Distributed Multi-Robot Obstacle Avoidance via Logarithmic Map-based Deep Reinforcement Learning

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ABSTRACT

Developing a safe, stable, and efficient obstacle avoidance policy in crowded and narrow scenarios for multiple robots is challenging. Most existing studies either use centralized control or need communication with other robots. In this paper, we propose a novel logarithmic map-based deep reinforcement learning method for obstacle avoidance in complex and communication-free multi-robot scenarios. In particular, our method converts laser information into a logarithmic map. As a step toward improving training speed and generalization performance, our policies will be trained in two specially designed multi-robot scenarios. Compared to other methods, the logarithmic map can represent obstacles more accurately and improve the success rate of obstacle avoidance. We finally evaluate our approach under a variety of simulation and real-world scenarios. The results show that our method provides a more stable and effective navigation solution for robots in complex multi-robot scenarios and pedestrian scenarios. Videos are available at https://youtu.be/r0EsUXe6MZE.

Keywords: deep reinforcement learning, robot navigation, obstacle avoidance, logarithmic map

1. INTRODUCTION

With the increasing application scale of mobile robots, the problem of multi-robot obstacle avoidance (MROA) becomes more and more important. MROA problem requires each robot moves from one point to another while avoiding obstacles and other robots successfully.

Methods for solving the MROA problem can be divided into two categories: centralized method and distributed method. For centralized methods [1] [2], all mobile robots are controlled by a central server. These centralized control methods generate collision avoidance actions by planning optimal paths for all robots simultaneously through a global optimizer. But this kind of method is computationally complex and requires reliable synchronized communication between the central server and all robots. When there is a communication problem or sensor failure of any single robot, the whole system will fail or be seriously disturbed. In addition, it is difficult to deploy centrally controlled multi-robot systems in unknown environments, e.g., in a workshop with human co-workers.

The distributed method enables each robot to make decisions through its own controller. Furthermore, distributed methods can be divided into two groups: the traditional method and the learning-based method. Many traditional methods make decisions based on the principles of robot kinematics through velocity, acceleration, and other environmental information. Existing traditional methods, such as [3]–[5], are reaction based method. They specify a one-step interaction rule for the current geometry configuration. [14], [15] are other excellent improved versions of the previous method. Although these methods have achieved good results in solving the MROA problem, they also have some shortcomings. Firstly, they need real-time status of other robots, Secondly, the perfect and realtime sensor information is also required.

Deep reinforcement learning (DRL) has made extraordinary achievements in many fields, like Alpha zero in Go game [6] and Open-AI Five in MOBA games [7]. A typical learning based method for the MROA problem is the deep reinforcement learning (DRL) based method. Although there have been some admirable learning-based works [8] [9], those works still require the movement data of nearby robots and obstacles. Exiting DRL-based methods can be roughly divided into two classes, i.e., sensor-level method and map-based method. The sensor-level method [10] [16] is limited to specific sensor data. The map-based method [11] [17] uses a grid map that can be easily generated by using multiple
sensors or sensor fusion. However, due to the limited computing resources, the grid map-based method uses a lower resolution to represent the whole environment, which will lead to the loss of some important obstacle information when the obstacles are close. For example, it may mark the grid with obstacles as idle. Although the resolution of the grid map can be very high when there are enough computing resources, it will also increase the state space, resulting in slower convergence.

In this paper, we propose a novel logarithmic map-based DRL method to handle the MROA problem. We use the down-sample skill mentioned in [12] [13], to reduce the dimension of the 2D laser information. Then we propose a logarithmic transformation method to process the laser information. At the same resolution as the grid map [11], our method uses more pixels to represent the near information. We use the logarithmic graph to help the robot pay more attention to the surrounding environment and learn stable and efficient obstacle avoidance strategies faster and better. We apply distributed Proximal Policy Optimization (DPPO) to train a neural network that maps high dimensional observations to low-dimensional actions. We train and evaluate our method in different complex scenarios. Our contributions can be summarized as the following points:

• We propose a logarithmic map-based multi-robot obstacle avoidance approach in communication-free scenarios, where the logarithmic map can help the robot pay attention to the nearest information and avoid obstacles in complex scenarios efficiently.

