Explore-Bench: Data Sets, Metrics and Evaluations for Frontier-based and Deep-reinforcement-learning-based Autonomous Exploration

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Abstract—Autonomous exploration and mapping of unknown terrains employing single or multiple robots is an essential task in mobile robotics and has therefore been widely investigated. Nevertheless, given the lack of unified data sets, metrics, and platforms to evaluate the exploration approaches, we develop an autonomous robot exploration benchmark entitled Explore-Bench. The benchmark involves various exploration scenarios and presents two types of quantitative metrics to evaluate exploration efficiency and multi-robot cooperation. Explore-Bench is extremely useful as, recently, deep reinforcement learning (DRL) has been widely used for robot exploration tasks and achieved promising results. However, training DRL-based approaches requires large data sets, and additionally, current benchmarks rely on realistic simulators with a slow simulation speed, which is not appropriate for training exploration strategies. Hence, to support efficient DRL training and comprehensive evaluation, the suggested Explore-Bench designs a 3-level platform with a unified data flow and $12 \times$ speed-up that includes a grid-based simulator for fast evaluation and efficient training, a realistic Gazebo simulator, and a remotely accessible robot testbed for high-accuracy tests in physical environments. The practicality of the proposed benchmark is highlighted with the application of one DRL-based and three frontier-based exploration approaches. Furthermore, we analyze the performance differences and provide some insights about the selection and design of exploration methods. Our benchmark is available at https://github.com/efc-robot/Explore-Bench.

I. INTRODUCTION

Autonomous exploration of unknown environments aiming to acquire information and to build a map is a fundamental task for mobile robotic systems that has been widely investigated in a single-robot or multi-robot setup. Traditional exploration methods are based on frontiers that separate the free from the unknown regions [1]–[4]. The main difference among these strategies considers selecting the frontiers to be visited next, with the majority of these techniques being greedy or heuristic, e.g., cost-based [5], [6], sample-based [7], and potential field-based exploration [8].

While mobile robot exploration approaches have been widely investigated, there is still a lack of a unified benchmark for performance evaluation. The researchers typically challenge their newly proposed exploration strategy against other approaches through custom-designed simulation or experimental scenarios, with the relevant data sets usually being unavailable. Moreover, some specific scenarios may be explicitly chosen in favor of their proposed approach. Hence, the lack of unified data sets discourages the evaluation from being reproducible and objective. Adding to the unavailable public data sets, there is also a lack of a complete and principled evaluation system appropriate for mobile robot exploration approaches. Currently, the performance metric quantifying the exploration results is usually limited to the exploration cost or efficiency, as there is no metric to evaluate the multi-robot cooperation and task allocation, which are essential in multi-robot exploration scenarios.

Deep reinforcement learning (DRL) approaches have been proposed to address the exploration tasks, outperforming traditional approaches in several scenarios [9]–[11]. However, DRL-based methods require iterative interactions with the environment to obtain training data. Current robotics benchmarks utilize realistic-but-slow simulation platforms such as Gazebo [12], and Player/Stage [13], which are incapable of providing sufficient training data for DRL in a reasonable time frame. Both simulators consume enormous computing resources, as first they render the sensor data and then build the corresponding map.

Given that DRL algorithms exclude the specific method of location and mapping, we design a grid-based simulator that directly provides the localization and mapping results for DRL-based exploration achieving $12 \times$ speed-up compared to Gazebo. Moreover, DRL-based exploration strategies require diverse training data. Opposing to Gazebo, which provides dozens of scenarios manually, the proposed grid-based simulator can automatically generate thousands of scenarios.

In addition to the fast grid-based simulator, the realistic simulators (such as Gazebo) and the real world deployment are mandatory for comprehensive evaluation. Therefore, we design a 3-level platform including a fast grid-based simulator, Gazebo, and a real-world testbed. To guarantee the consistency of the evaluation results and reduce the difficulty of deployment on different levels, we employ a unified data flow and interface. Overall, we propose an autonomous exploration benchmark called Explore-Bench, providing unified data sets, evaluation metrics and fast-to-deploy platform. We further evaluate the traditional and DRL-based methods on our 3-level benchmark, verify the metrics’ effectiveness and practicality, and provide some insights regarding the selection and design of exploration strategies.

