TÉCNICO LISBOA

Pioneer 3-DX with EKF-SLAM

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Autonomous Systems

Group 17

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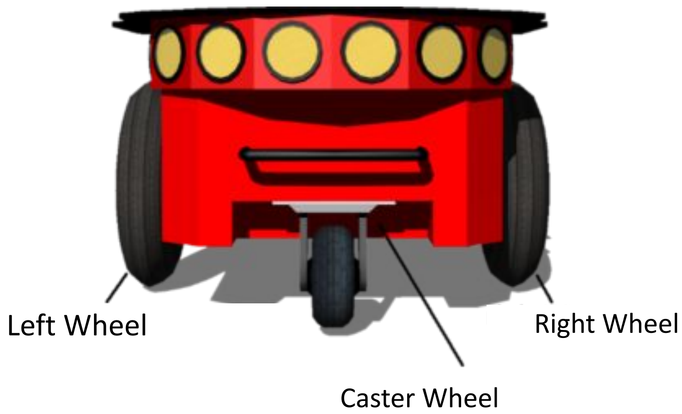
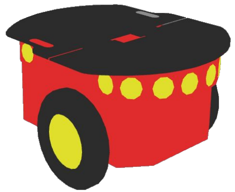
The project

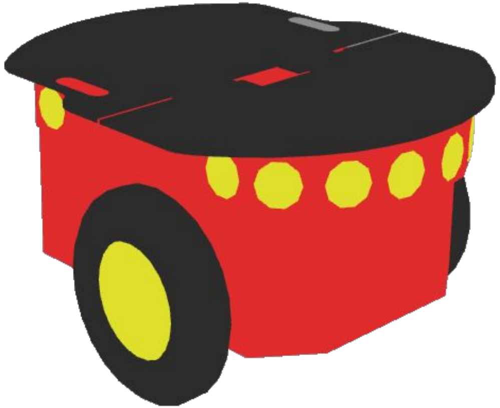
Implement a **S**imultaneous **L**ocalization **A**nd **M**apping (**SLAM**) algorithm

using an **E**xtended **K**alman **F**ilter (**EKF**) on a **Pioneer 3-DX** robot.





Sensors

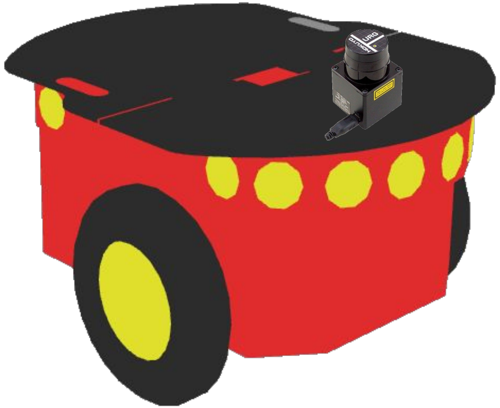


Incorporated in the robot

Odometer (left+right wheels)

8+8 sonars (front and back panels)

Sensors



<u>Incorporated in the robot</u>

Odometer (left+right wheels) ✓

~~8+8 sonars (front and back panels)~~

<u>Connected through USB</u>

Hokuyo Laser ✓

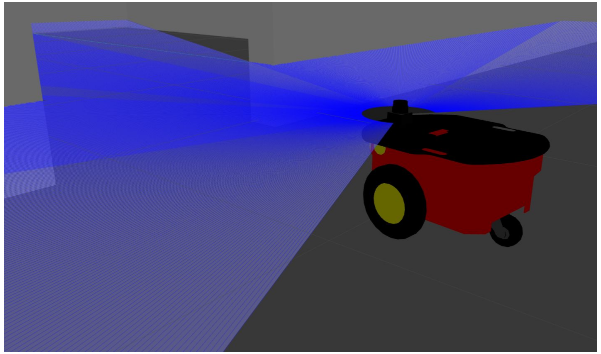
Hokuyo laser

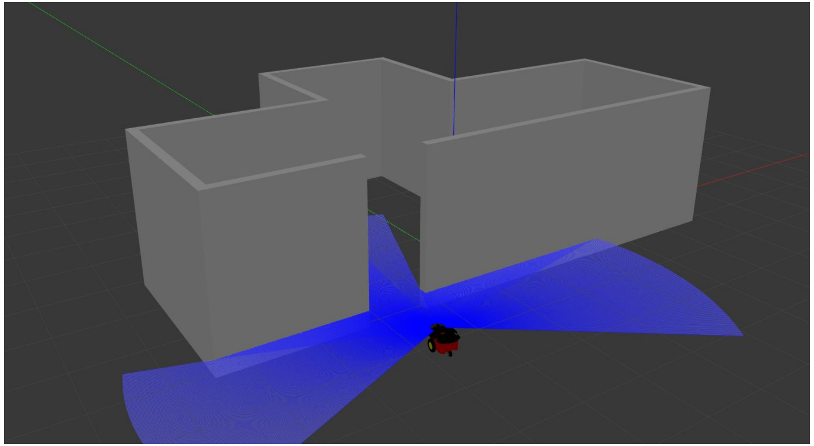
Model No.	URG-04LX-UG01
Power source	5VDC±5%(USB Bus power)
Light source	Semiconductor laser diode(λ=785nm), Laser safety class 1
Measuring area	20 to 5600mm(white paper with 70mm×70mm), 240°
Accuracy	60 to 1,000mm : ±30mm, 1,000 to 4,095mm : ±3% of measurement
Angular resolution	Step angle : approx. 0.36°(360°/1,024 steps)
Scanning time	100ms/scan

