

**F1/10**

# Autonomous Racing

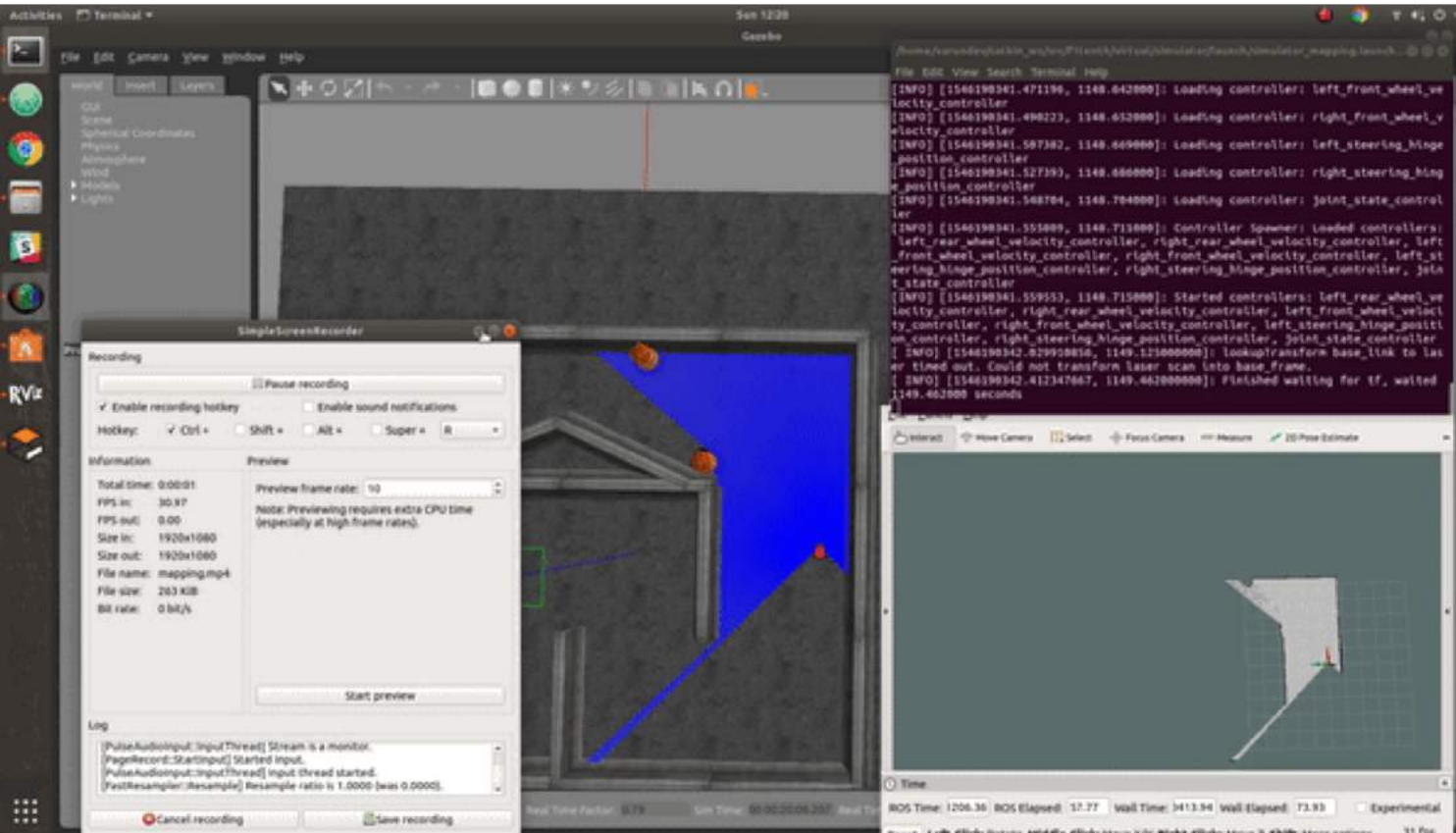
## Simultaneous Mapping Localization & Planning

Varundev Sukhil

CS 4501/SYS 4582

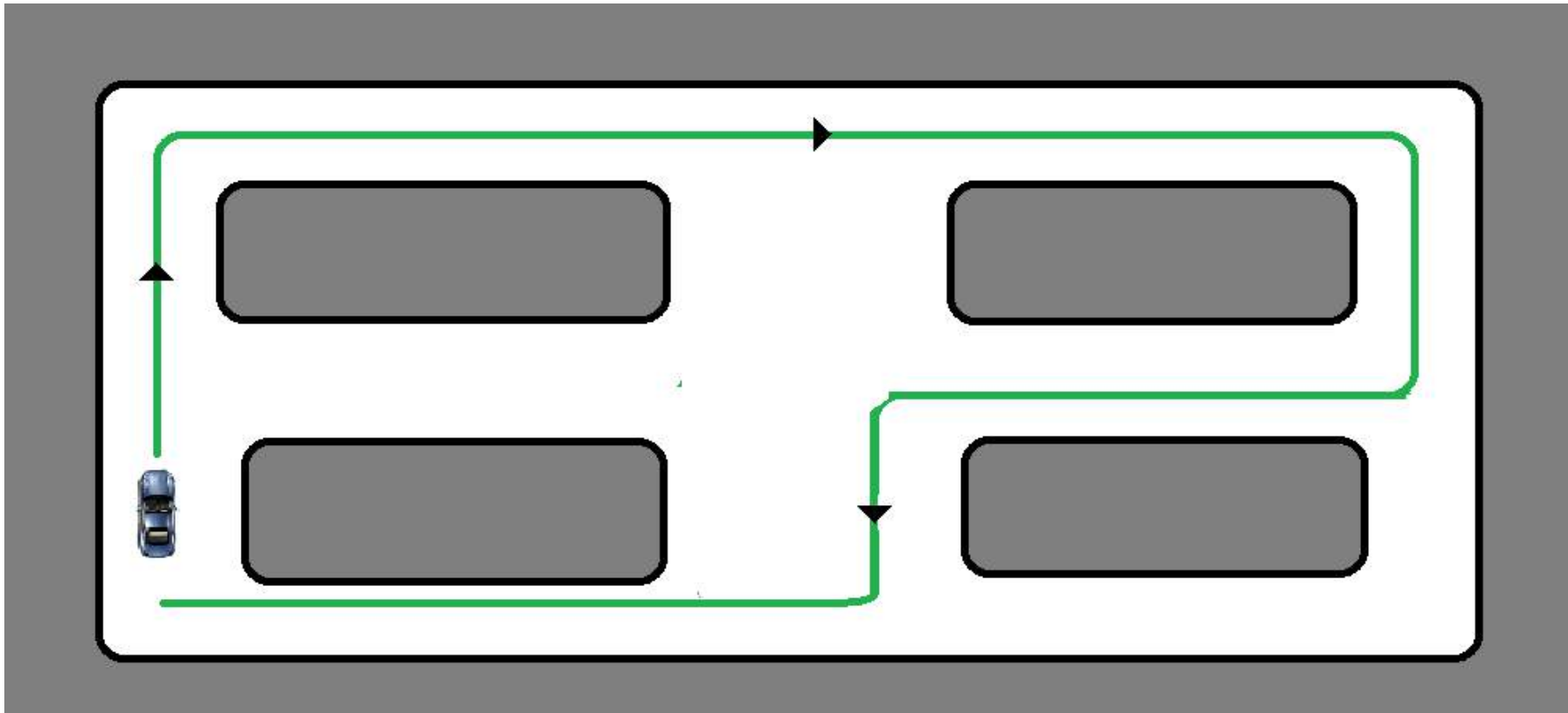
Spring 2019

Rice Hall 120

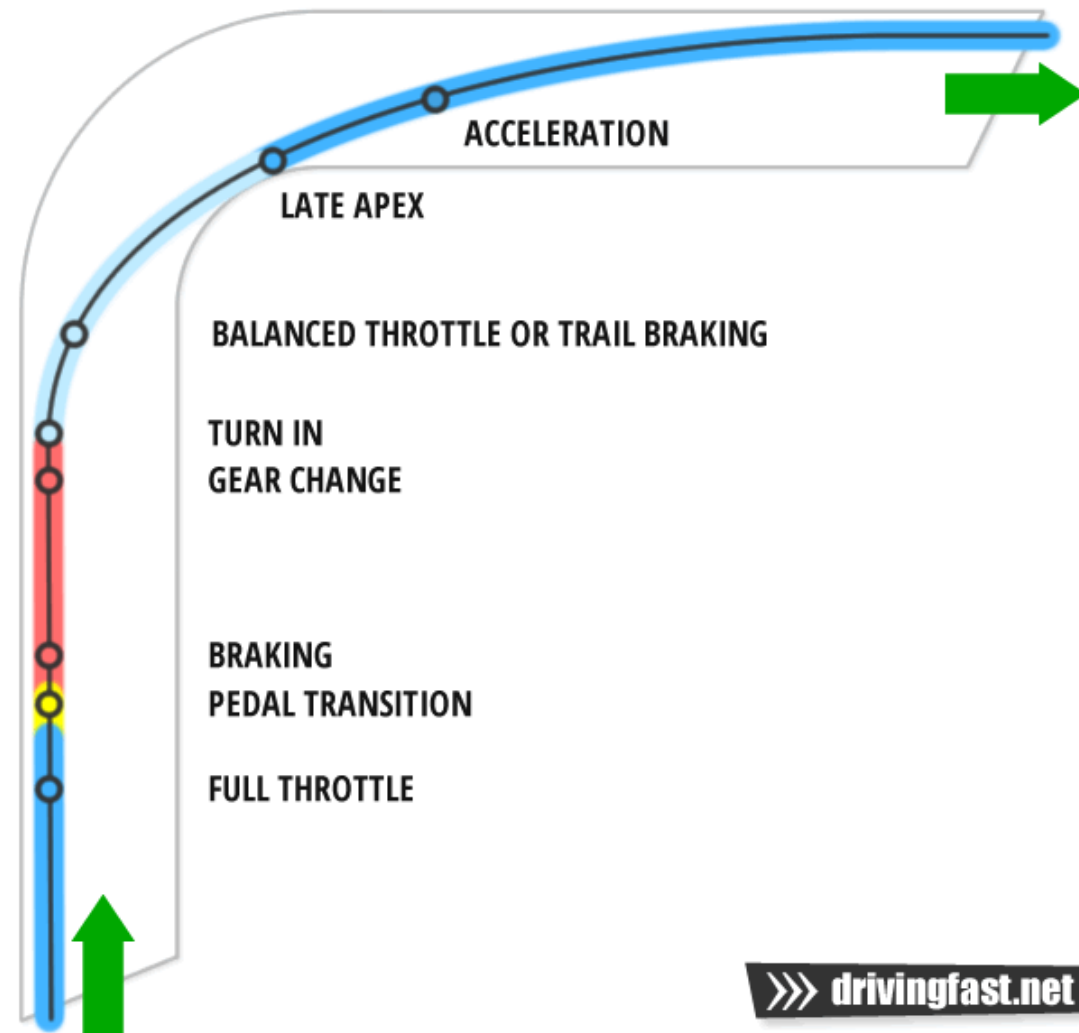


# Limitations : Basic Path Planning

- High Level Path Assignments
  - 2<sup>nd</sup> right, 2<sup>nd</sup> right, 1<sup>st</sup> right, 1<sup>st</sup> left, 1<sup>st</sup> right

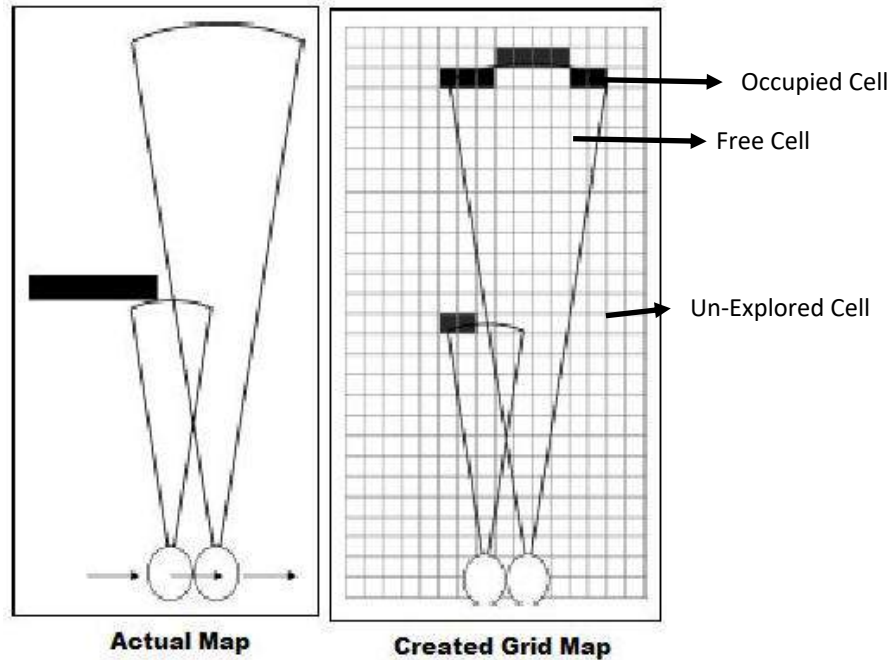


# Race Lines



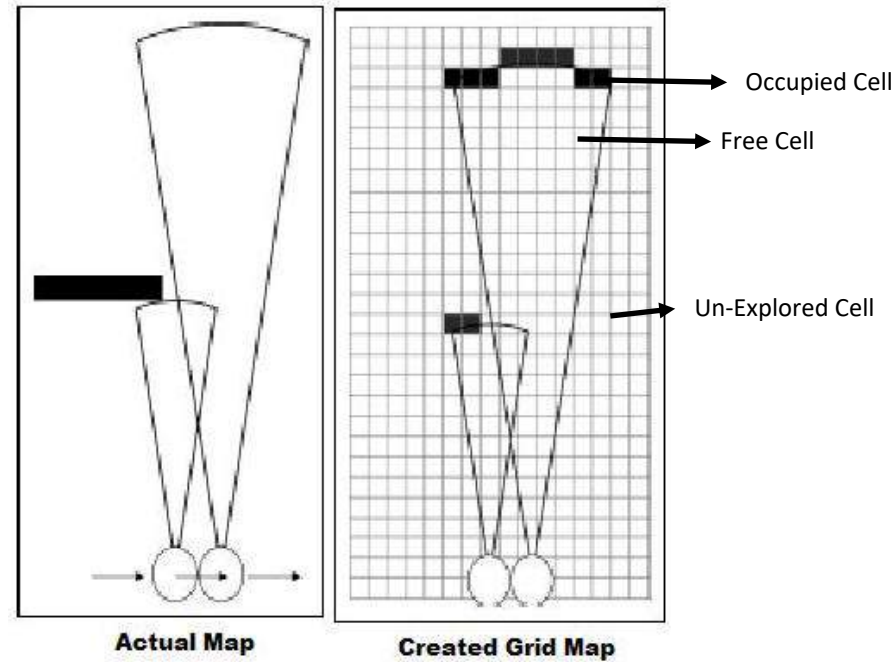
# Occupancy Grid Mapping

## Measurement Model



- Measurement :  
 $m_{x,y} = 1$  LiDAR hit  
 $m_{x,y} = 0$  No occlusion
- Map Cell:  
 $Z = 1$  Occupied  
 $Z = 0$  UnExplored  
 $Z = -1$  Free
- Measurement Model :  
 $p(z|m_{x,y})$

