Machine Learning for Probabilistic Robotics with Webots

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Robot Positioning Problem

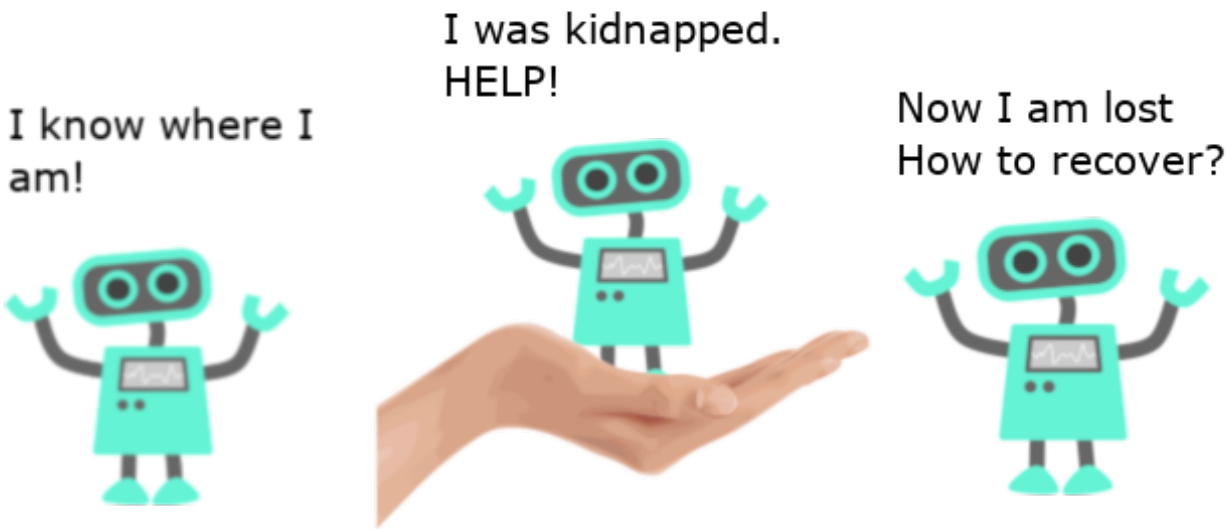
- A robot needs to deal with uncertainty most of the time.
- It needs to predict and preserve its current position and orientation within the environment.

Robot Positioning Problem

- Navigation is about controlling and operating the course of a robot and it is one of the most challenging skills that a mobile robot needs to master in order to successfully moving through the environment.
- Succeeding in navigation means to succeed likewise in:
  - Sense
  - Localization
  - Cognition
  - Control Action

