Path Planning under High-dimensional Input States Based on Deep Q-Network

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Abstract. The field of autonomous navigation continues to face challenges in path planning, particularly when addressing the complex, high-dimensional input states that conventional algorithms struggle to process efficiently. This study presents a novel path-planning approach that utilizes Deep Q-Networks (DQN) to manage intricate and multidimensional environmental data. By integrating a DQN with path planning, this study aims to develop an adaptive system capable of making real-time decisions in dynamic environments. The methodology involves training a neural network to approximate the Q-function, enabling the agent to learn optimal strategies directly from unprocessed sensor data such as visual or LiDAR inputs. Experiments conducted in both simulated and real-world scenarios demonstrated the efficacy of this method, revealing significant improvements in route optimization, computational efficiency, and robustness against unforeseen obstacles compared to traditional techniques. The proposed system was evaluated in diverse settings, including urban environments and challenging terrain, illustrating its versatility. These findings suggest that DQN-based path planning has considerable potential for applications in robotics, autonomous vehicles, and other domains requiring intelligent decision-making under uncertainty.

Keywords: Robotics; DQN; Path planning.

1. Introduction

In the rapidly evolving fields of robotics and intelligent systems, navigational planning remains a critical challenge that impacts both practical applications and theoretical research. As robots are increasingly deployed in complex environments, conventional path-planning algorithms, particularly those based on traditional control theories, encounter difficulties in maintaining their efficiency and effectiveness when confronted with high-dimensional input states. This increasing complexity necessitates the exploration of advanced methodologies that can address the intricacies of high-dimensional spaces [1-2]. Among these innovative approaches, Deep Reinforcement Learning (DRL) has emerged as a promising solution, with DQN garnering significant attention owing to their exceptional learning capabilities and robust generalization across various tasks, including navigational planning.

High-dimensional input states encompass spatial coordinates, dynamic obstacles, and sensory data substantially increase the complexity of path-planning problems, and exponentially expand the state space [3-5]. For traditional algorithms, this expansion renders real-time computations increasingly challenging, often resulting in suboptimal solutions or computational infeasibility. By leveraging deep learning techniques, DQNs can effectively manage high-dimensional inputs by mapping them to action-value functions (Q-values) [6-7]. This capability reduces the need for manual feature extraction and enables the system to learn optimal policies autonomously through experience-based interactions with the environment. Consequently, this not only enhances the efficiency of path planning but also improves the system's adaptability to dynamic and uncertain environments, where obstacles may suddenly appear or disappear, and necessitating continuous adjustments to the planned route.

The application of a DQN in path planning is particularly promising owing to its ability to integrate diverse information sources [6]. For instance, the capacity of deep networks to process visual inputs (from cameras and LiDAR) along with proprioceptive data (from sensors) facilitates the development of more comprehensive and informed decision-making models. Furthermore, DQNs can learn to

navigate complex environments involving multiple agents, uncertain dynamics, and varied terrains, which are prevalent in real-world scenarios. These capabilities have positioned deep reinforcement learning as a revolutionary approach for addressing path-planning challenges. This study explored a Deep Q-Network-based approach for path planning in high-dimensional input states. Research begins by examining the current path planning literature, highlighting the advantages and drawbacks of conventional algorithms, and the progress made through deep reinforcement learning. The proposed methodology is then detailed, including the neural network structure, training procedures, and specific test environments [8]. This study incorporated novel techniques in reward shaping, experience replay, and network optimization to enhance learning efficiency.

This study seeks to push the boundaries of path planning, particularly in addressing the challenges associated with high-dimensional input states. This paper's findings offer new insights and solutions applicable to autonomous robotics, self-driving vehicles, and related domains. By showcasing the potential of deep reinforcement learning in practical applications, this study encourages further exploration and adaptation of these techniques to enhance the autonomy and intelligence of robotic systems in increasingly complex and variable environments. Ultimately, this study aims to narrow the gap between theoretical AI advancements and concrete solutions to enhance the navigation and operational efficiency of autonomous agents in real-world contexts.

2. Methodology

This section delineates the methodology employed to develop and evaluate a DQN for navigational planning in scenarios characterized by complex input states. The methodology encompasses the problem formulation, the architectural design of the DQN, and the network training protocol.

