A Prior Information Heuristic based Robot Exploration Method in Indoor Environment

Jie Liu†, Yong Lv†, Yuan Yuan, Wenzheng Chi*, Guodong Chen, and Lining Sun

***Abstract*—The Rapidly-exploring Random Tree (RRT) based method has been widely used in robotic exploration, which achieves better performance than other exploration methods in most scenes. However, its core idea is a greedy strategy, that is, the robot chooses the frontier with the largest revenue value as the target point regardless of the explored environment structure. It is inevitable that before a certain area is fully explored, the robot will turn to other areas to explore, resulting in the backtracking phenomenon with a relatively lower exploration efficiency. In this paper, inspired by the perception law of bionic human, a new exploration strategy is proposed on the basis of the prior information heuristic. Firstly, a lightweight network model is proposed for the recognition of the heuristic objects. Secondly, the prediction region is formed based on the position of the heuristic object, and the frontiers in this region are extracted by the method of image processing. Finally, a heuristic information gain model is designed to guide the robot to explore, which allocates priority to the frontiers within the heuristic object area, so that the robot can make effective use of the prior knowledge of the room in the scene. Priority is given to the exploration of one room completely and then to the next, which can greatly improve the efficiency of exploration. In the experimental studies, we compare our method with RRT based exploration method in different environments, and the experimental results prove the effectiveness of our method.**

***Index Terms*—Robot Exploration, Frontier Detection, Deep Learning, Prior Information Heuristic**

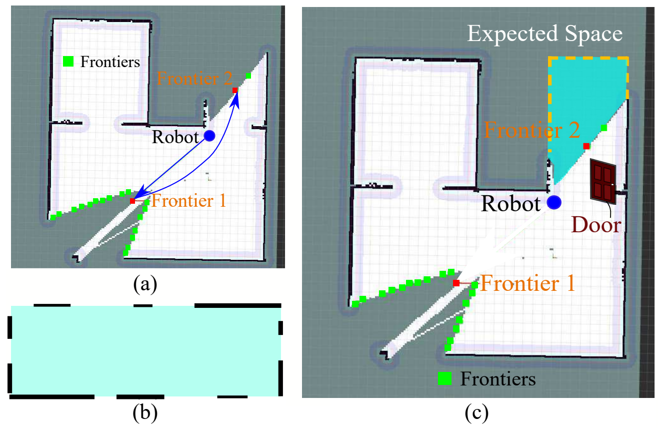

Fig. 1: An illustration of the influence of prior information heuristic on the selection of frontiers. (a) shows the case without heuristic information. (b) shows the law of closure.(c) shows the case with heuristic information, namely the geometric space expectation (cyan) under the heuristics of some semantic objects, e.g. a door. The blue dot denotes the current position of the robot, and the red and green squares denote the candidate frontiers.

I. INTRODUCTION

Robot exploration is a key step for robots to complete various tasks independently. Recently, the robot exploration methods based on frontier [1] have been widely used, in which the boundary with frontiers divides the exploration space into the known area and the unknown area, and guides the robot to gather information for updating the map. In order to explore the environment more effectively, the focus of this kind of exploration methods is mainly how to detect and select the frontiers. The Rapidly-exploring Random Tree (RRT) [2] based method records the place of the tree top as the frontier. Compared to the image based method for frontier detection [3], [4], this method saves computing resources and improves the extraction speed of frontiers, especially in a relatively large environment. The frontier selection influences the exploration efficiency directly. Currently, most of the existing robot exploration strategies focus on how to design the information gain model of the frontier to choose a frontier with a large revenue. As shown in Fig. 1(a), the robot firstly chooses frontier 1 to explore according to its information gain at the current moment. During the motion of the robot to frontier 1, frontier 2 may obtain a larger revenue in turn and then the robot moves back to frontier 2, resulting in the backtracking phenomenon. This is because the greedy strategy exploration evaluates the candidate frontiers independently and ignores the geometric continuity of obstacles in the environment.

