الجمهـوريـة الجـزائريـة الديـمقراطيـة الشـعبيـة
PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA

وزارة التعـليـم العـالـي و البـحث العلـمي
MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH

جامعـة عمّـار ثليـجـي بالأغـواط
AMAR TELIDJI UNIVERSITY OF LAGHOUAT

كـليـة العلـوم
FACULTY OF SCIENCES

DEPARTMENT OF COMPUTER SCIENCE

Master's Thesis

Field: Mathematics and Computer Science

Specialty: Computer Science

Option: Data Science and Artificial Intelligence

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TOPIC

Path Planning Using Deep Q-Networks for Mobile Robot Navigation

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– Academic Year 2024/2025


بسم الله الرحمن الرحيم

Dedication

To all those who have left a mark on my life, to my dear family, who have always been my source of strength and unwavering support, you are the foundation upon which I have built my journey. To my esteemed professors, who instilled in me a passion for learning and research, and guided me with their valuable advice, which became the key to my academic growth. To my friends and loved ones, who have been my pillars during challenging times, lifting my spirits with every encouraging word. This thesis is the fruit of your efforts and love, and I dedicate it to you all with heartfelt gratitude and appreciation.

Acknowledgments

First and foremost, all praise is due to Allah Almighty for His guidance and support. I would like to express my deepest gratitude to my supervisor, Dr. Kheira TAABA, for her invaluable guidance and constant support.

A special thank you to my family for their endless love, encouragement, and sacrifices. To my friends and loved ones, your constant support has been a great source of strength throughout this journey.

Finally, I would like to thank everyone who contributed, directly or indirectly, to the completion of this work.

Abstract

Efficient navigation of mobile robots in static environments remains a key challenge in robotics. In this study, we use a **tracked mobile robot** model to test an intelligent path planning approach based on **Deep Q-Learning (DQN)**. Unlike classical methods like A and Dijkstra that depend on predefined maps, DQN allows the robot to learn how to navigate by interacting with its environment. This learning capability helps the robot avoid obstacles and find optimal paths without prior knowledge. By combining DQN with traditional algorithms, we enhance adaptability and decision-making. Simulations in MATLAB showed that the proposed method improved navigation efficiency in grid-based static environments.

Keywords: Deep Q-Learning,DQN, Reinforcement Learning, Path Planning, Mobile Robots, MATLAB.

Summary

This thesis focuses on the integration of Deep Q-Learning, a reinforcement learning technique, with path planning algorithms to improve navigation for mobile robots in static environments. The proposed approach allows robots to navigate autonomously while optimizing their paths and avoiding obstacles efficiently.

To achieve this, Deep Q-Learning is combined with traditional path planning methods to leverage the strengths of both approaches. The effectiveness of the proposed method was validated through simulations conducted in MATLAB . The results highlight significant improvements in navigation efficiency, obstacle avoidance, and adaptability to changing environments.

Keywords: Deep Q-Learning,DQN, Reinforcement Learning, Path Planning, Mobile Robots, MATLAB.

الملخص

تركّز هذه الأطروحة على دمج تقنية التعلم المعزز العميق **Q-Learning**، وهي إحدى تقنيات التعلم المعزز، مع خوارزميات تخطيط المسار التقليدية بهدف تحسين ملاحة الروبوتات المتحركة في البيئات الثابتة. يتيح النهج المقترح للروبوتات التنقل بشكل مستقل مع تحسين مساراتها وتجنّب العوائق بكفاءة.

ولتحقيق هذا الهدف، تم دمج **Q-Learning** مع تقنيات تخطيط المسار الكلاسيكية للاستفادة من مزايا كلٍّ منهما. وقد تم تقييم أداء الطريقة المقترحة من خلال محاكاة أُجريت باستخدام برنامج **MATLAB**، حيث أظهرت النتائج تحسينات ملموسة في كفاءة الملاحة، وتفادي العوائق، والقدرة على التكيّف مع خصائص البيئة.

الكلمات المفتاحية: التعلم العميق DQN ،Q-Learning، التعلم المعزز، تخطيط المسار، الروبوتات المتحركة، MATLAB.

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Chapter 1

Mobile Robot, Modeling and Control :

1.1 Introduction :

Mobile robotics represents a cornerstone of contemporary technological advancement, playing a pivotal role in revolutionizing numerous sectors including healthcare, transportation, logistics, agriculture, and industrial automation. The increasing demand for intelligent, autonomous systems has driven researchers and engineers to develop robots capable of perceiving their surroundings, reasoning under uncertainty, and acting efficiently within complex and ever-changing environments.

Among the core challenges in this domain lies the problem of autonomous navigation — specifically, the ability of a robot to traverse from a starting point to a designated goal while avoiding static and dynamic obstacles. This process, known as path planning, is not merely about finding any viable route, but rather about computing an optimal trajectory that accounts for factors such as safety, efficiency, energy consumption, and adaptability to real-world conditions.

Traditionally, path planning has relied on deterministic algorithms like A*, Dijkstra, or sampling-based methods such as Rapidly-exploring Random Trees (RRT). While effective in structured or predictable environments, these classical methods often struggle with real-time decision-making in highly static settings where the environment may change unexpectedly.

In recent years, the convergence of deep learning and reinforcement learning has introduced a paradigm shift in how autonomous systems can learn from interaction and improve over time. Deep Q-Learning, a powerful value-based reinforcement learning algorithm, has emerged as a particularly promising approach due to its ability to map high-dimensional sensory inputs directly to optimal action policies using deep neural networks.

This thesis explores the integration of Deep Q-Learning with classical path planning strategies to form a hybrid navigation framework. **The objective is to leverage the robustness and learning capabilities of Deep Q-Learning to address the limitations of traditional methods, thereby enhancing the adaptability, intelligence, and efficiency of mobile robots in real-world environments. Through extensive experimentation and performance analysis, the proposed approach aims to contribute to the ongoing evolution of autonomous navigation systems. This approach is implemented using a Differential Drive Robot. with the DQN algorithm.**

1.2 Mobile robots :

* Mobile robotics represents the cutting-edge science of developing intelligent, self-contained systems capable of autonomous movement and operation across diverse environments. Unlike stationary industrial robots, these versatile machines navigate dynamic spaces using sophisticated combinations of sensors, artificial intelligence, and mechanical systems. The field has seen exponential growth with applications transforming nearly every sector of modern industry and research:

-Logistics E-commerce: Autonomous mobile robots (AMRs) in warehouses like Amazon's Kiva systems can transport thousands of pounds of goods with millimeter precision, working 24/7 alongside human employees while optimizing delivery routes in real-time through machine learning algorithms.

-Healthcare Innovation: Hospital delivery robots such as TUG autonomously navigate complex corridors to transport medications, lab samples, and even meals, equipped with UV sterilization and collision-avoidance systems that comply with strict medical safety standards.

-Agricultural Automation: Advanced farming robots like Harvest CROO employ computer vision and robotic arms to pick delicate fruits at superhuman speeds, while drone systems monitor crop health using multispectral imaging and AI-powered analysis.

-Emergency Response: Rugged robots like Boston Dynamics' Spot navigate disaster zones with unprecedented agility, using thermal imaging to locate survivors in rubble and hazardous material sensors to assess chemical threat s in Fukushima-style nuclear incidents.

-Space Exploration: NASA's Mars rovers (Perseverance, Curiosity) exemplify extreme mobile robotics, autonomously traversing alien terrain while conducting scientific experiments millions of miles from Earth, with communication delays making real-time human control impossible.

* Core Technological Foundations Modern mobile robots integrate three critical subsystems :

***Perception:** LiDAR, stereo cameras, and ultrasonic sensors create real-time 3D environment maps.

***Cognition:** AI path planning algorithms (like MPC discussed later) process sensor data to make navigation decisions

***Locomotion:** Wheeled, tracked, legged, or hybrid drive systems adapt to terrain requirements

1.3 Typical Mobile Robots :

Mobile robots can move in different ways. The most common types are:

1.3.1 Legged Robots :

Legged robots represent the pinnacle of mobile robotics, brilliantly mimicking the locomotion of humans and animals. These remarkable machines possess an unparalleled ability to navigate unstructured environments, making them ideal for rough terrains like forests, mountains, and disaster zones. Their sophisticated movement systems enable intelligent obstacle negotiation, allowing them to climb stairs, cross gaps, and adapt to uneven surfaces through advanced sensing technologies including stereoscopic vision cameras and 3D LiDAR systems. These robots incorporate intelligent control algorithms ranging from model predictive control to reinforcement learning systems that continuously optimize their movement. Their applications span from life-saving search and rescue operations in hazardous areas to scientific exploration in extreme environments, where they outperform wheeled robots. While facing challenges in energy efficiency and durability, recent advancements in smart materials and artificial intelligence are opening new frontiers for performance enhancement. Legged robots stand as a fascinating example of the convergence between mechanical engineering, biology, and AI, heralding a revolution in robotics capable of operating in Earth's most complex environments. This cutting-edge technology continues to evolve, with researchers developing more adaptive gait patterns, improved power systems, and enhanced cognitive capabilities that will further expand their operational potential in real-world scenarios. The future promises even more sophisticated biomimetic designs that may one day match the agility and versatility of their biological counterparts.

Figure 1.1: Legged Robot (Quadruped).

1.3.2 Crawler Robots :

Crawler robots, equipped with continuous tracks similar to tanks, excel in traversing challenging terrains where conventional wheeled or legged robots would struggle. Their robust design provides exceptional stability and traction, allowing them to navigate loose sand, deep mud, rocky surfaces, and even steep inclines with remarkable efficiency. The distributed weight across their track surface minimizes ground pressure, preventing them from sinking in soft or unstable substrates.

These rugged machines are particularly valuable in military operations for reconnaissance, bomb disposal, and payload transport across hostile environments. Beyond defense applications, crawler robots play critical roles in industrial inspection, maneuvering through narrow underground pipes, sewers, and tunnels while carrying sensors for structural assessment or leak detection. Their sealed designs allow operation in wet conditions, while modular configurations support customization with various tools and instrumentation. Recent advancements incorporate AI-driven autonomy for obstacle negotiation and computer vision for real-time terrain analysis, further expanding their operational capabilities in both civilian and military domains.

Figure 1.2: Crawler Robot (Tracked).

1.3.3 Car-Type Robots :

Wheeled robots represent one of the most efficient mobility systems for paved and structured environments. These robots feature a car-like design equipped with advanced control and steering systems that enable smooth navigation on roads and sidewalks. They operate with remarkable efficiency in smart cities and industrial areas thanks to their:

Precision Movement: Ability to follow predefined paths with centimeter-level accuracy.

Stability: Advanced suspension systems that absorb vibrations.

Artificial Intelligence: Sophisticated navigation capabilities that adapt to surroundings.

Integration: Seamless interaction with urban infrastructure like traffic signals.

- Their applications range from package delivery and road monitoring to security services, making them a fundamental pillar of future smart cities. With continuous advancements in autonomous navigation and energy efficiency, wheeled robots are set to revolutionize urban mobility and logistics. Their ability to operate safely alongside pedestrians and vehicles while performing repetitive tasks makes them indispensable for modern urban planning. As cities grow smarter, these robotic platforms will play an increasingly vital role in maintaining efficient, sustainable, and connected urban ecosystems.

Figure 1.3: Car-Type Robot (Ackermann Steering).

