Efficient Autonomous Robotic Exploration With Semantic Road Map in Indoor Environments

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***Abstract*—This letter presents a novel and integrated framework for Next-Best-View (NBV) selection toward autonomous robotic exploration in indoor environments. A topological map, named semantic road map (SRM), is proposed to represent the explored environment during the exploration. The basic concept of the SRM is to construct a graph with nodes containing the exploration states and with edges satisfying the collision-free constraints. Especially, the SRM integrates both semantic and structure information of the environment, which possesses the beneficial properties of using a topological map in the exploration. It is worth noting that the proposed SRM is incrementally built along with the exploration process, thereby, avoiding the unnecessary reconsideration of the explored areas when constructing the topological map. Based on the SRM, a novel decision model with semantic information is presented for determining the NBV during the exploration. Moreover, the decision model takes into account both information gain and cost-to-go of a candidate NBV, which can be queried efficiently on the SRM, enabling the efficient exploration of the environment. The effectiveness and efficiency of the proposed system are assessed and demonstrated using both simulated and real-world indoor experiments.**

***Index Terms*—Search and rescue robots, motion and path planning, surveillance systems.**

I. Introduction

AUTONOMOUS exploration has an increasing number of applications such as disaster relief [1], search and rescue [2], and environmental monitoring [3]. To provide rapid response in these application scenarios, a robot must select an efficient exploration strategy, in which the NBV selection plays an important role. In the past few decades, the NBV selection has been addressed by several researchers [4]–[6], but still remains an open problem.

Previous approaches have used the frontier based method [7] and the information-gain based method [8] to determine the NBV while considering the cost-to-go. To get the frontier or the information gain, these approaches often use the metric map (e.g., occupancy grid map [9], octomap [10]). However, it is time-consuming in complex or large-scale environments. Besides, the calculation of cost-to-go to the candidate NBVs is computationally expensive using the metric map. The broadly adopted Rapidly-exploring Random Tree (RRT) [11] in the autonomous exploration utilizes sampling techniques with the metric map to plan paths in the configuration space, which improves the planning efficiency and avoids the curse of dimensionality, making the cost-to-go evaluation more efficient and admissible. Without considering the exploration history, these planners need to replan a path at each NBV selection step. However, the robot might already obtain a route from its current location to a candidate NBV that is previously left unexplored. Apparently, these planning methods consume extra computational resources in the exploration.

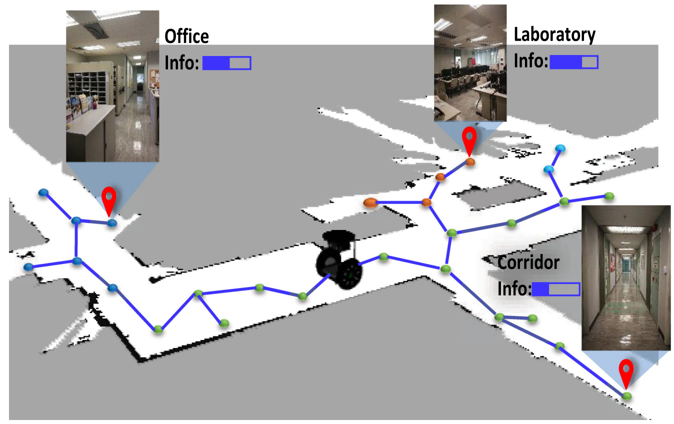

Fig. 1. SRM for autonomous exploration. The color of the nodes indicates the semantic information of the environment. The blue lines represent the collision-free edges on SRM.

This letter presents a novel topological map, namely SRM, to improve the efficiency of robotic exploration by facilitating the NBV selection. As shown in Fig. 1, the SRM has a graph structure, where the nodes and edges are added to the graph incrementally along with the exploration process. The nodes on the graph that contain the semantic information and the information gain at corresponding locations are used as the candidate NBVs for guiding the exploration. Consequently, the NBV selection is performed directly on the SRM, which is proposed in this study to take into account the semantic information, the information

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gain, and the cost-to-go in this study. The SRM facilitates the NBV selection in the following aspects:

- With the SRM, not only the information gain but also the cost-to-go can be obtained efficiently from the graph structure, thereby providing the efficiency guarantee for the NBV selection.
- The proposed framework utilizes semantic information for the NBV selection, which offers significant benefits for the exploration efficiency by involving high-level decision support.

The experimental studies demonstrate that by using the proposed system framework, the robot is capable of exploring an unknown environment in a more efficient manner.

The rest of this letter is organized as follows. In Section II, the related work is discussed and the need for efficient NBV selection is highlighted. Section III provides the preliminaries of the present methodology, which is detailed in Section IV. Experimental studies are reported in Section V. Finally, Section VI presents the conclusions of the work and introduces the future work.

II. Related Work

Various techniques have been proposed for continuous NBV selections in autonomous exploration, among which the most investigated approach is the nearest frontier method [7]. The mentioned frontiers are the boundaries between the known and unknown regions on the map. In this scheme, the robot always pursuits the nearest frontier for exploration. Similarly, Dornhege *et al.* [12] proposed a frontier-void-based approach, which further considered the unexplored volumes in 3D environment in the exploration. However, these methods adopt a greedy exploration strategy without considering the information gathered in the long run.

