Case Study - Deploying a Mixed Strategy Profile into Pioneer3at Robots for Robust Multi-robot Exploration

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I. Introduction

This report presents a solution for a Multi-agent Exploration [1], [2] problem based on a set of Mixed Strategies heuristically approximated from a Correlated Equilibrium generated through a Probability Density Function over viable outcomes. Furthermore, this study is dedicated to the deployment of a mixed strategy in a real robot simulation using the Robot Operating System (ROS). ROS was used since it is a major platform for robot interaction. It is described as a set of programs that allows communication between a computer, low-level controllers, and robot peripherals. Furthermore, it provides network infrastructure for distributed computing based on publishing and subscribing mechanisms for real-world deployments or realistic simulations, which encompass, noise, uncertainties, and failures. Next, the general deployment method is presented followed by the experimental configuration.

A. Method

To compute mixed strategies during a real exploration procedure it is proposed to deploy a robust SLAM algorithm, with global localization, robust local and global planners, and pose estimates x_t extracted from the fusion of the robot's individual maps. A mixed strategy can be formed when the robots are in the range of communication and can perform map fusion. The map fusion, on the other hand, is done in all individual maps and it produces a new representation that can guide the correlated equilibrium through pose matching. To decide which zones the robots can explore, or the PDF (Probability Density Function) Υ, both robots use a hint given by the global localization performed in the map generated from the fusion process.

B. Experimental Configuration

For the purpose of the evaluation conducted on the simulator, assume the following.

Assumption 1. *The robots have an already formed mixed strategy profile. This assumption is done since the main objective is to verify if all the infrastructure will behave well guided by a randomized action selection policy over a mixed strategy distribution.*

Assumption 2. *For this evaluation, all the robots comply with the definitions of all mobile robotics sub-problems, where all uncertainties, errors, and failures are incorporated into the simulation. Consequently, the subsequent proposals for environment construction are the hardest possible ones for any mobile robot-related task.*

Considering Assumption 1, one mixed strategy will be deployed on both robots simultaneously. The main objective of this evaluation is to check if the robots will be able to explore the suggested zones with the current stack in a robust manner. In the rest of this section is presented the infrastructure developed to validate the mixed strategies deployment.

C. Robots Deployment

To evaluate the deployment, a multi-agent SLAM simulation was developed using ROS (Robot Operating System) Gazebo simulator. Two Pioneer3AT robots were assembled for the Multi-agent SLAM problem and equipped with a lidar sensor. The robot is depicted in Fig. 1 and is described as a nonholonomic mobile robot.

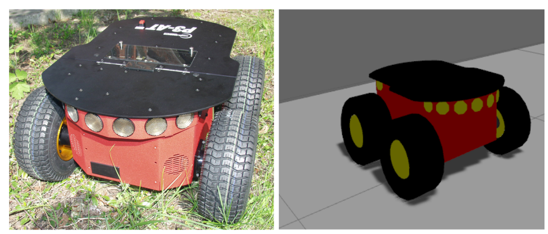

Fig. 1: Pioneer 3AT robot (left) and its simulation in Gazebo/ROS (right).

D. Gazebo Environment

On the other hand, the Gazebo simulator allows the simulation of any arbitrary number of robots which a great variety of sensors. For the purpose of this research, as depicted in Fig 2 one environment was developed for evaluation. The environment is planar and it is composed of several static boxes that are able to reflect all lidar measurements consistently. For the purpose of evaluation, it was also configured as a mirror in the x-axis since it adds a source of uncertainty to the problem being approached.

E. Robust SLAM

To achieve robust SLAM, a ROS package called Gmapping was used. This package is able to generate an Occupancy Grid at specified time steps. Furthermore, it provides a Monte Carlo Localization method and also incorporates a Pose Graph correction mechanism. A picture of an Occupancy Grid being generated from one robot presented in Fig 2 is shown in Fig 3. It is important to note that the occupancy grid is not generated at all time steps, in reality, it is updated much less often due to lack of processing power on real robots or due to energy consumption restrictions.