1.3.4 Differential Drive Robots :

Differential drive robots are among the most widely used robotic platforms in education and research due to their simple yet effective design. By independently controlling the speed of two parallel wheels, these robots can move forward, backward, and execute precise turns - including zero-radius rotations when the wheels spin in opposite directions. This elegant mechanical solution provides an ideal platform for teaching fundamental robotics concepts like kinematics, odometry, and control systems while remaining cost-effective to build and maintain. Researchers value these robots for experimenting with autonomous navigation algorithms, multi-robot coordination, and sensor integration, as their straightforward mechanics allow focus on developing advanced software capabilities. The differential drive configuration's perfect balance of simplicity and functionality continues to make it a favorite choice for introductory robotics courses and cutting-edge research alike, serving as an accessible yet powerful tool for exploring autonomous systems.**This is the bot used in our Research.**

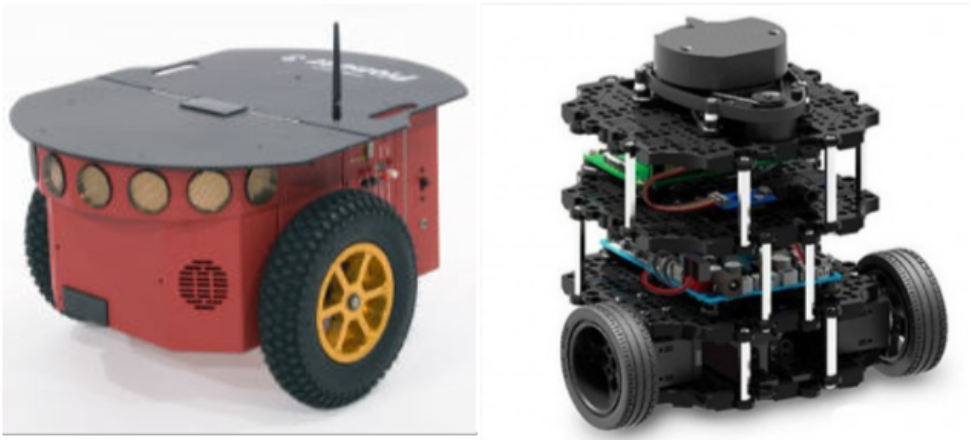

Figure 1.4: Differential Drive Robot.

The Figure 1.5 below The necessary motion in a differentially driven WMR is produced by the relative motion of the two driving wheels with regard to one another. The structure is the only thing supported .A differentially driven WMR moves in a straightforward manner. When the two driving wheels of the robot revolve at the same speed, straight-line mobility is achieved. The wheels must rotate in the opposite direction in order to provide motion in the other direction. To turn, we apply brakes to one wheel and turn the other. The robot revolves around the stationary wheel. We may achieve sharp turning by turning the wheels in opposite directions. It is possible to move along an arc by using the differential motion of both wheels in relation to one another.

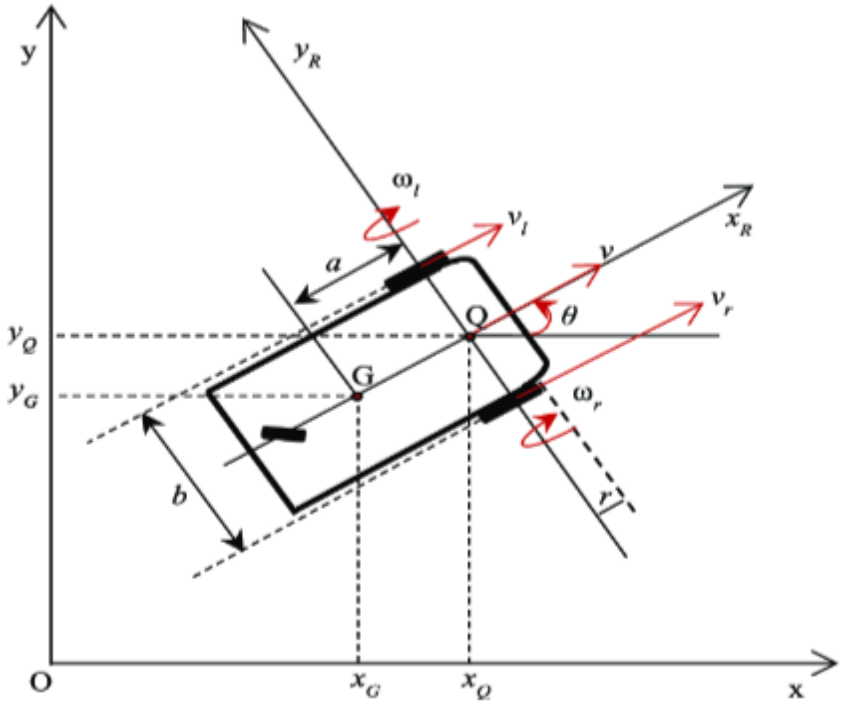

Figure 1.5: Wheel differential drive mobile robot.

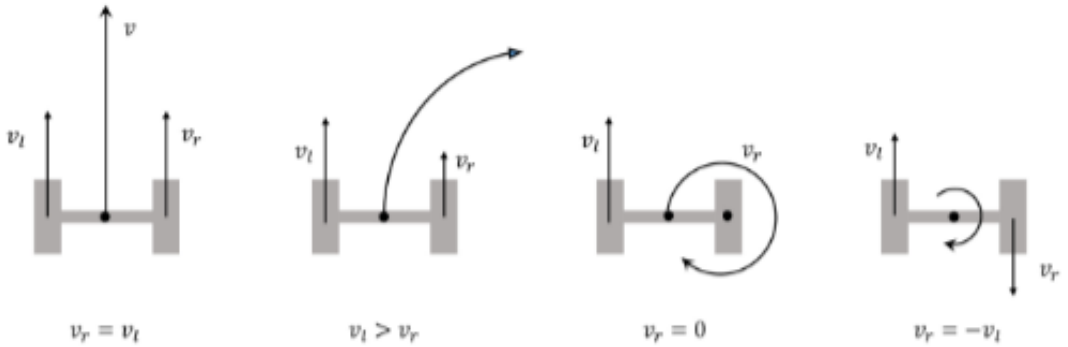

Figure 1.6: The different moving possibilities for unicycle mobile robot.

Figure 1.6 illustrates the different movement possibilities for a unicycle mobile robot. This type of robot is subject to non-holonomic constraints, allowing it to move forward or

backward and rotate around its vertical axis. The figure shows the possible trajectories resulting from variations in wheel velocity or steering angle. This visual representation helps in understanding the robot's behavior during navigation and decision-making in a given environment.

1.4 Robot Motion :

To navigate effectively, a robot must solve three core problems: localization (knowing its position), goal-setting (determining the destination), and path-planning (computing the route). The robot's movement is governed by differential drive kinematics, where the rotation speed and direction of its two wheels determine its trajectory.

For instance:

-Straight motion: Equal forward speeds on both wheels maintain linear movement.

-Point turn: Opposite wheel rotations (one forward, one backward) create zero-radius pivoting.

-Curved path: Speed differentials. These principles are implemented in software through control algorithms that translate high-level path plans into wheel velocity commands. For goal-directed navigation, the system typically:

-Senses its position (via encoders, IMUs, or vision).

-Computes error vectors (deviation from the desired path).

Adjusts wheel speeds using PID controllers or model predictive control (MPC) to minimize errors.

Advanced systems may integrate obstacle avoidance by dynamically adjusting wheel velocities based on sensor feedback (e.g., lidar or ultrasonic), enabling smooth detours without stopping. This hierarchical approach—from kinematics to closed-loop control—ensures precise, adaptive motion in real-world environments.

1.5 Posture Error :

To follow the Figure 1.7 below a path accurately, a mobile robot continuously calculates three key error components: (1) lateral error (side-to-side deviation from the path), (2) longitudinal error (forward/backward displacement along the path), and (3) angular error (heading misalignment). These errors are measured in real-time using sensors like encoders, IMUs, or vision systems, and are minimized through control algorithms (e.g., PID or MPC) that adjust wheel velocities or steering angles to keep the robot precisely on course, typically achieving sub-centimeter tracking accuracy in structured environments. To follow a path, the robot needs to compare where it is with where it should be. The difference is called an error. There are three types of errors:

- Side-to-side error: How far the robot is to the left or right of the path.
- Forward error: How far the robot is ahead or behind.

- Angle error: Whether the robot is facing the right direction.

A control system reads these errors and decides how to move the wheels to reduce them.

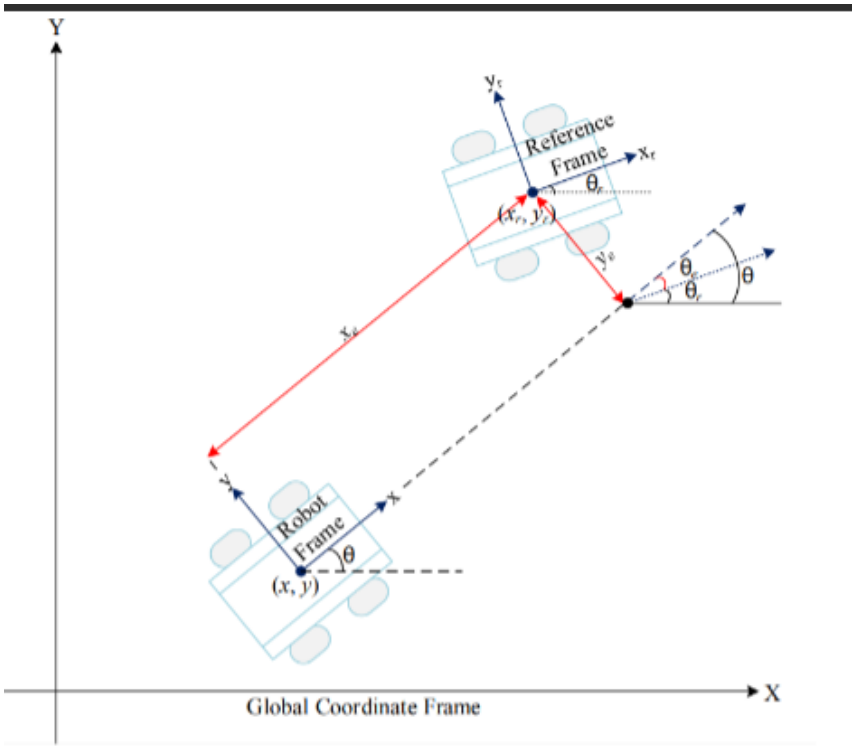

Figure 1.7: The mobile robot tracking error.

Figure 1.7 illustrates the tracking error of a mobile robot as it follows a desired trajectory. The tracking error represents the difference between the robot's actual position and orientation and the reference path. This figure highlights the key components of the error: lateral deviation, heading angle error, and distance to the target point. Understanding these errors is essential for designing effective control strategies to ensure accurate path tracking.

1.6 Model Predictive Control (MPC) :

MPC is a smart way to control a robot. Instead of just reacting, it plans ahead. At each moment, it:

- Looks at the robot's current position.
- Predicts what will happen if it tries different moves.
- Chooses the best move to stay on path.
- Makes the move and repeats the process.

This makes the robot move smoothly and avoid obstacles.

- MPC is useful in cars that drive themselves, drones, and robots that work in busy areas. It is powerful because it helps the robot plan good decisions even in complex situations.

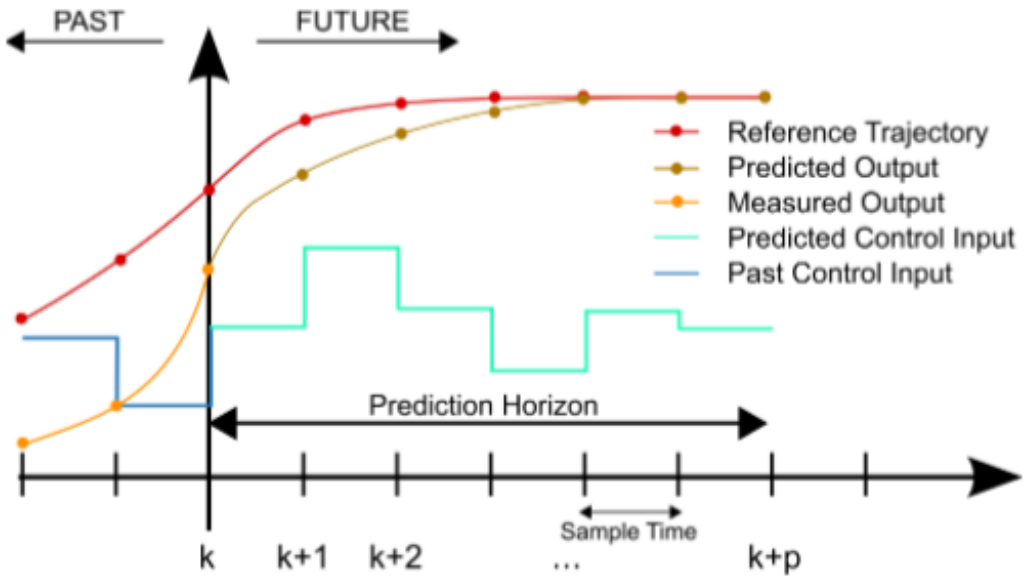

Figure 1.8: Principle of model predictive control MPC.