In order to address the above problems, we obtain inspirations from the bionic human perception law, especially the law of closure. The principle of the law of closure is that when the human brain receives incomplete sound or visual image, it tries to ignore the incomplete sound and image. As shown in Fig. 1(b), when people see the figure, he recognizes it as a rectangle, and then the incompleteness of the rectangle will appear in his mind. This occurs since a connection between these intermittent lines and the geometric shape has been established according to its prior knowledge. The exploration process is similar. For example, many rooms are separated by doors in indoor environments and when people see a door, he

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usually expects a room behind it. The connection from such kind of semantic information to geometric heuristic can also be utilized as prior information for the robot exploration. As shown in Fig. 1(c), when a room is expected behind the door, the higher expected information gain will guide the robot to explore the rest of the room firstly, namely frontier 2 and then turn to frontier 1. In this work, we hope to bring this idea into the robot exploration strategy and propose a systematic framework for the robot exploration with prior knowledge.

The rest of this paper is organized as follows. In Section II, we first review the related work of the frontier-based robot exploration methods. Exploration strategy based on prior information heuristic is described in detail in Section III. We conduct a series of experiments and discuss the results in Section IV and finally draw conclusions in Section V.

II. RELATED WORK

The frontier-based exploration method has been favored by many scholars [5]–[7] for its obvious advantages over other algorithms and the research topics of frontier-based exploration methods have mostly focused on how to extract and select frontiers.

In the extraction of frontiers, some scholars use image processing technology to extract frontiers. At the beginning of exploration, the size of the map is quite small and the speed of extracting frontiers is relatively quick, however, with the expansion of the map, the computing resource occupancy increases, and the speed of frontier extraction decreases. Keida and Kaminka [8] proposed to process the newly generated sensor data to extract frontiers. Senarathne *et al.* [9] proposed a method to generate frontiers by tracing the latest changes in the grid values of the map. Umari *et al.* [2] proposed to use RRT [10] to extract frontiers, this method records the nodes of the tree top at the boundary as the candidate frontiers. The RRT-based frontier extraction method is widely used since it does not need the precise construction of the whole map and thus saves computing resources. However, due to the randomness of tree growth, this method cannot extract the frontiers at corners and narrow corridors in time, leading to some backtracking phenomenon. Wu *et al.* [11] put forward the method of combining RRT with image processing technology. When the size of the map is relatively small, the method based on image processing proves to be faster.

The selection of frontiers is a decision-making process to maximize the efficiency of environmental exploration by using the information of the known environment and current robot position. Some scholars adopt the decision-making method of randomized motion. Oriolo *et al.* [12] proposed a randomized increments of a data structure called Sensor-based Random Tree, which represents a roadmap of the explored area with an associated safe region and the nodes on this tree denote the visited explored locations. A subsequent improvement in [13] is proposed to bias the selection of the target point towards the local boundary arc of the current safe area. When the unexplored area cannot be found on the current node, the robot will return through previous nodes on the tree to find new unexplored area. Therefore, this scheme usually cannot avoid the backtracking problem. In order to improve the efficiency of exploration caused by the backtracking phenomenon, EI-Hussieny *et al.* [14] made further improvements. The new algorithm directly determines the most informative node instead of traversing all previous nodes in order. On the other hand, some scholars integrate their exploration strategies into the revenue function of the frontier, and choose the frontier with the largest revenue value as the target point to explore. Yamauchi *et al.* [1] put forward the exploration strategy of the nearest-frontier, whose revenue function is inversely proportional to the length of the path. Bourgault *et al.* [15] proposed a revenue function that combines the expected information gain and the length of the expected path. Umari *et al.* [2] proposed a new information gain estimation method, which only considers the unknown grid inside of the circle centering at the frontier with a predefined radius, and further combined the information gain with the path cost in the benefit function. However, most of them evaluate the candidate frontiers independently and ignore the geometric continuity of obstacles in the environment.