The contributions of this paper are summarized as follows:

1) Data Sets: We design various open-source exploration scenarios to improve the comprehensiveness and objectivity of the evaluation system. Opposing to current benchmarks...
that involve several fixed simulation scenes, we define the critical elements of common exploration scenarios, i.e., loop, narrow corridor, corner, and multiple rooms, and combine them to form rich data sets.

2) Metrics: We propose two types of metrics to evaluate the exploration strategies’ performance from various aspects. Specifically, efficiency metrics, as a form of quantitative metrics, utilize the total exploration time and the intermediate time when robots cover most unknown regions. Collaboration metrics include the standard deviation of the independent exploration areas and the ratio of the overlapping exploration area by multiple robots.

3) Platform: We assist researchers to efficiently develop and evaluate their DRL-based exploration algorithms by designing a fast grid-based simulator with 12× speed-up compared to realistic simulators. Combined with Gazebo and the real remotely accessible testbed, our benchmark forms a 3-level platform.

4) Evaluations: We highlight the effectiveness of the proposed benchmark on four representative exploration methods: cost-based frontier exploration [14], sample-based RRT-explore [7], potential field exploration SMR-explore [8] and DRL-based exploration [11], [15]. Each method is implemented in a single-robot setup and a multi-robot one.

II. RELATED WORK

Autonomous exploration of unknown environments has been widely investigated in mobile robotics. Traditional methods adopt frontier-based techniques, first proposed by Yamauchi et al. [1]. Cost-based methods [5], [6], [16] always navigate robots towards the nearest frontier and can be easily extended to a multi-robot setup, where robots share information but select the nearest frontier independently [4]. To enable efficient exploration, Umar et al. [7] propose a sample-based exploration method that employs multiple Rapidly-exploring Random Trees (RRTs) to detect the frontier. Yu et al. [8] design a potential field exploration method termed SMR-Explore to eliminate the goal’s back-and-forth changes. Deep reinforcement learning (DRL) allows a robot to learn from its own experiences and to generate adaptive goals for unknown environments. Nirouei et al. [9] design an Asynchronous Advantage Actor-critic (A3C) [17] network to output the goal frontier when the map, robot’s location, and all possible frontiers are a priori known. Zhu et al. [10] also train an A3C policy, but the output is the next visiting direction. Chaplot et al. [11] adopt a global policy and predict a long-term goal for the entire unknown area.

In the context of autonomous robotic exploration, the literature offers several performance evaluations and benchmarking studies. For example, Amigoni et al. [18] experimentally assess the strengths and weaknesses of four single-robot exploration strategies. Couceiro et al. [19] introduce two performance metrics and conduct several simulation experiments to benchmark five multi-robot exploration and mapping algorithms. Faigl et al. [20] develop an evaluation methodology and provide a benchmark to compare frontier-based approaches in a well-defined evaluation environment.

Fig. 1: Screenshots of typical simulation scenarios in Gazebo
(a) loop: square loop, (b) narrow corridor, (c) corner: clutter environment with many corners, (d) multiple rooms, (e) square loop with four narrow corridors, (f) four rooms with many corners.

Yan et al. [21] present a collection of metrics to objectively compare different algorithms that can be applied to collaborative multi-robot exploration. However, none of these works provide public data sets to evaluate exploration approaches nor principled metrics to evaluate each method’s exploration efficiency and multi-robot coordination capabilities. Furthermore, the slow simulation speed of the experimental platforms employed does not afford to develop and evaluate DRL-based approaches.

III. DATA SETS

Our data sets contain the following typical basic scenarios and their combinations.

A. Loop

A loop often appears in indoor scenarios as an environmental structure, with Fig. 1(a) presenting a simple 20 × 20m² square loop. The shape of a loop can also be circular or other. Robots are more likely to revisit areas that have already been explored when the task involves a loop closure. This process is known as overlapping and is a significant source for exploration inefficiency. Therefore, the scenarios involving loops are appropriate for evaluating the stability and sustainability of an exploration approach.

B. Narrow Corridor

Narrow corridors often appear as the junction of two regions. The corridor can be winding or straight, and the width can also be changed. For example, the scenario illustrated in Fig. 1(b) has a 6m long narrow corridor connecting two 7 × 20m² spaces. When robots come across a narrow corridor, they must decide whether to enter it or to continue exploring the current space. It should be noted that a robot’s ability to pass through a corridor smoothly and quickly is essential for autonomous exploration. This scenario is designed to challenge the flexibility and safety of the exploration algorithm under evaluation.