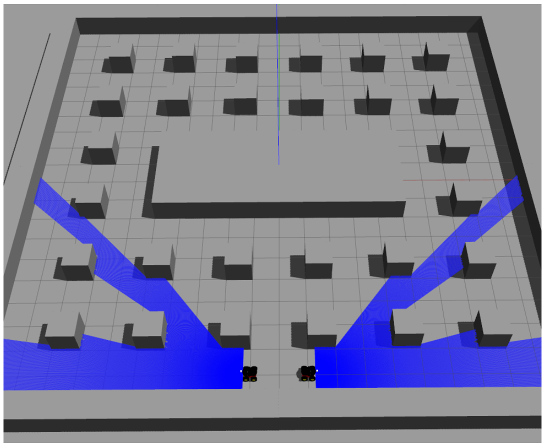

Fig. 2: Environment simulation with two Pioneer robots created using the Gazebo simulator for SLAM evaluations. The blue regions are lidar beans used to sense the environment for each robot.

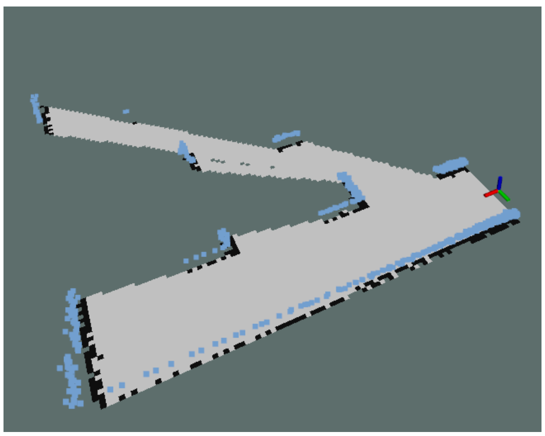

Fig. 3: Occupancy Grid generated for one robot in the configuration shown by Fig. 2. Each blue point represents a lidar bean intensity and the reference frame on the left of the picture is the robot reference frame in relation to the Occupancy Grid and the robot's odometry.

F. Robust Navigation Stack

For the purpose of this research, it was to develop a full navigation stack. It consists of global and local planners that used M_T to generate and execute fail-safe navigation plans. The local planner encompasses a Potential Field based navigation which enhanced a Configuration Space obtained from M_t. On the other hand, the global planner uses the Configuration Space to create safe global plans that allow a robot to reach a frontier, follow a strategy, or go to any location in a reachable area. The representations generated by both planners are illustrated in Fig 4.

G. Frontier Generation and Selection Mechanism

As depicted in Fig 5. One frontier filtering and selection mechanism was developed for this research. It is based on the average frontier positions to generate the set F. However, since several frontiers can be generated, F is further filtered

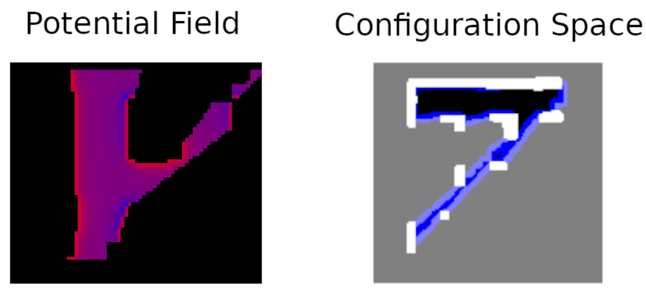

Fig. 4: (Left) is the potential field heat map generated by the created local planner with enhanced information from M. (Right) is the Configuration Space generated from M_T. It is interesting to note that the Configuration Space has blue pixels that represent frontiers.

with a k-nearest neighbor-like approach. To select a frontier, it is used the Euclidean distance to all reachable frontiers, where a frontier is reachable if a path from the robot's current pose x_t to a frontier $f_i \in F$ can be done in time t.