2.1. Problem Definition

2.1.1. Environment Setup

In autonomous navigation, path planning is a fundamental task that involves determining a collision-free trajectory from a starting point to a goal. Traditional path-planning approaches often rely on low-dimensional representations of the environment, such as occupancy grids or graph-based models, which may be insufficient when addressing complex perceptual inputs derived from modern sensors, including cameras, LiDAR, or sonar systems. These high-dimensional inputs provide detailed information about the surroundings but present significant challenges owing to their complexity and the computational requirements necessary for effective processing.

2.1.2. State Representation

This study addresses the problem of path planning under high-dimensional input states by leveraging advancements in deep learning and reinforcement learning techniques. Specifically, this research focuses on the application of DQNs to learn optimal policies directly from raw sensor data, without the need for manual feature engineering. The objective was to develop a framework capable of managing the inherent complexity of real-world environments, wherein the agent must navigate through dynamic and partially observable scenes characterized by cluttered spaces, moving obstacles, and varying lighting conditions.

2.1.3. Action Space

The set of possible choices an agent can make at each decision point to advance toward the objective is defined by the action space. Accurately defining this space is crucial for ensuring the planner can generate viable and optimal routes while remaining computationally feasible. Establishing the action space is a critical initial step in creating a DQN-based path planner for high-dimensional input states. Through meticulous selection of the available actions, this research ensures the planner can efficiently and safely navigate complex environments. Striking a balance between expressiveness and manageability in the design of the action space is essential for achieving optimal performance while maintaining the feasibility of the learning process.

2.2. Design of the DQN Architecture

2.2.1. Network Structure

To address the path planning problem with high-dimensional inputs, this paper developed a specialized DQN architecture that processes complex sensor data and learns effective navigation policies. This architecture includes components designed to manage the complexity and diversity of input space, ensuring the network's ability to generalize to new environments. Q-learning serves as the foundation for the DQN algorithm [9]. The Q-learning process employs the time-difference equation to update the value function. The update rule for Q-learning can be expressed as follows:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left[R + \gamma \max_{a'} Q(s',a') - Q(s,a)\right] \quad (1)$$

Here, $Q(s,a)$ represents the quality of taking action a in state s, R is the reward received after performing a, α is the learning rate that determines the extent to which the new information overrides the old information, and γ is the discount factor that diminishes the importance of future rewards compared to immediate ones. The term $\max_{a'} Q(s',a')$ represents the maximum Q-value for the next state s', effectively capturing the expected future reward under optimal behavior.

Fig. 1 presents a conceptual diagram of the DQN architecture employed for the path-planning tasks. This network processes complex, high-dimensional input states through a series of convolutional and fully connected layers to compute the Q-values for each potential action. The network design is optimized to facilitate effective learning and decision-making in environments characterized by intricate input data. The core of DQN features a convolutional neural network (CNN) that extracts key features from high-dimensional sensory inputs. With state representations including RGB images, depth maps, and semantic segmentation masks, the initial network layers process these modalities independently. Convolutional layers with suitable filter sizes and strides capture local patterns in RGB and depth images, while fully connected layers interpret the semantic segmentation masks.

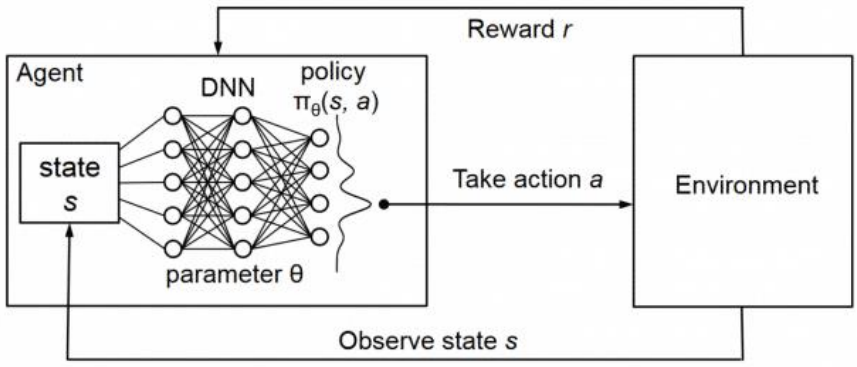

Fig 1. Working principle of DQN [9].

2.2.2. Experience Replay

A vital element of DQN architecture that greatly improves the learning process is the use of experience replay. This method enhances data efficiency and stabilizes training by breaking temporal correlations in observed experiences [10-11]. In path planning, where the agent constantly interacts with the environment, experience replay helps prevent the network from overfitting to recent experiences and enables learning from a broader range of past data.

