An improved Frontier-Based Approach for Autonomous Exploration

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***Abstract*—A new approach for autonomous exploration in an unknown scenario based on the concept of frontiers is proposed in this paper. Exploration frontiers introduced by [4], are the regions on the boundary between open space and unexplored space. A mobile robot is able to construct its map by adding new space and moving to unvisited frontiers until the entire environment has been explored. However, the original frontier strategy, suffering from local minima, only considers distance and size of unknown spaces, resulting in low exploration efficiency in complex environments. By making use of the robot heading information using wheel odometry and coarse graph representation of the environment, the modified exploration method is able to balance the mapping coverage and time expenditure to a greater extent. The proposed method is experimentally verified on a mobile platform, exploring a real-world office environment cluttered with a variety of obstacles.**

I. Introduction

Normal robotic navigation requires a known or predefined map before navigation goals can be determined and executed by the robot planner and actuator. Off-line mapping processes carried out by human operators (remote control) are commonly adopted by different types of autonomous systems, such as car-like Autonomous Vehicle (AV) [1], Unmanned Aerial Vehicle (UAV) [2] and Autonomous Underwater Vehicle (AUV) [3]. As the robotics industry grows rapidly, the ability to investigate and operate independently in an unknown environment becomes essential for an advanced robot to be considered fully autonomous.

Self-exploration is one of the key milestones in developing an autonomous robot which is free of human intervention. According to [4], robot self-exploration can be defined as the action of autonomously moving through an unknown environment while building a map that can be used for subsequent navigation. An efficient exploration strategy can be considered as the one that maximizes the search coverage with minimal time and motion expenditure. Hence, the central technique lies in how to generate a series of safe motion commands that minimize exploration time while maximizing the expected utility of robot motions.

In literature, works on robot exploration in unknown environments have been reported and can be typically divided into two categories: frontier-driven strategies [4], [5], [6], [7] and information theoretic strategies [13], [14], [15], [17].

The key idea in the frontier-driven strategies is to determine the next desired positions for the robot based on frontiers, i.e., boundaries between the known and unknown cells in an occupancy grid map. In the pioneer work of [4], frontier edges are required to be segmented from a dynamical occupancy grid map in order to determine potential targets. The selected target will be sent to the robot planner as the temporary destination point. In [5] Gonzalez-Banos and Latombe propose an algorithm that searches for a series of target points in the grid map by revealing the quality of the candidate points around a frontier according to some criteria. For example, a view with the largest area is chosen as a candidate. However, during the autonomous exploration phase the map will be dynamically updated and become larger and larger, requiring more computational resources [6], [7]. Senarathne et al. develop an efficient approach to segment frontiers by only detecting intermediate changes to cells in the current exploration map and only the updated grid cells are considered for the frontier segmentation [7].

Based on the frontier-based mechanism, some researchers also propose non-myopic exploration by applying randomized search techniques. The Sensor-based Random Tree method (SRT) [8], [9], which can be considered as a goal-oriented exploration strategy, biases the randomized generation of configurations towards unexplored areas. Recently, a new exploration strategy leveraging on Rapidly-exploring Random Trees (RRT) unitizes the randomized tree expansion to detect and prioritize the frontiers [10]. Although, RRT techniques ensure complete search overage and can be extended to 3D space [11], they might lower the exploration efficiency by sending the visited position.

The purpose of information theoretic solutions is to minimize the uncertainties in the belief space about the unknown environments as the uncertainties associated with the map and robot pose grow with time. One approach based on information gain makes use of particle filters to represent the posterior about maps [13]. It employs a decision-theoretic framework to evaluate the expected utility of robot potential actions, under which the uncertainties of the map and the pose are jointly considered. Mutual information (MI) is introduced and employed as a measure of uncertainty for exploration in an unexplored region by [14], [16], where actions with maximal MI rewards would bias toward unexplored space for exploration. Subsequently, [15] combines entropies for an exploration strategy that can jointly reduce mapping and localization uncertainties. Recently, a safe exploration strategy for autonomous map building is presented in [17], in which a Bayesian optimization (BO) technique is used to minimize the number of expensive function evaluations and thus it is likely to yield optimal results and satisfy the constraints with high confidence. This method searches for optimal continuous paths that inherently satisfy motion and safety constraints. Although various works in information theoretic driven exploration strategy have been proposed, it still remains an open problem in the robotic community.