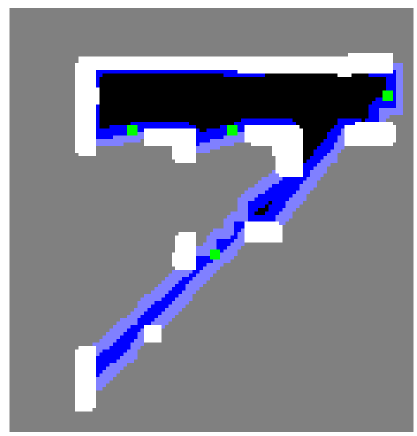

Fig. 5: Detected frontiers in the Configuration Space enhanced representation as green dots.

H. Merged Map Pose Estimation

To achieve pose estimation when both robots can communicate, it is proposed to use a map merge module that can be used for global localization. In this research, the pose of each robot is set into a Monte Carlo Localization system where the input of the system is a merged map. The process of pose estimation for each robot can be seen in Fig 6,
where each vector inside the Occupancy Grid is a particle that collects information about the environment. The particles will be filtered until a minimum set of them can be used to approximate the robot's current pose x_t. The pose approximation should be done in an external representation since according to the Multi-agent SLAM problem, each robot has its own map.

I. Qualitative Results

Three experiments were conducted using a setup of two robots. The starting orientation of both robots was set to π

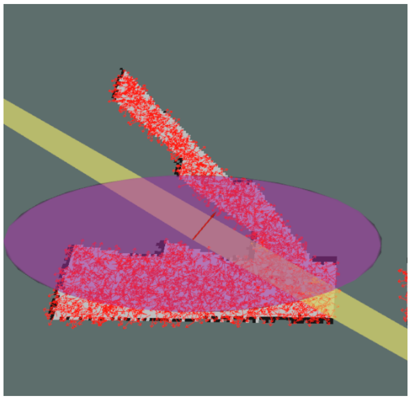

Fig. 6: Monte Carlo Localization performed in the Fusion of all the Robots Occupancy Grids.

for both experiments. The robot exposure time was around 5 minutes each. A clearing behavior was deployed in both robots before starting the SLAM algorithm to remove any meaningful noise and bias from the initial frontier set. During the first experiment the mixed strategies $\Pi_1 = \{0.5, 0.5\}$ and $\Pi_2 = \{0.5, 0.5\}$ were used. In the second experiment, the strategies $\Pi_1 = \{0.9, 0.1\}$ and $\Pi_2 = \{0.1, 0.9\}$ was set on both robots. The third experiment used the same strategies as experiment two, however with an exposure time of 9 minutes. A video of each experiment is available[1,2,3].

As shown in Fig 7, During the execution of the first experiment with strategies (0.5,0.5), both robots explored very similar zones and frontiers during the first minutes. This behavior seems to happen due to the fact that the robots select the nearest frontier in the zone being visited. Since they have their own representation of the map, then it is likely that they will explore the same places without any incentive to do differently. In addition, the obtained fusion of the randomized strategy was poor since there were fewer features for pose matching due to the lack of efficient exploration. On the other hand, the map obtained with strategies (0.9,0.1) and (0.1,0.9) portrayed better coverage with a higher information gain. Another benefit of the equilibrium strategy is the fact that with more features, the map fusion also performed better. Consequently, besides a higher information gain, the proposal was also able to achieve better global maps.

As shown in Fig 8, during the third experiment with equilibrium and a total exposure time of 9 minutes the robots were able to explore a broader area. The quality of the map being created by the fusion module stayed similar to the 5 minute exposure experiment. Despite, being able to create a meaningful representation with the deployed equilibrium, deformations appeared near the end of the exposure time. That stems from the fact that the pose graph optimization was not able to fully close the visited zones to perform correction on all poses and adjust the representation. It was also observed that the robots were almost able to cover

[1] no equilibrium: https://youtu.be/0xqYxiQCdbA
[2] equilibrium short: https://youtu.be/i3V1tRCEIRQ
[3] equilibrium long: https://youtu.be/sF5uBQC0rJ4

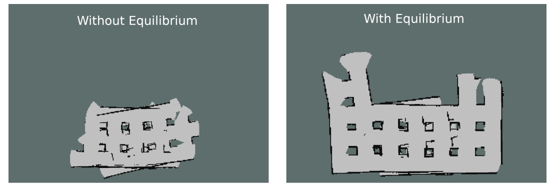

Fig. 7: Quality of the generate map fusion obtained from the two robots. (Left) shows the map generated from a randomized (0.5,0.5) strategy, whereas (Right) shows the mixed strategies (0.9,0.1) and (0.1,0.9).