• We deployed our model in a real robot and demonstrated the practical effect of our proposed obstacle avoidance method although there are many interference factors in the actual environment.

The rest of this paper is organized as follows. In section 2, our work will be discussed in detail. Section 3 presents the simulation experiment results and the real-world experiments, followed by conclusions in section 4.

2. APPROACH

In this section, we first describe our method of logarithmic map generating. After that, we briefly describe our mobile robot obstacle avoidance problem from the perspective of reinforcement learning, and then introduce the network structure and training details.

2.1 Logarithmic map generation

Fig.1 shows the difference between raw laser date, grid map [11] and logarithmic map. The process of logarithmic graph generation can be specified as follows: First, we use the down sampling skill to reduce the dimension of the raw radar information, 

\[ o_{ds} = [\min(o_{s_1}), \min(o_{s_2}), \ldots] \]

where \( \min(o_{s_i}) \) means we take the minimum of every a degrees’ laser scans as the generalized representation of corresponding radar information. Secondly, while some paper [11], [12], [18] use the traditional skill (Fig.1(b)) to process the raw laser scans, we find that the grid map can not distinguish the importance of different distance, but we know that the closer the more essential. Our method uses concentric rings if a certain width to intercept a circle of radar and straighten it into an one-dimensional vector according to its grid map-like representation: 0.0 for free place, 1.0 for obstacle and 0.5 for unknown area. The we introduce the implementation of our transformation. We set \( n_s \) the sample number, \( O_{s_{max}} \) the max range of laser, \( o_s \) is the distance of each laser in \( O_s \), our transformation equation is

\[ f(x) = e^x - 1, \]  

we can calculate interception intervals \( g \) by

\[ g = \frac{\log(O_{s_{max}} + 1)}{n_s}, \]
the width of ring can be defined as

\[ w = (f(g \times k), f(g \times (k + 1))), k = [0,1,2,\ldots,n_s - 1], \]  

where \( f(g \times k) \) is the lower bound and can be included; \( f(g \times (k + 1)) \) is the upper bound but cannot be included. We set 1.0 while \( w \) includes \( o_s \), 0.0 while the upper bound smaller than \( o_s \) and 0.5 while the lower bound bigger than \( o_s \). Finally, the data will be transformed from polar coordinates to Cartesian coordinates by the linear-polar inverse transformation tool in OpenCV. After that, we will get the final logarithmic map(\( o_{p,t} \)) in Fig.1(c). In this paper, we set \( n_s=48 \) and \( O_{s,max}=6.0 \) meter.

2.2 Problem set up

Multi-robot obstacle avoidance requires N independent robots can successfully move from the current position to the target point without collision. At time step \( t \), robot \( i \) receives it’s laser information(\( o_{s,i} \), relative angle(\( \theta_i \)) and distance(\( d_i \)) to the target point. Then it takes an action(\( a_i \)) by its policy(\( \pi_i \)).

The problem can be seen as a partially observed Markov decision process (POMDP) which is defined by a tuple (\( S,A,P,R,\Omega,O \)), where \( S \) is the state space, \( A \) is the action space, \( P \) is the transition probability from the previous state to the next state, \( R \) is the reward function, \( \Omega \) is the observation space, and \( O \) is the observation function that captures the relationship between the state and the observations.

In this paper, we use Distributed Proximal Policy Optimization (DPPO) algorithm to train our agent. DPPO is an extended version of the Proximal Policy Optimization (PPO) algorithm [19] which uses multiple robots to collect trajectories in different training environments. The goal of reinforcement learning [20] is to learn an optimal policy of the agent \( \pi_s(a,s) \) that maximizes the expectation of the cumulative discounted rewards. The key components of our algorithm are as follows:

