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ROBOT AUTONOMOUS FRONTIER EXPLORATION STRATEGY BASED ON THE IDEA OF IMAGE PROCESSING

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Abstract. *Autonomous exploration of unknown environment is a well-known problem in the field of robotics. Frontier-based exploration technique is a frequently used autonomous exploration strategy for two-dimensional environment. This paper proposes a modified frontier exploration strategy based on the idea of image processing. The strategy includes partitioning the frontier from the map image using image processing methods and then choosing the best exploration frontier and best exploration goal, using a combination of DWA (Dynamic Window Approach) and D* algorithm to guide the robot to the exploration goal. The whole project is realized on the ROS (Robot Operating System) platform. First, we use the Cartographer SLAM algorithms and laser radar to obtain current environment map. Then, OpenCV is used to process the environment map, extract the frontiers and determine the best exploration target. Finally, guide the mobile robot to the exploration target with the move base package in ROS. Iterate over the process until the whole environment is explored. To validate the efficacy of the strategy, it is compared with the classic closest frontier exploration and the maximum information gain exploration.*

Keywords: Frontier-based, Autonomous exploration, Image processing, ROS

1. Introduction.

Autonomous exploration of an unknown territory has drawn more and more researchers' attention in recent years. The technology of autonomous mobile robot exploration has also been widely applied to various occasions with different purposes, such as rescue [1], planetary exploration [2], and water exploration [3]. One of the most important key points of an autonomous robot is its ability to construct spatial models and maps about their environments. For a robot to autonomously expect such an unknown environment, it must sequentially sense the environment at new sensing locations where the robot could perceive the environment to expand the existing mapped area [4].

During exploration, autonomous mobile robot must be able to find the next best target location or point to guide mobile robot to explore the unknown environment. In literature, one of the most popular autonomous exploration strategies in unknown environment is the frontier-based exploration [5]. The key idea in the frontier-based exploration is to determine the next desired positions for the mobile robot based on frontiers [6]. The frontiers mean the cells in the boundary between the mapped free and unmapped cells from an Occupancy Grid Map, and the exploration strategies based on this theory are called frontier-based exploration.

Different criteria used for the selection of the next intermediate target have resulted in various extensions of the basic frontier-based explorations strategy, such as electing the closest frontier cell, and balancing the information gain of frontier cells with travel cost [7, 8]. In the pioneer work of [9], a heading informed frontier exploration method is developed and tested on a mobile robot to a challenging take of self-exploration in

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unknown space. With an additional rotation cost function, this method is more efficient than the basic frontier-based exploration. However, this method does not improve the exploration efficiency of two-wheeled mobile robots, because the cost of robot rotation is very small. In [10], the authors presented a novel approach to dynamically generate safe and reachable frontier points. Only the current laser data and topological information are processed. The disadvantage of this method is that it is more complex and costs more to calculate. In [11], the authors proposed a novel approach to predict a robot's most informative exploring a priori unknown environments with a range-sensing mobile robot. In this paper, only the local unknown environment exploration is studied, and the global environment exploration is not considered. Therefore, engineering practicability is low.

In this work, on the purpose of improving the engineering realizability and exploration efficiency, we present an autonomous exploration strategy based on the idea of image processing. The whole project is realized on the ROS (Robot Operating System) platform. First, we use the Cartographer SLAM algorithms and laser radar to obtain current environment map. Then, OpenCV is used to process the environment map, extract the frontiers and determine the best exploration target. Finally, guide the mobile robot to the exploration target with the move base package in ROS. Iterate over the process until the whole environment is explored.

The rest of this paper is organized as follows. The proposed approach is described in detail in Section 2. The system composition is detailed in Section 3. The experimental results are shown in Section 4. In Section 5, conclusion is presented.

2. Proposed Methods.

The method of robot autonomous exploration proposed by us is mainly divided into three parts: environment map acquisition, frontiers extraction, and calculation of the best frontier exploration point. The detailed description of each part is given and defined below.