# Occupancy Grid Mapping



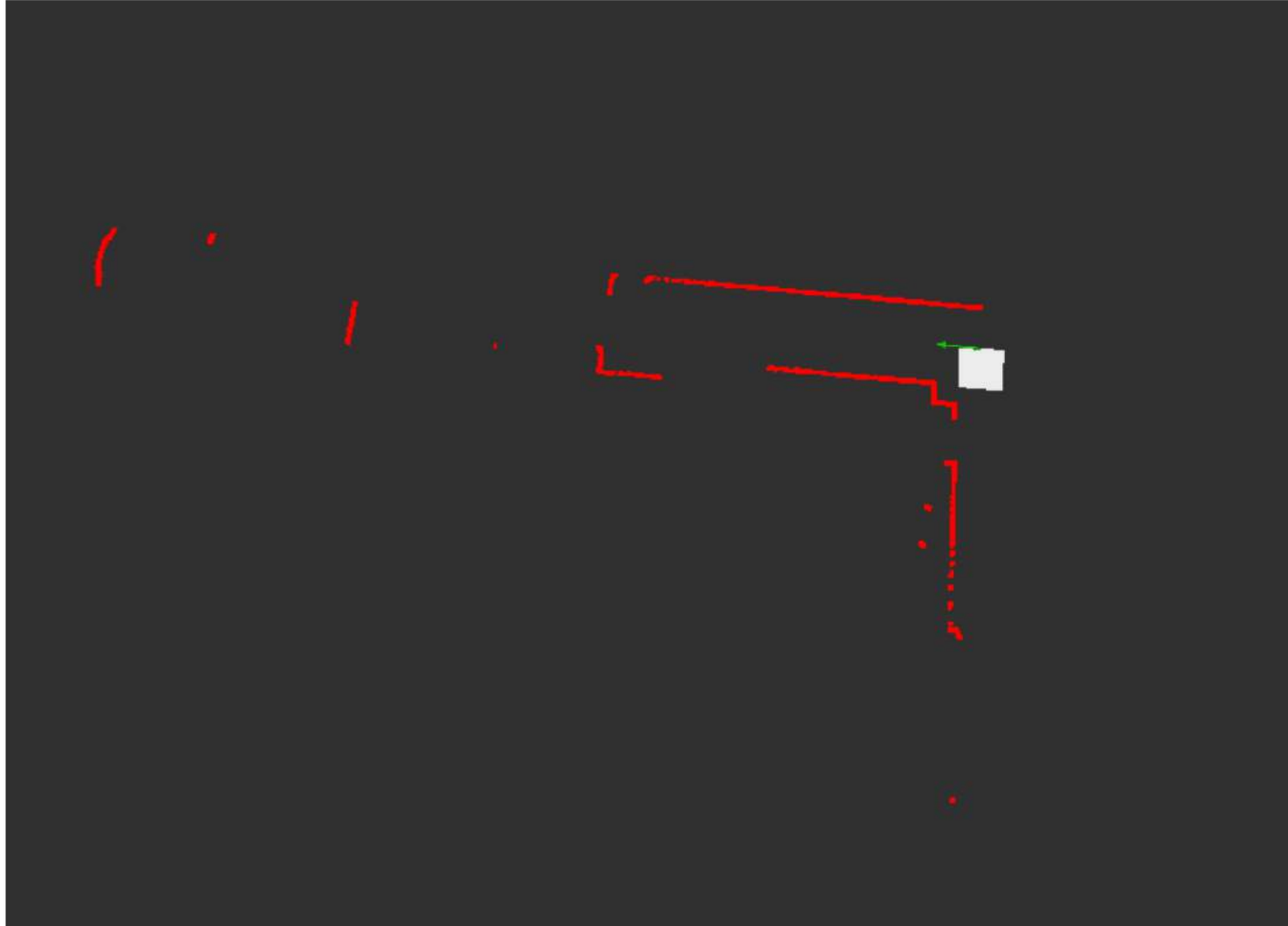
$$\log odd_{occ} := \log \frac{p(z = 1 | m_{x,y} = 1)}{p(z = 1 | m_{x,y} = 0)}$$

Log Probability for occupied cells

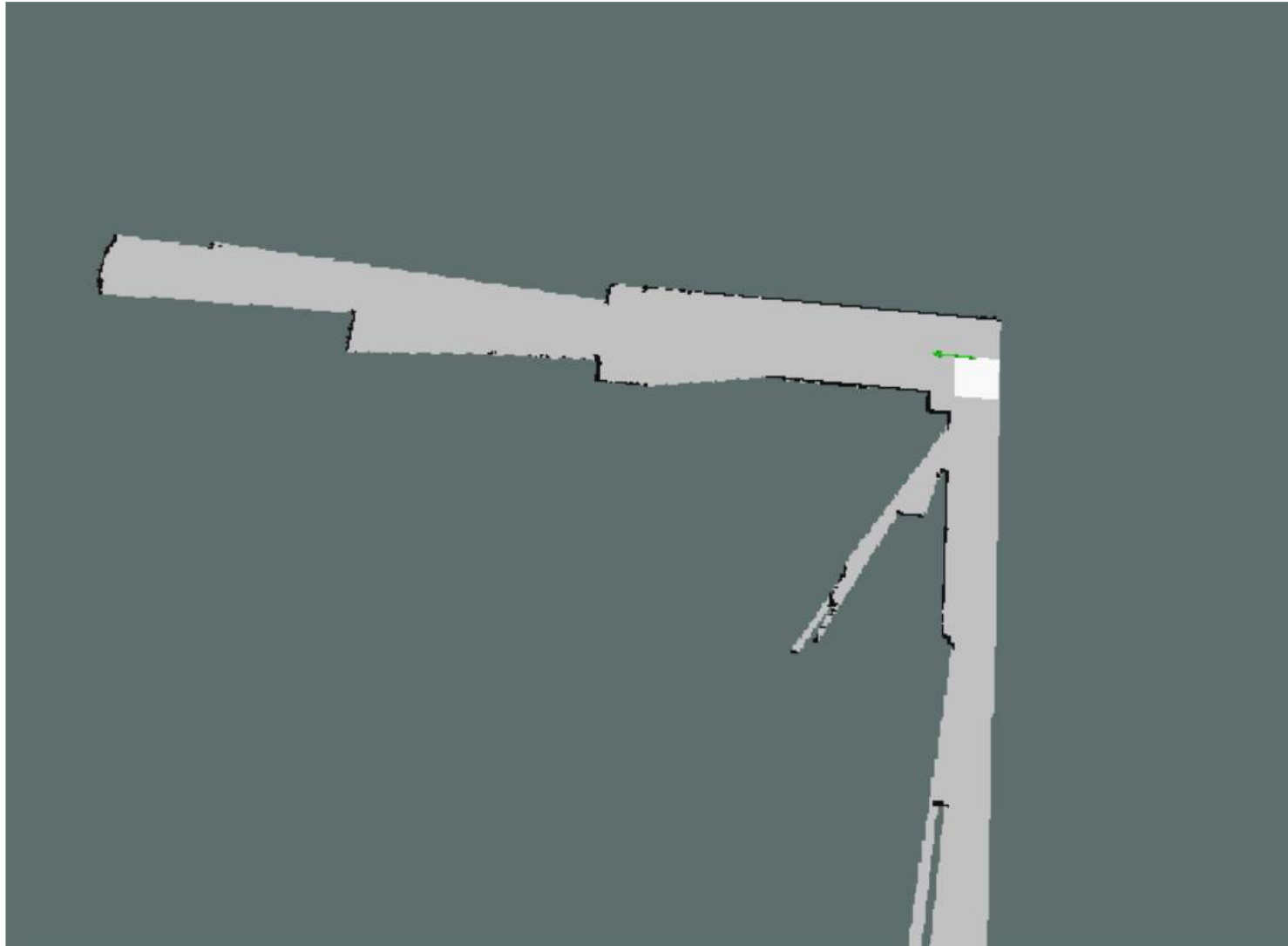
$$\log odd_{free} := \log \frac{p(z = -1 | m_{x,y} = 0)}{p(z = -1 | m_{x,y} = 1)}$$

