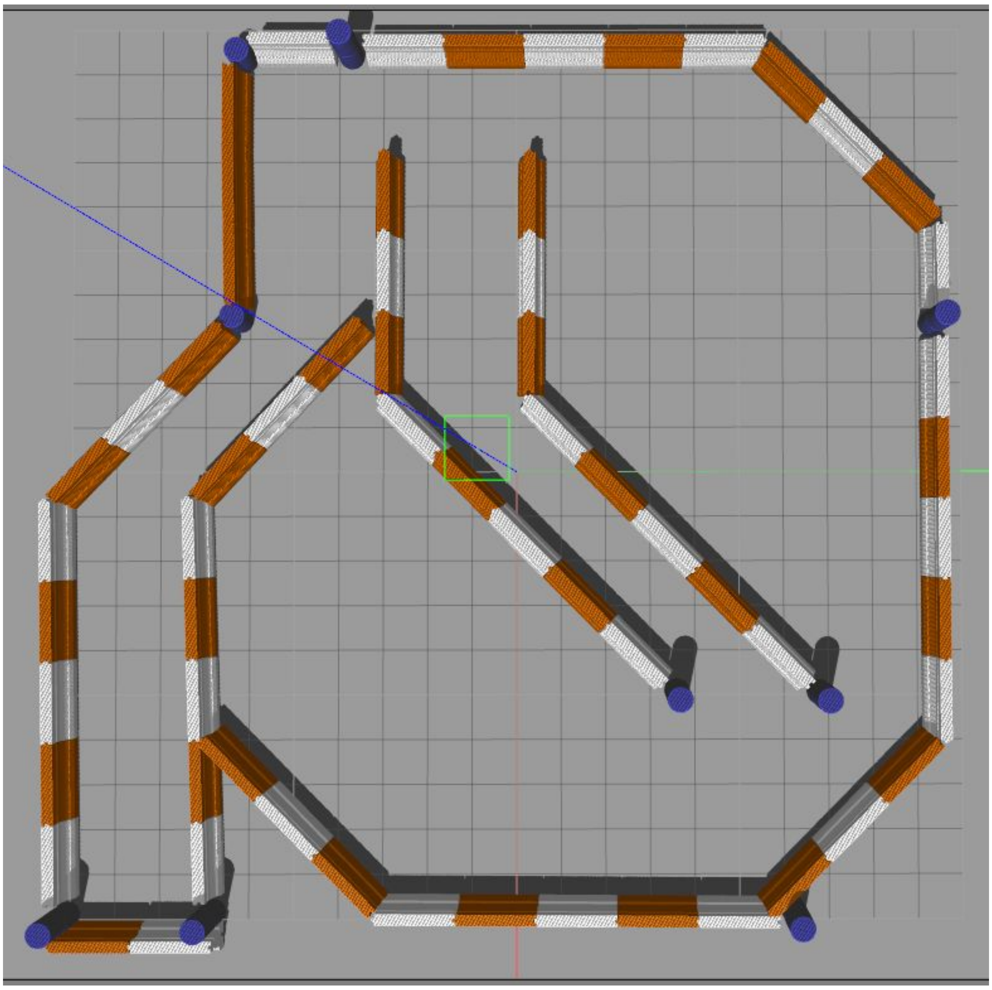
Project: Where Am I?

Abstract

Robot localization is the process of determining where a mobile robot is located with respect to its environment

Introduction

Robot localization provides an answer to the question: Where is the robot now? A reliable solution to this question is required for performing useful tasks, as the knowledge of current location is essential for deciding what to do next, the project contains two parts:
1- we are given a robot model and asked to use the AMCL package to localize the robot and use navigation stack package to move the robot to a given goal.
2- we have to build our own model and asked to repeat the experiment on our robot.



