Robotics Software Engineer Nanodegree: Slam Project

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Abstract—Simultaneous localization and mapping, SLAM, is the problem of building a map of an unknown environment while simultaneously localize a robot relative to this map. In this project a 2D and 3D occupancy grid map was created from both a simulated environment provided by the Udacity team and an environment that was created from scratch. A robot with two differential drives and equipped with a Lidar and a RGB-D camera was used in the simulated environment.The library RTAB-Map was selected to solve the slam problem because: it offers a good performance and memory management, a good portfolio of development tools, and a good quality of the documentation.

Index Terms—slam, udacity, rtab-map.

1 Introduction

THERE are some applications where a Robot is provided with a map of its environment and it is able to estimate its pose based on this map, the odometry data and some sensor data like a Lidar or RGB-D camera. Furthermore, in some case the map is unknown, either because the area is unexplored or because the surrounding change often and the map may not be updated. In that case the Robot must construct a map, the Robot's pose is known and the Robot is equipped with sensor data to measure its environment. There are several difficulties when building a map: high dimensionality of the space, size, noise, perceptual ambiguity , Robot moving in cycles. The high dimensionality problem can be overcome by using an occupancy grid map where the space is represented by a fine-grained grid over the continuous space in the environment. The noise or incertains is manages by using probabilistic estimations. Finally, in the most general case neither the Robot's pose and map is available, this is where slam cames in. In slam, the Robot will use the odometry and the sensor data to build a map of its environment while simultaneously localize itself relative to this map. The slam problem is quite challenging, with noise in the Robot pose and measurement, the Robot's pose will be uncertain and the construction of the map will be uncertaion as well, they are interrelated. The slam algorithm can be classified into full slam or local slam; in full slam the full trajectory of the robot is used to inference the location and to build the map, in local slam just the last sensor read data is used. Finally, the loop-clousure detection is used to improve the accuracy of the map by detecting and identifying features in the scene. This project will use an implementation of slam called real time appearance based mapping or RTABmap. This implementation is based on Graph Slam. GraphSlam is a slam algorithm that solves the full slam problem, this means that the algoritm recovers the entire path and map, instead of just the most recent pose and map. [1] [2]

2 Background / Formulation

The SLAM problem is considered the most fundamental problem in robotics. It is considered as a prerequisite for truly autonomous robot navigation. In the following section two different algorithms are explained. For the project the Graph SLAM algorithm was selected since it has both a better performance and accuracy.

2.1 Grid-based FastSLAM

FastSLAM algorithm uses the particle filter approach along with the low dimensional extended Kalman filter to incrementally estimate the posterior distribution over Robot pose along with the positions of some landmarks. FastSLAM decomposes the SLAM problem into a Robot localization problem, and a collection of landmark estimation problems that are conditioned on the Robot pose estimate. In order to solve the SLAM problem FastSlam uses a modified particle filter for estimating the posterior over Robot path, for every particle in the filter there are K Kalman filters that estimate the K landmark locations conditioned on the path estimate. An implementation of this idea requires O(MK) time, where M is the number of particles and K the number of landmarks, by using a tree-based data structure the running time can be reduced to O(MlogK). Finally, there are different versions of the algorithm. The one used during the course is called Grid-based FastSLAM which adapts FastSLAM to grid maps with the main advantage of no need for predefining landmark, that means it will work in arbitrary environments.

$$p(x_{0:t}, m|z_{1:t}, u_{1:t}) = p(x_{0:t}|z_{1:t}, u_{1:t})p(m|x_{1:t}, z_{1:t}) \quad (1)$$

The Grid-base FastSLAM use three different techniques: sampling motion, map estimation and importance weight.

In the sample motion technique estimates the current pose given the K-th particles previous pose a the current controls.

$$p(x_t|x_{t-1}^{[k]}, u_t) \quad (2)$$

The map estimation technique goal is to estimate the current map giving the current measurement, the current K-th particle pose and the previous K-th particle map. The occupancy grid mapping algorithm is used at this stage.

$$p(m_t|z_t, x_t^{[k]}, m_{t-1}^{[k]}) \tag{3}$$

Finally, the importance weight technique which compute the importance weight of each individual particle.

$$p(z_t|x_t^{[k]}, m^{[k]}) \tag{4}$$

2.2 GraphSLAM

GraphSLAM uses constraints to represent relationships between Robot poses and the environment, and then tries to resolve all of these constraints to create the most likely map given the data. GraphSLAM solves the full slam problem. Furthermore, GraphSLAM has several advantages over FastSLAM including the reduced need for onboard processing capability and an important improvement in accuracy since FastSLAM uses particles and it can happen that there is no particle in the actual pose of the Robot.