Log Probability for free cells

# Registering the first Scan

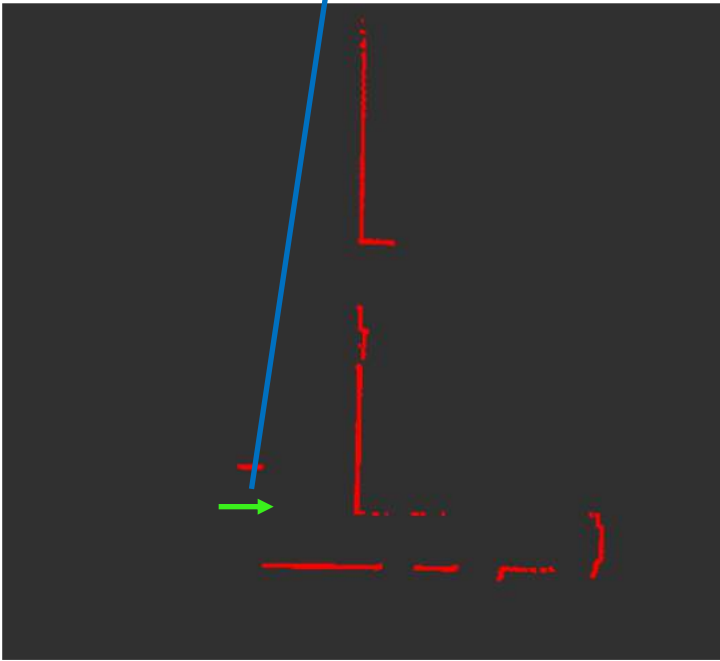


# Registering the first Scan

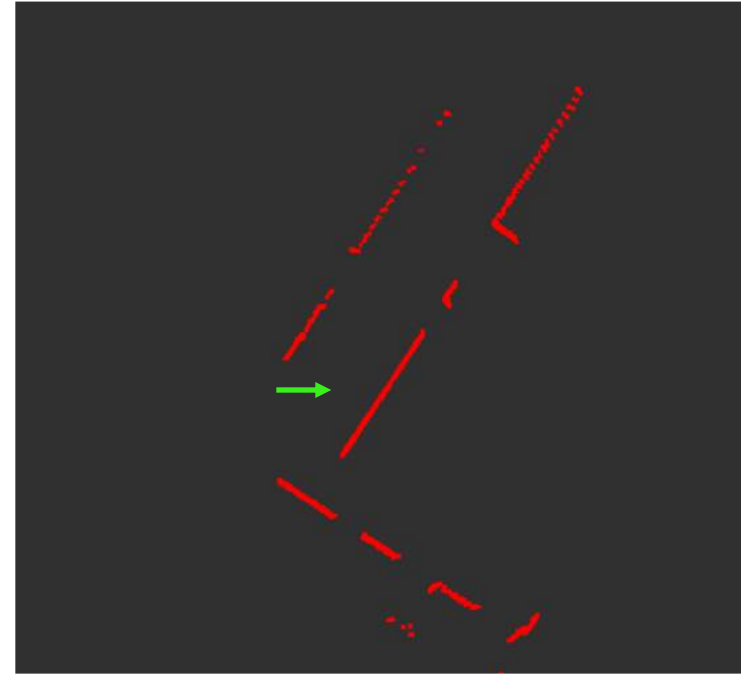


# Scan Matching

Pose of the Car at  $t = t_1$



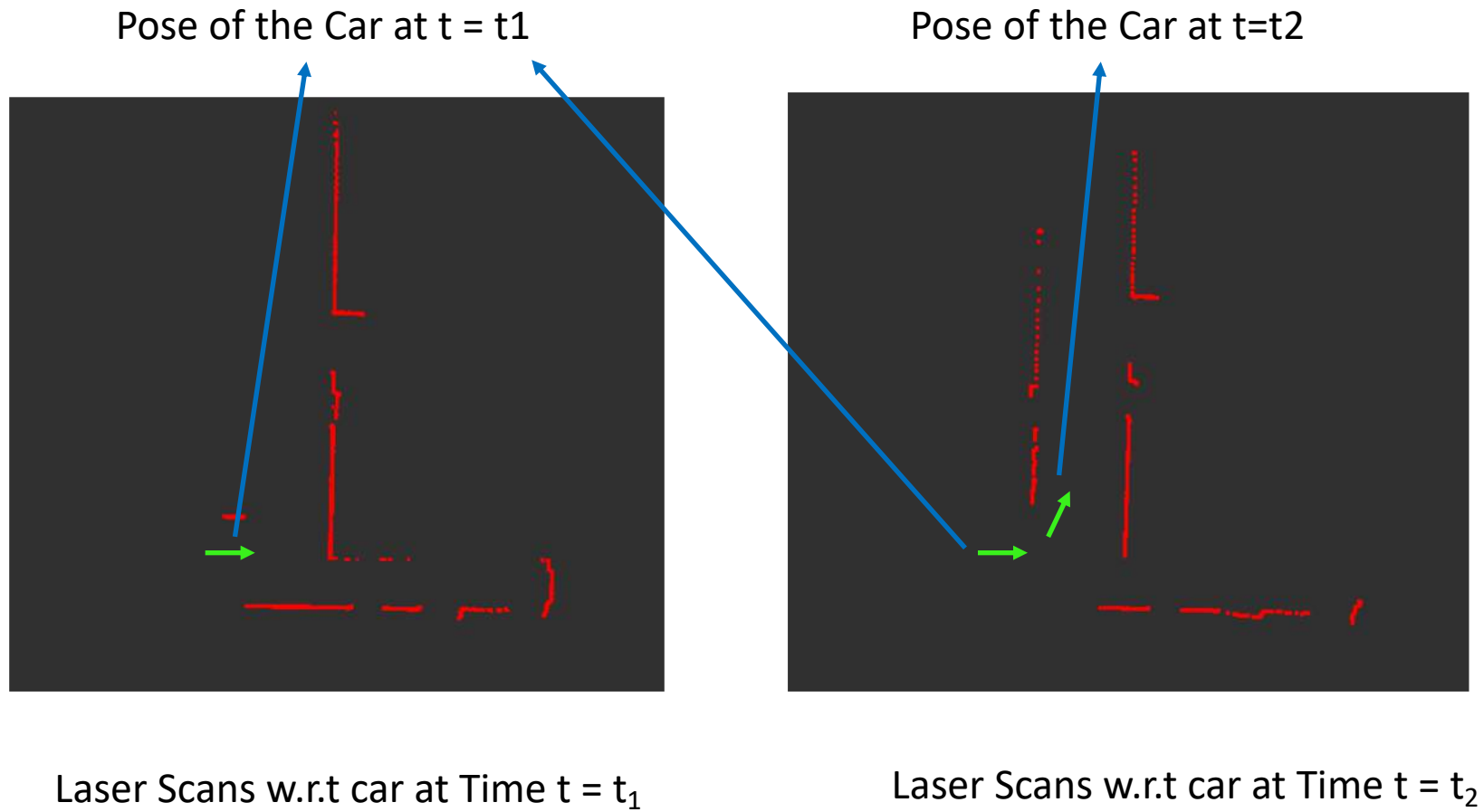
Laser Scans w.r.t car at Time  $t = t_1$



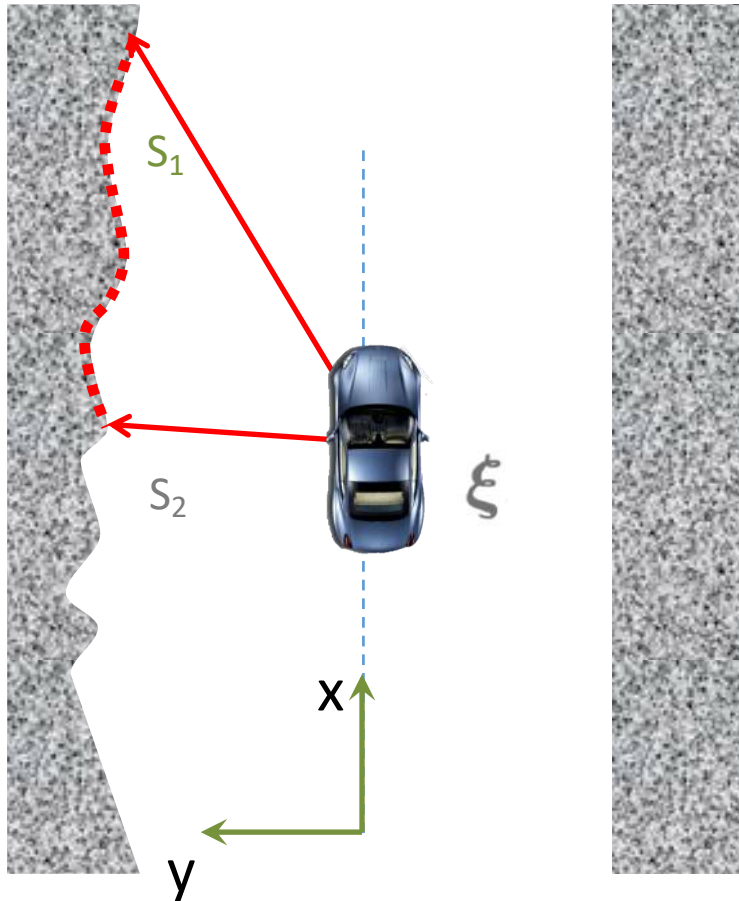
Laser Scans w.r.t car at Time  $t = t_2$



# Scan Matching



# Scan matching: Hector Slam



Robot Pose  $\xi = (p_x, p_y, \psi)^T$

Impact coordinates of  $i^{\text{th}}$  scan in world frame

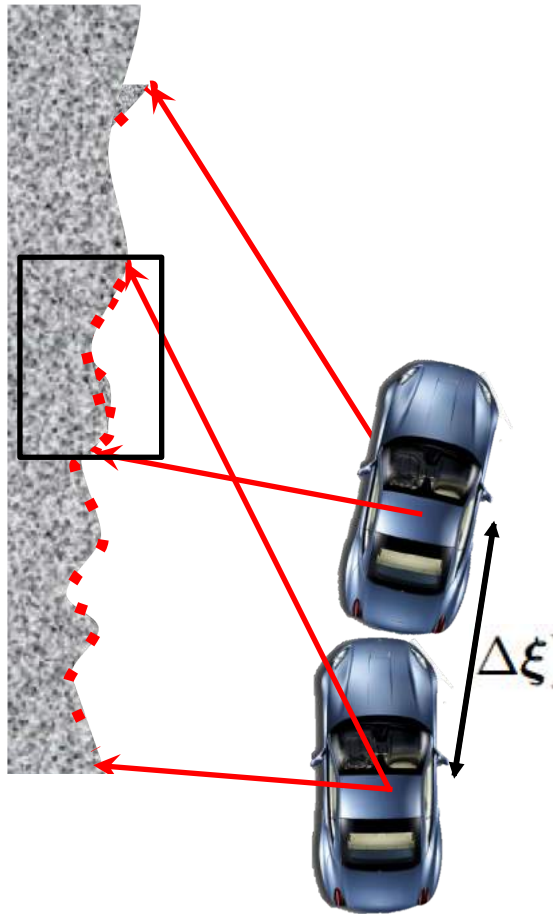
Total of  $n$  scans

$$\xi^* = \underset{\xi}{\operatorname{argmin}} \sum_{i=1}^n [1 - M(\mathbf{S}_i(\xi))]^2$$

Map Value at coordinates given by  $S_i$

The diagram shows the equation for scan matching. Above the summation symbol  $\sum$  is the variable  $n$ , with an upward arrow and the text "Total of  $n$  scans". Below the term  $M(\mathbf{S}_i(\xi))$  is a downward arrow and the text "Map Value at coordinates given by  $S_i$ ". An upward arrow points from the term  $M(\mathbf{S}_i(\xi))$  to the text "Impact coordinates of  $i^{\text{th}}$  scan in world frame".

# Scan matching: Hector Slam



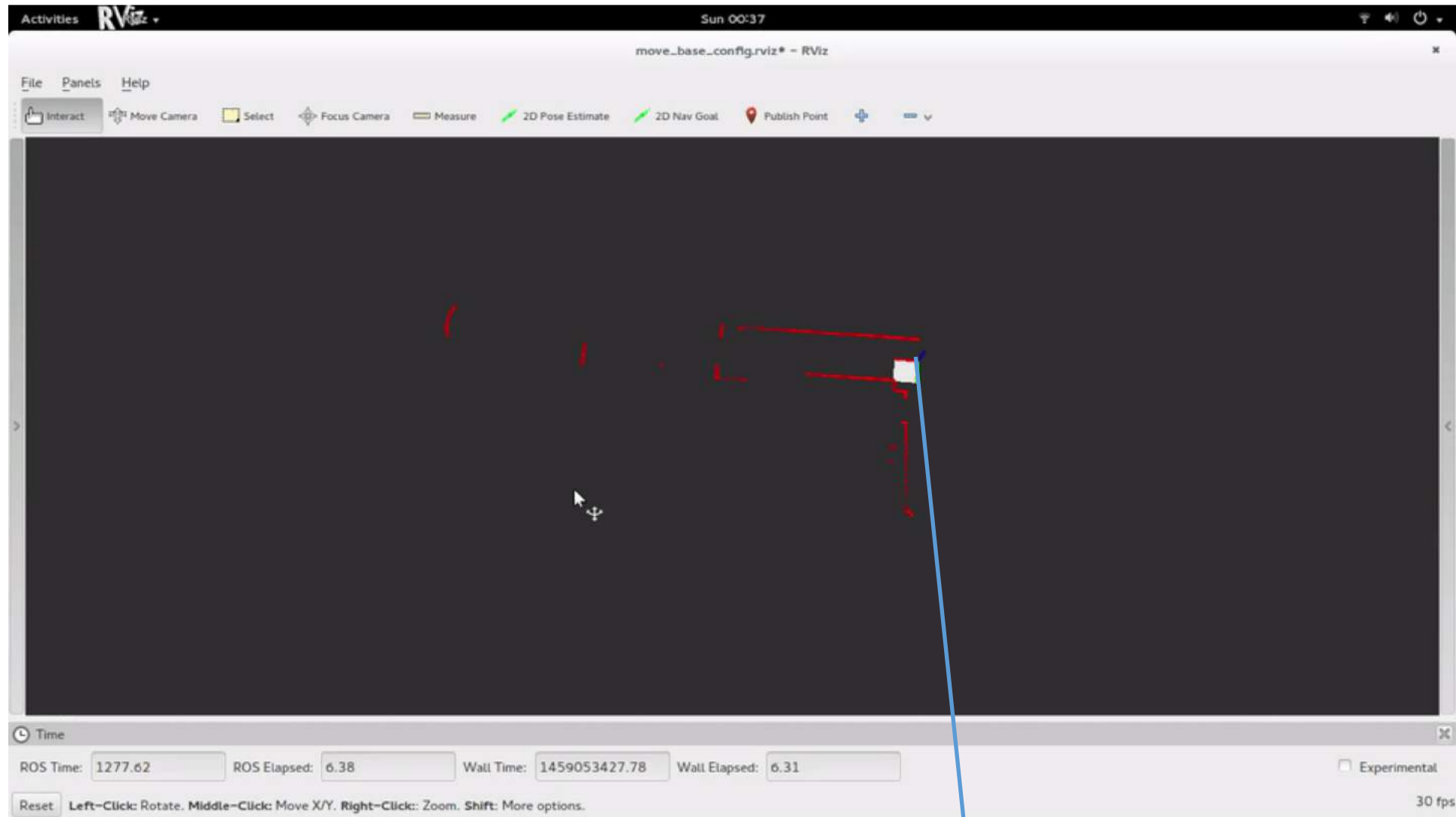
$$\sum_{i=1}^n [1 - M(\mathbf{S}_i(\boldsymbol{\xi} + \Delta\boldsymbol{\xi}))]^2 \rightarrow 0.$$