Besides the frontier based methods, the information gain metric is also frequently adopted in the context of autonomous exploration [8], [13], where the NBV is determined by evaluating the amount of information gain at candidate NBVs. Moreover, combining with the information gain, the cost-to-go is also incorporated into the NBV evaluation process [14]. However, the frontier region, the information gain, and the cost-to-go, might be computationally expensive in large-scale or high-dimensional environments, hindering the efficient assessment of NBVs.

To improve the efficiency of NBV evaluation, Shen *et al.* [6] determined the NBV based on the evolution of stochastic differential equation, which alleviated computational difficulties by only considering the known occupied space in the map. Quin *et al.* [15] proposed to detect the NBV around the explored NBVs to improve the searching efficiency. The configuration space was limited and this technique was not immediately scalable to more complicated environment scenarios. More recently, Umari *et al.* [16] presented an exploration method based on multiple RRTs, in which the frontier regions could be detected efficiently. Yet the cost-to-go was obtained on the metric map frequently with the search-based planning method [17], the constructed road map was not utilized to further improve the path planning efficiency.

Different from the approaches that use the metric map to extract the information for NBV evaluation, the appeal of topological representations for the exploration has been noted by several researchers who suggest the use of the topological map that is directly computed from 2D data [18], [19]. Choset *et al.* [20] developed a hierarchical generalized Voronoi graph (HGVG), with which the robot could query a path, alleviating the path planning problem during the exploration. Rezanejad *et al.* [21] suggested the use of online constructed flux skeletons to represent the environment, and the resulting road map could guide the exploration with a safe and smooth path. Nevertheless, these methods adopted a straightforward NBV evaluation strategy, and no high-level decision-making information is involved.

Our SRM framework builds upon the recent developments of topological mapping of the environment during exploration. Unlike existing methods, the graph structure in the proposed approach is built incrementally along with the exploration process, with which the ingredients for NBV evaluation can be obtained efficiently. Moreover, in the present work, the widely adopted semantic information [22] and the knowledge of the environment [23] are incorporated into the decision-making model in the NBV selection process.

III. Preliminaries

The main goal of the present work is to efficiently explore the environment space $\mathcal{S}$ using a mobile robot. That is, to divide the entire space into occupied space $\mathcal{S}_{occ} \subset \mathcal{S}$ and unoccupied space $\mathcal{S}_{free} \subset \mathcal{S}$, subject to the vehicle motion constraints and the endurance constraint. The adopted representation of the environment is an occupancy grid map [9], which is denoted as $\mathcal{M}_o \subset \mathbb{R}^2$, marking every grid $m \in \mathcal{M}_o$ as free, occupied or unknown. To evaluate the NBVs, information gain I, cost-to-go ℓ and semantic information Ψ are taken into consideration in the decision-making process. Similar to [3], mutual information is leveraged to evaluate the information gain of candidate NBVs. Suppose that there are n candidate locations $\{x_1, x_2, \ldots, x_n\}, x_i \in \mathcal{M}_o$ on the map to be explored, then, the information gain I_i of the region x_i is obtained using the entropy change of $\mathcal{M}_o$. The entropy $H(\mathcal{M}_o)$ is used to evaluate the information of the map $\mathcal{M}_o$, which is defined as:

$$H(\mathcal{M}_o) = -\sum_i \sum_j p(m_{i,j}) \log p(m_{i,j}), \tag{1}$$

where $m_{i,j} \in \mathcal{M}_o$ is the grid cell of the map at location (i, j) and $p(m_{i,j})$ is the occupancy probability of grid $m_{i,j}$. The mutual information for x_i is then defined as:

$$I(\mathcal{M}_o; x_i) = H(\mathcal{M}_o) - H(\mathcal{M}_o | x_i). \tag{2}$$

The present SRM $\Re = \{N, E\}$ has a graph structure with N representing the nodes and E representing the edges. The nodes on the graph are used to represent the candidate NBVs to be explored, i.e., $n_i \equiv x_i, n_i \in N$. The information gain $I(n_i)$ is then calculated using Eq. (2). There is a semantic label Ψ_i continually attached to a node n_i indicating the environmental information at the corresponding location. We assume the semantic information is not specially designed for this exploration task, and hence,

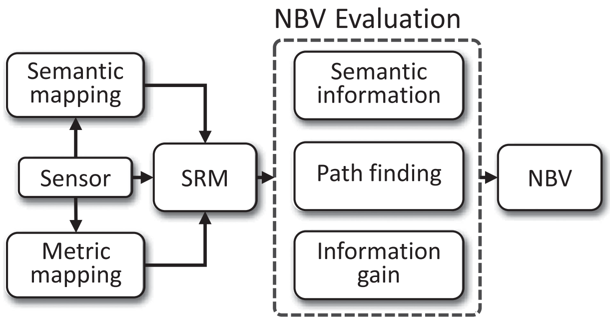


Fig. 2. Overview of the proposed system framework. The main modules and their connections are shown in the system diagram.