C. Corner

Although corners represent an environmental feature type with limited information gain, they still must be explored for completeness. Fig. 1(c) presents a typical scenario that is
cluttered with small corners. When a robot meets a corner, it can make one of the following decisions. Either pursue the short-term gain, i.e., not exploring the remaining unexplored small corners and prioritize the exploration of large areas, or plan for the long term, i.e., visit every corner in time to avoid backtracking, as these missing unexplored parts might impose a high backtracking cost. This type of scenario can comprehensively reflect the balance between exploration completeness and efficiency and the trade-off between an exploration approach’s short and long-term gain.

D. Multiple Rooms

Multiple rooms are common in indoor exploration tasks, with a typical office-like environment considering five 6 × 6m² rooms presented in Fig. 1(d). A specific scenario may vary in the number, size, and distribution of the rooms. In this work, we design scenarios involving multiple rooms to evaluate the overall performance of an exploration method.

E. Combination

The above basic scenarios are simple in structure and evaluate specific key properties of the exploration algorithms. Nevertheless, we combine these and build more complex scenarios to evaluate the overall performance of the exploration approaches. Fig. 1(e)-(f) depict two combination examples: a square loop with four narrow corridors and rooms with many corners. It is worth noting that more combinations are open-source on our website and welcome the contribution from the community to enrich the data sets.

Considering Gazebo and real environment scenarios, these must be created manually. Therefore, we design ten simulation scenarios for Gazebo and five for the real testbed. Our benchmark also aims to provide rich data sets on the grid-based simulator for efficient DRL training, and therefore we provide thousands of scenarios generated automatically on the proposed fast simulator. The generation details of the latter will be introduced in Section IV.

IV. METRICS

A. Efficiency Metrics

In current autonomous exploration studies, common performance evaluation metrics are the total time required for exploration and the distance traveled per robot at the end of an exploration run. An exploration run terminates when the target exploration percentage of the entire environment is completed, e.g., 99%.

Typically, an autonomous exploration task is defined as a process where robots gradually explore unknown regions. Therefore, the robot’s behavior during exploration is equally important to the final exploration results, reflecting the algorithm’s performance from a new perspective. Hence, two efficiency metrics are proposed as follows:

- The total time $T_{total}$ when the exploration ratio is 99%.
- The time $T_{topo}$ when the exploration ratio is 90%.

In most scenarios, a 90% coverage indicates that the robots have acquired essential topological information, including the overall terrain structure and connectivity, which for exploration tasks such as disaster relief and target search are more important features than map completeness.

Exploiting these two metrics simultaneously reflects the strength and weakness of an exploration algorithm, as low exploration efficiency in the early stage to model all the details produce a small $T_{total}$ but large $T_{topo}$, which does not pose an optimum solution.

B. Collaboration Metrics

Our benchmark scheme supports multi-robot systems evaluation, and therefore we design the corresponding robot collaboration metrics to analyze the multi-robot exploration performance quantitatively. The rationality and fairness of the multi-robot exploration region allocation are evaluated through the load balance metrics. A well-performing multi-robot exploration approach should balance the areas explored by different robots, enhancing the system’s efficiency and robustness, and avoid uneven task distribution.

Let $N$ robots explore and map an unknown environment, with $S_i, 1 \leq i \leq N$ the area covered by the $i$-th robot when the exploration run ends. In this work, we evaluate the load balance of an exploration method utilizing the standard deviation $\sigma$ of the independent exploration areas:

\[ \sigma = \sqrt{ \frac{\sum_{i=1}^{N} (S_i - \bar{S})^2}{N} } \]

(1)

\[ \bar{S} = \frac{\sum_{i=2}^{N} S_i}{N} \]

(2)

Collaborative multi-robot exploration approaches greatly enhance exploration efficiency. Thus we evaluate the collaboration effectiveness by calculating the ratio $r_o$ of the overlapping area $S_o$ explored by multiple robots:

\[ r_o = \frac{S_o}{S_{total}} = \frac{\sum_{i=1}^{N} S_i - S_{total}}{S_{total}} \]

(3)

where $S_{total}$ is the total area of the terrain to be explored.

V. PLATFORM

To deploy and evaluate various exploration methods on the proposed data sets and metrics, we develop a 3-level platform involving a grid-based simulator (Level-0), a realistic simulator Gazebo (Level-1), and a real robot testbed (Level-2) as shown in Fig. 2(a). It is worth noting that the Level-0 simulator is especially designed for fast DRL training.