Taylor Expansion of  
Function M

Solving for  $\Delta\xi$  to  
yields Gauss-  
Newton Equation

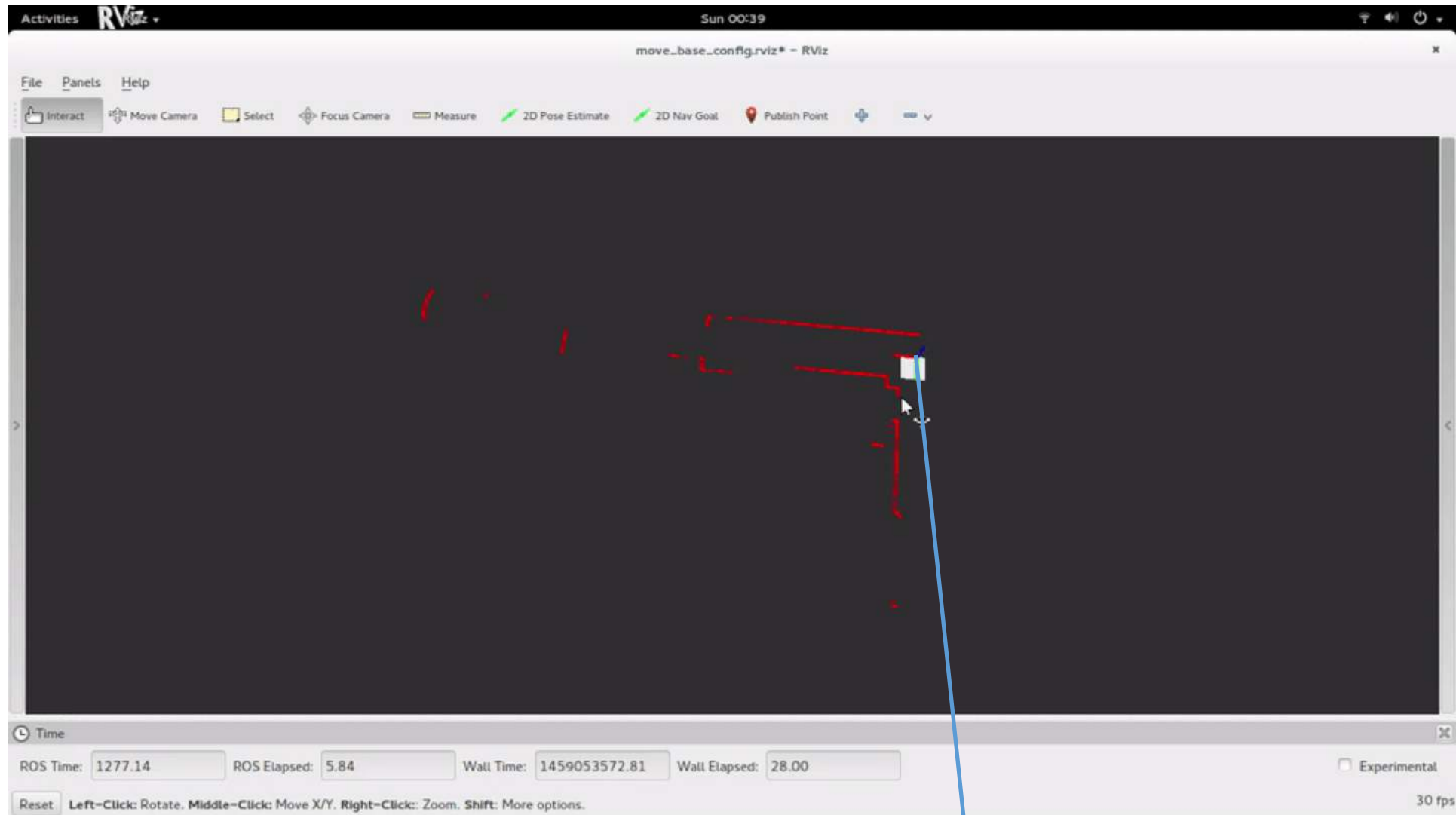
Evaluation of Gauss-Newton equation  
gives a step  $\Delta\xi$  that minimizes the  
objective function

# Raw LiDAR Scans



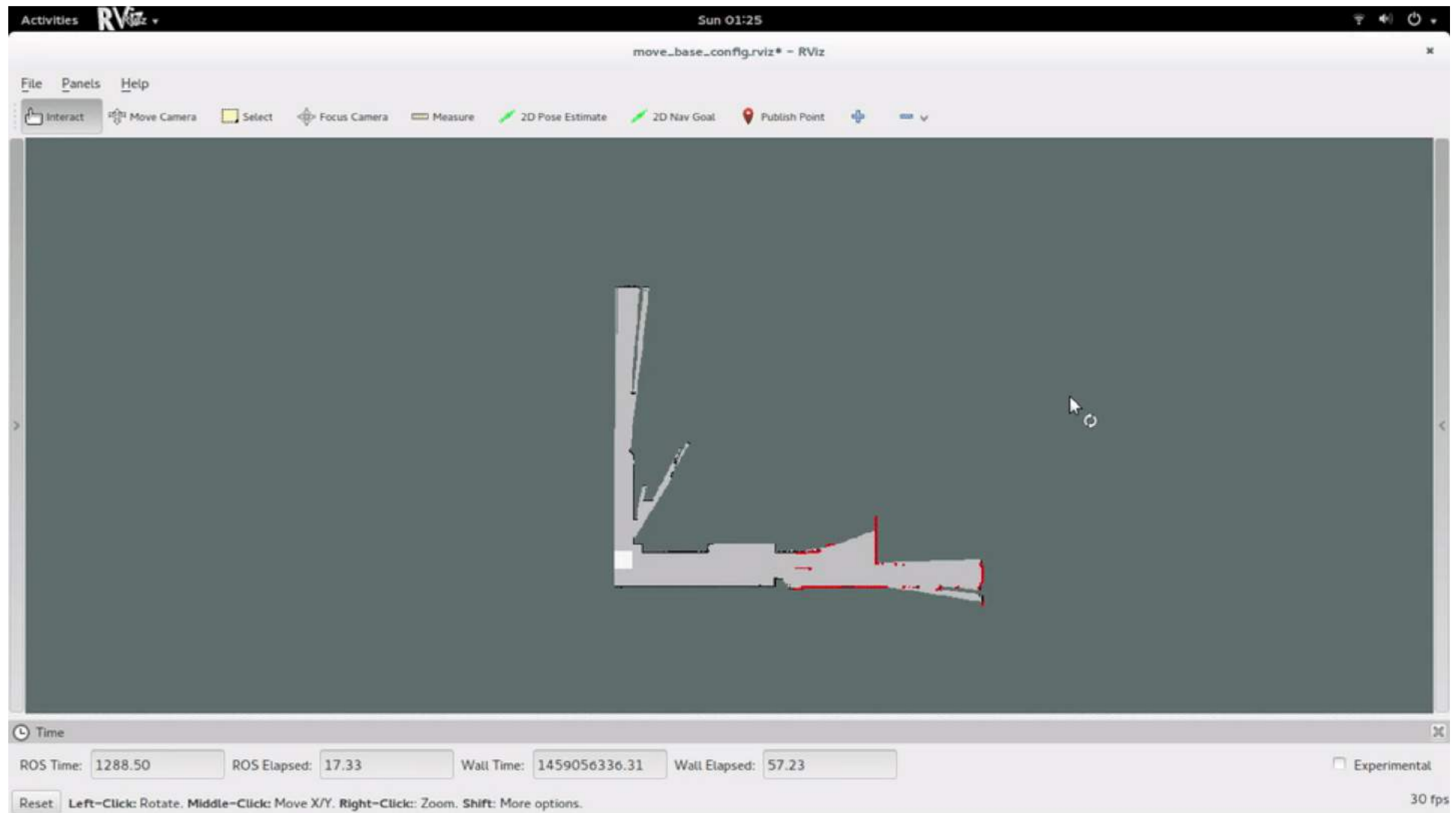
Baseframe Axes

# Scans after transforming by $\Delta\xi$ at each stage



Mapframe Axes

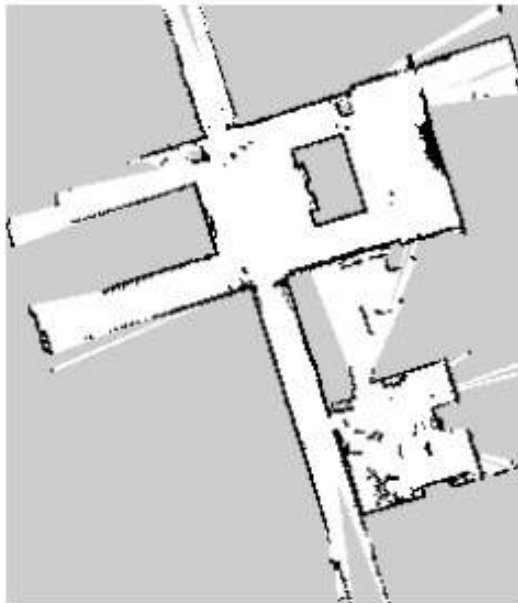
# Map Update



# Multi-Resolution Map Representation



20 cm Grid Cell

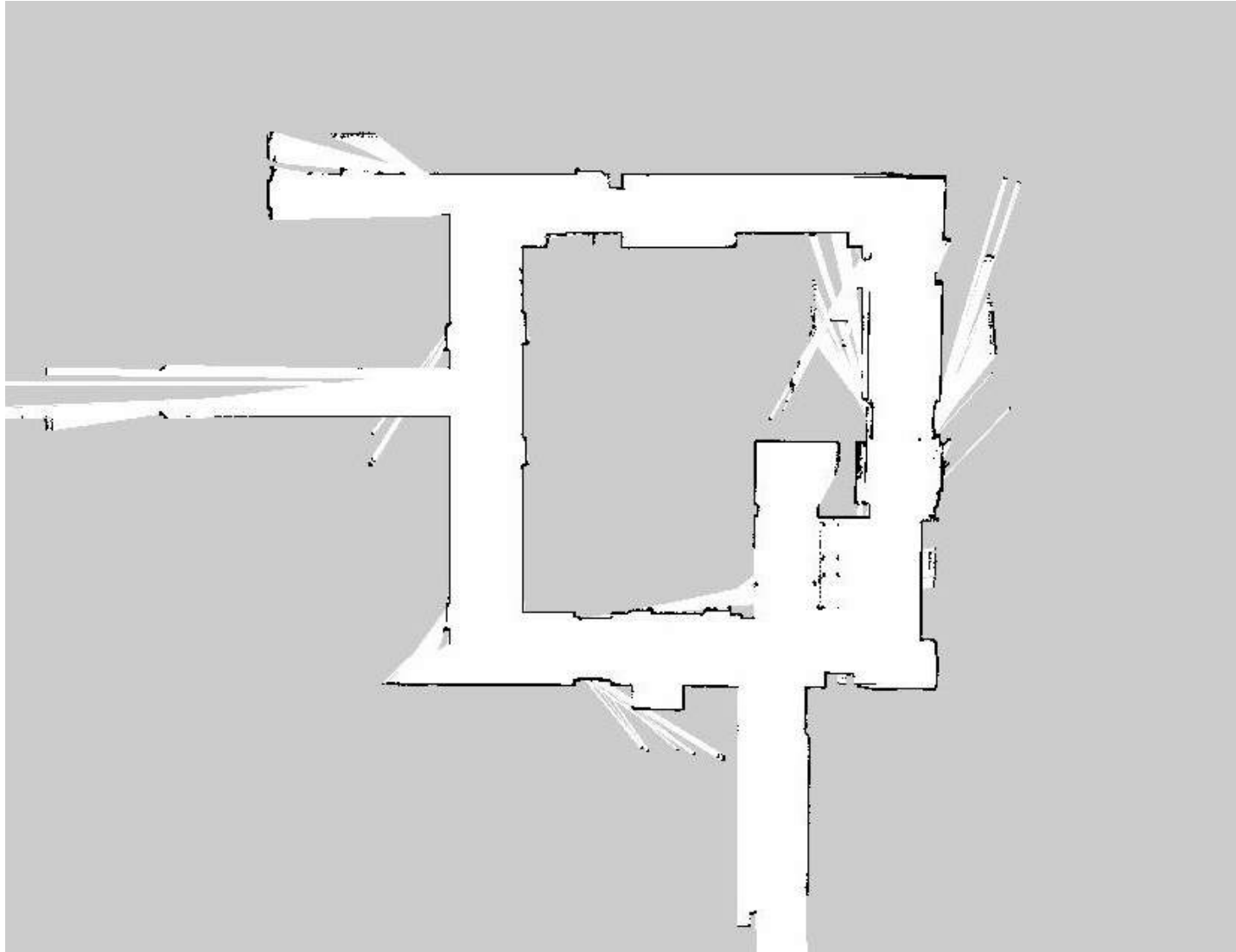


10 cm Grid Cell



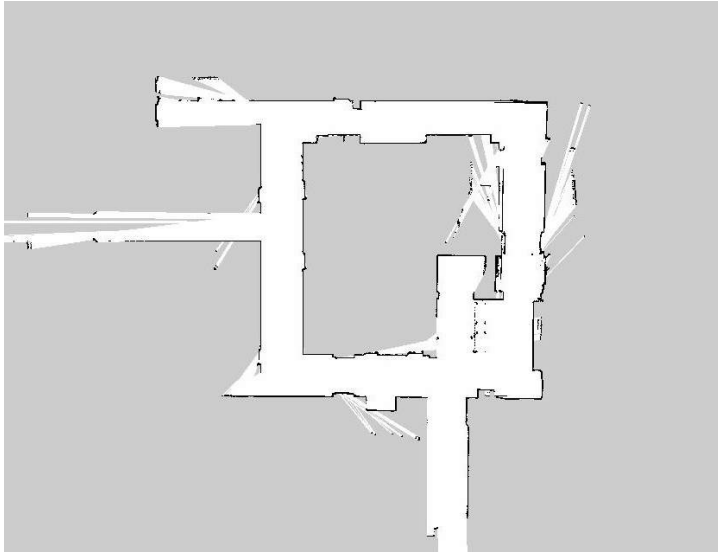
5 cm Grid Cell

# Saving the map



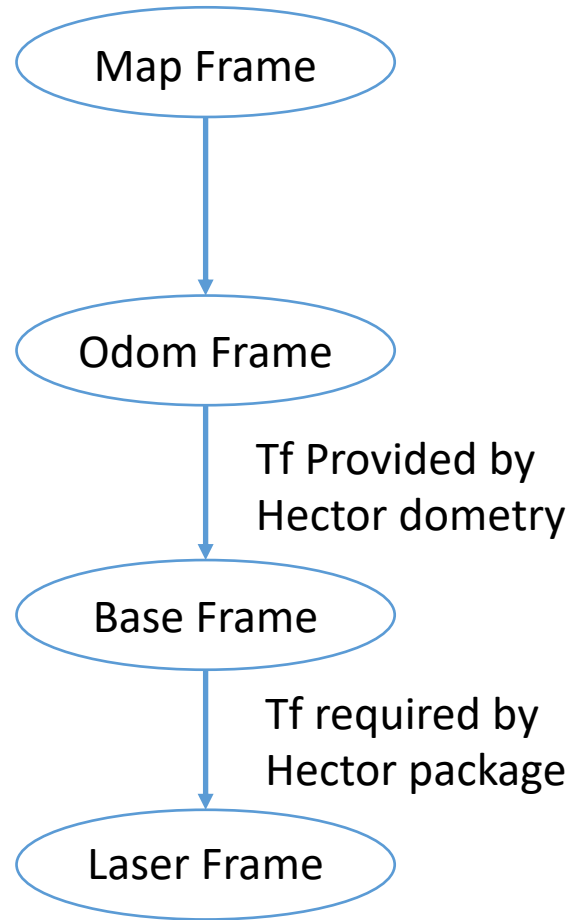


# Saving the map



- ROS Package called **MAP Server**
- Allows saving a map currently being published over /map topic
- The saved map can be loaded for future tasks.