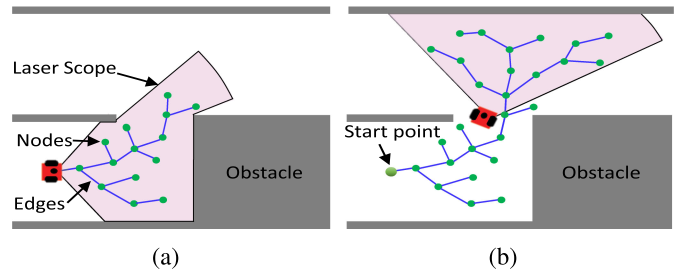


Fig. 3. SRM extension with exploration. The nodes are generated in the sensor scope and the graph structure is built incrementally.

it can be used for other navigation purposes as well. Therefore, the increased computational burden due to the semantic mapping is not under consideration in the present study. In addition, the path $\hat{\mathcal{P}}$ from the robot current location x_r to a target node n_i can be queried efficiently on the graph $\Re$. Then, the cost-to-go of a node $\ell(n_i)$ is calculated by:

$$\ell(n_i) = \mathcal{L}(n_i, \Re, \mathcal{M}_o), \tag{3}$$

where $\mathcal{L}(\cdot)$ contains the path-finding module on $\Re$ and the optimization module of the found path $\hat{\mathcal{P}}$. Using the efficiently obtained information gain and cost-to-go, combined with the semantic information, the robot is able to select the NBV efficiently, leading to the efficient exploration of the environment.

IV. Methodology

First it is assumed that the robot can acquire the information accurately through the available sensors. The SRM is built incrementally based on the sensor information along with the exploration. Simultaneously, a semantic map and a metric map are maintained, as shown in Fig. 2. To evaluate a candidate NBV, the information gain and the cost-to-go are considered and also, the semantic information is leveraged, to provide high-level decision support. The main modules of the system are detailed in the following subsections.[1]

A. Semantic Road Map Construction

The SRM is the graph structure with nodes and edges continuously generated during the exploration. At first, there is only one start node, i.e., $N = \{n_{start}\}, E = \emptyset$. The sample points within the sensor scope are utilized as the candidate nodes for extension of the graph. In Fig. 3, the pink areas indicate the current sensor scope, within which the points are randomly sampled. A random point $n_r \in N_{rand}$ is attached with a semantic label Ψ_r, which represents the environment type as detected by the semantic mapping pipeline. It finds the nearest nodes $\hat{n}$ on the existing graph $\Re$ according to:

$$\hat{n} = \underset{n_i \in (N \setminus N')}{\operatorname{argmin}} ||n_i - n_r||, N \sqsubset \Re, \tag{4}$$

[1]A video illustrating our approach is available at: https://youtu.be/IMHIT7QEf6I

where N' is the set of nodes on the graph wherein the connection from $n_i \in N'$ to n_r is not collision free. If $N \setminus N' = \emptyset$, which means n_r is not a feasible random point because n_i does not exist, then the sample point is discarded and another sample point in N_{rand} will be taken into consideration. When n_r is feasible, it is added to the existing graph $\Re$, together with the collision-free edge that connects n_r to its nearest feasible neighbor node $\hat{n}$, which completes one iteration of the graph extension. Moreover, to simplify the graph and ensure uniform distribution of the generated nodes, the following action is taken: for a candidate node n_r, if $||n_r - n_j|| < \delta, \exists\ n_j \in N$, where δ is preset according to the environment size, then the new point n_r will also be discarded. As the robot moves, new sample points are continuously added to N_{rand}, providing more nodes for the graph extension.

Algorithm 1 describes the process of SRM construction. Function $Random(\cdot)$ outputs a set of random points under the sensor scope. These points keep a distance δ away from the existing nodes on the graph. Besides, they are attached with semantic labels through the semantic mapping pipeline along with the exploration (Line. 11). The random point attempts to connect the nodes on $\Re$ from near to far (Line. 7). If there exists an $edge$ that connects the point $N_{rand}(i)$ and node $N(j) \sqsubset \Re$ that is collision free, then the point $N_{rand}(i)$ and the $edge$ are added to $\Re$ (Line. 8-16). To simplify the structure of the road map, the node $N_{rand}(i)$ will not connect to other nodes on $\Re$ (Line. 14).

B. Cost-to-Go Evaluation

The nodes on the graph are in fact the candidate NBVs for guiding the exploration, and through them the cost-to-go can be queried efficiently on the map $\Re$. We use A* [17] to search for a path $\hat{\mathcal{P}}$ from the current location of the robot to an NBV on the existing graph $\Re$. We use the incomplete occupancy grid map for collision checking of an edge, during which the unknown space is regarded as the collision-free area for the rapid extension of SRM. Hence some edges on the path $\hat{\mathcal{P}}$ might not be feasible when the unknown space is demonstrated to be partially or fully occupied. By closely following the concept of lazy collision checking [11], in the proposed method, the feasibility of the path is checked only if a path $\hat{\mathcal{P}}$ is generated. If one or more edges on $\hat{\mathcal{P}}$ are not collision-free, then the path is discarded and the edges on $\Re$ are also deleted. The path-finding mechanism is re-enabled and this process iterates until a feasible path $\hat{\mathcal{P}}$ is found.