2.1. Environment map acquisition.

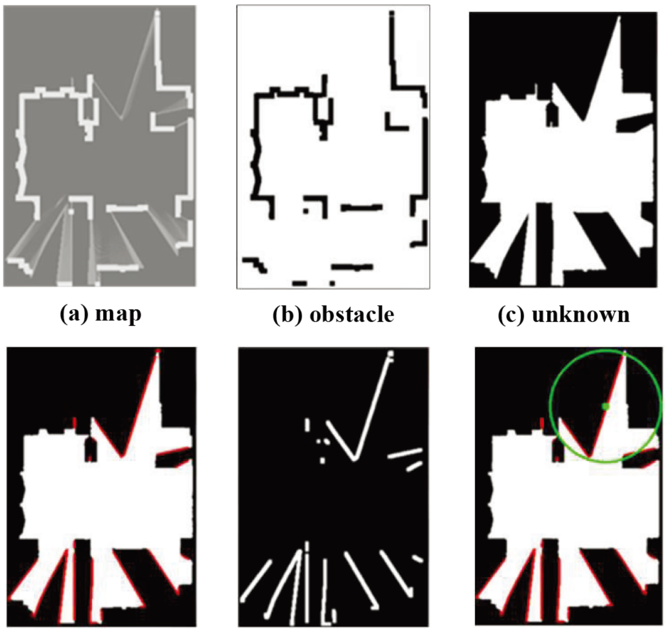
Simultaneous Localization and Mapping (SLAM) is the problem of building a map of an unknown environment while simultaneously keeping track of a robot's position within it. The Cartographer is an open source laser SLAM developed by Google, and it provides real-time simultaneous localization and mapping in 2D and 3D across multiple platforms and sensor configurations. In this work, we use the Cartographer SLAM algorithms and a 2D laser radar to obtain current environment map. The Cartographer has provided ROS integration, we just need to configure the specific parameters of our robot in the project, and then we can get the real-time environment map.

The Cartographer map provided is a one-dimensional array, with each element corresponding to the probability of occupation of a map grid. The array element values from 0 to 100 represent the probability of the map grid being occupied from 0 to 100 percent. The value -1 indicates that the map grid has not been explored yet. We use `CV_8S` Mat in OpenCV to store the map, and store the array elements in Mat in the order from bottom left to top right. An overview of the environment map can be observed in Figure 1(a).

Then, according to the pixel value, we need to divide the map image into obstacle layer and unknown layer. The obstacle layer is defined as:

$$S(x,y) = \begin{cases} 0 & \text{if } M(x,y) > 65 \\ 255 & \text{otherwise} \end{cases} \tag{1}$$

where S is the obstacle layer image, $S(x,y)$ is the pixel value of S at the point (x,y), M is the map image, and $M(x,y)$ is the pixel value of the M at the point (x,y). The extracted obstacle layer is shown in Figure 1(b).



(a) map (b) obstacle (c) unknown

(d) frontier point (e) frontier connectivity domains (f) exploration goal

FIGURE 1. The process of best frontier extraction

Similarly, the unknown layer is defined as:

$$U(x,y)=\begin{cases}0 & \text{if } M(x,y)=-1\\ 255 & \text{otherwise}\end{cases} \tag{2}$$

where U is the unknown layer image, $U(x,y)$ is the pixel value of U at the point (x,y), M is the map image, and $M(x,y)$ is the pixel value of the M at the point (x,y). The extracted unknown layer is shown in Figure 1(c).

2.2. **Frontier extraction.** In order to ensure the effectiveness of the frontier extraction, we need to expand the obstacles in the map image. The operation is defined as follows:

$$S_e = S \ominus B \tag{3}$$

$$M_e(x,y)=\begin{cases}100 & \text{if } S_e(x,y)=0\\ M(x,y) & \text{otherwise}\end{cases} \tag{4}$$

where S is the obstacle layer image in Formula (1), B is a rectangular structuring element, $\ominus$ is the erode operator, and S_e is the eroded obstacle layer image. M_e is the map image after expanding the obstacles, and $M_e(x,y)$ is the pixel value of M_e at the point (x,y). $S_e(x,y)$ is the pixel value of S_e at the point (x,y). $M(x,y)$ is the pixel value of the M at the point (x,y).

After the above processing of the map image, the next extract the frontier point. If a point (x,y) in the M_e satisfies any of the following rules, the point (x,y) is considered as the frontier point. The frontier point decision rule is defined as:

$$\begin{cases}0 \leqslant M_e(x-1,y) \leqslant 65 & \&\& \quad M_e(x,y)<0\\ M_e(x-1,y)<0 & \&\& \quad 0 \leqslant M_e(x,y) \leqslant 65\\ 0 \leqslant M_e(x,y-1) \leqslant 65 & \&\& \quad M_e(x,y)<0\\ M_e(x,y-1)<0 & \&\& \quad 0 \leqslant M_e(x,y) \leqslant 65\end{cases} \tag{5}$$

An example of frontier points extraction in this work is shown in Figure 1(d), the frontier points are marked. Drawing the frontier points in a single image, which is called

F, image F is processed as follows:

$$F_d = F \oplus B \tag{6}$$

where B is a rectangular structuring element, $\oplus$ is for dilation operation, and F_d is the dilated frontier points image, as shown in Figure 1(e). It can be seen form the figure that the frontier connectivity domains are formed through the frontier point of dilation. For each frontier connectivity domain, calculate its minimum bounding circle. Then calculate the center and radius of each minimum bounding circle. At this point, the frontier information of the map has been extracted.

