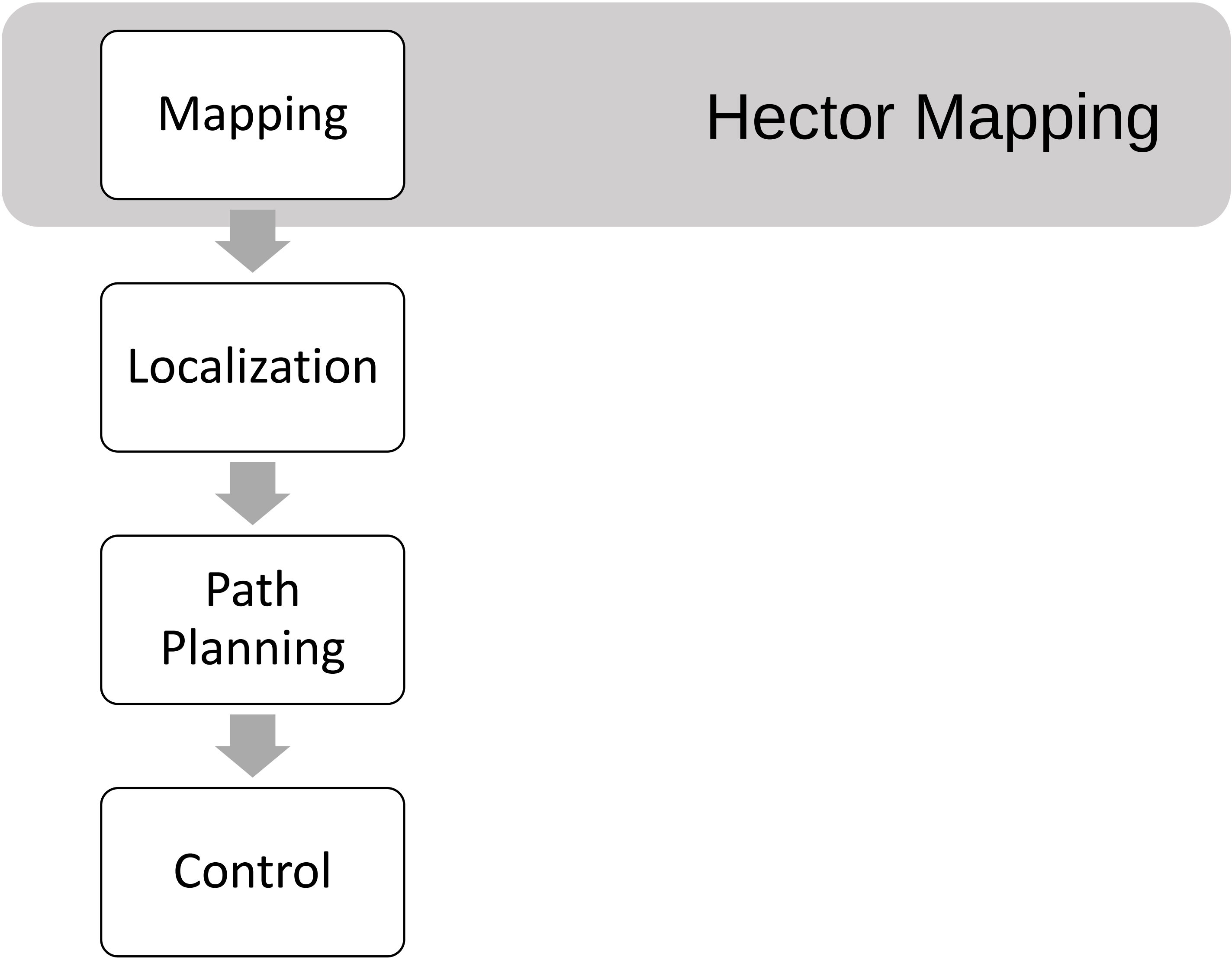
F1/10th Autonomous Racing

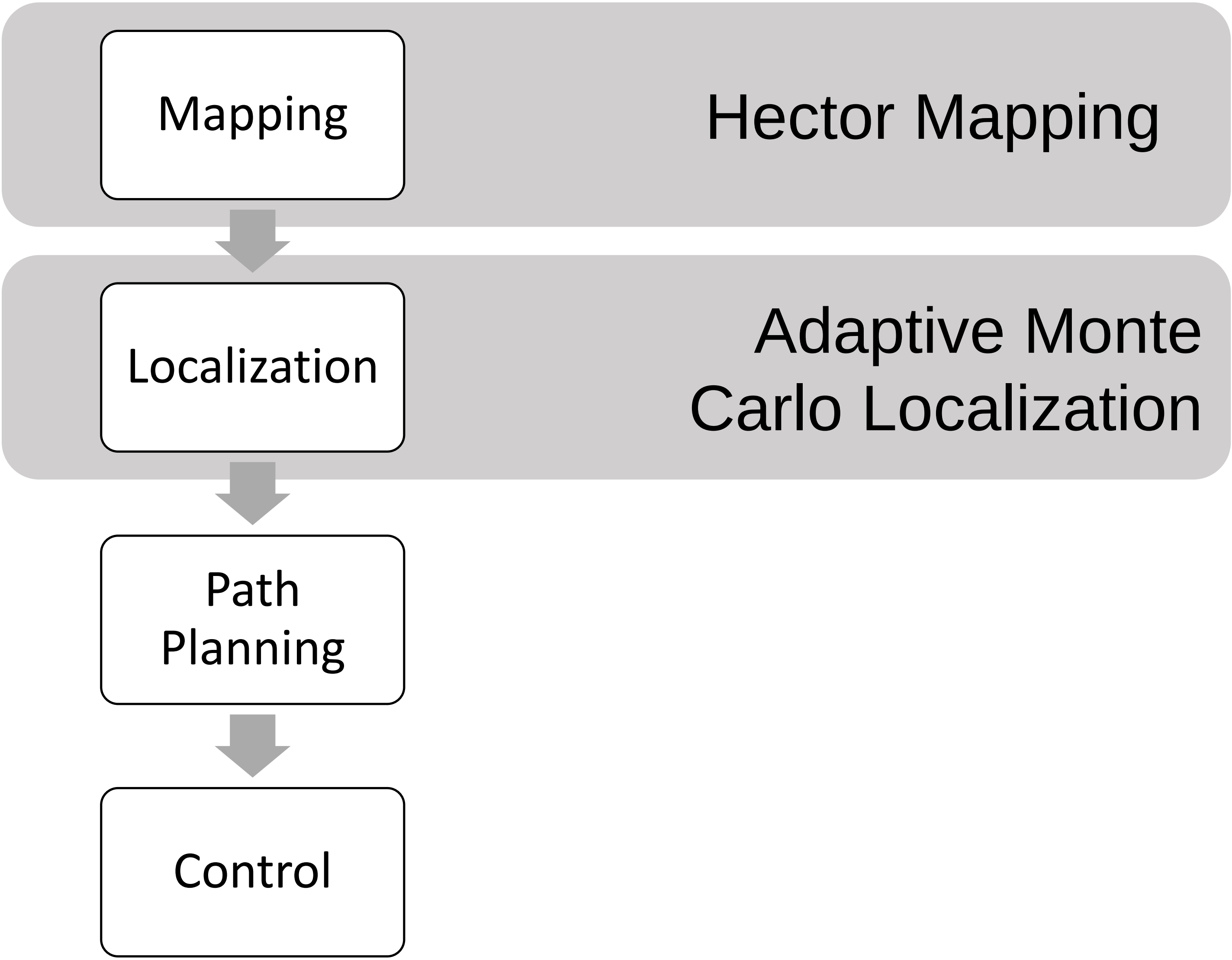
Localization

Nischal K N

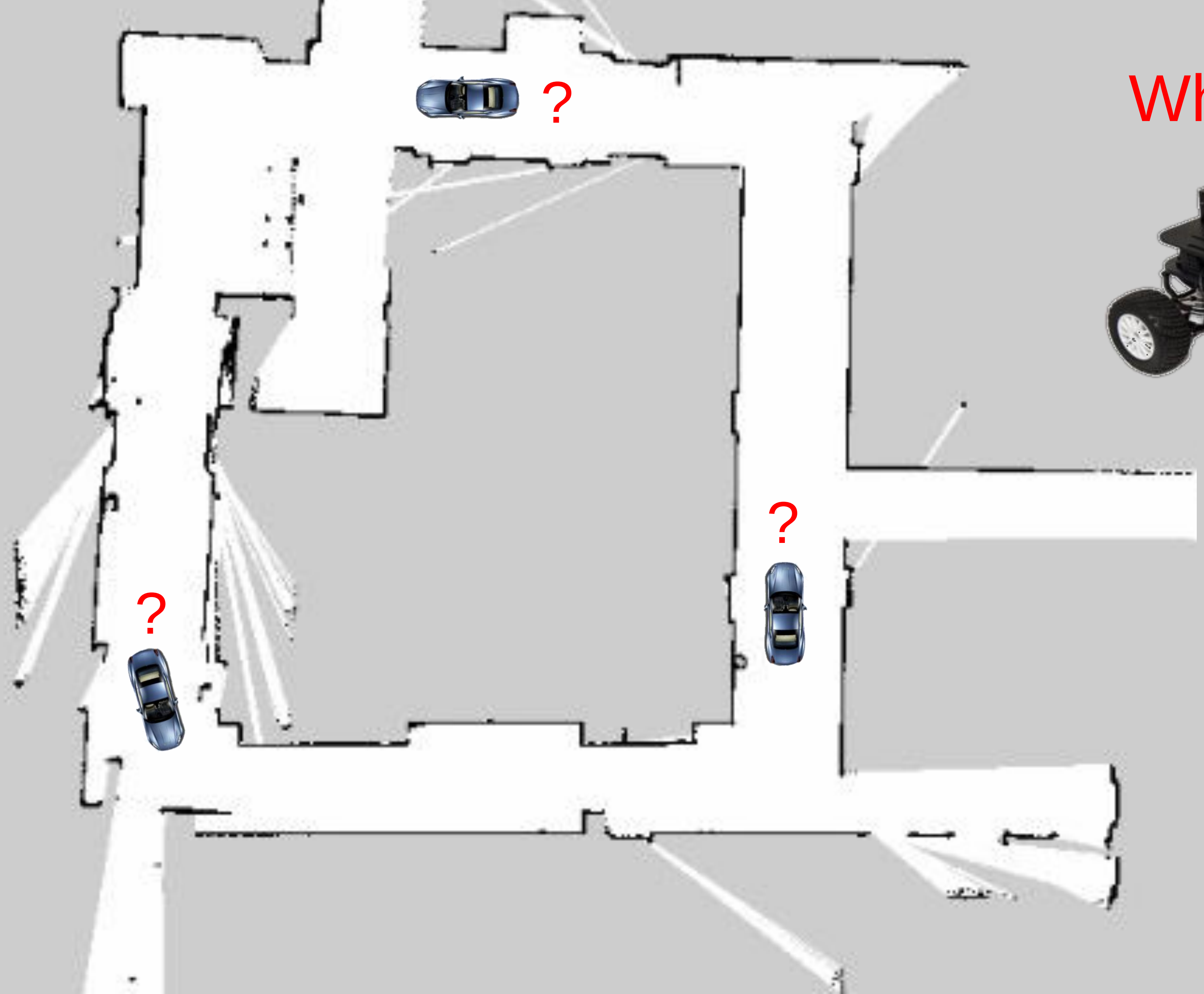
System Overview

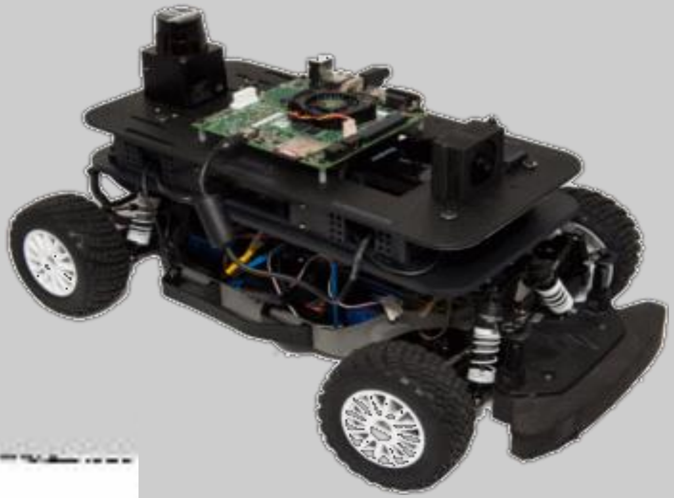


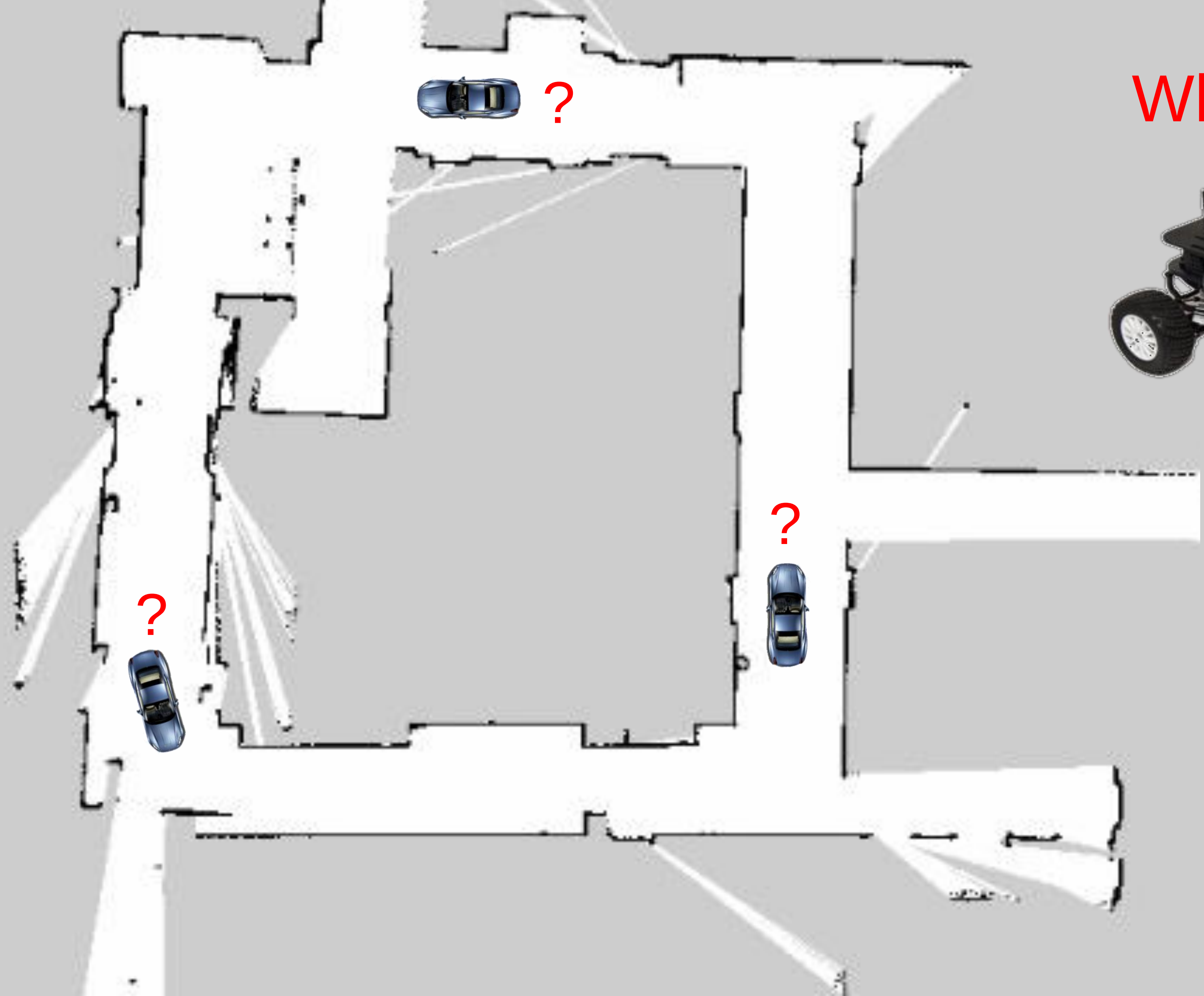
System Overview



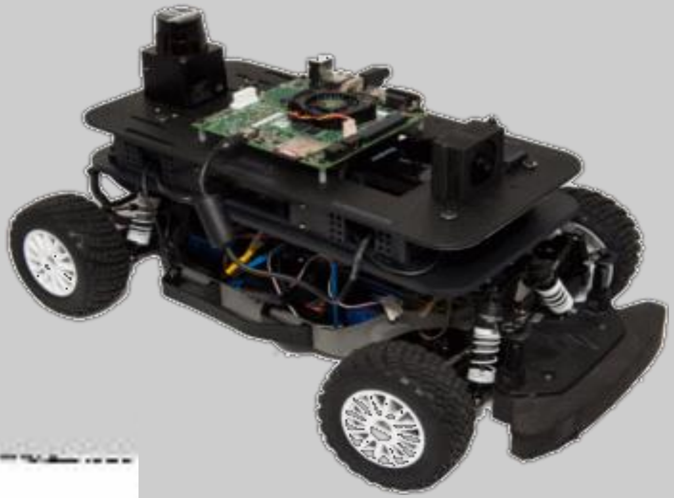
Where am I ???





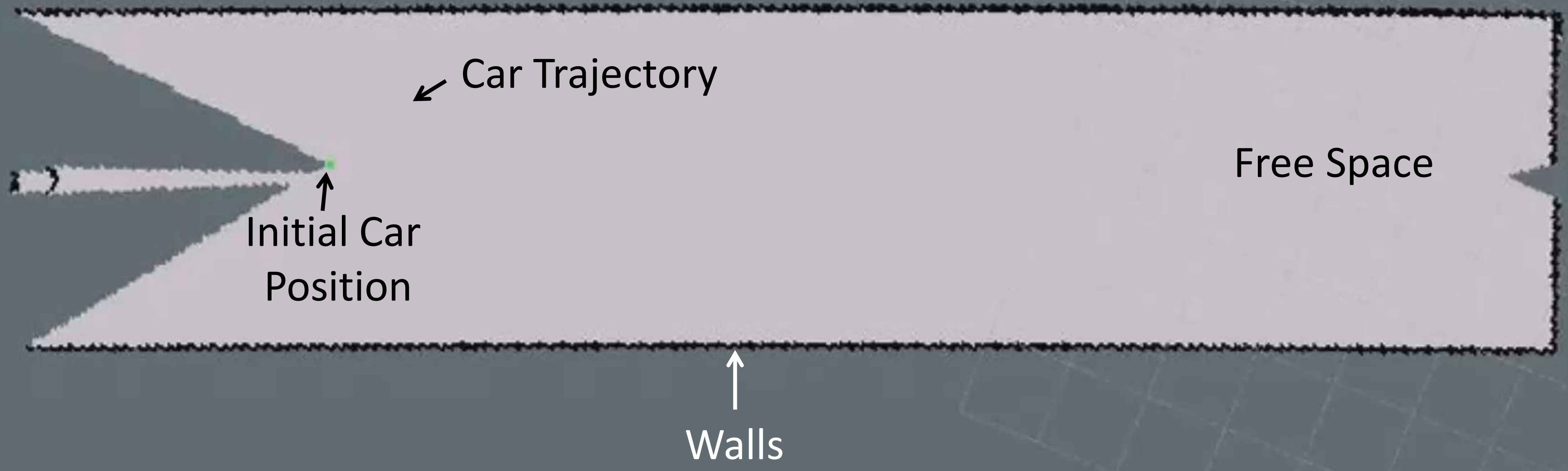


Where am I ???