Microsimulation

GAZEBO

Gazebo creates simulated environments to test a robotic system





GitHub mario-serna / **pioneer_p3dx_model** Public

The algorithm

$$\mu_t = \begin{bmatrix} x_t \\ y_t \\ \theta_t \\ m_{1,x,t} \\ m_{1,y,t} \\ \cdots \\ m_{N,x,t} \\ m_{N,y,t} \end{bmatrix}$$

The robot moves and the new predicted state estimate is computed from the previous estimate

Algorithm 1 Extended Kalman Filter $(\mu_{t-1}, \Sigma_{t-1}, u_t, z_t)$

Prediction step

1: $\overline{\mu_t} = f(u_t, \mu_{t-1})$

2: $\overline{\Sigma_t} = G_t \Sigma_{t-1} G_t^T + R_t$

Correction step

3: $K_t = \overline{\Sigma_t} H_t^T (H_t \overline{\Sigma_t} H_t^T + Q_t)^{-1}$

4: $\mu_t = \overline{\mu_t} + K_t(z_t - h(\overline{\mu_t}))$

5: $\Sigma_t = (I - K_t H_t)\overline{\Sigma_t}$

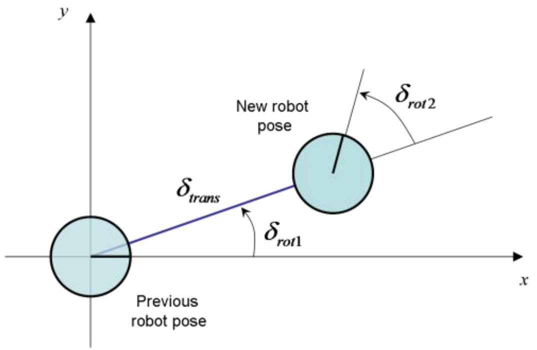
6: return μ_t, Σ_t

The laser identifies the known landmarks and the previous drawn map is corrected

Odometry and prediction step

Odometry

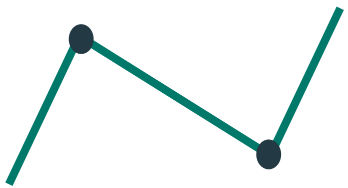
- The use of motion sensors to calculate the change of position of the robot in relation to a known position.
- 1st rotation + translation + 2nd rotation
- The motion model assumes that δ_{rot1}, δ_{trans} and δ_{rot2} are influenced by independent noise.



Prediction step

- The new estimate of the the predicted state is calculated from the previous estimate.

Landmarks



- We have used a mixture between lines and corners

Lines

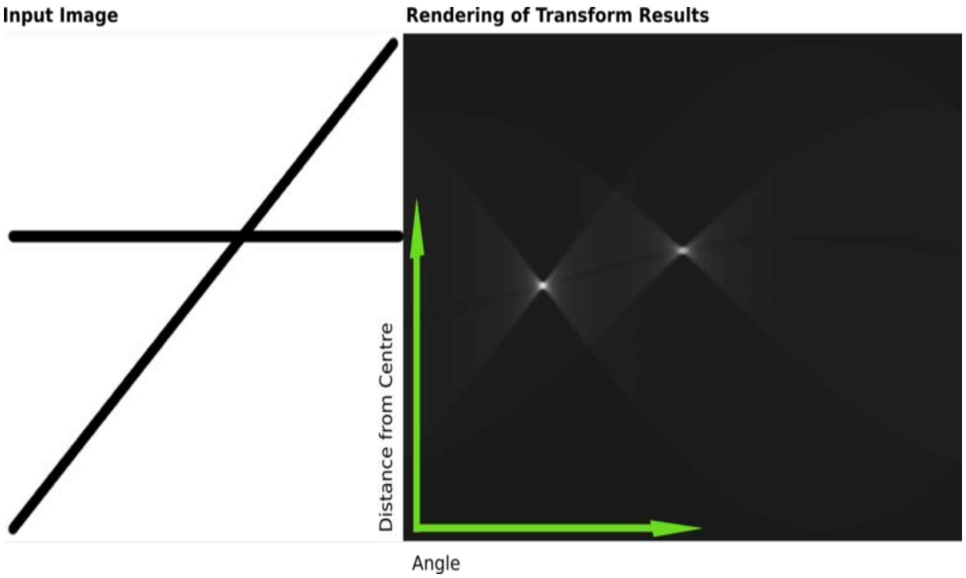
- Easy to identify
- Broad idea of the space around the robot
- Unexpected behavior in other more irregular environments

Corners

- Minimize the number of parameters exchanged between nodes
- Susceptible to noise
- The dots have to be connected to each other

Landmark detection and Hough transform

- Hough Transform is used to identify and isolate certain features presented in an image such as lines or circles.
- The points in Hough space have the form P(ρ,ϴ).

