Cooperative 3D and 2D Mapping With Heterogenous Ground Robots

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ABSTRACT

Efficient and accurate 3D mapping is desirable in disaster recovery as well as urban warfare situations. The speed with which these maps can be generated is vital to provide situational awareness in these situations. A team of mobile robots can work together to build maps more quickly. We present an algorithm by which a team of mobile robots can merge 2D and 3D measurements to build a 3D map, together with experiments performed at a military test facility.

Keywords: Mapping, robot cooperation, heterogenous sensor fusion

1. INTRODUCTION

Unmanned vehicle systems (UVS) can be used to provide situational awareness to first responders. Current 2D mapping technology is unable to adequately represent elevation transitions in multi-story structures or represent detail that exists outside of a single plane in the environment. Recent advancements in 3D sensing technologies enable algorithms for teams of autonomous agents to build 3D maps of the environment. These 3D maps can be used by first responders or soldiers to plan and coordinate ground operations with rich information while minimizing risk to personnel.

The mapping system presented in this paper makes 3D measurements of features in the environment. These measurements are optimized in a graph to determine the structure of the environment and the trajectory of the robot. Full 3D maps are generated by rendering sensor data along the robot's optimized trajectory, which can be used for operational planning. 3D feature mapping is desirable because of the accuracy and completeness of rendering map information which can be interpreted by users. Unfortunately, robots which can acquire 3D maps are more complex and expensive than robots which can acquire 2D maps. In addition, 2D data can be more efficiently analyzed and can produce measurements in real-time; 3D data can only be analyzed for map measurements at a much slower rate. In this paper, we consider an alternative heterogenous team consisting of a robot with a 3D sensor in addition to a robot with a 2D sensor which work together to build a complete map of an indoor environment.

These algorithms have been implemented on a team of iRobot PackBot systems that have been augmented with an onboard computer. One of the robots, referred to as the *3D robot* in this paper, has a 3D laser scanner. The other robot, referred to as the *2D robot* in this paper, has a 2D laser scanner.

Experimental evaluation of mapping performed by this robot team has been conducted at a US military MOUT site which simulates the challenges in modern urban warfare. The robots are tele-operated in one of the structures at the MOUT site. The resulting maps generated by each robot alone are compared to a map generated by both robots working together.

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2. RELATED WORK

The problem of simultaneous localization and mapping (SLAM) has been actively researched for the past 25 years, see[1] and[2] for a review of the initial and current state-of-the-art approaches to the SLAM problem. There are many approaches to mobile robot SLAM; the most relevant one to the approach used in this paper is the Square Root Smoothing and Mapping($\sqrt{SAM}$) algorithm[3].[4] $\sqrt{SAM}$ uses linear algebra least-squares system solving to compute the robot trajectory and landmark locations from a set of relative pose and landmark measurements.

Most approaches to the SLAM problem consider only a single robot. More recently, multi-robot mapping and exploration was addressed in[5] and.[6] In these papers, up to three robots are used to build a map, and the authors also implemented a decision-theoretic planner which trades off frontier exploration with robot rendezvous. In this approach, robots must localize each other in order to fuse their maps into a global map. Our approach instead performs global data association among landmarks across all robots so this step is unnecessary. Unfortunately, our approach has an additional constraint that is not needed in the rendezvous approach – we must specify the initial relative poses between robots.

3. APPROACH

We have developed a toolkit for mobile robot feature-based mapping with various types of landmark measurements called *OmniMapper*. OmniMapper has been demonstrated mapping 2D walls in[7],[8] for optimizing virtual measurements within landmark features in,[9] for object recognition mapping in,[10] and plane mapping in.[11]

OmniMapper uses the nonlinear optimization engine *GTsam* based upon Dellaert's *smoothing and mapping* technique described in.[3] Measurements are coordinated and synchronized with robot pose estimates via the Robot Operating System (ROS).[12] Each landmark measurement modality requires the definition of a nonlinear factor which describes a measurement function and its derivatives. In the experiments described in this paper, we make use of a plane measurement of walls described in[11] and a linear measurement of walls described in.[9]

To integrate measurements from multiple robots into a single map, we make use of a version of OmniMapper which maintains multiple robot trajectories with shared landmarks. Each individual robot builds a local map and sends relevant map data to the central map server. On the central map server, measurements are data associated to existing or new landmark entities via an implementation of joint-compatibility branch and bound (JCBB).[13]

Sensor data is analyzed to produce feature measurements through the line extraction module and the plane extraction module. The line extraction module is similar to the RANSAC-based technique described in.[14] Pairs of points are uniformly selected from the laser scan to form a putative line. If a significant portion of other points are co-linear this putative line, then it is selected as a measurement and the inliers are removed. This process is repeated for a fixed number of iterations per laser scan. The measured lines can then be used by the mapping system to build a map of the walls in the environment.