In order to address this problem, some scholars propose to enrich the revenue function and estimate the environmental information according to the geometric continuity of obstacles. Shrestha *et al.* [16] employed a state-of-the-art generative neural network to predict unknown regions of a partially explored map, and use the prediction to enhance the exploration in an information-theoretic manner. Bogoslavskyi *et al.* [17] proposed a method to match the region outside the boundary with the most similar map in the database, and calculated the expected information gain according to the matching results. Pimentel *et al.* [18] proposed a heuristic map prediction method to calculate the expected information gain by linearly extending or rotating the wall by 90°. These prediction methods are usually based on the prior knowledge of a certain type of environment, which have shown obvious advantages during the robot exploration. However, when predicting the geometric continuity of the environment, most algorithms only use the geometric heuristic information of the environment, such as the geometric shape of a known map, a part of a corridor, etc. In fact, semantic information can also provide much heuristic about the structure of the environment. For example, when seeing an open door, people usually expect a room behind it. In this paper, we explore the utilization of semantic information to predict unknown environmental structure and guide the robot exploration in indoor environment.

III. METHODOLOGY

In this section, we will introduce in detail the implementation process of the proposed exploration strategy based on prior information of indoor environment, and the framework of the algorithm is shown in Fig. 2. The SLAM module receives the sensor data to update the unknown map. Two fast search random trees grow in the free area of the known map for frontier detection [2], and then a utility function is used for the frontier selection and the frontier with the maximum revenue

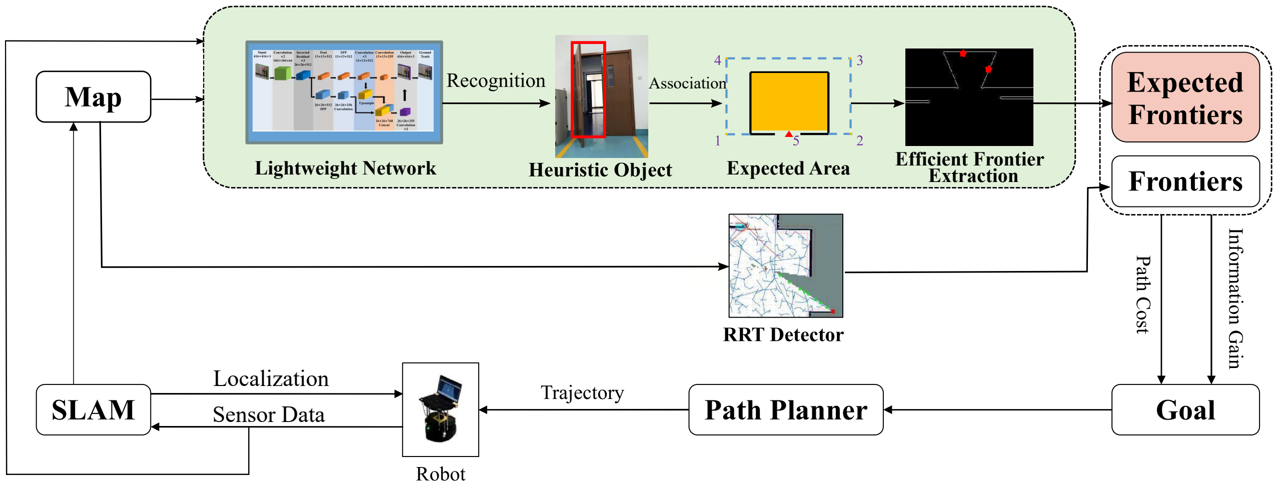


Fig. 2: Overall framework of the robot exploration algorithm.

is chosen as the target for the exploration. In this paper, we propose to associate the specific object with geometric heuristic by using the prior knowledge so as to select a frontier with more expected information gain. Firstly, we use the method based on deep learning to complete the recognition of the heuristic object. An improved lightweight network is proposed to quickly complete object recognition and obtain the location coordinates of the object. After that, a geometric area is associated with the location of the heuristic object. The association follows the perceptual knowledge of people and taking the door as an example, people usually expect a room behind a door. Then, the frontier inside the expected geometric area is efficiently extracted by using the image processing technology and the robot will first explore this area. In this way, the geometric continuity of the environment can be considered in the robot exploration, thereby avoiding the backtracking problem caused by ignoring the semantic information of the environment.