Due to high exploration efficiency and implementation simplicity when collaborating with the state-of-the-art SLAM techniques [18], [19], an autonomous exploration approach based on the idea of frontier-base exploration is presented in this paper. To map the unknown environment, the robot is assigned desirable frontiers such that it simultaneously explores and maps multiple unexplored areas. The problem then shifts to an optimization process of frontier assignment, namely, the best frontier associated position information will be treated as the temporary destination to move the robot. Bad frontier assignment may cause the problems of 1) circling in certain regions around local minima; 2) incomplete environment coverage; 3) revisiting explored areas, all of which influence the exploration efficiency.

Therefore, to solve the above-mentioned problems, two main contributions of this paper are summarized as: 1) designing a new utility function for optimal frontier assignment by considering the robot travelling distance, the frontier size and the turning cost simultaneously; 2) constructing a topological graph to keep record of visited key nodes and unknown states for systematic backtracking and map completion.

The rest of the paper is organized as follows. Necessary preliminary terminology used in the proposed exploration algorithm is provided in Section II. Section III presents the improved frontier exploration strategy. Experimental setup and results are shown in Section IV to validate the proposed method. Finally, in Section V, conclusion and relevant discussion are given.

II. Preliminary Terminology

In this section, we provide the definition of functions and symbols related to the proposed algorithm.

Search Space $\mathbb{R}^2$: The set of the whole search space. This set in $2D$ consists of free, occupied, and unknown space, i.e, $\mathbb{R} = \mathbb{R}_f \cup \mathbb{R}_o \cup \mathbb{R}_u$

Occupancy Grid: The representation of map that divides the space into grid cells. Each cell possesses an occupancy value of 1, 0 or -1, indicating whether the particular region is occupied by obstacles, free for thr robot to pass through, or unknown (unexplored in this case), respectively.

Free Space $\mathbb{R}_f \subseteq \mathbb{R}$: A subset containing all free space cells.

Occupied Space $\mathbb{R}_o \subseteq \mathbb{R}$: A subset that includes the occupied cells detected by perception components, such as a laser or depth camera.

Unknown Space $\mathbb{R}_u \subseteq \mathbb{R}$: The remaining cells in the search space, which have not been explored (sensed).

Topological Node N: A set of nodes $N = \{\nu_0, ..., \nu_k\}$ denoting $k+1$ different locations that have been explored and added to the topological graph G. Each node $\nu_i = [x_i \ y_i] \in \mathbb{R}^2$, indexed by its coordinates, is connected to one another by corresponding edges η_i.

Edge E: An edge $\eta_i \in E$, linking two nodes, is stored in terms of the spatial coordinated of the two endpoints.

Topological Graph G: A tree-structured map constructed by edges and nodes, i.e. $G = (N, E)$.

Frontiers $\mathcal{F}$: A set $\mathcal{F} = \{f_0, ..., f_j\}$ that stores all currently detected frontier nodes. The selected frontier $f^* \in \mathcal{F}$ will be sent to the robot as the next navigation goal.

Utility Cost C: This cost function is defined to determine the most desirable frontier to be explored next within in the set of $\mathcal{F}$.

A graphic example showing topological graph and detected frontiers at a particular time instance is illustrated in Fig. 1. As can be observed, the Graph G is constructed by Nodes N and corresponding Edges E. The Frontiers $\mathcal{F}^t$ highlighted in green numbers are detected when the robot reaches the current position marked as the red footprint at time t. The robot starts from the point indicated by a black circle. The yellow number "0" indicates the optimal frontier point f^* to be assigned among the 11 candidates. To be noted, the topological nodes listed in the graph can be explored via sensor observation or physically visited by the robot. Those visited nodes will be memorized as "visited" in the robots memory. The creation of topological map are presented in Section III.B.