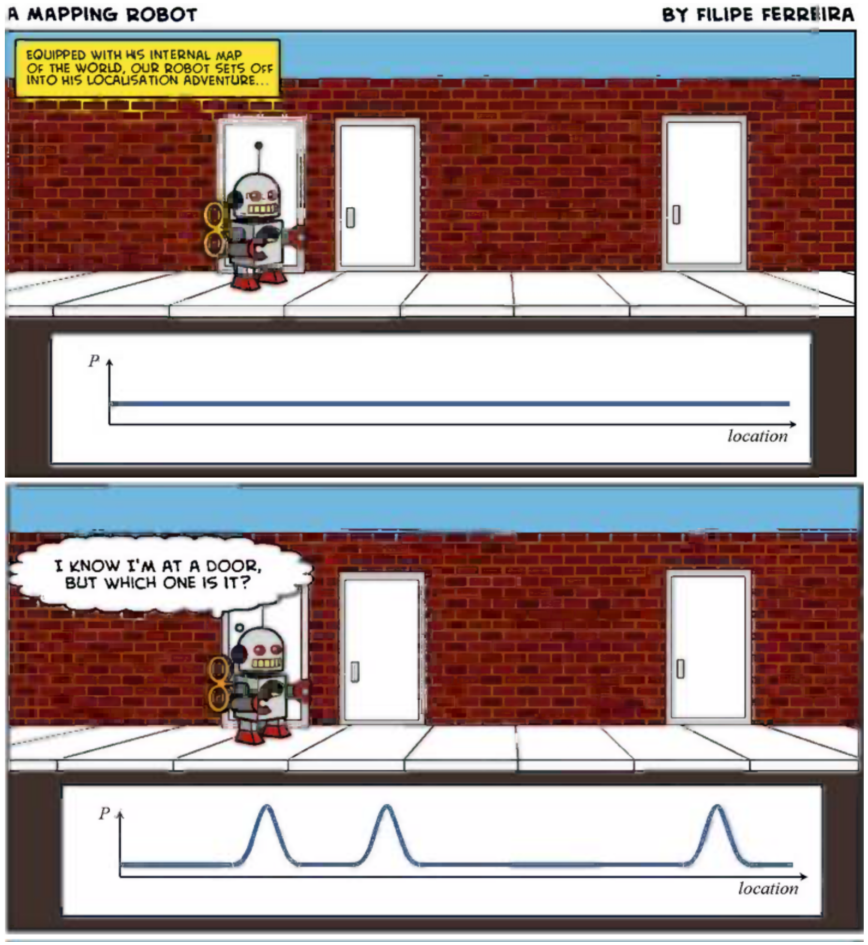
Robot Positioning Problem

- Local Robot Positioning (position tracking): The robot knows its initial position.
- Global Robot Positioning: The robot does not know its initial position and it is able to estimate it even in a global uncertainty. Ex. Kidnapped robot problem.