Algorithm 1: Semantic Road Map Construction.

Input: laserData, rgbdData, $N = \{n_{start}\}, E = \emptyset$
Output: Semantic Road Map $\Re = \{N, E\}$
while *existing unexplored area* **do**
  $\mathcal{M}_o \leftarrow metricMapping$(laserData);
  /* Candidate nodes generation */;
  N_{rand}= $Random$(laserData, δ);
  /* Add nodes to the existing $\Re$ */;
  for $i = 1$ *to size*(N_{rand}) **do**
    rank N according to the distance to $N_{rand}[i]$;
    for $j = 1$ *to size*(N) **do**
      $edge \leftarrow Line(N_{rand}[i], N[j])$;
      if *isValid(edge,*$\mathcal{M}_o$*)* **then**
        label node $N_{rand}[i]$ with semantic information using rgbdData;
        $N.pushback(N_{rand}[i])$;
        $E.pushback(edge)$;
        break; // to simplify the graph;
      end
    end
  end
end

As the path $\hat{\mathcal{P}}$ is sparse and not optimized for satisfying the vehicle motion constraints, when $\hat{\mathcal{P}}$ is found using $\Re$, it is further optimized by the elastic-band method proposed in [24]. This method can deform the sparse path and output an optimal trajectory for the robot to execute. Hence the cost-to-go ℓ is exactly the motion cost when the robot executes the trajectory, making it more admissible for the cost-to-go evaluation.

C. Information Gain of Node

For the sake of the map completeness, it is proposed to use the frontier grids that would uncover the unknown areas in the map to evaluate the information gain of a node. Suppose that there exists a set of frontier grids $\mathcal{M}_o^f$ around node n_i, and let $\mathcal{M}_o^k = \mathcal{M}_o \setminus \mathcal{M}_o^f$, then Eq. (2) becomes:

$$\begin{aligned} I(\mathcal{M}_o; n_i) &= H(\mathcal{M}_o) - H(\mathcal{M}_o|n_i) \\ &= H(\mathcal{M}_o^f \cup \mathcal{M}_o^k) - H(\mathcal{M}_o^f \cup \mathcal{M}_o^k|n_i) \\ &= H(\mathcal{M}_o^f) + H(\mathcal{M}_o^k) - H(\mathcal{M}_o^f|n_i) \\ &\quad - H(\mathcal{M}_o^k|n_i). \end{aligned} \tag{5}$$

With the forward simulation model [25], assume that the frontier grids, if exist around a node, will become occupied or unoccupied grids when the robot scans through the available sensor at the node location. In other words, performing a sensing operation around node n_i will result in $p'(m_k^f) \simeq 1$ or $p'(m_k^f) \simeq +0$, $\forall m_k^f \in \mathcal{M}_o^f$. Then,

$$H(\mathcal{M}_o^f|n_i) = -\sum_{k=1}^{R} p'(m_k^f) log(p'(m_k^f)) = 0, \tag{6}$$

where R is the number of grid m_k^f around a node. The occupancy probability of the grids in $\mathcal{M}_o^k$ will not change after performing

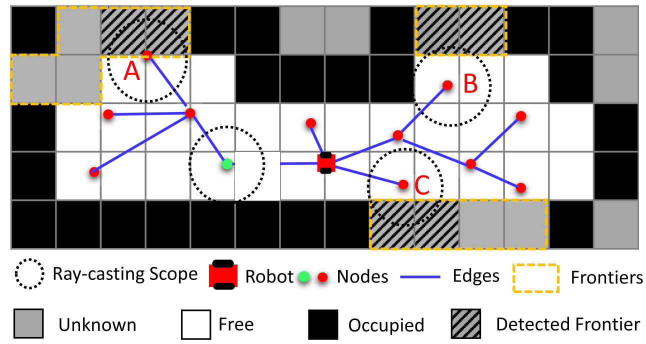


Fig. 4. Efficient frontier detection. The shaded circle indicates the ray-casting scope around a node for detecting a frontier grid.

the sensing operation, i.e., $H(\mathcal{M}_o^k|n_i) = H(\mathcal{M}_o^k)$. As a result:

$$I(\mathcal{M}_o; n_i) = H(\mathcal{M}_o^f) = -\sum_{k=1}^{R} p(m_k^f) log(p(m_k^f)), \tag{7}$$

where $p(m_k^f)$ is the occupancy probability before sensor scanning around node n_i with the forward simulation model. The information gain $I(n_i)$ is then calculated using Eq. (7).

It is seen that the frontier detection is a prerequisite for calculating the information gain of a node. In contrast to the current frontier detection methods which use the entire metric map with a greedy search strategy, an efficient frontier detection method is proposed in the present work based on the SRM framework. To get the frontier grid m_k^f, the nodes on $\Re$ are used for the detection. As shown by the black circle in Fig. 4, the ray-casting method [25] is performed around the node within a sensing scope to detect whether there is a frontier grid. Only the grids under the sensing scope are considered to detect the frontier gird, which is more efficient than taking all the grids in the metric map into consideration. As the nodes are generated within the sensor scope and the graph is consistently extending to uncover the unknown regions, the probability of finding a frontier grid around a graph node becomes high.

