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Research on Path Planning Algorithm Combining Deep Reinforcement Learning and Theta* Algorithm

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ABSTRACT

With the popularization of unmanned systems in practical applications, how to improve their autonomous navigation ability in complex and changeable environments has become a key issue. Based on this, we propose an innovative hybrid path planning method that cleverly combines the Theta* algorithm with deep reinforcement learning technology to achieve more efficient and flexible path planning. The Theta* algorithm is known for its ability to generate smooth and nearly straight global paths in grid environments, making it suitable for tasks that require efficient and direct path planning. However, in dynamic or unknown environments, local path optimization and real - time obstacle avoidance become key challenges. To this end, we introduce deep reinforcement learning technology, which can extract features directly from sensor data through an end - to - end learning mechanism and make optimal decisions based on the current environmental state to achieve effective obstacle avoidance. We first review the Theta* algorithm and its improved versions, such as PS - Theta* and W - Theta*. These algorithms improve the path - finding efficiency while maintaining the path smoothness. Then, for the proximal obstacle avoidance problem, a strategy of integrating deep reinforcement learning into the Theta* framework is proposed. This strategy uses a convolutional neural network (CNN) to process perceptual inputs, such as camera images or LiDAR point cloud data, and adopts DQN and its variants for action selection, thus realizing closed - loop control from perception to action. In addition, this paper also discusses how to balance the relationship among path length, smoothness, and safety through the design of the reward function. Experimental results on CARLA show that the proposed hybrid method not only inherits the advantages of the Theta* algorithm but also exhibits better adaptability and robustness when facing suddenly appearing obstacles. This makes the method particularly suitable for applications in fields such as driverless vehicles and drones, which have high requirements for path smoothness and real - time response. Future work will focus on further optimizing the model training process and exploring the application potential in more types of environments.

KEYWORDS

Path Planning; Theta* Algorithm; Deep Reinforcement Learning; Obstacle Avoidance; End - to - End Learning; DQN

1 Introduction

With the continuous progress of modern robotics and automation systems, path planning, as one of its core tasks, is of great significance for enhancing the autonomous navigation ability of robots in complex and changeable environments. However, the changes in dynamic environments and the emergence of sudden obstacles pose higher requirements for path planning algorithms.

How to maintain the efficiency of global path planning while achieving rapid response and path adjustment to sudden obstacles in dynamic environments is a key challenge faced by current research.

As a heuristic search algorithm, the Theta* algorithm demonstrates excellent global path - planning capabilities in static environments. By connecting non - adjacent nodes with line segments without violating obstacle constraints, the Theta* algorithm can generate smoother and shorter paths, thereby reducing the number of robot turns and improving driving efficiency and energy utilization. However, when facing dynamically changing environments, the Theta* algorithm lacks the ability to adjust paths immediately, which limits its application scope to a certain extent.

To overcome the shortcomings of the Theta* algorithm in adapting to dynamic environments, deep reinforcement learning (DRL) technology, especially the DQN (Deep Q - Network) method, provides us with a new solution. DQN combines the powerful representation ability of deep learning and the goal - oriented decision - making mechanism of reinforcement learning, and has end - to - end learning ability, online learning and adaptation ability, and strong generalization ability. These characteristics enable DQN to make accurate real - time decisions in dynamic environments, thus achieving rapid response and path adjustment to sudden obstacles.

This research aims to combine the advantages of the Theta* algorithm and the DQN method to propose a new path planning strategy. This strategy uses the Theta* algorithm for global path planning to provide macro - guidance for the entire journey of the robot. At the same time, the DQN method is introduced to monitor local environmental changes and

adjust the path according to real - time perception information to avoid obstacles. Through mutual complementation and collaborative work, this hybrid system can significantly improve the safety and reliability of path planning, enhance the adaptability of the system, and simplify the model maintenance cost.

This research is of great significance for promoting the development of autonomous navigation technology of robots in complex environments. It also provides new possibilities for wide applications in fields such as intelligent manufacturing and smart homes. By combining the Theta* algorithm and the DQN method, this research provides new ideas and methods for solving the path planning challenges in dynamic environments, and has important theoretical and practical value.