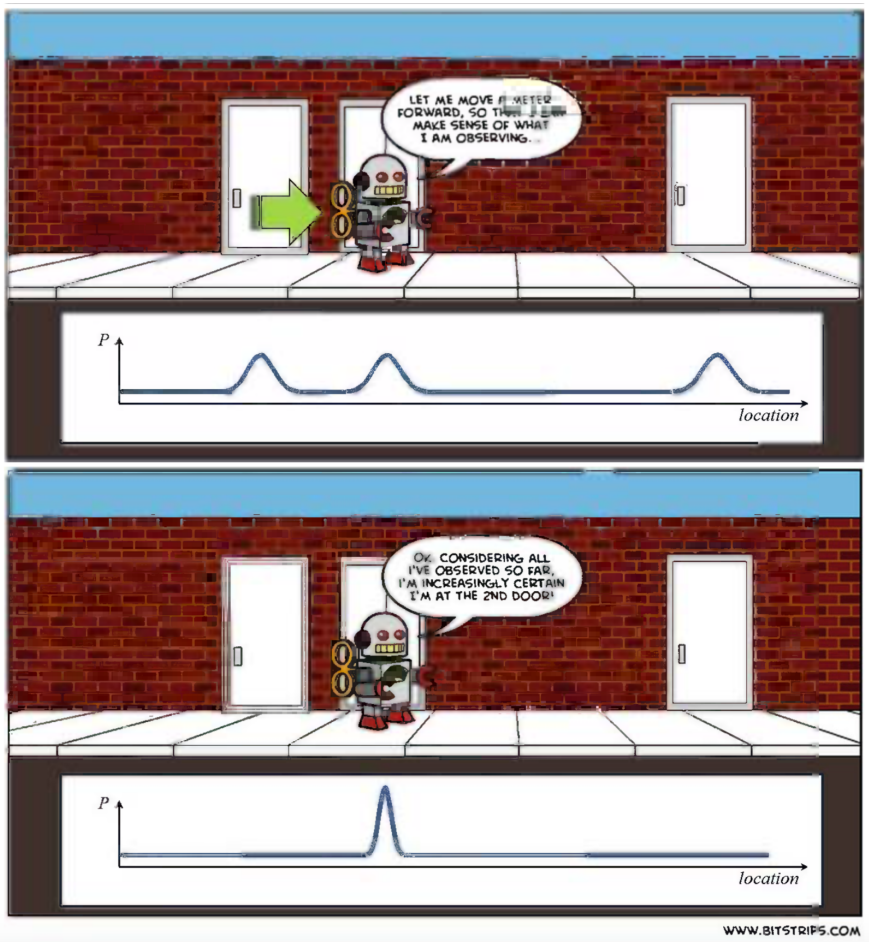


Bayes Filter

- Prediction

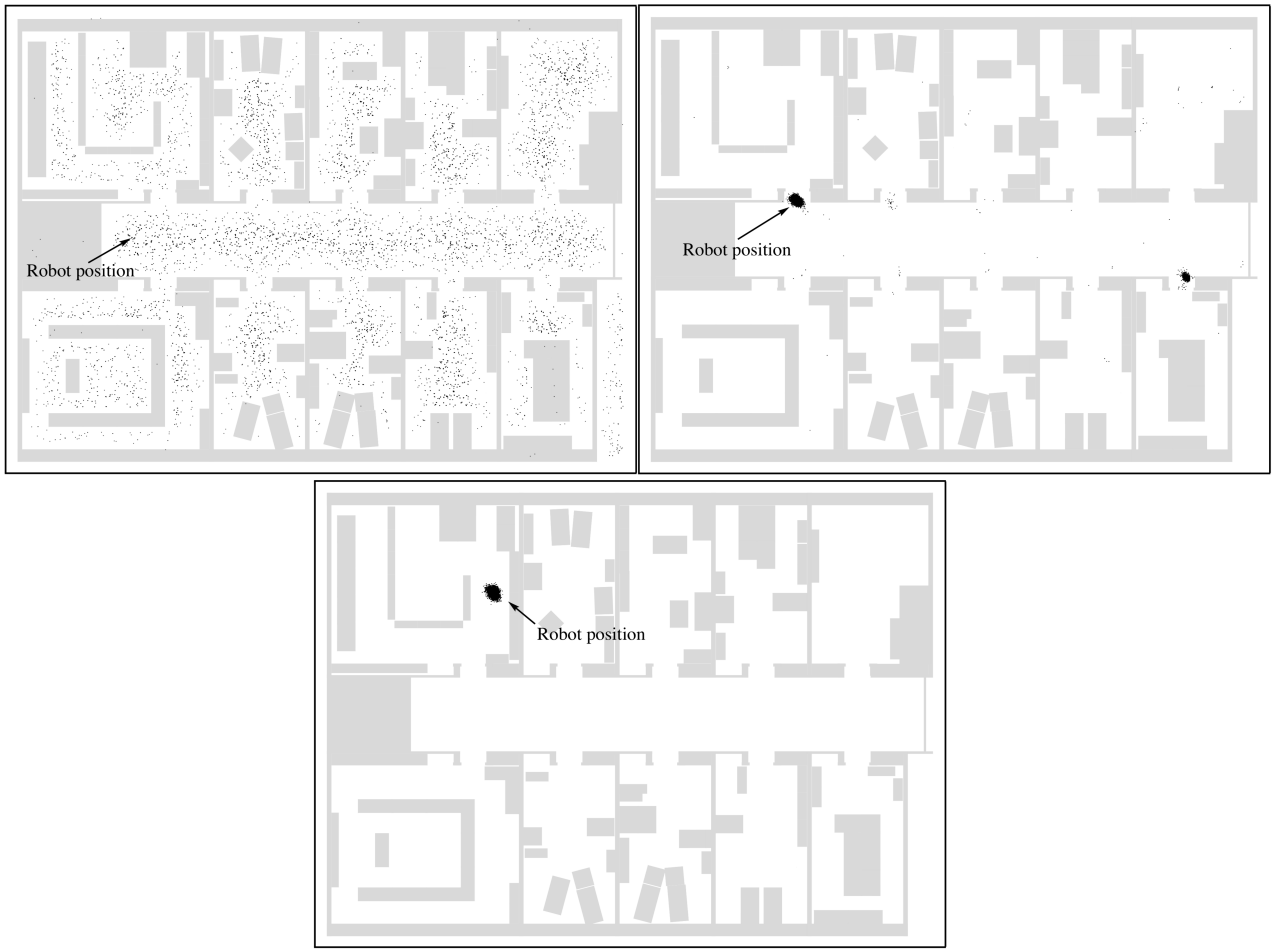


- Error Correction



Particles Filter

- Each particle has a state (x, y, θ) and a weight.
- The weight is an indicator of how close the particle' state is to the real state.



