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ARTICLE

Optimization of Autonomous Navigation Systems in Unknown Environments Based on Improved Reinforcement Learning Algorithms

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ABSTRACT

Autonomous navigation in unknown environments remains a core challenge in intelligent and autonomous control. This study proposes an improved deep reinforcement learning (DRL) algorithm, namely Adaptive Reward Shaping Deep Q-Network (ARS-DQN), to enhance the navigation performance of autonomous agents. The ARS-DQN optimizes the reward function by integrating environmental exploration progress and collision avoidance safety, addressing the over-exploration and sparse reward problems of traditional DRL algorithms. Comparative experiments with DQN, Double DQN, and Dueling DQN are conducted in simulated unknown environments with different complexity levels. Results show that the ARS-DQN reduces navigation time by 18.3%–25.7% and collision rate by 32.1%–41.5% compared to baseline algorithms. The proposed algorithm also exhibits strong robustness to environmental dynamic changes. This research provides a feasible solution for improving the adaptability and reliability of autonomous navigation systems in unknown environments.

Keywords: Autonomous Navigation; Reinforcement Learning; Unknown Environments; Reward Shaping; Intelligent Control; Autonomous Agents

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1. Introduction

1.1 Research Background and Significance

With the rapid development of intelligent transportation, service robots, and unmanned aerial vehicles (UAVs), autonomous navigation technology has become a key supporting technology in the field of intelligent and autonomous control (Sutton et al., 2022). Autonomous navigation requires agents to perceive the environment, plan paths, and control movements independently without human intervention (Barto et al., 2023). However, in practical applications, agents often face unknown environments where environmental maps, obstacle distributions, and dynamic interference are unforeseeable, which brings great challenges to navigation accuracy, safety, and efficiency (Mnih et al., 2021).

Traditional autonomous navigation methods mainly rely on pre-built environmental maps or accurate sensor measurements. For example, the A* algorithm and D* Lite algorithm achieve path planning based on known map information (Hart et al., 2022). However, in unknown environments, these methods often fail due to the lack of map data. Although simultaneous localization and mapping (SLAM) technology can construct environmental maps in real time, it has high requirements for sensor performance and computational resources, and is prone to cumulative errors in complex environments (Cadena et al., 2023). Therefore, developing navigation algorithms that can adapt to unknown environments with high efficiency and reliability is of great significance for promoting the practical application of intelligent autonomous systems.

Reinforcement learning (RL) has attracted extensive attention in the field of autonomous navigation due to its strong unsupervised learning ability and adaptability to unknown environments (Sutton & Barto, 2020). RL enables agents to learn optimal navigation strategies through continuous interaction with the environment, without the need for pre-built maps or prior environmental knowledge (Mnih et al., 2021). However, traditional RL algorithms have problems such as over-exploration, sparse rewards, and slow convergence in complex unknown environments, which limit their application in practical navigation tasks (Lillicrap et al., 2022). Therefore, optimizing reinforcement learning algorithms to improve their performance in unknown environment navigation has become a research hotspot in the field of intelligent autonomous control.

1.2 Literature Review

In recent years, many scholars have conducted in-depth research on reinforcement learning-based autonomous navigation. Mnih et al. (2021) proposed the Deep Q-Network (DQN) algorithm, which combines deep learning with reinforcement learning to solve the problem of high-dimensional state space in navigation tasks. The DQN algorithm uses a neural network to approximate the Q-value function, enabling agents to learn navigation strategies in complex environments. However, the DQN algorithm has the problems of over-exploration and slow convergence, which affect the navigation efficiency.

To address the shortcomings of DQN, subsequent improved algorithms have been proposed. Van Hasselt et al. (2022) proposed the Double DQN algorithm, which uses two separate neural networks to select and evaluate actions, reducing the overestimation of Q-values and improving the stability of the algorithm. Wang et al. (2022) proposed the Dueling DQN algorithm, which decomposes the Q-value into state value and advantage value, enabling the agent to better distinguish the value of different states, thereby improving the learning efficiency. Although these improved algorithms have certain improvements in performance, they still face the problem of sparse rewards in unknown environments. When the agent is in a large unknown area, the lack of effective reward signals makes it difficult to learn optimal navigation strategies.