2.3. **Calculation of the best frontier exploration point.** In the previous step, we have obtained the minimum bounding circle of each frontier. In this work, we define the radius of the minimum bounding circle as the information gain, and the distance from the center of the circle to the current position of the robot is the cost. In order to balance the two parameters, we define the evaluation function as:

$$e = radius/dis \tag{7}$$

where $radius$ is the radius of the minimum bounding circle, and dis is the Euclidean distance from the center of the circle to the robot position. Calculate e for each frontier, take the frontier with the largest value of e as the best exploration frontier, and take the center of its minimum bounding circle as the best exploration goal. An example of the best exploration frontier and best exploration goal in this work are shown in green circle and dot in Figure 1(f).

3. **System Composition.** This section discusses the principal aspects of the system under consideration and the framework required to implement the proposed modified frontier exploration algorithm.

3.1. **Computing platform.** The platform used for the implementation of this project is ROS (Robot Operating System). ROS is an open-source system used to control robots remotely. It is a collection of various libraries and packages, which simplifies tasks like manipulating complex robot behavior.

Gazebo simulator is chosen for simulating the entire autonomous exploration process. Gazebo provides the functionality to simulate complex indoor and outdoor environments containing one or more robots and includes physics engines using which certain physical systems can be simulated.

3.2. **Simulated environment.** The simulated environment is an indoor room built in Gazebo, and a mobile robot with a laser lidar on top is placed in the simulation environment, as shown in Figure 2.

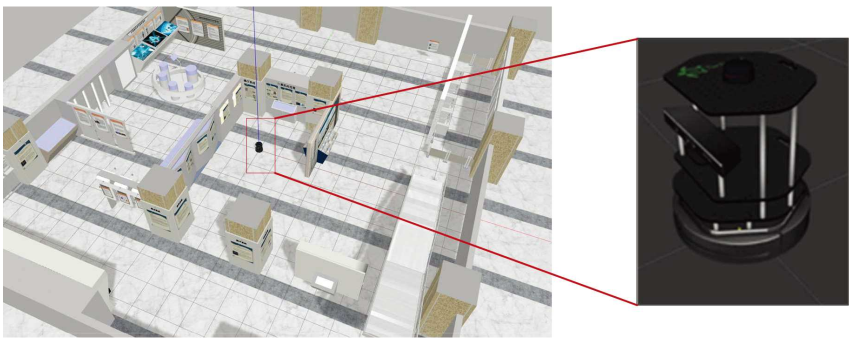


FIGURE 2. Simulated environment

3.3. **Robot's transform tree.** The transform tree reflects the coordinate relationship between the robot components and the map, which is the basis for the correct operation of the robot. In this work, the transform tree is built as shown in Figure 3.