In GraphSLAM the problem is decoupled in two tasks: to create a graph of all Robot poses and features in the scene and to find the most likely Robot's path and map of the environment. These two tasks are called Front-End and Back-End.

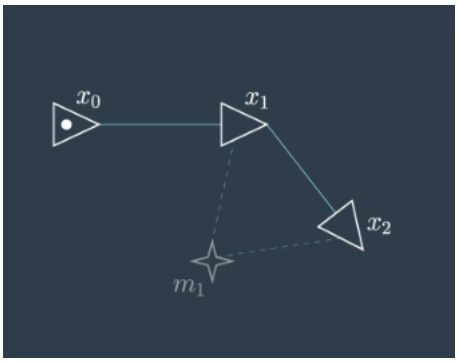


Fig. 1: Graph Slam

The Front-End of GraphSLAM constructs the graph using the odometry and sensory measurements collected by the Robot. This is done continuously as the Robot moves around the environment. This step can vary greatly from application to application depending on the desire accuracy, the Robot sensors etc. In this step the features in the environment that have been previously seen are treated.

The input of the Back-End is the complete graph with all the constraints that have already been built in the previous step. The output is the most probable configuration of the Robot poses and map features. It takes all the constraints and calculates the configuration that produces the smallest error. It is more consistent between different applications. This two-step can be applied iteratively.

3 Scene and Robot Configuration

3.1 World

A world in gazebo was created from scratch using a floor plan. Walls, doors and windows were added. Finally, few objects were put in the scene using the gazebo model editor. The result can be seen in the following figure.

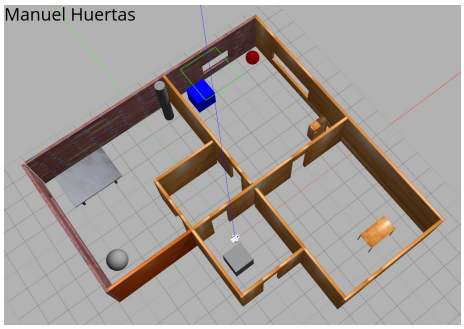
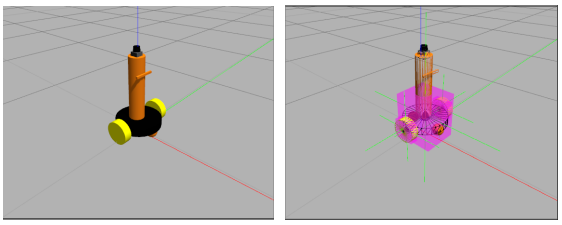


Fig. 2: Robot own world.

3.2 Robot

The model created from scratch is a 2W robot with two caster, one on the front and another on the back, to stabilise. A Lidar and a camera were added at the front, for the navigation stack. The inertial and friction parameters where adjusted in order to give a smooth movement to the robot. The robot was modified to include a RGB-D camera, kinect, in order to produce a 2D and 3D maps of the scene.



(a) Robot design: general (b) Robot design: inertia

Fig. 3: Robot design views

- Chassis: a cylinder with radius 0.15cm and length 0.05cm.
- Wheels: two wheels 0.075cm x 0.05cm.
- Casters: two caster one the back and another on the front.
- Lidar: a hokuyo lidar in the front.
- Camera: a RGB-D camera in the head of the platform
- IMU: Imu sensor.

3.3 Packing Structure

A module named slam_project was created with the follwing structure:

```
slam_project
├── CMakeLists.txt
├── config
├── launch
├── meshes
├── package.xml
├── scripts
├── urdf
└── worlds
```

Three different launches files were created:

1) roslaunch slam_project worldlaunch: creates the world and the robot inside the world in gazebo.
2) roslaunch slam_project teleoplaunch: creates a node to tele operate the robot.
3) roslaunch slam_project mappinglaunch: creates the rtabmap node.
4) roslaunch slam_project rvizlaunch: launch rviz.