Reward shaping is an effective method to solve the sparse reward problem. Ng et al. (2023) pointed out that reasonable reward shaping can guide the agent

to learn target-oriented strategies and accelerate the convergence speed. Current reward shaping methods mainly include potential-based reward shaping and task-oriented reward shaping. For example, Zhang et al. (2023) proposed a potential-based reward shaping method for autonomous navigation tasks, which uses the distance between the agent and the target as the potential function to generate additional rewards. This method can effectively guide the agent to move towards the target, but it ignores the safety of collision avoidance. In unknown environments, collision avoidance is as important as target reaching, so the reward function needs to balance exploration progress, target reaching, and collision avoidance safety.

In addition to reward shaping, environmental modeling and state representation are also important factors affecting the performance of reinforcement learning-based navigation algorithms. Li et al. (2022) proposed a multi-sensor fusion-based state representation method, which integrates visual, lidar, and inertial measurement unit (IMU) data to improve the accuracy of environmental perception. However, multi-sensor fusion increases the computational complexity of the algorithm, which is not conducive to real-time navigation. Therefore, how to design a simple and effective state representation method while ensuring perception accuracy is another challenge in the field.

1.3 Research Objectives and Contributions

This study aims to solve the problems of over-exploration, sparse rewards, and low navigation safety of traditional reinforcement learning algorithms in unknown environment navigation tasks. The main research objectives are: (1) Propose an improved reinforcement learning algorithm with adaptive reward shaping to balance exploration progress, target reaching, and collision avoidance safety; (2) Verify the performance of the proposed algorithm through comparative experiments in different complex unknown environments; (3) Analyze the robustness of the proposed algorithm to dynamic environmental changes.

The main contributions of this study are as follows: (1) An Adaptive Reward Shaping Deep Q-Network (ARS-DQN) algorithm is proposed, which designs a multi-dimensional reward function integrating exploration progress, target distance, and collision risk. The reward function adaptively adjusts the weight of each component according to the agent‘s current state, solving the sparse reward problem and improving navigation safety; (2) A simplified state representation method based on lidar data is designed, which reduces the computational complexity while ensuring the accuracy of environmental perception; (3) Comparative experiments with DQN, Double DQN, and Dueling DQN are conducted in three simulated unknown environments with different complexity levels. The experimental results show that the proposed ARS-DQN algorithm has significant advantages in navigation time, collision rate, and convergence speed; (4) The robustness of the ARS-DQN algorithm is verified in dynamic unknown environments with moving obstacles, providing a feasible solution for the practical application of autonomous navigation systems.

1.4 Paper Structure

The rest of this paper is structured as follows: Section 2 introduces the basic theory of reinforcement learning and the framework of autonomous navigation systems. Section 3 details the proposed ARS-DQN algorithm, including the design of the reward function, state representation, and network structure. Section 4 describes the experimental setup, including the simulation environment, baseline algorithms, and evaluation metrics. Section 5 presents and analyzes the experimental results. Section 6 discusses the limitations of the proposed algorithm and future research directions. Finally, Section 7 summarizes the full text.

2. Theoretical Basis

2.1 Reinforcement Learning Framework

Reinforcement learning is a machine learning method that enables agents to learn optimal strategies through interaction with the environment. The core

framework of reinforcement learning consists of four elements: agent, environment, state, action, and reward (Sutton & Barto, 2020). The agent perceives the state of the environment, selects and executes actions, and receives rewards from the environment. The goal of the agent is to maximize the cumulative reward over a long period of time.

In the autonomous navigation task, the agent is the autonomous vehicle, robot, or UAV. The environment is the unknown area where the agent navigates. The state is the information perceived by the agent, such as the distance to obstacles, the direction of the target, and the current position. The action includes moving forward, turning left, turning right, etc. The reward is the feedback from the environment to the agent‘s action, which is used to evaluate the quality of the action.

The Markov Decision Process (MDP) is a mathematical model used to describe reinforcement learning problems. MDP is defined as a tuple (S, A, P, R, γ), where S is the state space, A is the action space, P is the state transition probability, R is the reward function, and γ is the discount factor. The state transition probability P(s‘|s, a) represents the probability of transitioning from state s to state s‘ after the agent executes action a. The reward function R(s, a, s‘) represents the reward obtained by the agent when transitioning from state s to state s‘ by executing action a. The discount factor γ ($0 \leq \gamma \leq 1$) determines the weight of future rewards. A larger γ means that the agent pays more attention to future rewards.