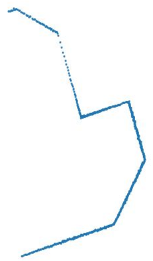


Hough transform

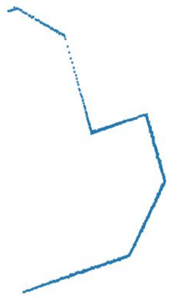
- It was implemented using the library in openCV

Probabilistic Hough Transform (used in order to detect lines/corners)

- Gives more accurate results
- Gives directly the starting and ending points of each line, which are the exact points the will be assumed as corners



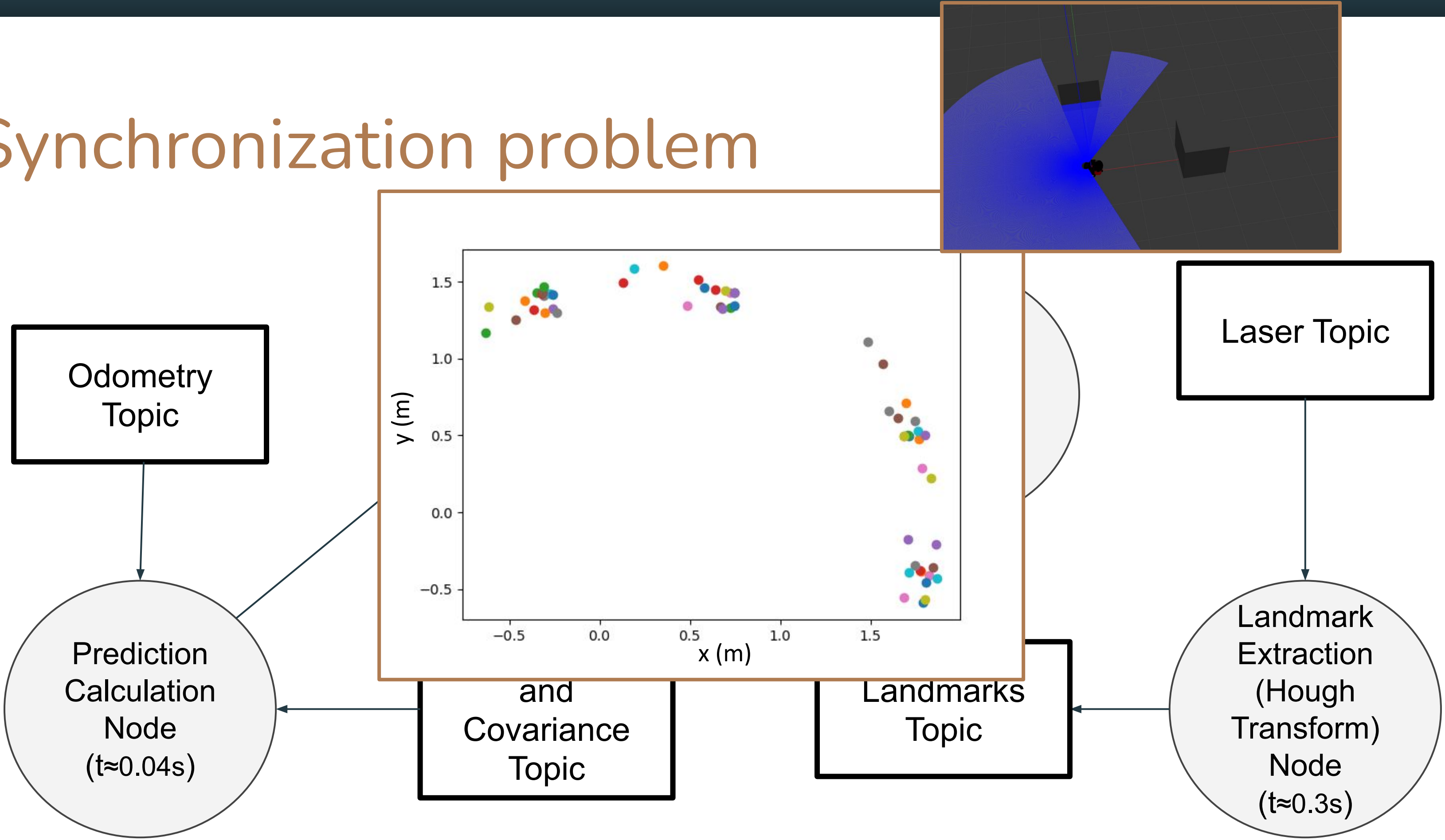
Standard method



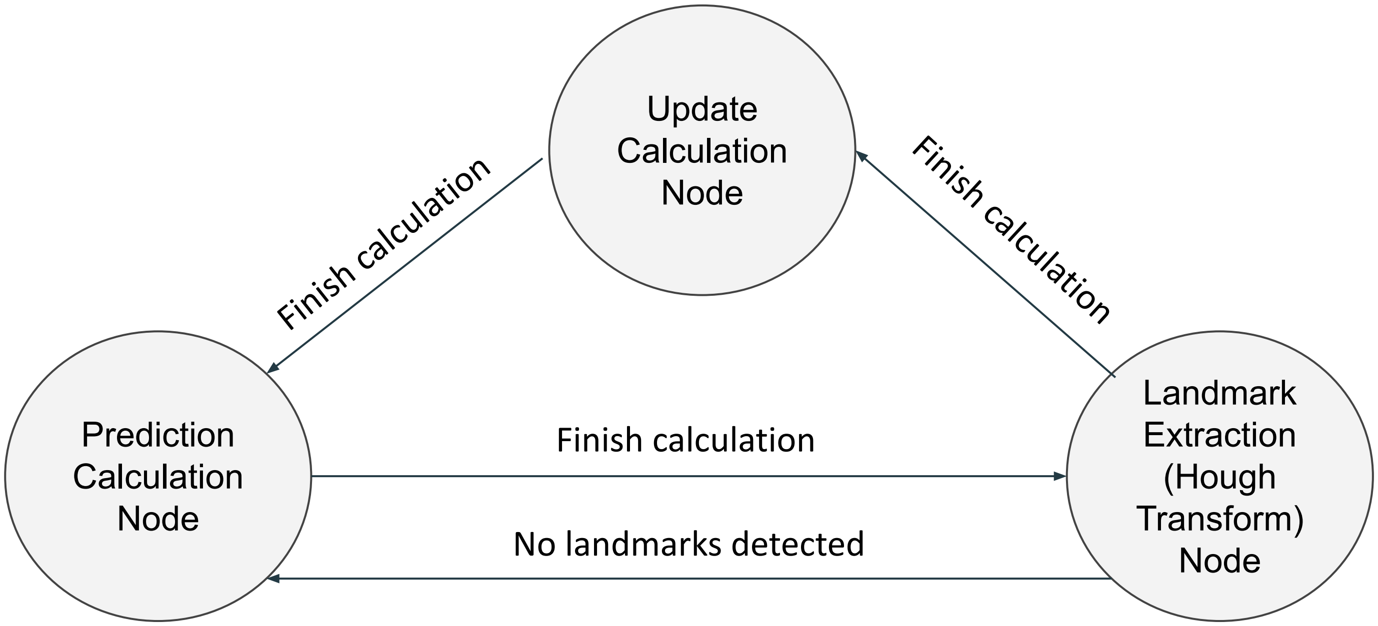