Experience replay ensures that the learning process remains stable and adaptable by enabling the network to revisit and relearn information from previous encounters. This is especially advantageous in dynamic environments, where the optimal path may evolve over time owing to changing conditions or obstacles. The ability to learn from a wide range of past interactions enables the agent to enhance its generalization capabilities and adapt its strategies more effectively when confronted with novel situations during path planning. Table 1 outlines the pseudocode for the experience replay mechanism,

which efficiently stores and samples transitions to reduce temporal correlation in training data, thereby improving the stability and effectiveness of the DQN-based path planning algorithm.

Table 1. The Experience Replay.

Algorithm 1 Deep Q-learning with Experience Replay
Initialize replay memory D to capacity N
Initialize action-value function Q with random weights
for episode = 1, M **do**
Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\emptyset_1 = \emptyset(s_1)$
for t=1, T **do**
With probability $\in$ select a random action a_t
otherwise select $a_t = max_a Q^*(\emptyset(s_t), a; \theta)$
Execute action a_t in emulator and observe reward r_t and image x_{t+1}
Set $s_{t+1} = s_t, a_t\, x_{t+1}$ and preprocess $\emptyset_{t+1} = \emptyset(s_{t+1})$
Store transition $(\emptyset_t, a_t, r_t, \emptyset_{t+1})$ in D
Sample random minibatch of transitions $(\emptyset_j, a_j, r_j, \emptyset_{j+1})$ from D
Set $y_j = r_j$ for terminal $\emptyset_{j+1}$
Set $y_j = r_j + \gamma max_{a'} Q(\emptyset_{t+1}, a', \theta)$ for non-terminal $\emptyset_{j+1}$
Perform a gradient descent step on $(y_j - Q(\emptyset_j, a_j, \theta))^2$
end for
end for

2.2.3. Target Network

The primary function of the target network is to provide a stable estimation of future rewards that can be anticipated from executing specific actions, thereby mitigating the volatility associated with Q-value predictions made by the main network during the training process [12]. The target network's parameters are periodically updated to align with those of the main network, typically after a predetermined number of training iterations or upon significant improvement in the main network's performance. This synchronization process facilitates a more gradual learning progression and prevents divergence caused by sudden fluctuations in Q-value estimates.

2.3. Training of the DQN

2.3.1. Reward Function

In the DQN-based path planner's learning process, the reward function serves as a critical component. It guides the agent to navigate complex environments effectively and safely by incorporating various factors. These include incentivizing proximity to the target, imposing penalties for obstacle collisions, promoting efficient route selection, discouraging inactivity, and providing positive reinforcement for goal attainment. Through these mechanisms, the reward function ensures the agent develops the capacity to traverse challenging terrains successfully.

The main purpose of the reward function is to encourage the agent to reach its destination quickly and safely while steering clear of obstacles and unnecessary diversions. The reward function should address the following objectives:

1). Encourage Goal-Oriented Movement: Higher rewards should be given as the agent gets closer to its target.

2). Discourage Obstacle Collision: Negative rewards must be applied when the agent collides with obstacles to prevent risky behavior.

3). Promote Efficient Navigation: The agent should be motivated to choose shorter paths to the destination, thus enhancing efficiency.

4). Prevent Inertia: The agent should be discouraged from staying in one place or moving away from the intended goal.

2.3.2. Network Exploration

In the training of DQN for path planning, efficient exploration plays a vital role. Exploration involves the agent's method of gathering new environmental information, which is crucial for developing an optimal policy. When dealing with high-dimensional input states, striking a balance between exploration and exploitation becomes increasingly important to ensure the agent can effectively navigate complex environments [12-13]. Exploration is essential as it allows the agent to gain a comprehensive understanding of its surroundings. Without sufficient exploration, the agent might become stuck in local optima or fail to discover all potential routes to the goal. In high-dimensional input states, the range of possible actions and states can be enormous, making thorough exploration both challenging and necessary.

A commonly used technique for balancing exploration and exploitation is the epsilon-greedy strategy. This approach involves the agent choosing the action with the highest Q-value most of the time, while occasionally selecting a random action to explore the environment.

A prevalent approach for achieving equilibrium between exploration and exploitation is the epsilon-greedy strategy. This methodology involves the agent predominantly selecting the action with the highest Q-value, while periodically choosing a random action to investigate the environment. The probability of opting for a random action versus the currently perceived optimal action is determined by the parameterε, which governs this trade-off in the agent's decision-making process.

$$Action = Random\ Action \quad with\ probability\ \varepsilon \tag{2}$$

$$Action = Greedy\ Action \quad with\ probability\ 1-\varepsilon \tag{3}$$

During training, ε is gradually reduced from a high initial value to a lower value to encourage initial exploration followed by exploitation of the learned policy.