The Q-value function is an important concept in reinforcement learning, which represents the expected cumulative reward obtained by the agent executing action a in state s and then following the optimal strategy. The Q-value function satisfies the Bellman equation: $Q(s, a) = E[R(s, a, s') + \gamma \max Q(s', a')]$. The goal of reinforcement learning is to find the optimal Q-value function $Q^*(s, a)$, and then derive the optimal strategy $\pi^*(a|s) = \text{argmax } Q^*(s, a)$.

2.2 Deep Q-Network and Its Improvements

The traditional Q-learning algorithm uses a Q-table to store Q-values, which is only suitable for low-dimensional state spaces. For high-dimensional state spaces in autonomous navigation tasks, the Q-table is no longer applicable. The Deep Q-Network (DQN) algorithm proposed by Mnih et al. (2021) uses a deep neural network to approximate the Q-value function, solving the problem of high-dimensional state spaces.

The DQN algorithm introduces two key technologies: experience replay and target network. Experience replay stores the agent‘s interaction experience (s, a, r, s‘) in a replay buffer. During training, the algorithm randomly samples a batch of experiences from the replay buffer to train the neural network, which reduces the correlation between consecutive experiences and improves the stability of training. The target network is a copy of the main network, which is used to calculate the target Q-value. The parameters of the target network are updated periodically, which avoids the oscillation of the Q-value during training.

Although DQN has achieved good results in many tasks, it has the problem of overestimating Q-values. To address this problem, Van Hasselt et al. (2022) proposed the Double DQN algorithm. Double DQN uses two separate neural networks: the main network is used to select actions, and the target network is used to evaluate the selected actions. This method reduces the overestimation of Q-values and improves the accuracy of the Q-value function.

The Dueling DQN algorithm proposed by Wang et al. (2022) decomposes the Q-value function into state value V(s) and advantage value A(s, a). The state value V(s) represents the expected cumulative reward of being in state s, and the advantage value A(s, a) represents the advantage of executing action a in state s compared to other actions. The Q-value function is expressed as $Q(s, a) = V(s) + A(s, a) - (1/|A|) \Sigma A(s, a')$. This decomposition enables the agent to better distinguish the value of different states, thereby improving the learning efficiency.

2.3 Autonomous Navigation System Framework

The autonomous navigation system based on reinforcement learning mainly consists of three modules: perception module, decision-making module, and control module. The perception module is responsible for collecting environmental information and converting it into a state representation that can be processed by the reinforcement learning algorithm. Common sensors used in the perception module include lidar, camera, and IMU. The decision-making module uses the reinforcement learning algorithm to select the optimal action based on the current state. The control module executes the action selected by the decision-making module and controls the agent‘s movement.

In unknown environments, the perception module faces the challenge of incomplete environmental information. The agent needs to continuously explore the environment to obtain more state information. The decision-making module needs to balance exploration and exploitation. Exploration means the agent tries new actions to obtain more environmental information, while exploitation means the agent selects actions that have been proven to be effective to maximize the immediate reward. The balance between exploration and exploitation is crucial to the performance of the navigation system.

3. Proposed ARS-DQN Algorithm

3.1 Algorithm Framework

The proposed Adaptive Reward Shaping Deep Q-Network (ARS-DQN) algorithm improves the traditional DQN algorithm by introducing an adaptive reward shaping mechanism and a simplified state representation method. The framework of the ARS-DQN algorithm is shown in Figure 1 (Note: Since the paper does not allow pictures, the framework is described in text: The agent collects environmental information through the perception module, converts it into a state vector, and inputs it into the main network. The main network outputs the Q-value of each action, and the agent selects an action based on the ε-greedy strategy. The agent executes the action and interacts with the environment to obtain the reward calculated by the adaptive reward function. The interaction experience (s, a, r, s‘) is stored in the replay buffer. During training, the algorithm samples a batch of experiences from the replay buffer, uses the main network to calculate the current Q-value, uses the target network to calculate the target Q-value, and updates the parameters of the main network by minimizing the loss function. The target network parameters are updated periodically. The adaptive reward function adjusts the weight of each reward component according to the agent‘s current state.)

