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**The evolution of mobile bases in robotics:
types, control techniques and applications**

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The evolution of mobile bases in robotics: types, control techniques and applications

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Abstract

Mobile robotics has rapidly advanced by integrating intelligent locomotion mechanisms and AI-based control. This review outlines the main types of wheeled, legged, hybrid, aerial, and aquatic mobile bases, and examines classical and modern control techniques like PID, MPC, and learning-based methods. Real-world applications span industries such as manufacturing, exploration, and healthcare. The work also highlights ongoing challenges and emerging trends in autonomy, perception, and swarm robotics.

Index Terms— Mobile Robotics, Locomotion Mechanisms, Control Techniques (PID, MPC, Learning-based), Perception and SLAM, Swarm Robotics.

1 Introduction

Mobile bases form the structural and functional foundation of autonomous robotic systems, enabling them to traverse diverse environments and perform complex tasks. The design and control of these bases are central to the mobility and versatility of robots across land, air, and water. Over time, the field has matured to include a wide range of configurations, including traditional wheeled platforms, biologically inspired legged robots, and hybrid designs that merge features for enhanced adaptability. Advanced forms, such as aerial drones and underwater vehicles, have further extended the operational domains of mobile robots.

This work presents a comprehensive analysis of mobile bases by first classifying their types such as differential drive, omnidirectional, and articulated structures and discussing their mechanical characteristics and operational benefits [1][2]. Thereafter addresses control methodologies ranging from basic feedback mechanisms to advanced adaptive and learning-based systems [3][4]. Applications span from industrial automation and smart logistics to healthcare assistance and hazardous environment exploration [5]. In light of emerging technologies, the study also reflects on key research trends aimed at improving control accuracy, minimizing energy usage, and enhancing situational awareness. Through this exploration, we emphasize how mobile bases are not

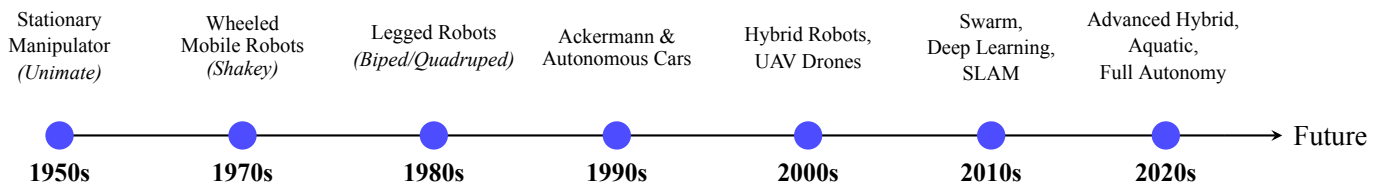


Figure 1: Timeline of the evolution of mobile robot bases.

just mechanical structures but integral components of intelligent, responsive robotic systems.

2 Classification of Mobile Bases

Mobile bases in robotics can be classified into five main categories: stationary, land-base (wheeled and legged), hybrid, aerial, and aquatic systems. Each type features unique kinematic structures and locomotion capabilities suited for specific environments and applications.

2.1 Stationary (Manipulator-Based) Robots

Stationary robots, typically robotic arms, operate from a fixed base with an open kinematic chain ending in a tool equipped end-effector [3]. They are widely used in industrial automation tasks such as welding, painting, and assembly.

Advantages: High precision, no balance issues, and the ability to perform repetitive tasks efficiently [6].

Limitations: Lack mobility and workspace flexibility [3].

2.2 Land-Based Mobile Robots

a. Wheeled Robots

Differential Drive Wheeled Mobile Robot (DDWMR): Consist of two independently driven wheels and a passive caster. Simple and cost-effective, suitable for indoor environments [1].

Omnidirectional Wheeled Mobile Robot (OWMR): Equipped with omni or mecanum wheels, allowing movement in any direction. Ideal for cluttered or narrow spaces [7].

Ackermann Steering: Mimics car-like turning with four wheels, enabling smooth curved

paths and high-speed motion [3].

Limitation of wheeled robots: Poor adaptability to rough terrain and complex dynamic modeling [3].

b. Legged Robots

Bipeds: Mimic human walking, capable of stair climbing and complex movements [3].

Quadrupeds and Hexapods: Offer greater stability and terrain adaptability [2].

Limitation: Complex control and balance maintenance [8].

2.3 Hybrid Mobile Robots

Hybrid systems combine multiple locomotion types (e.g., wheels and legs) for enhanced versatility across different terrains [2][9].

Limitation: Increased mechanical and algorithmic complexity.



Figure 2: Example of a hybrid mobile robot: a wheel-legged robot with an articulated arm.

2.4 Aerial and Aquatic Robots

Aerial Robots (Drones): Used in surveillance, agriculture, and delivery, with advantages in speed and access to hard-to-reach areas [3].

Aquatic Robots: These include underwater vehicles (ROVs and AUVs) and surface robots (e.g., autonomous boats), used for marine data collection and monitoring [8].

Challenges: Communication, stability, and energy constraints [10].