The agent can successfully navigate complex environments while avoiding overreliance on suboptimal policies by implementing strategies such as epsilon-greedy with decay schedules, count-based exploration, and curiosity-driven methods.

3. Results and Discussion

This section examines the proposed method's performance in terms of learning efficiency and effectiveness, with a particular emphasis on the average reward per episode as a crucial metric for evaluating the quality of learned policies.

3.1. Problem Metrics

3.1.1. Analysis of Learning Performance

To assess the learning dynamics of the DQN applied to path planning with high-dimensional input states, this study tracked the agent's average reward over time. This metric serves as a vital indicator of the agent's capacity to effectively navigate its environment, reflecting the total immediate rewards acquired during an episode.

Fig. 2 depicts the progression of the average reward as the DQN agent interacts with the environment across multiple episodes. Initially, the average reward was comparatively low due to the agent's limited understanding of optimal action selection. As learning progresses, a significant increase in average reward is observed, indicating the agent's growing proficiency in choosing actions that result in higher cumulative rewards. This trend demonstrates successful learning and adaptation to a high-dimensional state space.

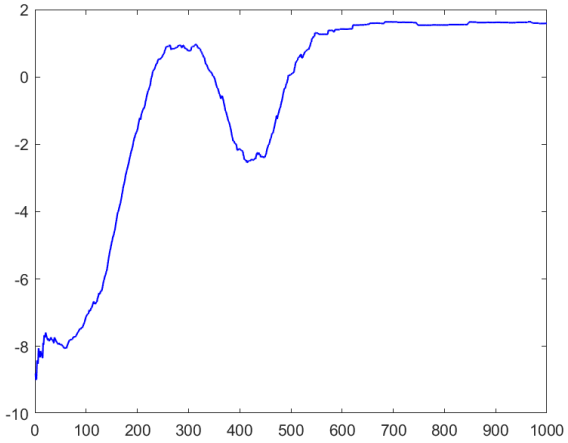

Fig 2. The average reward curve of DQN (Picture credit: Original).

The average reward curve exhibits initial fluctuations during training, which is anticipated as the agent explores the environment and learns from its experiences. These fluctuations decrease over time, suggesting that the agent's policy converges towards one that consistently achieves higher rewards. This convergence is particularly crucial in high-dimensional settings, where exploration can be challenging due to the vast number of possible states.

3.1.2. Path Length and Computation Time

An essential measure for assessing the effectiveness of the route planning algorithm is the length of the path, which measures the total distance covered by the agent from its starting point to its final destination. Reducing path length is beneficial because shorter routes lead to quicker travel times and lower energy use, which are important considerations in many real-world scenarios. The path length metric is particularly useful in evaluating the algorithm's performance in terms of distance optimization. When paths are shorter, it indicates that the agent is moving more directly toward its target, steering clear of unnecessary diversions or circular movements. This capability is crucial in dynamic settings where quick reactions are necessary.

Evaluating the practical efficacy of the path-planning algorithm hinges on computational time, which measures the duration needed to generate a route plan and execute navigation instructions. In real-world applications, rapid planning and execution are vital, especially in dynamic environments where delays can lead to suboptimal solutions or failures. Table 2 compares computational times between the proposed DQN-based method and two conventional approaches, O-learning and A*, across different map sizes (5x5, 10x10, and 20x20). The results indicate that the DQN algorithm is computationally more efficient than both alternatives, especially as the input state dimensions grow.

Table 2. Computation Time of three algorithms.

Size	DQN	Q-learning	A*
5*5	10.526	16.854	20.654
10*10	13.742	18.569	22.382
20*20	15.458	19.548	24.689

3.2. Comparative Analysis

This research assesses different path-planning algorithms for high-dimensional input states, with a particular emphasis on the effectiveness of DQN in intricate environments. To test the hypothesis that DQNs are more efficient in handling high-dimensional path planning, this paper juxtaposed the approach with A* search and conventional Q-learning.

The investigation was performed in a simulated setting featuring multiple obstacles, mimicking real-world conditions. While the A* algorithm performs well in lower-dimensional spaces, it showed notable decreases in efficiency when applied to high-dimensional, obstacle-rich environments.