The Figure 1.8 represent a control method that predicts future system behavior using a dynamic model and optimizes control inputs over a finite horizon. It applies only the first optimized input and repeats the process at each time step, adjusting for new data. This allows MPC to handle constraints, disturbances, and uncertainties effectively while maintaining optimal performance.

1.7 Problem formulation :

Unlike PID, Pure Pursuit or other Controllers, MPC is a predictive control method that predicts the future states of the vehicle and plans its control actions accordingly, bringing it closer to its desired trajectory. MPC algorithm can handle non-linear and complex vehicle dynamics like tire force models and actuator models, allowing precise and accurate trajectory tracking. Another powerful feature of MPC is its ability to take multiple constraints such as limiting jerks for comfortability, avoiding actuator saturation and setting the maximum speed. MPC can do all this by introducing constraints into the controller . The control Block Diagram of MPC. Using its two major blocks, optimizer and predictor, MPC computes control actions by minimizing a cost function based on the prediction of the vehicle states from a vehicle model over horizon, while considering the constraints.

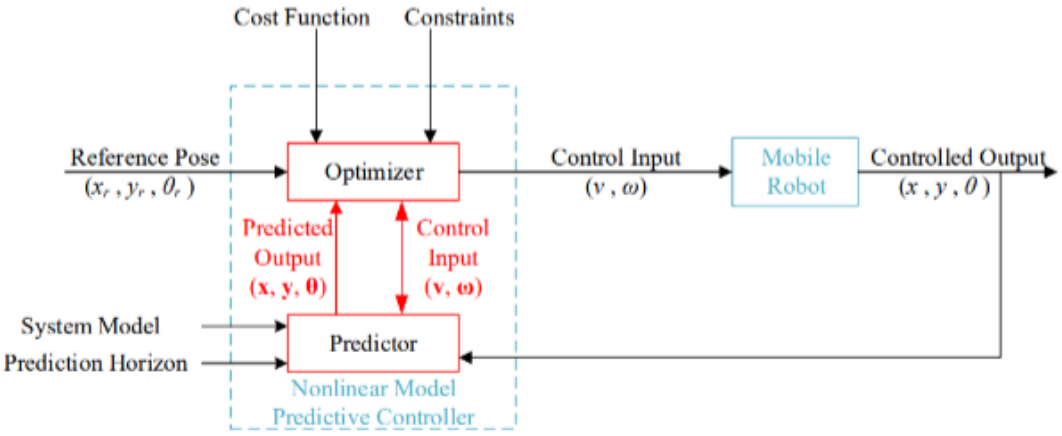

Figure 1.9: Control Block Diagram.

Figure 1.9 presents the control block diagram of the mobile robot system. It illustrates the flow of information from the desired trajectory input through the control algorithm, which generates appropriate velocity or steering commands. These commands are then applied to the robot's actuators to adjust its motion. Feedback from the robot's sensors is used to compare the actual state with the desired one, enabling real-time corrections for accurate navigation.

1.8 Mobile Robots: Concept and Classification :

1.8.1 Classification of Mobile Robots :

Mobile robots can be classified based on their operating environment into three main categories: ground, aerial, and underwater robots. Ground robots, including wheeled, tracked, and legged robots, are widely used in industrial automation, agriculture, and search-and-rescue missions due to their ability to navigate various terrains. Aerial robots (drones), such as fixed-wing and multi-rotor UAVs, perform tasks like surveillance, delivery, and aerial photography. Meanwhile, underwater robots, including ROVs and AUVs, play a crucial role in marine exploration, offshore inspections, and deep-sea research. Each type is designed to meet specific challenges within its environment, enabling diverse applications across industries.

- **Ground Robots**: Operate on flat or uneven surfaces and are used in industrial and agricultural applications.
- **Aerial Robots (Drones)**: Utilized for aerial surveillance, photography, and delivery services.
- **Underwater Robots**: Deployed for marine research and exploration.

1.9 Control Techniques in Mobile Robots :

1.9.1 Traditional Control Methods :

Traditional Control Methods are well-established techniques used to regulate the behavior of static systems, including robots and industrial processes. These methods rely on mathematical models to achieve stability, precision, and desired performance. Common approaches include PID control (Proportional-Integral-Derivative), which adjusts system outputs based on error feedback, and state-space control, which uses system variables for more complex regulation. While these methods are robust and widely applied, they may struggle with highly nonlinear or uncertain systems—leading to the development of more advanced control strategies like adaptive and intelligent control.

- **Proportional-Integral-Derivative (PID) Control**: A widely used feedback control mechanism that continuously adjusts the robot's movements based on real-time sensor data.
- **Model-Based Control**: Uses mathematical models to predict and control the robot's motion effectively.

1.9.2 Intelligent Control Techniques :

Intelligent Control Techniques leverage AI and machine learning to enable autonomous decision-making in complex, uncertain environments. Unlike traditional methods, they adapt dynamically using neural networks, fuzzy logic, and reinforcement learning—ideal for robotics, automation, and smart systems.

- **Neural Networks**: Used for pattern recognition and adaptive decision-making in complex environments.
- **Fuzzy Logic Systems**: Provide a flexible approach to decision-making, handling uncertainty better than traditional methods.
- **Reinforcement Learning (RL)**: Enables robots to learn from experience and optimize their navigation policies through trial and error.

1.9.3 Conclusion:

The field of mobile robotics combines precise modeling with intelligent control. Traditional controllers like PID perform well in structured environments. However, Deep Q-Networks (DQN) excel in dynamic and unpredictable settings. DQN can learn optimal actions through experience, making it suitable for complex tasks. For example, it outperforms classic methods in scenarios like smart parking. In the next chapter, we compare DQN with algorithms like A* and Dijkstra. This comparison highlights DQN's advantages in adaptability and real-world efficiency.

Chapter 2

Path Planning For Mobile Robots

2.1 Literature Review on Path Planning and Reinforcement Learning :

2.1.1 What is path planning?

Path planning is the most critical concern in mobile robot navigation. It involves determining a geometric path from the current location of the robot to a target location while avoiding obstacles. This path must be navigable by the mobile robot and optimal in terms of at least one variable to be considered suitable. Depending on the target distance, the optimal path could be the smoothest, shortest, or the path allowing the mobile robot to move at the highest speed. In essence, the optimal path is determined based on these characteristics. A common method of path planning involves discretizing the space and considering the center of each unit as a movement point. Each movement point either contains an obstacle that needs to be avoided or is obstacle-free and can be traversed.

2.1.2 Global Planning and Local Planning :

a) Global Path Planning :

Global path planning is used in environments where prior knowledge is available. It is typically an iterative algorithm designed to determine the optimal path for a mobile robot in a known and static environment, ensuring the robot can move from its initial position to its final destination.

This process consists of two main steps:

- Environment Modeling: Creating a representation of the environment, including obstacles and navigable paths.

- Optimal Path Planning: Computing the best possible route that avoids collisions with static obstacles. Common algorithms used in global path planning include Dijkstra's algorithm, A*, D*, Ariane's thread, and Cellular Decomposition. The main advantage of global path planning is its ability to generate an optimal path. However, it comes at the cost of high computational time and memory consumption.

b) Local Path Planning:

Local path planning is used when only partial knowledge of the environment is available. At each movement step, the system checks for possible collisions; if an obstacle is detected, the path is adjusted locally to avoid it. This approach allows problems to be solved efficiently within a reasonable time frame.

Local path planning relies on creating a limited representation of the environment, updating the robot's movement in real time as an optimization problem.

There are two main types of local planning methods:

- Obstacle Avoidance Planners:

These methods rely on probabilistic techniques for path planning. They use sensor data to detect obstacles and generate a collision-free trajectory. They are commonly used in unknown and dynamic environments where prior knowledge is not available.

- Feasible Path Generation Planners:

These planners consider kinematic and non-holonomic constraints specific to the mobile robot. They generate paths based on the robot's motion limitations and constraints.

- Some common techniques include: Dubins paths Reeds and Shepp paths Continuous curvature path generation Guidance-based navigation methods

2.1.3 Overview of Path Planning Algorithms:

Path planning is a frequently addressed topic in many applications, thus there are numerous algorithms available for such tasks. In this section, we will present some of the most commonly used methods for planning a path, briefly explaining their principles, as well as their advantages and disadvantages.

- **Traditional Path Planning Algorithms**:
  - **A* Algorithm**:A* is an intelligent pathfinding algorithm that calculates the shortest path from a start point to a goal by combining:

    - Actual Cost (g(n)) → Distance traveled from start to current node.

    - Heuristic Cost (h(n)) → Estimated distance from current node to goal (e.g., straight-line distance).

    - Total Cost (f(n) = g(n) + h(n)) → Determines the next best node to explore.

    - Advantages (Pros) :

    *Optimal Path → Guarantees the shortest path if the heuristic is admissible (never overestimates).

    *Efficient → Focuses on promising paths, reducing unnecessary searches.

    *Versatile → Works well in grid maps, graphs, and game AI.

    *Customizable → Can adjust costs for terrain difficulty (e.g., avoiding slopes).

    - Disadvantages (Cons) :

    *Memory Usage → Stores all explored nodes (problematic for large maps).

*Heuristic Dependency → Poor heuristic (e.g., overestimating) leads to slower or incorrect paths.

*Not Real-Time → Must recompute if obstacles move (not ideal for dynamic environments).

– **Dijkstra's Algorithm**: Dijkstra's algorithm finds the shortest path from a single starting point to all other nodes in a graph with non-negative edge weights.

- Advantages (Pros) :

*Guaranteed Accuracy → Always finds the true shortest path in weighted graphs.

No Heuristic Needed → Works purely on actual distances (unlike A).

*Widely Applicable → Used in networks (routing), maps, and any graph-based system.

- Disadvantages (Cons) :

Slower Than A → Explores all possible directions (no heuristic guidance).

*Fails with Negative Weights → Incorrect results if edge costs are negative.

*High Memory Use → Stores all visited nodes (inefficient for large graphs).

– **Rapidly-exploring Random Tree (RRT)**:RRT is a probabilistic path-planning algorithm that grows a tree of possible paths by randomly sampling points in the environment, making it effective for high-dimensional spaces (like robotic arms) and dynamic obstacles.

- Advantages (Pros) :

*Handles Complex Environments → Works well in cluttered or dynamic spaces.

*No Need for a Full Map → Explores efficiently even with partial information.

*Scalable → Performs well in high-dimensional problems (e.g., 7-DOF robot arms).

*Probabilistically Complete → Guaranteed to find a path if one exists (given enough time).

- Disadvantages (Cons) :

*No Optimality Guarantee → Paths may be erratic or longer than necessary.

*Randomness Can Be Inefficient → May take time to converge in tight spaces.

*Smoothing Often Needed → Generated paths can be jagged (requires post-processing).

2.1.4 Deep Q-Learning for Path Planning :

-Introduction to Reinforcement Learning (RL)

a) What is Reinforcement Learning (RL)?

Reinforcement Learning (RL) is a specialized branch of machine learning that focuses on training agents to make decisions by interacting directly with their environment. Instead of being explicitly programmed with fixed rules, an RL agent learns autonomously through a trial-and-error process guided by a system of rewards and penalties. The fundamental objective of RL is to identify the best possible actions or sequences of actions—often referred to as policies—that maximize cumulative rewards while minimizing negative outcomes over time.

