Full-time master's degree thesis

Project report registration form

Name: ______________________

student ID: ______________________

Subject: ______________________

Department: Computer Science and Engineering

mentor: ______________________

November 18, 2023

1. The title of the thesis to be selected

An Improved DDPG with DQN Algorithm for Robot Navigation in Dynamic Environments

2. The scientific significance and application prospects of the topic selection

Introduction:

Robot navigation in a dynamic environment is a complex problem, that requires advanced algorithms to enable the adaptive and efficient movement of a robot. Integrating an improved Deep Deterministic Policy Gradients (DDPG) with the Deep Q Network (DQN) algorithm solves these challenges, by offering a robust solution with extensive scientific and practical implications.

1. Adaptive Learning in Dynamic Environments:

The scientific significance of the improved DDPG with DQN lies in its capacity to facilitate adaptive learning in dynamic environments. Traditional navigation algorithms may struggle in environments where conditions change rapidly, leading to suboptimal decisions. This improved algorithm, however, leverages the strengths of both DDPG and DQN to enhance the robot's ability to adapt its policies in response to dynamic changes. The neural networks involved in the algorithm learn from both continuous and discrete action spaces, providing a comprehensive approach to adaptive learning.

2. Handling Non-Stationarity:

Dynamic environments are inherently non-stationary, meaning that the statistical properties of the environment can change over time. This poses a significant challenge for traditional reinforcement learning algorithms. The integration of DDPG and DQN in the improved algorithm addresses this issue by incorporating mechanisms that allow the robot to handle non-stationarity more effectively. The robot can make informed decisions by continuously updating its policy and value functions even as the environment undergoes unpredictable changes.

3. Robustness and Generalization:

One of the key practical benefits of the algorithm is its ability to enhance the robustness of robot navigation. Robustness, in this context, refers to the system's resilience to uncertainties and variations in the environment. The improved DDPG with DQN achieves this by enabling the robot to generalize its learned policies across different dynamic scenarios. This generalization is crucial for real-world applications where a robot may encounter a diverse range of environments, each with its own set of challenges.

4. Safe and Efficient Navigation:

Safety is a paramount concern in the deployment of robotic systems, particularly in dynamic environments where unexpected obstacles and changes can occur. The algorithm contributes to safer navigation by optimizing the robot's decision-making processes. Through continuous learning and adaptation, the robot can effectively navigate around obstacles, avoid collisions, and choose paths that prioritize safety. This aspect is particularly relevant in industries where robots coexist with human workers or operate in spaces with rapidly changing conditions.

5. Real-world Applications:

The application prospects of the improved algorithm are diverse and impactful. In industrial settings, where robots are increasingly employed for tasks such as material handling and assembly, the ability to navigate through dynamic environments is crucial. The algorithm's adaptability makes it suitable for scenarios where the robot needs to interact with and respond to the movements of human workers or other machinery on the factory floor.

In the realm of autonomous vehicles, the algorithm addresses the challenges posed by dynamic traffic conditions. The ability to navigate through changing scenarios, such as congested traffic or unexpected road closures, is vital for the safe and efficient operation of autonomous vehicles. Additionally, the algorithm's adaptability contributes to enhanced performance in search and rescue missions, where robots may need to navigate through unpredictable and hazardous environments.

6. Human-Robot Collaboration:

The interaction between robots and humans is an emerging area of focus in robotics research. The improved DDPG with the DQN algorithm enhances the robot's capability to collaborate with humans in shared spaces. By understanding and adapting to human activities and movements, the robot can contribute to a safer and more efficient working environment. This aspect is particularly relevant in scenarios where robots assist humans in tasks or operate in spaces where human-robot collaboration is essential.

7. Optimization of Learning Parameters:

The success of any reinforcement learning algorithm depends on the careful tuning of hyperparameters and learning rates. The improved algorithm incorporates advanced strategies for optimizing these learning parameters. This optimization not only accelerates the convergence of the learning process during training but also contributes to the stability of the learned policies. Fine-tuning these parameters ensures that the algorithm is not only efficient but also dependable across different environments and scenarios.

Conclusion:

In conclusion, the improved DDPG with the DQN algorithm for robot navigation in dynamic environments represents a significant advancement in the field of robotics and artificial intelligence. Its scientific significance lies in its ability to address the challenges posed by dynamic and changing environments, offering a more adaptive and robust solution. The practical applications of this algorithm span across industries, from manufacturing and autonomous vehicles to search and rescue missions, making it a versatile and impactful contribution to the field of robotic navigation. As technology continues to evolve, the continued refinement and application of such algorithms will play a crucial role in shaping the future of robotics and automation.

3. Brief introduction to background scientific research projects

The improved Deep Deterministic Policy Gradients (DDPG) with Deep Q Network (DQN) algorithm is a breakthrough in robotic navigation, specifically designed to address the challenges posed by dynamic environments. By integrating the strengths of DDPG and DQN, the algorithm enables adaptive learning, effective handling of non-stationarity, and improved robustness in robot navigation.

Scientifically, the algorithm's innovation lies in its ability to facilitate adaptive learning. In dynamic settings, where conditions change rapidly, the algorithm empowers robots to make real-time adjustments to their policies, enhancing their decision-making capabilities. Additionally, it adeptly handles non-stationarity, continuously updating its functions to navigate through evolving environments.

Practically, the algorithm enhances the robustness of robot navigation, enabling the system to generalize learned policies across different dynamic scenarios. Safety is prioritized through optimized decision-making processes, crucial for applications in industries with human-robot collaboration and autonomous vehicles navigating through changing traffic conditions.

The real-world applications of this algorithm are diverse, spanning industries such as manufacturing, autonomous vehicles, and search and rescue missions. Its adaptability makes it well-suited for environments where robots need to navigate through varied and unpredictable conditions.