Conventional Q-learning showed adaptability to dynamic changes but was hindered by the curse of dimensionality, as it relied on discretizing the state space, thus restricting its scalability in complex scenarios. In contrast, the DQN-based method, employing deep neural networks like Convolutional Neural Networks (CNNs), effectively extracted features from high-dimensional data and mapped them to actions. The experience replays mechanisms in DQNs addressed issues related to correlated data during training, resulting in stable learning and enhanced policy quality.

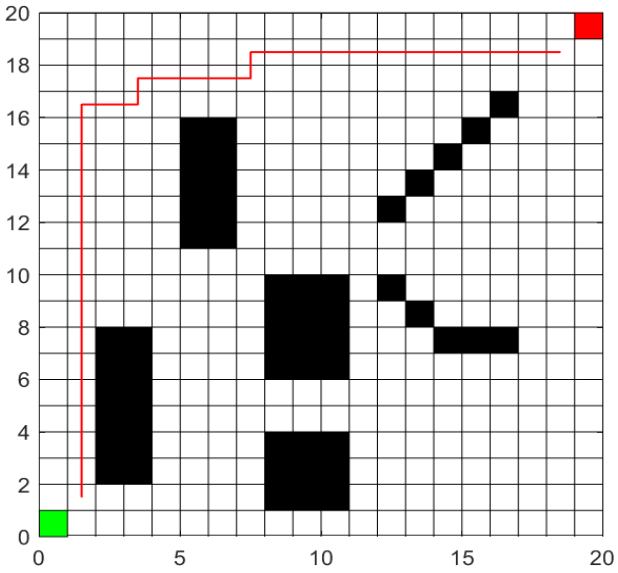

Fig 3. Path Planning Diagram of DQN Algorithm (Picture credit: Original).

The results of path planning using DQN, Q-learning, and A* are shown in Figs. 3, 4 and 5. DQN demonstrated superior performance compared to the other methods across all tested scenarios, particularly in terms of convergence rate and adaptability to diverse initial conditions and environmental configurations. In contrast to Q-learning, which necessitated extensive preprocessing and state discretization, DQN's capacity to learn from raw input states facilitated more efficient adjustment. Furthermore, DQN exhibited enhanced resilience to unanticipated environmental changes in comparison to A*, as it did not rely on predetermined heuristics. Experimental outcomes revealed that the DQN-based solution achieved better search efficiency and path quality in complex environments compared to alternative methods.

These findings are supported by quantitative metrics, indicating that DQNs provide a robust and scalable solution for high-dimensional path planning challenges.

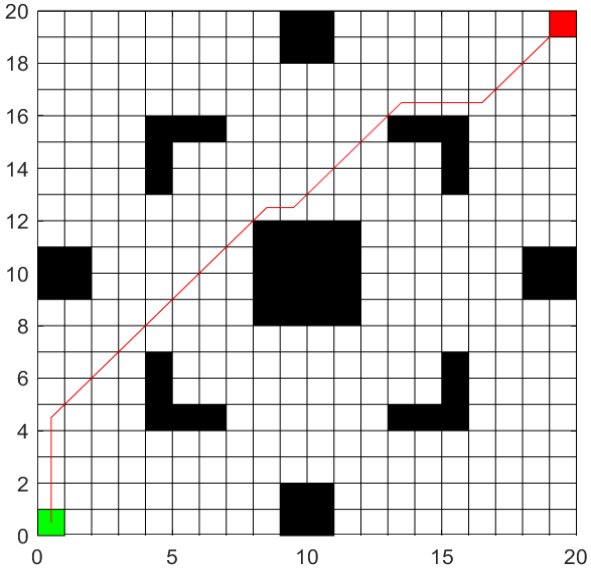

Fig 4. Path Planning Diagram of Q-learning Algorithm (Picture credit: Original).

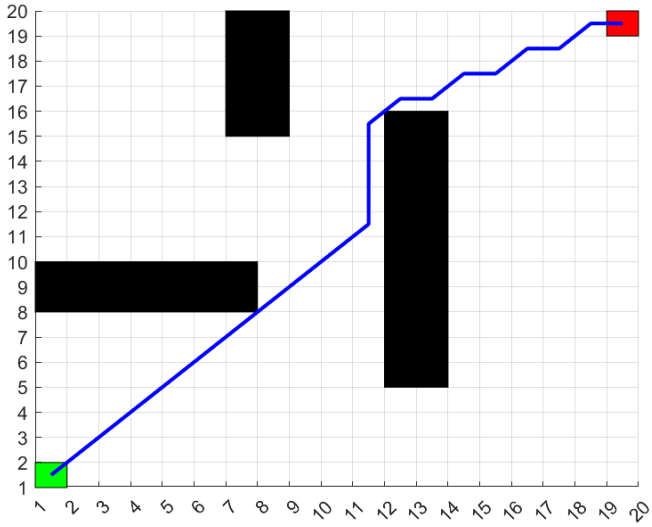

Fig 5. Path Planning Diagram of A* Algorithm (Picture credit: Original).