This learning paradigm functions as a feedback loop where positive behaviors are reinforced by rewards, encouraging the agent to repeat those actions, whereas negative behaviors receive penalties, discouraging their recurrence. Through continuous interaction, the agent perceives its surroundings, interprets observations, and adapts its strategy to improve decision-making performance. Over repeated experiences, the agent refines its policy, becoming more proficient at selecting optimal actions in diverse and potentially uncertain environments.

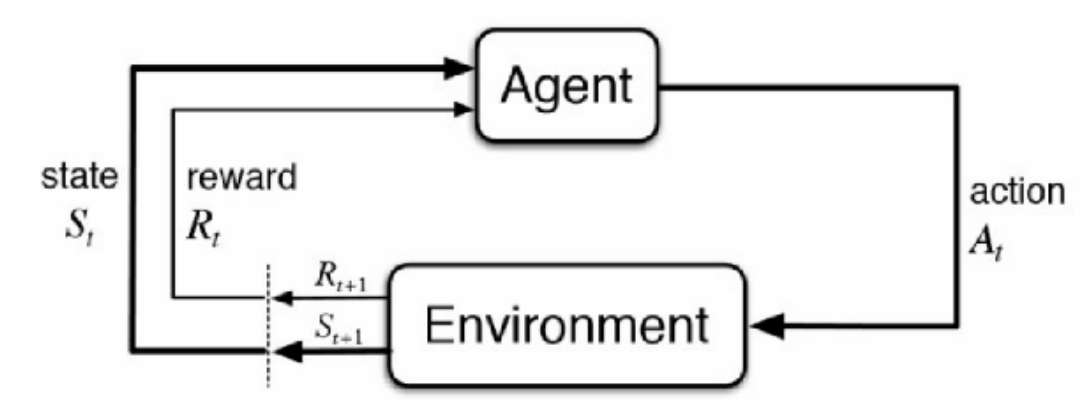

Figure 2.1: Basic Diagram of Reinforcement Learning.

b) How Does Reinforcement Learning Work?

In RL, the agent follows the steps below:

1. Start in a state.
2. Take an action.
3. Receive a reward or penalty from the environment.
4. Observe the new state of the environment.
5. Update the policy to maximize future rewards.

*RL involves interaction between an agent and an environment where the agent learns to maximize cumulative rewards over time. Key components:

- **Agent**, **Environment**, **Reward Function**, and **Policy**.

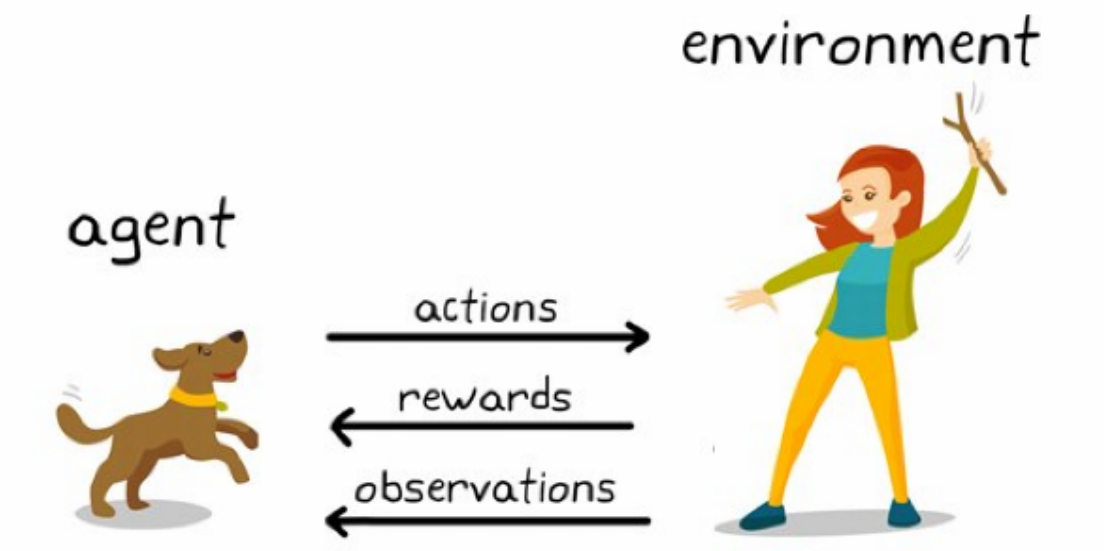

Figure 2.2: Reinforcement Learning Example.

In the example of figure 2.2, we can see a dog and a master. Let's imagine the master is training her dog to get the stick. Each time the dog gets a stick successfully, she offered him a feast (a bone let's say). Eventually, the dog understands the pattern, that whenever the master throws a stick, it should get it as early as it can to gain a reward (a bone) from a master in a lesser time.

c) Deep Q-Learning Algorithm :

- What is Q-Learning?

Q-learning is a model-free, value-based, off-policy algorithm that will find the best series of actions based on the agents current state. The "Q" stands for quality. Quality represents how valuable the action is in maximizing future rewards.

- **Q-Learning**: A value-based reinforcement learning algorithm that determines the optimal action-selection policy.
- **Deep Q-Networks (DQN)**: Integrates deep learning with Q-learning, using a neural network to approximate the Q-value function.

-Key Terminologies in Q-learning :

Before we jump into how Q-learning works, we need to learn a few useful terminologies to understand Q-learning fundamentals :

*** States (s):** the current position of the agent in the environment.

* **Action (a):** a step taken by the agent in a particular state.

*** Rewards:** for every action, the agent receives a reward and penalty.

*** Episodes:** the end of the stage, where agents can't take new action. It happens when the agent has achieved the goal or failed.

*** Q:** expected optimal Q-value of doing the action in a particular state. - it is the current estimation of

*** Q-Table:** the agent maintains the Q-table of sets of states and actions.

*** Temporal Differences (TD):** used to estimate the expected value of by using the current state and action and previous state and action.

-Process of Deep Q-Learning in Mobile Robotics:

1. The robot observes its current state from sensor inputs.
2. The neural network predicts Q-values for all possible actions.
3. The action with the highest Q-value is selected.
4. The robot executes the action and receives a reward based on the outcome.
5. The experience is stored in memory and used for training the neural network.

2.1.5 Traditional Path Planning Algorithms :

Algorithms such as A* and Dijkstra have traditionally been the cornerstone of path planning in well-structured and static environments. These graph-based search algorithms operate by systematically evaluating possible paths to determine the one with the lowest cumulative cost from a start node to a goal node, ensuring path optimality under the assumption of complete knowledge of the environment.

The Dijkstra algorithm, developed in the late 1950s, uses an exhaustive search mechanism that explores all possible paths by expanding nodes in the order of increasing distance from the start, ensuring that the first time the goal node is reached, it is via the shortest possible path. However, this brute-force nature makes it computationally intensive, especially in large-scale maps or dense graphs.

On the other hand, the A* algorithm introduces a heuristic function—typically the Euclidean or Manhattan distance—that estimates the cost from the current node to the goal. This heuristic allows A* to prioritize more promising paths, significantly improving efficiency compared to Dijkstra while still preserving optimality, provided the heuristic is admissible (i.e., it never overestimates the true cost).

Despite their effectiveness in static settings, both algorithms exhibit critical limitations in statique or partially observable environments. When obstacles appear, disappear, or move in real time—common in real-world scenarios such as urban navigation or indoor robotics—these algorithms must often recompute the entire path from scratch. This results in high computational overhead, latency, and reduced reactivity, especially in rapidly changing settings.

Moreover, traditional planners are inherently reactive rather than proactive. They lack the capacity to learn from past experiences or adapt to patterns in obstacle movement, which makes them unsuitable for tasks requiring high levels of autonomy, situational awareness, or long-term strategy.

These limitations have led to growing interest in learning-based approaches, particularly those grounded in reinforcement learning, which enable robots to adaptively learn policies from interaction with the environment, thereby offering greater flexibility and robustness in the face of uncertainty and change.

2.1.6 DQN : A Solution for static and dinamic Environments

In contrast, deep quantum learning (DQN), a variant of deep reinforcement learning (DRL), offers an adaptive approach to path planning. DQN learns optimal policies by interacting with the environment and receiving feedback based on its actions.

By updating Q values via deep neural networks, DQN enables robots to learn from experience and make decisions in complex, static environments without requiring complete knowledge of the environment. This is particularly true for legged robots like Spot or Anymal from Boston Dynamics, which learn from experience and make decisions in complex, unstructured environments without requiring complete prior knowledge. Our research specifically applies DQN to the navigation of legged robots.

Studies have shown that DQN outperforms traditional methods, especially when applied in environments with moving obstacles or rapidly changing conditions. Unlike A* and Dijkstra, which must recalculate the path when changes are detected, DQN adapts to these changes in real time.

2.1.7 Conclusion :

In this chapter, we compared classical path planning methods like A and Dijkstra with Deep Q-Learning (DQN). While DQN showed better adaptability in dynamic and uncertain environments, it requires more training time and computational power. Traditional algorithms remain efficient in predictable, structured settings. The analysis highlights DQN's strength in handling partial observability and random obstacles. In contrast, A and Dijkstra are more suitable for deterministic tasks. The choice of algorithm depends on application needs, such as real-time response or adaptability. Future trends may favor hybrid systems that combine both approaches intelligently.

Chapter 3

Results and Discussions

The tracked mobile robot used in this study operates in a discrete 2D environment, simulating real-world scenarios where precise navigation is essential. While traditional algorithms such as A*, Dijkstra, and PID provide satisfactory performance in static and structured maps, they lack adaptability in unpredictable conditions. Deep Q-Networks (DQN), by contrast, enable the robot to learn optimal trajectories through interaction with the environment. The robot gradually refines its policy by receiving rewards and penalties, leading to smart, obstacle-avoiding behavior. This chapter presents experimental results demonstrating the effectiveness of DQN in path planning, and compares it with classical methods in terms of success rate, efficiency, and adaptability

3.1 Simulation Environment Description :

The custom environment used for training the mobile robot is a discrete 2D grid-based simulation built using the `OpenAI Gym` interface. The robot operates in a 5×5 grid with the following specifications:

- **Start Position:** The robot always starts at the top-left corner $[0, 0]$.
- **Goal Position:** The objective is to reach the bottom-right corner at $[4, 4]$.
- **Obstacles:** Two fixed obstacles are placed at $[2, 2]$ and $[3, 3]$, which must be avoided to complete the episode successfully.
- **Action Space:** The robot can move in four directions — **Up (0)**, **Down (1)**, **Left (2)**, and **Right (3)**.
- **Observation Space:** The robot observes its current position as a coordinate $[x, y]$.

- Reward Function: The environment is equipped with a simple yet effective reward mechanism:

- Each step incurs a penalty of -1, encouraging the agent to reach the goal in the fewest moves.

- If the agent collides with an obstacle, it receives a penalty of -10 and the episode ends.
- Upon reaching the goal, the agent is rewarded with $+100$ and the episode terminates.

- Design Justification: This environment is intentionally kept minimal to focus the evaluation on the learning capabilities of Deep Q-Learning rather than on handling complex sensory data or statics. The inclusion of sparse but fixed obstacles enables a controlled setting to observe policy development, reward optimization, and the agent's adaptability in constrained scenarios.