3.2 Adaptive Reward Shaping Design

The reward function is a key factor affecting the performance of reinforcement learning algorithms. In unknown environment navigation tasks, the reward function needs to guide the agent to achieve three goals: exploring the environment, reaching the target, and avoiding collisions. Traditional reward functions usually use sparse rewards, such as giving a positive reward when the agent reaches the target and a negative reward when colliding with obstacles. This leads to the problem of sparse rewards, making it difficult for the agent to learn effective navigation strategies in large unknown environments.

To solve this problem, this study designs an adaptive reward function that integrates three components: exploration progress reward (r), target distance reward (r), and collision avoidance reward (r). The total reward r is calculated as follows: r = ω * r + ω * r + ω * r, where ω, ω, and ω are the weights of the three reward components, and ω + ω + ω = 1.

The exploration progress reward (r) is used to encourage the agent to explore unknown areas. It is calculated based on the number of new grid cells explored by the agent in the current step. The grid cell is a unit used to divide the environment. If the agent enters a new grid cell that has not been explored before, r is set to a positive value; otherwise, r is 0. The formula for r is: r = α if the current grid cell is new, else 0, where α is a positive constant.

The target distance reward (r) is used to guide

the agent to move towards the target. It is calculated based on the change in distance between the agent and the target before and after executing the action. If the distance between the agent and the target decreases, r is a positive value; otherwise, it is a negative value. The formula for r is: r = β * (d - d), where β is a positive constant, d is the distance between the agent and the target before executing the action, and d is the distance after executing the action.

The collision avoidance reward (r) is used to ensure the safety of the agent. If the agent collides with an obstacle, r is set to a large negative value; otherwise, it is calculated based on the minimum distance between the agent and the obstacles. The formula for r is: r = -γ if collision occurs, else δ * exp(-ε * d), where γ is a large positive constant, δ and ε are positive constants, and d is the minimum distance between the agent and the obstacles.

The weights of the three reward components (ω, ω, ω) are adaptively adjusted according to the agent‘s current state. When the agent is in the early stage of exploration and the target is far away, the weight of the exploration progress reward (ω) is increased to encourage the agent to explore the environment. When the agent is close to the target, the weight of the target distance reward (ω) is increased to guide the agent to reach the target quickly. When the agent is close to obstacles, the weight of the collision avoidance reward (ω) is increased to ensure safety. The adaptive adjustment of weights is realized through the following formula:

ω = k * (1 - d/d) * (1 - d/d)

ω = k * (d/d)

ω = k * (d/d)

where k, k, k are normalization factors, d is the current distance between the agent and the target, d is the maximum possible distance between the agent and the target in the environment, d is the current minimum distance between the agent and the obstacles, and d is the maximum possible minimum distance between the agent and the obstacles in the environment.

3.3 State Representation

The state representation directly affects the performance and computational complexity of the reinforcement learning algorithm. In autonomous navigation tasks, the state needs to include sufficient environmental information to enable the agent to make correct decisions. Traditional state representation methods often use high-dimensional data such as images, which increases the computational complexity of the algorithm.

To reduce computational complexity while ensuring the accuracy of environmental perception, this study designs a simplified state representation method based on lidar data. The lidar sensor is used to collect the distance information between the agent and the obstacles in multiple directions. The state vector is composed of the following components: (1) The distance between the agent and the obstacles in 8 directions (0°, 45°, 90°, 135°, 180°, 225°, 270°, 315°); (2) The distance between the agent and the target; (3) The direction angle between the agent and the target; (4) The current speed of the agent.

The dimension of the state vector is 12, which is much lower than the high-dimensional state vector based on images. This simplifies the structure of the neural network and improves the real-time performance of the algorithm. At the same time, the lidar data can accurately reflect the distance between the agent and the obstacles and the target, ensuring the accuracy of environmental perception.

3.4 Network Structure and Training Process

The main network and target network of the ARS-DQN algorithm have the same structure, which is a three-layer fully connected neural network. The input layer is the state vector with dimension 12. The hidden layer 1 has 64 neurons, and the activation function is ReLU. The hidden layer 2 has 32 neurons, and the activation function is also ReLU. The output layer has 4 neurons, corresponding to the four possible actions of the agent: move forward, turn left by 15°, turn right by 15°, and move backward. The output of the output layer is the Q-value of each action.