3 Mobile Base Control Techniques

Navigation by autonomous mobile robots in dynamic environments is a complex task that requires addressing challenges such as obstacle avoidance, path planning, and real-time decision making. To achieve this, a combination of advanced control techniques and intelligent algorithms is employed. Methods like **PID control**, **Adaptive Sliding Mode Control (ASMC)**, and **Model Predictive Control (MPC)** ensure precise motion control, while **Deep Learning** enhances adaptability and decision-making capabilities. Furthermore, path planning algorithms such as **A***, **Dijkstra**, and **RRT (Rapidly-exploring Random Trees)** enable efficient navigation through complex environments. Localization and mapping are facilitated by **SLAM (Simultaneous Localization and Mapping)** systems, along with perception modules using **LiDAR** or **stereo** cameras, enable robots to localize and map unknown environments. These technologies form a robust framework that allows autonomous robots to operate effectively in dynamic and unpredictable settings, making them indispensable for real-world applications.

3.1 Control Strategies

a. Classic Commands (PID controllers)

The performance of mobile robots is heavily dependent on the effective design of the controller, particularly in stabilization and trajectory tracking, which ensures precise movement by following a predefined path [11][12]. Among control techniques, PID controllers are widely used for position and trajectory tracking, regulating brushless DC motor speed for smooth motion [11][12][13][14]. However, their accuracy limitations have led to improvements such as Fuzzy-

PID controllers and kinematic model-based PID approaches [12][15].

PID controllers address non-linearity in trajectory tracking and optimize DC motor speed, ensuring responsiveness to changing conditions [14]. While model-based controllers like PID are effective, non-model-based approaches offer robustness and lower computational complexity [14]. Differential-drive mobile robots benefit from maneuverability but introduce positioning errors due to mechanical inconsistencies, mitigated by odometry-based navigation methods and systematic calibration [12][13][16].

PID controllers play a key role in precise path-following, with advanced tuning techniques like the Firefly algorithm enhancing fuzzy (PI+PD) controller performance [12]. Additionally, they contribute to the stability of brushless DC motor operation, ensuring smooth motion in mobile robots [13].

b. Advanced Commands

Adaptive Sliding Mode Control

Sliding Mode Control (SMC) helps mobile robots follow a planned path accurately, even with uncertainties or disturbances. It can be combined with adaptive control to estimate unknown parameters like tire wear or sensor errors, ensuring stable performance [17][15][18][19].

To improve efficiency, SMC can use event-triggering techniques to reduce the microcontroller's workload, making it useful for remote or networked control [17][15]. It is also effective for position control and handling nonlinear systems like mobile robots [18][19][15].

SMC works for various robots, including differential drive robots and UAVs [17][15][18]. A specialized version, ARSMC, enhances UAV stability in smart cities by compensating for disturbances [15]. Chattering, a common issue, can be reduced using techniques like the tanh function [19]. Additionally, SMC supports dynamic tracking and has an adaptive version (ASMC) for wheeled mobile robots [19][18].

Reinforcement Learning Controller

A deep learning controller enables a robot to perform tasks without requiring a dynamic system

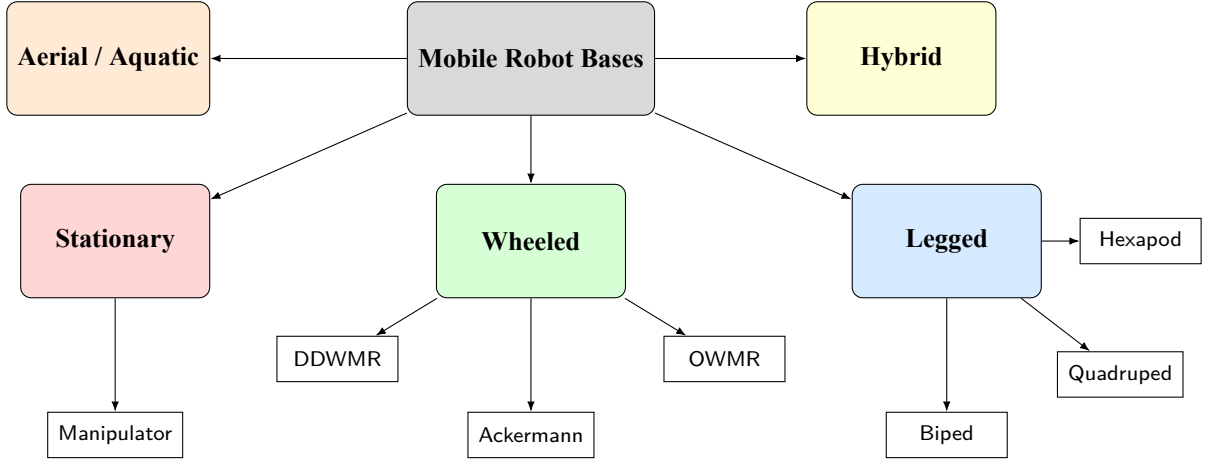


Figure 3: Classification of Mobile Robot Bases

model by learning an optimal control law through interactions with the environment. Unlike traditional methods, it adapts automatically using a recursive learning process and is often trained in simulation. Reinforcement learning (RL) further enhances control by optimizing performance without relying on predefined models [20].