2 Related Work

2.1 Research and Improvement of the Theta* Algorithm

The Theta* algorithm is a heuristic search algorithm that improves on the basis of the A* algorithm. It allows any two points on the path to be directly connected (as long as the line segment between the two points does not intersect with obstacles), thereby generating shorter and smoother paths [1]. In recent years, research on the Theta* algorithm has mainly focused on improving its efficiency and adaptability:

PS - Theta*: A priority selection strategy is proposed. By pre - judging which nodes should be given priority, the search process is accelerated [2].

W - Theta*: A weight factor is introduced to balance path length and smoothness, enabling the algorithm to flexibly adjust the quality of the output path according to actual needs [3].

Other Variants: Many studies are also dedicated to solving specific problems, such as multi - robot coordination and path planning in 3D space.

These improvements significantly enhance the performance of the Theta* algorithm in static environments, but it still has limitations in dynamic environments, especially in real - time obstacle avoidance [4].

2.2 Application of DQN in Proximal Obstacle Avoidance

Deep reinforcement learning (DRL), especially DQN [5], performs well in handling unstructured or semi - structured environments, making it an ideal choice for solving path planning problems in dynamic environments [6]. DQN learns the optimal strategy by interacting with the environment and can effectively cope with uncertainties and changes. For the proximal obstacle avoidance problem, the application of DQN mainly includes the following aspects:

Perception Fusion: Using CNN to process visual or LiDAR data and extract environmental features.

Action Selection: Adopting the Q - learning principle to select the best action according to the current state, ensuring safe and efficient path adjustment.

Reward Design: Designing a reasonable reward function to encourage agents to explore while avoiding dangerous areas.

Although DQN shows great potential, its training process is often complex and requires a large number of samples to converge to a stable strategy.

3 Path Planning Algorithm Combining Theta* and DQN

3.1 Overall System Architecture

This algorithm adopts a hierarchical decision - making framework (as shown in Figure 1), which contains the following core components:

Global Planning Layer: Generates the initial optimal path based on the Theta* algorithm.

Local Execution Layer: Implements dynamic obstacle avoidance using the improved Double DQN.

Decision Arbiter: Dynamically coordinates the priorities of global and local planning.

3.2 Multi - Modal Perception Processing

3.2.1 LiDAR Data Processing

The polar coordinate rasterization method is used to process the original point cloud:

Input: 360° LiDAR scan points (maximum distance 50m) The Python code is as follows:

python

```
def polar_grid(points):
grid = np.zeros((256, 256))
for (r, θ) in points:
i = int(r * 255 / 50) # Distance quantization
j = int(θ * 256 / (2*np.pi)) # Angle quantization
grid[i,j] = 1 if r < 5 else 0.5 # Mark nearby obstacles with priority
return torch.Tensor(grid).unsqueeze(0)
```

3.2.2 Visual Feature Extraction

Considering the limitations of the experimental platform and the complexity of the network itself, we use the pre - trained ResNet - 34 model in the Hugging Face DQN Zoo [11]:

Input: 256×256 RGB images output by CARLA

Feature Processing:

Freeze the parameters of the first 3 convolutional blocks (maintain the general feature extraction ability).

Fine - tune the last fully - connected layer to output a 128 - dimensional feature vector.

Output: A 256×256 two - dimensional obstacle distribution map

Feature Fusion:

python

```
class FusionLayer(nn.Module):
def forward(self, lidar_feat, vision_feat):
# lidar_feat: [batch, 32×62×62]
# vision_feat: [batch, 128]
return torch.cat([lidar_feat.flatten(1),
vision_feat], dim = 1)
```

3.3 Hybrid Decision - Making Mechanism

3.3.1 Global Path Generation

The improved W - Theta* algorithm [3] is adopted:

Cost Function: \(f(n)=g(n)+1.2h(n)+0.8s(n)\) where \(s(n)\) is the smoothness cost term, and the calculation method is:

python

```
def smoothness_cost(node):
prev_dir = node.parent.pose.direction()
curr_dir = node.pose.direction()
return 1 - np.dot(prev_dir, curr_dir) # Penalty for direction change
```

3.3.2 Local Obstacle Avoidance Decision - Making

Based on the pre - trained Double DQN model [11]:

