Udacity Robotic Localisation

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Abstract—Simultaneous Localisation and Mapping (SLAM) was successfully applied in order to create 2D and 3D maps of a surrounding environment by a tele-operated robot in a simulated environment equipped with an RGBD camera and a laser scanner. The robot was tested successfully in two separate environments.
The project utilised the Real Time Appearance Based Mapping (RTAB-Map) stack and the Robot Operating System (ROS) using a robot equipped with an RGBD camera and a laser scanner.
It was found that the techniques for mapping open world and closed world environments were markedly different. In the closed world the robot can map from within without issue, whereas in the open world the robot needed to circumnavigate the perimeter, and turn inwards periodically. The wheeled robot was found to be most suited to mapping closed world environments.

Index Terms—Robot, IEEEtran, Udacity, LaTeX, Localisation.

1 Introduction

A Robot was tasked with mapping two separate simulated environments using the Simultaneous Localisation and Mapping (SLAM) algorithm called Real-Time Appearance-Based Mapping (RTAB-Map). The goal was to create a high quality map with at least three loop closures.

Simultaneous localization and mapping (SLAM) is the problem of constructing or updating a map of an unknown environment while simultaneously keeping track of an agent's location within that environment. There are several algorithms available for approximating this problem to a useful degree of accuracy and certainty, which are explored further in this paper.

The purpose of this project is to create a robot that is able to map a defined interior environment to a recognisable degree of accuracy with three Graph-SLAM 'loop closures'. The performance of this robot in the interior world was then comapred to a more open simulated Petrol Station forecourt environment.

2 Background

The main challennges associated with SLAM are as follows:

- Map Size: the most common Gaussian filter for non-linear navigation models.
- Sensory noise: the noiser the surroundings, the harder it is to filter the salient data from the noise.
- Ambuigity: As the robot views a different place that is similar at different points in time, it has trouble distinguishing between the new and old location.
- Cycles: If a robot traverses exactly the same path twice, up and down, it is easy to correct for odometry errors on the return path. A robot freely moving about a 2D plane, however, cannot so easily correct for these errors.

Occupancy Grid Mapping, Grid-based FastSLAM and GraphSLAM all accomodate for these errors, however.

2.1 Occupancy Grid Mapping

Occupancy Grid Mapping (OGM) excels at creating relaible maps from noisy and uncertain data. The algorithm assumes that the robot's pose is fully known. The algorithm separates the field of perception of the robot into uniformly spaced grid, analogous to voxels, whose values are initially randomised but are refined as they are perceived by the robot's sensors.

OGM is most valuable as a means of post-processing of the SLAM algorithm, as SLAM, by itself, does not produce maps that are suitable for path planning and navigation.

2.2 Simulation Localisation and Mapping (SLAM)

As the name suggests, SLAM performs both localisation and mapping at the same time. Neither the robot's pose nor its location are provided.

2.3 Grid-Based FastSLAM

FastSLAM preserves a set of particles in order to approximate the posterior probability over the course of the trajectory and uses an Extended Kalman Filter (EKF) to solve for specfic features of the map, which are mapped with a local Gaussian distribution.

FastSLAM not only estimates for the robot's full path but each particle distribution is a representation of the robot's current pose. Thus FastSLAM solves both the full SLAM and online SLAM problems.

Grid-based FastSLAM applies Occupancy Grid Mapping to the FastSLAM algorithm, allowing for random and or sparse environments free to discernable landmarks.

2.4 GraphSLAM

GraphSLAM improves upon the FastSLAM model by representing the positional particles as network graphs constrained by known measurements. Thus the non-linear inter-relational 'weights' of each individual measurement with respect to each other can be linearised and itteratively calculated and updated at each time step to a reasonable degree of accuracy.

Real Time Appearance-Based Mapping (RTAB-Map) uses GraphSLAM in addition to 'loop closure' which is able to identify what the robot has and has not seen before.

3 Scene and Robot Configuration

For the purposes of mapping both the kitchen dining and Willow Garage environments were chosen.

The robot configuration was was identical to the original Udacity Bot used for the first previous localisation project, but with the addition of an RGBD XBox Kinect camera instead of the regular camera used before. The RTAB-Map algorithm augmented the depth measurements of the RGBD camera with the measurements from the Hoyoku laser scanner.

An extra camera joint was also added to rotate the RGBD camera by -90 degrees on the z and x axis to ensure than it was pointing in the correct direction.

The kitchen dining environment is a pre-made model available with the Gazebo model database. This was the first environment to be mapped.

The second environment to be mapped was a petrol station forecourt. Various vehicles (an SUV, an ambulance and a hatchback) were added to the scene as well as walking and standing models of people. In addition some typical urban features were added to give the scene a sense of place. These were a lamp post and a fire hydrant.