A. Heuristic Object Recognition and Pose Estimation Based on Lightweight Network

Many state-of-the-art methods have been proposed for object recognition [19], [20] and methods based on deep learning have shown great superiority recently [21]–[23]. However, their high computational cost still hinders the application on robots. In this work, we propose an optimized lightweight network to access the heuristic object recognition.

On the basis of the YOLOv4_tiny network, we designed a lightweight YOLO for service robots, namely YOLO_SR. This lightweight network is mainly composed of convolutional layer, inverted residual block, pooling layer, and SPP(Spatial Pyramid Pooling) layer, with a total of 42 layers, and the output is simplified to two layers. As shown in Fig. 3, when the input scale is $416 \times 416 \times 3$, the corresponding output layers are $13 \times 13 \times 255$ and $26 \times 26 \times 255$, respectively. The inverted residual block in the backbone network can effectively improve the feature extraction dimension, while the SPP layer located in the deep layer integrates the local

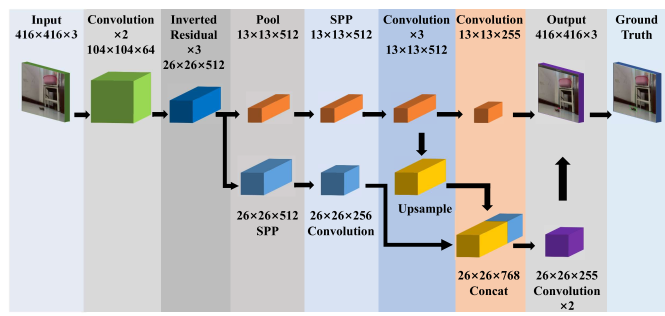


Fig. 3: The proposed lightweight network for heuristic object recognition.

and overall features in space. In the training process, we collect samples in the actual environment and combine with online supplementary methods to establish a data set about the heuristic object. In this paper, we mainly consider the heuristic function of the door. Considering the similarity between many objects and the door structure in the actual environment, in order to reduce the false detection rate during the detection process, we added common objects such as bed, cabinet, table, chair, and refrigerator as negative samples. Compared with YOLOv4_tiny, the detection accuracy of YOLO_SR has increased by 19.2%, which is close to that of YOLOv4, but the speed is almost four times than that of YOLOv4. In general, YOLO_SR is extremely effective in terms of speed and accuracy, it is suitable for heuristic object recognition.

After the heuristic object recognition, the image coordinate of the recognized object can be obtained. Next, we realize the mapping from two-dimensional point in the image coordinate to three-dimensional point in the robot coordinate. We assume that the coordinate of the center point P of the heuristic object on the image plane is (x', y'), and its coordinate in the robot coordinate system is (x, y, z). The mapping process can be formulated as follows:

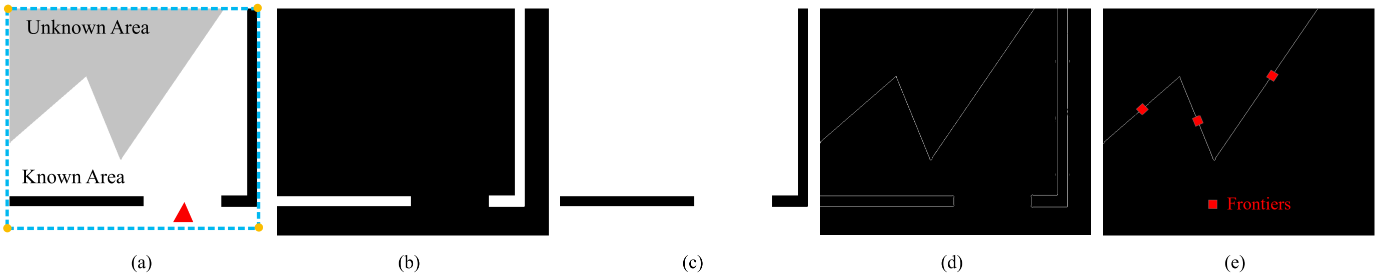


Fig. 4: The frontier extraction based on image processing. (a) the map within the expected area; (b) binary processing; (c) obstacle extraction; (d) canny edge detection; (e) frontiers at the gravity centers of the extracted edges.