A. Data flow and interface

A complete autonomous exploration system follows the unified data flow presented in Fig. 2(b). The robots initially perceive their surroundings exploiting their onboard sensors, localize themselves and build the corresponding map. In a multi-robot system setup, the individually built maps are shared among all robots and merged into a single unified map. Then the exploration algorithm exploits the merged map and robot pose as input and outputs the goal locations to explore the environment further.
Our benchmark scheme utilizes the Robot Operating System (ROS) [22] and its open-source or modified packages to implement the unified data flow and interface for the Level-1 and Level-2 evaluation stages, containing the following modules:

- **Location Module**: The ground truth pose originating from the Gazebo parameters is employed for accurate localization. Given that in real environments the ground-truth robot pose is unknown, we utilize the `robot_pose_ekf` [23] package to estimate its 3D pose.
- **Mapping Module**: We adopt `Cartographer` [24] to perform a laser-based SLAM to build a 2-D occupancy grid map. Our platform also supports other laser-based mapping algorithms, such as `gmapping` [25]. In multi-robot scenarios, we modify the `multirobot_map_merge` [26] package to merge the maps created from all robots by exploiting their relative positions.
- **Exploration Module**: This module affords users to design their exploration algorithms and compare in our provided algorithm library. Each exploration method utilizes a unified 2D-map and the robots’ locations as input and outputs a goal (coordinates of a position) to navigate to. Hence, the proposed 3-level platform provides a unified interface for different exploration methods and different levels.
- **Motion Module**: We adopt the `move_base` [27] package for the path planning and collision avoidance.

**B. Fast grid-based simulator (Level-0)**

**Level-1** and **Level-2** are sufficient for evaluating traditional exploration methods. However, the expensive data resulting from the slow simulation speed prohibits efficiently training and evaluating deep learning techniques. The perception part in the unified data flow consumes huge computing resources and limits the simulation speed, with the most computation-intensive operations being the **Render Data** and **Mapping Algorithm** (Fig. 2c)). The former acquires sensor data from the environment and the latter converts the data into a map and optimizes the robot pose. These two operations impose the highest processing burden during a single processing step. Therefore, current exploration benchmarks do not consider DRL-based methods. To speed up the robots’ perception during simulation, we exploit the simplicity and controllability of our grid-based simulator and directly extract the local ground-truth map to quickly provide the inputs for the exploration methods under evaluation. Concretely, we first intercept the unobstructed perceptible area according to the robot’s current location and sensor range and then use Bresenham’s line algorithm [28] to simulate the 2D LIDAR scanning and mapping process. In the multi-robot setup, as a grid map is stored as an array, map merging is achieved by traversing the elements in the array and updating the status.

Considering the remaining modules:

- **Location Module**: The grid-based simulator updates a list with the robots’ states and poses.
- **Motion Module**: We provide a global planner utilizing the A* algorithm that aims to find the optimal and collision-free path. Then we calculate the robot’s approximate orientation and velocity at each grid cell along the path. Compared with Gazebo and the real robotics testbed, simulating the robot’s actual continuous motion can be neglected in the grid-based simulator, i.e., the robot “teleports” between the grid cells accelerating the simulation.

**C. Diverse simulation scenarios generator**

Diverse training scenarios benefit obtaining a robust and efficient DRL-based exploration policy. Unlike the scenarios in **Level-1/2** that are constructed manually, we present for **Level-0** two methods to create data sets automatically:

1) Relying on the Gazebo’s simulation scenario blueprints. Once designing a scenario in Gazebo is completed, we employ the `gazebo_ros_2Dmap_plugin` [29] to generate a 2D
occupancy map from the simulated world. The grid map from Level-1 can be directly added to the data sets of Level-0.

2) A built-in tool for automatically generating scenarios. A simulation scenario in the Level-0 is essentially a ternary matrix (occupied, free and unknown cases). Setting the value of elements in the matrix affords dividing rooms, building narrow corridors and loops, and placing corners. According to our combination of rules presented in Section III, we can generate countless simulation scenarios with little effort.

VI. EXPERIMENTS AND RESULTS

A. Setup

As already mentioned, we rely on Gazebo for the Level-1 simulator and implement the autonomous mapping and exploration utilizing some modified ROS packages. The simulation robot is a Turtlebot3 Burger [30] with a 360° laser scanner, whose distance range is 7m. The Level-0 grid-based simulator is implemented in Python and is accelerated through multiprocessing. All simulations and evaluations are performed on a Desktop PC with an Intel Core i7-7920 processor and an NVIDIA 1080Ti GPU. Considering the Level-2 testbed, we employ a real Xtrak robot [31] equipped with a laser scanner, an IMU sensor, and a wheel odometer.

