Path planning for Indoor Partially Unknown Environment Exploration and Mapping

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Abstract

This paper addresses a problem of partially unknown environment exploration and mapping. The proposed path planning algorithm provides global and local goals search taking into account limited sensing range and visibility constraints that arise from obstacles. Looking for local goals near a global path maximizes robot utility and helps avoiding returns to regions with low potential gain. All stages were tested in ROS/Gazebo simulations and results were compared with a naive algorithm that was proposed earlier.

Keywords: robotics, algorithm, modelling, mapping, ROS/Gazebo, indoor exploration, path planning

1. Introduction

Unknown environment automatic mapping is a fundamental task for all kinds of mobile robots. It is essential for every autonomous robotic system to perform mapping as precise as possible to make feasible further effective usage of a generated map in navigation procedures. A result of such mapping that is performed by one robot could be applied then for localization and path planning by other robots. However, previously these maps are often incomplete since every robot has its own operational limits (e.g., sensory limitations, time and power limitations) and robots that reuse such imperfect map are forced to operate in partially unknown environment, which constrains robot capabilities and may significantly decrease its effectiveness. Thus, it is important to have a good strategy to make possible efficient map update when its part is still undiscovered.

The problem of partially unknown or uncertain environment exploration[1] is discussed in research dedicated to single-robot exploration based on best exploring position search[2]; in terms of multi-robot exploration[3] using greedy tactics[4] or sophisticated algorithms designed specially for indoor environment exploration[5]. However, these approaches are tested in simulations with synthetic input maps or used high-quality maps without artifacts that are impossible to avoid during a mapping process (e.g., impulse noises, incorrect sensory processing results, sensory limitations of real robotic system, etc.). In this paper, we propose a path planning method for an indoor partially known environment exploration and mapping. It was tested in simulations that were created using real sensory data. The algorithm performance was compared with previously proposed methods.

2. Partially unknown environments exploration challenges

A popular and effective way of mapping is using laser range finder (LRF) devices, which provide quite precise data about local landscape around a robot. The obtained data is represented in a form of height map images. Each pixel of the height map stores data about corresponding region of the environment. Pixels can have three possible values: black (usually interpreted as occupied region), white (obstacle-free) or gray (no occupancy data)[6].

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Fig. 1. A region of the original map with odometry caused artifact (obstacle-free space behind the wall).

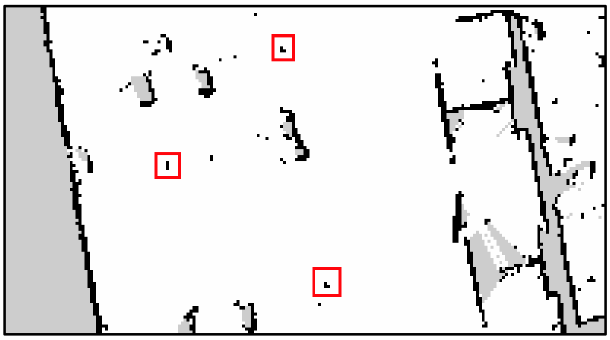

Fig. 2. A region of the original map with noisy regions (several examples of noise are encapsulated within red rectangles).

However, mapping algorithms during mapping procedures heavily rely on odometry data, which decrease map precision and cause various artifacts in the map (Fig. 1). Scanning device imperfection leads to eventual noises in sensory data (Fig. 2) or/and incomplete data (Fig. 3). Another problem is that a scanning LRF is constrained by obstacles (e.g. walls, doors, etc.) and this should be taken into account during path planning to unknown regions of the map. In addition, it is very important to use predictable forms and assumptions on indoor environments, e.g., they are structured and walls should surround every location (room, corridor, etc.).

3. Proposed approach

This section describes our algorithm, which is partially based on our previous research work. First, noise reduction within a map is performed using our modified median filter built-in map preparation tool[7].

Fig. 3. A region of the original map with highlighted space between distinct laser rays.

Then, the robot takes the filtered map as an input and, assuming its initial position within the map, one of many localization techniques could be applied to determine robot location. For localization we had selected Adaptive Monte Carlo Localization[8] (AMCL) method. Next, the robot preforms as follows:

1. Reachable information gain regions are marked.
2. A global goal is selected with a greedy approach based on information gain property of regions.
3. Local goals are selected taking into account LRF limitations and a path toward the global goal.
4. The robot sequentially travels through the local goals toward the global goal.
5. Return to step No.1 until reachable information gain regions are available within the map.

3.1. *Reachable information gain regions marking*

Reachable information gain regions are unknown map regions, which (possibly) could be explored by the robot (shown on Fig. 4). The definition of such regions is recursive:

- Every unknown cell of the map, which is adjacent to an obstacle-free cell, is included in reachable information gain region.
- Every unknown cell, which is adjacent to another reachable information gain cell is also included in reachable information gain region.
- Recursion depth is set in advance or controlled manually, and depends on map resolution. Using approximate wall thickness as a base depth value produces good results in practice.

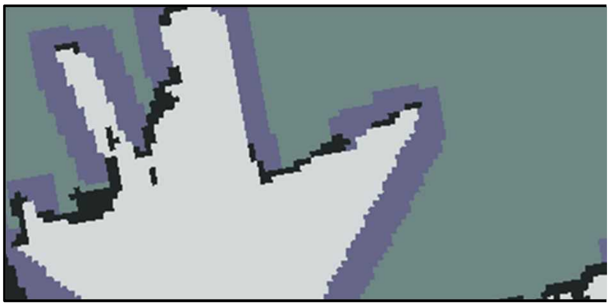

Fig. 4. A region of the original map with highlighted (in purple color) reachable information gain regions.