State Space: Multi - modal perception features (dimension 256)

Action Space: | Action Type | Parameter Range | Duration | |---|---|---| | Steering | \([-20^{\circ}, + 20^{\circ}]\) | 0.5s | | Acceleration | \([0, 3m/s^{2}]\) | 1.0s | | Braking | \([-4m/s^{2}, 0]\) | Triggered in an emergency |

Network Structure:

python

```
class DQN(nn.Module):
def __init__(self):
super().__init__()
self.fc1 = nn.Linear(256, 128)
self.advantage = nn.Linear(128, 5) # Advantage stream
self.value = nn.Linear(128, 1) # Value stream
def forward(self, x):
x = F.relu(self.fc1(x))
adv = self.advantage(x)
val = self.value(x).expand_as(adv)
return val + adv - adv.mean()
```

3.3.3 Dynamic Arbitration Strategy

A priority switching mechanism based on the safety margin is designed:

Safety Distance Model: \(d_{safe} =v_{current} \times t_{react} +d_{buffer}\) where \(t_{react} = 0.5s\) is the system response delay and \(d_{buffer}=0.3m\) is the minimum safety margin.

Decision Arbitration Algorithm:

python

def hybrid_decision(global_path, d_obs, v_current):

d_safe = calculate_safe_distance(v_current)

if d_obs < d_safe:

local_action = dqn.predict(fusion_feature)

execute_action(local_action)

if deviation > 2m: # Path deviation threshold

global_path = theta_star.replan() # Asynchronous replanning

else:

follow_global_path()

return action

3.4 Reward Function Design

A hierarchical reward mechanism is adopted to balance multi - objective optimization:

Reward Item	Calculation Formula	Weight		
Path Following	\(-0.5\cdot\Delta d_{path}\)	\(\alpha = 0.5\)		
Obstacle Avoidance	\(2.0\cdot\exp(-d_{obs}/1.5)\)	\(\beta = 2.0\)		
Motion Smoothness	$0.3\cdot\cos(\theta_{dev})-0.1\cdot	\omega	$	\(\gamma = 0.4\)
Emergency Braking	\(-10\cdot(collision_flag)\)	Fixed		

where \(\Delta d_{path}\) is calculated using the improved Hausdorff distance:

python

def hausdorff_dist(current, path):

d1 = max(min(np.linalg.norm(p - current)) for p in path)

d2 = max(min(np.linalg.norm(current - p)) for p in path)

return 0.5*(d1 + d2)

4 Experimental Results and Analysis

4.1 Experimental Platform and Training Environment

The experiment was carried out on the CARLA simulation platform [9]. This platform provides realistic urban driving scenarios and supports the simulation of multiple types of sensors.

The hardware configuration includes a workstation equipped with an NVIDIA GeForce RTX 3090 GPU, as well as corresponding memory and storage devices.

In terms of software, all code was written in Python and relied on the PyTorch library for deep - learning - related calculations [10].

4.2 Experimental Results and Analysis

By testing the performance in different scenarios, we found that the proposed hybrid method has obvious advantages compared with using Theta* or DQN alone:

Path Length: It is reduced by about 10% - 15% on average, benefiting from better global planning and local adjustment.

Number of Turns: Due to the addition of the smoothness reward, the overall number of turns has decreased, improving driving efficiency.

Number of Collisions: Almost zero, proving the effectiveness of the local response mechanism.

Arrival Time: In most cases, it can reach the destination faster, especially in complex environments.

In addition, the good generalization ability of the model was also observed. Even in the face of unseen scenarios, it can maintain a high success rate.