3.3. Additional Considerations

3.3.1. Data Augmentation

Data augmentation constitutes a critical methodology in deep learning that enhances model robustness and generalization, particularly when training datasets are limited or biased. This approach is especially valuable in path planning challenges, where input states can be highly dimensional and complex. Through the implementation of data augmentation strategies, the performance and reliability of DQN-based planners can be significantly improved, enabling them to more effectively address the intricacies and variations inherent in these problems.

3.3.2. Safety and Reliability

Addressing the complex issue of safety and dependability in a DQN-based path planner with high-dimensional input states requires a thorough examination of both conceptual frameworks and real-world applications. The planner demonstrates improved safety and reliability features through the incorporation of sophisticated collision avoidance systems, redundant sensor arrays, stability assessments, and ongoing monitoring protocols. Future studies should persist in investigating innovative approaches to enhance the robustness of these systems, particularly in unpredictable and changing environments.

4. Conclusion

This study addresses the challenge of path planning with high-dimensional input states using DQN. The integration of a DQN with path planning has resulted in a versatile system capable of instantaneous decision-making in complex and dynamic environments. This methodology significantly enhances the capacity of autonomous agents to navigate efficiently and safely even in densely populated areas with unforeseen obstacles.

This methodology involved training a deep neural network to estimate the Q-function, enabling the agent to acquire optimal policies directly from raw sensor data. The application of a DQN in this context offers several advantages over conventional path-planning algorithms. This facilitates the management of high-dimensional input spaces, surpassing the limitations of traditional methods. Furthermore, the adaptive nature of the DQN allows for continuous learning and improvement in the agent's decision-making capabilities.

To evaluate the efficacy of the method, this study conducted comprehensive tests in simulated and real-world environments. The simulations encompassed urban areas with high traffic densities and off-road terrain with unpredictable obstacles. The results demonstrated that the DQN-based approach achieved superior path optimality, computational efficiency, and resilience against unforeseen

challenges compared with traditional path-planning techniques. The system generates more direct and safer routes while maintaining faster processing times, even in complex scenarios.

For real-world trials, this study implemented the algorithm on a mobile robot equipped with a camera and a LiDAR. The robot successfully navigated various environments by adjusting its path in real time to avoid obstacles and efficiently reach its destination. These experiments not only corroborated the theoretical findings but also demonstrated the practical applicability of the proposed method.

This study also investigated various training strategies, such as epsilon-greedy and experience replay, to enhance an agent's environmental exploration capabilities. The analysis of these techniques provided valuable insights into optimizing the learning process and improving the generalizability of learned policies. Experience replay proved particularly crucial in preventing the agent from overfitting to recent experiences and in ensuring a more balanced exploration of the state-action space.

This research indicates that DQN-based path planning has significant potential for applications in robotics, autonomous vehicles, and other fields that require intelligent decision-making under uncertainty. Their ability to handle high-dimensional input states and make real-time decisions creates new possibilities for advanced autonomous systems. Future research could focus on further optimizing the training process, exploring transfer learning techniques to improve the agent's adaptability across different environments, and incorporating multiagent coordination for cooperative navigation in autonomous vehicle teams.

In conclusion, this study demonstrated the potential of integrating a DQN with path planning to address the challenges posed by high-dimensional input states. The proposed method offers a robust and adaptable solution for autonomous navigation and establishes a foundation for more sophisticated and reliable autonomous systems in various real-world applications.

There are several avenues for future research. First, while the DQN has demonstrated efficacy in learning from unprocessed sensory data, the incorporation of hierarchical reinforcement learning could enhance long-range planning and mitigate the computational burdens associated with high-dimensional information. Second, it is imperative to address state-space explosions in practical applications, indicating the necessity for sophisticated feature extraction methods or convolutional neural networks to process perceptual inputs more effectively. Furthermore, the integration of a DQN with symbolic reasoning approaches can yield hybrid solutions that efficiently navigate and evaluate actions, thereby enhancing the safety and intelligence of autonomous systems. This comprehensive approach could significantly advance autonomous navigation, progressing towards fully self-governing, situationally aware machines capable of maneuvering through dynamic and unpredictable environments.

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