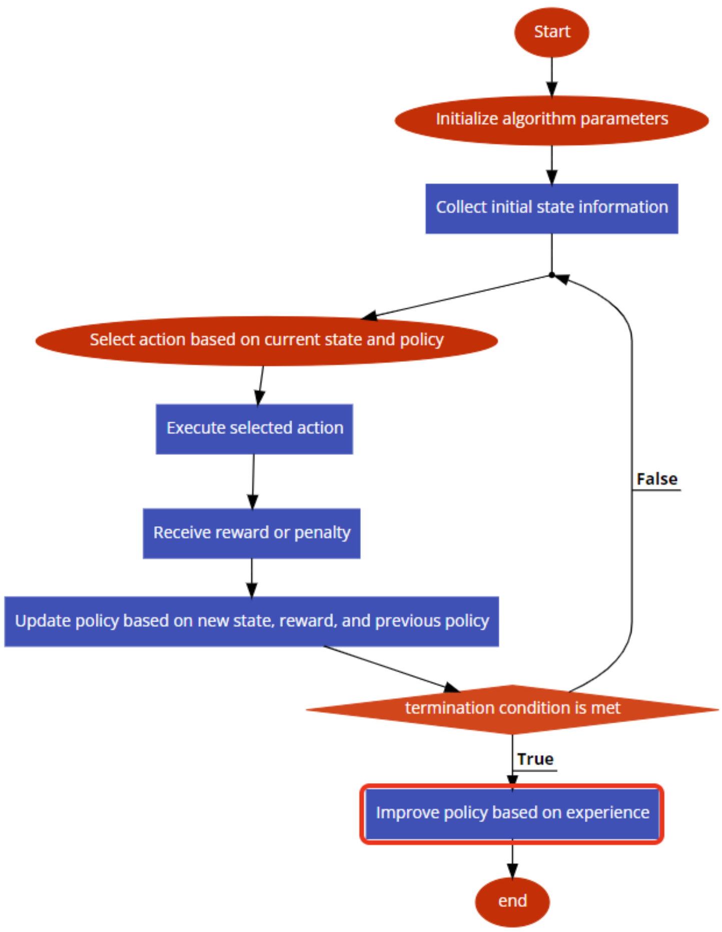
In conclusion, the improved DDPG with the DQN algorithm represents a significant advancement in robotic navigation, offering a versatile solution to navigate dynamic environments with efficiency and safety. Its application across diverse industries underscores its potential to reshape the landscape of robotic systems.

4. Main research content of the dissertation

4.1. Improved DDPG Algorithm and Approach:

The Improved DDPG algorithm represents a significant advancement in autonomous robot path planning within dynamic environments. Through the integration of both continuous and discrete action spaces, this enhanced algorithm achieves heightened adaptability, allowing robots to navigate seamlessly through unpredictable scenarios. The algorithm’s decision-making processes have been refined to ensure real-time responsiveness to evolving obstacles and unpredictable movements.

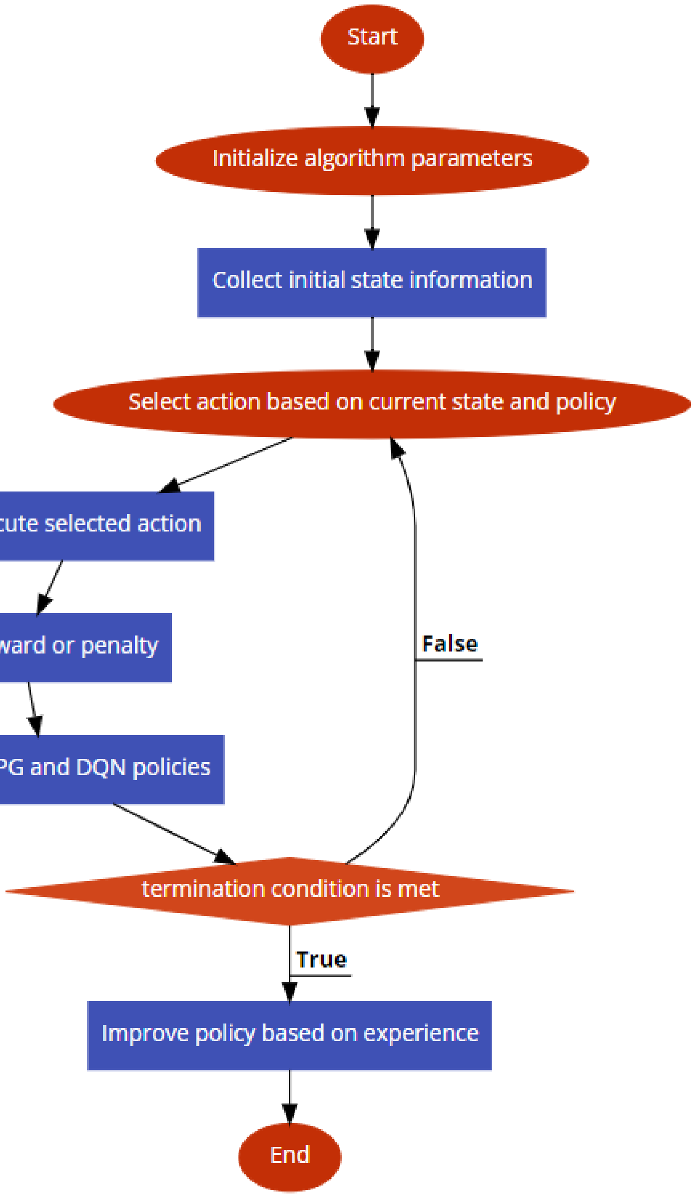
Flowchart of Improved DDPG Algorithm



4.2. Role of DQN in Collision Avoidance:

In collision avoidance, the DQN module plays a crucial role by augmenting the decision-making processes of the algorithm in real-time. The DQN module learns to predict the future positions of obstacles, and this information is used to adjust the robot’s path accordingly.