The world in which our robot should localize itself and move to the goal

Background

Knowledge of the reliability of the location estimate plays an important role in the decision making processes used in mobile robots as fatal consequences may follow if decisions are made assuming that the location estimates are perfect when they are uncertain. Bayesian filtering is a powerful technique that could be applied to obtain an estimate of the robot location and the associated uncertainty. Both extended Kalman filter (EKF) and particle filter provide tractable approximations to Bayesian filtering

Kalman Filters

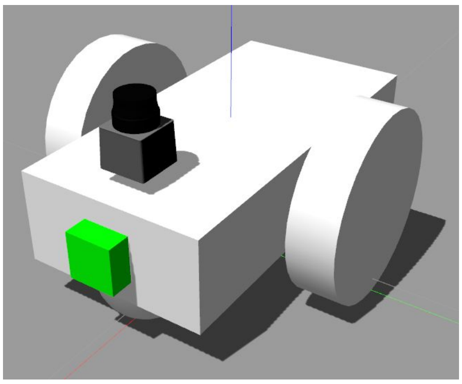
Kalman filter is a technique for filtering and prediction in linear Gaussian systems.

Particle Filters

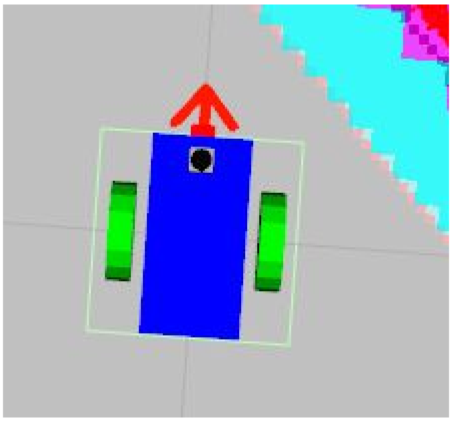
In the particle filter localization (also known as Monte Carlo localization) a weighted set of robot location estimates, termed as particles, is used to describe the probability distribution of the robot location. In the particle filter, each particle in effect provides a guess as to the location of the robot.

Kalman Filter	Particle Filter
Gaussian probability distribution	Any probability distribution
Unimodal	Multimodel
Local localization	Local and global localization
Continuous state space	Discrete state space

Models

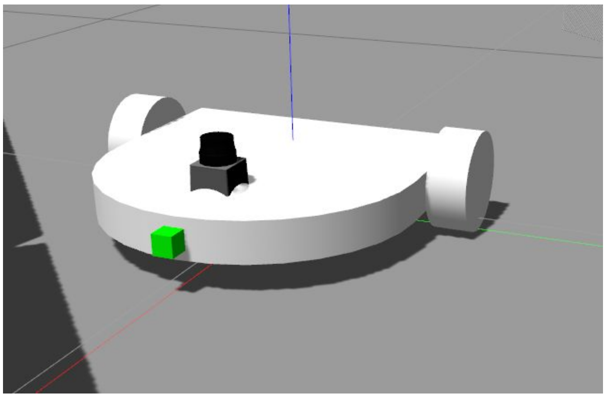


The given model

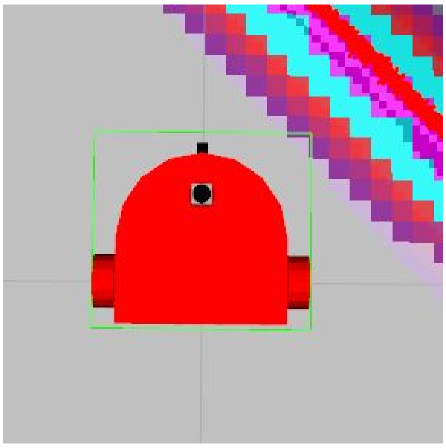


The footprint of the given robot

footprint: [[0.2, 0.2], [0.2, -0.2], [-0.2, -0.2], [-0.2,0.2]]



The customized model



The footprint of the customized robot

footprint: [[0.35, 0.25], [0.35, -0.25], [-0.1, -0.25], [-0.1,0.25]]

Results

The following two links show how the robots was able to go to goal successfully.

The customized model	The given model

Discussion

The results show an Adaptive Monte Carlo localization implementation of two robots in a simulation environment. Both robots were able to localize autonomously in the given map and successfully reach the set target position while simultaneously avoiding all obstacles.

AMCL would not work too well for the kidnapped robot problem, but we can use another algorithms using visual features to recognize places (visual features are usually more distinguishing than laser features).

Conclusion / Future work

1- Testing it on a real robot.
2- Writing my own path planner, trajectory planner.
3- Play with more parameter to see if it enhances the implementation.