Probabilistic method

Threshold: the minimum number of intersections in the parameters space to detect a line/corners

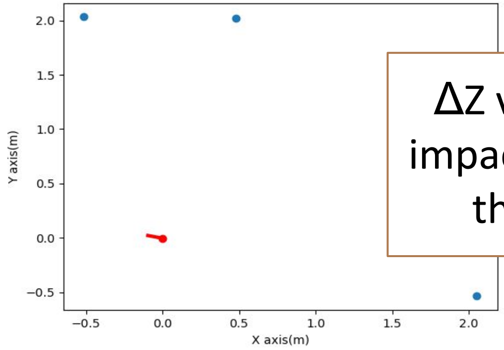
Synchronization problem



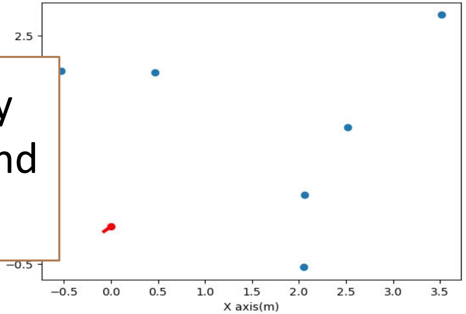
State machine implementation

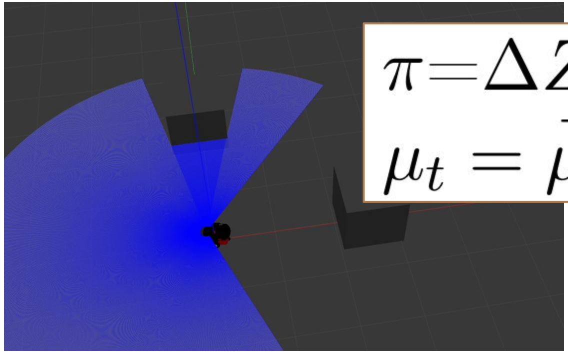


Discontinuity Problem



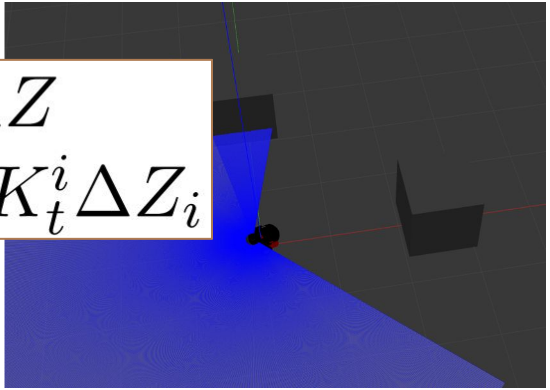
ΔZ vector discontinuity impacts the matching and the correction step