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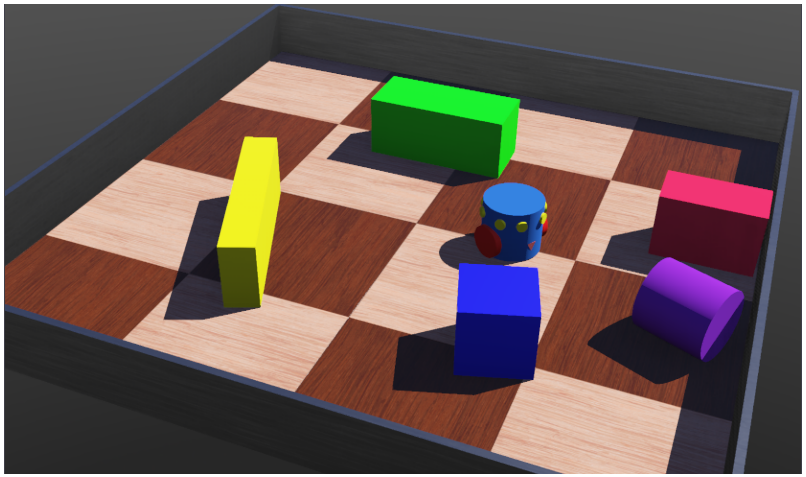
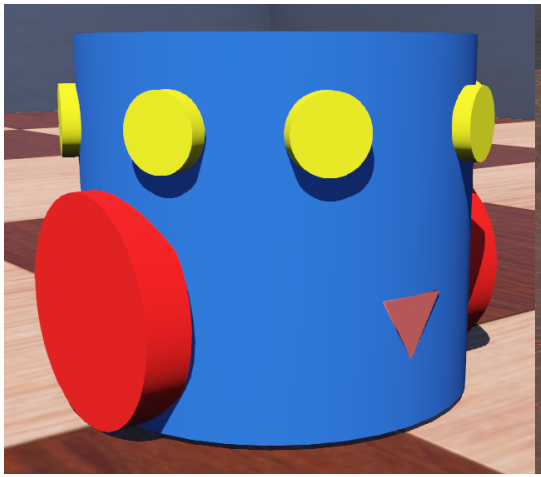
What is Webots?

- Tool for simulating robots in virtual environments
- Open Source
- Python, C++, Java, etc.
- 44 robot models
- Robot model creation/customization
- Robust documentation





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Objectives:

- The objective will be to exploit the simulation benefits of Webots to introduce Machine Learning techniques together with non-parametric filters (such as Particles Filter) for robot positioning estimation for in-door environments.
- Find a solution in which the learned knowledge can be transferred from one environment to another without the need to go through the training process using transfer learning techniques.

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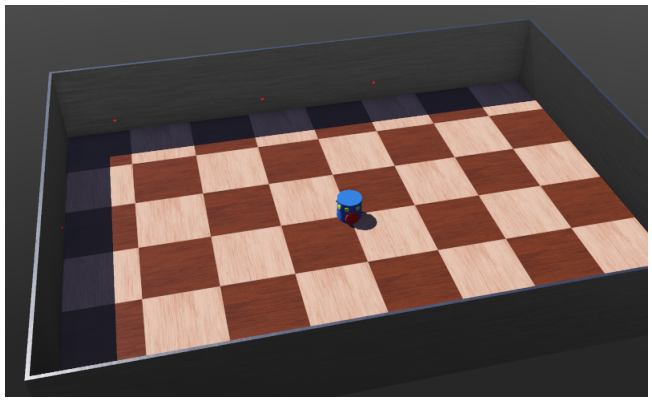
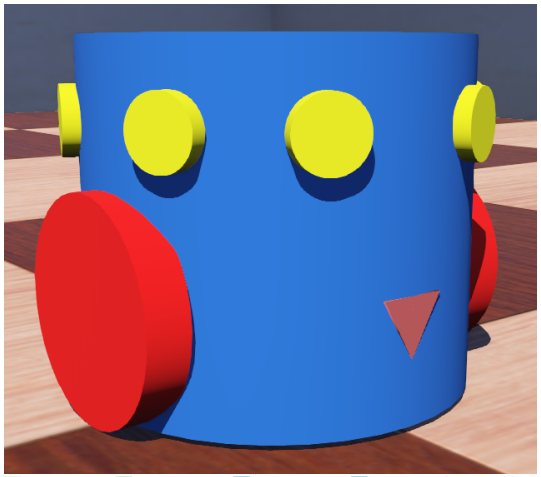
Problem Formulation

