

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Fox, D. (2002). « KLD-Sampling: Adaptive Particle Filters ». In: *Advances in Neural Information Processing Systems*. Ed. by T. Dietterich, S. Becker, and Z. Ghahramani. Vol. 14. MIT Press.

Fox, D., Burgard, W., Dellaert, F., and Thrun, S. (1999). « Monte Carlo Localization: Efficient Position Estimation for Mobile Robots. ». In: *AAAI/IAAI*. Ed. by J. Hendler and D. Subramanian. AAAI Press / The MIT Press, pp. 343–349.

Tslil, O. and Carmi, A. (2018). « Information Fusion Using Particles Intersection ». In: *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 4269–4273.

Next: Path Planning.