Position &
Orientation

Localization using Odometry

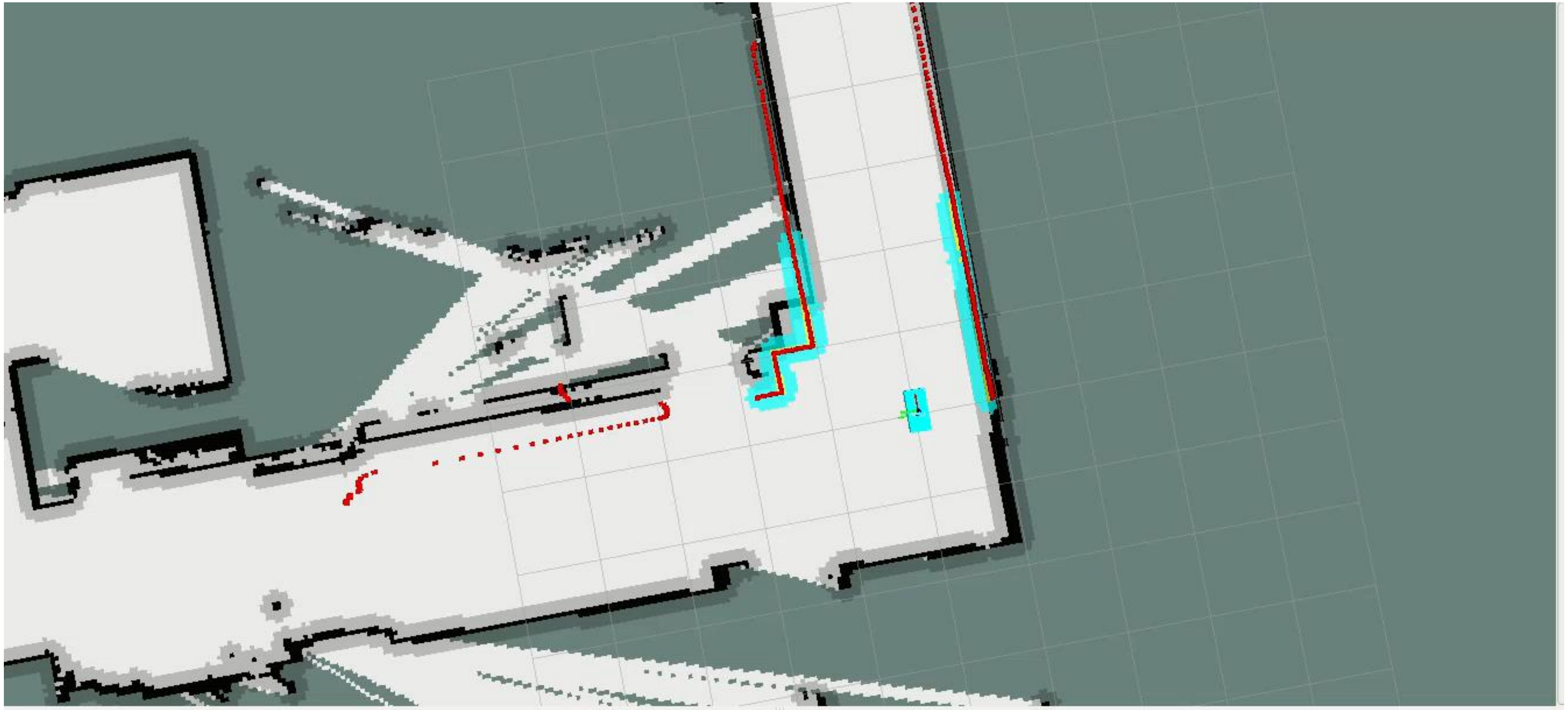


Drawbacks of Localization using Wheel Odometry

Wheel spin due to lack of traction

Drawbacks of Localization using Hector odometry

Failed scan matching due to lack of features



Issue

- A mechanism to compensate the mistakes committed by odometry
- A solution robust to compensate for lack of information on initial position

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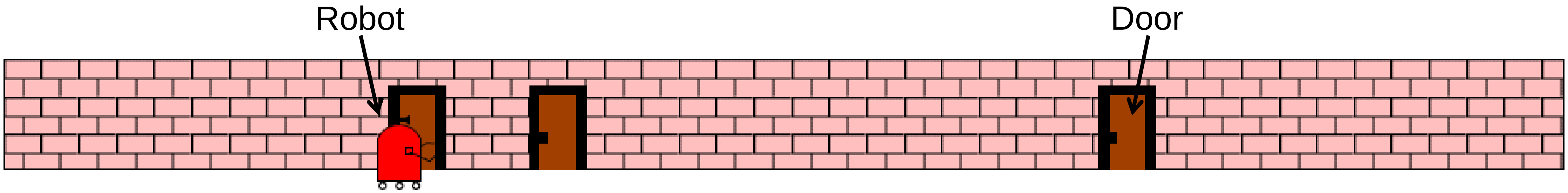
- A solution robust to compensate for lack of information on initial position

Solution: Monte Carlo Localization

Alternate Solutions: Kalman Filter, Topological Markov Localization

Particle Filter

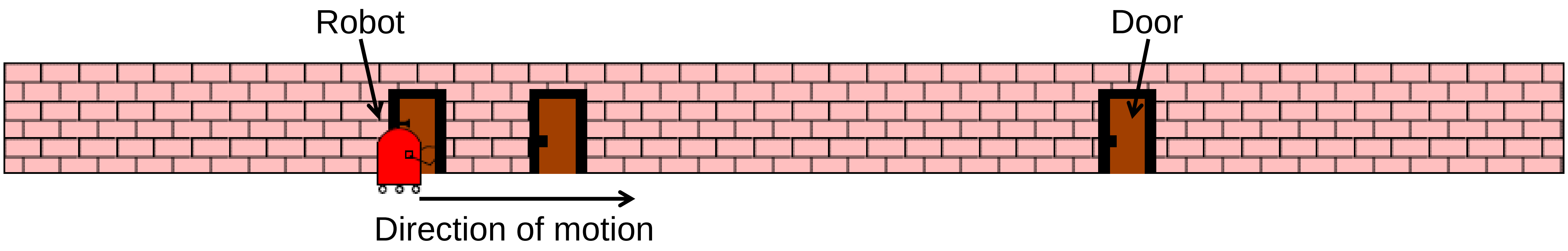
A Example in 1 Dimension



Belief State

Particle Filter

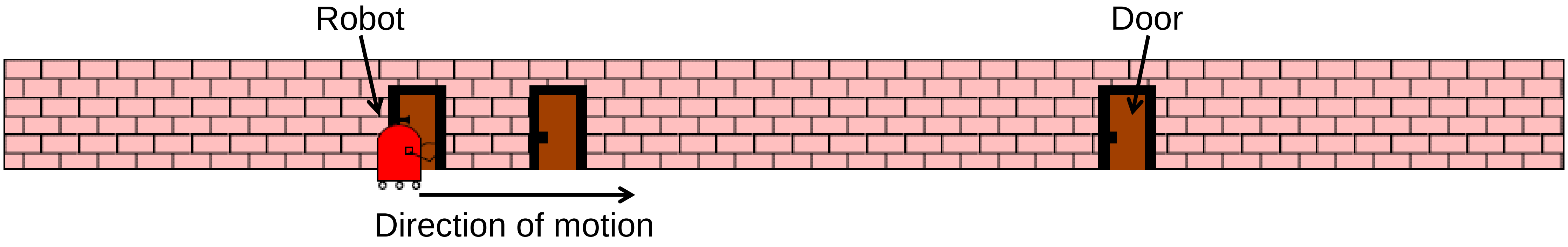
A Example in 1 Dimension



Particle Filter

A Example in 1 Dimension

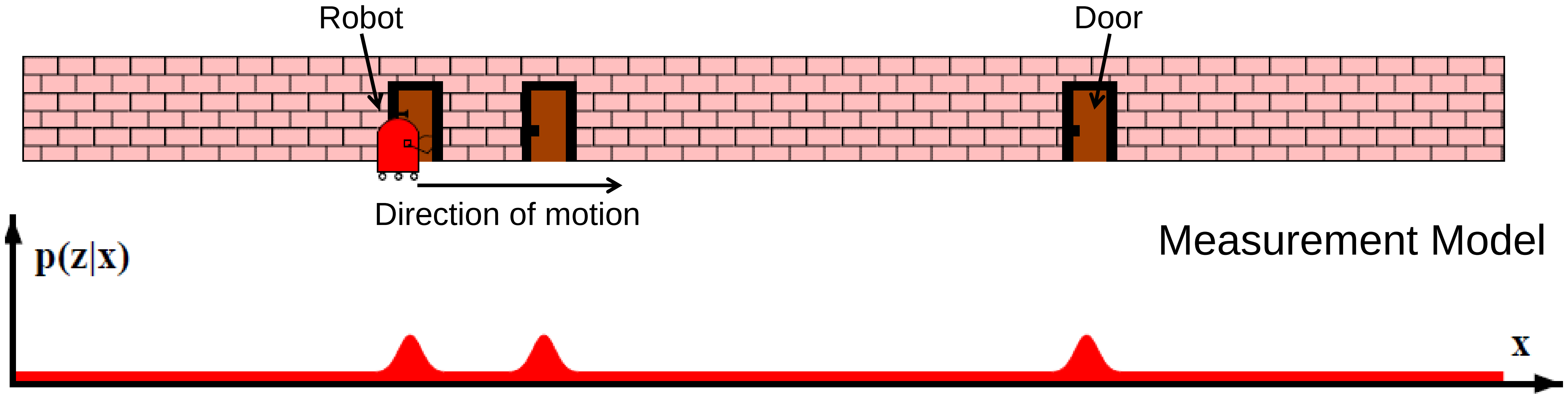
At time t = 1



Particle Filter

A Example in 1 Dimension

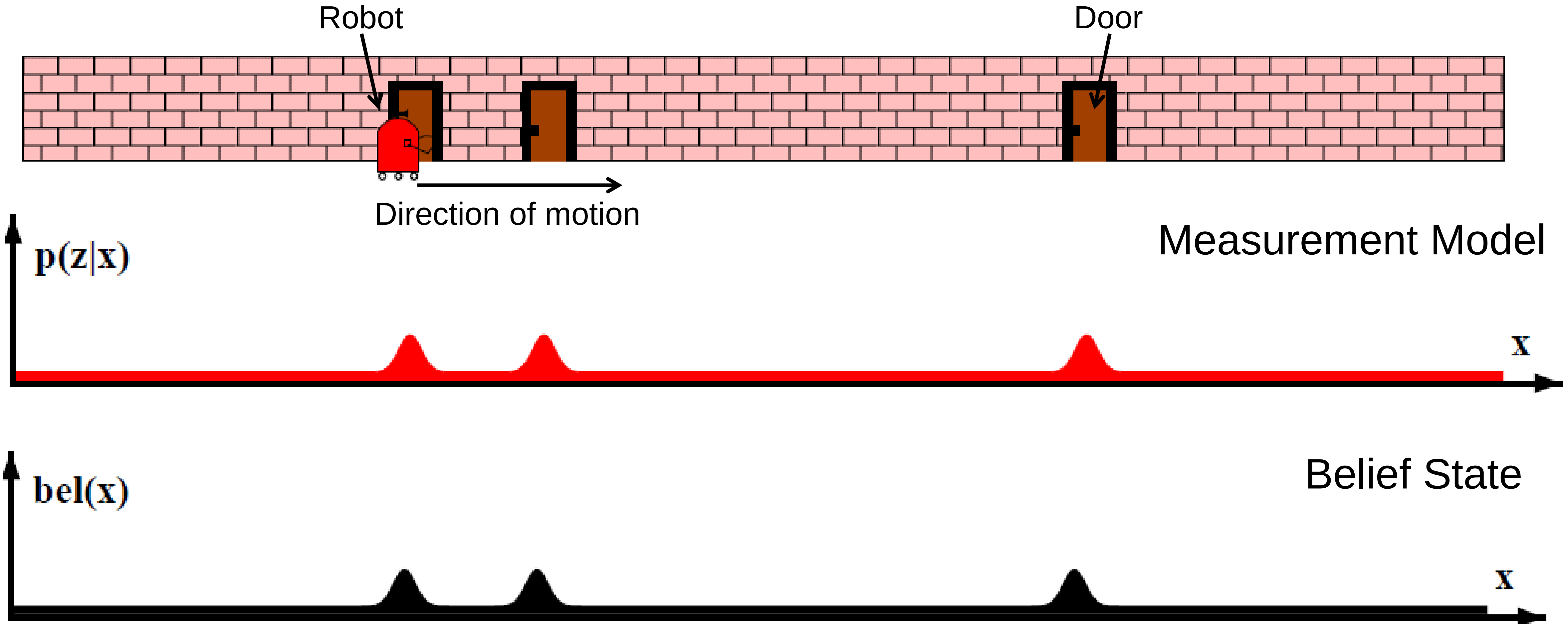
At time t = 1



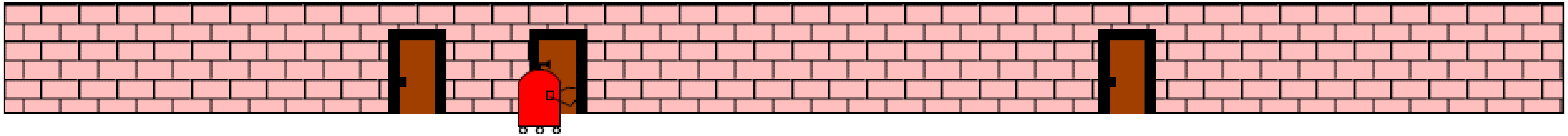
Particle Filter

A Example in 1 Dimension

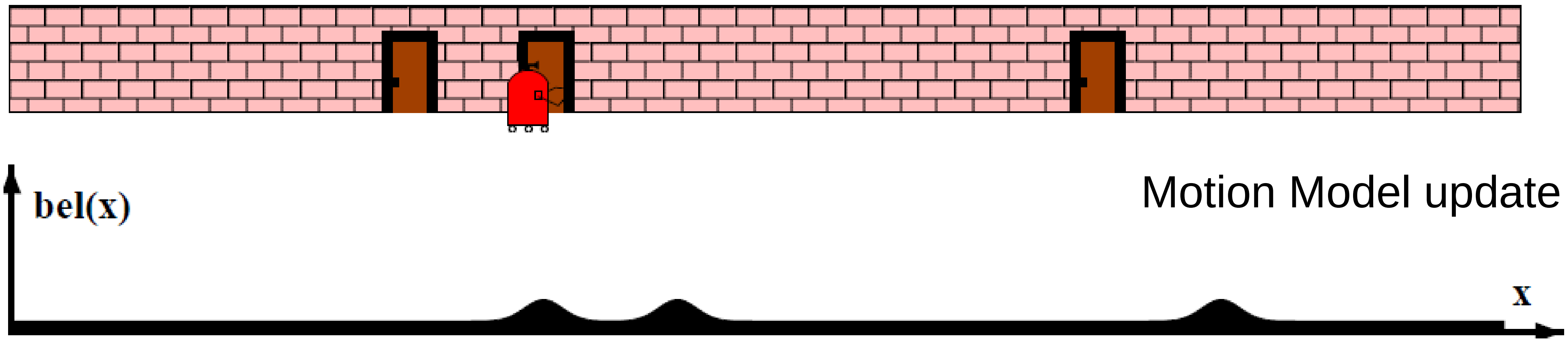
At time t = 1



At time t = 2, robot moves forward a certain distance



At time t = 2, robot moves forward a certain distance



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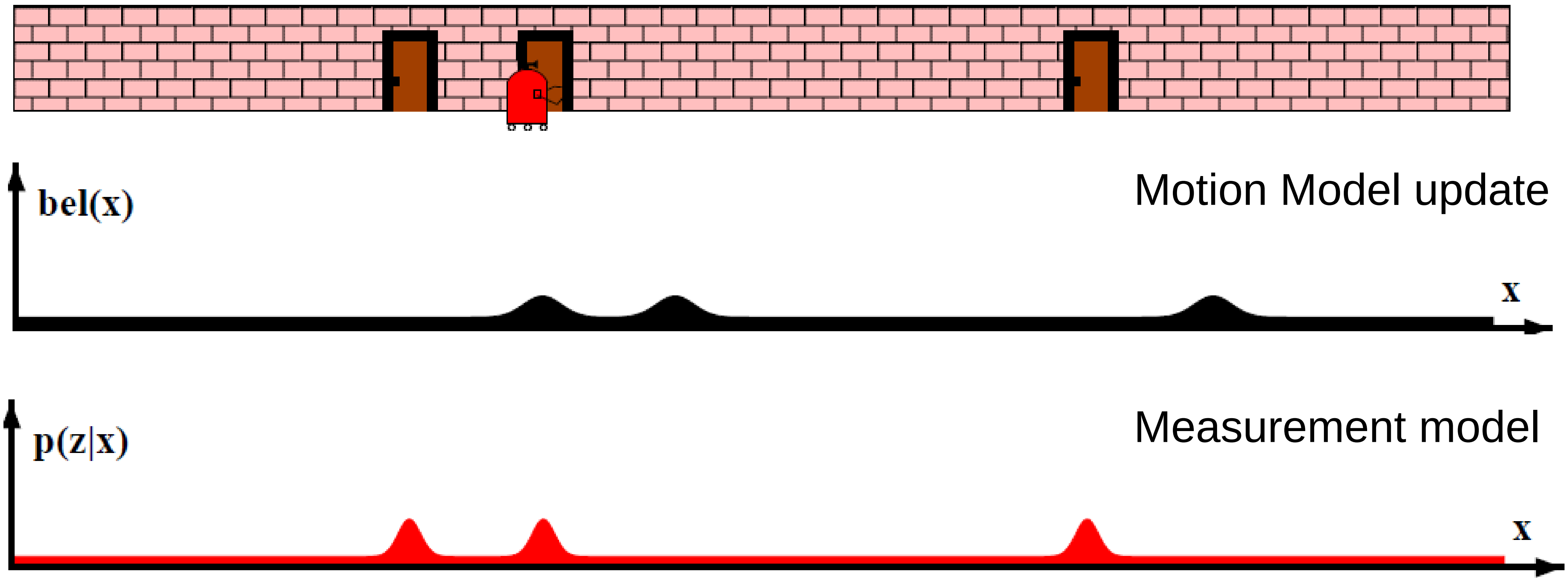