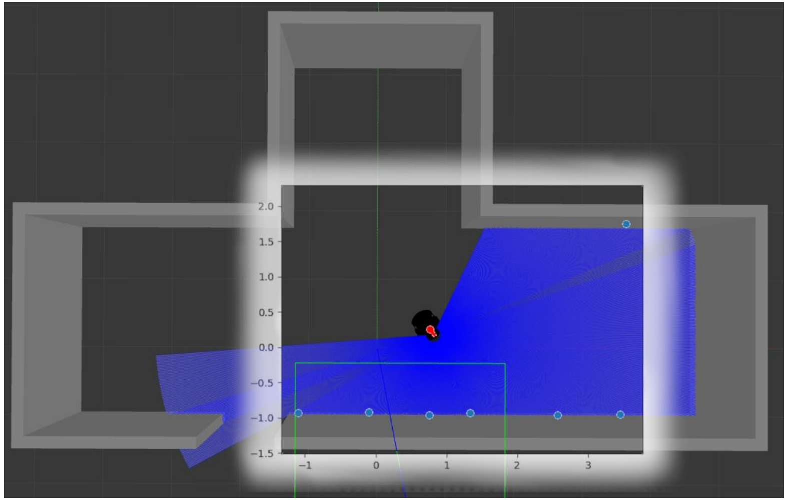
$$\pi = \Delta Z^T \Psi^{-1} \Delta Z$$

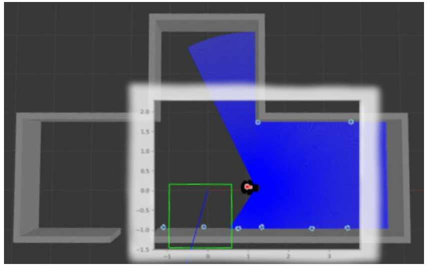
$$\mu_t = \bar{\mu}_t + \sum_i K_t^i \Delta Z_i$$