However, there still exist frontier grids that are not under the sensing scope, as the gray squares in the frontier region indicate in Fig. 4. Thus they cannot be detected directly using the ray-casting method. It is noted that when a frontier grid is found around a node, there is a high probability that some of its adjacent grids are also frontier grids. This is a very useful trait for detecting as many as possible frontier grids in the map. Through checking the neighboring grids of the found frontier grid, a frontier cluster can be obtained efficiently, which maximizes the number of frontier grids to be detected.

Not all nodes on the graph are needed in the frontier detection; as the green point in Fig. 4 indicates, there is no frontier grid can be detected around the node. Hence, these nodes are not considered during the frontier detection, which further improves the searching efficiency. To this end, let the nodes on the graph $N = \{N_c \cup N_o\}$, where N_c represents the closed nodes with which no frontier grid can be detected, while N_o is the set of open nodes that can be used for frontier detection. Before the exploration, $N = N_o$. When a node does not appear to provide

Algorithm 2: Fast Frontier Detection.

Input: $\mathcal{M}_o$, $n \in \{N \setminus N_{closed}\}$
Output: frontier set $\mathcal{M}_o^f$
1 $P_r \leftarrow rayCasting(n)$;
2 /* check every grid in P_r to find new frontiers */;
3 **for** $k = 1$ *to* $size(P_r)$ **do**
4 $P_{temp} = \{P_r(k)\}$;
5 **while** *notEmpty* (P_{temp}) **do**
6   $P_{new} = \emptyset$; // initialize the frontier set;
7   **for** $j = 1$ *to* $size(P_{temp})$ **do**
8   **if** $isFrontier(P_{temp}(j))$ **then**
9     $F \leftarrow findFrontierNbr(P_{temp}(j), \mathcal{M}_o)$;
10     $P_{new}.pushback(F)$;
11     $\mathcal{M}_o^f.pushback(F)$;
12   **end**
13   **end**
14   $P_{temp} = P_{new}$; // break if P_{new} is empty;
15 **end**
16 **end**

a frontier grid, it is put into N_c. As the ray-casting operation around a node is time-consuming, the proposed method can further reduce the frontier detection time by only considering the open nodes $n \in N_o$ on the graph.

Algorithm 2 outlines the frontier detection method. First, a set of grids P_r is acquired using the ray-casting method around a node (Line. 1). If a point in the set P_r is a frontier cell, then this point is stored and its neighbors are checked to find new frontier grids with the function $findFrontierNbr(\cdot)$ (Line. 9). The new frontier grid is also used for finding more frontier grids (Line. 14). This iteration ends when all the grids within a circle around the node are checked and no more frontier gird can be found (Line. 3-15), until when all the frontier grids around a node are obtained.

D. NBV Selection

It is proposed to use the semantic information provided by the SRM to guide the exploration. In this manner, the robot can determine the environment type and where to go, by using the high-level decision-support mechanism. This makes the robot achieve human-like performance during exploration.

It is assumed that the indoor environment to be explored consists of separate rooms, which is typical in most office buildings. The scene the robot encounters during the exploration is divided into two categories, the rooms $\mathbb{O}$ and the connections $\mathbb{C}$ that are used to connect the rooms, i.e., the corridors. The robot can distinguish between these two types by using the semantic information of the node on SRM. The room $O \in \mathbb{O}$ is bounded and the connection $C \in \mathbb{C}$ is deemed to be visited multiple times during the exploration. Moreover, the bounded rooms are always terminals for the SRM extension and robotic exploration. Motivated by this, the robot is made to firstly explore the room instead of the connections when there exist unexplored rooms $\hat{\mathbb{O}}^i$. Here i indicates the time stamp since the set of unexplored rooms $\hat{\mathbb{O}}^i$ is changing with the exploration time i. During the exploration, the NBV will be selected according to the following decision-making model:

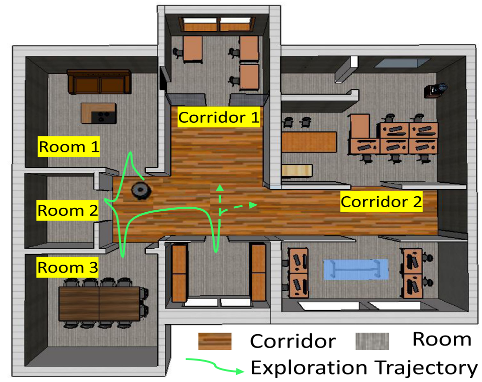


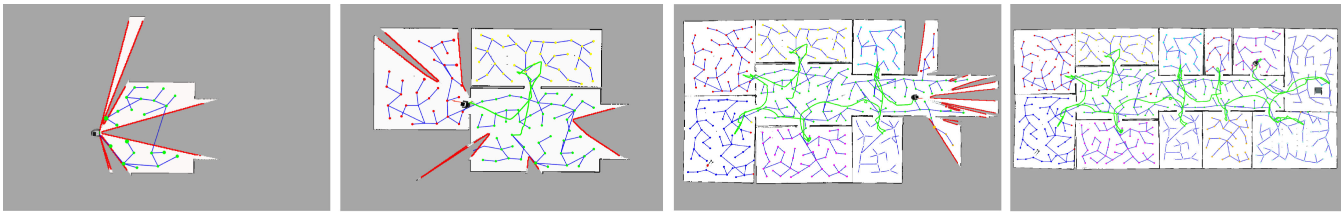
Fig. 5. Decision-making during the exploration. The semantic information of the environment are taken into consideration.