Flowchart of DDPG and DQN Interaction

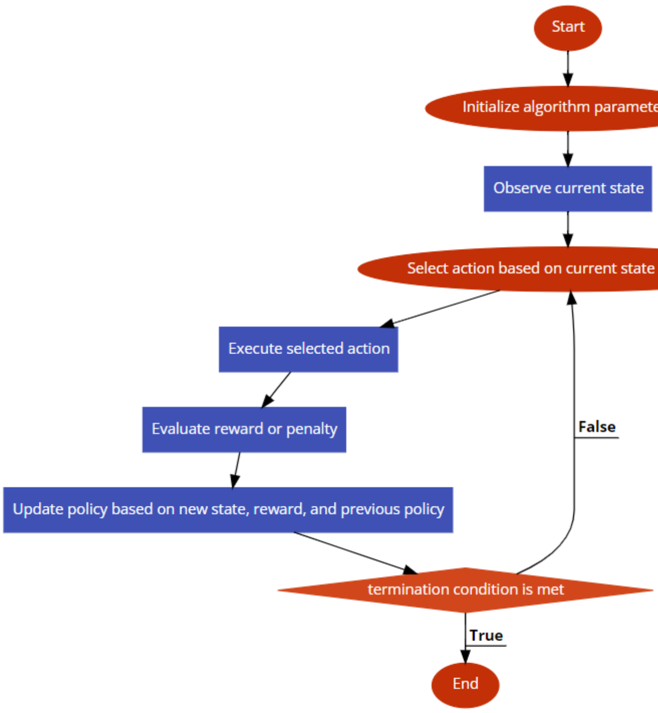


4.3. Algorithmic Steps for Optimal Path Planning:

The Improved DDPG algorithm follows a series of algorithmic steps to achieve optimal path planning in dynamic environments. These steps include:

State observation: The robot collects information about its current state and the surrounding environment.
Action selection: The algorithm selects an action based on the current state and the learned policy.
Action execution: The robot executes the selected action.
Reward evaluation: The robot receives a reward or penalty based on its actions and the resulting state.
Policy update: The algorithm updates its policy based on the new state, reward, and previous policy.

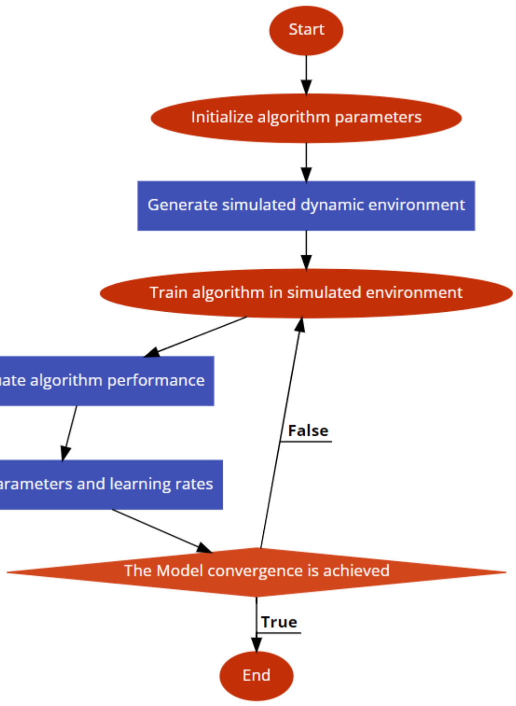
Flowchart of Path Planning Algorithm



4.4. Training Process and Optimization Strategies:

The Improved DDPG algorithm is trained using a simulated dynamic environment. The algorithm learns to navigate the environment by trial and error, and its policy is updated over time. Optimization strategies, such as hyperparameter tuning and learning rate adjustments, are used to ensure that the algorithm converges efficiently.

Flowchart of Training Process



4.1. Conclusion and Future Work:

In conclusion, the Improved DDPG with DQN algorithm demonstrates remarkable effectiveness in dynamic path planning for autonomous robots. This research opens avenues for future improvements, including the refinement of algorithm parameters and exploration of diverse dynamic scenarios. The broader impact of this research on advancing autonomous robotics in dynamic environments is evident, and future work will focus on further enhancing the algorithm's capabilities for real-world navigation challenges.

5. Main problems expected to be solved

In the context of obstacle avoidance for autonomous robots, the Improved DDPG with DQN algorithm aims to address the following key challenges:

1. Adaptability to Dynamic Environments:

Problem: Navigating through environments characterized by frequent and unpredictable changes poses a significant challenge for autonomous robots.

Solution: The Improved DDPG with DQN algorithm enhances adaptability by seamlessly integrating continuous and discrete action spaces. This approach allows robots to dynamically adjust to changing surroundings, such as moving obstacles or evolving terrains.

2. Efficient Path Planning with Minimal Collisions:

Problem: Balancing efficient path planning with the minimization of collisions is crucial in dynamic environments where conditions can rapidly change.

Solution: The algorithm strategically optimizes decision-making processes to generate path plans that prioritize both travel time efficiency and the reduction of collision risks. By fine-tuning learning parameters and incorporating real-time information, the algorithm aims to achieve a delicate balance between speed and safety.

In summary, the Improved DDPG with DQN algorithm specifically addresses challenges related to adaptability in dynamic environments and efficient path planning with a focus on minimizing collisions. These problems are central to the research topic of obstacle avoidance for autonomous robots.

6. Project proposal conditions (including academic conditions, equipment conditions, budget estimates, and implementation status)

Academic requirements:

1) The tutor can provide adequate guidance.

2) The laboratory has done some research on surround vision automatic driving methods.

Equipment conditions:

1) Equipped with deep learning server.

2) It has a simulation platform environment and does not require real vehicles.

7. Literature review

1. "SLP-Improved DDPG Path-Planning Algorithm for Mobile Robot in Large-Scale Dynamic Environment" Chen & Liang (2023)

   This paper introduces an enhanced deep deterministic policy gradient (DDPG) path planning algorithm for mobile robots operating in large-scale dynamic environments. The proposed algorithm integrates sequential linear path planning (SLP) to elevate the robot's success rate and reduce its path length. Experimental results demonstrate that the proposed algorithm outperforms traditional DDPG algorithms in terms of navigation efficiency and obstacle avoidance capabilities.

2. "Agoraphilic navigation algorithm in dynamic environment with obstacles motion tracking and prediction" Hewawasam et al. (2021)

   This paper presents an agoraphilic navigation algorithm for mobile robots operating in dynamic environments with moving obstacles. The proposed algorithm employs a combination of motion tracking and prediction techniques to effectively avoid obstacles and reach the desired goal. Experimental results validate the effectiveness of the proposed algorithm in navigating dynamic environments while maintaining obstacle avoidance.