4 Results

The following images show both the occupancy grid and 3D map for the Udacity world and the own world created from scratch. After moving around the scene the robot, the map was successfully built. The same place was visited several times in order to test the capacity of the algorithm to detect closures to improve the accuracy of the map. It was possible to successfully construct the map.

(a) Occupancy Grid Map (b) 3D octomap

Fig. 4: Udacity world

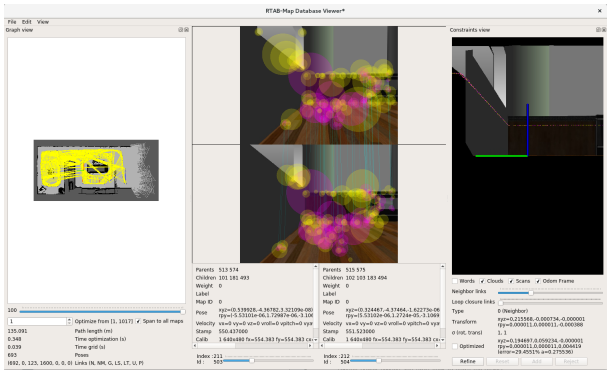
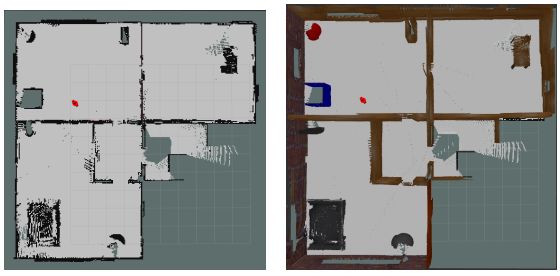


Fig. 5: RTAB-MAP database viewer



(a) Occupancy Grid Map (b) 3D octomap

Fig. 6: Own world

Analysing the database generated by rtabmap more than one hundred closures were detected.

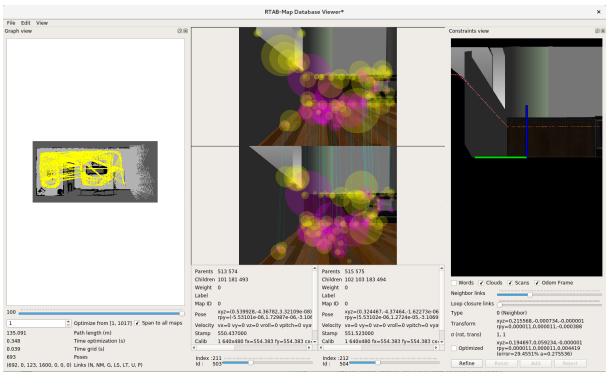


Fig. 7: RTAB-MAP database viewer

5 Discussion

The project setup was done using the debugging tools in ROS. In order to check the correct definition of links and joints the coordinates frames was checked using the tf library tools. After few corrections, the correct configuration was finally archive. At the beginning the map 3D map was quite strange; the camera orientation was adjusted to solve this problem. Once the coordinates frames and camera orientation was defined the robot was move around the scene to generate the 2D and 3D map. It was detected that the quality of the map was quite related to the trajectory of the robot. If the robot was moving in small loops turning around a lot the quality of the 3D map was worse than if the robot was doing large loops around the environment.

A way to improve the quality of the map is to increase the detection to increase the number of loop closures found when returning to a previous area but because the processing power needed and dead lines to finish the project this option was not investigated in deep. The final solution was to change the way in which the robot was moving in the scene, the robot follows long loops and passing the locations in the scene several time. This was enough in order to achieve the desire quality.

At the beginning a map with empty room was created and the quality was poor. The conclusion was that due the scene was quite similar in different robot positions, the robot was not detecting closures and when passing the same place was identifying the position as new. After adding few objects, the quality of the map improve.

6 Conclusion / Future work

The ability to build a map and to detect the position of the robot relative to this map can be used in several applications. A robot with these capabilities will be able to navigate in environment unexplored or where changes are frequents: people or obstacles changing its positions. I am planning to use this functionality to build a tour-guide robot for the Gran Telescopio Canarias in which a robot will be moving around the environment autonomously and reacting to change in the environment.

References

[1] https://eu.udacity.com *Robotics Software Engineer Nanodegree program.*
[2] Sebastian Thrun, Wolfram Burgard, Dieter Fox *Probabilistic Robotics.*