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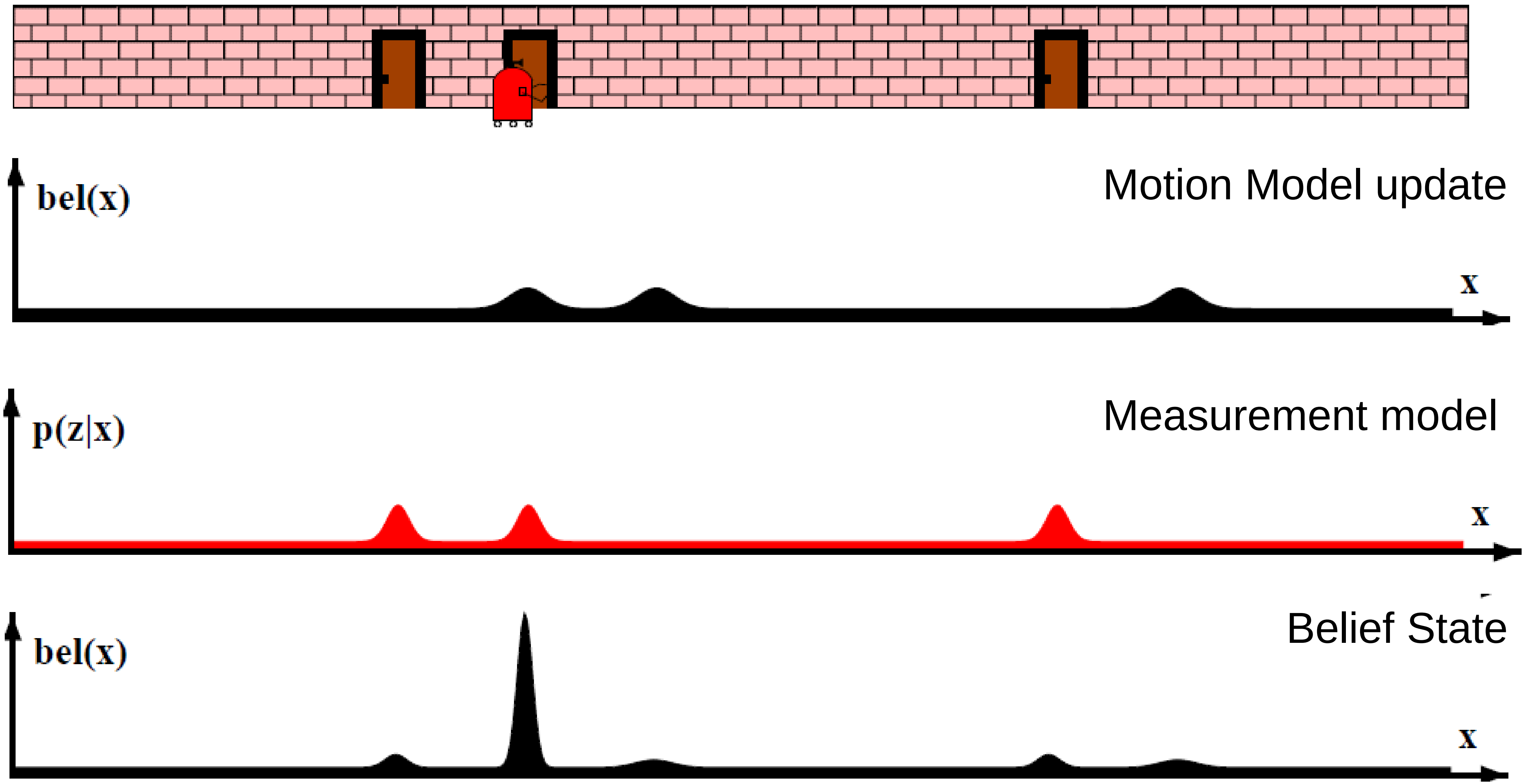
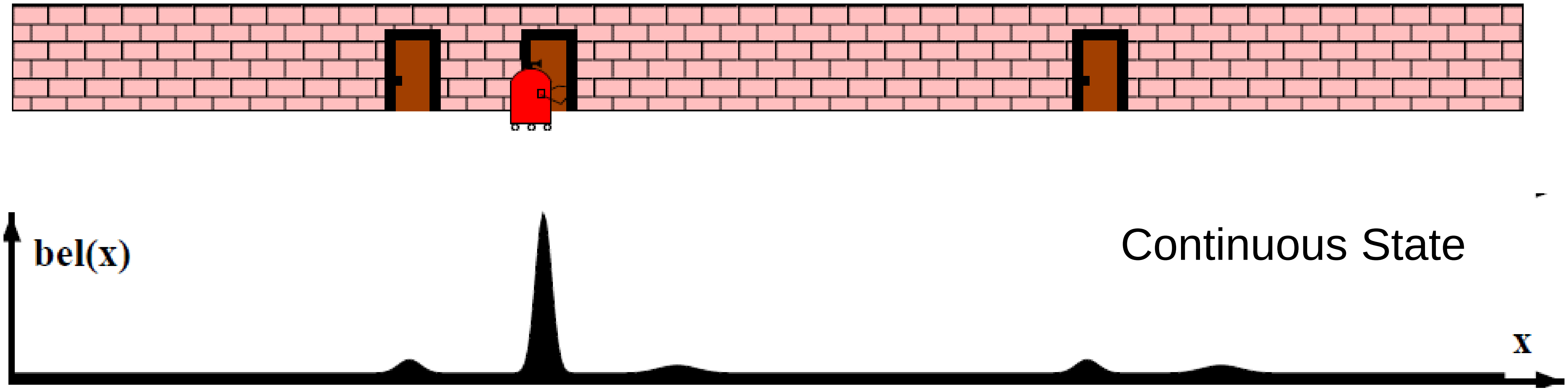
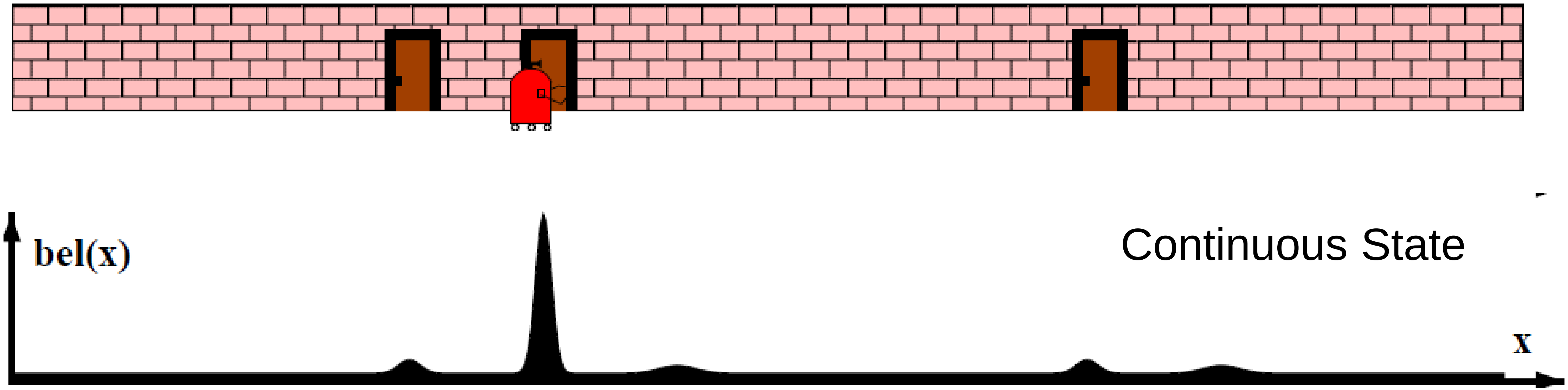