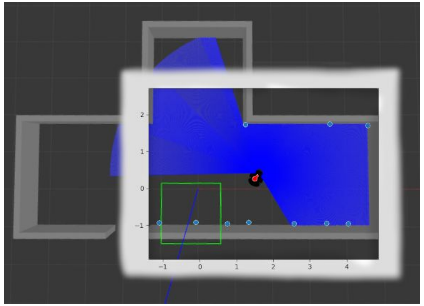


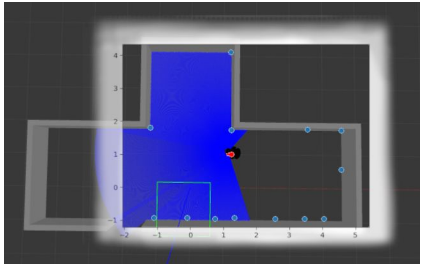
Microsimulation results

Using Gazebo to run and test our model



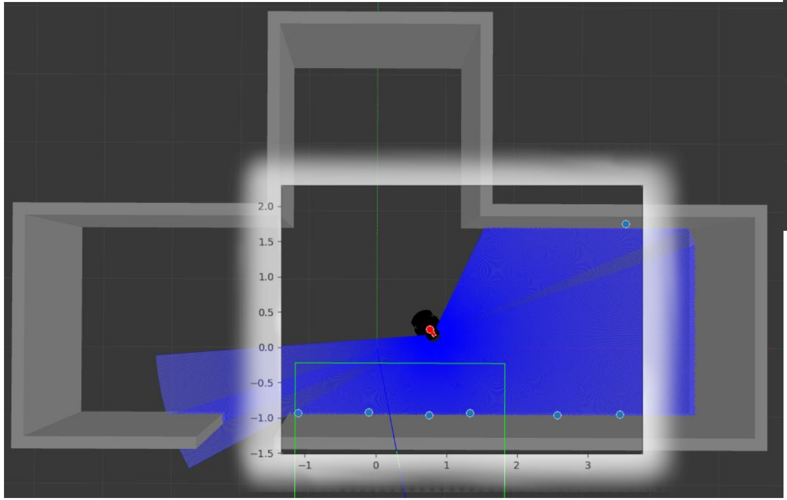


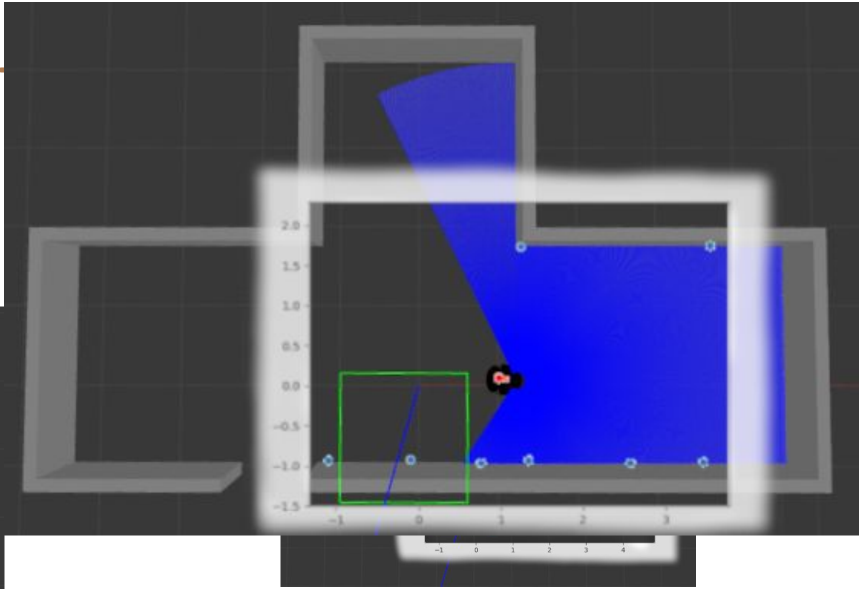


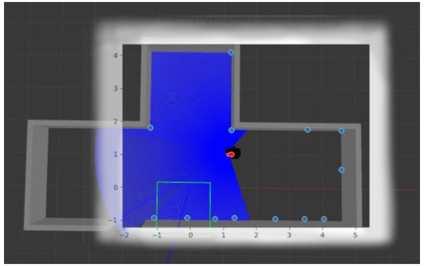


Microsimulation resul

Using Gazebo to run and test our model







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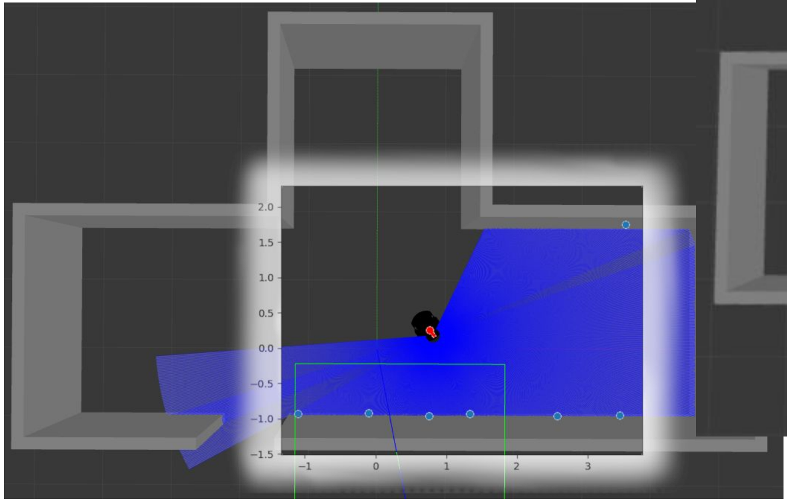

