Naïve but Efficient – Using Greedy Strategies for Exploration, Inspection and Search

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Abstract: For operating in initially unknown and dynamic environments, autonomous mobile robots need abilities to explore their workspace and construct an environment model as well as to perform searches in that model and re-explore the environment to keep the model up-to-date. This paper focuses on the efficiency of using simple *frontier-based* greedy strategies for exploration and search that provide an autonomous mobile robot with these abilities.

1 Introduction

Autonomous mobile robots need internal representations or *maps* of their environment in order to act in a goal-directed manner, plan actions and navigate effectively. Exploring and mapping are fundamental prerequisites when operating in initially unknown environments (when a map is not available). In addition, when the environment is dynamic, i.e., changes over time, robots need to actively re-explore and inspect their workspace in order to update the map in regions where changes have taken place.

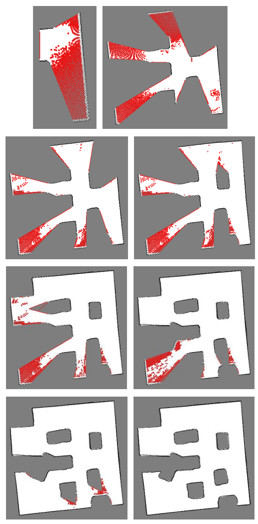

Figure 1: From left to right and top to bottom: frontier cells in the progress of exploration and mapping.

Exploration is related to well-known problems from the field of computational geometry, namely art gallery, illumination and shortest watchmen problems. Since the original art gallery problem is NP-complete [Agg84] and requires complete knowledge about the environment, exploring an unknown environment is usually performed in a reactive or greedy fashion. Instead of planning all locations where the robot needs to acquire sensory information, a greedy exploration strategy solely plans one step ahead by determining a next best view (NBV) that provides new information about the environment while minimizing some objective function. Over the last decades different exploration strategies have been proposed [AG05, BMSS05, SR05, SB03]. Comparative evaluations of different strategies have been presented in [LR97] and [Ami08]. This paper focuses on the efficiency of frontier-based exploration strategies [Yam97] and presents two improvements together with achieved results (Chap. 2) as well as how to apply them in inspection and search tasks (Chap. 3).

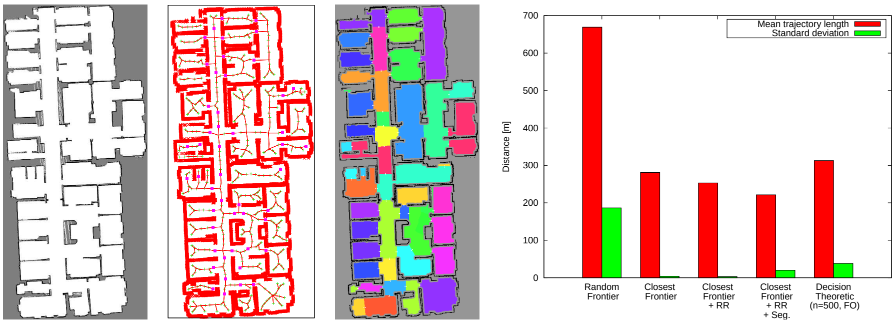

Figure 2: Map segmentation for roomwise exploration. Shown are (from left to right): the (final) input map, the Voronoi diagram with the critical points, the refined segmentation, and the measured path lengths for the different strategies (*RR.* = repetitive re-rechecking, *Seg.* = map segmentation).

2 Frontier-based Exploration and Extensions

Frontier-based exploration strategies usually operate on grid maps [ME85] that distinguish between known free regions (Fig. 1: white) and unknown regions (Fig. 1: gray). Frontiers (Fig. 1: red/dark gray) are transitions between cells known to be free and unknown regions. Always selecting the frontier being closest to the robot as the NBV, yields a reasonably short total path length while being computationally inexpensive as shown by [KTH01]. However, if the closest frontier does not lie within the same room, a room might need to be explored twice. To account for that, we segment the so far built map into individual rooms and prefer those frontiers that lie in the same room thereby exploring the environment room-wise. Referring to Fig. 2, we 1) construct the Voronoi diagram for the free space in the map, 2) determine *critical points* and 3) split the map at the critical points [Thr98, WSB08]. We define critical points to be local minima with respect to the distances to the closest Voronoi site, nodes of degree 2, and to be itself adjacent to a junction node or adjacent to another node that is adjacent to a junction node since [Thr98] yields too many segments and [WSB08] is too restrictive in the vicinity of doors.