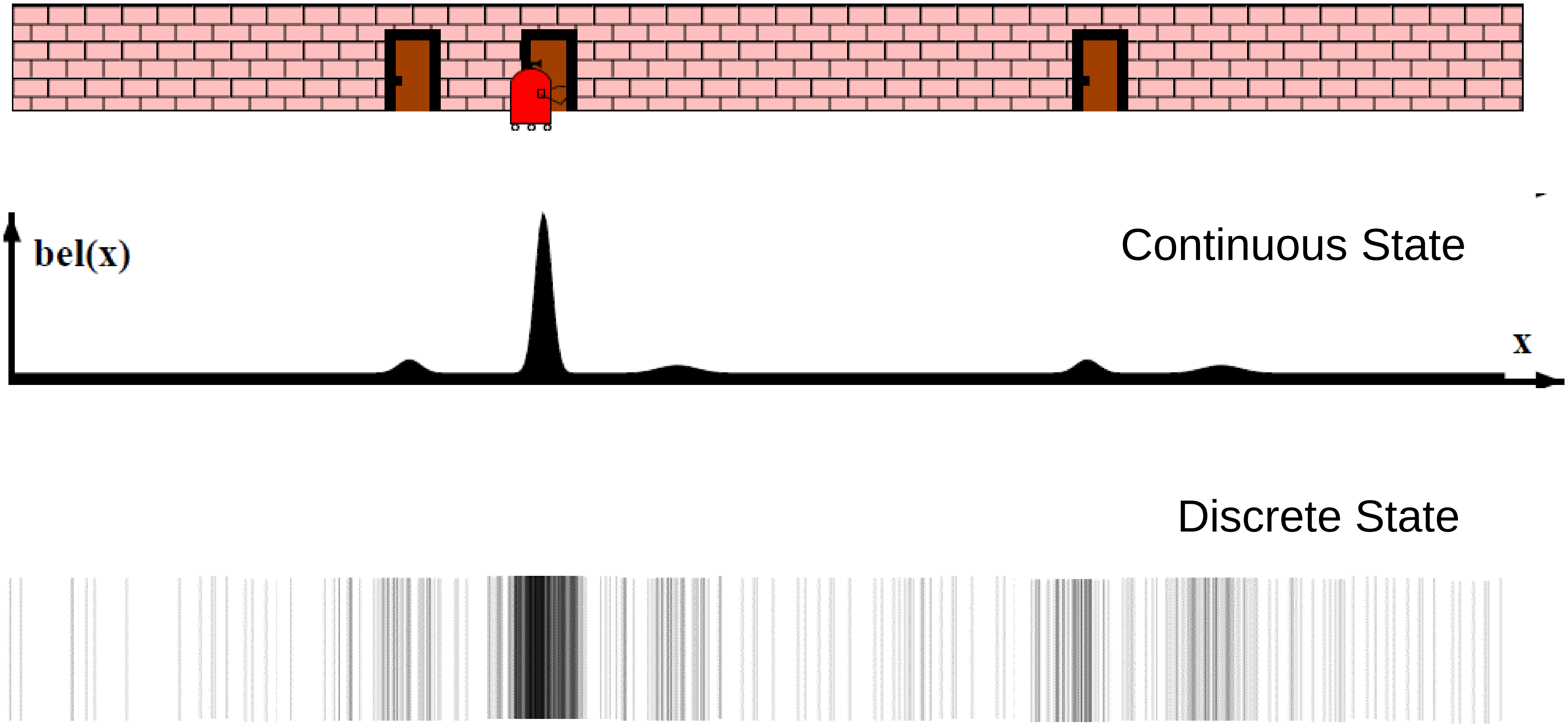
Continuous State



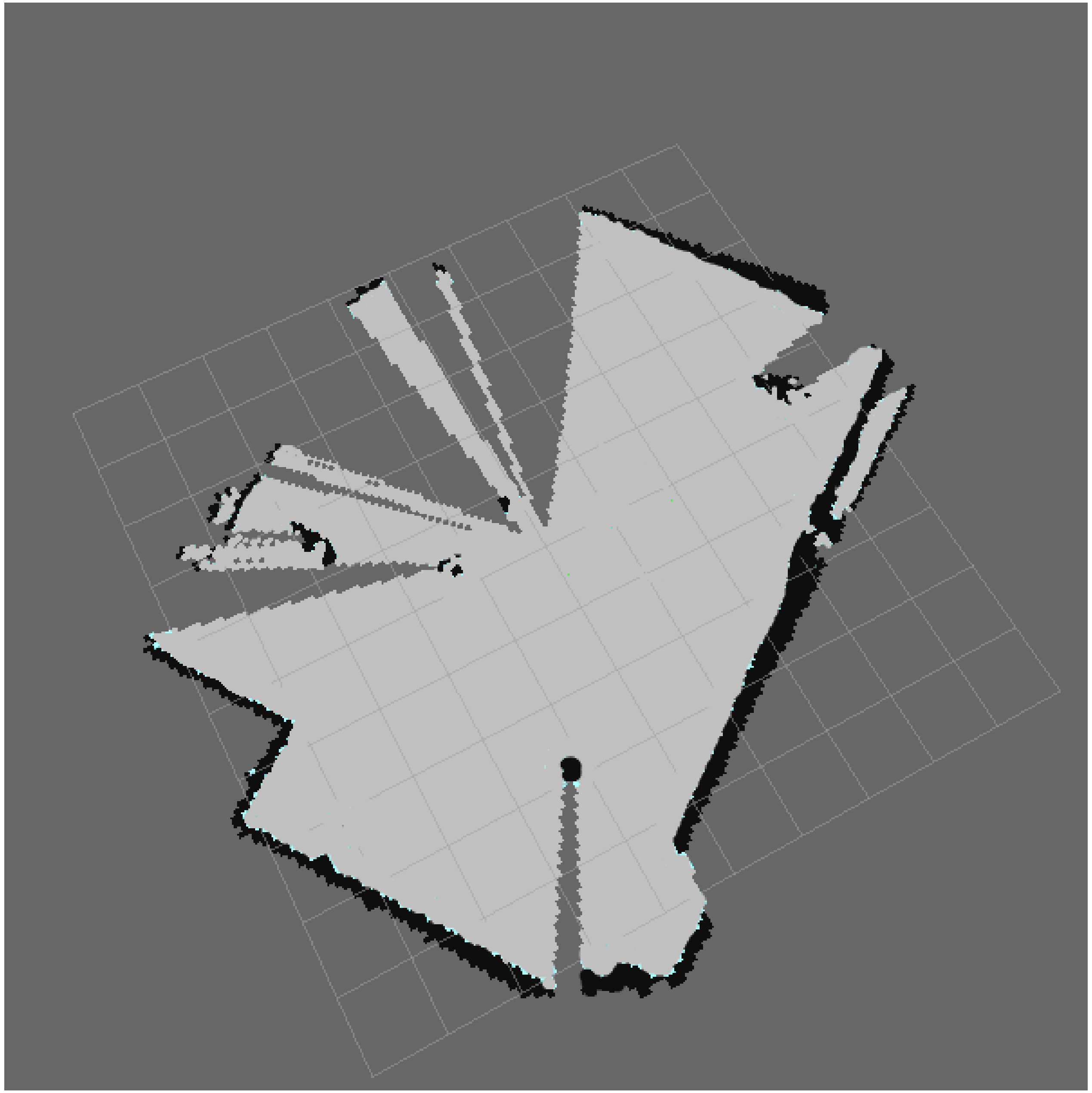


Continuous State

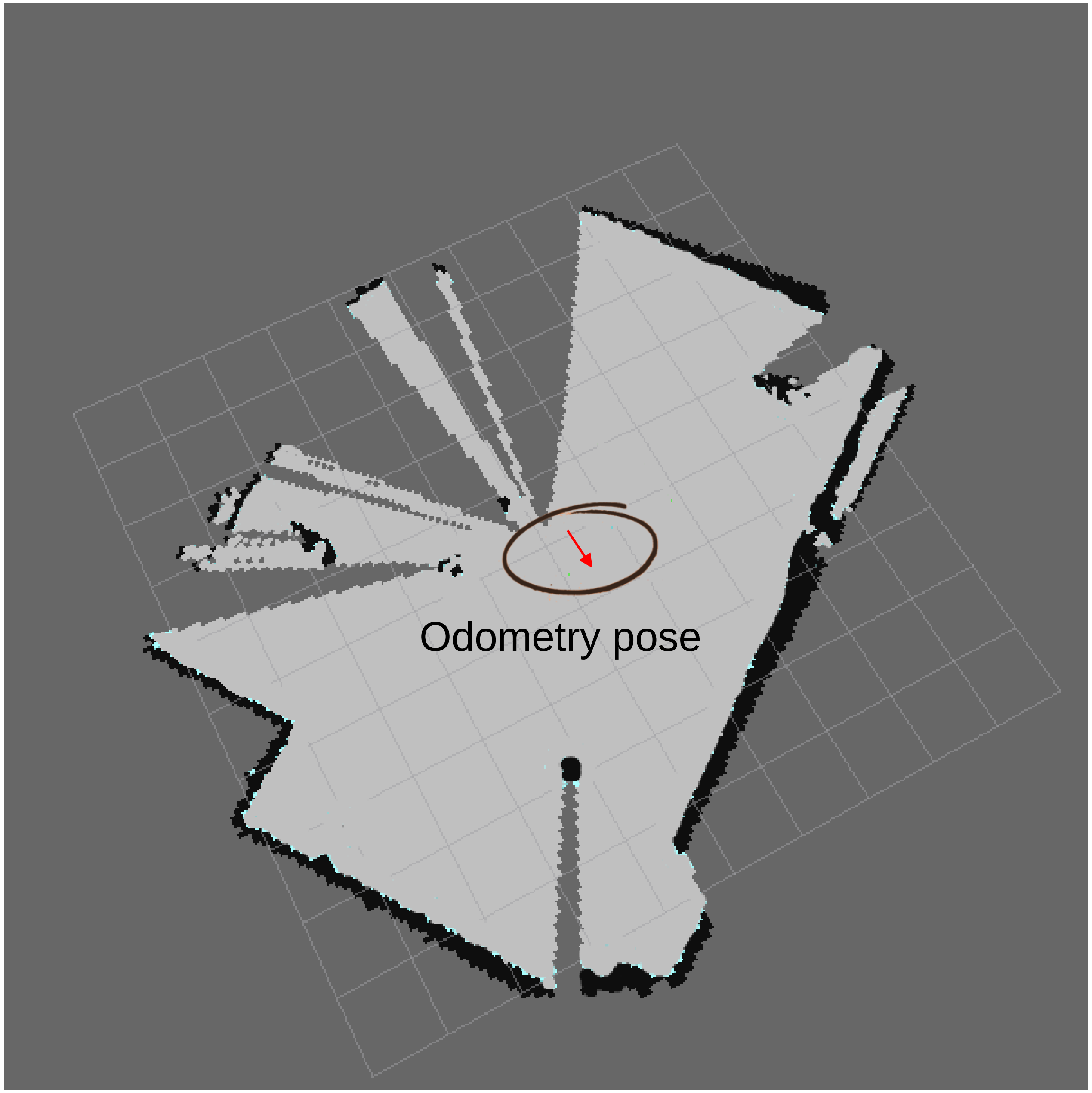
Discrete State


bel(x)
Continuous State
x
Discrete State

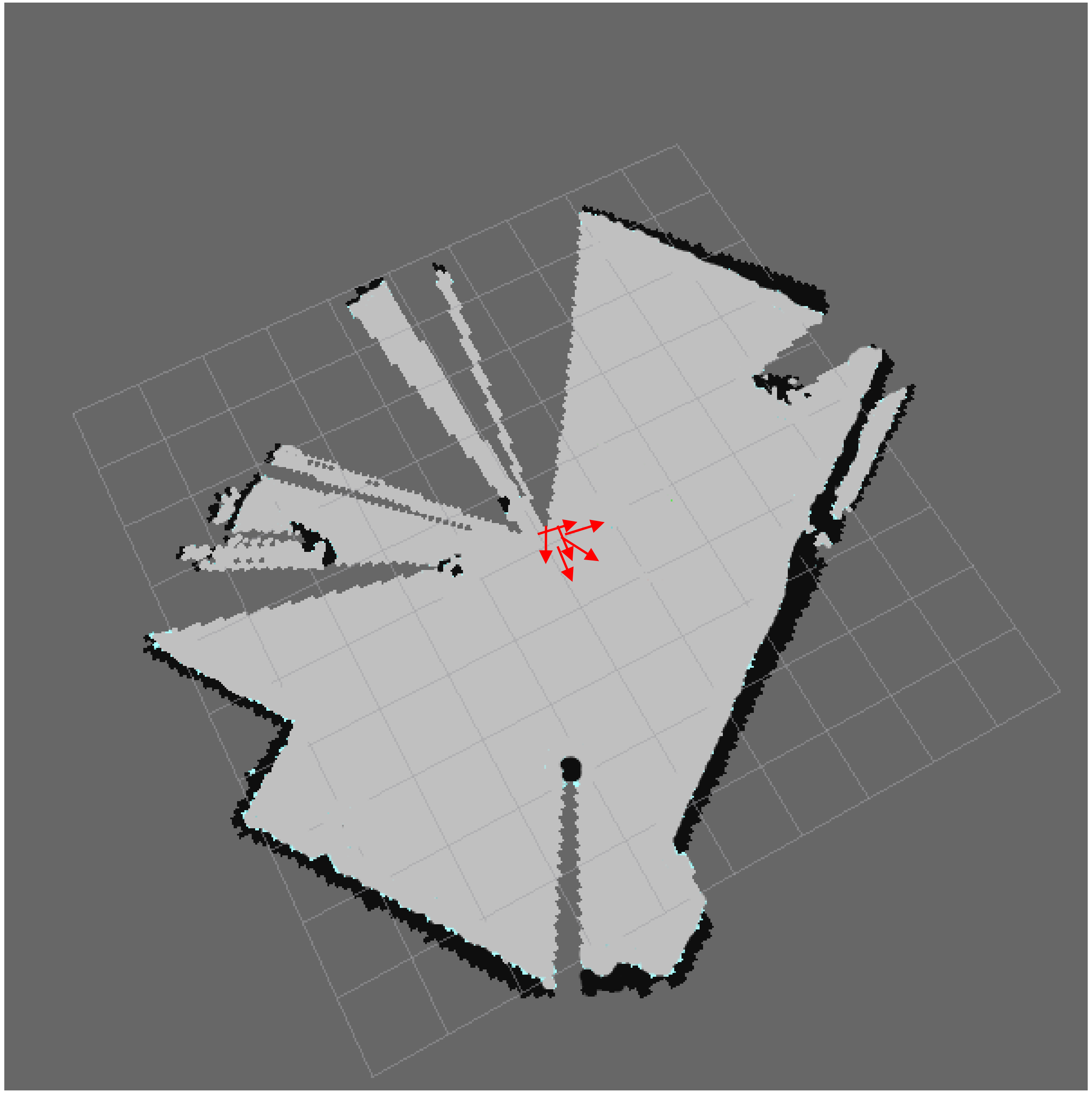
Particle Filter in 2D



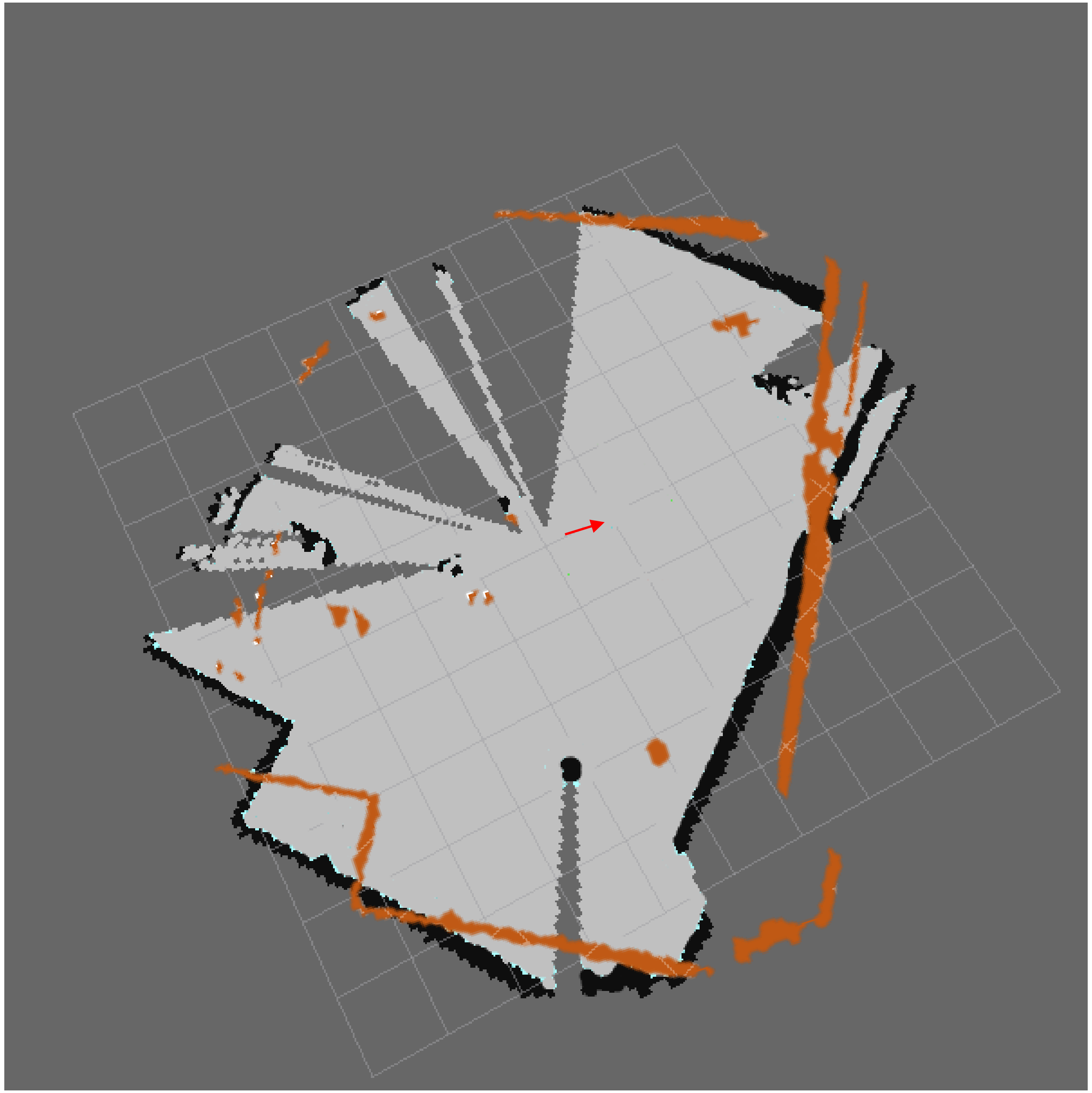
Particle Filter in 2D



Particle Filter in 2D

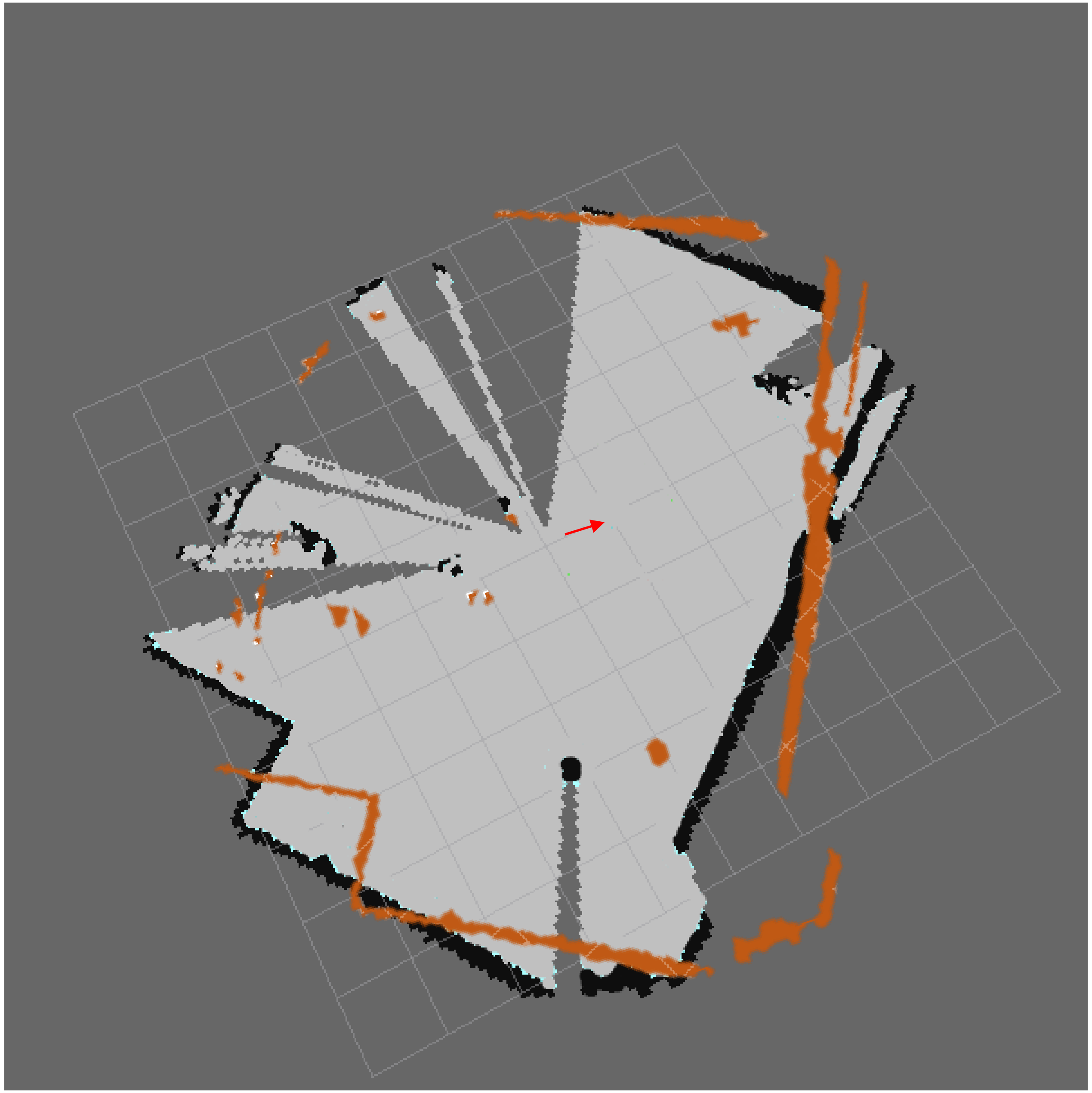


Scan Correlation



Scan Correlation

$$S = \frac{\sum_m \sum_n (Amn - \overline{A})(Bmn - \overline{B})}{\sqrt{\left(\sum_m \sum_n \left(A_{mn} - \overline{A}\right)^2\right)\left(\sum_m \sum_n \left(B_{mn} - \overline{B}\right)^2\right)}}$$



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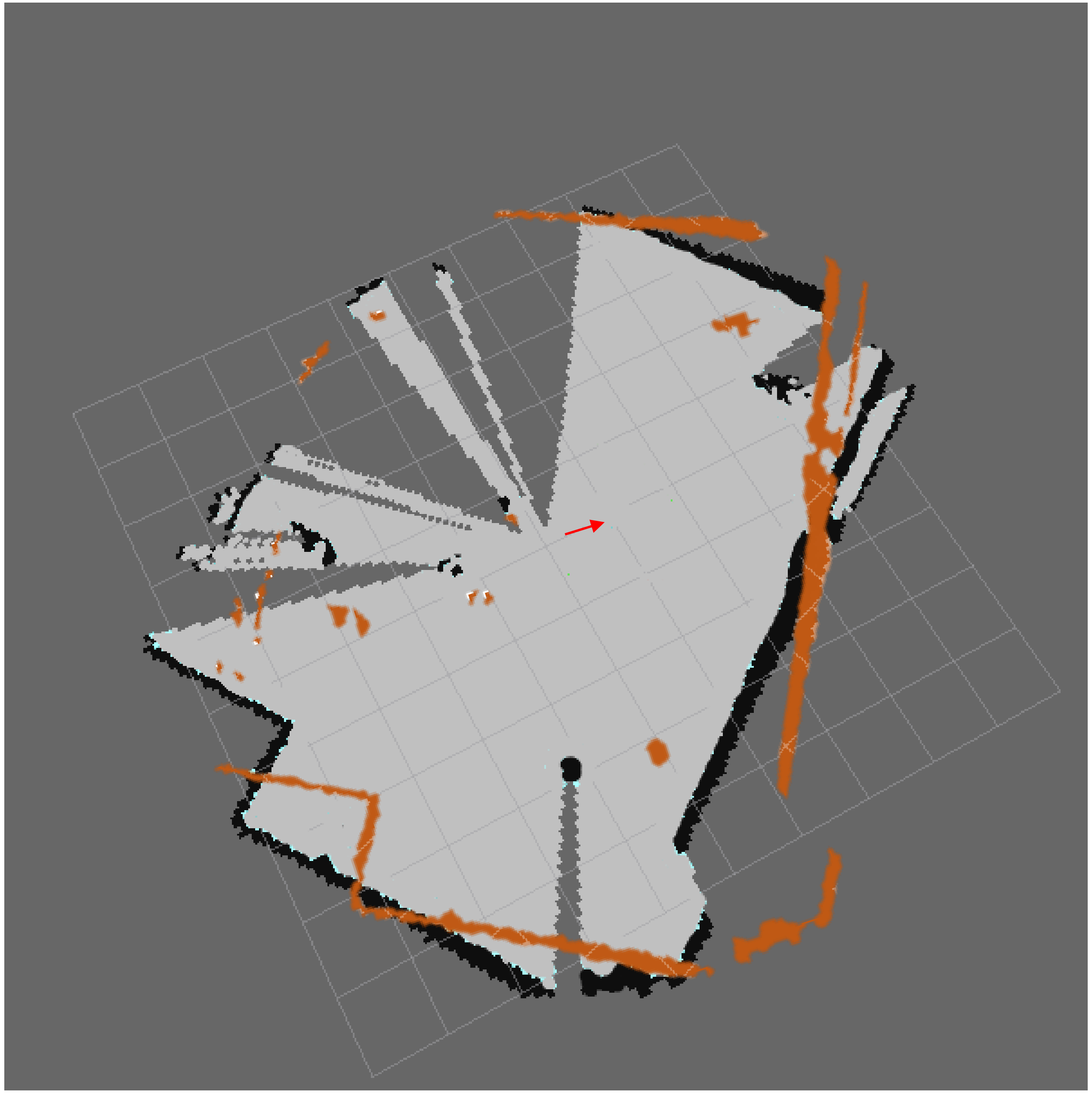
Particle	Weight
Particle 1	S_1



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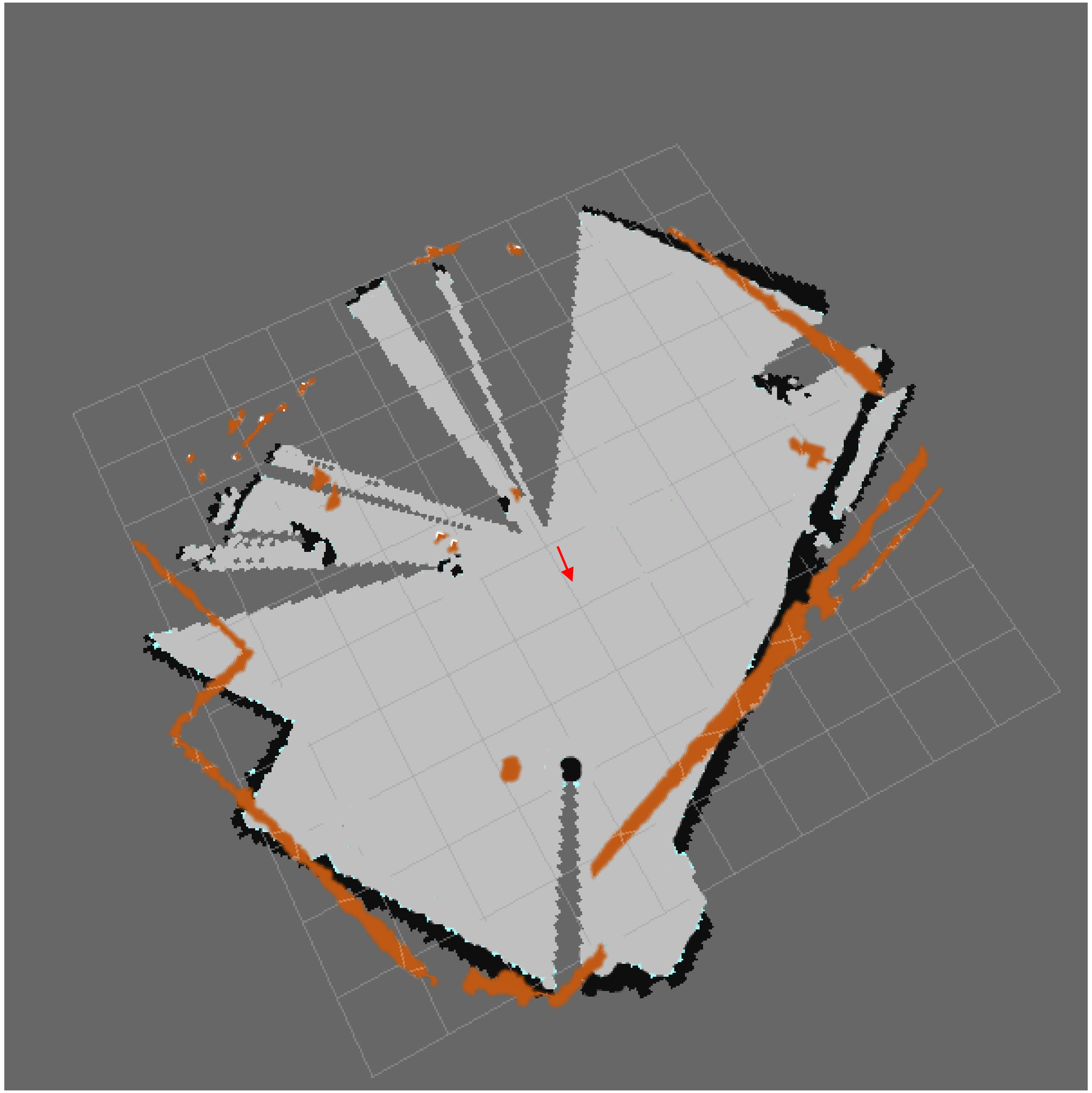
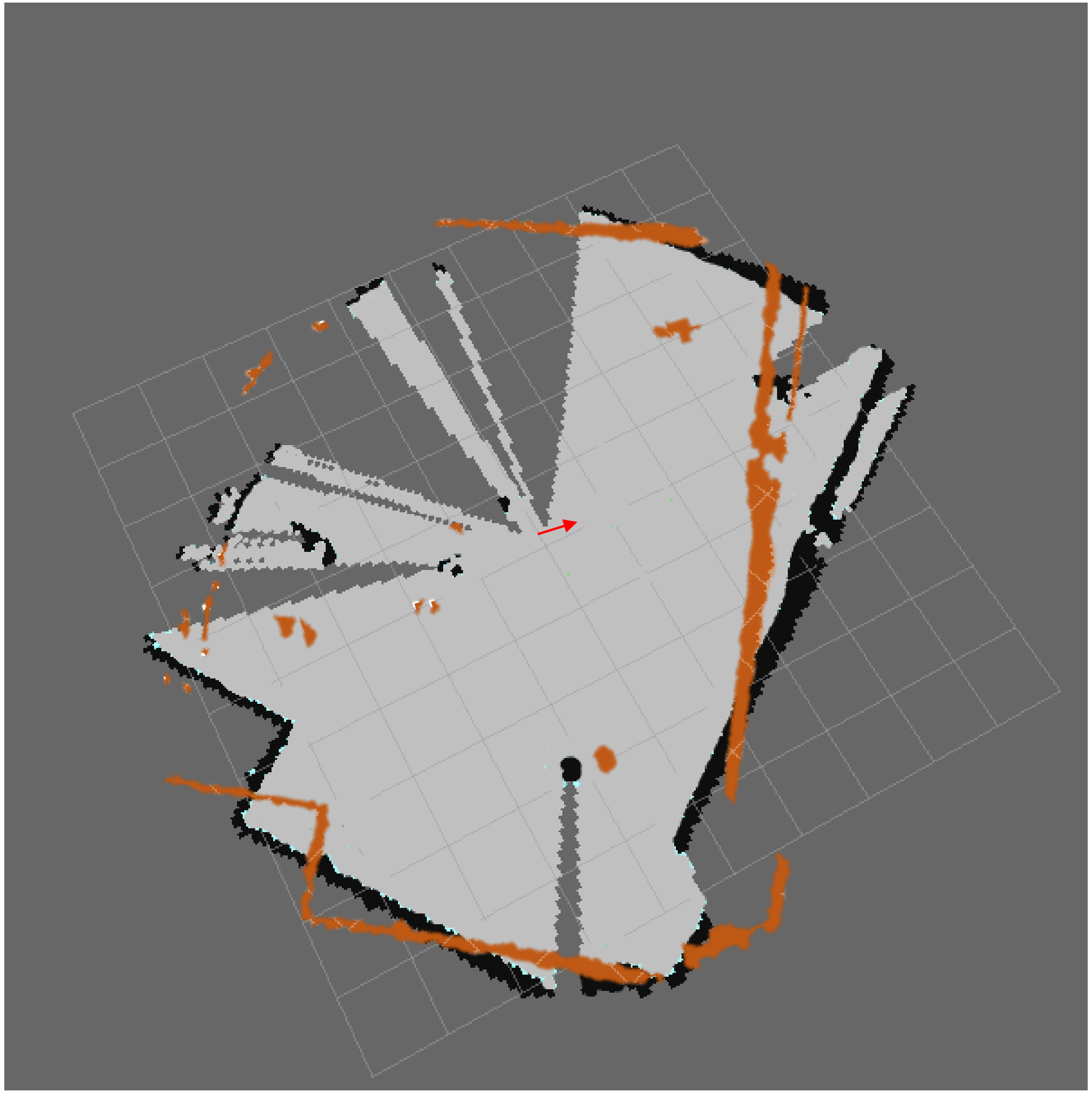
Particle	Weight
Particle 1	S_1
Particle 2	S_2



Scan Correlation

$$S = \frac{\sum_m \sum_n (Amn - \overline{A})(Bmn - \overline{B})}{\sqrt{\left(\sum_m \sum_n \left(A_{mn} - \overline{A}\right)^2\right)\left(\sum_m \sum_n \left(B_{mn} - \overline{B}\right)^2\right)}}$$