1) Observation space: We set every robot \( i \) can only get two types of observation information at each time step \( t \), \( O_i = [o_s^{t,i}, o_p^{t,i}] \), where \( o_s^{t,i} \) is the radar information for 180 degrees, \( o_p^{t,i} = [x_i^t, y_i^t, \phi_i^t] \) is the relative posture of the robot and the target point. After we map the radar information to a logarithmic map(\( o_{p,t}^{i} \)), the final observation is \([a_i^{t,i}, o_{p,t}^{i}]\).
2) Reward design: The reward function of all robots in the training scenarios are independent and the same. The rewards are designed as follows:

\[ r^f = r^f_a + r^f_c + r^f_d + r^T, \]  
\[ r_a = \begin{cases} r_{\text{arrive}} & \text{if arrive,} \\ 0 & \text{otherwise,} \end{cases} \]  
\[ r_c = \begin{cases} r_{\text{collision}} & \text{if collision,} \\ 0 & \text{otherwise,} \end{cases} \]  
\[ r_d^T = \tau(||p^t - p_g||) - ||p^T - p_g||, \]  
\[ r^T = r_{\text{step}}, \]  
\[ (4) \]  
\[ (5) \]  
\[ (6) \]  
\[ (7) \]  
\[ (8) \]

where \( p^f \) is the current position of robot, \( p_g \) is goal’s position. We use \( d_c \) to denote the distance between robot and obstacles, \( d_{g\text{min}} \) and \( d_{c\text{min}} \) to denote the minimum distance to goal and obstacle. When \( ||p^f - p_g|| < d_{g\text{min}} \), the robot arrives. \( r_{\text{collision}} \) specifies the penalty when the robot encounters a collision. \( r^T \) encourages the robot to move towards the target point and punishes the behavior away from the target point. \( r^T \) help the robot reach the target point with fewer steps. We set \( r_{\text{arrive}} = 500 \), \( r_{\text{collision}} = -500 \), \( r_{\text{step}} = -5 \), \( \tau = 200 \).

3) Action space: The action of each robot \( i \) at time step \( t \), including linear velocity(\( v_i^t \)) and angular velocity(\( \omega_i^t \)), is limited to a fixed range. In this paper, we use continuous action space and set \( v_i^t \in [0, 0.6] \) (in meters per second), \( \omega_i^t \in [-0.9, 0.9] \) (in radians per second).

### 2.3 Network Architecture

Fig.2 shows the framework of our policy network, our value network also uses the same network structure. We use three frames logarithmic map which is mentioned in section 2 and relative goal position as input. The last fully-connected layer outputs two-dimensional vectors as our action space is continuous.

Specially, we first process high-dimensional laser inputs through three convolutional layers, each layer is followed by a maximum pool layer. All convolutional layers convolve filters with kernel size = 3, stride = 1 over the three input logarithmic maps and applies ReLU nonlinearities [21]. The output of the last convolutional layer is connected to a fully connected layer with 512 units. Then we concatenate the output of the fourth layer with relative posture together as the input of the next fully connected layer followed by another fully connected layer with 512 units. The last layer output the mean of linear velocity and the mean of angular velocity. For continuous action space, the actions are sampled from the Gaussian distribution whose log standard deviation is generated by a standalone network.

### 2.4 Training

The simulation environment we use is specially designed for laser-based navigation. It supports the simultaneous training of multiple robots in different scenarios. Fig.3 shows three types of scenarios used in our training phases. The
environment in Fig. 3(a) is designed for robots to learn good obstacle avoidance strategies. The other two environments are designed for robots to learn strategies in special scenarios.

To prove the effectiveness of our method in various complex scenarios, our training strategy has the following special points:

• We train our strategies in multiple scenarios in parallel, which brings robust performance.

• Two combination scenarios (Comb1 and Comb2) are designed to train our strategies. Comb1 consists of a crowd scenario and a circle scenario, Comb2 consists of a crowd scenario and a narrow scenario. Comparing the policies trained in different environments can better prove the effectiveness of our method.
• The shape and size of obstacles in all scenarios are random.

• The starting point and target point of each robot are random in a certain range.

Fig.4 shows the training results, including average reward curves and reach rate curves of both Comb1 and Comb2. We test our model every 20 epochs for 20 epochs while training to get the reach rate. It can be found that, in both two scenarios, our method converges faster and has the highest reward and success rate. Especially in Comb2, the effect of our method is more obvious.