# System Tf tree



# Parameters for Hector SLAM : ROS

- map\_resolution
- map\_update\_distance\_thresh
- map\_update\_angle\_thresh
- laser\_max\_dist
- update\_factor\_free
- update\_factor\_occupied

mapping\_demo.rviz\* - RViz

File

se Estimate


2D Nav Goal

Publish Point

+

-

▼



Topic

Alpha

Color Scheme

Draw Behind

Resolution

Width

Height

+ Position

+ Orientation

- Path

+ Status: Ok

/map

0.7

map

☐

0.05

2048

2048

-51.225; -51.225; 0

0; 0; 0; 1

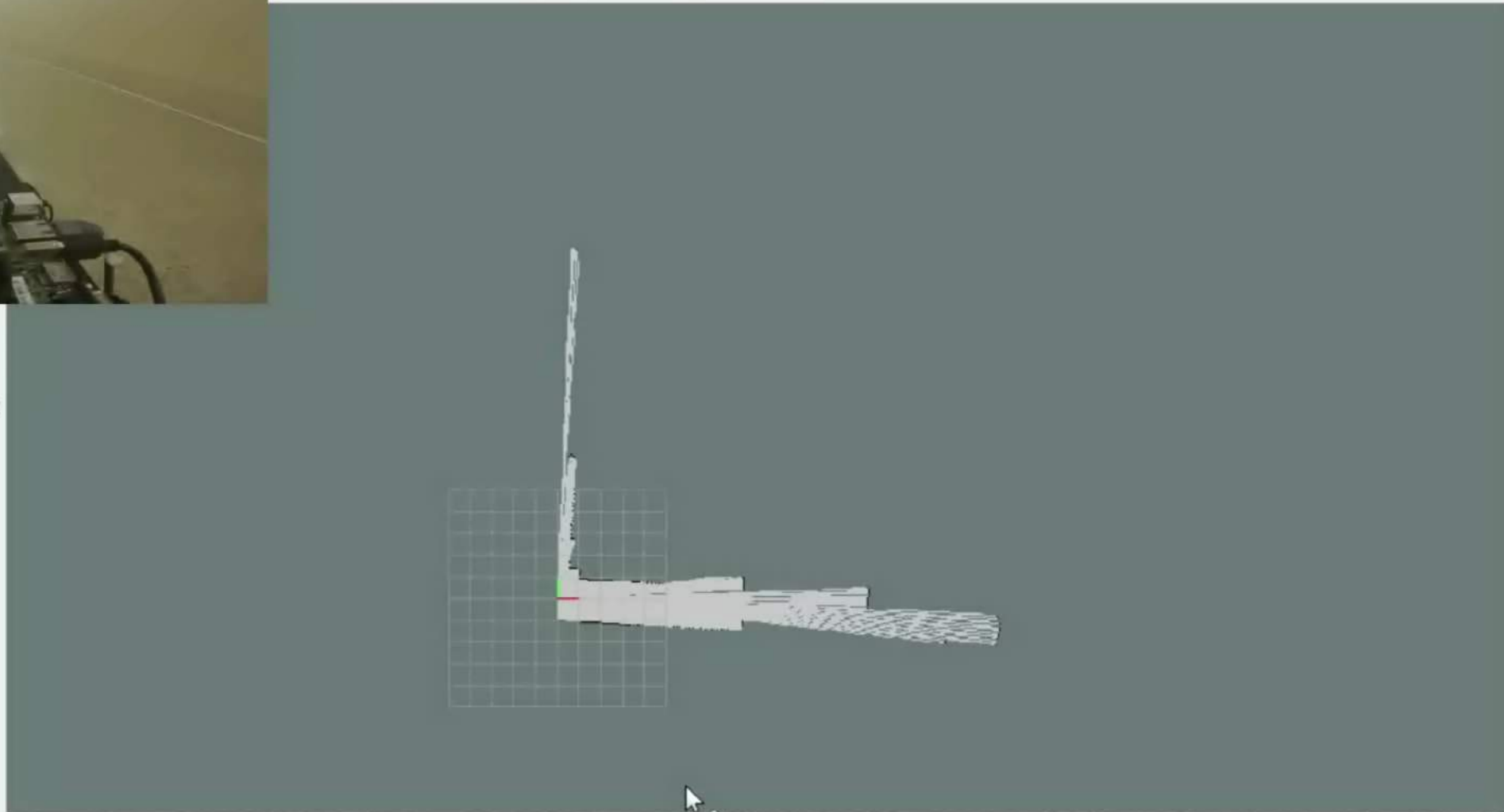
☒

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Add

Remove

Rename



Time

ROS Time: 1458504023.35

ROS Elapsed: 2.01

Wall Time: 1460591289.42

Wall Elapsed: 22.83

Experimental

Reset

Left-Click: Rotate. Middle-Click: Move X/Y. Right-Click: Zoom. Shift: More options.