Particle	Weight
Particle 1	S_1
Particle 2	S_2
Particle 3	S_3



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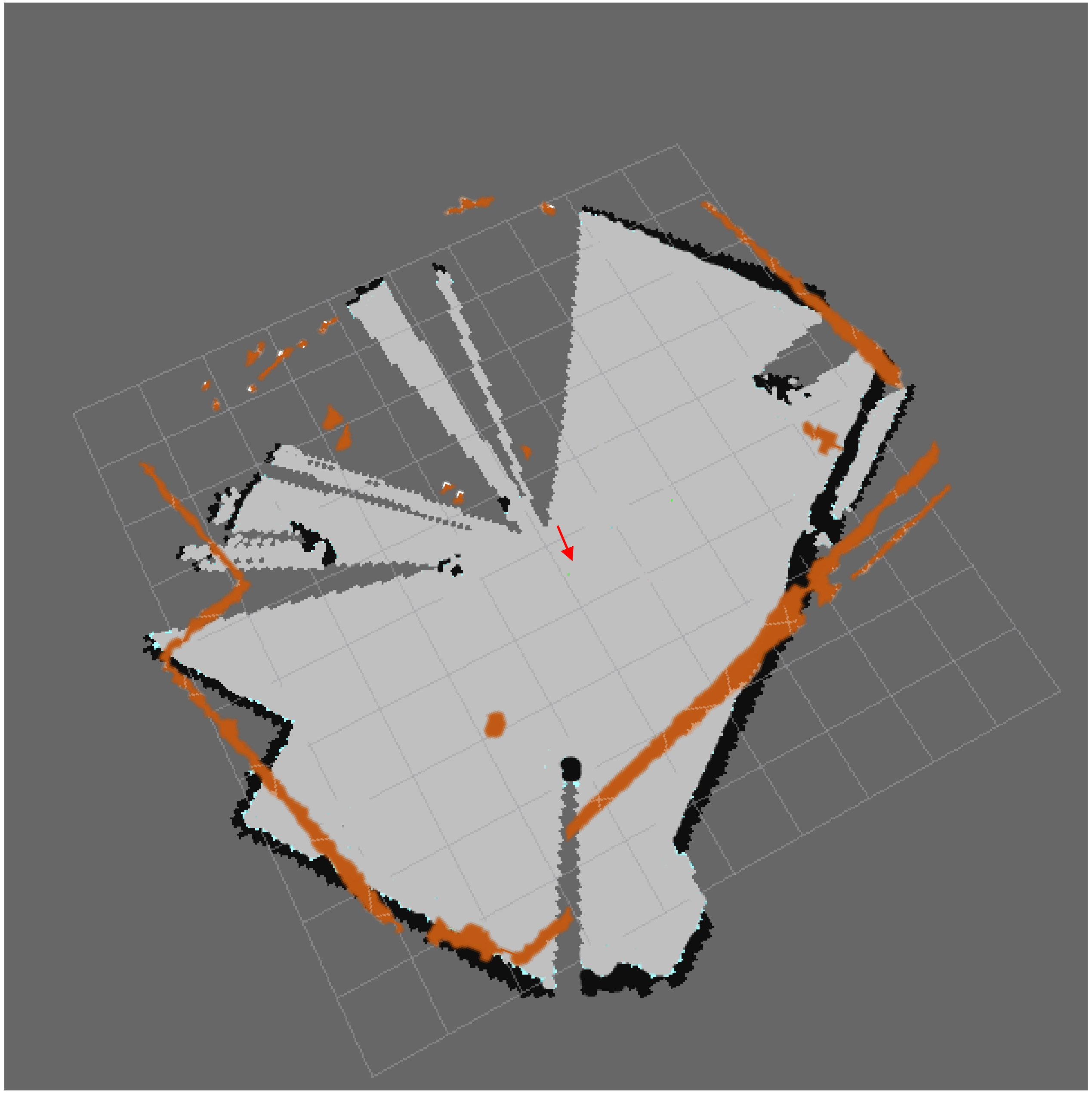
Particle 3	S_3
Particle 4	S_4



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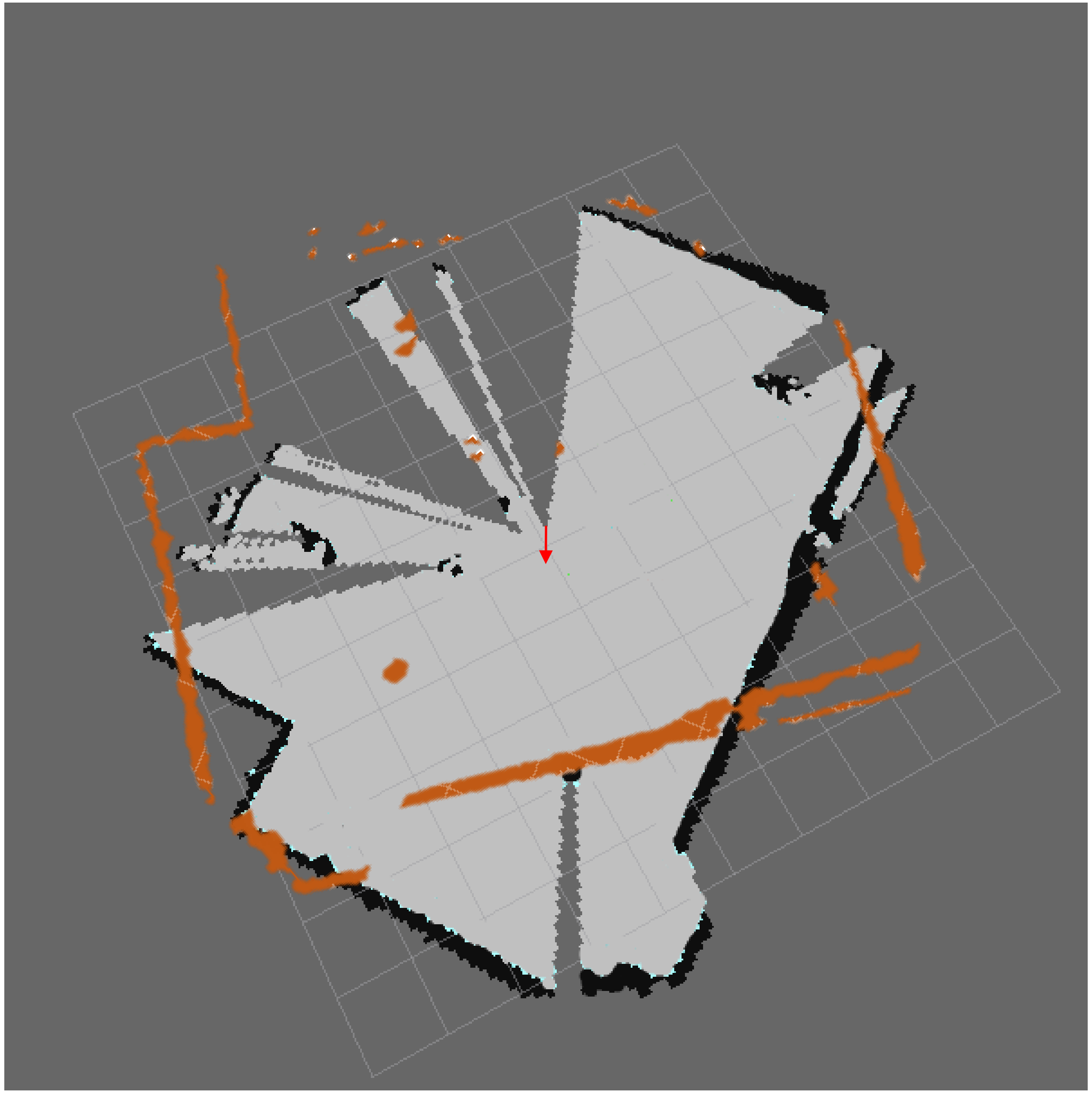
Particle 3	S_3
Particle 4	S_4
Particle 5	S_5



Scan Correlation

$$S = \frac{\sum_m \sum_n (Amn - \overline{A})(Bmn - \overline{B})}{\sqrt{\left(\sum_m \sum_n \left(A_{mn} - \overline{A}\right)^2\right)\left(\sum_m \sum_n \left(B_{mn} - \overline{B}\right)^2\right)}}$$

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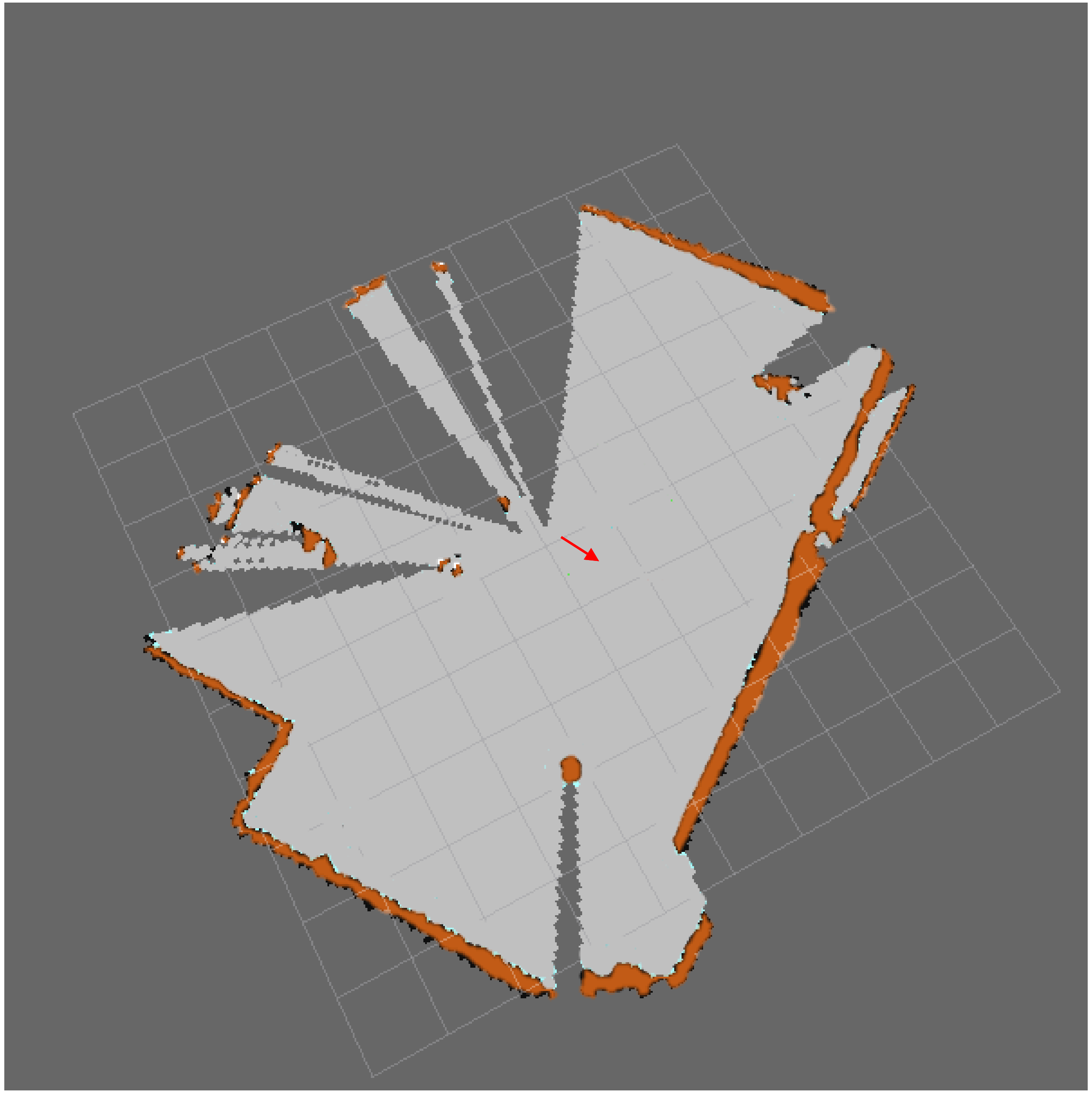
Particle 2	S_2
Particle 3	S_3
Particle 4	S_4
Particle 5	S_5
Particle 6	S_6



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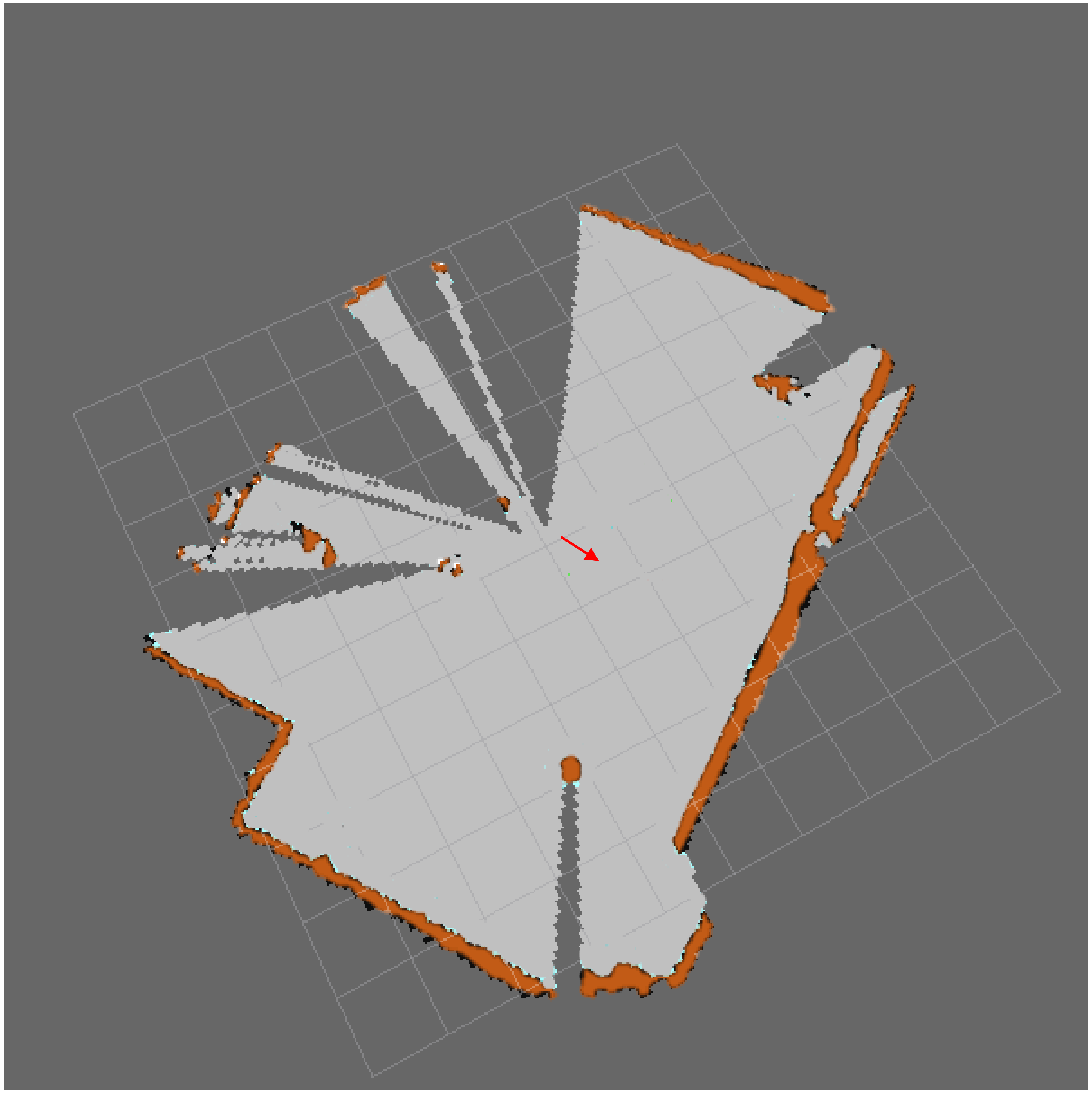
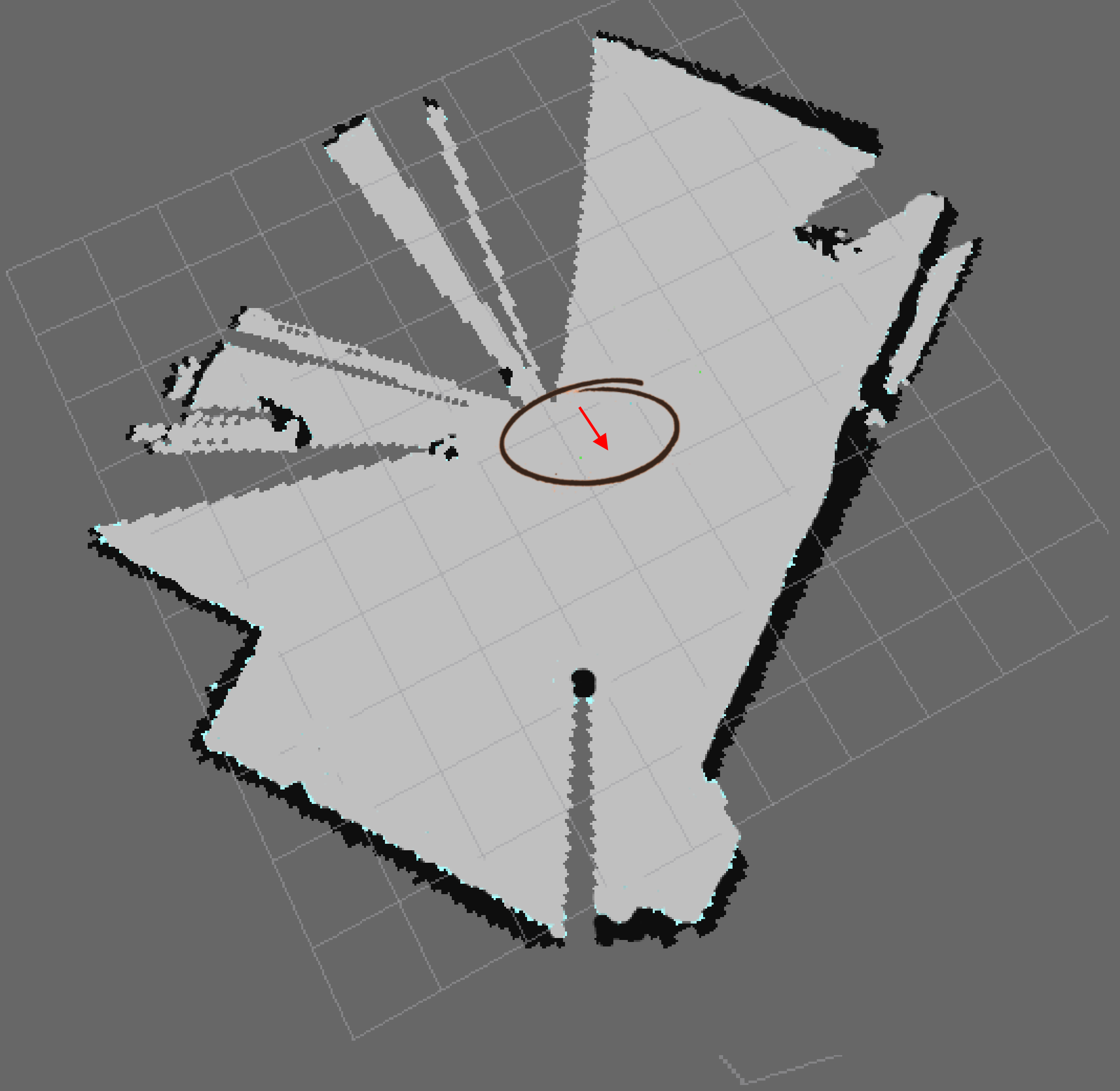
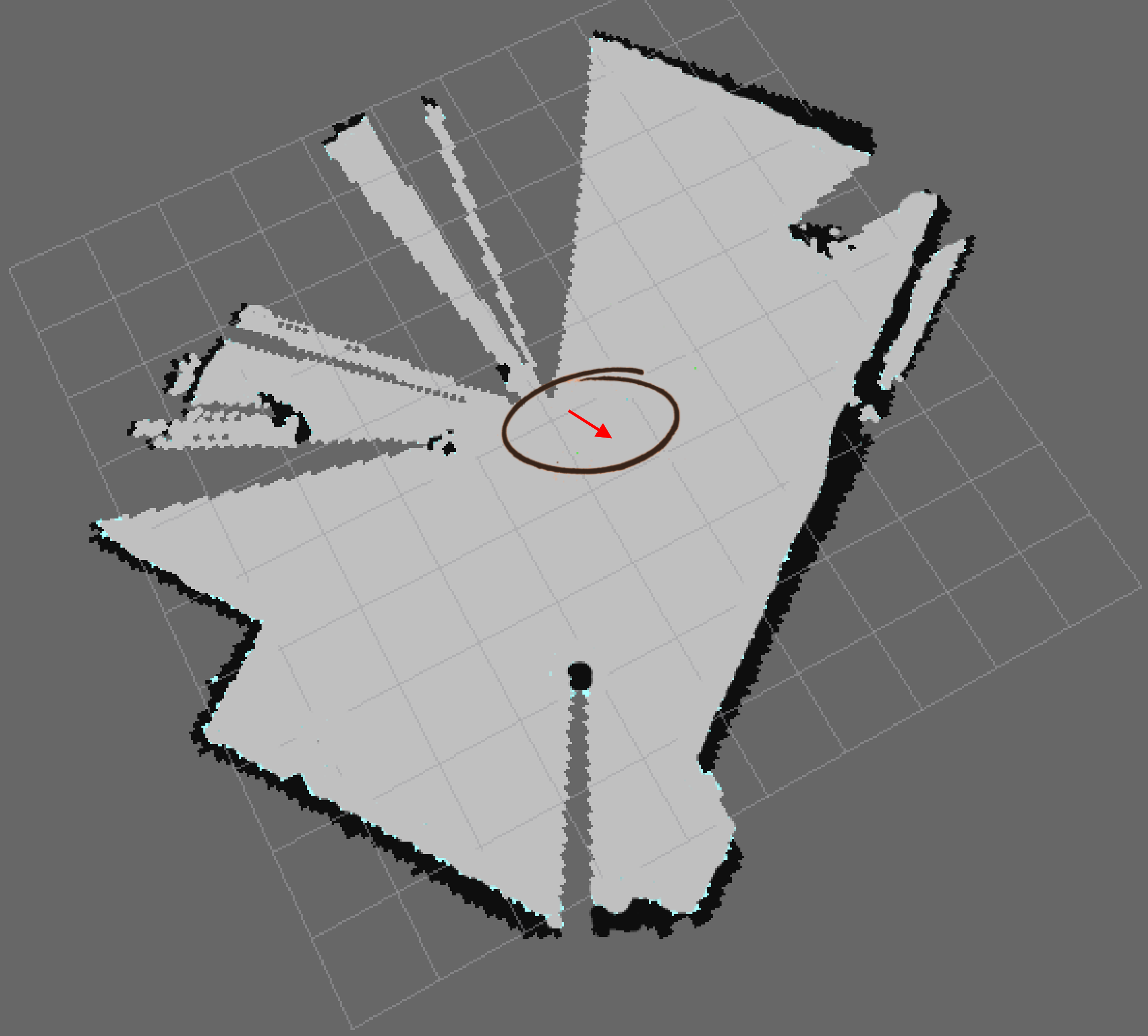


