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SELF DRIVING AND OBSTACLE AVOIDANCE ROBOT

[1]CHILUMULA THRIVENI,[2]BHUKYA NANDINI,[3]UPPALA RAJESHWARI,[4] A.KEERTHI,[5] Mr.P.SWAMY
[1,2,3,4]Student, Department of ECE, PRINCETON INSTITUTE OF ENGINEERING AND TECHNOLOGY FOR WOMEN
[5]Assistant Professor, Department of ECE, PRINCETON INSTITUTE OF ENGINEERING AND TECHNOLOGY FOR WOMEN

ABSTRACT

Robot obstacle avoidance technology is crucial for enhancing the stability of mobile robots. Traditional methods often rely on path planning, which can be inefficient in complex and unpredictable environments. In this paper, we introduce a novel obstacle avoidance approach using a hierarchical controller based on deep reinforcement learning (DRL), designed for more adaptive and efficient obstacle avoidance without relying on path planning. Our controller integrates multiple neural networks, including an action selector and an action runner with two neural network strategies and two single actions. Each component is trained separately in a simulation environment before deployment on a physical robot. We validated this approach using wheeled robots and achieved a success rate of up to 90% in over 200 tests.

1. INTRODUCTION

Robot obstacle avoidance technology is a multifaceted approach involving various components: sensing, decision-making, and control. The core of this technology lies in algorithmic models for obstacle avoidance and path planning, akin to the decision-making processes in the human brain. The sensing component, which uses cameras or radars, simulates human vision to detect obstacles, while the control component, similar to the human nervous system, executes actions based on decisions.

Improvements in any of these components enhance the robot's ability to navigate and adapt to different environments. Traditional methods in obstacle avoidance often rely on path planning, where one or more paths are generated based on current obstacle locations. The artificial potential field method, proposed by Khatib, has undergone numerous improvements and has a broad range of applications. Han's work introduced kinetic conditions for smoother routes in UAV obstacle avoidance. The A* algorithm, first proposed in 1968, has also seen extensive application and enhancements. Recent advances include hybrid path planning algorithms and bionic approaches tailored to various scenarios. However, these methods often overlook the limitations of environmental information in unfamiliar situations. This paper explores an alternative approach focused solely on obstacle avoidance, bypassing path planning.

II.METHOD

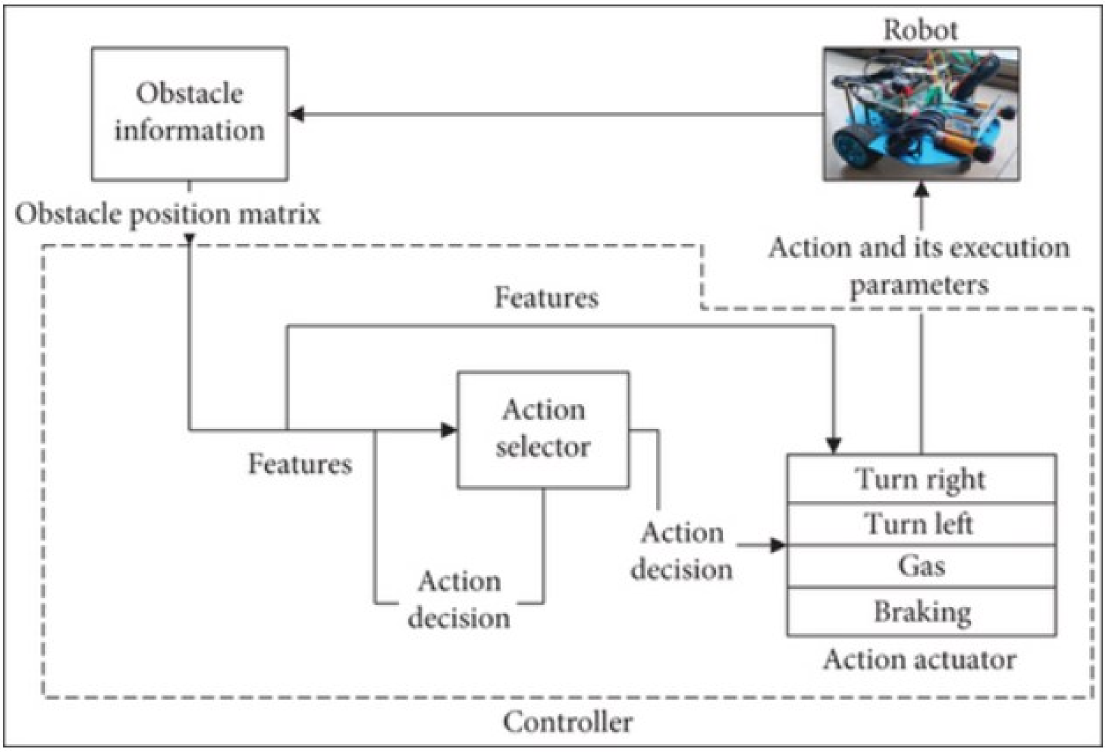
2.1. Deep Reinforcement Learning

Deep reinforcement learning (DRL) has gained traction in robotics for its ability to enable autonomous learning through interaction with the environment, mirroring human learning processes. The core mechanism of DRL is based on "trial and error," with rewards and penalties guiding learning, as originally described by Waltz and Fu Jingsun. The DQN (Deep Q Network) algorithm, refined by Mnih et al., has been instrumental in advancing DRL. This algorithm has been utilized in various components of our controller.