- **Case 1:** The unexplored space $\mathcal{S}^i$, as far as the robot knows at time i of the decision making, contains both rooms and connections to be explored, i.e., $\mathcal{S}^i = \hat{\mathbb{O}}^i \cup \hat{\mathbb{C}}^i$. Then the robot will choose rooms to explore; that is, $\mathcal{S}_T^i = \hat{\mathbb{O}}^i$. For the candidate yet not explored rooms $\hat{\mathbb{O}}^i = \{\hat{O}_1^i, \hat{O}_2^i, \ldots, \hat{O}_n^i\}$, the next room $\hat{O}_T$ to be explored is selected according to: $\hat{O}_T = \text{argmin}\, ||\hat{O}_j^i \rightarrow \mathcal{R}||, \hat{O}_j^i \in \hat{\mathbb{O}}^i$. This means that the nearest room nearby the robot $\mathcal{R}$ will be explored first.
- **Case 2:** If there are only connections to be explored in the environment, i.e., $\mathcal{S}_T^i = \hat{\mathbb{C}}^i$, or when the robot enters a room, which can be distinguished easily through the semantic information, the robot selects the NBV according to the reward function [26] $\gamma = -I(n)e^{-\lambda \ell(n)}$, where I is the information gain and ℓ is the cost-to-go to a candidate NBV, respectively. λ is a predefined parameter according to the environment and n is the node on SRM representing a candidate NBV.
- **Case 3:** Based on Case 2, if the robot finds new rooms to be explored during the exploration, then jump to Case 1 to choose a new NBV.

As Fig. 5 shows, for example, there are rooms and corridors at the beginning. The robot chooses to first explore the rooms according to the distance, as governed by Case 1. When there is no room in the view of the robot, it will choose the NBV according to Case 2 in the decision-making model. The NBV evaluation model encompasses the high-level semantic information, hence the robot can distinguish the rooms from the connections and select an area to explore accordingly, making the robot achieve an efficient and human-like performance during the exploration.

V. Experiments and Results

This section evaluates the SRM framework through experiments in both simulation and real-world environments. For the



(a) T=1s (b) T=32s (c) T=180s (d) T=230s

Fig. 6. Autonomous exploration with the proposed SRM framework in a typical indoor simulation environment (30 × 12 m^2). With the SRM, the robot is capable of exploring the environment completely in 230 s. Green lines show the exploration trajectory.

Simultaneous Localization and Mapping (SLAM), the well-known techniques described in [27] are adopted and implemented in the GMapping package.[2] The parameters in this package are well-tuned to perform accurate SLAM in all of the experiments.

Firstly, to demonstrate the effectiveness of the proposed SRM framework, we conduct experiments in a simulated office environment with corridors and rooms.[3] As shown in Fig. 6, the candidate nodes can be generated under the sensor scope of the robot and the SRM can be extended along with the exploration process, which demonstrates the effectiveness of the proposed SRM extension method. The red stripes show the frontiers in the map that are detected by the proposed frontier detection method. It is clear that all the frontiers in the map can be detected with the developed method. The color of the node on the graph indicates the room type acquired from a semantic mapping process using RGB-D images, providing valuable semantic information for improving the decision-making process. In this experiment, the proposed framework is effective in making the robot successfully explore the environment within 230 s.

To demonstrate the benefits of the node pruning mechanism during the frontier detection, experiments are conducted in the simulated environment (see Fig. 6) with and without the node pruning mechanism while keeping the other variables the same. Fig. 7 shows the frontier detection time for each NBV evaluation during the exploration. The blue line shows the robot exploration without the node pruning mechanism. Note that this strategy takes into account all the nodes during the NBV evaluation, as more nodes are generated along during exploration, the frontier detection time increases with the exploration time. In contrast, by placing the nodes with which no frontier is detected into N_c set, fewer nodes are used in the NBV evaluation. The detection time will not increase even when more nodes are generated, as shown by the red line in Fig. 7. Therefore, the node pruning mechanism is able to drastically reduce the frontier detection time in a round of NBV evaluation process.

The efficiency of the proposed cost-to-go evaluation method is validated by comparing it with the broadly adopted RRT* method in four environment scenarios with different scales (see Fig. 8). Table I presents the total time cost for the cost-to-go evaluation. As given in Table I, the proposed method can acquire the cost-to-go more efficiently than the RRT* method in all these four environments. Even the time difference in a cost-to-go evaluation is minor when compared to the exploration time, the suggested method is still significant because numerous cost-to-go evaluations are performed during the exploration. It is seen that our method provides a cumulative contribution in reducing the computational time. Moreover, the proposed method can be immigrated into 3D environments, where more time can be saved.