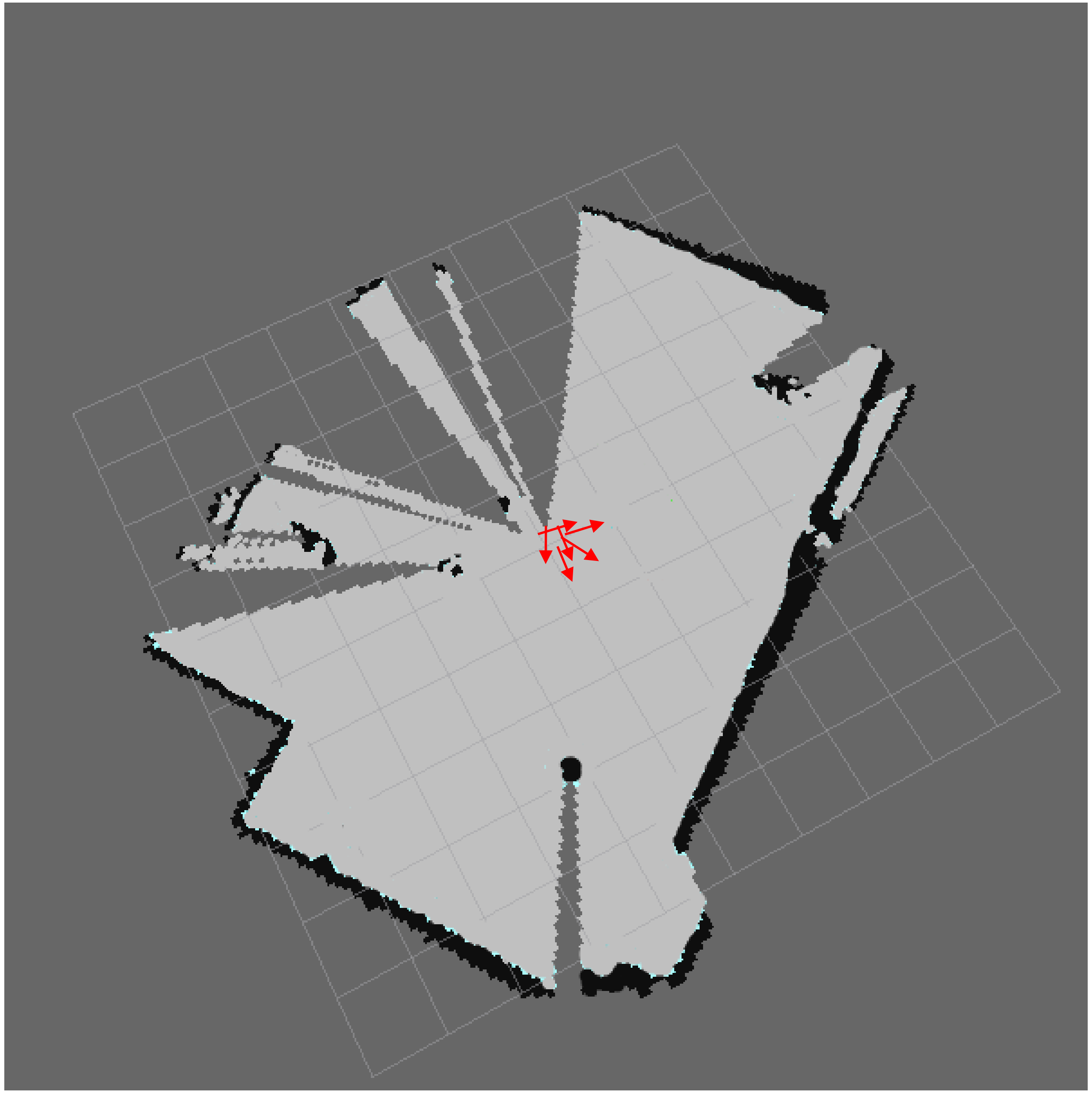
Localization using

Odometry



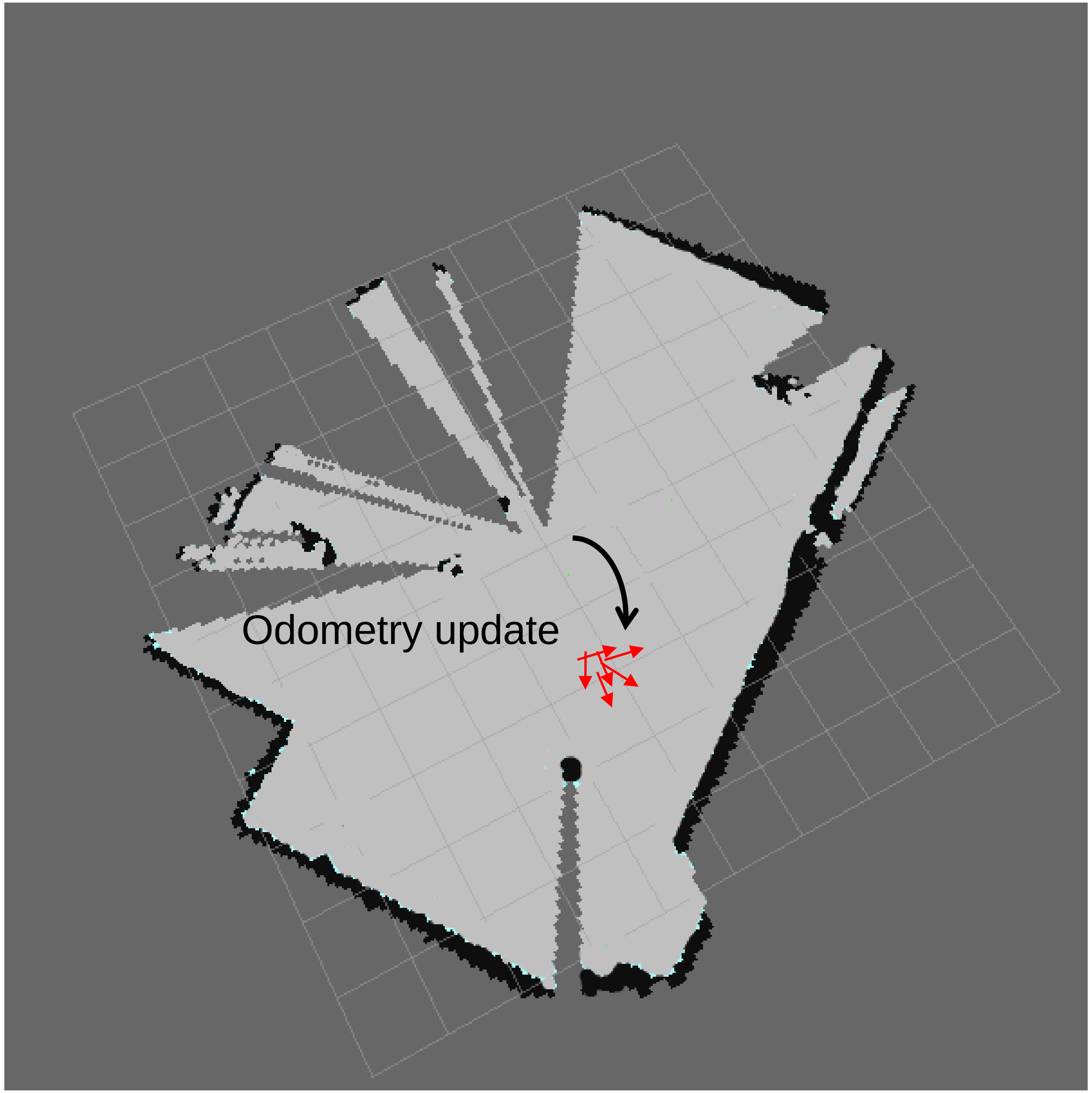
Particle Filter





Update step

- Update the particle cloud with the update in position from the odometry
- Repeat Scan matching process for each particle and determine the weights.



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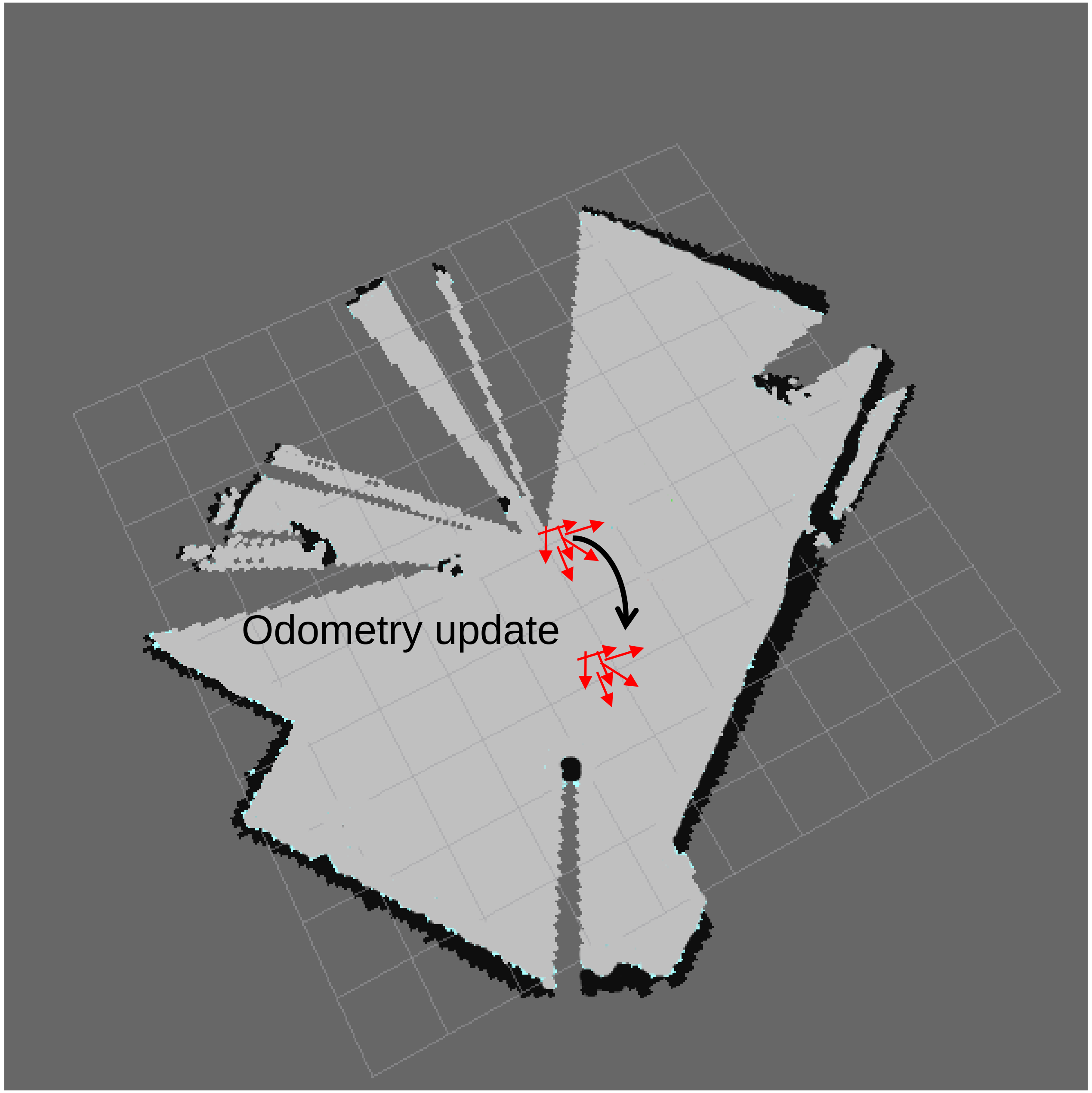


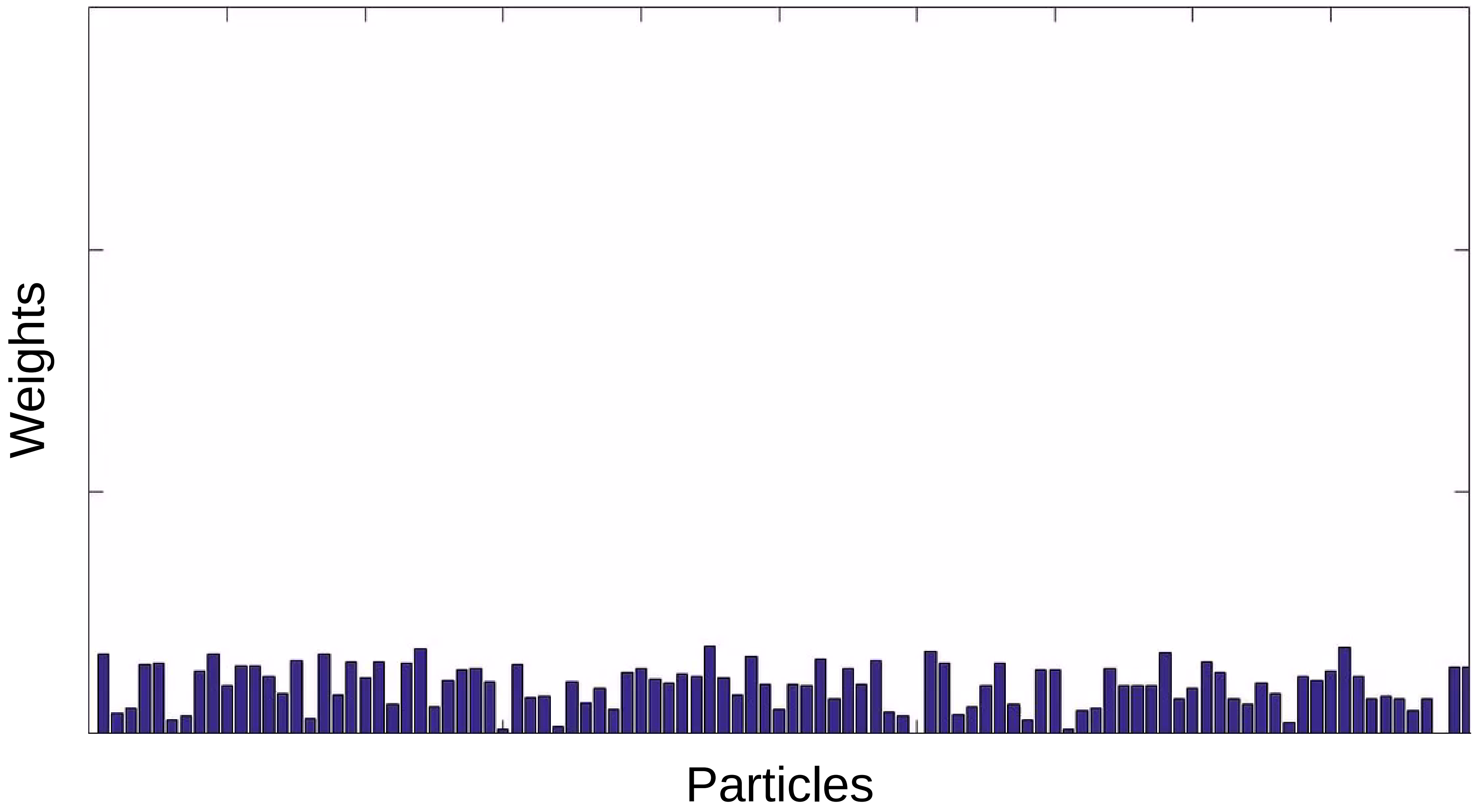
Update step

- Update the particle cloud with the update in position from the odometry
- Repeat Scan matching process for each particle and determine the weights.