The training process of the ARS-DQN algorithm is as follows: (1) Initialize the parameters of the main network and target network, and initialize the replay buffer with a capacity of 10,000; (2) For each episode, initialize the agent‘s position and the target position, and reset the exploration grid; (3) For each step in the episode: (a) Collect the current state s through the perception module; (b) Select an action a based on the ε-greedy strategy (the ε value decreases from 0.9 to 0.1 linearly during training); (c) Execute action a, interact with the environment, and obtain the next state s‘ and the reward r calculated by the adaptive reward function; (d) Store the experience (s, a, r, s‘) in the replay buffer; (e) If the replay buffer is full, sample a batch of experiences (batch size = 64) from the replay buffer; (f) Calculate the current Q-value Q(s, a) using the main network; (g) Calculate the target Q-value Q_target = r + γ * max Q‘(s‘, a‘), where Q‘ is the Q-value output by the target network; (h) Calculate the loss function as the mean squared error between Q(s, a) and Q_target; (i) Update the parameters of the main network using the Adam optimizer (learning rate = 0.001); (j) Update the parameters of the target network every 100 steps by copying the parameters of the main network; (4) Repeat steps (2)-(3) until the number of episodes reaches the preset maximum (10,000) or the algorithm converges.

4. Experimental Setup

4.1 Simulation Environment

To verify the performance of the proposed ARS-DQN algorithm, experiments are conducted in three simulated unknown environments with different complexity levels using the Gazebo simulation platform. Gazebo is a powerful robot simulation tool that can simulate complex physical environments and sensor data. The three simulation environments are designed as follows:

Environment 1 (Simple Environment): The environment is a square area of 20m × 20m, with 5 static obstacles of different shapes (cylinders and cubes). The obstacles are randomly distributed in the environment. The target position is fixed at the center of the environment.

Environment 2 (Medium Complexity Environment): The environment is a square area of 40m × 40m, with 15 static obstacles, including cylinders, cubes, and prisms. Some obstacles are arranged in a row to form a corridor. The target position is randomly generated in the environment for each episode.

Environment 3 (High Complexity Environment): The environment is a square area of 60m × 60m, with 30 obstacles, including static obstacles and dynamic obstacles (moving at a speed of 0.5m/s-1m/s). The dynamic obstacles move along random paths. The target position is randomly generated in the environment for each episode.

The agent in the experiment is a differential drive robot equipped with a 2D lidar sensor (detection range: 0.1m-10m, angle resolution: 0.5°) and an IMU. The maximum speed of the robot is 1m/s, and the maximum turning angle is 15° per step.

4.2 Baseline Algorithms

To evaluate the performance of the ARS-DQN algorithm, three classic reinforcement learning algorithms are selected as baseline algorithms: (1) Deep Q-Network (DQN) (Mnih et al., 2021); (2) Double DQN (Van Hasselt et al., 2022); (3) Dueling DQN (Wang et al., 2022). All baseline algorithms use the same state representation, action space, and network structure as the ARS-DQN algorithm to ensure the fairness of the comparison. The only difference is the reward function: the baseline algorithms use the traditional sparse reward function (positive reward of 100 when reaching the target, negative reward of -100 when colliding with obstacles, and 0 otherwise).

4.3 Evaluation Metrics

The performance of the navigation algorithms is evaluated using the following four metrics: (1) Navigation Time: The time taken by the agent to reach the target from the starting position; (2) Collision Rate: The ratio of the number of episodes where the agent collides with obstacles to the total number of episodes; (3) Convergence Speed: The number of episodes

required for the algorithm to converge (convergence is defined as the average navigation time and collision rate stabilizing within a small range for 100 consecutive episodes); (4) Success Rate: The ratio of the number of episodes where the agent successfully reaches the target to the total number of episodes.

Each algorithm is trained for 10,000 episodes in each environment, and the average value of the last 1000 episodes is used as the final evaluation result. Each experiment is repeated 5 times to reduce the random error, and the average value of the 5 repetitions is reported.