$$\Phi(x, y, z) \rightarrow (x', y') \tag{1}$$

$$x' = \frac{x * f_x}{z} + c_x \tag{2}$$

$$y' = \frac{y * f_y}{z} + c_y \tag{3}$$

In this work, a depth camera is utilized and the depth coordinate z of the point P can be obtained directly, and then the 3D points in the global coordinate system can be obtained by the back projection equation. In order to facilitate the actual conversion calculation, we use homogeneous coordinates to represent the camera parameters, so the conversion from 2D point to 3D point can be expressed as:

$$\begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}. \tag{4}$$

The camera internal parameter (f_x, f_y, c_x, c_y) can be obtained from the internal parameter calibration of the depth camera.

B. Extracting Frontiers in the Expected Area

After the heuristic object recognition, an association between the heuristic object with an expected area is formulated firstly. The association process is inspired by the prior knowledge about the indoor environment. Herein, we take the door as an example again. As shown in Fig. 5, the red triangle represents the position of the door, and the yellow circle indicates the position of the robot. According to the prior knowledge that the area behind the door is usually a room, we use the relative position relationship between the robot and the door in the map to determine the location of the expected area on the map. Because in the indoor environment, the shape of the room is often similar, and the heuristic area we build is a rectangular area with the position of the door as the center, extending a to the left and right, and extending back $2b$, in which the parameter aline b is set by experience. In order to enable the robot to explore the room area completely, the expected area we constructed is slightly larger than the room area of the actual map. After that, the four vertex coordinates of the expected area are obtained on the map and the frontiers are then extracted in this area.

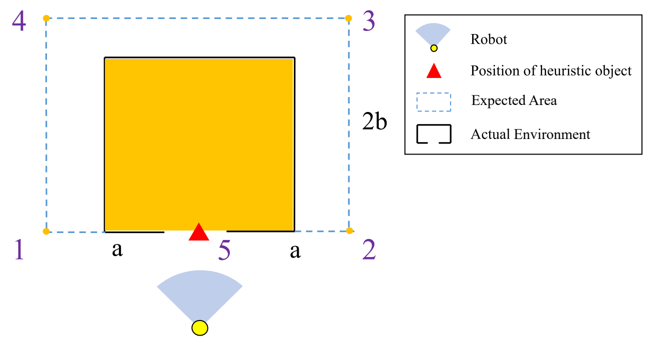


Fig. 5: The association from the heuristic object to the expected area.

Herein, we firstly compare the two methods of extracting frontiers based on image processing and RRT, respectively. As mentioned in Sec. II, the image processing process based method is usually more efficient when the size of the map is small. With the expansion of the map, it consumes more computing resources, and the speed of frontier extraction is slower than that of the method based on RRT. The frontier extraction method based on RRT is to randomly scatter points in the known area of the map and each time the tree grows a branch in the direction of the random point. When the branch grows to the boundary, a frontier is then found. Because the growth direction of the tree is random every time, the extraction speed of the frontiers in the corner of the map is slow. In this work, a high frontier extraction efficiency is required, otherwise, the robot will leave the current room before completing the exploration in the expected area. Moreover, the size of the expected area is also limited. Therefore, we use image processing technology to extract the frontiers within the expected area, and adopt the RRT-based method in other areas outside the expected area.