- There is a robot with 8 laser sensors around it.
- The sensors measure the distance between the robot and the closest object.
- There is an arena of 2x1.5m with four walls.
- The robot has odometry data available.
- The robot is positioned in the middle of the arena and knows its initial position.
- The robot needs to track its position.





Solution Approach

- Capture data with the simulator.
  - True robot position (x, y, θ).
  - Sensor measurements $(s_1, s_2, ..., s_8)$.
- Train ML Models
  - Train 8 neural networks that receives a robot state as input and returns the estimated sensor measurements.
- Put the particles filter together with the ML Models to get the robot position estimation.
- Correct the position of the robot using the robot position estimation.

Capture data with the simulator

- Robot turns with a probability of 0.2; otherwise, it goes straight.
- Robot turns randomly to left or right maximum 30 degrees.
- Robot avoids colliding with the walls.
- Data is captured each 20 robot steps.
- The Data is captured for 10 minutes in fast simulation mode.

Train ML Models

- The data is normalized and shuffled.
- Many NN architectures were tested. The one that gave better results was:
  - Input Layer: 3 neurons
  - Intermediate Layer: Fully connected with 10 neurons
  - Intermediate Layer: Fully connected with 6 neurons
  - Intermediate Layer: Fully connected with 3 neurons
  - Output Layer: 1 neuron

Particles Filter + ML Model

input : deltaMove, sensorsData
output: particles

```
particles.state = particles.state + deltaMove
addRandomMove(particles.state)
foreach particle ∈ particles do
    particle.weight ← predictError(particle.state, sensorsData)
end
normalizeWeights(particles)
particles = resamplingBasedOnWeights(prob=particles.weight,
  replace=True)
return particles
```

Correction Step

- Take the weighted average state of all the particles.
- This value becomes the estimated state of the robot.
- Apply the correction step at each robot step.

Experiments

- Robot walks in the arena avoiding to hit the walls.
- The experiment was run during 2200 robot steps.
- The experiment was repeated each time with different number of particles: 30, 100, 500, 2000.
  - At each robot step two errors are calculated: one for the (x, y) coordinates and another for the angle θ.