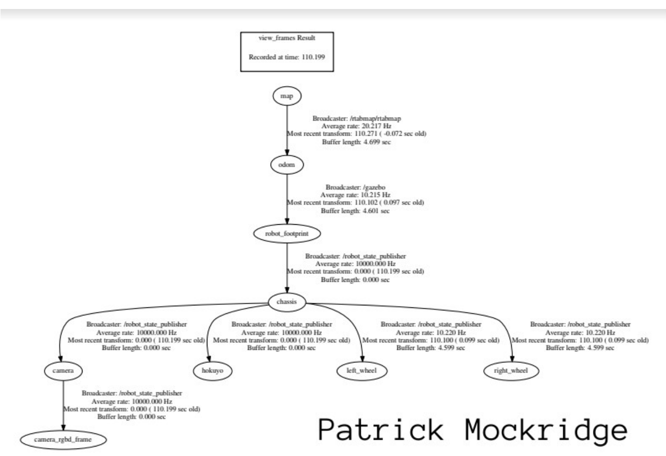

Fig. 1. TF Frame of the robot used

4 Results

For the kitchen dining world, each segment of the map was looped around three times: the welcoming area, the kitchen area and the dining area.

Five loop closures were performed. Best results were achieved when the robot performed two or three consecutive journeys down the same linear path. Also it was important in the tight space of the dining area not to map too closely to the table, giving the robot ample space for adequate perspective of the whole area.

For the Petrol Station environment, the majority of the area was mapped successfully, following numerous failed attempts.

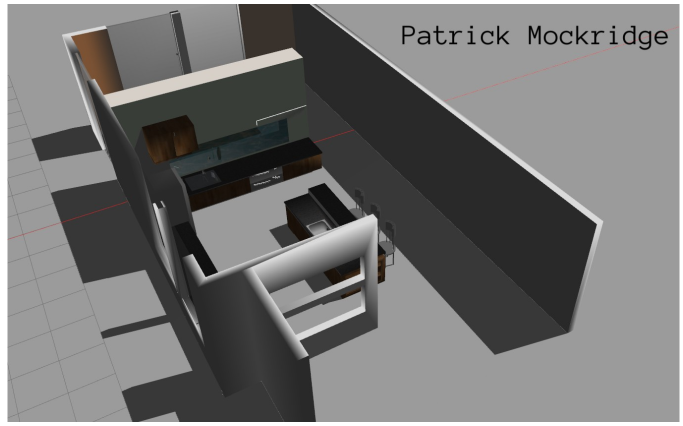

Fig. 2. Kitchen Dining model layout

Fig. 3. Petrol Station model layout

Fig. 4. Point cloud of the mapped kitchen dining model with localisation path from RTAB Map

Fig. 5. RVIZ Occupancy grid for Kitchen Dining environment

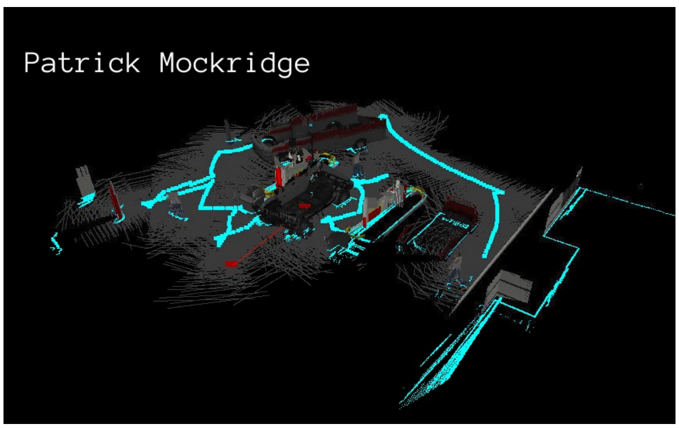

Fig. 6. Mapped petrol station model with localisation path from RTAB Map GUI

Fig. 7. RVIZ Occupancy Grid for Petrol Station

5 DISCUSSION

Mapping the open world of the petrol station forecourt required a different mapping strategy to mapping the closed environment of the supplied kitchen dining model.

For the petrol station numerous models were created to find an environment in which RTAB-Map would not create spurious loop closures. As each bay is similar it was necessary to place vehicles of differing shapes in each bay such that RTAB-Map would not falsely confuse separate bays as the same bay and thus collapse point clouds on top of each other.

Also in order to gain a good perspective for mapping it was necessary to drive the robot to the outskirts of the petrol station environment and look inwards, as opposed to the kitchen dining enclosed rectangular world where relative perspective is easier to calculate. The mapping procedure for the petrol station was thus akin to a videographer looking from the outside in at a subject, whereas the kitchen$_{d}iningworldwasmappedfromtheinside - out$.

Also for the petrol station world it was necessary to map each vehicle from numerous perspectives, to allow RTab Map to more easily correlate its location and, again, not create spurious loop closures when separate vehicles are confused to be alike. It was found that colour alone is not enough of a preventative measure, and when blue and red 'hatchback' Gazebo models were used in separate bays, RTAB-Map would routinely perform a loop closure, putting the red points of the red hatchback over the blue points of the blue hatchback, and collapsing the rest of the mapped points.

6 FUTURE WORK

In future it would be interesting to study the performance increases that might be possible with improvements to the robot. Stereoscopic RGBD imaging with LiDAR would definitely aid the robot in keeping its bearings with the respect to nearby landmarks at all times.

Flight capability would aid the robot in gaining a full 3D perspective in open environments, such as the Petrol Station environment. A swarm of 3 or 4 of drones each equipped with an RGBD camera, with each a known distance from each other, would greatly increase the accuracy of triangulated depth and the speed of mapping.

Overall, while the wheeled robot performed adequately mapping the open petrol station area, it was unable to map the full height and depth of the space, which for serious architectural, civil engineering or surveying purposes would preclude it from commercial application.