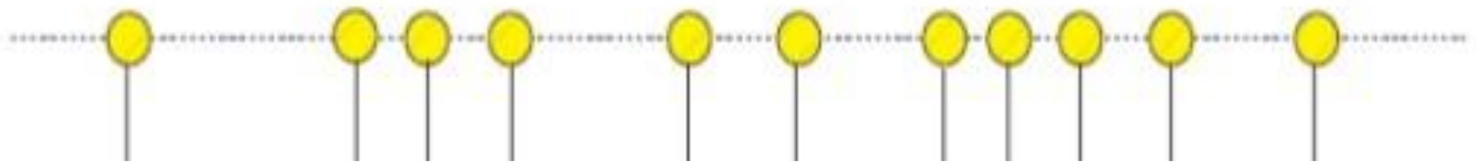
Particle Weights

$$W_t \leftarrow W_{t-1} \times S$$

Particle Filter without Resampling

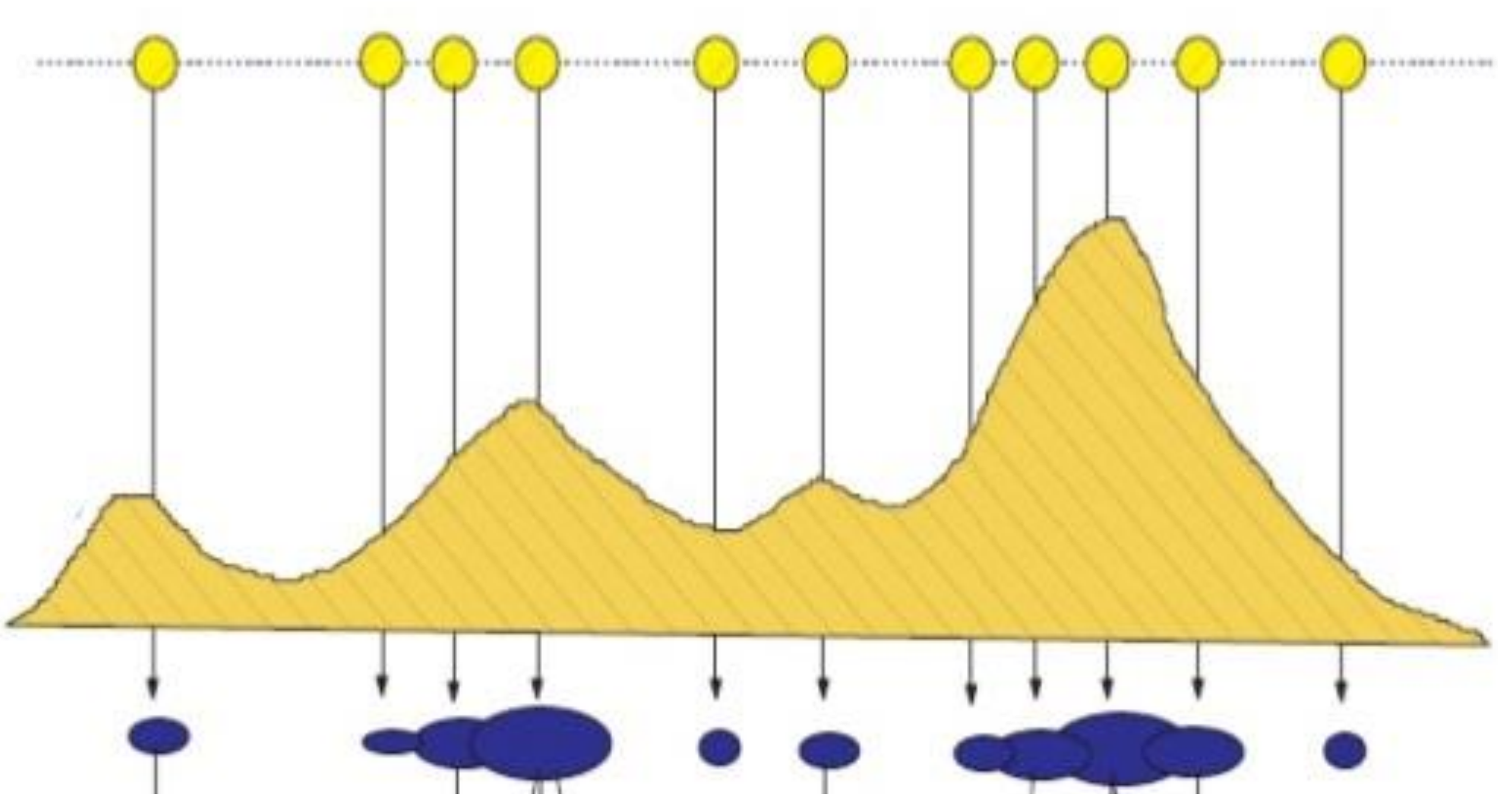


Resampling



Original Particles

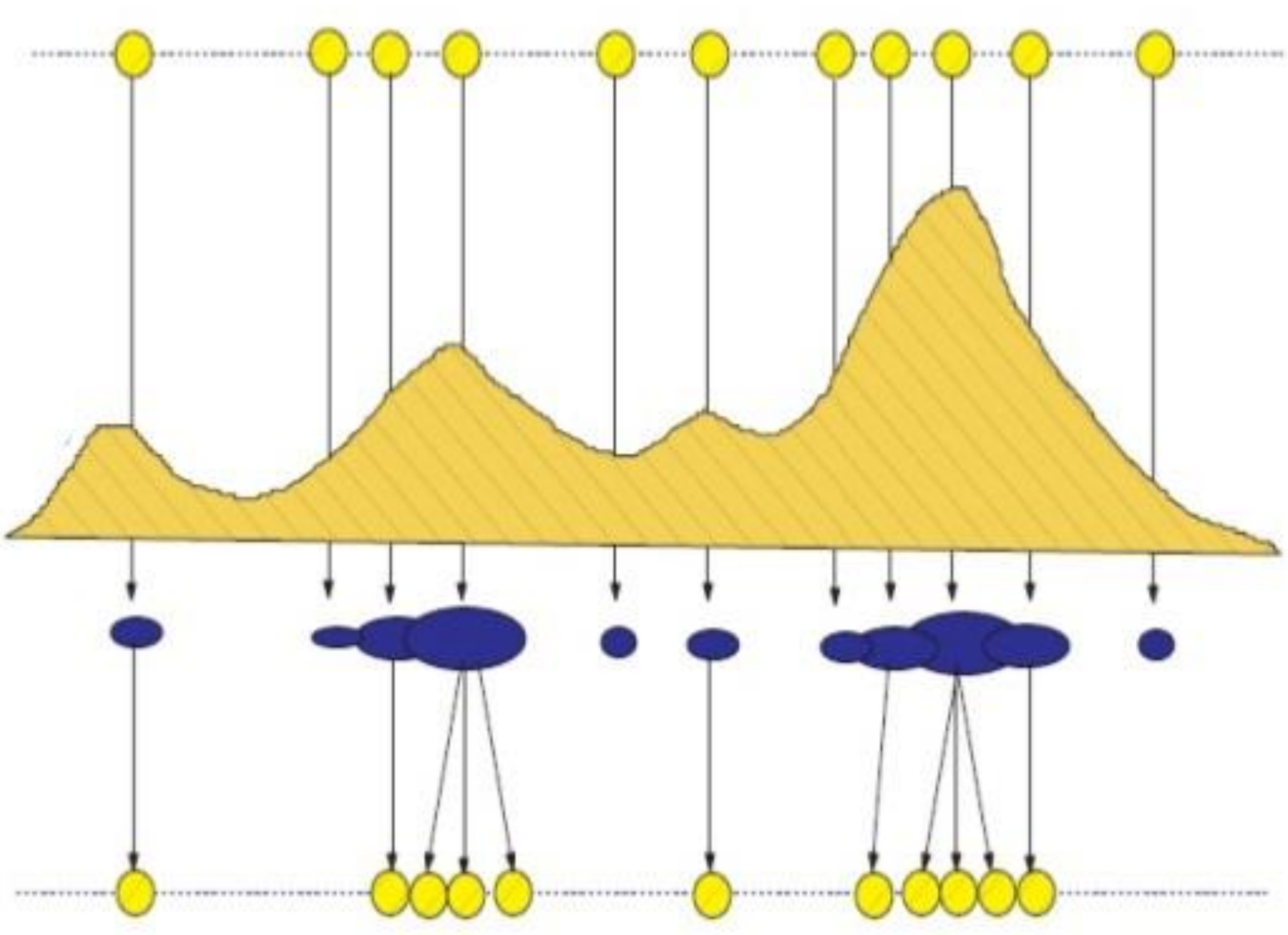
Resampling



Original Particles

After N iterations

Resampling

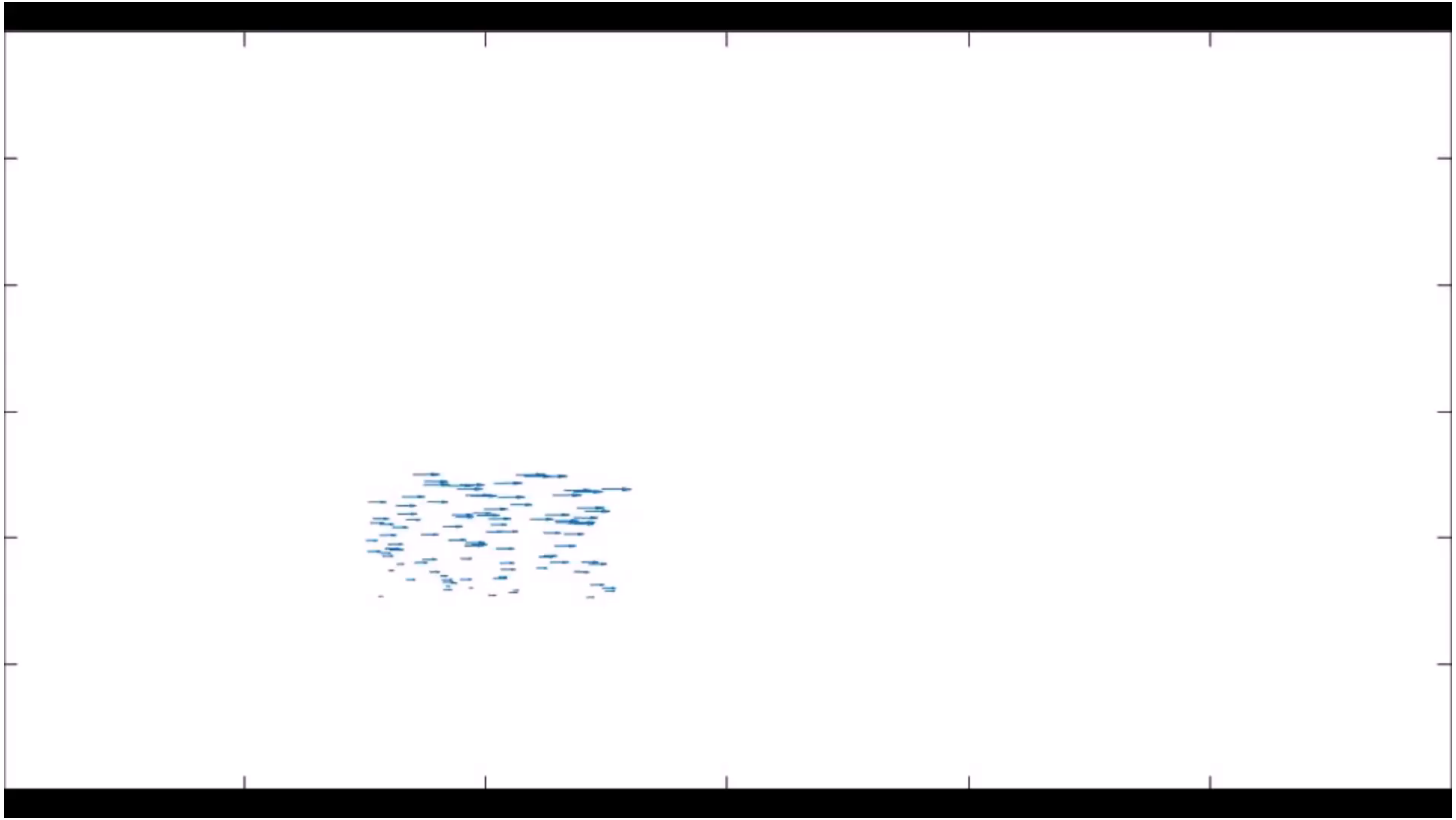


Original Particles

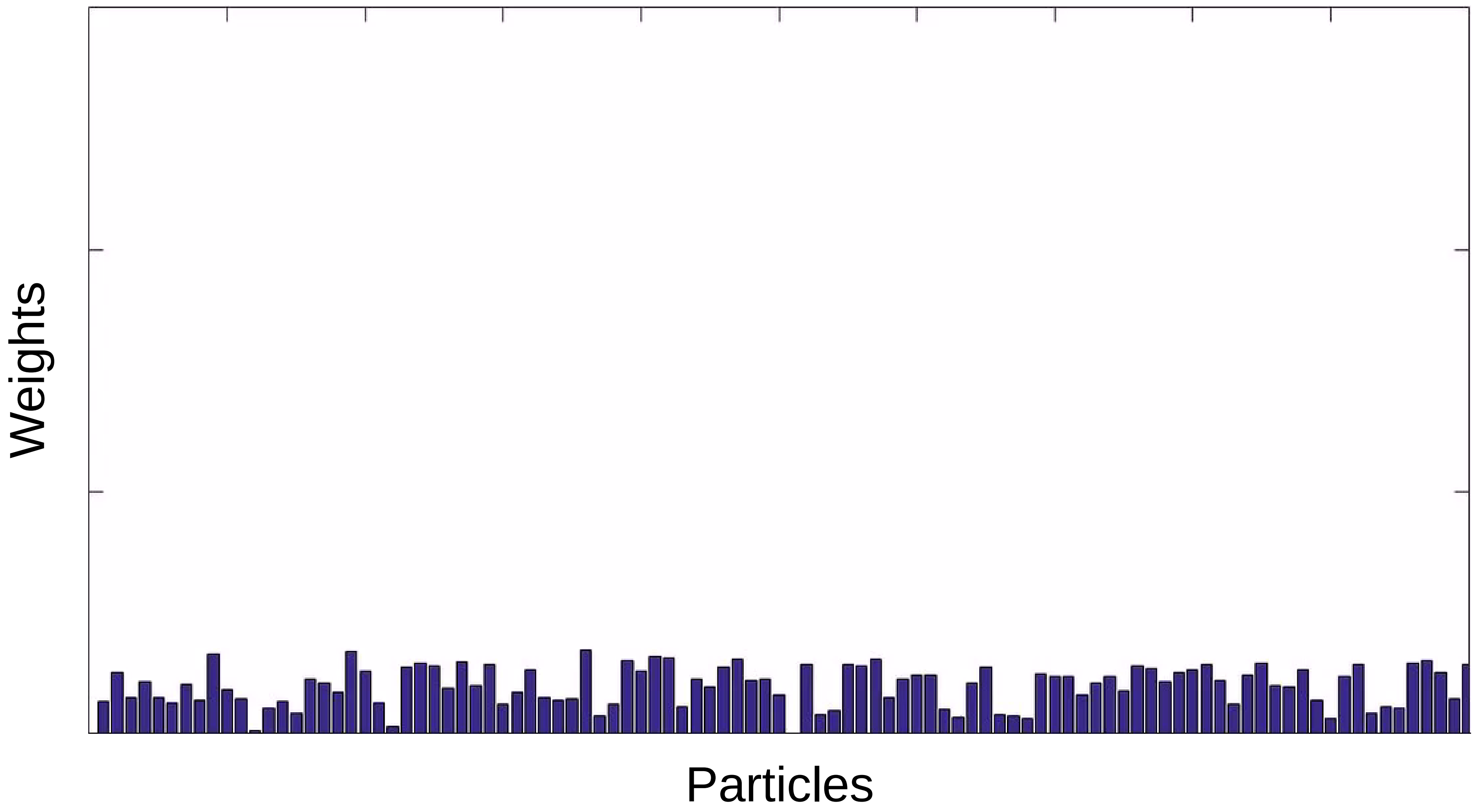
After N iterations

Resampling

Particles

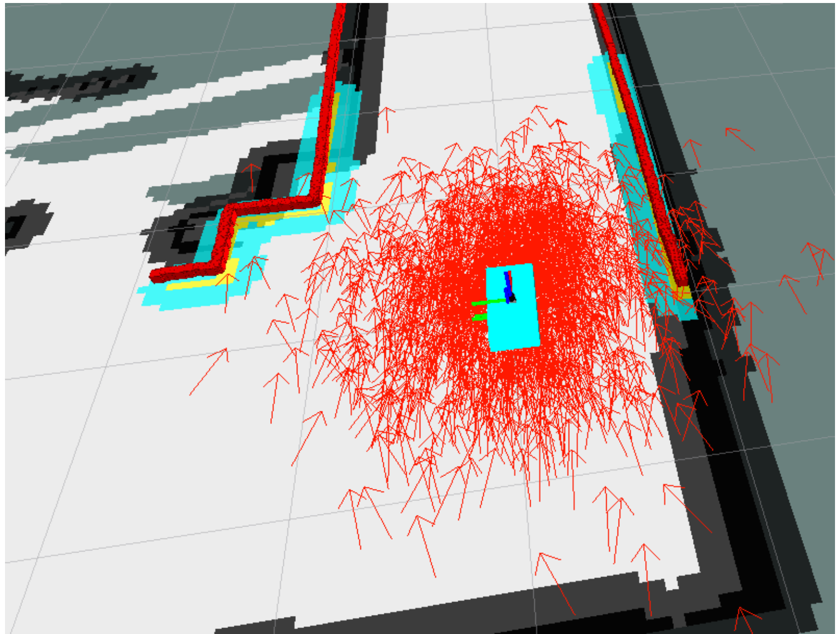


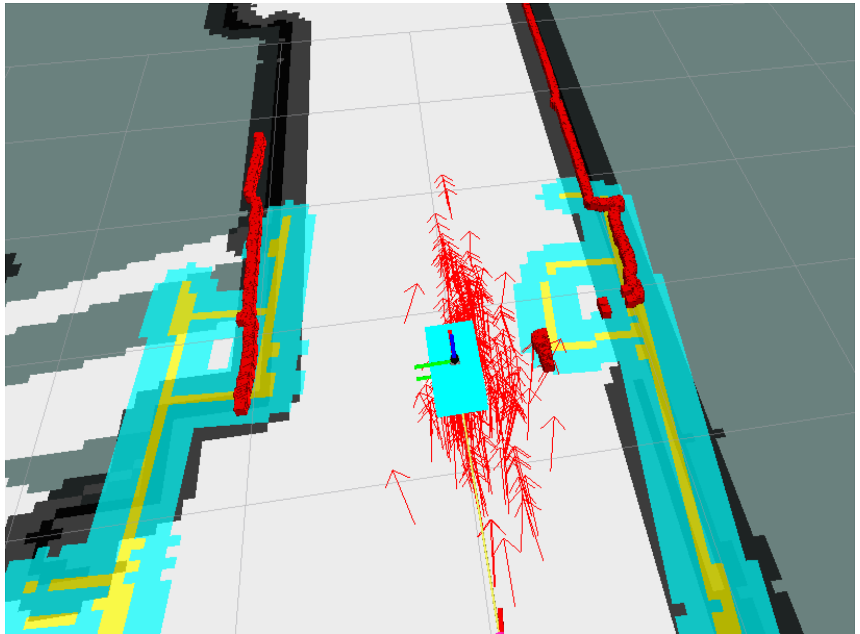
Particle filter with Resampling



Kullback–Leibler divergence (KLD Sampling)

- Variable Particle size
- Sample size is proportional to error between odometry position and sample based approximation
- i.e smaller sample size when particles have converged

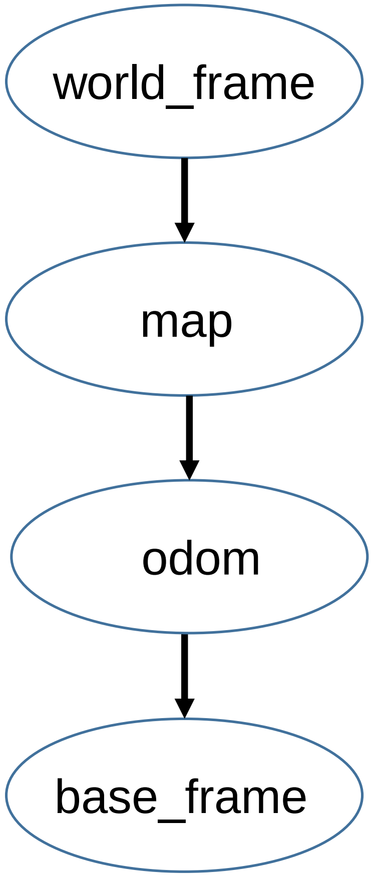




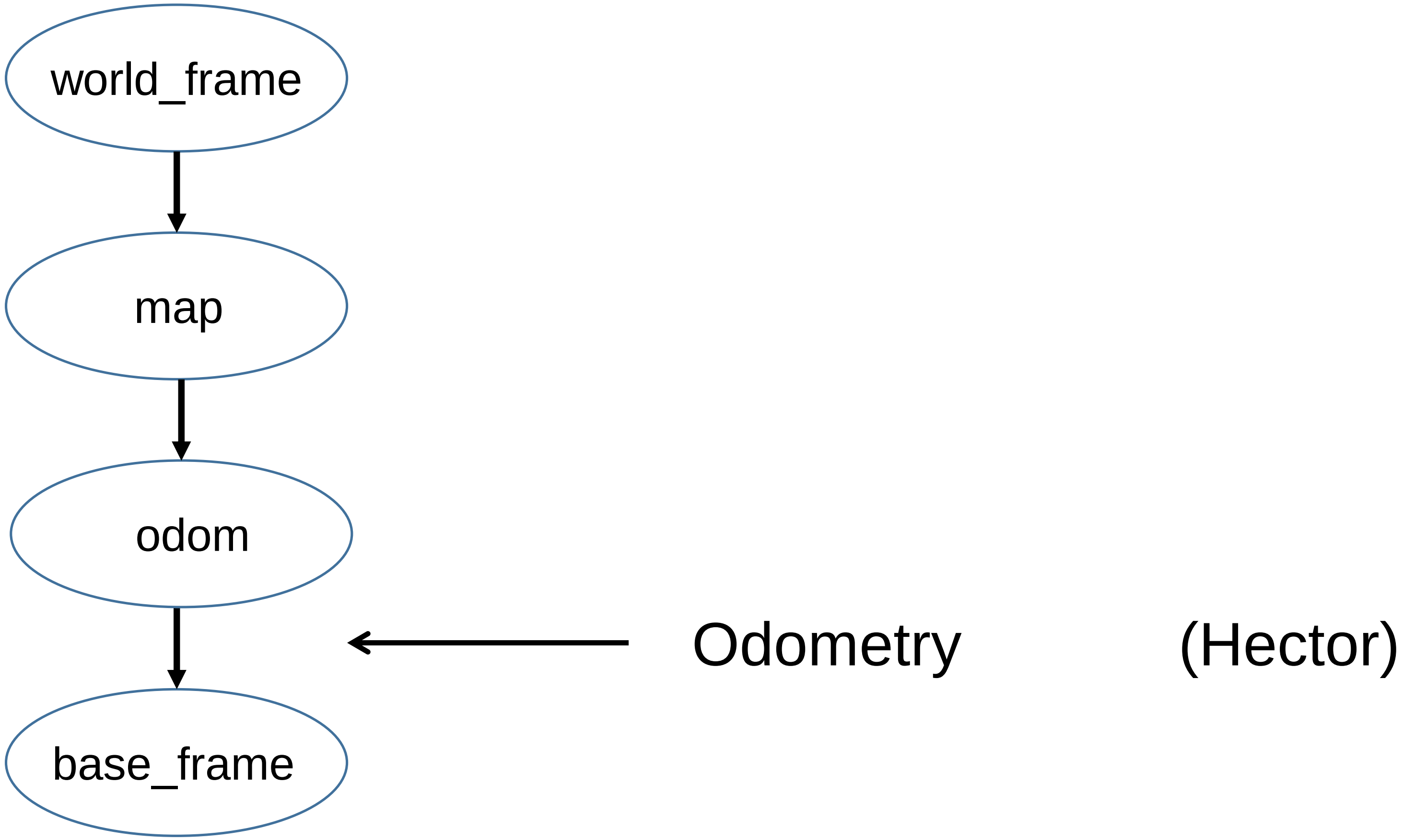
Particle Filters in ROS

- Adaptive Monte Carlo Localization Package
- Localization for a robot moving in a 2D space
- Localizes against a pre-existing map