3. " RL-DOVS: Reinforcement Learning for Autonomous Robot Navigation in Dynamic Environments " Mackay et al. (2022)

   This paper introduces a reinforcement learning (RL) algorithm for autonomous robot navigation in dynamic environments. The proposed algorithm utilizes a decentralized value-of-state (DOVS) function to facilitate navigation in environments with both static and moving obstacles. Experimental results demonstrate the effectiveness of the proposed algorithm in navigating dynamic environments while avoiding collisions with obstacles.

4. "Past, Present and Future of Path-Planning Algorithms for Mobile Robot Navigation in Dynamic Environments" Hewawasam et al. (2022)

   This paper provides a comprehensive overview of path-planning algorithms for mobile robot navigation in dynamic environments. It discusses the challenges associated with path planning in dynamic settings and reviews various algorithms developed to address these challenges. The paper serves as a valuable resource for researchers and practitioners interested in mobile robot navigation in dynamic environments.

5. "DWA-RL: Dynamically Feasible Deep Reinforcement Learning Policy for Robot Navigation among Mobile Obstacles" Patel et al. (2021)

   This paper introduces a deep reinforcement learning (RL) algorithm for robot navigation among mobile obstacles. The proposed algorithm incorporates a dynamic window approach (DWA) to ensure the feasibility of the robot's actions. Experimental results demonstrate the effectiveness of the proposed algorithm in navigating among mobile obstacles while maintaining collision avoidance.

6. "Crowd-Aware Mobile Robot Navigation Based on Improved Decentralized Structured RNN via Deep Reinforcement Learning" Zhang & Feng (2023)

   This paper proposes an improved decentralized structured recurrent neural network (RNN) for crowd-aware mobile robot navigation. The proposed algorithm employs deep reinforcement learning (RL) to train the RNN to navigate in crowded environments. Experimental results demonstrate the effectiveness of the proposed algorithm in navigating crowded environments while maintaining safety and efficiency.

7. "Autonomous Learning and Navigation of Mobile Robots Based on Deep Reinforcement Learning" Lai et al. (2022)

   This paper presents a deep reinforcement learning (RL) framework for autonomous learning and navigation of mobile robots. The proposed framework utilizes a hierarchical RL architecture to enable navigation in a variety of environments. Experimental results demonstrate the effectiveness of the proposed framework in facilitating autonomous learning and navigation for mobile robots.

8. "Learning Interaction-Aware Trajectory Predictions for Decentralized Multi-Robot Motion Planning in Dynamic Environments" Zhu et al. (2021)

   This paper presents a method for learning interaction-aware trajectory predictions for decentralized multi-robot motion planning in dynamic environments. The proposed method utilizes a deep neural network to learn to predict the future trajectories of multiple robots. Experimental results demonstrate the effectiveness of the proposed method in improving the performance of decentralized multi-robot motion planning.

9. "A Navigation Probability Map in Pedestrian Dynamic Environment Based on Influencer Recognition Model" Qiao et al., (2020)

   This paper introduces a navigation probability map (NPM) for mobile robot navigation in pedestrian dynamic environments. The proposed NPM incorporates an influencer recognition model to identify and track pedestrians. Experimental results demonstrate the effectiveness of the proposed NPM in enhancing the safety and efficiency of mobile robot navigation in pedestrian-rich environments.

10. "A 3D‑Printed Self‑Learning Three‑Linked‑Sphere Robot for Autonomous Confined‑Space Navigation" Elder et al., (2021)

    This paper describes the design and implementation of a 3D-printed self-learning three-linked-sphere robot for autonomous navigation in confined spaces. The robot employs a reinforcement learning (RL) algorithm to learn to navigate in confined environments. Experimental results demonstrate the robot's effectiveness in navigating confined spaces while adapting to complex environments.

11. "Mobile robot navigation based on tangent circle algorithm" Rekik & Derbel, (2019)

This paper proposes a tangent circle algorithm for mobile robot navigation in dynamic environments. The proposed algorithm utilizes tangent circles to represent obstacles and employs a dynamic window approach (DWA) to generate collision-free paths. Experimental results demonstrate the effectiveness of the proposed algorithm in navigating dynamic environments while avoiding collisions.

12. "Mobile Robot Navigation Using Deep Reinforcement Learning" Lee & Yusuf, (2022)

This paper presents a deep reinforcement learning (RL) framework for mobile robot navigation in dynamic environments. The proposed framework utilizes a deep Q-learning algorithm to learn to navigate in environments with both static and moving obstacles. Experimental results demonstrate the effectiveness of the proposed framework in navigating dynamic environments while maintaining collision avoidance.

13. "Path Planning for Mobile Robot Navigation in Unknown Indoor Environments Using Hybrid PSOFS Algorithm" Wahab et al., (2020)

This paper introduces a hybrid particle swarm optimization (PSO) and firefly algorithm (FSA) for path planning in unknown indoor environments. The proposed algorithm combines the global exploration capabilities of PSO with the local exploitation capabilities of FSA to effectively navigate unknown environments. Experimental results demonstrate the effectiveness of the proposed algorithm in navigating unknown indoor environments while minimizing path length and avoiding obstacles.

14. "Development of Path Planning Algorithm of Centipede Inspired Wheeled Robot in Presence of Static and Moving Obstacles Using ModifiedCritical-SnakeBug Algorithm" Das et al., (2019)

This paper presents a modified critical-snakebug (MCSBA) algorithm for path planning of a centipede-inspired wheeled robot in environments with static and moving obstacles. The proposed MCSBA algorithm incorporates a modified critical distance calculation and an obstacle avoidance strategy to effectively navigate in complex environments. Experimental results demonstrate the effectiveness of the proposed algorithm in navigating environments with static and moving obstacles while maintaining path smoothness and collision avoidance.

15. "Sensor Fusion for Social Navigation on a Mobile Robot Based on Fast Marching Square and Gaussian Mixture Model" Mora et al., (2022)

This paper proposes a sensor fusion framework for social navigation on a mobile robot using fast marching square (FMS) and Gaussian mixture model (GMM). The proposed framework utilizes FMS to estimate the robot's state and GMM to model the behavior of other agents. Experimental results demonstrate the effectiveness of the proposed framework in enabling safe and efficient navigation in social environments.