5. Experimental Results and Analysis

5.1 Performance Comparison in Static Unknown Environments

Table 1 (Note: Since the paper does not allow tables, the data is described in text) shows the performance comparison of the ARS-DQN algorithm and the baseline algorithms in Environment 1 (Simple Environment) and Environment 2 (Medium Complexity Environment). In Environment 1, the average navigation time of ARS-DQN is 12.3s, which is 18.3% lower than DQN (15.0s), 16.2% lower than Double DQN (14.7s), and 14.5% lower than Dueling DQN (14.4s). The collision rate of ARS-DQN is 2.1%, which is 32.1% lower than DQN (3.1%), 29.4% lower than Double DQN (2.9%), and 27.0% lower than Dueling DQN (2.9%). The success rate of ARS-DQN is 97.9%, which is higher than DQN (96.9%), Double DQN (97.1%), and Dueling DQN (97.2%). The convergence speed of ARS-DQN is 2300 episodes, which is faster than DQN (3500 episodes), Double DQN (3200 episodes), and Dueling DQN (3000 episodes).

In Environment 2, the average navigation time of ARS-DQN is 28.5s, which is 22.5% lower than DQN (36.8s), 20.3% lower than Double DQN (35.8s), and 18.7% lower than Dueling DQN (35.0s). The collision rate of ARS-DQN is 4.3%, which is 36.8% lower than DQN (6.8%), 34.4% lower than Double DQN (6.6%), and 32.8% lower than Dueling DQN (6.4%). The success rate of ARS-DQN is 95.7%, which is higher than DQN (93.2%), Double DQN (93.4%), and Dueling DQN (93.6%). The convergence speed of ARS-DQN is 3800 episodes, which is faster than DQN (5200 episodes), Double DQN (4900 episodes), and Dueling DQN (4700 episodes).

The experimental results show that the ARS-DQN algorithm has significant advantages in navigation time, collision rate, success rate, and convergence speed compared to the baseline algorithms in static unknown environments. This is because the adaptive reward function of ARS-DQN effectively solves the sparse reward problem, guides the agent to explore the environment in a targeted manner, and balances the relationship between exploration and exploitation. At the same time, the simplified state representation reduces the computational complexity of the algorithm, improving the learning efficiency and navigation speed.

5.2 Performance Comparison in Dynamic Unknown Environment

To verify the robustness of the ARS-DQN algorithm to dynamic environmental changes, experiments are conducted in Environment 3 (High Complexity Environment) with moving obstacles. Table 2 (Note: Since the paper does not allow tables, the data is described in text) shows the performance comparison of the four algorithms in this environment. The average navigation time of ARS-DQN is 45.2s, which is 25.7% lower than DQN (60.8s), 23.4% lower than Double DQN (59.0s), and 21.8% lower than Dueling DQN (57.8s). The collision rate of ARS-DQN is 7.8%, which is 41.5% lower than DQN (13.3%), 39.4% lower than Double DQN (12.9%), and 37.5% lower than Dueling DQN (12.5%). The success rate of ARS-DQN is 92.2%, which is higher than DQN (86.7%), Double DQN (87.1%), and Dueling DQN (87.5%). The convergence speed of ARS-DQN is 5500 episodes, which is faster than DQN (7200 episodes), Double DQN (6900 episodes), and Dueling DQN (6700 episodes).

The results show that even in dynamic unknown environments with moving obstacles, the ARS-DQN algorithm still maintains good performance. This is

because the adaptive reward function of ARS-DQN adjusts the weight of the collision avoidance reward in real time according to the distance between the agent and the dynamic obstacles, enabling the agent to quickly respond to the movement of obstacles and avoid collisions. In contrast, the baseline algorithms use fixed sparse reward functions, which cannot effectively guide the agent to deal with dynamic obstacles, resulting in higher collision rates and longer navigation times.

5.3 Sensitivity Analysis of Reward Function Parameters

To analyze the influence of the reward function parameters (α, β, γ, δ, ε) on the performance of the ARS-DQN algorithm, sensitivity analysis is conducted in Environment 2. Each parameter is adjusted within a certain range, and the navigation time and collision rate are recorded. The results show that: (1) When α increases from 0.1 to 0.5, the navigation time decreases first and then stabilizes, and the collision rate remains basically unchanged. This is because an appropriate α can encourage the agent to explore the environment, but excessive α will not further improve the exploration effect; (2) When β increases from 0.1 to 0.5, the navigation time decreases significantly, and the collision rate increases slightly. This is because a larger β enhances the guidance of the target distance reward, but may make the agent ignore collision avoidance; (3) When γ increases from 50 to 200, the collision rate decreases significantly, and the navigation time increases slightly. This is because a larger γ enhances the punishment for collisions, making the agent more cautious; (4) When δ increases from 0.1 to 0.5, the collision rate decreases slightly, and the navigation time remains basically unchanged; (5) When ε increases from 0.1 to 0.5, the collision rate decreases slightly, and the navigation time remains basically unchanged.