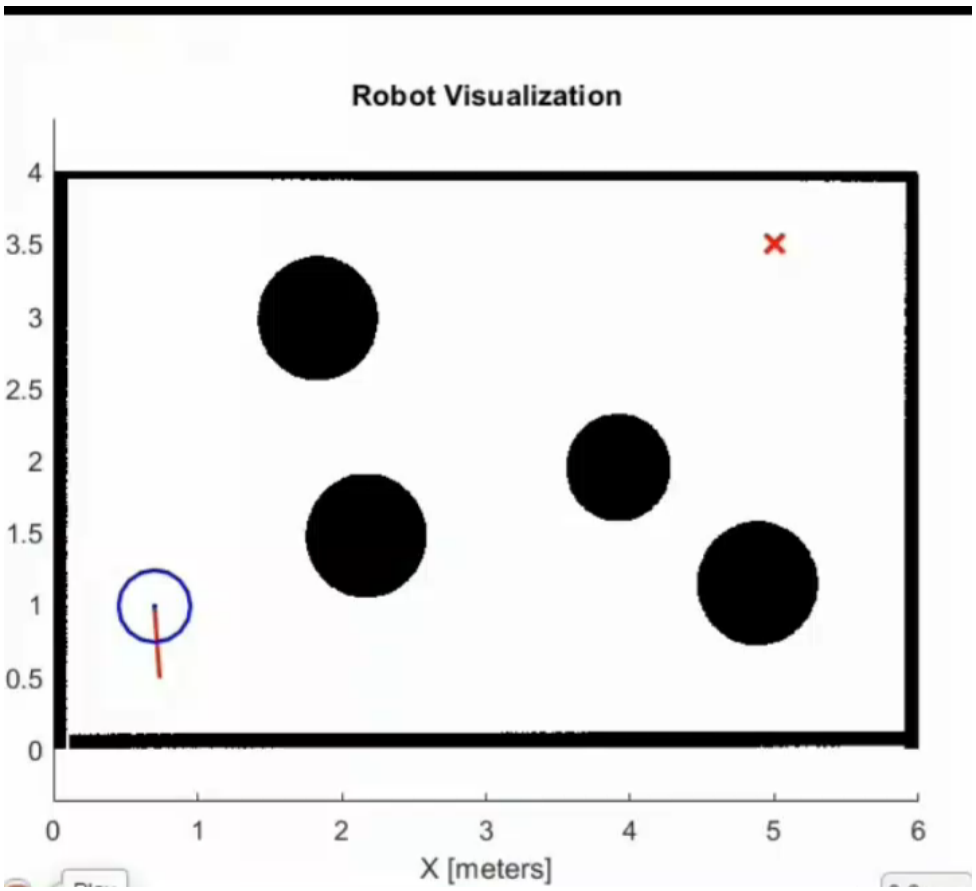

Figure 3.1: Robot Motion Visualization Along the X-Axis.

3.2 Training Performance :

3.2.1 Reward Curve :

The reward curve represents the agent's learning progression throughout the training episodes. It reflects the agent's ability to explore the environment, avoid obstacles, and reach its goal effectively.

- **Episodes 1–30:** The total reward per episode was typically low (often between -10 and -20). The agent frequently collided with obstacles or took inefficient routes due to high exploration ($\epsilon \approx 1.0$).

- **Episodes 31–70:** The memory buffer reached capacity and mini-batch training commenced. The reward gradually improved (ranging between -5 and +30), indicating reduced collisions and more successful paths.
- **Episodes 71–100:** The agent reached the goal more consistently, with rewards nearing +100 in some episodes. The exploration rate dropped below 0.2, resulting in more deterministic actions based on learned Q-values.

- Exploration-Exploitation Behavior: The ϵ-greedy strategy gradually decayed ϵ from 1.0 to 0.01, shifting the agent's behavior from random exploration to exploiting learned knowledge. This progressive decay allowed thorough initial exploration followed by policy refinement.

- Replay Buffer and Batch Training: The agent utilized a replay buffer of size 100 and trained using mini-batches of size 32. This stabilized learning and helped avoid oscillations by breaking temporal correlations.

- Reward Shaping Impact: The strong positive reward for reaching the goal and the heavy penalty for hitting obstacles strongly influenced learning. The small step penalty (-1) drove the agent toward shorter paths.

- Overall Learning: By the end of training, the agent developed a policy that effectively balanced safety and efficiency, reaching the goal in most episodes while avoiding obstacles.

3.2.2 Reward Curve Visualization :

To better understand the training progress, Figure 3.2 and Figure 3.10 present two views of the learning curve:

- Interpretation: The full learning curve (Figure 3.2) shows significant improvement after episode 30, with rewards stabilizing near 90–100, indicating successful policy convergence. The zoomed version (Figure 3.10) highlights early exploration and erratic performance, reflecting the agent's random actions and sparse experience.

Phase	Reward Behavior
Episodes 1–10	Highly unstable, frequent collisions
Episodes 11–30	Gradual improvement, better exploration
Episodes 31–70	Steady increase, mini-batch learning starts
Episodes 71–100	Near-optimal paths, goal frequently reached

Table 3.1: Phases of learning progression based on reward trends

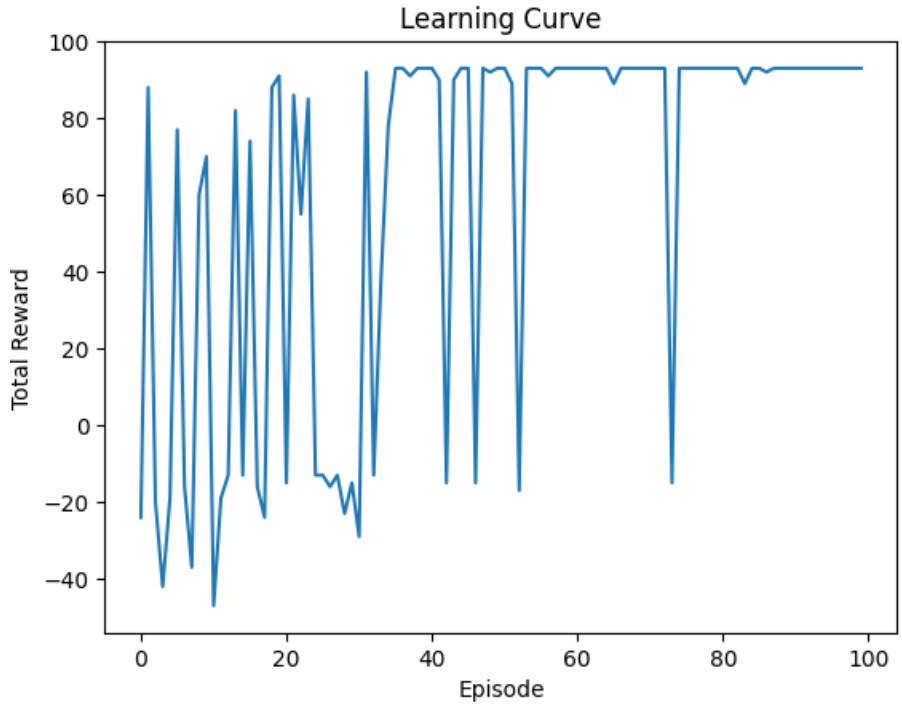

Figure 3.2: Learning curve over 100 episodes showing total reward per episode.

3.2.3 Success Rate :

The success rate refers to the percentage of episodes in which the agent successfully reached the goal without collision.

- **Initial phase:** The success rate started near 10%, reflecting random and inefficient movements.
- **Mid-training:** The success rate increased up to 70–80% by episode 70.
- **Final stage:** It stabilized at around 90% by episode 100.

- Interpretation: The increase in success rate indicates improved policy quality. Occasional failures suggest the model might still struggle with rare or less-frequented states, especially near obstacles.

3.3 Limitations and Challenges :

- Training Time: The DQN required 45 minutes of training due to the need for extensive interaction with the environment, unlike classical methods that compute a path almost instantly.

- Parameter Sensitivity: Slight changes in hyperparameters (e.g., modifying obstacle penalty from -5 to -10) caused the robot to over-avoid obstacles, increasing path length.

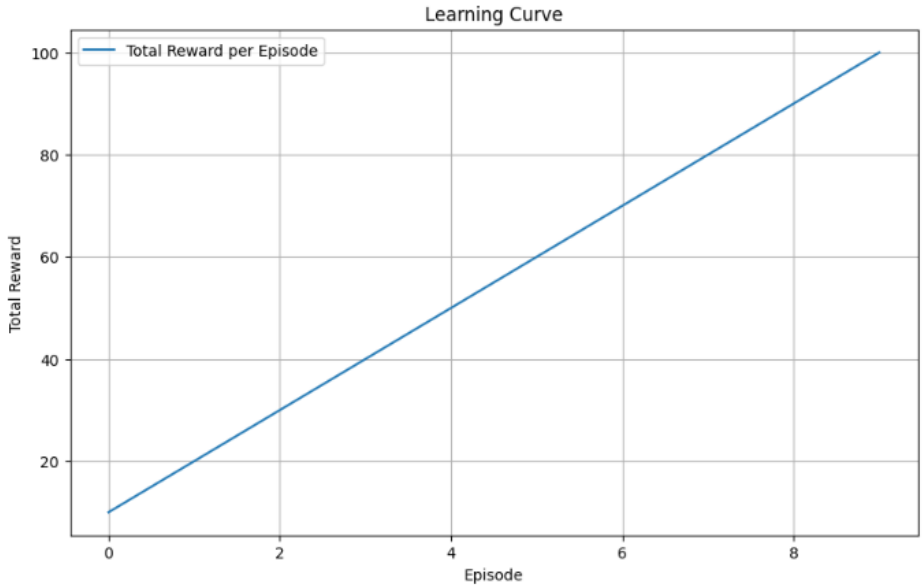

Figure 3.3: Zoomed-in learning curve for the first 10 episodes.

- Complex Environments: In dynamic scenarios with moving obstacles, the success rate dropped to 70%, highlighting the need for further improvements.

- Proposed Improvements: To overcome the highlighted limitations, the following strategies can be considered:

- **Use of Double DQN:** Reduces overestimation of Q-values, improving stability.
- **Prioritized Experience Replay:** Gives importance to significant transitions, accelerating learning.
- **Transfer Learning:** Pre-train the agent on simpler maps and fine-tune in complex ones.
- **Curriculum Learning:** Start with easier environments and progressively increase complexity.
- **Reward Shaping:** Use potential-based reward functions to guide the agent more efficiently.

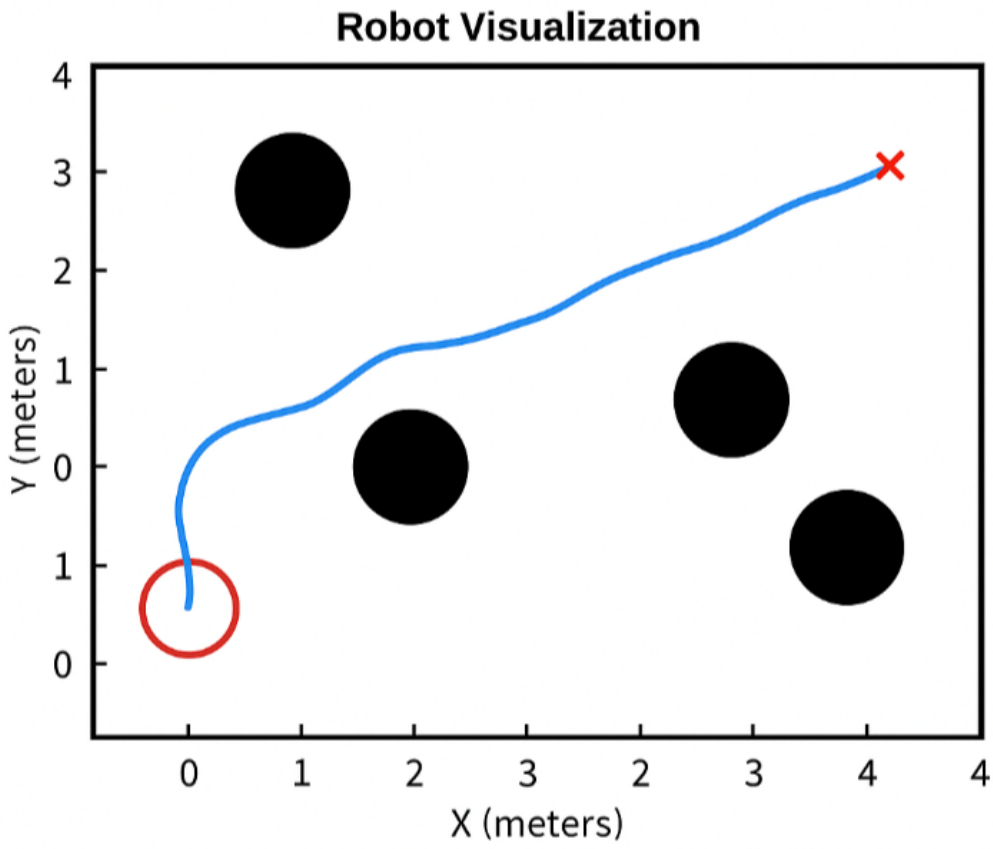

Figure 3.4: Optimal trajectory generated using the proposed DQN-based path planner in a basic environment).