30 fps

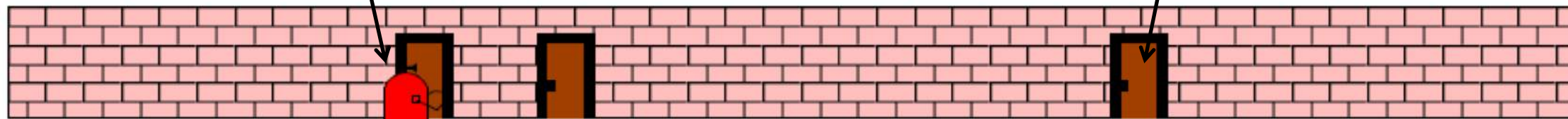
# Particle Filter

A Toy Example in 1 Dimension

At time  $t = 1$

Robot

Door



Direction of motion

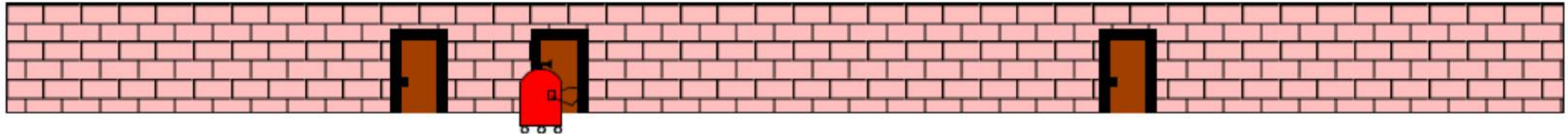
Measurement Model

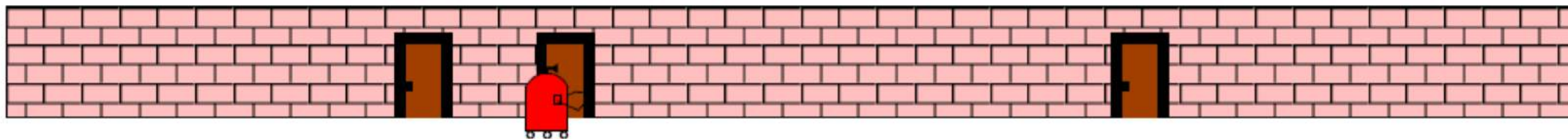


Belief State

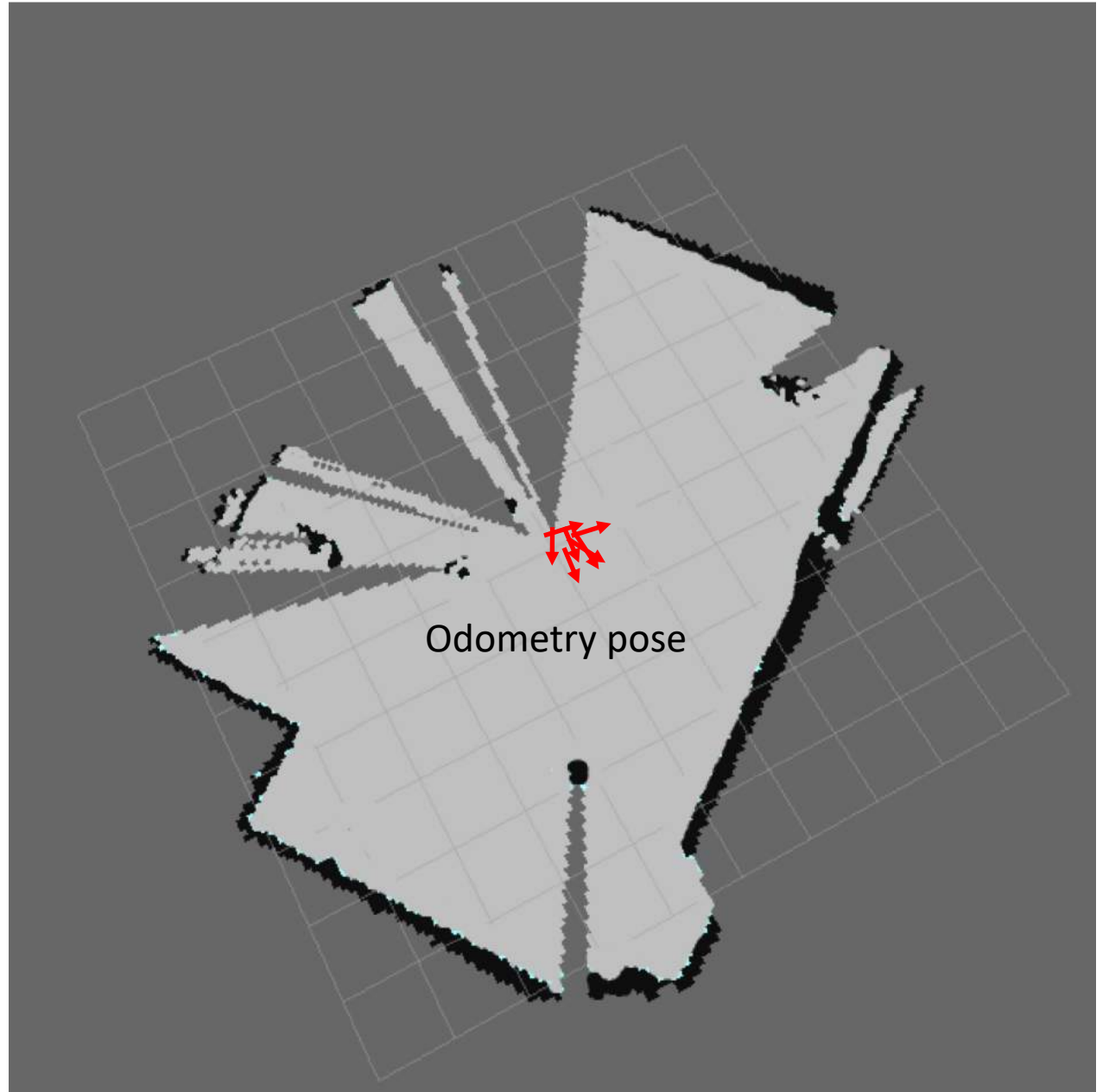


At time  $t = 2$ , robot moves forward a certain distance





# Particle Filter in 2D



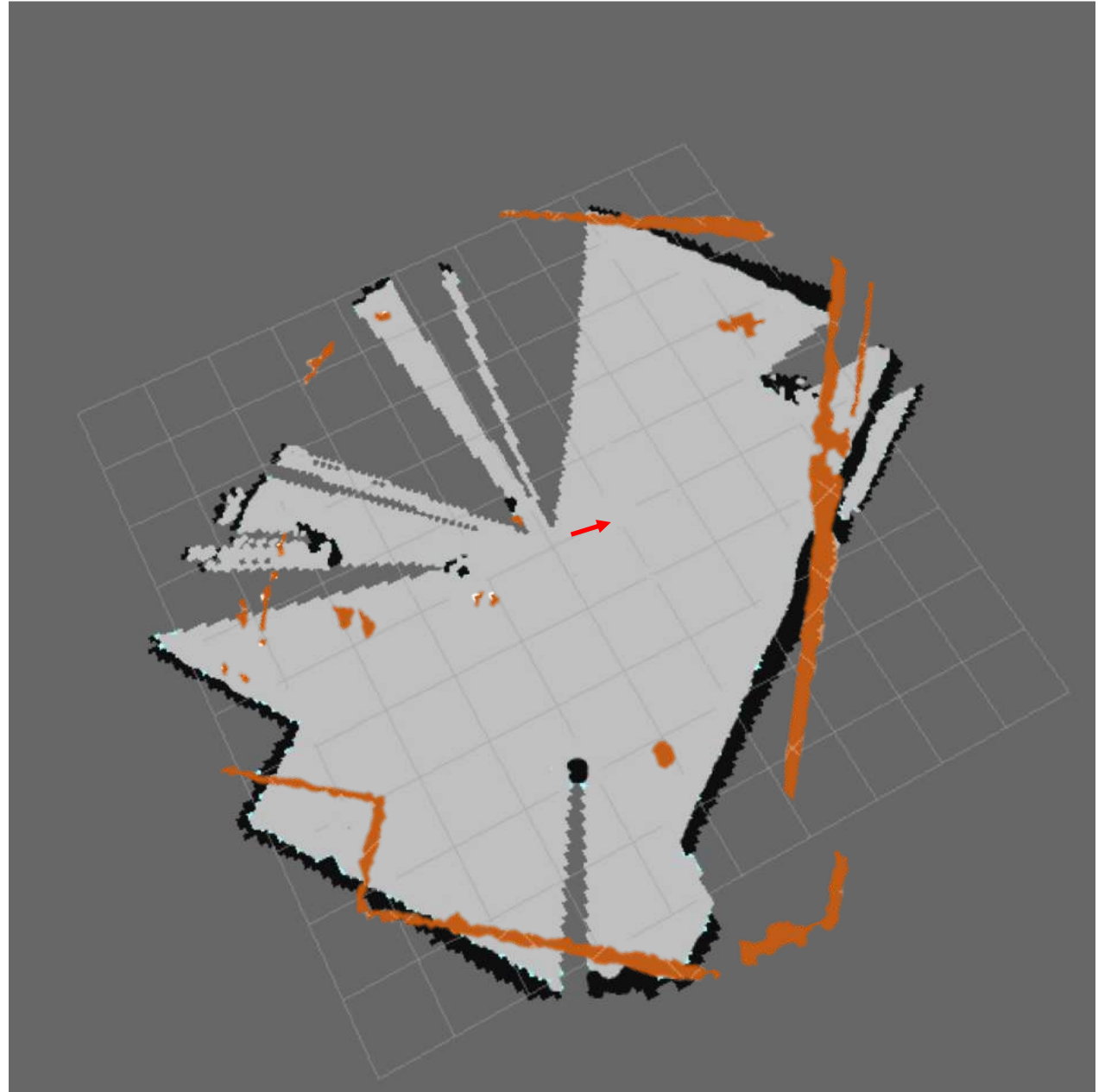


# Scan Correlation

$$W = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left(\sum_m \sum_n (A_{mn} - \bar{A})^2\right) \left(\sum_m \sum_n (B_{mn} - \bar{B})^2\right)}}$$

Particle

Weight



# Scan Correlation

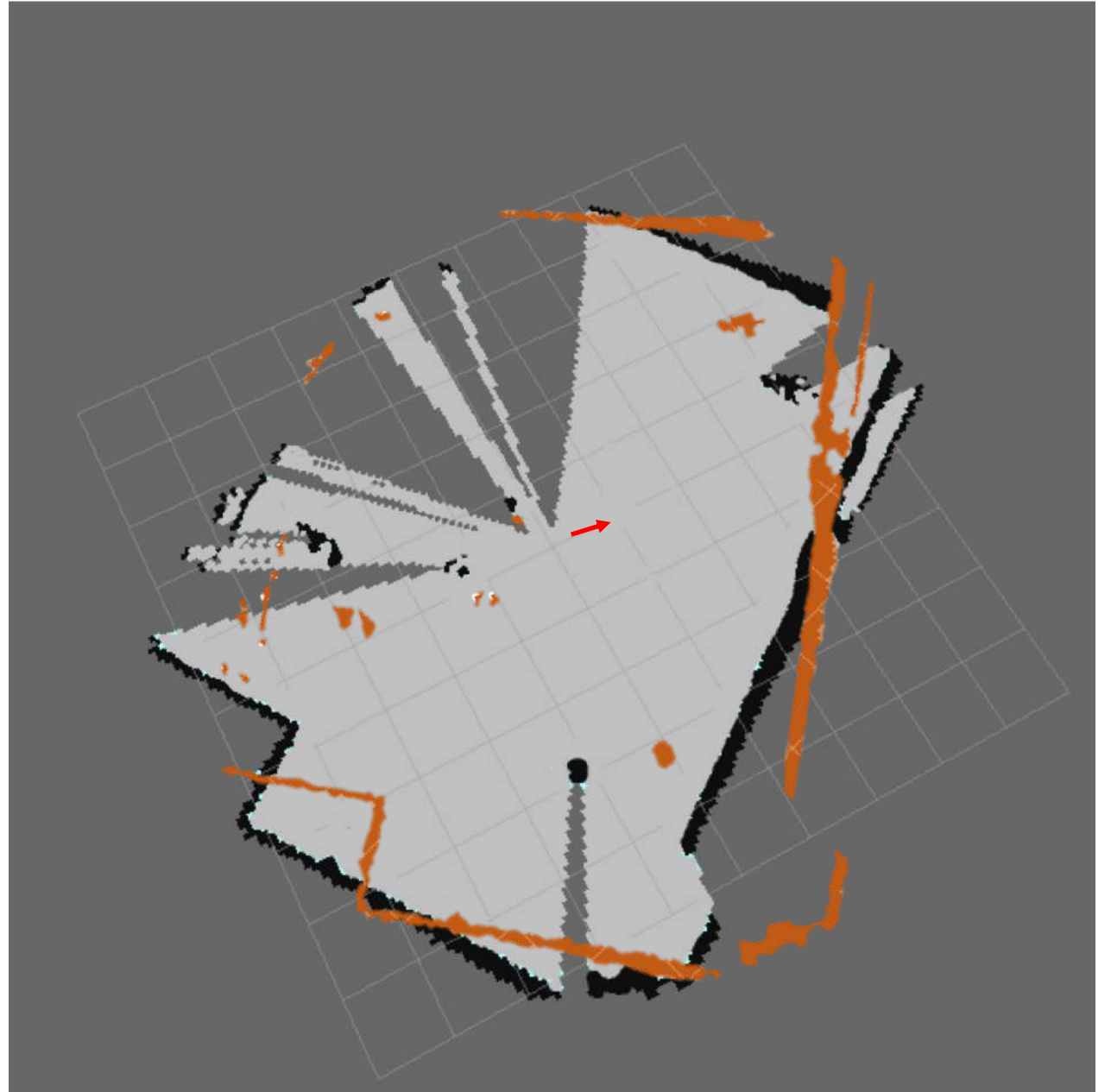
$$W = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left(\sum_m \sum_n (A_{mn} - \bar{A})^2\right) \left(\sum_m \sum_n (B_{mn} - \bar{B})^2\right)}}$$

Particle

Weight

Particle 1

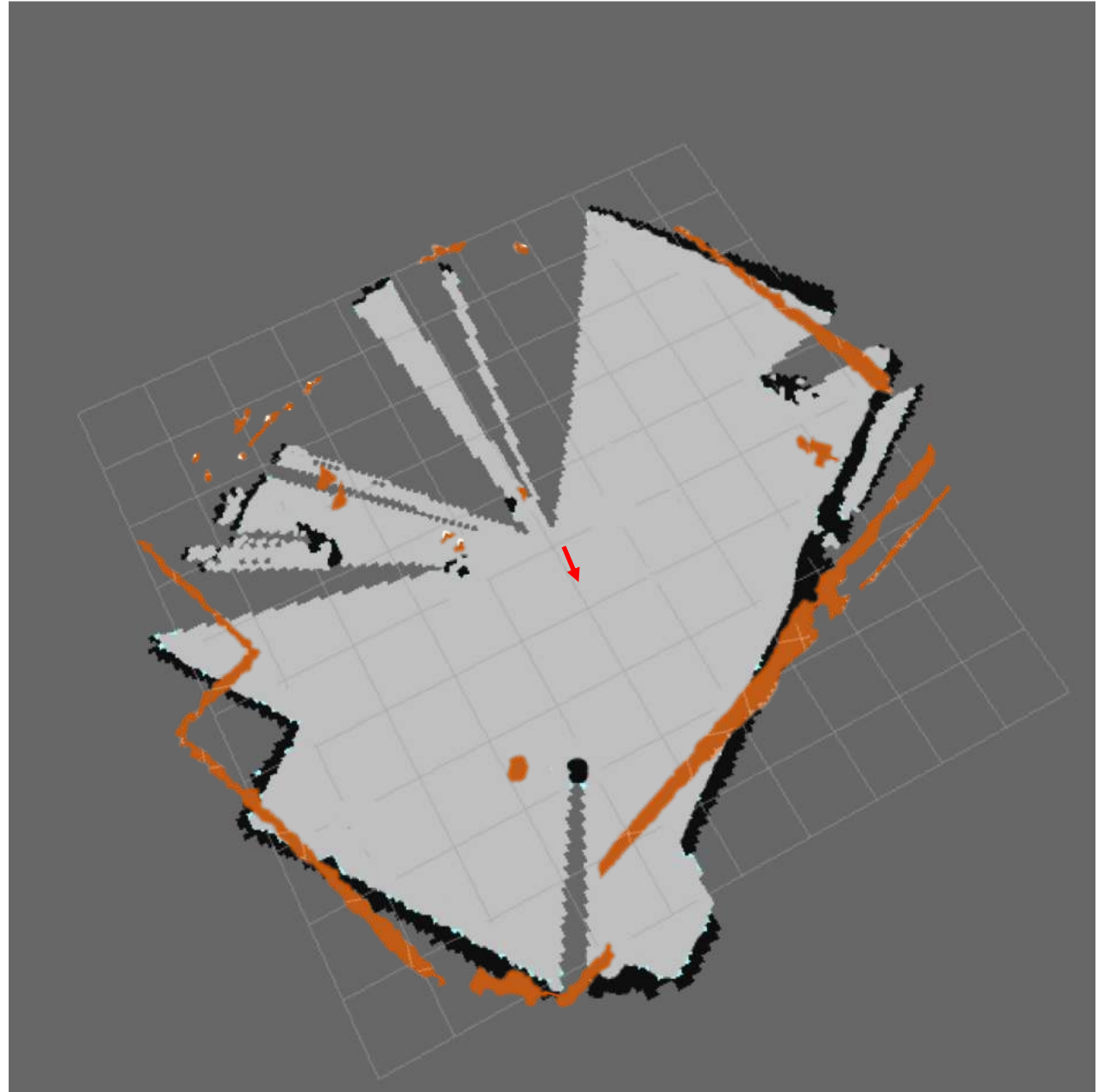
$W_1$



# Scan Correlation

$$W = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left(\sum_m \sum_n (A_{mn} - \bar{A})^2\right) \left(\sum_m \sum_n (B_{mn} - \bar{B})^2\right)}}$$

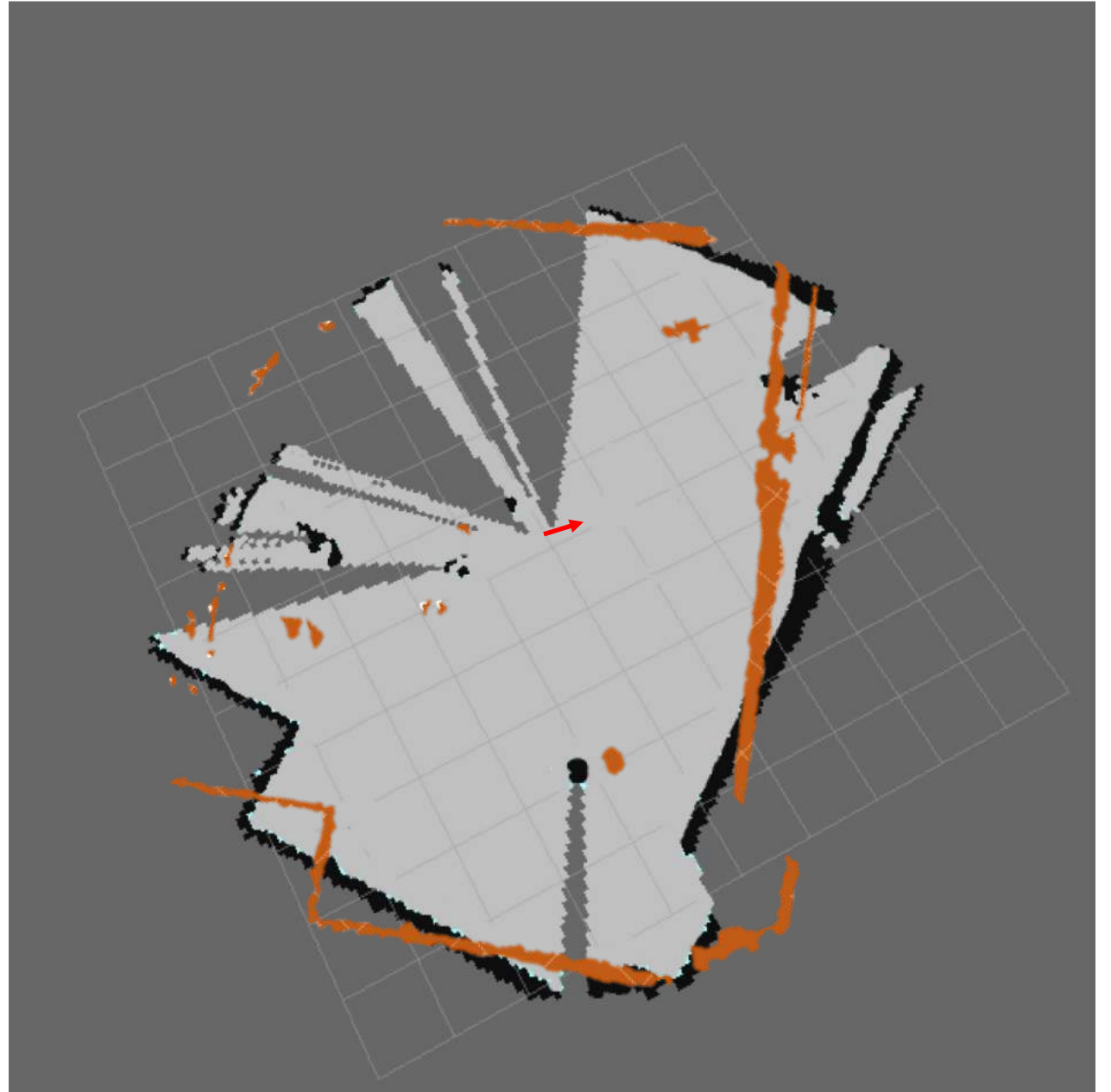
Particle	Weight
Particle 1	$W_1$
Particle 2	$W_2$