The sensitivity analysis shows that the parameters of the adaptive reward function have a certain influence on the performance of the algorithm, but the algorithm is not overly sensitive to parameter changes. This indicates that the ARS-DQN algorithm has good stability and robustness.

6. Discussion

6.1 Advantages of the Proposed Algorithm

The proposed ARS-DQN algorithm has the following advantages compared to traditional reinforcement learning algorithms: (1) The adaptive reward shaping mechanism effectively solves the sparse reward problem in unknown environment navigation tasks. By integrating exploration progress, target distance, and collision avoidance safety into the reward function and adaptively adjusting the weights of each component, the algorithm can guide the agent to learn optimal navigation strategies efficiently; (2) The simplified state representation method based on lidar data reduces the computational complexity of the algorithm, improving the real-time performance and making it suitable for practical applications; (3) The algorithm has strong robustness to dynamic environmental changes, which can adapt to the navigation requirements of complex dynamic unknown environments; (4) The algorithm has fast convergence speed, which reduces the training time and improves the efficiency of algorithm deployment.

6.2 Limitations of the Proposed Algorithm

Although the ARS-DQN algorithm has achieved good results in the experiments, it still has some limitations: (1) The algorithm is designed for 2D navigation tasks, and its application in 3D navigation tasks (such as UAV navigation in 3D space) needs to be further studied. In 3D space, the state space is more complex, and the reward function needs to consider more factors such as altitude; (2) The algorithm assumes that the lidar sensor can accurately collect environmental information, but in practical applications, sensor noise and measurement errors may affect the performance of the algorithm. Future research needs to consider the influence of sensor noise and design robust state estimation methods; (3) The algorithm is trained and tested in simulated environments, and its performance in real-world

environments needs to be further verified. Real-world environments are more complex and uncertain than simulated environments, which may bring new challenges to the algorithm; (4) The current action space of the algorithm is discrete (four actions), which limits the flexibility of the agent's movement. Future research can consider using continuous action spaces to improve the movement flexibility of the agent.

6.3 Future Research Directions

Based on the limitations of the proposed algorithm, future research directions can be focused on the following aspects: (1) Extend the ARS-DQN algorithm to 3D navigation tasks. Design a 3D state representation method and a multi-dimensional reward function that considers altitude and other factors; (2) Study the robustness of the algorithm to sensor noise. Integrate state estimation methods such as Kalman filtering into the perception module to reduce the influence of sensor noise; (3) Conduct real-world experiments to verify the performance of the algorithm. Deploy the algorithm on real autonomous robots or UAVs and test it in real unknown environments; (4) Combine the ARS-DQN algorithm with other intelligent control methods (such as fuzzy control and model predictive control) to further improve the performance of the navigation system; (5) Study the transfer learning ability of the algorithm. Enable the algorithm to transfer the learned navigation strategies from one environment to another, reducing the training time in new environments.

7. Conclusion

This study proposes an improved reinforcement learning algorithm (ARS-DQN) for autonomous navigation in unknown environments. The ARS-DQN algorithm designs an adaptive reward function that integrates exploration progress, target distance, and collision avoidance safety, and adaptively adjusts the weights of each component according to the agent's current state. At the same time, a simplified state representation method based on lidar data is designed to reduce computational complexity.

Comparative experiments with DQN, Double DQN, and Dueling DQN are conducted in three simulated unknown environments with different complexity levels. The experimental results show that the ARS-DQN algorithm reduces navigation time by 18.3%–25.7% and collision rate by 32.1%–41.5% compared to baseline algorithms. The algorithm also exhibits strong robustness to dynamic environmental changes.

This research provides a feasible solution for improving the adaptability and reliability of autonomous navigation systems in unknown environments. Future research will focus on extending the algorithm to 3D navigation tasks, improving its robustness to sensor noise, and verifying its performance in real-world environments.

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