Map My World

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Abstract

The goal of this project was to use state-of-the-art SLAM techniques to generate maps for two gazebo environments, one is supplied and the other was constructed in gazebo. Specifically real time appearance based mapping or RTAB-Map was used to map both environments. The robot could successfully map both environments

1 Introduction

This project continued the previous project on localization, by exploring how SLAM techniques like RTAB-Map to generate maps of the surrounding environments. This would be very useful as most of the time supplying a map of the environment to the robot would not be an option. The robot used an RGB-D camera and a lidar to get depth and laser scan data to generate 2D and 3D maps of two environments,estimates its trajectory and map feature poses as it moves through the environment.

2 Background

SLAM is very important in robotics applications, especially autonomous robots as they need to identify and navigate the environment on their own. SLAM is more challenging than localization only mainly because of the added uncertainty of the map. Constructing the map itself represents a major challenge because of the highly dimensional space and the huge amount of objects that the robot sees.

There are many different SLAM algorithms, some of the most important ones are:

- FastSLAM: this is a landmark-based algorithm which uses the Monte Carlo Localization to estimate both the landmarks and robot poses. The Grid-based FastSLAM algorithm is a version of FastSLAM that combines the MCL and Occupancy Grid Mapping, an algorithm that represents the map as grid cells which are occupied, free or unknown. However, both versions have problems with arbitrary environments since they assume known landmark locations.

- GraphSLAM: is an algorithm that represents the SLAM problem as a graph where the poses of the trajectory and the measured objects are the nodes, and the links are the estimated motion and measurement distances represented as constraints. The goal of the algorithm is to solve the graph to reach the best configuration which satisfies the constraints as much as possible, thus solving the Full SLAM problem, which is the estimation of the full trajectory of the robot and the map features.

Real Time Appearance Based Mapping (RTAB-Map) is used in the project which is an upgraded version of GraphSLAM that uses a bag of words approach to identify correspondences between frames using visual similarity. The algorithm tries to detect loop closures which result in a much less noisy and more accurate mapping. At every frame, the camera image would be compared against previously found map features in a constant-size working memory. The algorithm uses a bag-of-words representation of features to make the comparison more efficient. It also uses a constant size or amount of features to achieve constant time performance. It uses memory management techniques to choose which features to be put in this constant memory space.

3 Scene and Robot Configuration

The new environment was a single room with 4 walls and multiple objects spread around the room. Each walls had a different finish or paint to create more features in the map. The robot could be confuse a wall with another if they both had the same finish. Also, totally different objects were chosen for the same reasons.

It was originally intended to use personal robot from the localization project, which used skid steering but the robot had

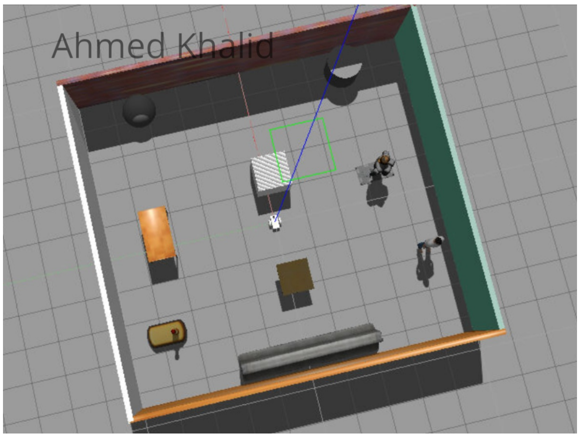

Figure 1: Personal World

issues with steering that driving it harder and could potentially mess with the odometry data.