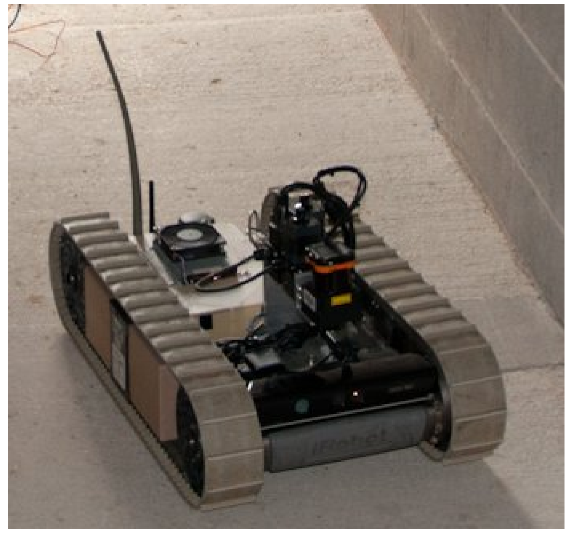
The plane extraction module is also a RANSAC-based technique from.[15] Coplanar points are extracted and removed from a 3D point cloud. These coplanar points are used to form a plane measurement; a normal vector and range, together with the convex hull which tightly encloses the inlier points to this plane. As the number of points evaluated by the plane extraction module is many orders of magnitude greater than the number of points evaluated by the line extraction module, plane extraction requires several seconds per frame while line extraction occurs in real-time.

4. EXPERIMENTS

Experiments were performed with two iRobot PackBots as seen in figure 4. One robot is performing 2D line mapping of walls with a Hokuyo UTM30 laser scanner in figure 1(a). The second robot is equipped with a Hokuyo UTM30 laser scanner which is mounted on a Directed Perception PTU-46-70 pan-tilt unit in figure 1(b). This pan-tilt unit is actuated and synchronized with the laser scanner to produce a 3D point cloud of the walls in the environment.

The experiments are performed on log data taken at the MOUT (military operations in urban terrain) training/test site at Camp Lejune US Marine Corps base in North Carolina, shown in figure 4. The buildings

(a) An iRobot PackBot equipped with a 2D laser scanner.



(b) An iRobot PackBot equipped with a pan-tilt unit and a laser scanner, capable of making 3D measurements of planar features such as walls.

Figure 1. The team of iRobot PackBots which are used in the experiments in this paper

where the experimental data was collected are designed to simulate typical urban combat terrain. The building where the data which is used in this paper was collected is called the *Hotel*; it is typical of a hotel with many smaller rooms with adjoining bathroom-sized rooms connected with main hallways.

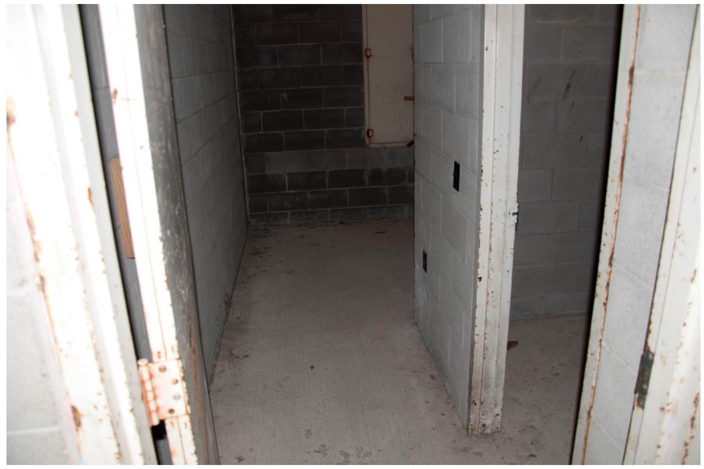
When the data was collected for the experiments in this paper, we tele-operated the robots. We currently are experimenting with autonomous collaborative exploration and mapping; however, this autonomous control was not available when these experiments were carried out. Under tele-operative control, we carefully selected the paths of the robots to perform three classes of collaborative mapping.

In the first class of collaborative mapping experiments, the two robots follow the same path. Both robots start in the second-floor atrium and immediately turn to their right and move through a room and out into a large room and back into the atrium. Here the loop is closed back to where the robots started. The 3D mapping robot proceeds in front of the 2D robot, which follows about 3 meters behind. Obviously, here the two robots are unable to achieve any time efficiency benefit when both are used because they are redundant; however, we can expect that the thoroughness of their mapping should feature additional detail that neither robot could have achieved alone.