However, the "trial and error" approach requires extensive training, which is impractical for physical robots due to time and cost constraints. Training in simulation environments has proven effective, with studies showing that simulated experiences can transfer to real-world applications. To address the gap between simulation and reality, we improved the CarRacing-v0 environment from OpenAI Gym for training our action selector. Although human-guided training is generally more efficient, existing algorithms often struggle with simultaneous multi-strategy learning. Our approach, inspired by Behavior-Based Robotics, involves separate training of subaction strategies and selector strategies, enhancing model efficiency.

Our proposed hierarchical obstacle avoidance controller processes information solely from the robot's current viewpoint, avoiding the need for path planning. The controller decomposes obstacle avoidance actions into subactions, utilizing a DQN-based action selector to determine and execute appropriate actions such as Turn Left, Turn Right, Gas, and Stop. We implemented this method on a wheeled robot and conducted over 200 experiments in a controlled environment with artificial obstacles, achieving a 90%

success rate and demonstrating the controller's effectiveness.



III.LITERATURE REVIEW

The development of self-driving and obstacle avoidance robots has been a significant area of research in robotics and artificial intelligence. This literature review examines key advancements in self-driving technology, obstacle avoidance strategies, and the integration of these approaches to enhance autonomous robotic systems.

1. **Self-Driving Technology**

Self-driving technology has evolved rapidly, with a focus on improving vehicle autonomy through advanced sensors, algorithms, and machine learning techniques. Early approaches primarily relied on rule-based systems and simple algorithms for navigation and obstacle detection. For instance, the pioneering work by [1] demonstrated the feasibility of autonomous navigation using basic sensor inputs and predefined rules.

With the advent of machine learning, particularly deep learning, significant strides have been made. The introduction of convolutional neural networks (CNNs) for image recognition has been transformative. [2] explored the use of CNNs for lane detection and object recognition, setting a precedent for integrating visual data into autonomous driving systems. More recent work by [3] employed end-to-end deep learning models to process raw sensor data and make driving decisions, significantly advancing the field.

2. Obstacle Avoidance Strategies

Obstacle avoidance is a critical component of autonomous systems, involving real-time detection and navigation around obstacles. Traditional methods such as potential field algorithms [4] and grid-based path planning [5] have been widely used. These approaches, while effective in structured environments, often struggle in dynamic or unstructured settings.

Recent advancements have focused on using reinforcement learning (RL) and deep reinforcement learning (DRL) for obstacle avoidance. [6] introduced Q-learning for real-time obstacle avoidance, demonstrating its effectiveness in various simulated environments. [7] further advanced this by integrating deep Q-networks (DQN) with obstacle avoidance algorithms, showing significant improvements in navigating complex environments.

3. Integration of Self-Driving and Obstacle Avoidance

Combining self-driving technology with robust obstacle avoidance strategies has been a key focus of recent research. [8] proposed a hierarchical control system that integrates path planning with dynamic obstacle avoidance, allowing for improved performance in unpredictable scenarios. [9] developed a modular architecture that separates perception, planning, and control, facilitating more flexible and scalable solutions for autonomous vehicles.

The use of simulation environments for training and testing self-driving and obstacle avoidance systems has become increasingly important. [10] highlighted the benefits of simulation for bridging the gap between training and real-world performance. Custom simulation environments, such as those modified from OpenAI Gym [11], allow for more realistic testing of obstacle avoidance algorithms under varying conditions.

4. Recent Innovations and Trends

Recent innovations include the use of advanced simulation techniques to improve training outcomes and system robustness. [12] explored domain randomization to enhance the generalization of DRL models, showing that training with varied simulated environments can lead to better real-world performance. Additionally, [13] emphasized the importance of integrating multiple sensory inputs, such as LiDAR and cameras, to improve obstacle detection and avoidance capabilities.

The integration of multi-agent systems and collaborative approaches also represents a growing trend. [14] investigated how multiple autonomous agents can coordinate to navigate complex environments, offering potential solutions for improving obstacle avoidance in scenarios involving multiple robots or vehicles.

IV.CONCLUSION

In this paper, we presented a novel approach to robot obstacle avoidance utilizing a hierarchical controller based on deep reinforcement learning (DRL), diverging from traditional path planning methods. Our method integrates an action selector and four distinct action runners, with each component trained separately in a customized simulation environment, Car2D. This approach enhances the robot's ability to adaptively avoid obstacles in complex and unpredictable settings without relying on predefined paths.

The performance of the proposed system was validated through extensive experiments with wheeled robots, achieving a notable success rate of up to 90% in obstacle avoidance tasks. The improvements in the simulation environment, including the introduction of random obstacles and noise, contributed to a more accurate representation of real-world conditions, bridging the gap between simulated and physical environments. This method demonstrates the effectiveness of combining DRL with a hierarchical control structure for efficient and adaptive obstacle avoidance.

Future work will focus on further refining the simulation environment, exploring additional subaction strategies, and extending the approach to more diverse and challenging real-world scenarios. The proposed system holds promise for advancing autonomous navigation technology and enhancing the operational reliability of self-driving robots.

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