# Scan Correlation

$$W = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left(\sum_m \sum_n (A_{mn} - \bar{A})^2\right) \left(\sum_m \sum_n (B_{mn} - \bar{B})^2\right)}}$$

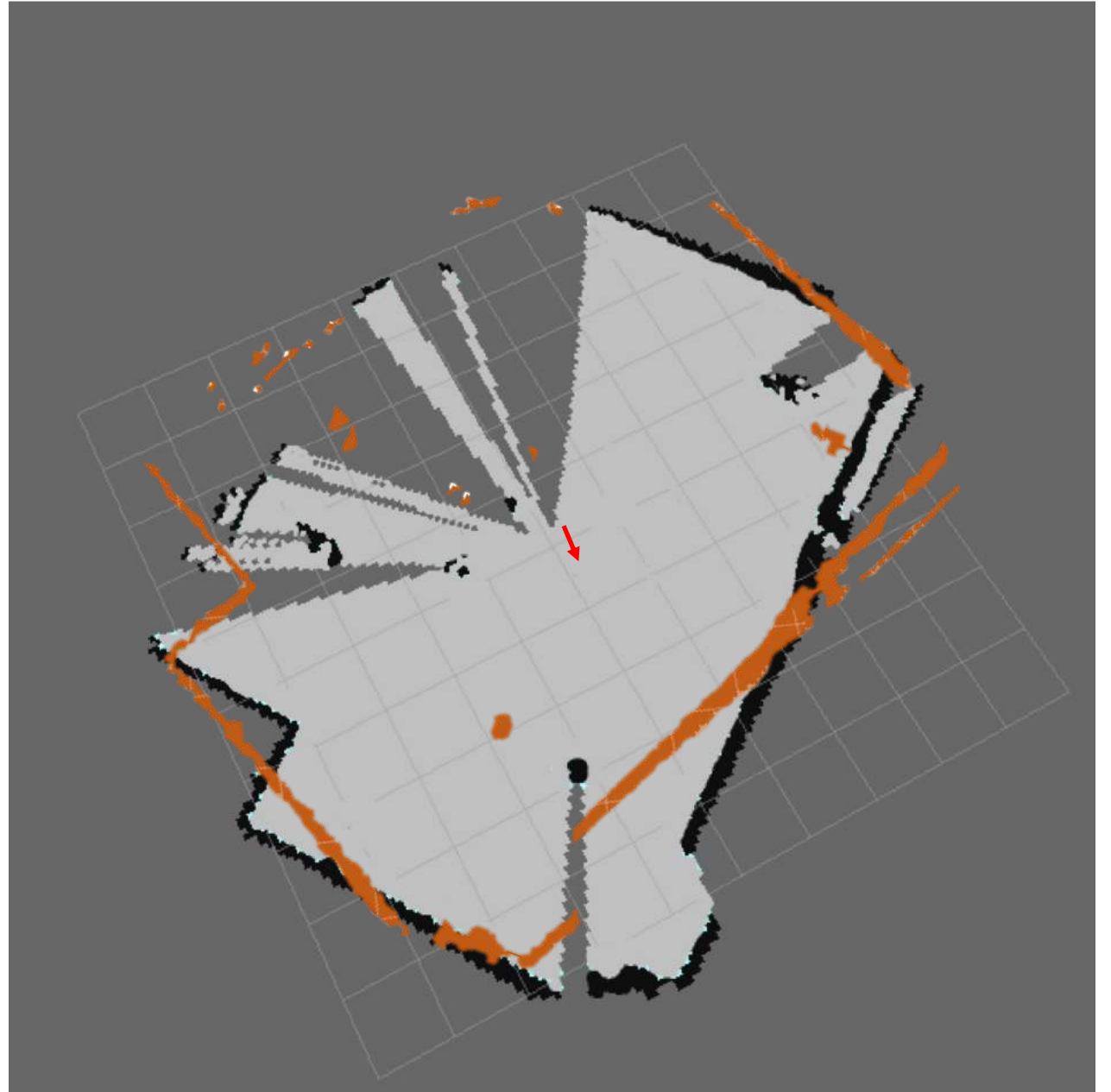
Particle	Weight
Particle 1	$W_1$
Particle 2	$W_2$
Particle 3	$W_3$



# Scan Correlation

$$W = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left(\sum_m \sum_n (A_{mn} - \bar{A})^2\right) \left(\sum_m \sum_n (B_{mn} - \bar{B})^2\right)}}$$

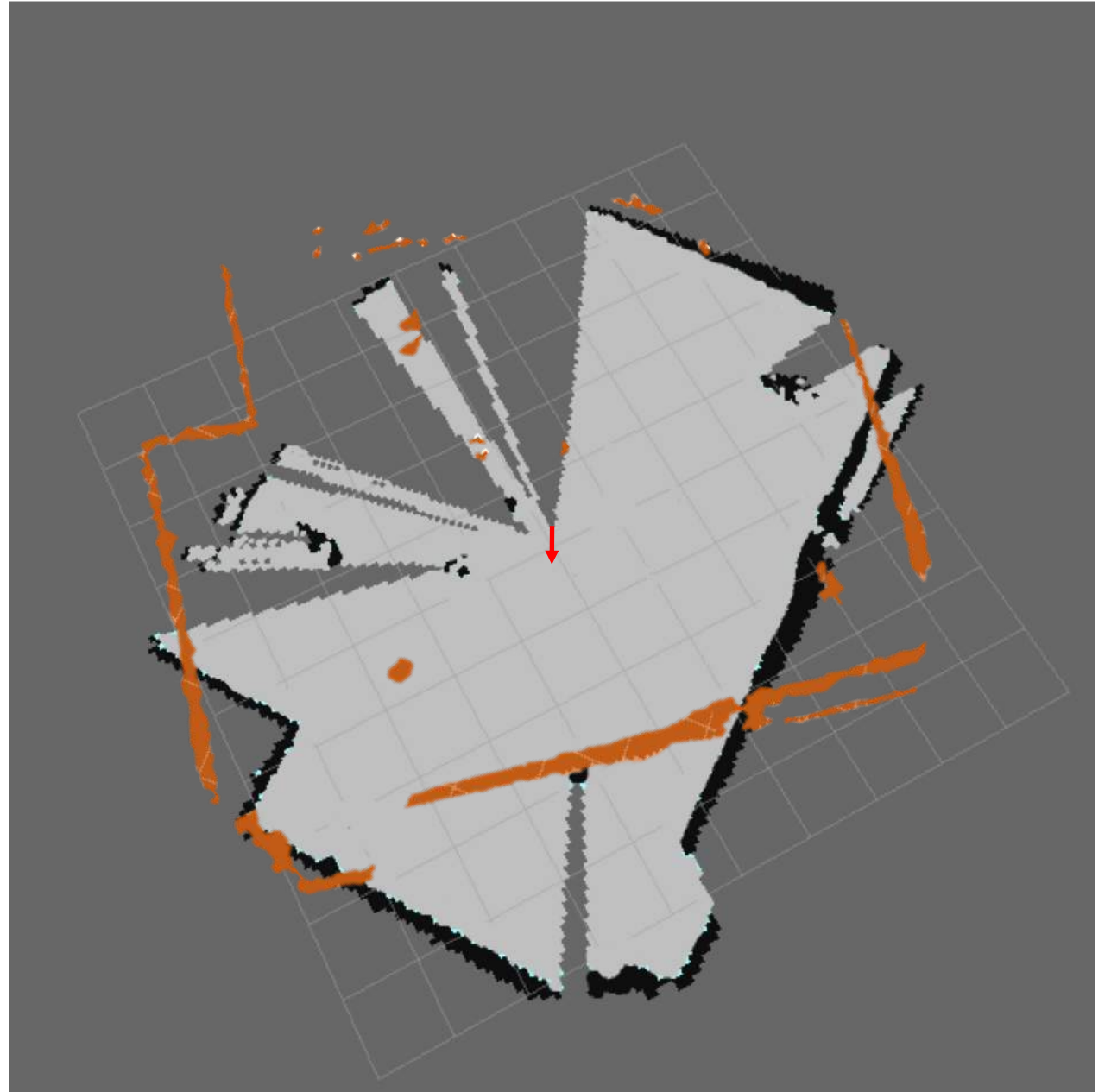
Particle	Weight
Particle 1	$W_1$
Particle 2	$W_2$
Particle 3	$W_3$
Particle 4	$W_4$



# Scan Correlation

$$W = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left(\sum_m \sum_n (A_{mn} - \bar{A})^2\right) \left(\sum_m \sum_n (B_{mn} - \bar{B})^2\right)}}$$

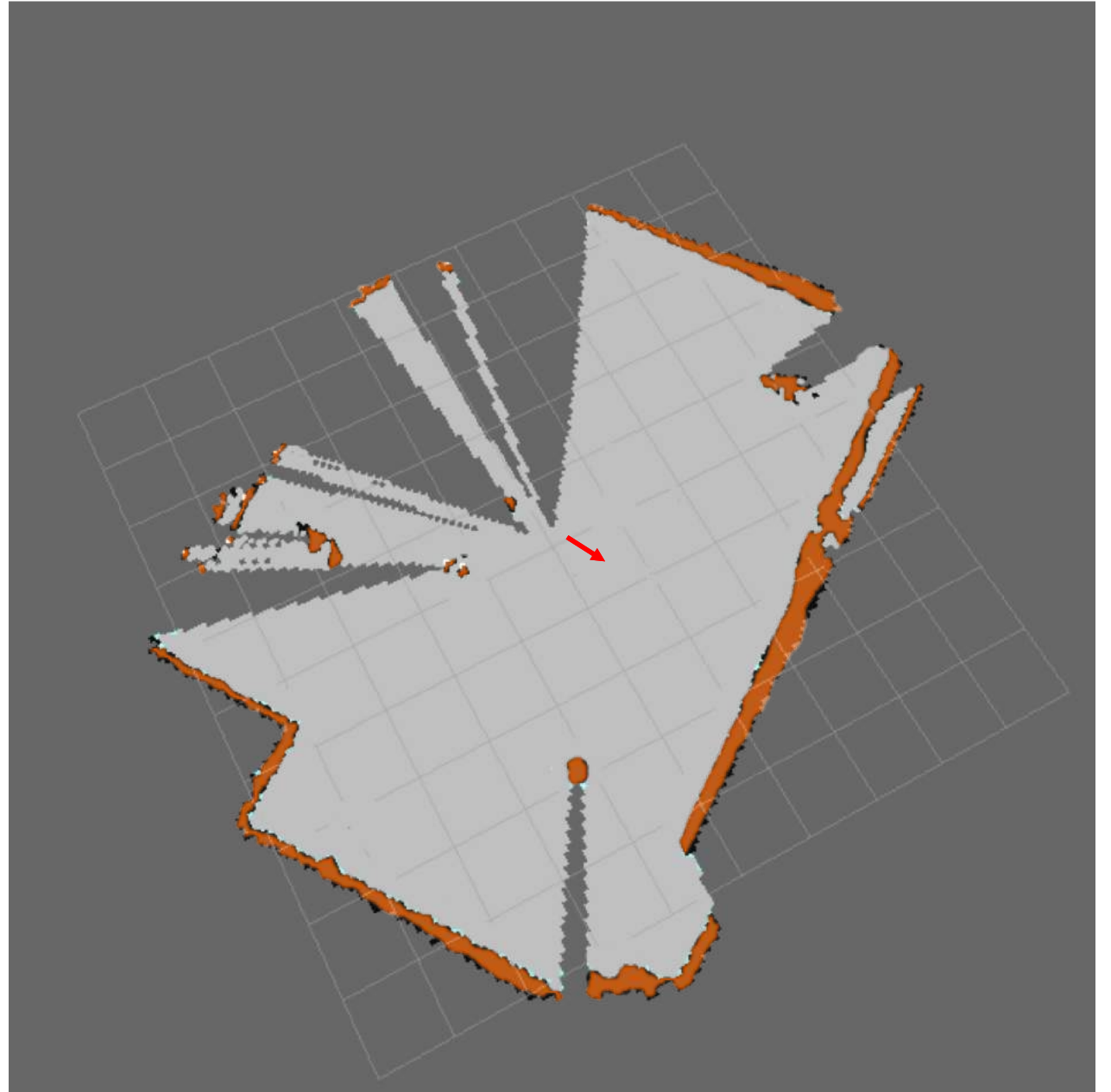
Particle	Weight
Particle 1	$W_1$
Particle 2	$W_2$
Particle 3	$W_3$
Particle 4	$W_4$
Particle 5	$W_5$