3. EXPERIMENTS

In this section, we evaluate our method in both simulators and the real world. Firstly, we introduce the main details of our method, including the hyper-parameters, hardware, and software for training. Then we define the performance metrics in virtual environments and evaluate our method by comparing it with two comparative groups and one ablation group. Finally, we also deploy and verify our method on a real robot. The result shows that the policy we trained allows robots to perform better in different scenarios and it also works well in reality. The following are four experimental groups.

• Sensor-level: The method proposed by [10].

• Map-based: The method proposed by [11].

• Logarithmic map-based: The method proposed in this paper.

Considering the fairness, we use the same training tricks as well as our method. In particular, the number of frames is three, the number of raw lasers is 960, the size of the local grid map and the logarithmic map is (48,48).

3.1 Training setup

The training of our policy is implemented in PyTorch. The training hardware is a desktop PC with one i7-10700 CPU and one NVIDIA RTX 2060 super GPU. All methods are trained for about 800 epochs to ensure convergence. The model with the highest reach rate will be saved during training.
3.2 Simulation Experiments

The performance metrics we use are as Arrive rate (Ar), Average angular velocity (Aav), Average trajectory distance (Atd).

To verify the effect of our method, we test our method and other approaches in a variety of scenarios in Fig.5. Table 1 summarizes the detailed test result. We test 50 epochs in each scenario.

1) Crowd and narrow scenarios: Fig.5(a) used to test the model we trained in Comb2, two scenarios both have six robots with random positions. The robots in the left scenario need to avoid 16 random obstacles to reach the random target point, and the robots in the right scenario need to pass through the narrow road and avoid 3 random obstacles to reach the random target point opposite the channel.

2) Circle scenarios: All robots form a circle and need to pass through random obstacles to reach the target point. We test the model we have trained in Comb1. Fig.5(b) has 20 robots and 16 obstacles.

3) Corridor scenarios: The initial position and angle of each robot and the position of each target point are random in a certain range. In Fig.5(c), two groups (three robots in each group) exchange their positions via a narrow corridor connecting two open regions.

According to the result, our method (logarithmic map based) performs more stable, reliable, and efficient with the highest arrive rate and the lowest average angular velocity in all three scenarios. The ablation experiment also proves that the logarithmic map can greatly improve the obstacle avoidance ability of the robot. Please refer to the video for more details.

3.3 Real-world Experiments

In the real experiment, our hardware includes turtlebot2, rplidar A2, laptops with i5-7300HQ CPU and NVIDIA GTX 1060 GPU. We design six real-world scenarios to demonstrate the performance of our model, namely:

- Fast scenario: a scene in which fast-moving obstacles suddenly appear;
- Blocked scenario: a scenario where the passage is blocked suddenly.
- Pedestrian scenario: a scenario with two pedestrians.
- Corridor scenario with moving people: a corridor scenario with one moving people.

We apply the model trained in Comb2 in a real robot as the real environment is crowded and narrow.

Fig.6 shows the test results and the corresponding trajectories of the robot in different kinds of scenarios. In Fig.6(a) we throw a box in front of the robot, and the robot stops in time and turns left to continue its task. In Fig.6(b) when the robot is about to pass through a passage, a man suddenly blocks the passage, even if the original path is blocked, the robot can quickly select alternative routes. In Fig.6(c) two people walk around the robot, and the robot can avoid pedestrians and complete navigation tasks. In Fig.6(d) a person moves in the scenario while two robots moving in opposite directions swap their positions.

4. CONCLUSIONS

In this paper, we propose a logarithmic map-based reinforcement learning multi-robot obstacle avoidance method that can help robots focus nearby and avoid obstacles efficiently. We train our agents in two types of scenarios and test them in more complex scenarios. With the help of the logarithmic map, the robot can make a rapid response strategy to the obstacles around, so that it can have a satisfactory obstacle avoidance ability in a crowded and narrow environment. Besides, our method is easy to deploy on physical robots, and the real robot experiments also show that our method is more stable and efficient while moving in complex scenarios by using the logarithmic map.
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