$$Error_{xy} = \sqrt{(x - \hat{x})^2 + (y - \hat{y})^2} \quad (1)$$

$$Error_{\theta} = 180 - |180 - |\theta - \hat{\theta}|| \quad (2)$$

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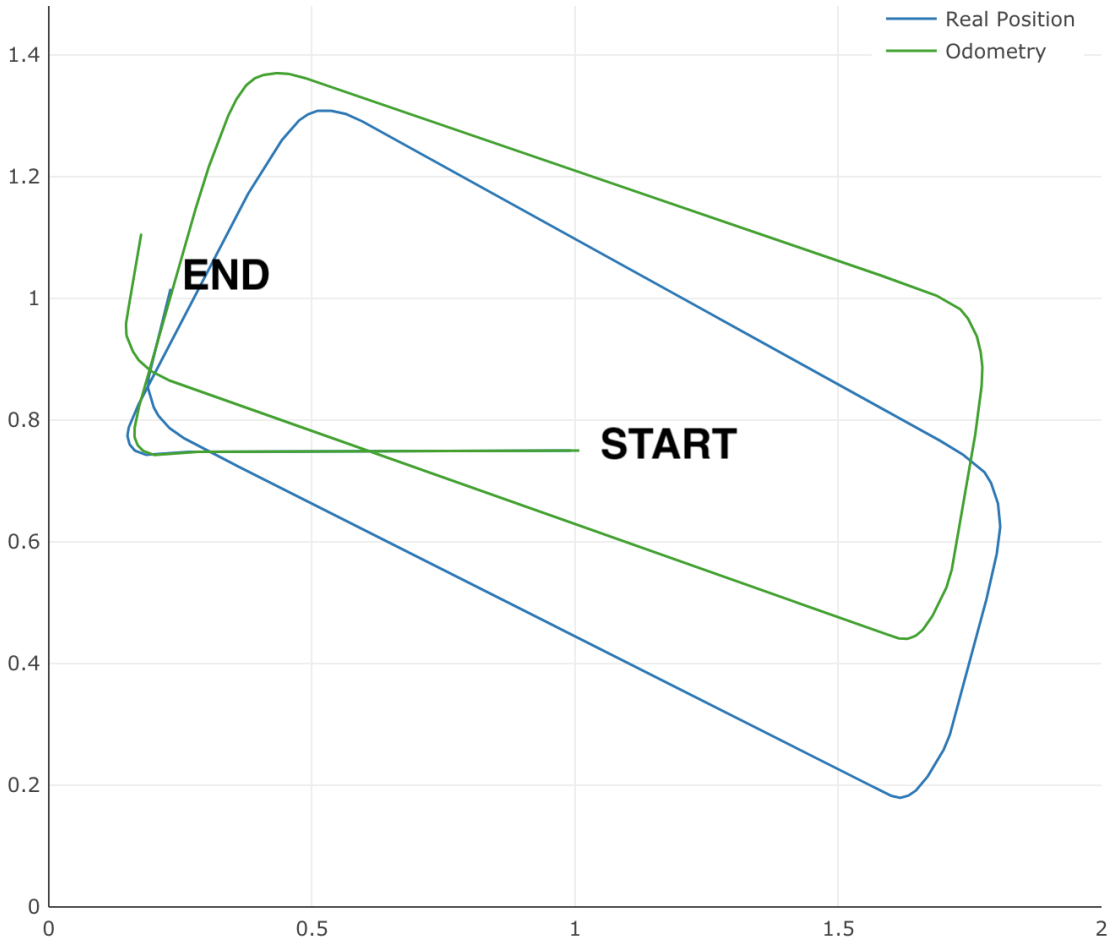
Odometry vs Real position