The frontier extraction process based on the image processing is shown in Fig. 4. Fig. 4(a) shows the map within the expected area, where the grey represents the unknown area, the white denotes the free area and the black denotes the obstacle area. The extraction process can be divided into the following steps:

- Firstly, a binary processing is performed on the original map, where the obstacles are marked as white and the

TABLE I: Statistics of the environmental sizes.

size	$map1$	$map2$	$map3$
map	$11 \times 14\ m^2$	$20 \times 15\ m^2$	$24 \times 10\ m^2$

rest turns black, as shown in Fig. 4(b);

- By reversing Fig. 4(b), the obstacles are then extracted as black, as shown in Fig. 4(c);
- A canny edge detection is carried out on Fig. 4(a) on the basis of OpenCV, and the edge of the image is white and the rest is black, as shown in Fig. 4(c);
- The image obtained in the second and third step is operated according to the bit, and the corresponding image is white only when the corresponding place is white. The boundary of the unknown area of the map is then obtained, as shown in Fig. 4(e), which is composed of straight lines;
- Take the centers of gravity of straight lines as the frontiers.

C. The Robot Exploration Strategy based on the Expected Frontiers

After the frontier extraction in the expected area, a series of expected frontiers can be obtained. A utility function is then designed for the frontier selection, which is formulates as follows:

$$U_f = h * I_f - N_f \tag{5}$$

$\boldsymbol{I_f}$ **(Information Gain):** the number of unknown grids in the circle with the location of the frontier as the center and the information gain radius r as the radius.

$\boldsymbol{N_f}$ **(Path Cost):** the Euclidean distance between the current position of robot and the position of frontier.

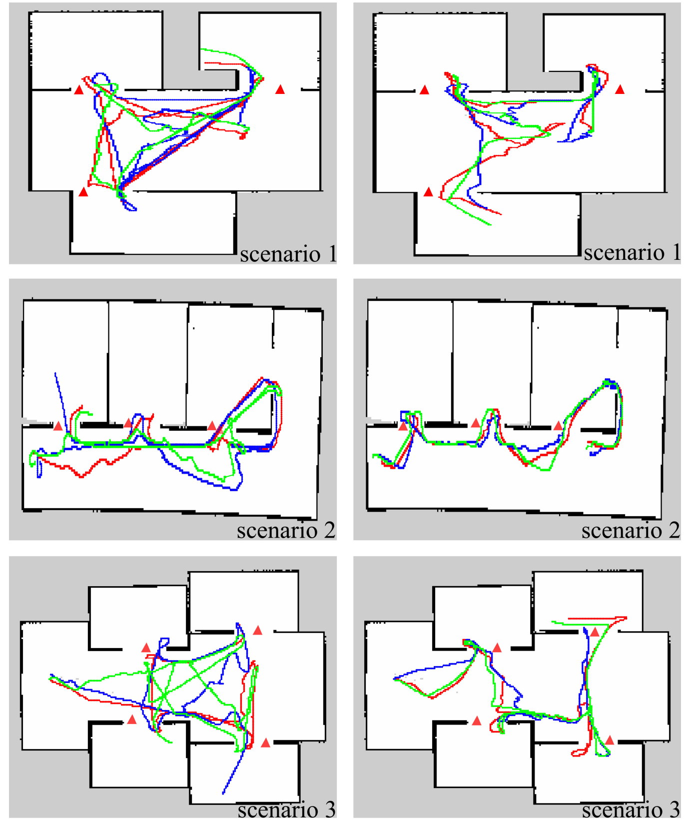
where h is user-defined constant which is used as a weight.

Our exploration strategy is that when a heuristic object is identified, it means that the robot is near an unexplored room area. After the frontiers are extracted by image processing technology, the robot will be guided to enter the room area. When all the expected frontiers have been explored, indicating that the exploration of the expected area has been completed, the robot then turns to the RRT frontiers to explore. When a expected area is explored, the expected area model is destroyed immediately, which makes it easy for the robot to identify the next expected area and avoids the repeated establishment of the same expected area.