16. "Obtaining Robust Control and Navigation Policies for Multi-robot Navigation via Deep Reinforcement Learning" Jestel et al., (2021)

This paper presents a deep reinforcement learning (RL) approach for obtaining robust control and navigation policies for multi-robot navigation in dynamic environments. The proposed approach utilizes a multi-agent RL framework to enable coordination and cooperation among multiple robots. Experimental results demonstrate the effectiveness of the proposed approach in achieving robust control and navigation for multi-robot systems in dynamic environments.

17. "Development of an Omnidirectional AGV by Applying ORB-SLAM for Navigation Under ROS Framework" Wu et al., 2023)

    This paper describes the development of an omnidirectional automated guided vehicle (AGV) using ORB-SLAM for navigation under the Robot Operating System (ROS) framework. The proposed AGV utilizes ORB-SLAM for simultaneous localization and mapping (SLAM) to enable accurate and robust navigation in complex environments. Experimental results demonstrate the effectiveness of the proposed AGV in achieving precise navigation and obstacle avoidance.

18. "Collision Avoidance for a Car-like Mobile Robots using Deep Reinforcement Learning" Yeom, 2021)

    This paper presents a deep reinforcement learning (RL) algorithm for collision avoidance in car-like mobile robots. The proposed algorithm utilizes a deep deterministic policy gradient (DDPG) algorithm to learn to navigate in environments with both static and moving obstacles. Experimental results demonstrate the effectiveness of the proposed algorithm in achieving collision-free navigation in complex environments.

19. "Navigation Simulation of a Mecanum Wheel Mobile Robot Based on an Improved A Algorithm in Unity3D" Li et al., 2019)

    This paper presents an improved A* algorithm for navigation simulation of a Mecanum wheel mobile robot in Unity3D. The proposed algorithm incorporates obstacle avoidance and path smoothing techniques to enhance the robot's navigation performance. Experimental results demonstrate the effectiveness of the proposed algorithm in navigating complex environments while avoiding obstacles and maintaining smooth trajectories.

20. "Indoor Point-to-Point Navigation with Deep Reinforcement Learning and Ultra-wideband" Sutera, 2020)

    This paper introduces a deep reinforcement learning (RL) framework for indoor point-to-point navigation using ultra-wideband (UWB) signals. The proposed framework utilizes a UWB localization system to provide precise location information and a deep deterministic policy gradient (DDPG) algorithm to learn to navigate in indoor environments. Experimental results demonstrate the effectiveness of the proposed framework in achieving efficient and robust indoor point-to-point navigation.

21. "Decentralized Structural-RNN for Robot Crowd Navigation with Deep Reinforcement Learning" Liu et al., 2020)

    This paper presents a decentralized structural recurrent neural network (RNN) for robot crowd navigation using deep reinforcement learning (RL). The proposed RNN architecture enables multiple robots to learn their own navigation policies while considering the actions of other robots. Experimental results demonstrate the effectiveness of the proposed approach in achieving coordinated and collision-free navigation in crowded environments.

22. "Autonomous Warehouse Robot using Deep Q-Learning" Peyas et al., 2021)

This paper describes the development of an autonomous warehouse robot using deep Q-learning for navigation and task execution in a warehouse environment. The proposed robot utilizes a deep Q-learning algorithm to learn to navigate in the warehouse, pick up items, and deliver them to designated locations. Experimental results demonstrate the robot's effectiveness in performing warehouse tasks efficiently and safely.

23. "Success Weighted by Completion Time: A Dynamics-Aware Evaluation Criteria for Embodied Navigation" Yokoyama et al., 2021)

    This paper proposes a new evaluation criterion for embodied navigation, namely "success weighted by completion time" (SWCT). SWCT considers both the success rate of navigation tasks and the time taken to complete them. Experimental results demonstrate the effectiveness of SWCT in evaluating the performance of embodied navigation algorithms in dynamic environments.

24. "A novel mobile robot navigation method based on deep reinforcement learning" Quan et al., (2020)

    This paper introduces a novel deep reinforcement learning (RL) algorithm for mobile robot navigation. The proposed algorithm utilizes a deep deterministic policy gradient (DDPG) algorithm and incorporates a hierarchical reinforcement learning (HRL) framework to enable effective navigation in complex environments. Experimental results demonstrate the effectiveness of the proposed algorithm in achieving efficient and robust navigation in dynamic environments.

25. "Path Planning via an Improved DQN-Based Learning Policy" Wang et al., 2021

    In this paper, the authors introduce an efficient Path Planning Network with Deep Q-Network (PN-DQN) algorithm, emphasizing the importance of comprehensive and diverse learning experiences in mastering new skills. The algorithm dynamically adjusts the ratio of deep and broad experiences based on the learning stage, using a value evaluation network to control depth during initial learning stages and a parallel structure to increase breadth when addressing path wandering phenomena. The incorporation of a dense connection enhances the learning ability of the network model. Experimental results demonstrate the superiority of the proposed algorithm over traditional DQN algorithms, showcasing improvements in learning speed, path planning success rate, and path accuracy. The study concludes by suggesting potential applications of the algorithm in obstacle avoidance and aircraft navigation, with future research focusing on further algorithm enhancements. The presented approach stands out for its adaptability to discrete state spaces and its potential to expedite the learning process in various scenarios.

26. "A Hierarchical DDPG-DQN Framework for Robot Navigation in Large-Scale Environments" :

    This work addresses the challenge of robot navigation in novel environments by introducing a hierarchical approach inspired by human navigation. Unlike existing methods that either rely on precise high-level information or extensive learning from interaction with the environment, the proposed approach utilizes a rough 2-D map to navigate in unseen environments without the need for further learning. The key contribution is the introduction of a dynamic topological map, initialized from the rough 2-D map, and a high-level planning method to propose reachable 2-D map patches between start and goal locations.

To utilize the proposed 2-D patches, a deep generative model is trained to generate intermediate landmarks in the observation space. These landmarks serve as subgoals for low-level goal-conditioned reinforcement learning. Notably, the low-level controller is trained solely on local behaviors in existing environments (e.g., crossing intersections, turning left at corners). This framework enables generalization to novel environments with only a rough 2-D map, eliminating the need for additional learning. Experimental results demonstrate the effectiveness of the proposed framework in both familiar and unseen environments.