# Scan Correlation

$$W = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left(\sum_m \sum_n (A_{mn} - \bar{A})^2\right) \left(\sum_m \sum_n (B_{mn} - \bar{B})^2\right)}}$$

Particle	Weight
Particle 1	$W_1$
Particle 2	$W_2$
Particle 3	$W_3$
Particle 4	$W_4$
Particle 5	$W_5$
Particle 6	$W_6$



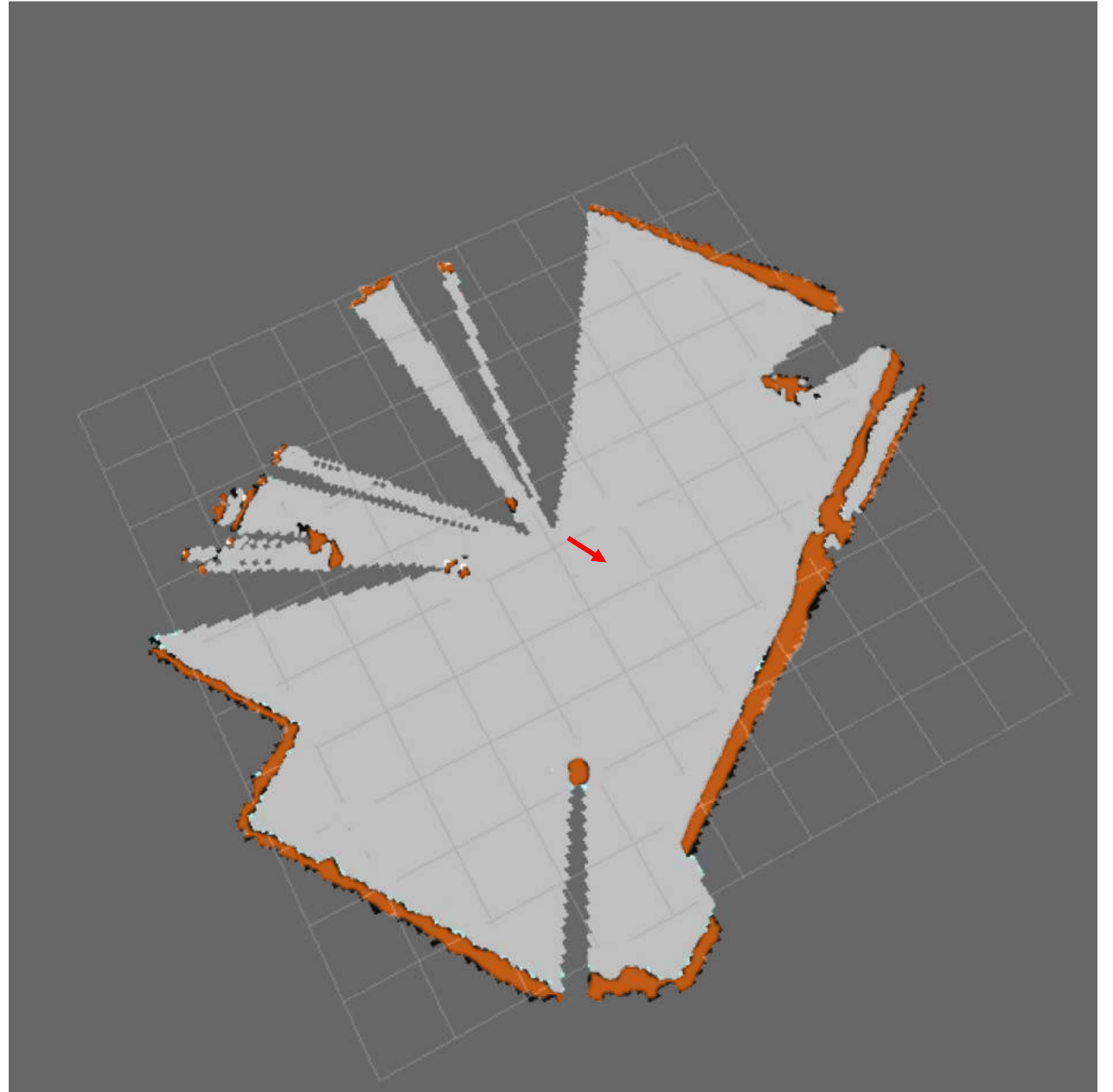


# Scan Correlation

$$W = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left(\sum_m \sum_n (A_{mn} - \bar{A})^2\right) \left(\sum_m \sum_n (B_{mn} - \bar{B})^2\right)}}$$

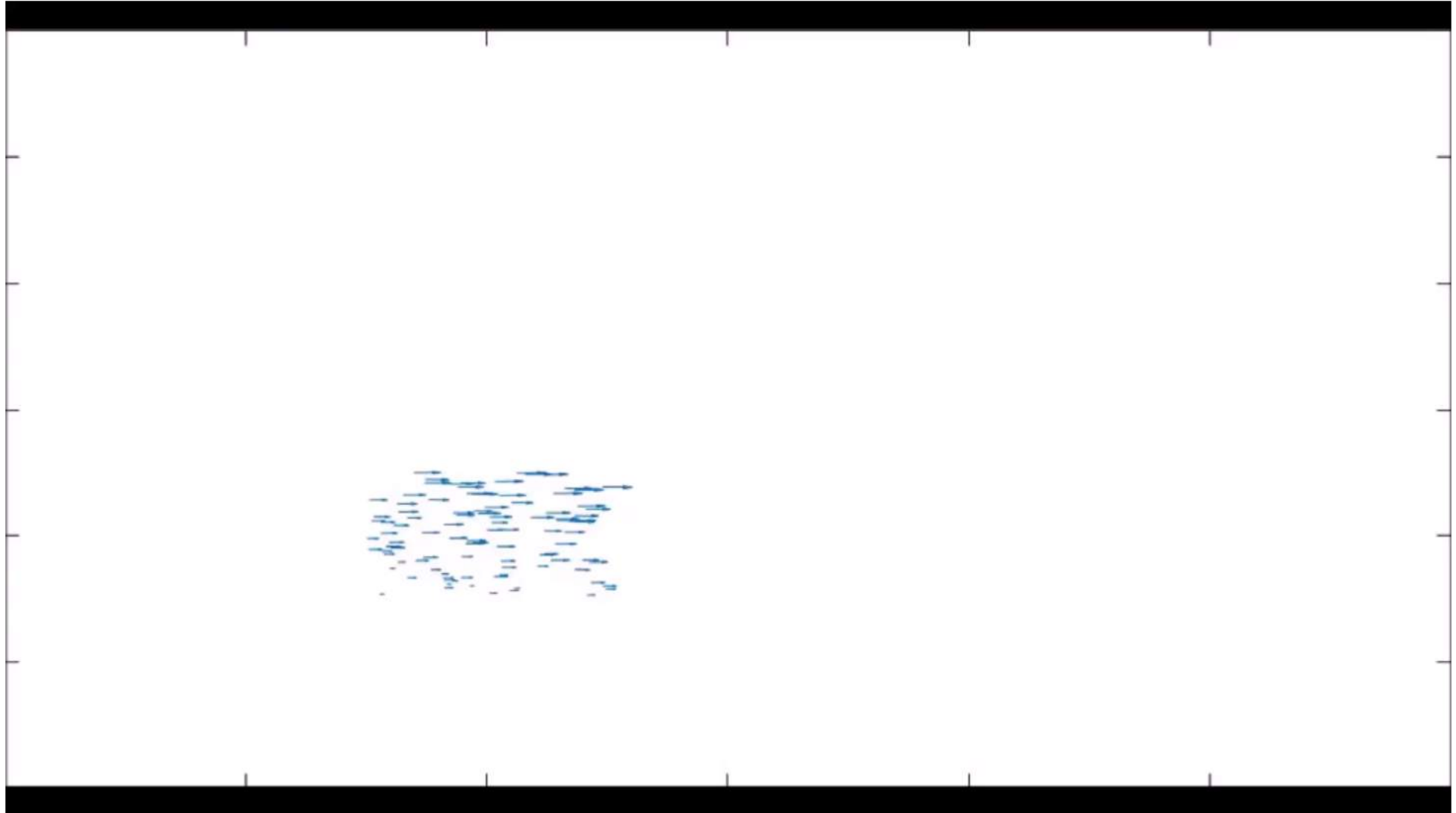
Particle	Weight
Particle 1	$W_1$
Particle 2	$W_2$
Particle 3	$W_3$
Particle 4	$W_4$
Particle 5	$W_5$
Particle 6	$W_6$

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





# Particles



# Particle Filters in ROS

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

# 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

<code>initial_pose_x</code>	Default: 0
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<code>initial_pose_y</code>	Default: 0
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<code>initial_pose_a</code>	Default: 0
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The initial mean position of the particles to initialize the particle filter

# AMCL Parameters

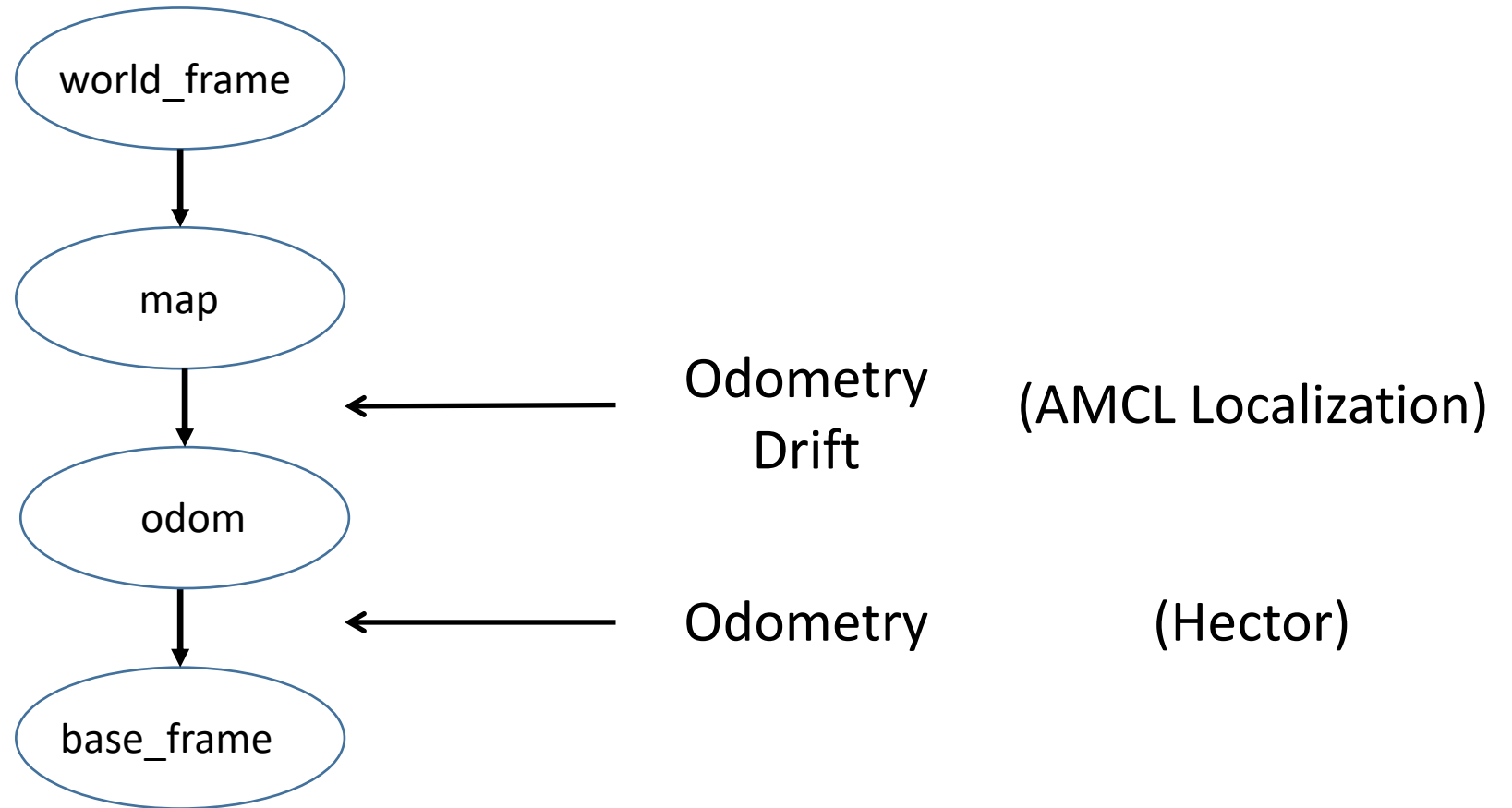
<code>initial_cov_xx</code>	Default: 0
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<code>initial_cov_yy</code>	Default: 0
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<code>initial_cov_aa</code>	Default: 0
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The covariance of particles distributed around the mean

# Tf tree – Where does AMCL fit in



# Input and Output Parameters

## Input Parameters:

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

## Output Parameters:

1. AMCL pose
2. Particle Cloud