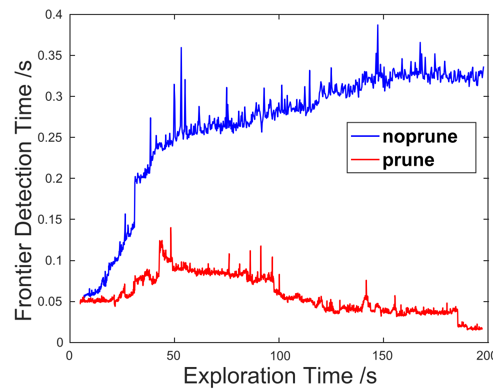


Fig. 7. The frontier detection time for every round of NBV evaluation with and without the pruning mechanism during the exploration.

In these four different simulated environment scenarios, the developed exploration strategy is evaluated by comparing it with the following two widely used NBV evaluation methods in the exploration:

1) *Max Info:* This method always chooses an NBV that contains maximum information.
2) *Nearest Frontier:* This method always chooses the nearest frontier region to explore.

Both *Max Info* and *Nearest Frontier* adopt the same planning framework as the SRM except that the NBV evaluation strategies are different from the developed strategy. Specifically, when implementing the *Nearest Frontier* method using the proposed SRM framework, a node will be considered a frontier node if there exist frontier grids around it. Fig. 8 shows the entropy of the map that shows how the map completeness varies with the exploration process. If the entropy is sufficiently small and remains unchanged, the environment is regarded as fully explored. As shown in Fig. 8, in all these four environments, the proposed

[2]http://wiki.ros.org/gmapping

[3]A video demonstration is available and can be found at: https://youtu.be/GTkp8tb38aI

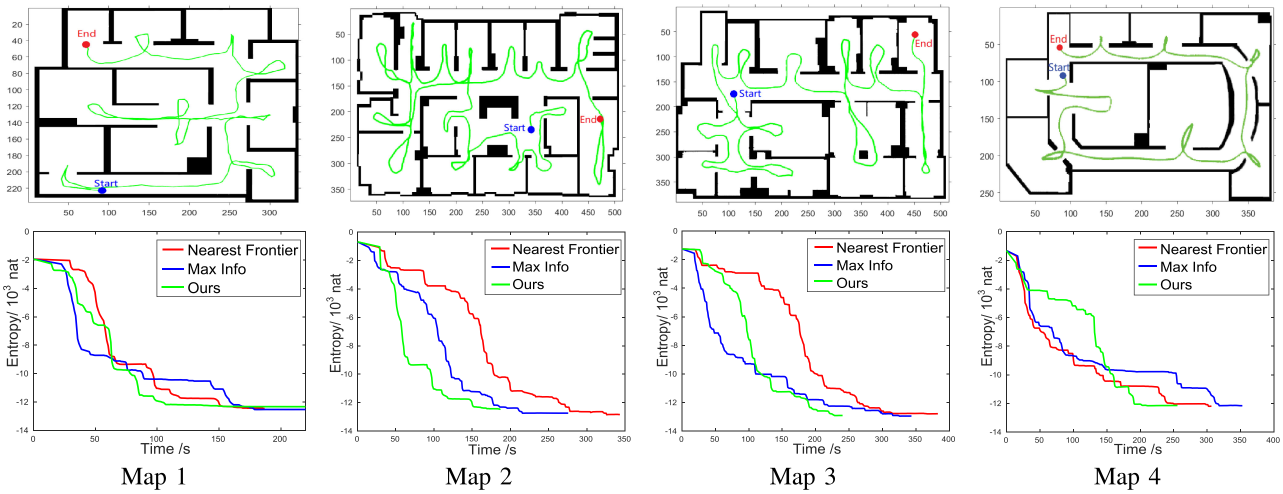


Fig. 8. Simulation experiments in four different environment scenarios. The first row shows the simulation environment setting (scale unit: cm), in which the green line shows the exploration trajectory using the proposed method. As a result, our method is able to explore the environment successfully. The second row shows the corresponding map entropy changes with the exploration.

TABLE I
THE TIME COST (MS) OF COST-TO-GO EVALUATION BY USING OUR PROPOSED PLANNER AND THE RRT* PLANNER

Methods	Map1	Map2	Map3	Map4
Our planner	2.1	8.7	9.5	2.8
RRT*	17.2	50.9	55.2	20.3

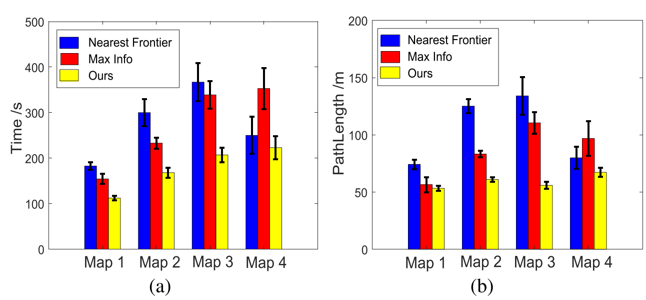


Fig. 9. Time and path cost of the exploration with the three methods in four different environment scenarios.

system framework outperforms the others in terms of the exploration efficiency.