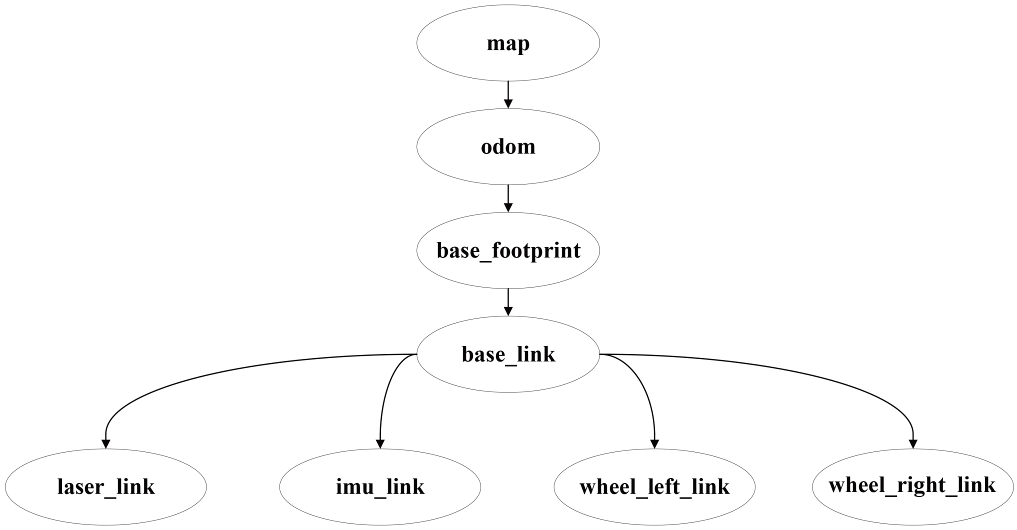


FIGURE 3. Robot's transform tree

3.4. **ROS node relationship.** The ROS node relationship in this work is shown as Figure 4. The robot node provides the cartographer node sensor data, such as laser scan and odometer information. Then the cartographer node subscribes to the sensor data while publishing the environment map and current robot location. The frontier exploration node acquires the map and robot location, and uses the method described in Section 2 to calculate the optimal goal point. Finally, the move base node uses DWA (Dynamic Window Approach) and D* algorithms to guide the robot to the exploration goal. Iterate over the process until the whole environment is explored.

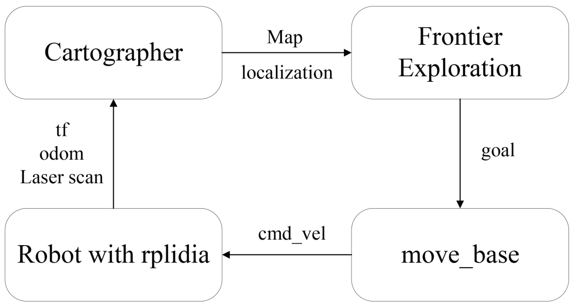


FIGURE 4. ROS node relationship

4. **Experiment Conclusion.** The proposed approach is tested in a 1 : 1 museum simulation environment in gazebo, as shown in Figure 2. The system is running on a computer with Intel i7-7700HQ processor and 16 GB memory. In order to evaluate the performance of our proposed method, we compare this method with the closest frontier method and the maximum information gain method.

The process of the closest frontier method is shown as Figure 5. Due to the unreasonable choice of exploration points, the robot will be easily trapped in a narrow exploration position. In Figure 6, since the robot only tends to explore the target to obtain the maximum information, there are too many repeated paths in the exploration process. In Figure 7, we can see that the exploration path of the method we proposed has no repeated parts, and the exploration process is smooth and efficient.