27. Navigation robot training with Deep Q-Learning monitored by Digital Twin:

    This paper focuses on the application of the Deep Q-learning algorithm to enhance the movement and task execution capabilities of a vehicular navigation robot. The primary objective of the robot is to autonomously transport parts within a confined environment containing various obstacles. The authors developed a decision system based on the Deep Q-learning algorithm, incorporating an artificial neural network that utilizes sensor data for autonomous navigation. The article details the application process and experimental outcomes of the DQN algorithm, showcasing the results of the learning process. Notably, the paper introduces the concept of digital twins to monitor the robot's movement and signals, which are transmitted to a Cloud service. This innovative approach enables the visualization of navigation through augmented reality, providing a comprehensive and technologically advanced perspective on the robot's performance and learning outcomes.

28. "An autonomous navigation approach for unmanned vehicle in outdoor unstructured terrain with dynamic and negative obstacles" :

    This paper addresses the challenges of autonomous unmanned ground vehicle navigation in unstructured environments, with relevance to scenarios involving search and rescue robots, planetary exploration robots, and agricultural robots. The proposed method relies on terrain constraints to navigate through such environments. The authors introduce an approach that involves efficient path search and trajectory optimization on an octree map, aiming to generate trajectories that can navigate off-road landscapes, avoiding various obstacles like dynamic and negative obstacles to reach a predefined destination. Empirical experiments conducted in both simulated and real environments demonstrate that the proposed method outperforms traditional 2-dimensional or 2.5-dimensional navigation methods, particularly excelling in dynamic obstacle avoidance tasks and mapless navigation tasks.

29. "Success weighted by completion time: a dynamics-aware evaluation criteria for embodied navigation" :

    This paper introduces a novel metric, Success weighted by Completion Time (SCT), designed to evaluate the navigation performance of mobile robots. Unlike the commonly used Success weighted by Path Length (SPL), which has limitations in assessing agents with complex dynamics, SCT explicitly considers the agent's dynamics model. The focus is on unicycle-cart dynamics, aligning with the dynamics of popular mobile robotics platforms. The paper presents RRT*-Unicycle, an algorithm tailored for unicycle dynamics, estimating the fastest collision-free path and completion time from a starting pose to a goal location in environments with obstacles. Deep reinforcement learning and reward shaping are employed to train and compare agents with different dynamics models, demonstrating that SCT effectively captures the advantages of a unicycle model in navigation speed over simpler models like point-turn dynamics. Moreover, the paper successfully deploys trained models and algorithms in real-world scenarios, showcasing generalization capabilities in a zero-shot manner as agents navigate an apartment with a real robot.

30. Intelligent navigation of indoor robot based on improved DDPG algorithm”:

    This paper introduces an autonomous online decision-making algorithm based on deep reinforcement learning to address the challenge of indoor robot navigation in large-scale, complex, and unknown environments. Traditional path planning methods relying on environment modeling are replaced with a combination of sensors detecting obstacles and the DDPG (deep deterministic policy gradient) algorithm. This integration enables robots to autonomously navigate and distribute tasks without the need for environment modeling. The proposed algorithm preprocesses learning samples with Gaussian noise to enhance the agent's adaptability to noisy training environments, improving robustness. Simulation results demonstrate the efficiency of the optimized DL-DDPG algorithm in online decision-making for indoor robot navigation, allowing for autonomous and intelligent control.

    In conclusion, the paper highlights the increasing significance of the path planning problem in robotics. Traditional algorithms, dependent on environmental modeling, are limited to static off-line environments and struggle with complex distribution scenarios. Deep reinforcement learning, with its strong perception and decision-making abilities, is identified as a promising approach for path planning in dynamic environments. The proposed algorithm in this paper achieves direct control from environmental perception to action output through end-to-end learning, incorporating sensors based on the partially observable Markov model. The DL-DDPG strategy introduces noise to enhance the robot's decision-making robustness. While the simulation results are promising, the authors acknowledge the need for real-world testing in more complex environments, proposing future research involving real image perception equipment and convolutional neural networks to further improve model applicability.

31. Research on dynamic path planning of mobile robot based on improved DDPG algorithm. Mobile Information Systems:

    This paper addresses the challenges of low success rates and slow learning speeds in the Deep Deterministic Policy Gradient (DDPG) algorithm for mobile robot path planning in dynamic environments. An enhanced DDPG algorithm is proposed, incorporating the RAdam algorithm as a replacement for the neural network optimizer, and integrating the curiosity algorithm to improve success rates and convergence speed. Priority experience replay and transfer learning are introduced to further enhance training effectiveness. Through the establishment of a dynamic simulation environment using the ROS robot operating system and Gazebo simulation software, the improved DDPG algorithm is compared to the original DDPG algorithm for dynamic path planning tasks. Simulation results demonstrate a 21% increase in convergence speed and a 90% success rate for the improved DDPG algorithm compared to the original DDPG algorithm. The proposed algorithm proves to be effective in dynamic path planning for mobile robots with continuous action spaces, showcasing improved adaptability and performance.

32. Path planning of mobile robot in unknown dynamic continuous environment using reward‐modified deep q‐network. Optimal Control Applications and Methods:

    This article focuses on the path planning challenge for a mobile robot operating in an unknown dynamic environment (UDE) through the creation of a continuous dynamic simulation environment. The paper employs the reinforcement learning theory with a deep Q-network (DQN) to enable the robot to learn optimal decisions for achieving a collision-free path in the UDE. A specifically designed reward function, incorporating weight, is implemented to strike a balance between obstacle avoidance and reaching the goal. The study identifies those abnormal rewards, arising from relative motion between moving obstacles and the robot, can potentially lead to collisions. To mitigate this issue, two reward thresholds are introduced to modify abnormal rewards, resulting in successful obstacle avoidance and goal attainment in experiments. Additionally, the article explores the application of double DQN (DDQN) and dueling DQN, comparing the outcomes of reward-modified DQN (RMDQN), reward-modified DDQN (RMDDQN), dueling RMDQN, and dueling RMDDQN. The conclusion asserts that RMDDQN yields the best results among the tested variants.