More specifically, Fig. 9 presents a comparative result of the exploration time and the path cost of the proposed method and the baseline methods in 10 experiments in the four simulated environments. It is shown that our method is capable of exploring the environment with the least time cost and the shortest path length. Moreover, the standard deviation of the proposed method is also the least in each environment scenario, demonstrating that the proposed method is more robust than the other methods.

These results in Fig. 8 and Fig. 9 demonstrate the benefits of using the NBV selection model involving the information gain, the cost-to-go, and the semantic information. As shown by the green trajectories in Fig. 8, by incorporating the semantic information in the decision-making process, the robot visits the adjacent rooms one after the other in order, and seldom does the robot need to backtrack to a room that it has already passed by through a long corridor. This avoids repeated exploration trajectories on the corridor, thus reducing the exploration time and path cost.

The proposed method is compared with the *Balanced* approach in [26], which considers both the information gain and the cost-to-go for the NBV evaluation with the reward function γ. The experiments are conducted in a real-world environment with a popular mobile robot. As in the simulated environment, the other counterparts, such as the frontier detection, the information gain, and cost-to-go acquisition are kept the same in these two methods. The λ in the reward function γ, which is used in both two methods, is set to 0.6 empirically. As shown in Fig. 10, the proposed method and the *Balanced* method are implemented on the Segway mobile robot platform and the experiments are conducted in an indoor environment with the size of 33×21 m^2. The proposed approach is able to explore the environment with a shorter path length (72.2 m) compared with the *Balanced* method (96.5 m), which further demonstrate the effectiveness of the proposed decision-making process in the real environment.

To evaluate the robustness of the proposed method in the real environment, the robot is placed at different starting locations, and the laser detection Field of View (FoV) are set to 120°, 180°, and 270°, respectively. As Fig. 10 indicates, A, B, and C are three different locations for starting the exploration. As specified in Table II, with similar velocity profiles, the proposed method can achieve better performance with less exploration path cost compared with the *Balanced* method in all these three starting locations with respect to different sensor ranges. Different starting locations lead to different room visiting order, thus causing varies of the exploration path cost in the same room. Meanwhile, it is noteworthy that the sensor with a larger FoV helps reduce the exploration path cost as the robot can detect a larger region with less movement.

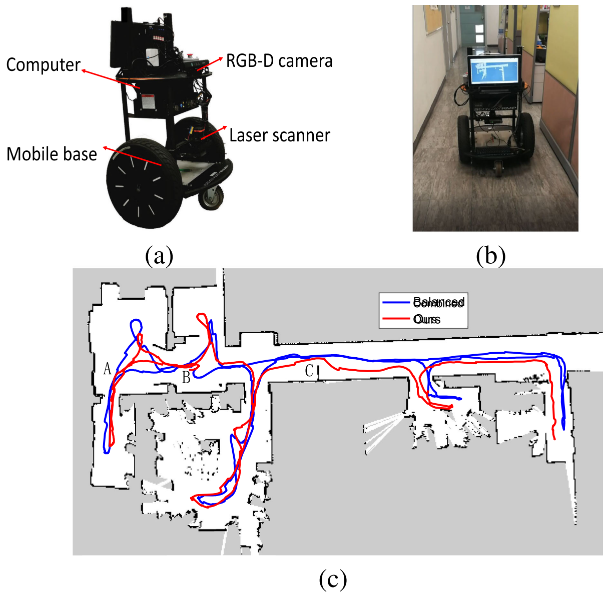


Fig. 10. Real-world experiments. (a) Segway mobile robot. (b) Real-world experimental scene. (c) Performance of indoor exploration by using the proposed method and the Balanced approach.

TABLE II
COMPARISONS BETWEEN OUR METHOD AND THE BALANCED METHOD AT DIFFERENT STARTING LOCATIONS (VEL.=VELOCITY)

	FoV(°)	Balanced		Ours	
		Path(m)	Vel.(m/s)	Path(m)	Vel.(m/s)
A	120	83.1	0.29	81.3	0.34
	180	74.3	0.30	72.1	0.36
	270	69.2	0.33	62.7	0.28
B	120	107.2	0.29	96.4	0.27
	180	98.2	0.33	75.8	0.31
	270	77.1	0.31	70.1	0.35
C	120	82.3	0.34	73.2	0.27
	180	79.7	0.25	74.5	0.27
	270	70.2	0.32	66.3	0.37

VI. CONCLUSIONS AND FUTURE WORK

In this study, we presented a novel topological map for efficient NBV selection to facilitate autonomous indoor exploration. The proposed SRM is an integrated framework with every module tightly coupled within the system. To evaluate an NBV, the information gain, the cost-to-go, and the semantic information were considered in this framework. It was shown that with the SRM, the information gain and the cost-to-go to the candidate NBVs could be rapidly acquired, which accelerated the evaluation of the NBV. More significantly, by involving the semantic information, the decision-making model could further consider the structure of the environment for the NBV selection process. Therefore, the robot was found to be capable of exploring the environment more efficiently, as verified through both simulation and real-world experiments.

In the future, the more general decision-making model based on the semantic information in 3D environment will be investigated. Moreover, the proposed SRM framework will be implemented to explore the environment while considering the uncertainties in the SLAM module.

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