This method takes into account the structured pattern of an indoor environment to properly estimate the utility of each position on the map: the farther the robot moves from frontier cells, the more chances it has to find a particular obstacle, which limits information gain.

Fig. 5. A region of the original map. A preferred observing position by naive approach (left) and by the proposed approach (right). Circles and arrows show sensory radius of the robot.

3.2. *Global goal selection*

A global goal is computed with the following strategy: the global goal is an obstacle-free cell with maximum count of reachable information gain cells in the LRF-sensing radius. This is a greedy approach that was used in previous works[4]. Previous methods considered only frontier points as candidates for the global goal. Our approach uses a different strategy: the global goal could be any obstacle-free point within the map. This makes the global goal selection more optimal in cases when several information gain regions could be observed from a single point. Figure 6 illustrates advantages of this approach.

3.3. *Local goals selection*

Local goals are reachable information gain regions that are located within a predefined radius from a global path. Local goals allows the robot to explore small reachable regions while following the global path toward the global goal. Such algorithm prevents the robot from returning to the previously explored locations, thus providing a more efficient time and energy consumption. Figure 6 demonstrates an example of different behavior of the greedy approach (top image) and our algorithm (bottom image). The robot starts at red X-mark, but while with the greedy approach it begins from exploring a large unknown area (region 1) and then returns back to the small region (region 2), the exploring sequence of our algorithm is the opposite is, which saves time for passing the same region (region 1) twice.

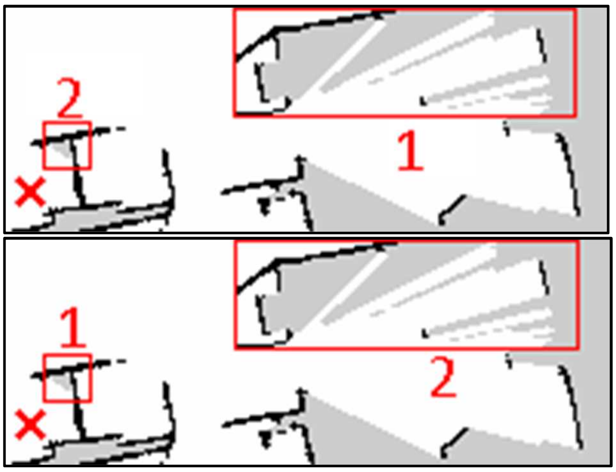

Fig. 6. The robot starts at red X-mark. Greedy approach exploring sequence (top) and our approach sequence (bottom).

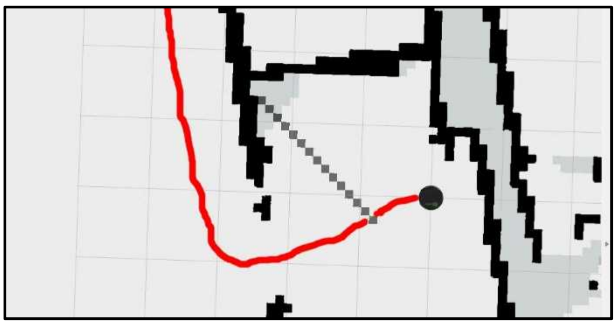

Fig. 7. Red spline represents the global path. The line starting on the global path is the LRF ray towards the local goal.

It is important to emphasize that local goals must be within the LRF line of sight, i.e., there should be no obstacles on the way of the LRF ray. This condition is verified by simulating LRF rays from a robot pose on the global path toward a region of interest: when the ray does not intersect any obstacle, it is possible to observe the region of interest from the pose. Bresenham's line algorithm[9] is used to simulate such rays on occupancy grid (illustrated in Fig. 7). This algorithm allows to raster straight LRF rays and visualize them on occupancy grid.

4. Comparison with the greedy approach

To prove the efficiency of our approach, a comparison with the greedy method[3] was performed. Both algorithms were simulated in ROS Gazebo environment and for the simulations we used a system with i7-4700HQ CPU, NVIDIA GeForce 770M GPU, and 24GB RAM.

The results are summarized in Table 1. Two approaches were tested for a simulated exploration task that was run for 3, 5, 15 and 20 minutes within the same map. The results demonstrated that the naive algorithm performs better and collects more data if the exploration time is limited; in such case it is more efficient to skip exploration of low information gains and to proceed directly toward high information gain regions exploration. However, when only low information gain regions remain, the naive method produces long distance paths with multiple returns. This way, as exploration time grows, our approach becomes more and more efficient.

Table 1. Map exploration percentage depending on the method and exploration time.

Approach	Simulation time in min.			
	3	5	15	20
Naive method	73%	77%	85%	88%
Proposed method	72%	73%	83%	95%

5. Conclusions and future work

Path planning for partially known environments is an important task in robotics. The results of previous explorations could be reused, and an efficient exploration algorithm saves time and energy consumption of a robot. In this paper we proposed an exploration algorithm that shows better performance than a naive greedy approach for long-time exploration of indoor environments. As a part of future work, we plan to test the proposed algorithm within various environment in ROS Gazebo simulation[10]. The algorithm will be integrated into the control system of a real robot “Servosila Engineer” and tested in real-world exploration scenarios.

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