IV. EXPERIMENTAL STUDIES AND RESULTS

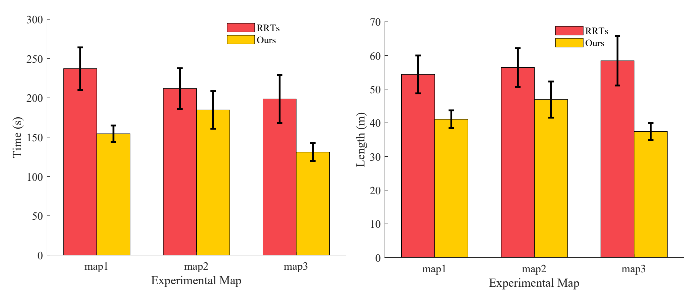
In order to verify the effectiveness of our proposed robot exploration method, the experimental studies are carried out and a laptop computer with Intel Core i7-9750H CPU @2.6 GHz and 16 GB RAM is adopted as the computing platform. The RRT-based robot exploration algorithm [2] is adopted as a reference.

The experiment is conducted on the basis of the Robot Operating System (ROS) [24]. Three different exploration environments are included, and their corresponding size are listed in Table I. The experimental environments are randomly constructed, and each environment contains different heuristic objects, namely the doors. The difference lies in the relative positions of the heuristic objects: some are close to each other, and some are far away, as shown in Fig. 6. The perception range of the laser rangefinder is set with 180° field of view, and the sensing distance is all set to 7 m. For each experimental environment, 10 times repeated trials are conducted for each method.



(a) RRT-Exploration (b) Ours

Fig. 6: Robot exploration trajectories in three typical scenarios. The red triangle indicates the location of the heuristic object.



(a) (b)

Fig. 7: Experimental results of the robot exploration. The left figure shows the time of exploration, and the right figure shows the length of exploration path.

As shown in Fig. 6, the trajectories during the robot exploration in three environments are recorded and the left column shows that of the RRT-Exploration and the right column shows that with our algorithm. In order to show the trajectories more clearly, we only randomly select three sets of data to display. We can see that the backtracking phenomenon of the RRT-Exploration method is serious and many repeated routes are generated in the environment, while the exploration trajectories of our method have no great twists and turns. It indicates that the proposed method can solve the backtracking phenomenon well. In addition, the runtime and path length of the robot are also recorded, as shown in Fig. 7. The experimental results show that in the first map, our method reduces the exploration time by 34.9% and the length of exploration path by 24.5% compared with the RRT-based algorithm. In the second map, our method reduces the exploration time by 12.8% and the exploration path length by 16.9%. In the third map, our method reduces the exploration time by 34.0% and the exploration path length by 35.9%.

From the experimental results, we can see that our method has a significant improvement in exploration efficiency compared with the RRT-based method. Due to the randomness of the sampling, the RRT-Exploration method often can not detect the frontiers at the corner of the unknown map in time. Moreover, since the RRT-Exploration method does not distinguish the frontiers inside and outside the expected area, when the utility value of the frontier outside the expected area is larger, the robot will stop exploring the current area and turn to another. Therefore, its backtracking phenomenon is serious and the exploration efficiency is relatively low. On the other hand, the proposed method makes full use of the geometric continuity of the environment structure and distinguishes the frontiers inside and outside the expected area, which effectively avoids the backtracking phenomenon. In conclusion, the effectiveness of our algorithm has been fully proved from the two indicators of exploration time and path length.

V. CONCLUSIONS

In this paper, we have proposed an exploration method based on the prior information heuristic for the indoor environment. Firstly, the lightweight network model has been designed for the heuristic object recognition. Secondly, the expected area is associated with the heuristic object, and the frontiers inside the expected area are efficiently extracted by the method of image processing. Finally, the robot is guided to explore the frontiers in the expected area until the exploration of the expected area is completed. The experimental studies have been carried out on different scenarios and the experimental results have revealed that the proposed strategy greatly reduces the backtracking phenomenon and improves the exploration efficiency, which prove the effectiveness of our proposed method.

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