In order to further shorten the robot's trajectory we repetitively re-check, during navigation, whether the currently approached frontier is still a frontier and start to approach the next NBV if not. As can be seen in Fig. 2, exploring closest frontiers yields a shorter trajectory than the decision-theoretic strategy from [GBL02] and both extensions, *map segmentation* and *repetitive re-checking* further improve the achievable results.

3 Using Greedy Exploration Strategies for Inspection and Search

In contrast to exploration, inspection and searches are carried out when the robot has already fully explored the environment and constructed a complete map. Inspection problems can be solved by 1) solving the corresponding art gallery problem to determine a minimum set of vehicle poses and 2) solving a Traveling Salesman problem to determine the shortest route through the complete set of poses. Although this procedure is likely to

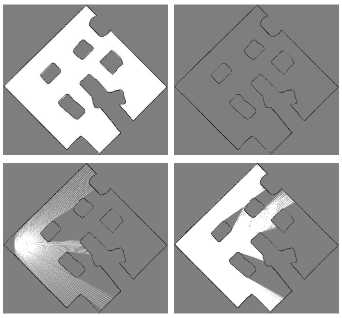

Figure 3: Using frontier-based exploration for inspection. From left to right: fully explored environment, cleared free space, and the map after the first update and after 50% inspection time.

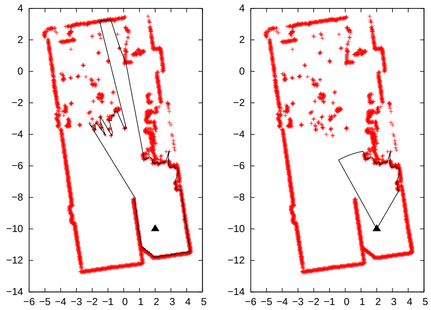

Figure 4: Incorporating field and range of view of the actively used sensor in inspection and search tasks. The map is updated only using the information in the resulting area.

find optimal solutions, it is computationally expensive. Another possibility being computationally efficient is to simply re-explore the environment using the aforementioned frontier-based exploration strategy, though it might not yield optimal solutions. In order to apply it, we simply reset the known free regions in a local copy of the map as being unknown and start exploring and updating the local copy (Fig. 3).

For search tasks, for example when searching for an object using a camera, the limited field of view (and range of vision) can be incorporated by projecting the respective volumes into the map plane and only updating the covered regions (Fig. 4).

4 Results

An example trajectory, recorded in a simulated environment, of a robot consecutively exploring and inspecting is shown in Fig. 5. With 66m and 54m both parts of the robot's trajectory are reasonably short. An example of exploring a real-world environment is given in Fig. 6.

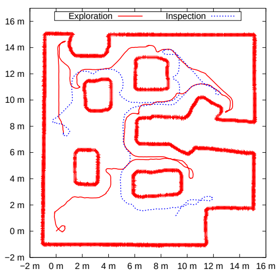

Figure 5: Consecutive exploration and inspection in a simulated environment.

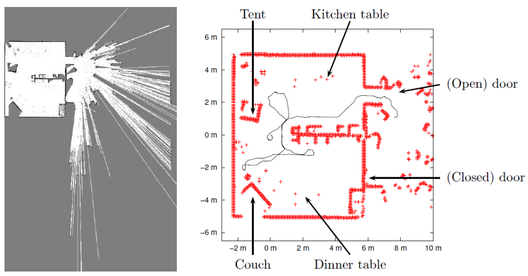

Figure 6: Exploring a real-world environment (the RoboCup@Home arena at the GermanOpen 2009). Left: final map, right: trajectory of the robot.

For mapping we use a matching algorithm that is described, in detail, in [HB10]. Videos of a robot using the algorithms presented herein are available at
`http://www.b-it-bots.de/media`.
The robot won the RoboCup@Home World Championship 2009.

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