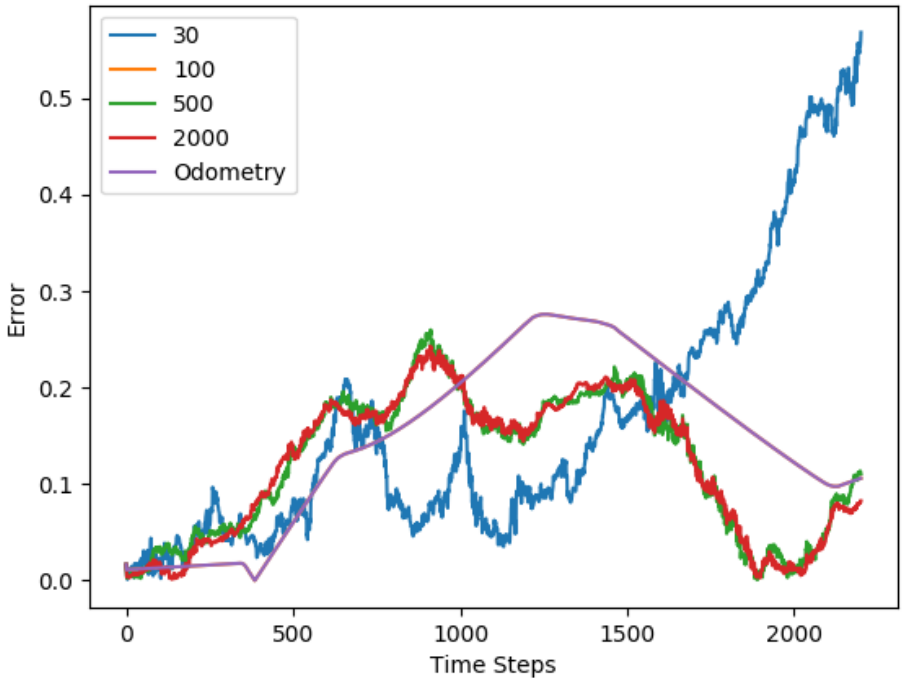


Particles vs Real position

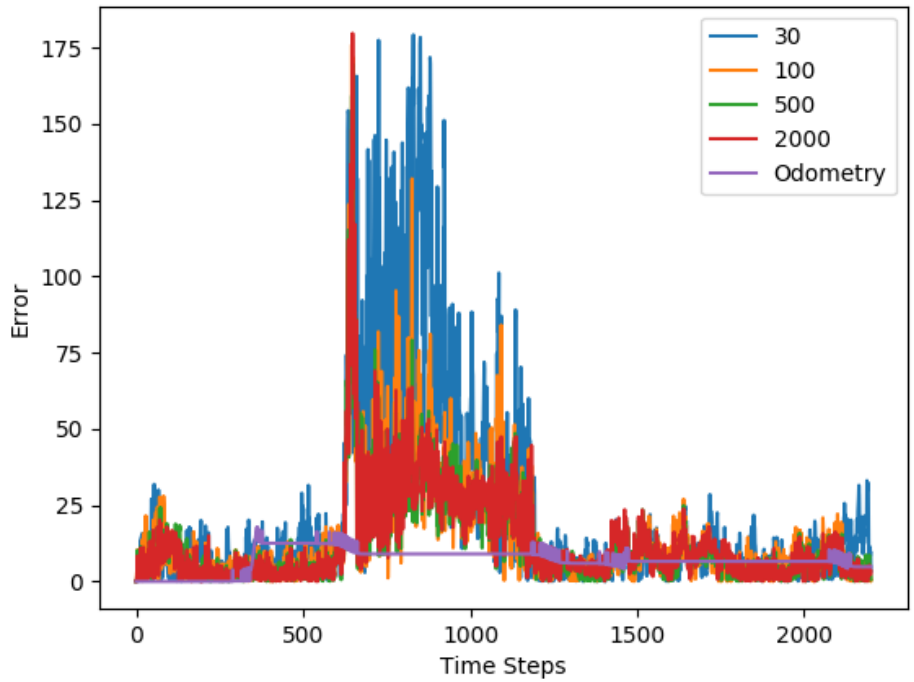
- 1000 particles used

Results

$Error_{xy}$



$Error_{\theta}$



Drawbacks

- The problem requires to train 8 models which is time consuming.
- It does not generalize for unseen environments.
- The particle's filter algorithm works slow for a big amount of particles.
- Model highly dependent of odometry data.

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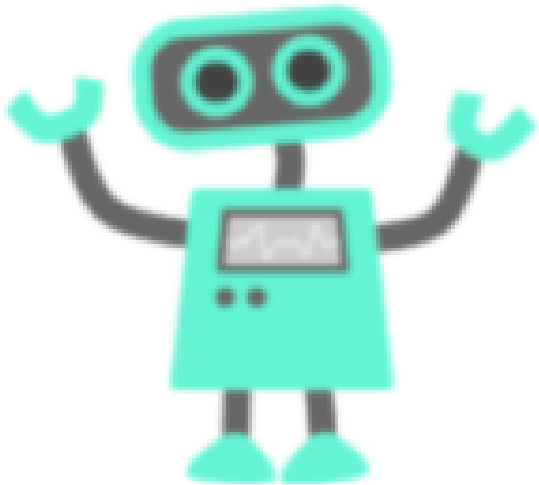
- Find an efficient model that receives as input the sensor measurements and predicts the robot position. Combine it with the previous model to improve the performance.
- Train a model that receives $(\delta x, \delta y, \delta\theta)$ as input and predicts $(\delta s_1, ..., \delta s_8)$ and equivalently that receives $(\delta s_1, ..., \delta s_8)$ as input and predicts $(\delta x, \delta y, \delta\theta)$.
- Produce results for different training sizes, different robots and room configurations.
- Implement online learning to improve gradually the models.

Any question?



(Suggestions and critics are also welcomed)