B. Comparison of inference speed

Considering a single exploration task, we evaluate the simulation time and the CPU usage to illustrate the speed-up of the proposed platform, and demonstrate its appropriateness for fast DRL training and evaluation.

Suppose the scenario where a robot explores a straight corridor of 10m long. The maximum translational velocity is less than $1m/s$ [30], [31]. Hence, a real robot requires at least 10s to complete this task. Gazebo can achieve a high simulation speed-up, only accelerating the motion of the robot. However, as processing laser scan and mapping consume lots of computing resources, the largest speed-up factor for Gazebo during exploration is $3\times$ on our desktop, raising the CPU usage to 515\% and requiring 3.3s to complete the simulation. For the same task, our Level-0 grid-based simulator requires 1.43s imposing a 100\% CPU usage and thus affords parallelizing five more environments under the same computing resources. Hence, the training and evaluation efficiency increases by $12\times$ compared to Gazebo and $36\times$ to a real-world scenario as illustrated in Table I.

C. Consistency of evaluation results

We also evaluate the consistency of the experimental results obtained from our benchmark by deploying two exploration approaches in the five rooms scenario illustrated in Fig. [1(d)]. Table II indicates that the order (field performs better than cost) is preserved on different levels and the robot travels along a similar trajectory. Hence, the evaluation results remain consistent, highlighting that simulation acceleration through our grid-based simulator is effective.

D. Evaluation

We implement four typical autonomous exploration methods on our benchmark, with each technique implemented in a single and a multi-robot (two robots) version. The challenged methods are:

1) Cost: This approach always selects the nearest frontier during exploration [1]. For the multi-robot version, robots share perceptual information but select the nearest frontier independently [4].

2) Sample: This method detects frontiers utilizing the rapidly-exploring randomized trees (RRT) [7]. In this work, we extend RRT to facilitate multi-robot scenarios by growing multiple trees independently.

3) Potential Field: This approach builds the potential field from the surroundings and selects the frontier with the largest potential gradient [8]. Multi-robot cooperation is enabled by introducing a new repulsive potential between the robots.

4) Deep Reinforcement Learning: This technique deploys a DRL-based policy to determine the global goal [11] and then the nearest frontier to the global goal is selected. Training the policy for multiple robots requires exploiting the shared information through the entire robotic network, including the merged map and the robot’s relative pose. In this work, we only train the policy on the Level-0 simulator and evaluate the performance on all levels.

Table III and Table IV enumerate the quantitative statistics of the exploration approaches in Level-1 Gazebo for a single-robot and a multi-robot system, respectively. The data sets for evaluation are the six exploration scenarios depicted in Fig. [1]. For simplification, we use $loop$, $corridor$, $corner$, $room$, $comb1$ & 2 to represent them. The evaluation results in Level-0 and Level-2 are not shown in our paper due to the consistency of our platform. Given that the robots’ start pose affects the exploration performance, especially in the multi-robot system, we study two extreme cases: robots being far away from each other and being close to each other. The parameters of all modules except exploration module keep the same and researchers can refer to our website for details.

1) Comparison on Efficiency: The $T_{topo}$ and $T_{total}$ metrics of Table III and Table IV reveal an exploration efficiency ranking from high to low as follows: Potential field, sample, cost and DRL. The potential field method exploits the global information and integrates the distance to the frontier and the potential information gain. The sample-based method does not utilize global information and the frontier detection only relies on random tree generation. Although the frontier selection depends on distance and information

| TABLE I: Speed comparison on different levels |
|-----------------|-----------------|-----------------|
| Level-0     | 1.43 | 100 | 36x |
| Level-1     | 3.5  | 515 | 3x  |
| Level-2     | 10   | -   | 1x  |

| TABLE II: Consistency evaluation for different levels |
|-----------------|-----------------|-----------------|-----------------|-----------------|
|                | $T_{topo} (s)$  | $T_{total} (s)$ | $\sigma (m^2)$ | $r_o (%)$       |
| Level-0        | 134             | 100             | 172             | 125             |
| Level-1        | 145             | 101             | 201             | 131             |
| Level-2        | 119             | 84              | 130             | 93              |
TABLE III: Performance evaluation of exploration approaches in single-robot scenarios.