33. Reinforcement learning for self-exploration in narrow spaces”:

In the context of navigating narrow spaces, the traditional hierarchical autonomous system, when relying on mapping, localization, and control processes, may lead to collisions, especially in the presence of noises. Moreover, it becomes disabled when operating without a map. This paper addresses these issues by employing deep reinforcement learning for self-decision-making in narrow spaces without a map, with a focus on collision avoidance. The approach is demonstrated using the Ackermann-steering rectangular-shaped ZebraT robot in its Gazebo simulator.

The proposed methodology introduces a rectangular safety region to represent states and detect collisions specifically tailored for rectangular-shaped robots. A well-thought-out reward function for reinforcement learning is crafted, eliminating the need for destination information. Five reinforcement learning algorithms, namely DDPG, DQN, SAC, PPO, and PPO-discrete, are benchmarked in a simulated narrow track. After training, the DDPG and DQN models exhibit strong performance, successfully transferring their learned capabilities to three new simulated tracks and further to three real-world tracks. This suggests the effectiveness of the deep reinforcement learning approach in autonomous exploration and collision avoidance in confined spaces, even without relying on pre-existing maps.

34. An optimized path planning method for coastal ships based on improved DDPG and DP. Journal of Advanced Transportation:

This paper addresses the limitations of existing Deep Reinforcement Learning (DRL)-based methods in coastal ship path planning, particularly in terms of the algorithm's inability to learn optimal strategies due to discrete action spaces and a lack of consideration for historical state information. The proposed solution combines an improved Deep Deterministic Policy Gradient (DDPG) with the Douglas–Peucker (DP) algorithm for optimized path planning. The introduction of Long Short-Term Memory (LSTM) enhances the DDPG network structure, leveraging historical state information to improve the accuracy of predicted actions. The reward function of traditional DDPG is also refined through mainline and auxiliary components to enhance learning efficiency and convergence speed. An improved DP algorithm further optimizes the planned path to address the issue of excessive turning points, promoting safer and more economical navigation. Simulation experiments validate the method's effectiveness in terms of path planning and convergence trends, demonstrating its capability to plan safe, economical paths with stability and convergence. The conclusions highlight the proposed method's advantages in terms of path length and number of inflection points compared to other algorithms. However, the paper acknowledges the need for future research to address dynamic obstacles at sea and collision avoidance operations when ships encounter each other during voyages.

35. An autonomous path planning model for unmanned ships based on deep reinforcement learning. Sensors:

    This paper introduces an autonomous path planning model for unmanned ships in unknown environments using Deep Reinforcement Learning (DRL), specifically the deep deterministic policy gradient (DDPG) algorithm. The model learns optimal action strategies through continuous interaction with the environment and historical experience data in a simulation environment. Navigation rules and ship encounter situations are transformed into navigation-restricted areas, ensuring safe and accurate path planning. Ship data from the Automatic Identification System (AIS) is utilized to train the path planning model. An improved DRL, achieved by combining DDPG with the artificial potential field (APF), is integrated into an electronic chart platform for experiments. Comparative experiments demonstrate that the improved model achieves autonomous path planning with good convergence speed and stability.

    The conclusions highlight the limitations of traditional path planning algorithms in recycling historical experience data for online training, leading to less accurate and smooth path plans. The proposed DDPG-based autonomous path planning method successfully addresses these challenges. By combining APF with DDPG, an improved DRL approach is presented, showing faster convergence speed, increased accuracy, continuous operation output, and reduced navigation errors compared to classical DRL methods. However, the paper acknowledges the absence of consideration for the ship's motion model and the actual verification environment. The focus of future research is outlined to address these aspects and validate the proposed method in a real, complex sea environment.

36. Asynchronous episodic deep deterministic policy gradient: toward continuous control in computationally complex environments:

    This article presents an extension of the deep deterministic policy gradient (DDPG) algorithm called asynchronous episodic DDPG (AE-DDPG), addressing issues of data insufficiency and training inefficiency, particularly in computationally complex environments. AE-DDPG introduces an asynchronous data collection scheme, aiming for more effective learning in less training time. The modification involves redesigning experience replay with episodic control, allowing the agent to quickly latch onto valuable trajectories. Additionally, a new type of noise in action space enhances exploration behaviors. Experimental results demonstrate that AE-DDPG outperforms popular reinforcement learning (RL) algorithms in tasks involving computationally complex environments, achieving higher rewards with reduced time consumption. The effectiveness of each proposed technique is further verified through an extensive ablation study. In MuJoCo environments, AE-DDPG not only attains higher rewards but also exhibits two to four times improved sample efficiency compared to other DDPG variants. The article emphasizes the versatility of AE-DDPG across different environments and underscores its potential in enhancing sample efficiency and training stability in RL tasks.

37. Probability Dueling DQN active visual SLAM for autonomous navigation in indoor environment":

This paper introduces a novel approach to improve obstacle identification speed using the Monodepth method and enhances path optimization with the Probability Dueling DQN algorithm for faster navigation compared to the traditional Dueling DQN algorithm. The proposed method is integrated into an active simultaneous localization and mapping (SLAM) framework designed for autonomous navigation in indoor environments with both static and dynamic obstacles. This framework combines a path planning algorithm with visual SLAM to reduce navigation uncertainty and create an environment map.

The results indicate that the proposed method outperforms the existing Dueling DQN in addressing navigation uncertainty in real-world indoor environments with varying numbers and shapes of static and dynamic obstacles. The novelty of this approach lies in the active SLAM framework, incorporating the Probability Dueling DQN algorithm, which represents an improved path planning strategy based on Dueling DQN. The framework is further enhanced by utilizing the Monodepth depth image prediction method for quicker obstacle identification. Overall, this integrated approach demonstrates effective autonomous navigation capabilities in diverse indoor environments.

38. ″A Study on the Effect of Parameters for ROS Motion Planer and Navigation System for Indoor Robot” :

This study focuses on the autonomous navigation of office assistant robots within office environments, a rapidly growing sector in the service robot industry. Navigation algorithms and motion planners, essential components for enabling autonomous movement, were implemented on these robots using the Robot Operating System (ROS). The study evaluates and compares the performance of different global and local planners on a robot in both simulation and real-world environments.