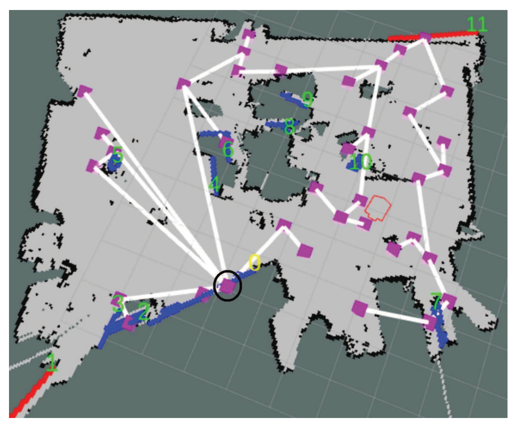


Fig. 1. An example of frontiers detection and topological map generation.

III. Methodology

A. Heading informed Frontier Exploration

The main idea behind frontier-based exploration is to obtain as much as new information by moving the robot to the boundaries between open space ($\mathbb{R}_f$) and unknown space ($\mathbb{R}_u$). Within the occupancy grid any unknown cells adjacent to free cells are grouped together into regions. The centroid of each region (above a certain minimum size) can be considered as a frontier node f_j. The frontier list $\mathcal{F}_t$ contains all the valid frontier nodes at time t.

In the existing methods [4], [10], [20], once $\mathcal{F}_t$ has been determined, the robot tries to select the nearest, accessible and unvisited frontier with largest grid size as the goal. Hence, the desirable frontier f^* is selected by minimizing the following utility function:

$$C(f_j) = (\omega_d \times f_j^D - \omega_s \times f_j^S)$$
$$f^* = Arg \min_{f_j \in \mathcal{F}} \Big(C(f_j) \Big) \tag{1}$$

where f_j^D, f_j^S are the spatial distance between robot and frontier node, the grid size of frontier area, respectively. ω_d, ω_s are weighting parameters associated with the two terms. To be noted, the utility function is minimized when distance is small and frontier size is large. Then the robot should be able to take the shortest obstacle free path from its current cell to the cell containing the map coordinate.

It has been reported in [4] that by constantly moving to new frontiers, the robot is able to extend its map into new space until the entire environment has been explored. However the current procedure of desirable frontier selection can be inefficient when the robot is moving around office environment with narrow corridors and secluded cubicles. In fact, it is highly possible for the robot to be trapped into the cubicle areas and keep revisiting some places that are already explored. To solve this problem, the exploration strategy is refined as that exploring as far as possible in the current direction before turning or backtracking. Based on the new strategy, a modified utility function $\widetilde{C}(f_j)$ can be written as:

$$\widetilde{C}(f_j) = (\omega_d \times \|f_j^D\| - \omega_s \times \|f_j^S\| + \omega_r \times \|f_j^R\|) \tag{2}$$

where f_j^D, f_j^S are defined the same as Eq. (1). f_j^R denotes the steering angle to face each frontier node. The three cost components are also normalized into the range of $[0, 1]$ to balance the overall utility cost. The normalized individuals $\|f_j^D\|$, $\|f_j^S\|$, $\|f_j^R\|$ are computed as below:

$$\|f_j^D\| = \frac{f_j^D - f_{min}^D}{f_{max}^D - f_{min}^D}$$
$$\|f_j^S\| = \frac{f_j^S - f_{min}^S}{f_{max}^S - f_{min}^S}, \ \|f_j^R\| = \frac{f_j^R - f_{min}^R}{f_{max}^R - f_{min}^R} \tag{3}$$