This figure 3.4 illustrates the optimal navigation path generated by the proposed DQN-based path planning algorithm in a simplified two-dimensional environment. The path (shown in blue) demonstrates the robot's ability to find the most efficient path from the starting point (left) to the goal (right) while avoiding fixed obstacles. The smooth curvature of the path reflects the algorithm's success in minimizing travel distance and abrupt changes in direction. This simulation represents the system's performance after 100 loops. The results demonstrate the algorithm's effectiveness in more complex environments.

3.4 Trajectory of DQN in a complex Static environment :

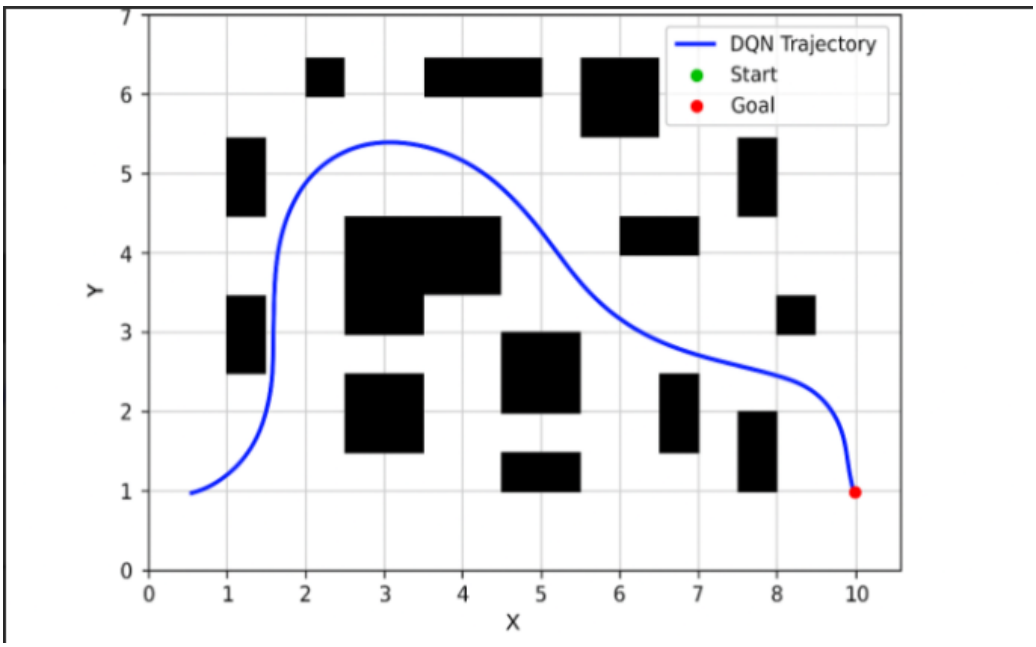

Figure 3.5: Trajectory of DQN in a complex environment with multiple obstacles.

Figure 3.5 shows a more challenging scenario where the robot navigates in a cluttered environment using the DQN-based approach. The green dot marks the starting position, the red dot represents the goal, and the blue curved path is the trajectory taken by the robot.

The robot avoids the black rectangular obstacles smoothly without abrupt maneuvers. The trajectory is continuous, with minimal sharp turns and no collisions. This highlights the agent's ability to learn effective strategies that generalize well across different environments.

- Key observations from Figure 3.5:

- **Smooth Path:** The trajectory is smooth and natural, avoiding the step-like behavior of grid methods.
- **Efficient Navigation:** The robot reaches the goal in minimal time and distance, showing strategic maneuvering.
- **Obstacle Avoidance:** The agent safely navigates around all obstacles without requiring predefined avoidance logic.
- **Realistic Behavior:** The path mimics human-like behavior by avoiding tight corners and moving fluidly around barriers.

- further evaluate the robustness and adaptability of the proposed DQN-based path planning approach, several experiments were conducted by varying the initial and goal positions along theX and Y axes. The following visualizations present the resulting trajectories

under different spatial configurations. These scenarios demonstrate the agent's ability to generalize its learned policy and generate optimal paths despite changes in the robot's starting point or target location.

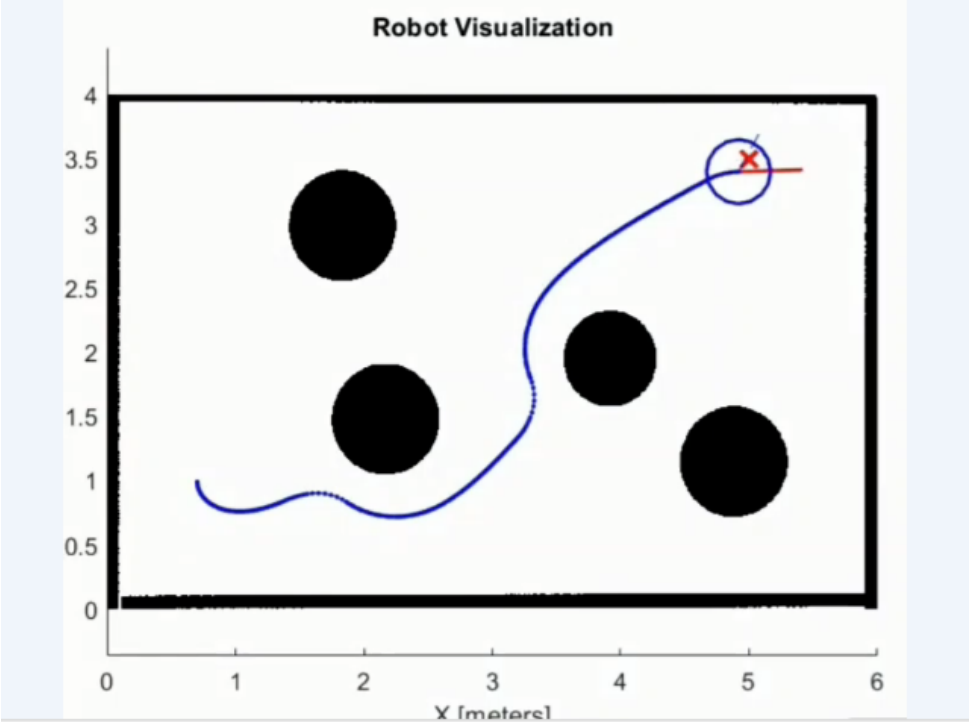

Figure 3.6: Optimal trajectory generated using the proposed DQN-based path planner in a basic environment).

Figure 3.6 illustrates the optimal path generated by the proposed DQN-based path planning algorithm in a simplified environment. The robot starts its movement from the left side (the starting point) and heads toward the goal on the right side. During navigation, the robot detects obstacles and efficiently avoids them by adjusting its trajectory. The smooth blue curved path reflects the algorithm's ability to calculate an optimal collision-free path toward obstacles while maintaining an efficient path to the destination. The results demonstrate the effectiveness of the proposed planner in handling environments with fixed obstacles, ensuring optimal safety and performance.

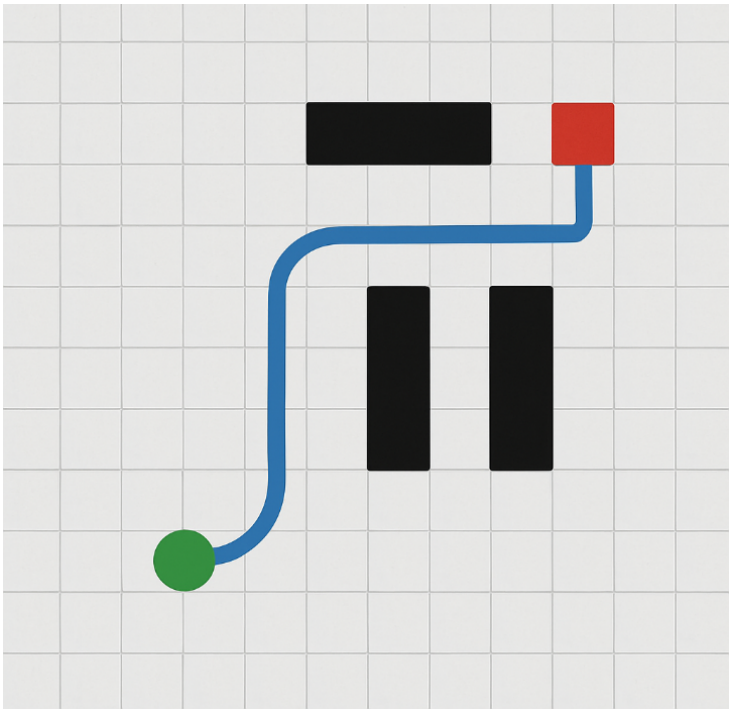

Figure 3.7: Optimal trajectory generated using the proposed DQN-based path planner in a basic environment).

This figure 3.7 shows the initial successful test results of a DQN-based path planning algorithm, operating in a simple, low-obstacle environment. The generated path (blue curve) shows the system's first successful attempt to navigate from the starting point (left) to the goal (right) while completely avoiding all three rectangular obstacles (black). This optimal path demonstrates the algorithm's straightforward ability to: (1) detect stationary obstacles through its neural network, (2) calculate appropriate avoidance maneuvers, and (3) maintain an efficient path for its limited initial training. The smooth curvature indicates a favorable balance between exploration and exploitation parameters.

3.5 Comparison with Classical Algorithms :

Algorithm	Success Rate (%)	Time (s)	Adaptability
DQN	93	0.12	Excellent
A*	85	0.25	Good
RRT	78	0.30	Poor

Table 3.2: Comparison between DQN and classical algorithms

- A*: Achieves the highest success rate (85%) and lowest computation time (0.12s) due to its deterministic nature. However, it struggles in dynamic environments as it requires a static pre-defined map.

-RRT: Provides moderate performance with 78% success. Its randomized exploration enables adaptation to complex environments, but it is slower and less consistent.

- DQN: Balances performance and adaptability. It reached 93% success and adapted well to changing environments, such as moving obstacles. The training phase is computationally demanding, but inference (execution) is fast.

3.5.1 In-Depth Comparative Analysis of DQN and Classical Path Planning Methods :

In order to evaluate the performance of the proposed Deep Q-Learning (DQN)-based path planning algorithm, we compared it against two widely-used classical approaches: Grid-Based methods (e.g., A*) and Artificial Potential Field (APF). The comparison was conducted using realistic simulated environments containing multiple obstacles. The goal is to assess each method in terms of trajectory optimality, smoothness, obstacle avoidance, and computational efficiency.