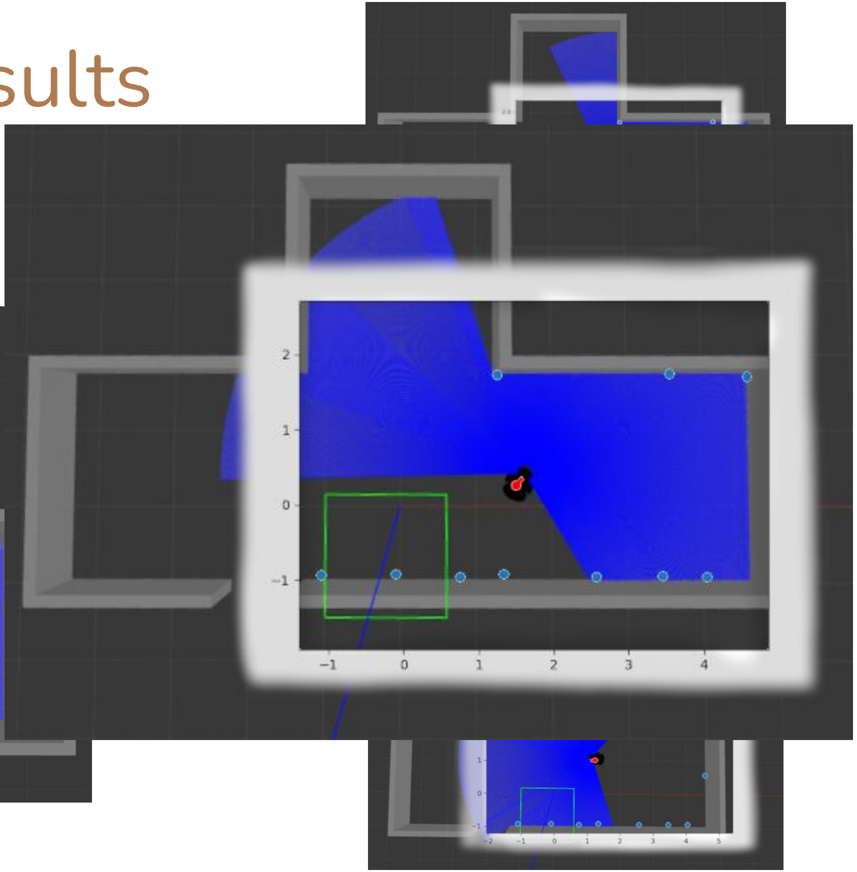

Microsimulation results

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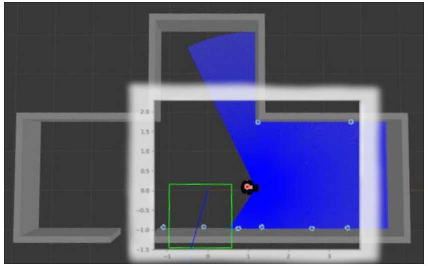
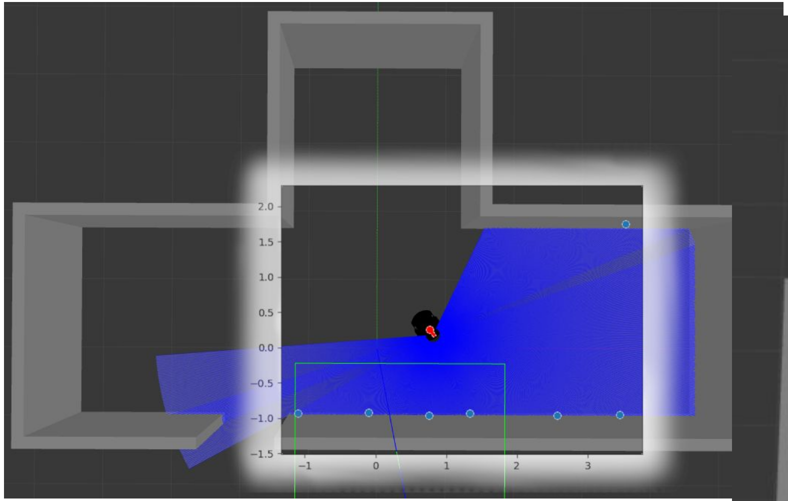
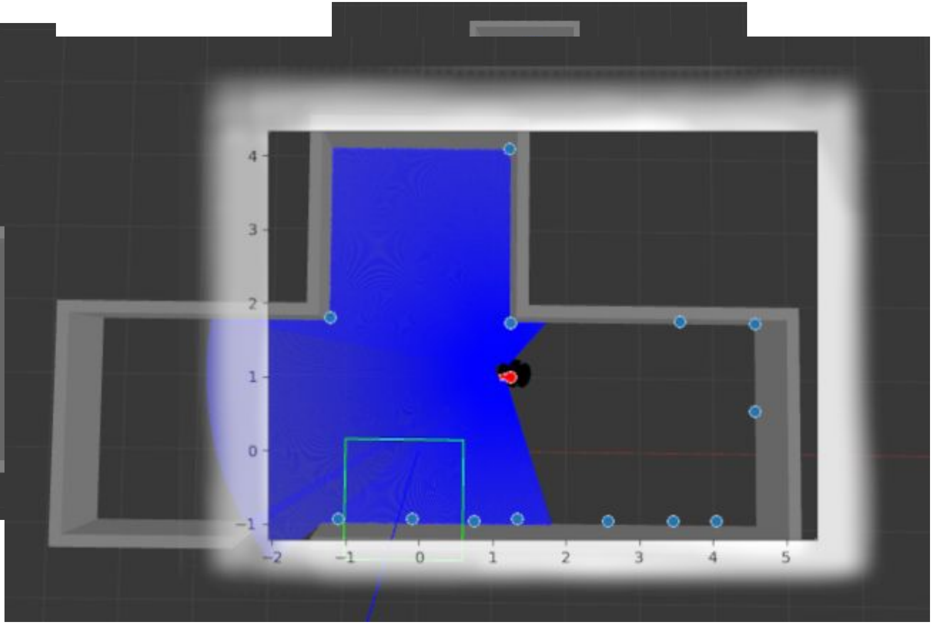
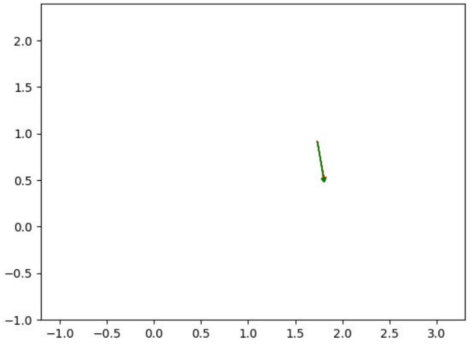




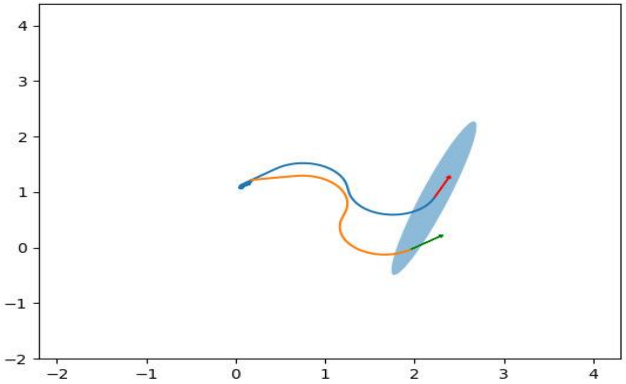


Other results

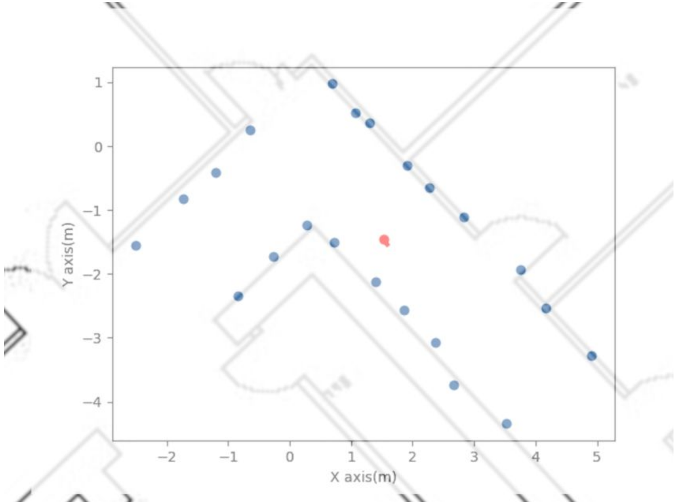


The pose prediction of the prediction method with noise influence (blue **path,** red **arrow**) and the truth position and orientation (orange **path,** green **arrow**).