Two global planners, A* and Dijkstra algorithms, were implemented and tested, along with two local planners, Dynamic Window Approach (DWA) and Time Elastic Band (TEB) algorithms. The experiments aimed to assess the impact of various planners and parameters on the robot's performance. Results indicate that both A* and Dijkstra algorithms can achieve the required performance for office robot applications. Additionally, the Time Elastic Band (TEB) algorithm outperforms the Dynamic Window Approach (DWA) as a local planner, demonstrating superior feasibility in avoiding dynamic obstacles during the conducted experiments. These findings provide insights into the effectiveness of different navigation strategies for office assistant robots, contributing to advancements in the service robot industry.

39. Temporal Consistency-Based Loss Function for Both Deep Q-Networks and Deep Deterministic Policy Gradients for Continuous Actions″:

In this study, the focus is on enhancing the stability of deep reinforcement learning (DRL) algorithms, specifically deep Q-networks (DQNs) and deep deterministic policy gradients (DDPGs), applied to power grid control and energy management in building automation. The common practice of using replay buffers and target networks with a delayed temporal difference backup to minimize loss functions in DRL is acknowledged, but the study addresses the limited exploration of techniques for improving these loss functions in both DQNs and DDPGs. The proposed modification introduces a novel temporal consistency (TC) loss function, adapted for target network updates in both DQN and DDPG, with particular emphasis on the critic network in DDPG. Experimental results in OpenAI Gym environments, including ″cart-pole″ and ″pendulum,″ demonstrate significantly improved convergence speed and performance, especially in the critic network of DDPG.

The conclusion emphasizes the contribution of the proposed TC loss function as a family of target-based temporal difference learning. The flexibility of the target network update in dealing with estimate-true value mismatches is highlighted, showcasing the adaptability of the TC loss function in both DQN and DDPG. While the TC loss function exhibits noteworthy improvement in continuous environments with DDPG, its performance in DQN is not as pronounced, though statistically validated. The study underscores the potential applicability of the proposed TC loss functions in applications such as autonomous voltage control and load shifting. The authors suggest that, with further improvements in DQN, the efforts can be applied to DDPG, considering both as off-policy temporal difference learning algorithms.

40. "A Neural Network Approach to Navigation of a Mobile Robot and Obstacle Avoidance in Dynamic and Unknown Environments":

    This paper addresses the challenging problem of mobile robot navigation and obstacle avoidance in dynamic and unknown environments. The complexity arises from the need for real-time interaction with the surroundings, limited sensing range, inaccurate data, and noisy sensor readings. The proposed solution employs a neural network approach integrated with statistical dimension reduction techniques to achieve precise and efficient robot navigation and obstacle avoidance. To enhance the speed and accuracy of network learning while reducing noise, kernel principal component analysis is applied to the training patterns of the network. The method utilizes two feed-forward neural networks based on function approximation with a backpropagation learning algorithm. Training is conducted on two different datasets, using 180° laser range sensor (SICK) readings to visualize the robot's environment. Experimental results on real-world data demonstrate the effectiveness of the proposed method, validating its capabilities in enhancing the speed, precision, and noise reduction in robot navigation and obstacle avoidance.

8. Dissertation work progress arrangement			
serial number	time	research content	expected result
1	December 2022	Research on privileged path planning network based on semantic bird's-eye view	Plans to complete experiments on predicting vehicle trajectories based on bird's-eye views generated from surround vision images
2	January February 2023	Research on end-to-end path planning algorithm integrating trajectory prediction and control prediction	Plan to complete autonomous driving experiments integrating control prediction and trajectory prediction
3	March 2023	essay writing	Plans to complete a paper on vehicle trajectory prediction based on bird's-eye view generated from surround vision images
4	April 2023	Comparative Experiment	Plans to complete comparative experiments on autonomous driving based on bird's-eye view prediction of vehicle trajectories generated from surround vision images and autonomous driving that fuses control prediction and trajectory prediction
5	May 2023	Big paper comparative experiment	Plan to complete a comparative experiment between the method in this paper and the baseline method
6	June to December 2023	Graduation thesis writing	Plan to complete graduation thesis
Graduate student signature: year month day			

9. Documents/papers

Articles published or planned to be published in domestic and foreign publications since enrollment

serial number	Essay topic	Post a message	Ranking	category	Corresponding dissertation chapter

10. Opinions of instructors

The topic of the thesis proposal report is reasonably chosen, the content is clear, and the plan is reasonable. The proposal is approved.

Instructor’s signature:

years day

Check the main literature list

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注：本表可加页。

Master's student's explanation of the revised topic report

1. Teacher Liu: There is a mismatch between the thesis title and the research content.

Modification: Based on the research content, considering that the final output of the research is the control action of the driverless car, the original title "Research on End-to-End Path Planning Algorithm Based on Surround Vision" is not very accurate, so the title is changed to "End-to-End Path Planning Algorithm Based on Surround Vision" Research on end-to-end motion planning methods.

2. Teacher Liu: Does the main question 3 to be solved in the dissertation have theoretical support from relevant literature?

Modification: By reviewing the literature, we searched for end-to-end autonomous driving papers in 2022, found theoretical support, and provided theoretical foundations and problem-solving ideas for this academic paper research. According to the reference literature, it is reasonable to rely on and lay the foundation for the next scientific research work.

3. Teacher Guo: Different robot motion structures have different control algorithms. How to achieve unified comparison?

Solution: Current end-to-end autonomous driving research based on surround vision is trained, tested, and verified on the more authoritative carla simulation platform. The simulation platform has defined the motion structure of autonomous vehicles to avoid experimental comparisons with unmanned vehicles. The problem of inconsistency in the car's motion structure.

Graduate student signature:

Instructor's signature:

Instructor review comments It has been modified according to the opinions of the defense team and the proposal is approved.
Review opinions of the college (department) subcommittee (whether it can enter the thesis work stage) Signature of the chairman of the college (department) subcommittee: Official seal of the college (department):

Note: This form is kept by the college (department) and will be provided to the defense committee members during the dissertation defense for their reference.