|       | cost | sample | DRL |
|-------|------|--------|-----|
|       | $T_{\text{topo}}$ (s) | $T_{\text{total}}$ (s) | $T_{\text{topo}}$ (s) | $T_{\text{total}}$ (s) | $T_{\text{topo}}$ (s) | $T_{\text{total}}$ (s) |
| loop  | 124  | 145    | 145 | 180 | 131 | 152    |
| corridor | 162  | 169    | 166 | 170 | 158 | 162    |
| corner | 210  | 425    | 171 | 331 | 133 | 324    |
| room  | 159  | 210    | 176 | 211 | 156 | 191    |
| comb1 | 169  | 175    | 141 | 192 | 165 | 183    |
| comb2 | 230  | 537    | 249 | 439 | 223 | 547    |

TABLE IV: Performance evaluation of exploration approaches in multi-robot scenarios.

|       | cost | sample | DRL |
|-------|------|--------|-----|
|       | $T_{\text{topo}}$ (s) | $T_{\text{total}}$ (s) | $\sigma$ (m²) | $r_o$ (%) | $T_{\text{topo}}$ (s) | $T_{\text{total}}$ (s) | $\sigma$ (m²) | $r_o$ (%) | $T_{\text{topo}}$ (s) | $T_{\text{total}}$ (s) | $\sigma$ (m²) | $r_o$ (%) |
| loop  | 1*   | 84     | 91   | 0.04 | 0.21 | 69     | 85     | 0.12 | 0.18 | 60     | 74     | 0.03 | 0.13    |
| corridor | c^2  | 111     | 131   | 0.03 | 0.91 | 80     | 84     | 0.06 | 0.13 | 68     | 73     | 0.05 | 0.15    |
| corner | f    | 51     | 74    | 0.02 | 0.06 | 66     | 88     | 0.01 | 0.01 | 50     | 54     | 0.01 | 0.01    |
|        | c    | 124     | 130   | 0.08 | 0.46 | 121    | 126    | 0.01 | 0.70 | 102    | 106    | 0.06 | 0.43    |
| room  | f    | 168     | 185   | 0.07 | 0.72 | 173    | 233    | 0.36 | 0.23 | 157    | 172    | 0.01 | 0.13    |
|        | c    | 174     | 185   | 0.13 | 0.54 | 101    | 132    | 0.03 | 0.21 | 129    | 152    | 0.11 | 0.67    |
| comb1 | f    | 145     | 201   | 0.08 | 0.32 | 113    | 138    | 0.13 | 0.32 | 101    | 131    | 0.04 | 0.16    |
|        | c    | 200     | 240   | 0.10 | 0.20 | 125    | 135    | 0.18 | 0.22 | 108    | 194    | 0.10 | 0.33    |
| comb2 | f    | 156     | 167   | 0.03 | 0.58 | 202    | 213    | 0.02 | 0.03 | 94     | 116    | 0.02 | 0.01    |
|        | c    | 296     | 299   | 0.10 | 0.10 | 118    | 127    | 0.10 | 0.10 | 114    | 116    | 0.02 | 0.02    |
|       | f    | 120     | 330   | 0.07 | 0.54 | 189    | 527    | 0.24 | 0.36 | 151    | 248    | 0.09 | 0.49    |
|        | c    | 146     | 168   | 0.05 | 0.19 | 144    | 260    | 0.03 | 0.34 | 154    | 189    | 0.08 | 0.54    |

*Robots are far away from each other. †Robots are close to each other.

VII. CONCLUSION & FUTURE WORK

In this paper, we propose an autonomous exploration benchmark called Explore-Bench. To comprehensively evaluate frontier-based and deep-reinforcement-learning-based autonomous exploration approaches, Explore-Bench provides 1) diverse data sets, 2) efficiency and collaboration metrics, and 3) a 12× speed-up grid-based simulator to quickly train and evaluate exploration strategies. With the application of one DRL-based and three frontier-based exploration approaches on the benchmark, we show that the potential field-based method achieves the best all-around performance and the DRL-based method needs a more elaborate design to outperform traditional methods. We also find that the trade-off between travel cost and potential information gain affects exploration efficiency significantly, and the proper use of shared information between robots results in good cooperation during exploration.

As future work, we would like to design additional varied exploration scenarios, including field and subterranean environments, to enrich our data sets and evaluate more DRL-based exploration approaches on our benchmark.
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