Similarly $\omega_d, \omega_s, \omega_r$ are user defined weightings for the distance, size and steering angle. The desirable frontier node f_t^* at time t, thus, can be determined when $\widetilde{C}(f_j)$ is minimized as:

$$f_t^* = Arg \min_{f_j \in \mathcal{F}} \Big(\widetilde{C}(f_j) \Big) \tag{4}$$

Considering a 2D navigation scenario, the coordinates of frontier node $f_t^*(x, y, \theta)$ will be assigned to the robot to explore new space sequentially. Leveraging on the techniques of SLAM (gmapping) and autonomous navigation (ros-navigation-package), the robot is able to map the unknown environment while taking obstacle free path from one desirable frontier node to the next one. The self exploration process is illustrated by Fig. 3. In addition, the mapping performance with robot trajectory is compared to the case using previous utility function as shown in Fig. 4.

B. Graph-based Topological Exploration

The purpose of creating a topological graph is to provide a memory of what has been seen previously so that the robot may quickly search the graph to find a node that it may backtrack to. Each node $\nu_i \in N$ in the graph is a frontier that was previously one of the 10 lowest cost frontiers. Once reaching a unvisited place, if the system decides to add this location to node list, the topological map is updated with the new node as $N_i = N_{i-1} \cup \{\nu_i\}$. An edge $\eta_i \in E$ will connect this node to its closest neighbouring node. During the exploration, the robot stores the location information when it passes a nearby node, such node is marked as visited shown as the green "dot" whilst unvisited nodes are denoted as purple "dot" in Fig. 3.

It should be noted that upon start up all the nodes will be connected to a root node which is placed at the robot starting position. As each frontier may shift slightly, it is possible that multiple nodes end up being created at the same point. Thus nodes within a small distance of other nodes should be merged together to prevent the same frontier from generating multiple nodes. Along with the robot exploration, the topological graph $G = (N, E)$ will be created in a tree-like structure as illustrated by Fig. 3.

IV. Experiments

A. System overview

The robot platform, as shown in Fig. 2, is built based on a differential-drive mobile platform (Pioneer). An intense PC (IPC3) with *intel i7* processor is installed on the robot for data processing. A Hokuyo UTM-30-LX laser scanner is mounted about $30cm$ from the ground, which corresponds to scan of the environment around the robot. The 2D Lidar has 180 degree towards the front of the robot, which gives 720 sampling points with 0.25 degree separating each point.

The proposed method is implemented as a Robot-Operating-System (ROS) package on the mentioned platform and tested in our office environment (approximately $250m^2$), i.e., Fusionopolis building Level 9 in Singapore. The unknown environment consists of long and narrow corridors with shielded cubicles on both sides as indicated by the arrows in Fig. 2.

B. Experimental results

The experiment has been conducted as shown in Fig. 3. The exploration process, including map building and topological graph construction, is gradually demonstrated from the starting position (a) until the loop is closed up by visiting the same area in (f).

The exploration space $\mathbb{R}$ is represented by three occupancy grid. Cells with low occupancy probability represented by gray colour are considered as free space $\mathbb{R}_f$. Unknown space $\mathbb{R}_u$, where occupancy probability is unknown, are represented by a darker colour. And occupied cells with high occupancy