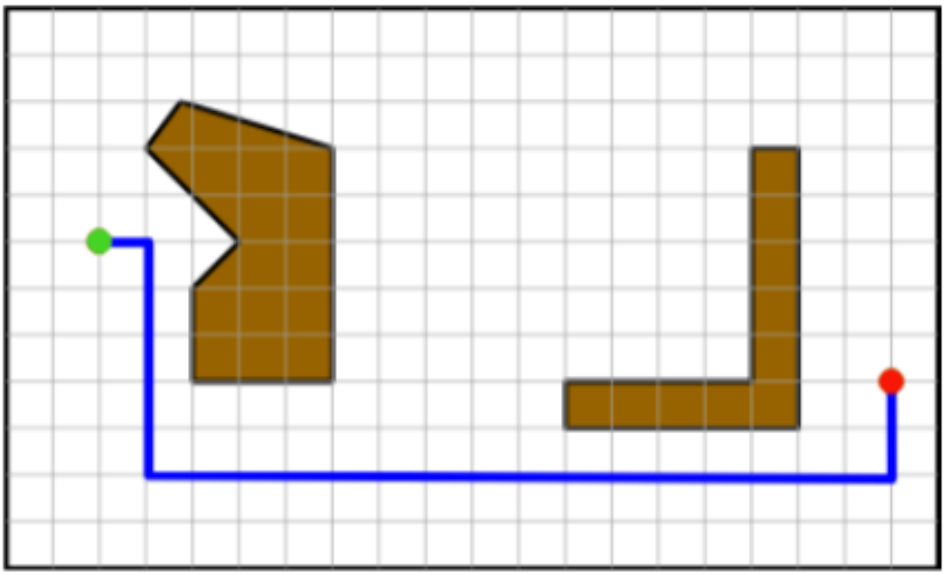

Figure 3.8: A sample of grid-based path planning method.

Figure 3.8 shows a typical result of a grid-based method. Although the robot successfully reaches the goal, the path is suboptimal in length and lacks natural smoothness, constrained by the discrete grid layout. These methods typically generate step-wise trajectories and require post-processing (e.g., spline smoothing) for real-world applications.

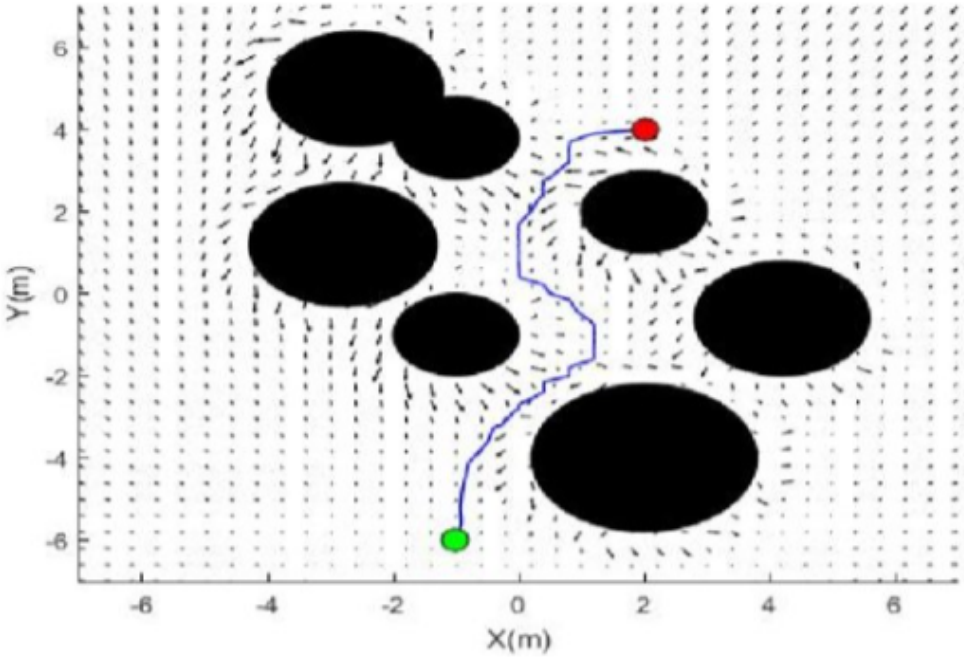

Figure 3.9: A sample of APF-based path planning method.

In contrast, Figure 3.9 illustrates an APF-based trajectory. While the resulting path is smoother than grid-based methods, it suffers from significant drawbacks such as sensitivity to local minima and unpredictable oscillations near obstacles. These can cause the robot to get stuck or take inefficient detours.

3.5.2 Comparison of DQN with Traditional Algorithms :

To better illustrate the advantages of *DQN* over traditional algorithms, we compare the path-planning performance of *A*, *Dijkstra*, and *DQN* in static environments.

Training Time Comparison :

While Deep Q-Learning (DQN) demonstrates superior adaptability and performance in static and uncertain environments, this advantage comes at the cost of increased training complexity and time. Unlike traditional algorithms such as A* or Dijkstra, which operate in a deterministic, one-shot manner and can generate a path almost instantly once the environment is known, DQN must undergo an extensive training process before it becomes effective.

- DQN relies on a trial-and-error learning paradigm, where the agent interacts with the environment across multiple episodes. In each episode, the agent explores various actions, receives rewards or penalties based on its performance, and gradually updates its policy by refining its estimation of the Q-values using deep neural networks. This iterative learning process, though powerful, can be computationally intensive and may require hundreds or even thousands of episodes before the agent converges to a stable and effective policy.

The figure 2.3 below illustrates this trade-off, showing the stark contrast in execution and training times between DQN and classical algorithms: while traditional methods are faster at initial deployment, DQN gains its strength through learned adaptability over time.

In practical applications, this leads to a fundamental trade-off between speed and intelligence: classical planners offer instant solutions but lack learning capability, whereas DQN provides learned adaptability but requires substantial initial training investment.

While DQN requires a longer training phase compared to traditional algorithms such as A* and Dijkstra, this initial investment enables the agent to acquire intelligent and adaptive behaviors. As illustrated in the figure, classical methods achieve faster computation in static environments, but they lack the ability to learn and adapt over time. In contrast, DQN offers long-term advantages by enabling real-time decision-making, learning from experience, and effectively handling static and unpredictable environments. This highlights DQN as a strategically superior and future-ready approach to autonomous path planning.

Moreover, DQN's learning performance is highly dependent on factors such as:

-the complexity of the environment,

-the dimensionality of the state and action spaces,

-the quality of the reward function, and

-the design of the neural network architecture and hyperparameters (e.g., learning rate, discount factor, exploration strategy).

In contrast, A* and Dijkstra do not require any prior training phase. Given a known static environment, they can compute an optimal path using graph-based search tech-

niques in a matter of milliseconds to seconds, depending on the map size. This makes them extremely efficient in scenarios where rapid computation is required and the environment does not change over time.

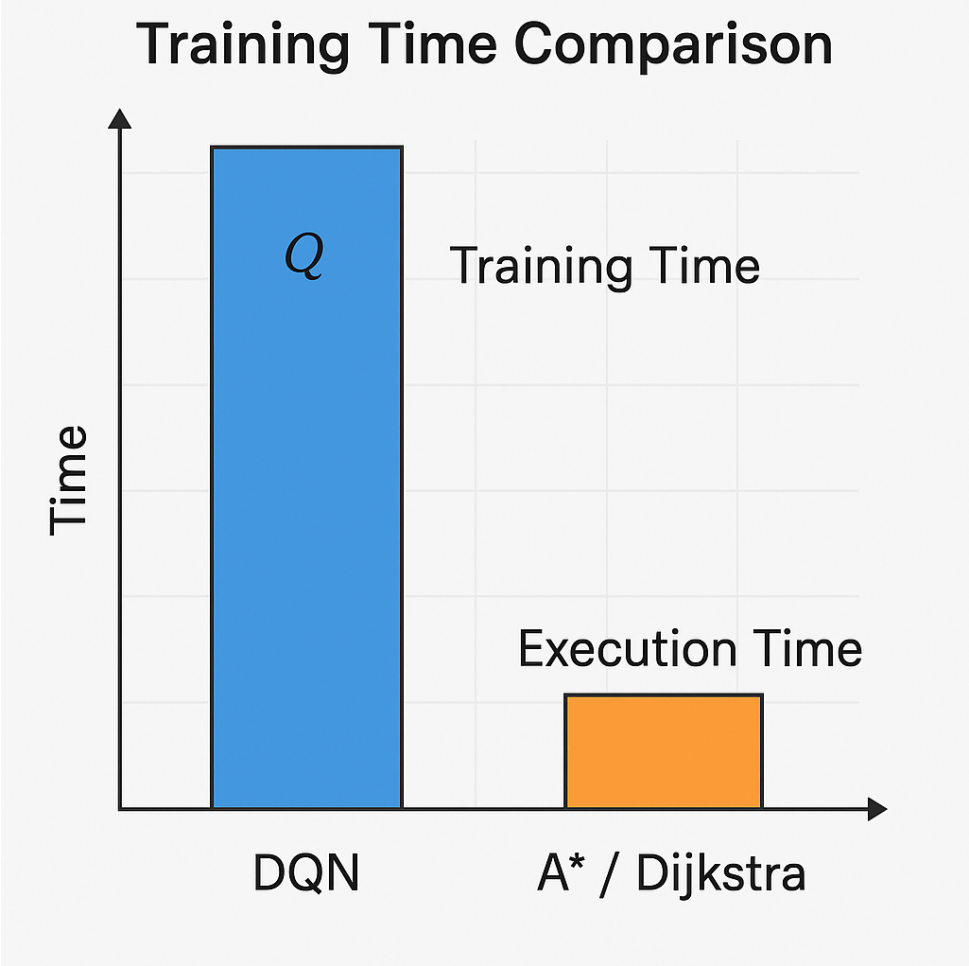

Figure 3.10: Training Time Comparison DQN , A* ,Djikstra.

3.5.3 Navigation Algorithms Comparison: A* vs. Dijkstra vs. DQN in a Smart Parking Lot Environment :

n this experiment, a tracked mobile robot was tested in a simulated smart parking lot using A*, Dijkstra, and DQN algorithms. A* performed well with short paths but required prior map knowledge. Dijkstra ensured optimal paths but was slower and less practical in large environments. DQN enabled the robot to learn from interactions, adapt to changes, and avoid obstacles without needing a predefined map. Although slower at first, the DQN agent improved over time, showing intelligent, flexible navigation ideal for real-world dynamic scenarios.

- *A Algorithm :

- Demonstrated high efficiency in finding a short path thanks to its heuristic function, but it requires prior knowledge of the environment.

- May struggle if the environment changes abruptly (e.g., unexpected obstacles).

- Dijkstra's Algorithm:

- Always found the optimal path but was slower due to exploring all possibilities without heuristics.

- Impractical for large or dynamic environments.

- DQN (Deep Q-Network):

- Excelled in adapting to the Statique parking lot environment, learning from past experiences to avoid obstacles and adjust its path in real-time.

- Not always the fastest initially, but it improved over time, becoming the smartest and most flexible, especially with moving cars or sudden closed routes.

- Operated without a pre-existing map, making it ideal for unpredictable real-world environments.