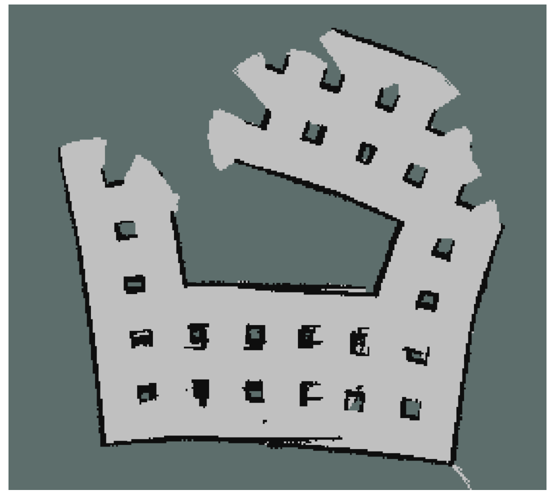

Fig. 8: Quality of the generate map fusion obtained from the two robots with an equilibrium strategy for a 9 minutes exposure time.

all of the environment and achieve the maximum possible information gain for this area.

J. Conclusion

This case study presented the deployment of a mixed strategy profile generated through the optimization of the problem instance described in Section **??** in a real robot simulation using the Robot Operating System (ROS). For the purpose of this evaluation, a simulation stack was built and integrated with a SLAM method. Furthermore, a full robust planning and navigation stack was developed. To evaluate the feasibility of mixed strategies in real robots, two mixed strategies were evaluated, where the former is a 50% chance of exploring each zone and the second represents an equilibrium state.

Several problems arose from the deployment, which substantially difficulted the evaluation. For instance, if the navigation stack is not robust or agile enough, then the robots would behave in an unpredictable way that may prevent the accomplishment of critical tasks. Tunning and calibrating all the solutions and robots were also a big barrier that took many hours of development. In general, it was observed that with an equilibrium state strategy both robots were able to achieve significantly better results even with a single instance of the planning phase. In future work, the method will be further refined to be deployed on real robots as also other forms of equilibrium.

II. General Discussion

This report presented a method for computing correlated equilibrium to solve the Multi-agent SLAM problem. Two case studies were provided where the first regards the generation of mixed strategies for two-player games whereas the second regards the deployment of a realistic robot simulation using the Robot Operating System (ROS). Videos were provided for each experiment. As it seems, the robots behaved well during the deployment. The mixed strategy policy was trivial to be integrated with the robot's controllers through ROS since it was basically an action selection mechanism. Several tunings were performed during the development to ensure the robustness of the solution. It was interesting to see that the fusion module was able to obtain better results when the robots act in an equilibrium state due to the aggregation of more meaningful features to all individual maps. Furthermore, the global localization is also portrayed well, however, due to its probabilistic nature, it demanded the most from the hardware being used during the simulations. As a future improvement, a fusion module will be developed from scratch to explore better performance options and enhance the general stability of the stack. Real robots will be also used in future work.

References

[1] M. U. M. Bhutta, M. Kuse, R. Fan, Y. Liu, and M. Liu, "Loop-box: Multiagent direct slam triggered by single loop closure for large-scale mapping," *IEEE Transactions on Cybernetics*, vol. 52, no. 6, pp. 5088–5097, 2022.

[2] M. Karrer, P. Schmuck, and M. Chli, "Cvi-slam—collaborative visual-inertial slam," *IEEE Robotics and Automation Letters*, vol. 3, no. 4, pp. 2762–2769, 2018.