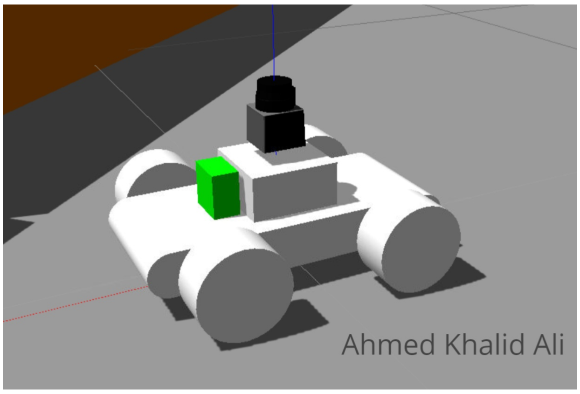

Figure 2: Personal Robot, Not Used

So the original benchmark udacity robot was used. It utilized differential driving. A lidar was put on top of it to capture laser scan data and an RGBD camera was put in front to capture depth data in addition to images.

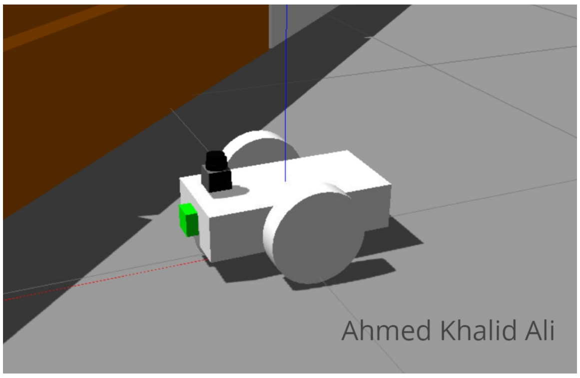

Figure 3: Benchmark Robot From Localization Project

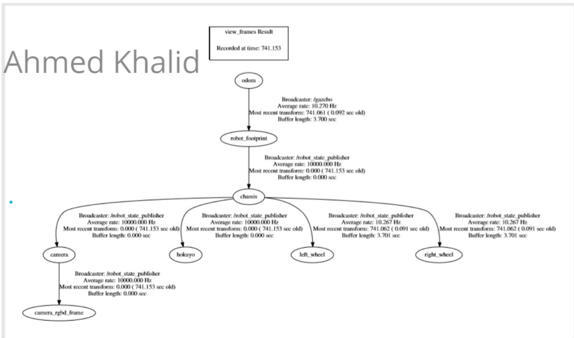

Figure 4: TF Frames of the Benchmark Robot

4 Results

The robot could map both environment successfully after a single pass but some areas required additional passing to be fully mapped. Also a second pass was done to capture loop closures. It should be noted that some objects had duplicates after more than a single pass.

Overall 99 loop closures were captured in the kitchen_dining environment and 78 loop closures in the personal world.