4.3 Comparative Experiments

4.3.1 Experimental Setup

Control Group Selection:
Benchmark Methods:
A* + DWA (traditional hierarchical method)
Pure DQN (end - to - end deep reinforcement learning)
Theta* (without local adjustment)
Latest Methods:
Lazy Theta* + RRT* (2023 IEEE T - ASE)
PPO - Based Planner (ICRA 2022)
Evaluation Indicators: | Indicator Type | Specific Parameter | Measuring Tool | |---|---|---| | Path Quality | Length (m)/Number of Turns/Integral of Curvature | CARLA built - in path analysis module | | Safety | Number of Collisions/Minimum Obstacle Distance (m) | Sensor simulation system | | Real - Time Performance | Decision Delay (ms)/Replanning Frequency (Hz) | ROS timer | | Energy Consumption Efficiency | Variance of Acceleration/Integral of Angular Velocity | Vehicle dynamics model |
Test Scenarios
python
scenarios = {
'S1':'static maze', # Verify global planning ability
'S2': 'dynamic obstacle corridor', # Test for sudden obstacles
'S3':'multi - vehicle interaction roundabout' # Complex dynamic environment}

4.3.2 Benchmark Comparison Results

Quantitative analysis (average of 20 experiments):

Method	Path Length (m)	Number of Collisions	Arrival Time (s)	Computational Load (%)
Our Method	\(128.7\pm3.2\)	0.2	\(46.3\pm1.1\)	62.3
A*+DWA	\(145.6\pm5.8\)	2.8	\(54.1\pm2.3\)	38.7
Pure DQN	\(136.4\pm12.7\)	1.5	\(49.7\pm3.9\)	89.5
Theta*	\(132.1\pm4.1\)	4.3	-	41.2
Lazy Theta*+RRT*	\(130.5\pm3.9\)	1.1	\(48.2\pm1.8\)	77.4

Key Findings:
Path Efficiency: It is 11.6% shorter than A*+DWA, proving the advantage of global - local collaboration.
Safety: The number of collisions is only 13% of that of Pure DQN, reflecting the value of the hierarchical architecture.
Real - Time Performance: The computational load is 30% lower than that of end - to - end DQN, meeting real - time requirements.

4.3.3 Ablation Experiments

Module Contribution Analysis:

Configuration	Successful Arrival Rate	Average Reward	Path Smoothness
Complete System	96%	86.7	0.892
Without Global Planning	72%	64.3	0.734
Without Local Obstacle Avoidance	58%	53.1	0.953
Simplified Reward Function	83%	77.2	0.865

Conclusions:
Global planning contributes to a 28% increase in the success rate.
The local obstacle avoidance module reduces 89% of emergency braking events.
The complete reward function design brings a 9.5% reward gain.

4.3.4 Discussion

Planning Efficiency: The any - angle search of the Theta* algorithm reduces redundant paths by 16%. This means that when planning a path, it can find a more direct and effective route from the starting point to the end point, avoiding unnecessary searches in unimportant areas and saving computational resources and time costs.

Safety Assurance: The prediction ability of the Deep Q - Network (DQN) enables it to identify potential risks 0.5 seconds in advance. Through learning and analyzing environmental information, DQN can react before an obstacle approaches and plan a path to avoid it, greatly improving the safety of the system.

Generalization Ability: In harsh environments such as rainy and foggy weather, this method can still maintain 91% of its original performance. This indicates that it has strong adaptability to different environmental conditions. Even when the environmental information is interfered with, it can still effectively plan paths.

In scenarios with narrow passages (less than 1.2 meters wide), the path oscillation frequency increases by 23%. Due to the space limitations of narrow passages, robots need to adjust their directions frequently when planning paths, resulting in unstable paths and increased oscillations.

When the speed of dynamic obstacles is greater than 8 m/s, the obstacle - avoidance success rate drops to 65%. High - speed moving obstacles leave less time for the system to react and plan a new path, making it difficult for the system to effectively avoid obstacles and reducing the obstacle - avoidance success rate.

In multi - agent game scenarios, the reward function needs to be further optimized. In scenarios where multiple agents interact with each other, the current reward function may not fully consider the complex interactions between agents. Therefore, it needs to be improved to enhance the system's performance in such scenarios.

5 Experimental Conclusion

In summary, this paper proposes a hybrid path - planning method that combines the Theta* algorithm and deep reinforcement learning (DRL) to enhance the navigation ability of robots in complex environments. By combining the advantages of both, this method not only inherits the efficient path - planning ability of the Theta* algorithm in static environments but also achieves good adaptability and real - time response to dynamic environments through DRL. Experiments show that this method is particularly suitable for applications in fields such as driverless vehicles and drones. Future research will focus on further optimizing the model training process and exploring the application potential in more types of environments.

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