The covariance matrix of the predicted pose can be represented as an ellipse



Experimental results



Results

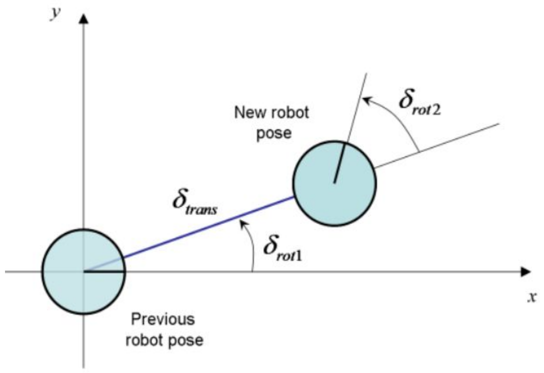
- The algorithm is stable even after approximately 30 cycles.
- Seems to represent correctly the state vector
- Correction step is too slow (can take up to 40 seconds if there are 20 landmarks stored)

Future improvements

- Change our **Hough transform** algorithm:
  - Find a way of **automating** the choice of the **optimal parameters**.
- Optimize the measurement update algorithm:
  - Only apply the update with the landmarks **near the robot.**
  - Re-analyse whether **using lines** instead of corners could benefit **landmark matching**, reducing the computational load.

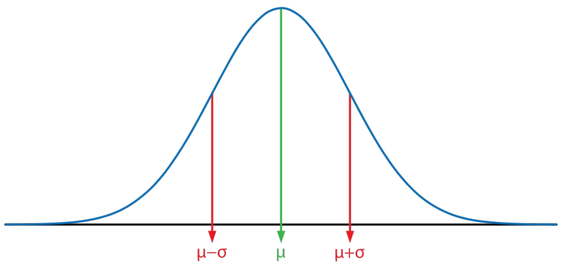
Thank you!

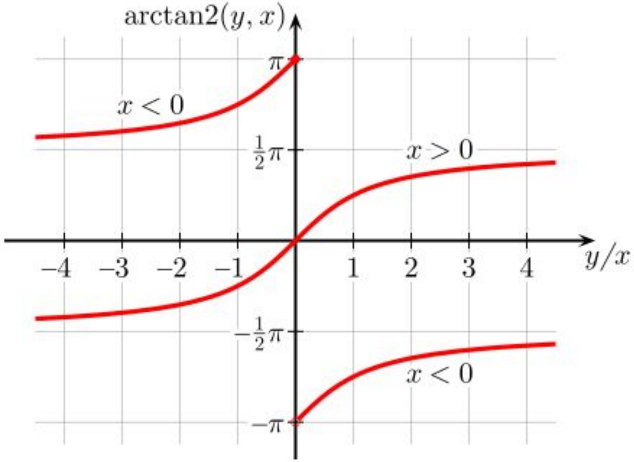
Adding noise to the simulation

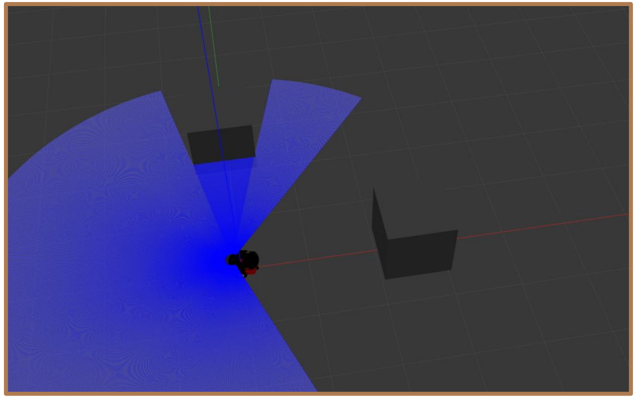


$$\begin{cases} \sigma_{rot1} = \alpha_1|\delta_{rot1}| + \alpha_2|\delta_{trans}| \\ \sigma_{rot2} = \alpha_1|\delta_{rot2}| + \alpha_2|\delta_{trans}| \\ \sigma_{trans} = \alpha_3|\delta_{trans}| + \alpha_4(|\delta_{rot2}| + |\delta_{rot3}|) \end{cases}$$

$$\begin{cases} \varepsilon_{rot1} \sim \mathcal{N}(0, \sigma^2_{rot1}) \\ \varepsilon_{rot2} \sim \mathcal{N}(0, \sigma^2_{rot2}) \\ \varepsilon_{trans} \sim \mathcal{N}(0, \sigma^2_{trans}) \end{cases}$$




arctan2(y, x)
π
x < 0
½π
x > 0
−4 −3 −2 −1 1 2 3 4
y/x
−½π
x < 0
−π



Covariance tests