In the second class of collaborative mapping experiments, there is very little overlap in robot trajectories. Both robots start in the second-floor atrium and move into the main hallway. The 3D mapping robot turns left; the 2D mapping robot turns right. Several rooms along the hallway are explored by each robot. The robots then proceed back to the start locations. Here we can expect that the time efficiency of the mapping operation is doubled from what a single robot could have accomplished (or the space covered is doubled in the same amount of time), while each robot might miss some detail and cannot leverage the efforts of their counterpart to improve accuracy.

The final class of collaborative mapping experiments is a hybrid of the first two classes. Here, the robots will explore rooms off of the same branch of the hallway. The robots overlap a significant portion of their trajectories, and explore separate alternating sets of rooms along the hallway. Here we expect to see good time efficiency improvement over single robot mapping, and the robots should also improve accuracy as more observations are made with each sensory modality.

(a) An indoor setting at the USMC MOUT site at Camp Lejune being mapped by a iRobot PackBot.



(b) One of the rooms in the *Hotel*

Figure 2. Example scenes from the USMC MOUT training site at Camp Lejune, NC where these experiments were performed.

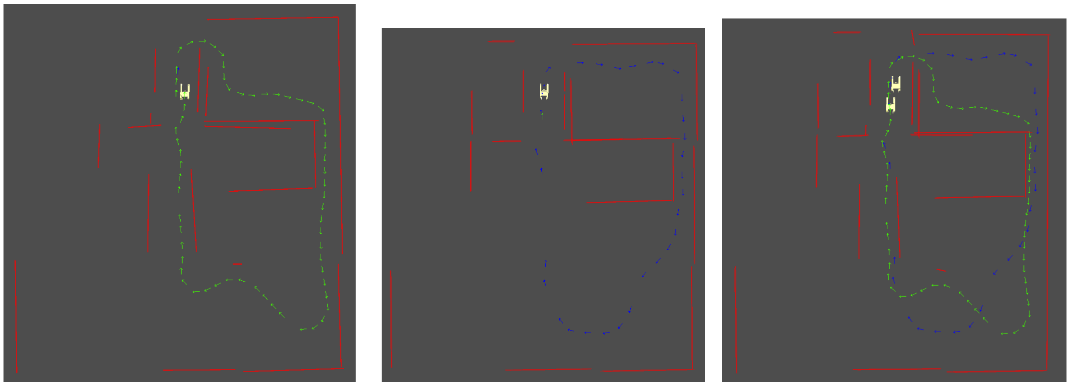
5. RESULTS

We collected five test data sets and present the results from three of them here which are representative of the three test cases detailed in the previous section: fully overlapping, mostly non-overlapping, and partially overlapping.

The results from the fully overlapping test run can be seen in figure 5. The 2D robot follows several meters behind the 3D robot. Both robots perform their respective mapping tasks well; however, some detail is lost in the 3D robot only map due to the low frequency nature of this measurement modality. Since the loop is closed by all of these maps successfully, the use of multiple robots does not significantly impact accuracy; however, the rightmost wall in the combined map is fused into a single wall, whereas it appears as broken segments in both individual maps. This complete wall is an important landmark because it is rigid and more useful for maintaining map correctness.

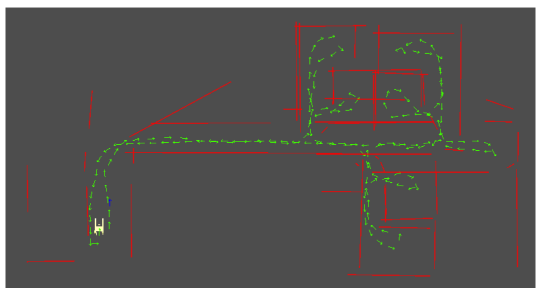
The results from the mostly non-overlapping test run can be seen in figure 5. The 3D robot proceeds down the left branch of the main hallway; the 2D robot proceeds down the right branch. The only overlapping portion of the two maps is in the starting location. Both robots map their respective wings of the *Hotel* and return to the start location. We claim that this experiment indicates that multi-robot mapping with heterogenous sensor modalities can improve time efficiency for the mapping task. Accuracy is not noticeably improved since both individual maps were generated correctly in this case.

The results from the partially overlapping test run can be seen in figure 5. Here, the 2D mapping robot makes some mistakes due to calibration and data association errors and an additional wall is placed in the environment along the main hall. The 3D mapping robot makes no such mistakes. When their map data is fused, the 2D mapping robot is able to map more correctly. Since both robots were operating simultaneously and did not interfere with each other, we contend that this indicates that this system is capable of building a map more efficiently while increasing accuracy.