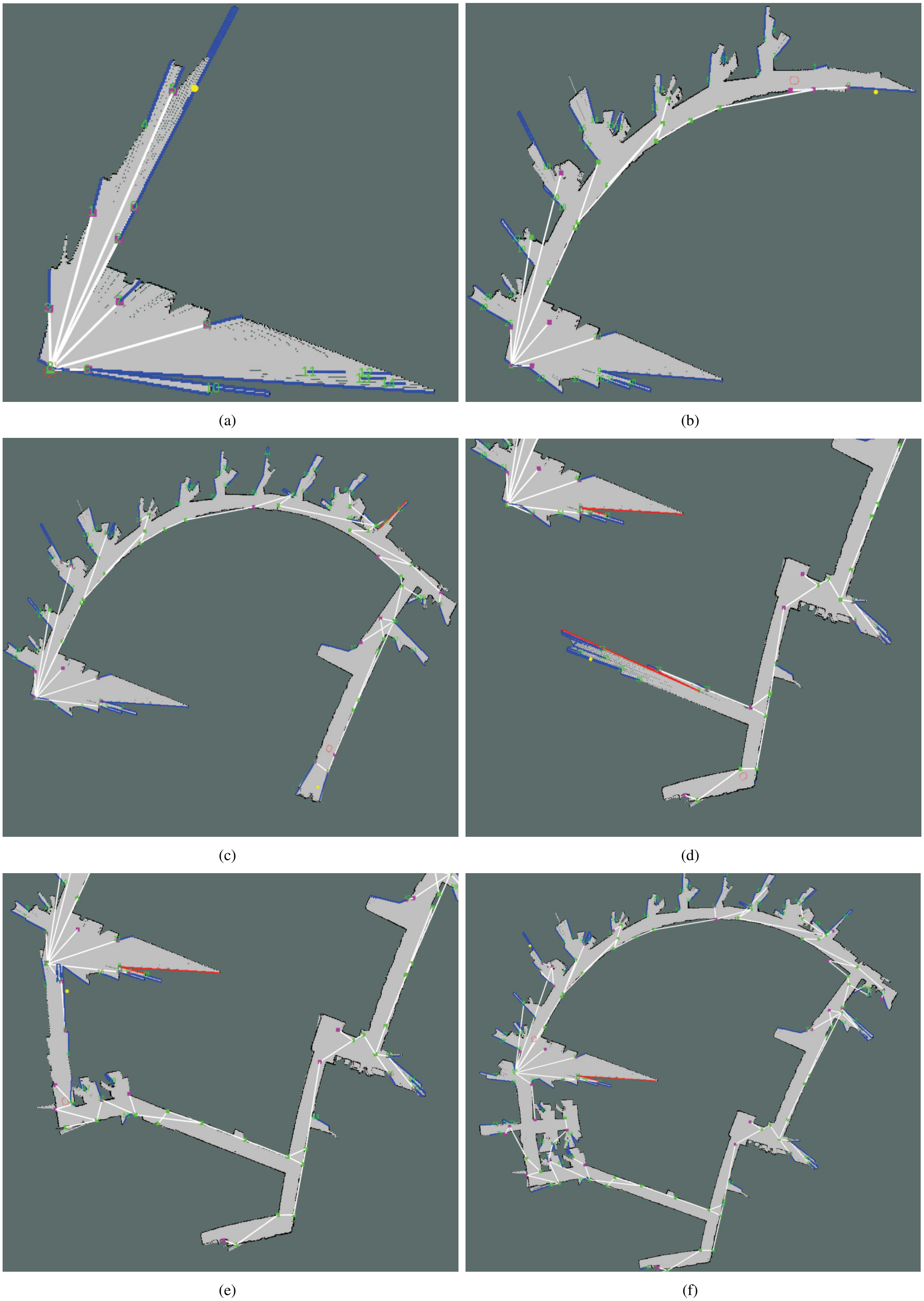


Fig. 3. Real world experiment for auto exploration in Fusionopolis Level 9. The exploration process is illustrated step by step as (a)-(f). Frontier list $\mathcal{F}_t$ denoted by green numbers and the topological graph G are kept updating with respect to the robot position. The yellow dot indicates the current desirable frontier f^* determined by the proposed utility cost.