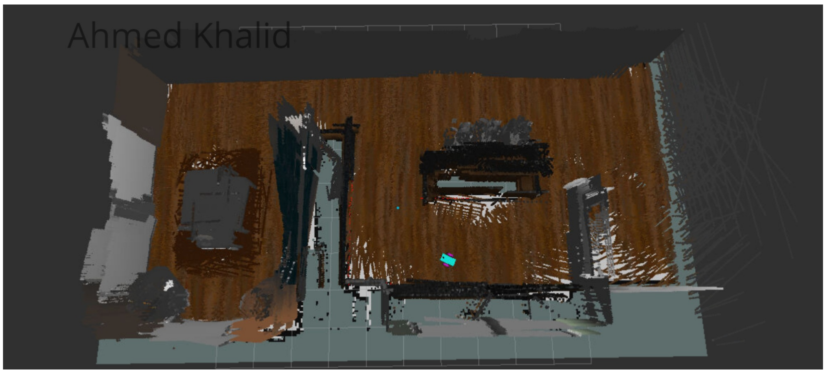

Figure 5: 3D map of Kitchen Environment

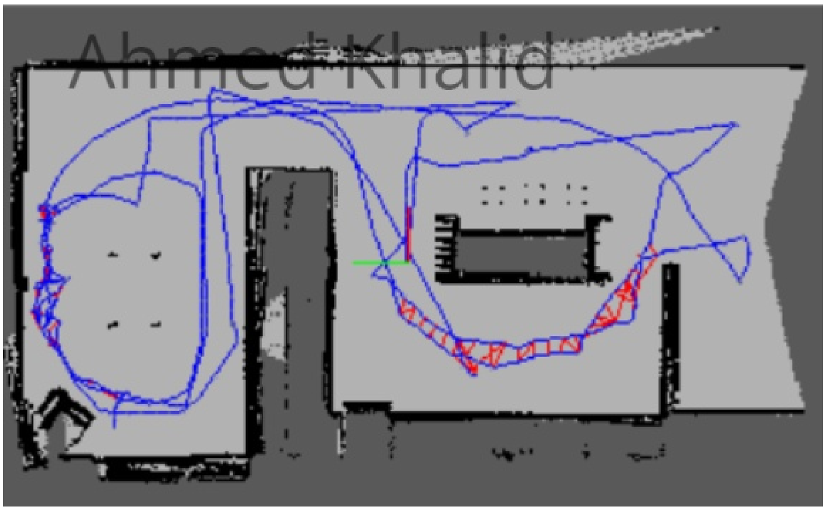

Figure 6: 2D map of Kitchen Environment

Figure 7: 3D map of Personal Environment

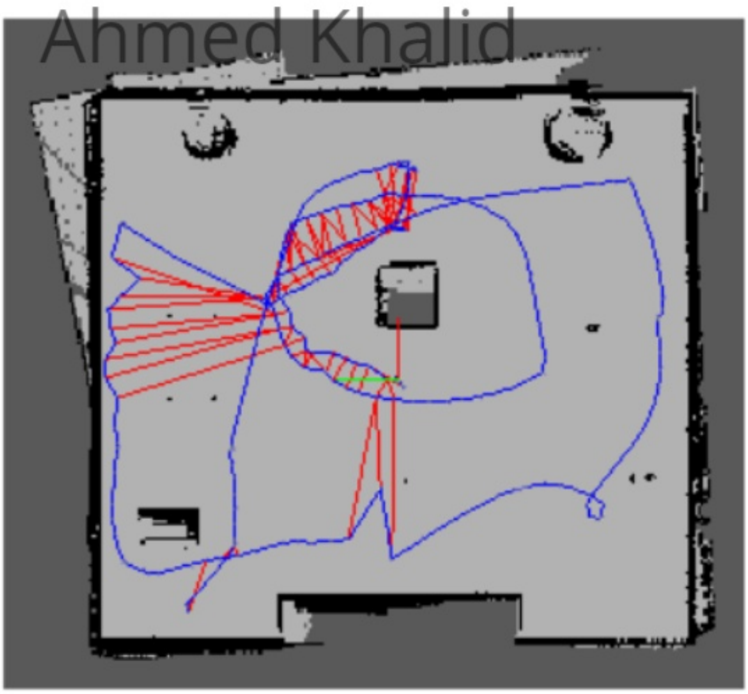

Figure 8: 2D map of Personal Environment

5 Discussion

The mapping was mostly done after a single pass in the environments. Additional passes had the benefit of increasing the loop closures but it made artifacts for some objects.

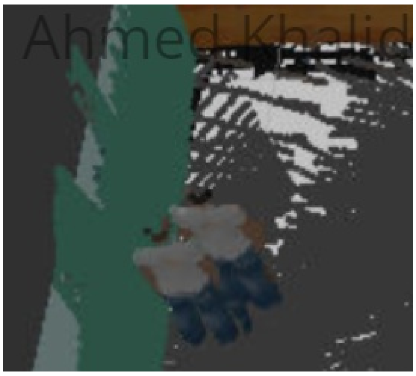

Figure 9: An object is misrepresented after multiple passes

Neither of the maps really stood out as being handled better than the other one. But the less detailed objects were generally better represented.

The low position of the camera caused tall objects like walls to be mis represented because the camera did not capture the full height.

6 Future work

SLAM applications are very diverse in robotics. It can be used in a vacuum cleaner to be able to navigate the room successfully on its own. Also it would be very beneficial to send robots to map environments that may be dangerous for humans to go into like in disaster situations. Also, autonomous robots deployed in factories can benefit from this technology, they would be able to map the environment on their own and transform objects successfully.