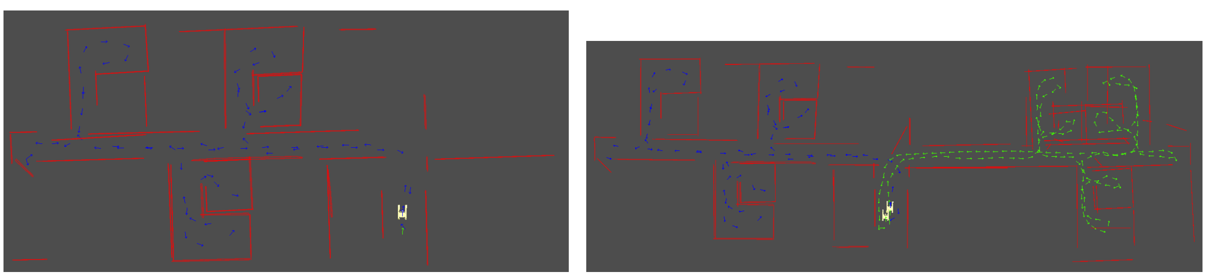


(a) 2D robot only (b) 3D robot only (c) Both 2D and 3D robots

Figure 3. Maps generated from data collected in the first class of test run. Both robots follow the same trajectory through a room adjacent to the starting area in the second floor atrium. The 2D mapping robot follows several meters behind the 3D mapping robot. Here, the 2D only map 3(a) is less accurate but has many more measurements than the 3D map 3(b), due to the fact that 2D data can be processed at frame rate while 3D requires several seconds per frame. The 3D only map is most accurate, but is missing some smaller details from the 2D map. The map built by both robots together 3(c) is nearly as accurate as the 3D map and contains all of the detail of the 2D map.



(a) 2D robot only



(b) 3D robot only (c) Both 2D and 3D robots

Figure 4. Maps generated with data collected in the second class of test run, with minimal overlap where both robots move in opposite directions to explore the entire length of the main hallway. The mapping results from both the 2D only robot 4(a) and the 3D only robot 4(b) perform well and are joined together into a global map 4(c). This effectively demonstrates the time efficiency of multi-robot mapping; the map can be generated in half the time with two robots.

6. CONCLUSIONS AND FUTURE WORK

We are currently preparing experiments with up to ten robots autonomously exploring and mapping in an indoor office environment. Additionally, we are working on higher-level landmark measurements on objects.

7. ACKNOWLEDGMENTS

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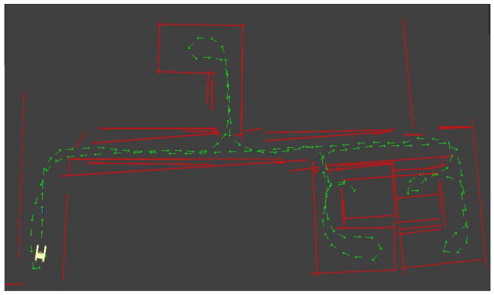
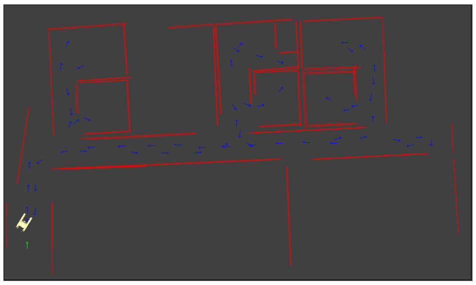
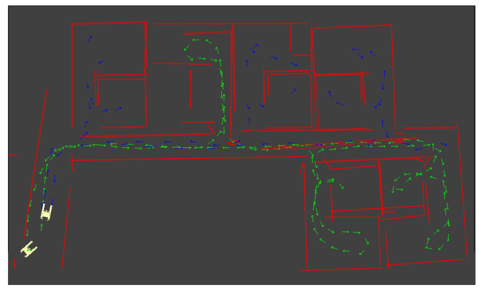


(a) 2D robot only



(b) 3D robot only



(c) Both 2D and 3D robots

Figure 5. Maps generated from the third class of multi-robot mapping, one in which there is partial overlap. The 3D robot performs very well on its portion of the map 5(b), whereas the 2D robot has some difficulty with data association on the main hallway 5(a). This is likely due to calibration errors coupled with data association errors, particularly angled open doors which may be data associated to the nearby wall. When both maps are fused 5(c), these errors are mitigated and the entire map is produced

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