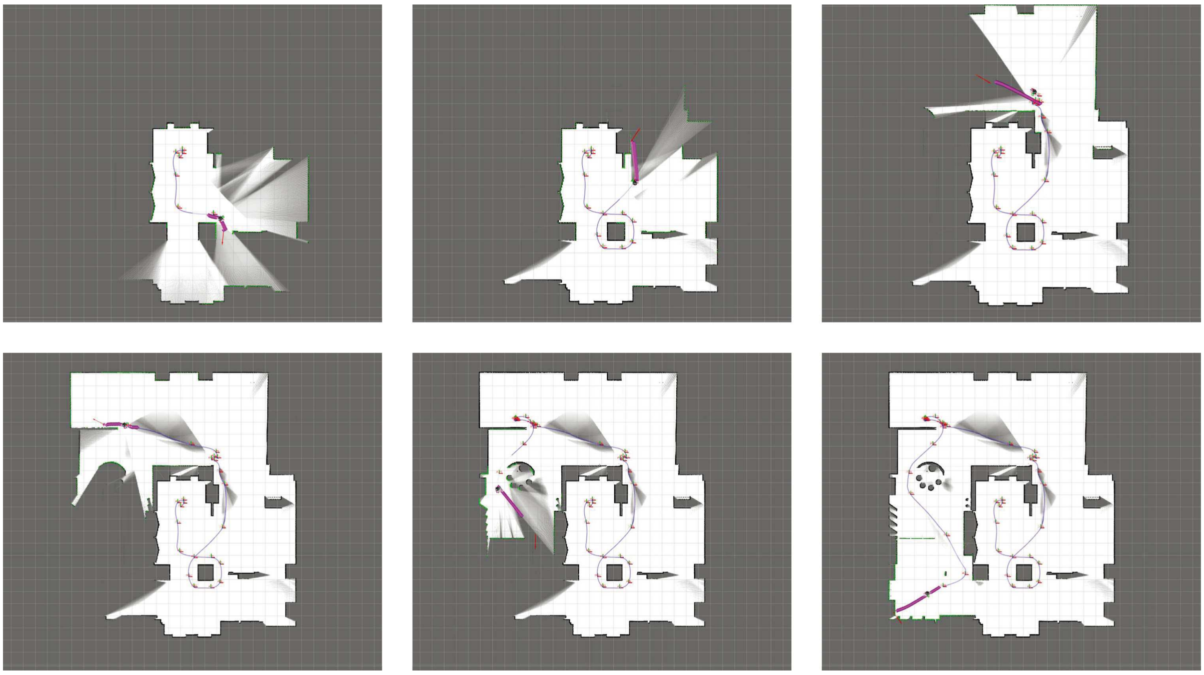


FIGURE 5. The process of the closest frontier method

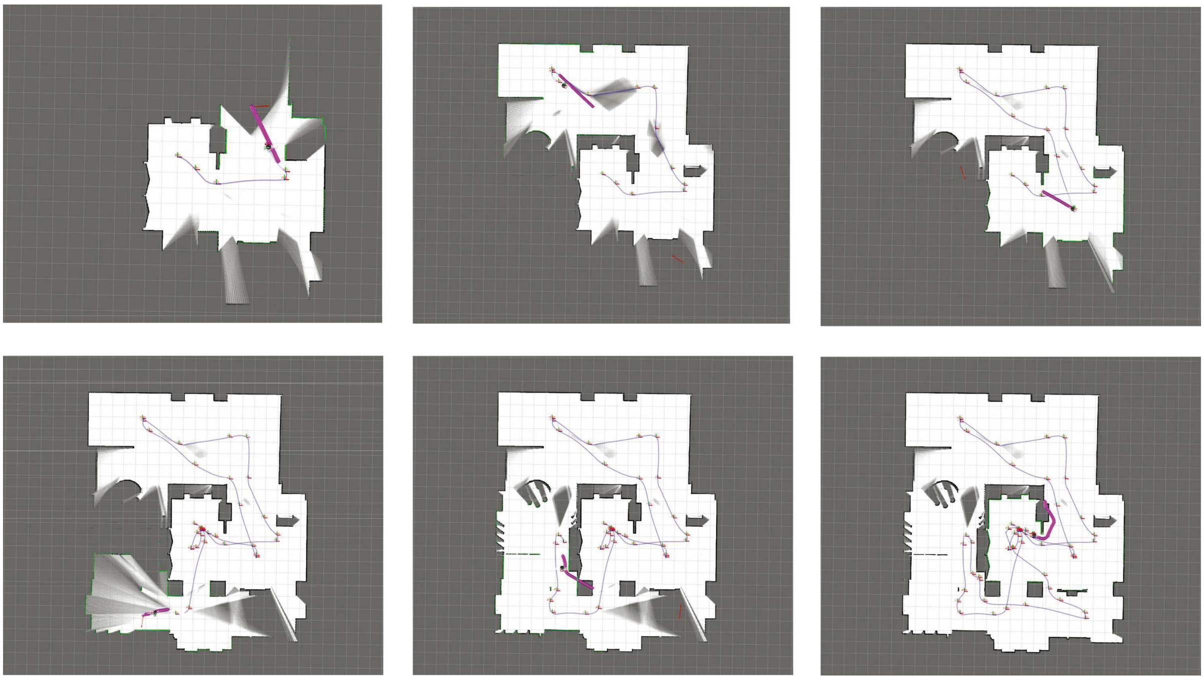


FIGURE 6. The process of the maximum information gain method

The result comparison of three methods is shown in Figure 8. The original point, end point and trajectory of the robot are marked in the figure. Compared with the other two methods, the exploration path obtained by the method proposed in this paper is more reasonable. In terms of exploring time, as shown in Table 1, the method proposed in this paper takes the least time. The experimental result validates the superior exploration efficiency of the proposed method compared to the traditional autonomous exploration methods.