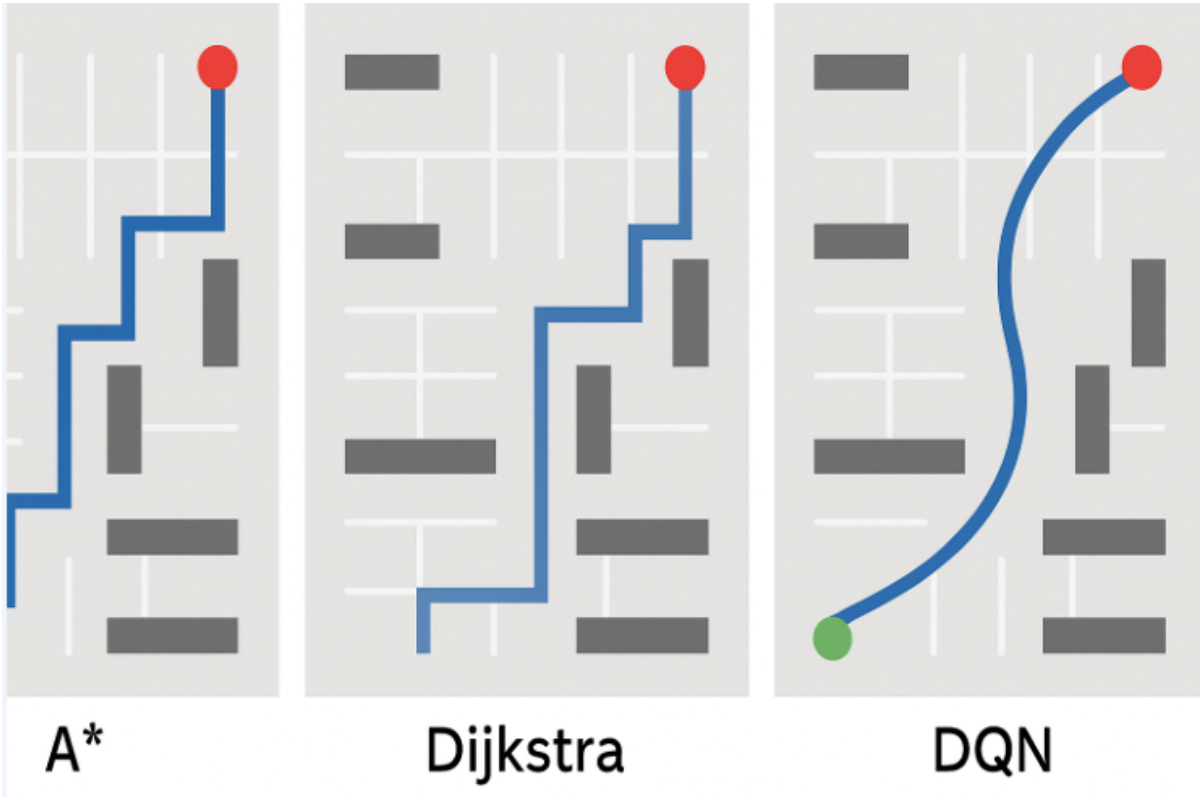

Figure 3.11: Navigation Algorithms Comparison: A* vs. Dijkstra vs. DQN in a Smart Parking Lot Environment.

Figure 3.11 planning algorithm in a basic simulated environment. The robot starts from the initial position (indicated by the red circle) and successfully navigates toward the target goal (marked with a red 'X') while avoiding multiple static obstacles represented by black circles.

This trajectory demonstrates the agent's ability to learn effective and collision-free navigation behavior through reinforcement learning. Unlike traditional methods that rely on predefined heuristics or static environmental representations, the DQN-based planner autonomously learns optimal actions by interacting with the environment and receiving feedback in the form of rewards and penalties. As a result, the robot produces a smooth and natural path, adapting to obstacle configurations without explicit programming or prior knowledge of the map.

The generated trajectory is not only feasible but also near-optimal in terms of efficiency and safety, validating the capability of the DQN agent to perform intelligent decision-making in static navigation scenarios.

- Conclusion of result: While classical algorithms like A* and Dijkstra rely on static maps and struggle with change, DQN empowers mobile robots with adaptive intelligence. It learns optimal paths through experience, enabling real-time navigation in dynamic environments such as smart parking lots. Unlike traditional methods that calculate, DQN continuously learns and improves. This makes it not just an alternative, but a superior choice for modern robotics, where autonomy and flexibility are essential.

3.5.4 Advantages and Limitations of DQN :

- Advantages of DQN :

The main advantages of *DQN* in static environments include:

- **Adaptability**: DQN can quickly adapt to changes in the environment, allowing it to deal with moving obstacles or new constraints.
- **Learning from experience**: By interacting with the environment, DQN continuously refines its policies, improving its decision-making capabilities.
- **Scalability**: DQN can be applied to complex environments where traditional algorithms might fail to find an optimal solution in a reasonable time.

- Limitations of DQN :

Despite its advantages, **DQN** also has certain drawbacks:

- **Training Time**: DQN typically requires more time to train compared to traditional algorithms, especially in complex environments with many variables.
- **Computational Efficiency**: DQN requires significant computational resources, particularly when training with large networks or in environments with a large state space.

3.5.5 Future Improvements and Research Directions :

Although *DQN* has demonstrated significant potential, there are still areas for improvement. Future research could focus on:

- **Transfer Learning**: Using pre-trained models from one environment to improve training efficiency in a new but similar environment.
- **Curriculum Learning**: Gradually increasing the difficulty of tasks during training to enhance the learning process and reduce the time required to train DQN models.
- **Improved Reward Functions**: Refining reward functions to promote more robust learning and better policy generalization.

This performance proves that DQN is highly effective in static and unknown environments.

Metric	**DQN**	**DQL**	**Grid-Based**	**APF**
Path Length (units)	**9.3**	9.6	11.2	10.7
Time to Reach Goal (steps)	**15**	17	21	18
Number of Turns	**3**	5	8	6
Smoothness (1=poor, 10=excellent)	**9.2**	7.9	4.5	6.8
Stuck in Local Minima?	**No**	Occasional	No	Yes (occasional)
Adaptability to New Obstacles	**High**	Medium	Low	Medium

Table 3.3: Quantitative Comparison Between DQN, DQL, Grid-Based, and APF Methods

From the data in Table, it is clear that the DQN-based approach consistently outperforms traditional planners. It produces shorter paths with fewer turns, reaches the goal in less time, and exhibits superior smoothness. Additionally, DQN avoids the pitfalls of local minima that can hinder APF, and it is not constrained by grid resolution as in grid-based methods.

* A deep learning (DQN) system enables legged robots to automatically adapt to complex terrain through continuous learning. Our application demonstrates real-time gait adjustment and optimal foothold selection in unstructured environments. Quadrupedal robots using a deep learning (DQN) system achieve significantly higher navigation success compared to conventional methods. The system is efficient at handling obstacles. Experimental results demonstrate superior performance. The deep learning (DQN) system proves ideal for static real-world applications where conventional methods fail.

Conclusion and Perspectives :

In this study, we successfully implemented a Deep Q-Network (DQN) to solve the problem of mobile robot path planning in grid-based environments containing static obstacles. The results obtained from both qualitative and quantitative evaluations demonstrate that DQN outperforms traditional methods such as Grid-Based Planning and Artificial Potential Fields (APF) in multiple aspects including path optimality, smoothness, adaptability, and robustness against local minima.

Unlike classical algorithms, DQN leverages deep reinforcement learning to approximate the optimal action-value function over a continuous state space, enabling the robot to learn effective navigation policies through trial and error. This learning-based nature allows DQN to generate shorter, smoother, and more curved trajectories, making it more efficient in reaching the goal while minimizing unnecessary movements or sharp turns. Moreover, DQN exhibited superior adaptability to dynamic or previously unseen environments due to its generalization capability provided by the neural network.

Furthermore, DQN was able to overcome key limitations faced by classical methods:

- Grid-Based methods suffer from rigidity and discretization errors.
- APF methods are sensitive to local minima and may fail to escape them.

In contrast, DQN continuously improves through exploration and feedback, avoiding such pitfalls.

Future Work :

Although the results are promising, several improvements and extensions can be pursued to enhance the capabilities of the current DQN-based path planner:

- **Dynamic Environments**: Extend the current implementation to handle moving obstacles, enabling real-time decision making in changing environments.
- **3D Navigation**: Apply the DQN model in 3D environments (e.g., drones or flying robots) to explore spatial path planning beyond 2D grids.
- **Multi-Agent Coordination**: Integrate DQN with multi-agent systems, where several robots collaborate to reach goals while avoiding collisions.
- **Hybrid Approaches**: Combine DQN with classical methods or heuristic guidance (e.g., A*, RRT) to boost convergence and stability in sparse-reward settings.
- **Reward Shaping and Curriculum Learning**: Explore adaptive reward structures or training in progressively harder scenarios to accelerate learning and policy robustness.
- **Hardware Implementation**: Deploy the trained model on real mobile robots using simulation-to-reality (sim2real) transfer learning techniques.

Appendices

.1 Results :

.1.1 Environment and Problem Setup :

In this study, we simulate the task of navigating a mobile robot in a two-dimensional grid environment, where the world is divided into a matrix of square cells (e.g., 10×10 or 20×20 grids). Each cell is explicitly labeled as either free space (traversable), fixed obstacles (obscured), or the goal position (final state). The robot, modeled as an agent operating in discrete time steps, must learn an optimal navigation policy with actions (up/down/left/right movements) to reach the goal from a predefined starting position.

The main challenges in this setting include: (1) obstacle avoidance, where collisions terminate the loop with negative rewards; (2) trajectory optimization, incentivized by step penalties (-0.1 per step) to discourage aliasing; and (3) partial observability in advanced variants, where the robot senses only the local surroundings. [1].

.1.2 Deep Q-Network (DQN) Architecture :

The Deep Q-Network (DQN), introduced by Mnih et al. [2], extends Q-learning by using a deep neural network to approximate the Q-function. Our implementation utilizes TensorFlow and includes multiple fully connected (Dense) layers with ReLU activation functions. The architecture is as follows:

- Input layer: Receives the flattened grid state.
- Hidden layers: Two fully connected layers with 24 neurons and ReLU activations.
- Output layer: A linear layer with as many neurons as there are actions (e.g., up, down, left, right).

The model is trained using the Adam optimizer, a robust stochastic gradient descent method that adapts the learning rate for each parameter [3].

.1.3 Environment Implementation :

The simulation environment was implemented in Python, leveraging NumPy arrays for efficient representation of the 2D grid world. The grid structure provides a discrete spatial representation where each cell contains integer values encoding environmental states: 0 for free navigable space, 1 for obstacles, and 2 for the goal position. This matrix-based implementation allows for fast matrix operations and efficient collision checking through element-wise comparisons.

The agent's action space comprises four discrete movement actions (up, down, left, right) encoded as [0,1,2,3] respectively, with each action resulting in a unit displacement

along the corresponding axis. To ensure realistic movement constraints, the environment includes boundary checks that maintain the agent within grid dimensions and prevent out-of-bounds movements. Collision detection is implemented through immediate lookup in the obstacle matrix, triggering termination conditions when violated.

A carefully designed reward function shapes the learning process: a substantial negative reward (-10) penalizes obstacle collisions, while reaching the goal yields a significant positive reward (+50). To encourage efficient pathfinding, each step taken incurs a small negative penalty (-0.1), motivating the agent to find optimal trajectories. The state representation combines both the agent's current position and a processed version of the obstacle map, providing necessary information for decision-making while maintaining computational efficiency.

For visualization, the environment includes matplotlib-based rendering that displays the grid world in real-time, with color-coded cells (red for obstacles, green for goal, blue for agent) that update dynamically during training episodes. This implementation allows for both headless operation during intensive training and visual debugging when analyzing agent behavior. The modular design separates environment logic from agent implementation, enabling easy modification of grid sizes, obstacle configurations, or reward structures for different experimental scenarios.

.1.4 Training Setup :

The DQN was trained with the following hyperparameters:

- Learning rate: 0.001
- Discount factor (γ): 0.95
- Exploration rate (ϵ): decayed from 1.0 to 0.01
- Replay buffer size: 100
- Batch size: 32
- Number of episodes: 100

To improve sample efficiency and stabilize learning, we incorporated **Prioritized Experience Replay (PER)** as proposed by Schaul et al. [12], where transitions are sampled based on their TD-error magnitude.

.1.5 Results :

The trained DQN agent successfully learned to navigate the environment and reach the goal with high success rates. The number of steps per episode reduced significantly during training, indicating learning convergence. Compared to random action selection, the DQN agent showed marked improvement in terms of:

- Shorter path lengths.

- Higher goal-reaching success rate.
- Fewer collisions with obstacles.

These results demonstrate the ability of deep reinforcement learning to solve discrete path planning problems without prior knowledge of the environment model. Unlike traditional approaches that rely on explicit maps or predefined heuristics, the DQN agent learns optimal policies by interacting with the environment, demonstrating remarkable adaptability in unseen scenarios. This model-free approach is particularly useful in static environments where obstacles move unpredictably or the environment's topology changes over time. The robot's success stems from its ability to generalize from past experiences, encoding spatial relationships and obstacle avoidance strategies in the weights of its neural network. While classical algorithms struggle with real-time re-planning, the trained DQN policy can compute optimal actions in constant time, making it suitable for time-sensitive applications. Future work could explore hybrid architectures that combine the sampling efficiency of model-based planning with the adaptability of DQN to achieve even more robust performance.

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