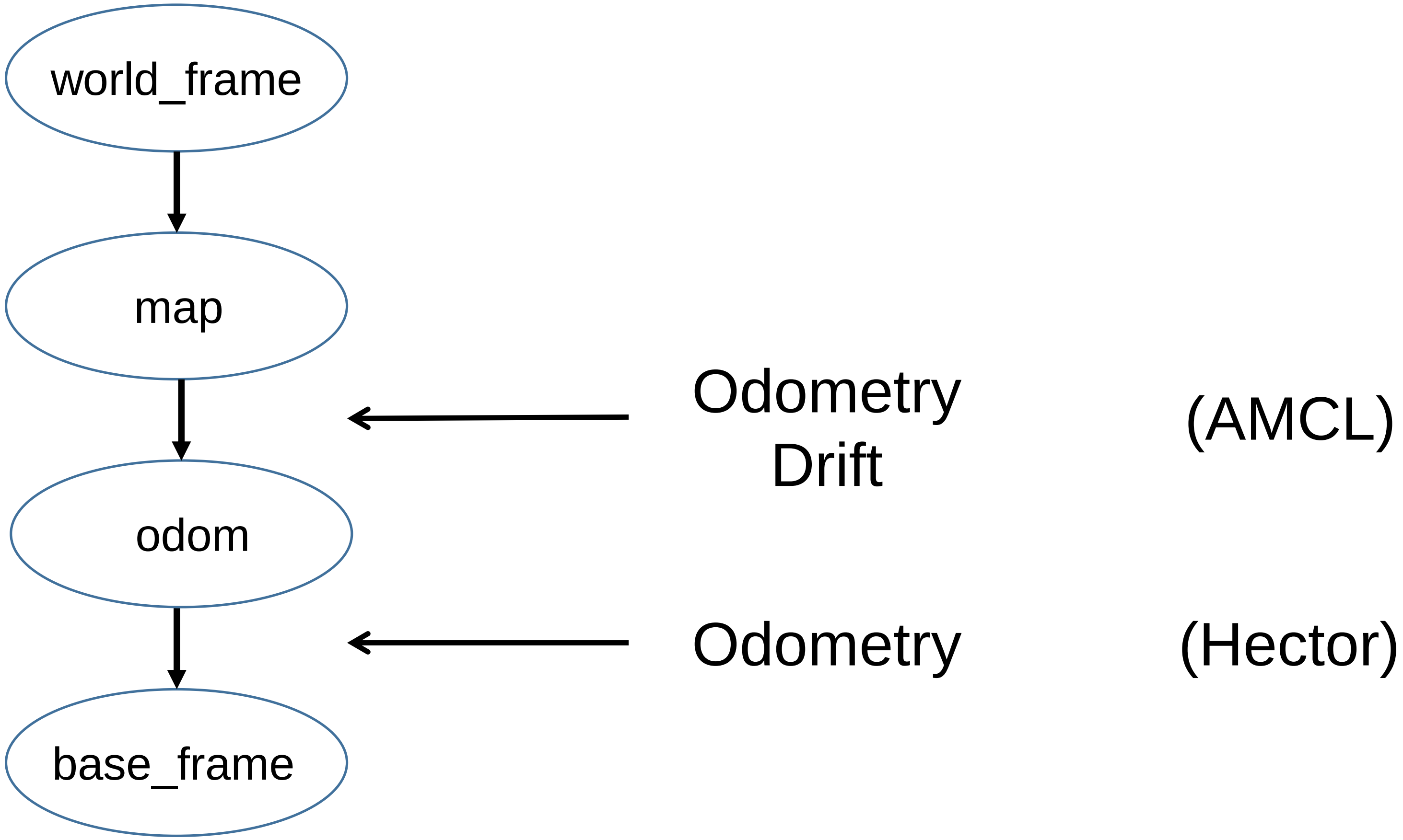
Tf tree – Where does AMCL fit in



Tf tree – Where does AMCL fit in



Tf tree – Where does AMCL fit in



Input and Output Parameters

Input and Output Parameters

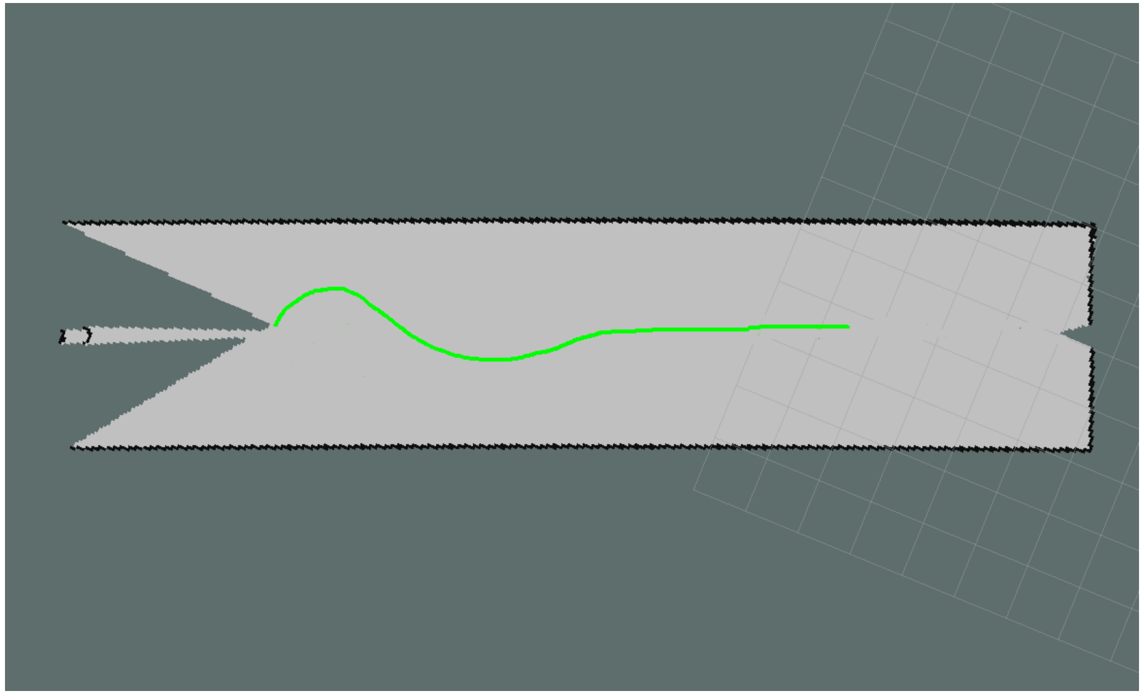
Input Parameters:

1. Laser Scan

Input and Output Parameters

Input Parameters:

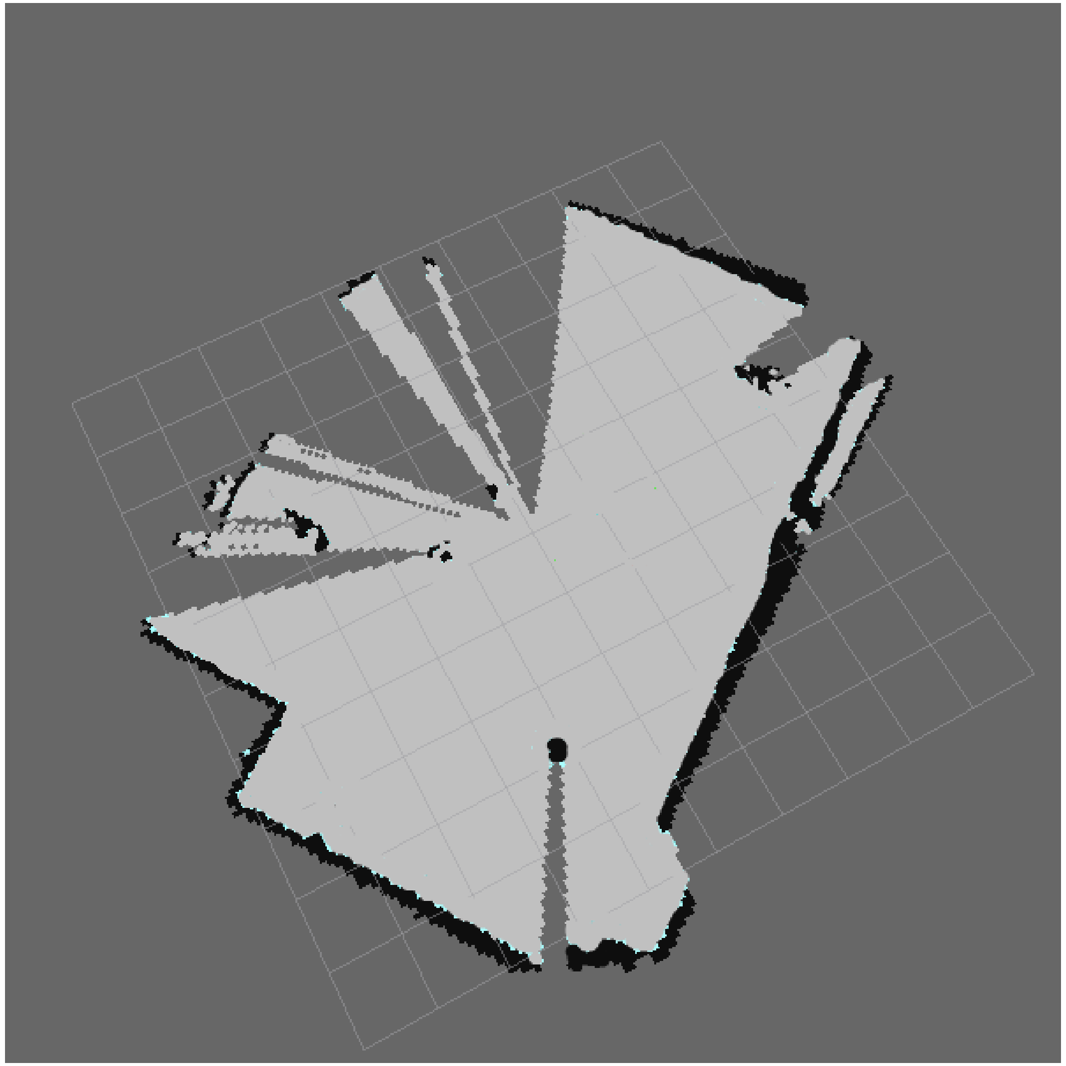
1. Laser Scan
2. Dead Reckoning/Odometry



Input and Output Parameters

Input Parameters:

1. Laser Scan
2. Dead Reckoning/Odometry
3. Map



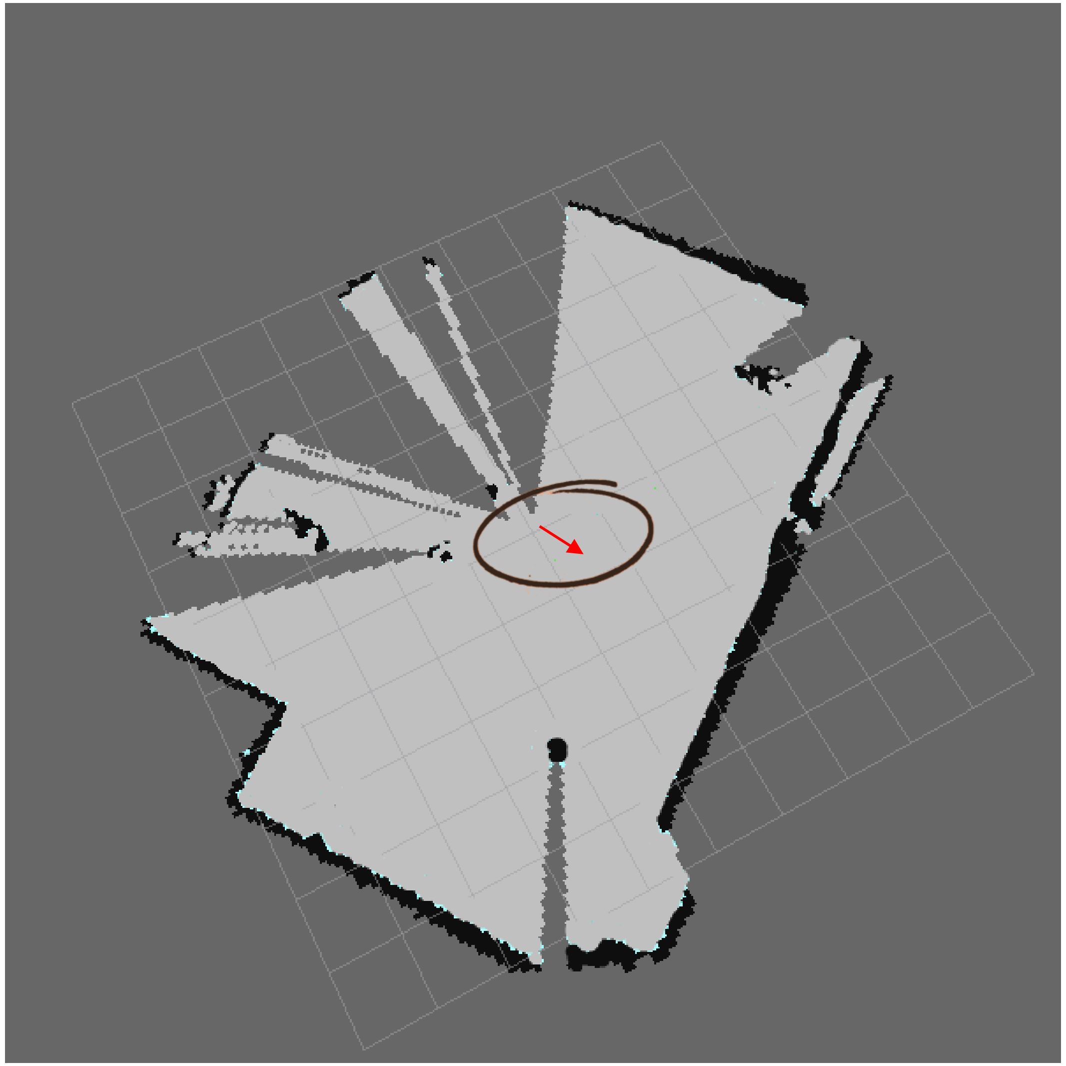
Input and Output Parameters

Input Parameters:

1. Laser Scan
2. Dead Reckoning/Odometry
3. Map

Output Parameters:

1. AMCL pose



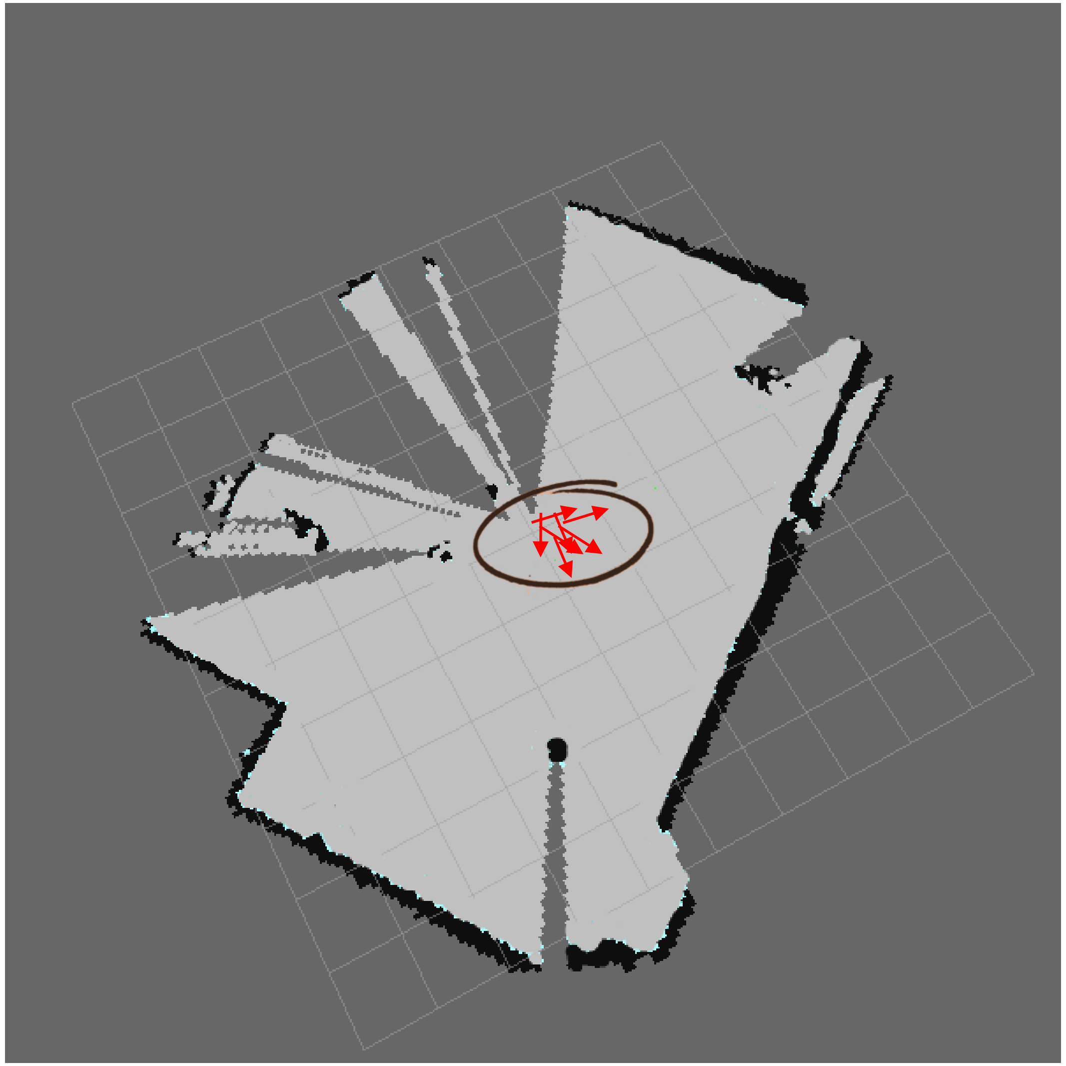
Input and Output Parameters

Input Parameters:

1. Laser Scan
2. Dead Reckoning/Odometry
3. Map

Output Parameters:

1. AMCL pose
2. Particle Cloud




amcl_config.rviz* – RViz
2D Pose Estimate
2D Nav Goal
Publish Point
Grid
Odometry
Status: Warn
Topic
/amclOdom
Color
15; 31; 255
Position Tolerance
0.1
Angle Tolerance
0.1
Keep
1
Length
1
Map
Map
Pose
PoseArray
Odometry
Keep
Number of arrows to keep before removing the oldest. 0 means keep all of them.
Add
Remove
Rename
Time
ROS Time:
1458504965.99
ROS Elapsed:
2.70
Wall Time:
1460587802.67
Wall Elapsed:
149.34
Experimental
Reset
Left-Click: Rotate. Middle-Click: Move X/Y. Right-Click/Mouse Wheel:: Zoom. Shift: More options.
30 fps

AMCL Parameters

`min_particles`

Default: 100

The minimum number of particles to be used for calculating correlation

`max_particles`

Default: 500

The maximum number of particles to be used for calculating correlation

AMCL Parameters

`update_min_d`

Default: 0.2m

The minimum translation movement required by the vehicle before an pose update is published

`update_min_a`

Default: $^{\pi}/_{6}$ radians

The minimum angular movement required by the vehicle before an pose update is published

AMCL Parameters

`initial_pose_x`	Default: 0
`initial_pose_y`	Default: 0
`initial_pose_a`	Default: 0

The initial mean position of the particles to initialize the particle filter

AMCL Parameters

`initial_cov_xx` Default: 0

`initial_cov_yy` Default: 0

`initial_cov_aa` Default: 0

The covariance of particles distributed around the mean

What Next?

- Path Planning and Trajectory Generation
- Cost Maps
- Control Algorithms For Navigation