5. **Conclusion.** This paper presents an autonomous exploration strategy based on the idea of image processing. The technique includes partitioning the frontier from the map

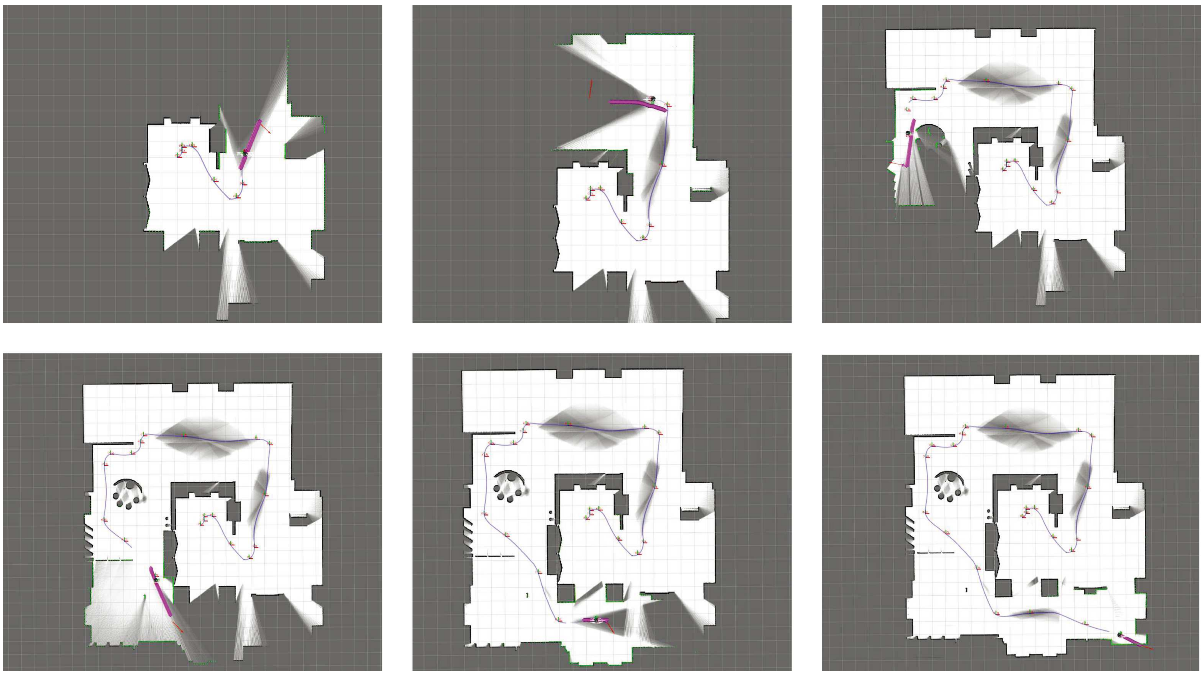
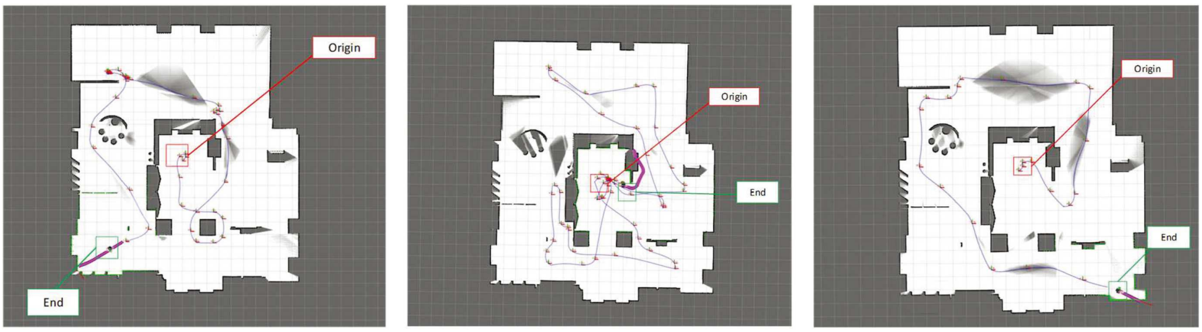


Figure 7. The process of the method in this paper



(a) Closest Frontier **(b) Maximum Information Gain** **(c) Method in this paper**

Figure 8. The result comparison of three methods

Table 1. The time cost comparison of three methods

Method	Time (s)
Closest frontier	431
Maximum information gain	515
Method in this paper	292

image using image processing methods and then choosing the best exploration frontier and best exploration goal, using a combination of DWA (Dynamic Window Approach) and D* algorithm to guide the robot to the exploration goal. The proposed strategy is found to significantly reduce time required when compared with the traditional closest frontier exploration algorithm and the maximum information gain exploration algorithm. The path taken by the mobile robot is also found to be simpler and efficient, thereby proving the effectiveness of the proposed exploration technique. In the future work, we will verify the effectiveness of the algorithm in the real environment. According to the actual operation, the camera data will be integrated into the autonomous exploration process of the robot to obtain more stable and reliable exploration results.

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