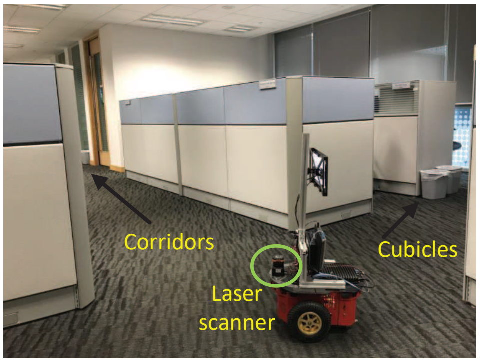


Fig. 2. Robotic system and office environment.

probability are illustrated by black lines and dots. The robot footprint denoted as the red marker indicates the robot position referring to the grid map. Desirable frontier f^* associated with navigation coordinate is assigned to robot as navigation goal. If this goal is unreachable due to occupancy or blockage, the next best frontier will be selected and assigned.

In Fig. 3(a), the robot starts in the center of the hallway and navigates to the frontier marked by a yellow "dot". In Fig. 3(b), the robot has arrived at its previous destination and added the visited nodes and unvisited leaves to the topological graph. Shown as Fig. 3(c) to (e), the robot keeps exploring along the main corridor without entering into the cubicles. In Fig. 3(f), the robot has completed its exploration of the main route. The total exploration time is about 7 minutes. Then, the robot should be able to make use of the graph G (unvisited leaves) to thoroughly cover the rest unexplored spaces.

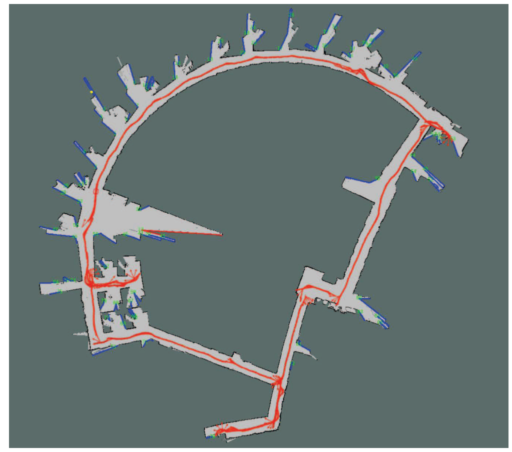
The exploration efficiency is then compared by using the proposed utility function and previous one. As can be observed from Fig. 4(a), the robot is able to explore the whole area and close the loop up. On the contrary, in Fig. 4(b), spending about 10 minutes, only part of the unknown space can be explored before the robot is trapped in one of the cubicles (no available frontiers to guide the robot back to the main road). The red "odometry" represents the robot trajectories in both cases. Due to the additional cost element on moving orientation in Eq. (2), the proposed approach tries to prioritize those frontiers in front of the robot, forcing the robot to maintain its current heading as much as possible. However, without the heading constraints, the optimal frontier f^* can be selected in any direction, including the unknown position inside the cubicles as shown by the "odomotry" in (b).

In terms of time expenditure and map coverage, the experimental result validates the superior exploration efficiency of the proposed method comparing to the fundamental frontier-based method in a complex office environment.

V. Conclusion

In this paper, a new heading informed frontier exploration method is developed and tested on a mobile robot to achieve a challenging take of self-exploration in unknown spaces. An additional rotation cost is added to the utility function for a more efficient frontier selection process, which enables the robot to maintain its orientation during the exploration. The desirable frontier assigned as the navigation goal can guide the robot to explore and map the environment. According to the real world experiments, the proposed approach show its efficiency when exploring in office area with cluttered corridors and narrow cubicles.

To address the problem of incomplete map coverage, the idea of topological map is introduced to the proposed framework. By constructing a topological graph to keep record of visited key nodes and unknown states, the robot has the ability to backtrack to the areas that have high potential to have more unexplored spaces. However this part has not been fully investigated in this paper, since the current SLAM technique used for mapping (gmapping) based on particle filter is not able to provide a stable global coordinate system. In our future work, a pose-graph based SLAM will be used to



(a)

(b)

Fig. 4. Self exploration map and moving trajectory using proposed utility cost function (a) and existing function (b)

systematically update the topological node position under an unified coordinate system. Additionally, more experiments will be carried out in different type of environment.

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