Mobile robots navigate while controlling their position using DRL-based systems, which rely on state space, action space, and a reward function [20][21]. These systems use reactive methods for tasks like obstacle avoidance and determine optimal policies through environmental interactions [22][21]. DRL navigation includes discrete motion actions, continuous velocity commands, and motor speed controls. Rewards, though sparse, are crucial for training RL agents to achieve effective navigation [21].

Model-based Predictive Control(MPC)

The predictive method, particularly Model Predictive Control (MPC), is a key technique for motion control in mobile robots[23][24]. It involves three main steps: model prediction, where a predictive model estimates the robot's future states by combining its current state with feasible control inputs[24] continuous optimization, which minimizes a cost function based on the error between the system output and the predicted output, adjusting control strategies at each interval[23][24] and feedback correction, which enhances robustness by reducing errors and delays[23]. MPC enables point stabilization, trajectory tracking, and real-time obstacle

avoidance, while incorporating system constraints for improved adaptability[23][24]. By integrating MPC with machine learning (ML) methods, it becomes possible to handle uncertain disturbances, enhancing performance in dynamic environments[24].

3.2 Motion Planning and Navigation

a.Planning Algorithms

Path finding methods: A* and Dijkstra.

The Dijkstra and A* path planning algorithms are key methods to find the shortest path in a graph, with diverse applications in navigation and routing [25][26]. Dijkstra uses a greedy approach to explore nodes in priority order, making it effective for small-scale maps [25][26], while A* incorporates a heuristic $h(x)$ to prioritize the most promising nodes, making it faster for large-scale maps [26]. Both are used in road networks, route planning, and locating points of interest, but A* is preferred for its increased efficiency in complex environments [26].

Rapidly-exploring Random Trees (RRT)

RRT is a probabilistic algorithm designed for efficient path planning in complex and high-dimensional spaces [27]. It incrementally builds a tree by randomly sampling the configuration space and connecting feasible nodes while avoiding obstacles [28]. Although RRT is not optimal, it is valued for its simplicity and speed, especially in environments where deterministic

methods are computationally costly [27]. Variants such as Bidirectional RRT and RRT* enhance performance by improving path quality and convergence toward optimality [27]. RRT is widely used in robotics for motion planning in dynamic and unstructured environments, though it faces limitations with path smoothness, narrow passage navigation, and dependency on sampling strategies [28][29].

Comparison

Table 1: Comparison of Motion Planning Algorithms

Feature	Dijkstra	A*	RRT
Type	Deterministic	Heuristic-based	Probabilistic
Completeness	Yes	Yes	Probabilistic
Optimality	Yes	Yes	No
Computation	High	Moderate	Low
Scalability	Poor (large maps)	Good	High dimensional
Suitability	Static maps	Static maps	Dynamic
Path Smoothness	High	High	Low

b. Localization and Mapping Techniques

Simultaneous Localization and Mapping (SLAM)

SLAM (Simultaneous Localization and Mapping) enables robots to map unknown environments while localizing themselves without relying on GNSS (Global Navigation Satellite System) [30][31]. It consists of a front-end, responsible for feature detection and sensor tracking, as in visual SLAM [30][31], and a back-end, which estimates the robot's position using filtering (e.g., Kalman and particle filters) or smoothing techniques (e.g., Graph SLAM) [30]. Filtering is suited for real-time applications, while smoothing optimizes the entire trajectory [30][31].

SLAM is widely used in autonomous navigation, augmented/virtual reality, and mobile mapping [30], ensuring accurate localization in environments denied GNSS such as indoor spaces and

urban canyons [30][31]. The methods vary based on the sensors, with visual SLAM using cameras and LiDAR SLAM relying on 2D/3D point clouds [30].

Challenges: include linearization errors, dynamic obstacles, sensor noise, and high computational demands, especially in environments with narrow passages [30][31].

GPS vs GNSS: GPS (Global Positioning System) is the American satellite navigation system, while GNSS (Global Navigation Satellite Systems) refers to all global systems, including GPS, Galileo (EU), GLONASS (Russia), and BeiDou (China).

Front-end: Responsible for detecting features and tracking sensor data in real-time.

Back-end: Handles global pose optimization and trajectory estimation using methods like graph optimization or Kalman filters.

c. Perception Systems

Perception is a fundamental component that enables a robot to operate autonomously by using sensors and algorithms to extract and interpret data from its environment. It comprises three main elements: sensor data processing, environmental modeling, and artificial intelligence algorithms. These elements allow the robot to detect humans, obstacles, terrain recognize gestures, voice commands, environmental changes and classify locations semantically. Sensors, which detect physical changes and convert them into electrical signals, are categorized as proprioceptive measuring internal parameters such as battery voltage or motor speed or exteroceptive measuring external environmental features. They are also classified as active (emitting energy, e.g., LiDAR) or passive (detecting natural energy, e.g., cameras). The selection of sensors depends on the robot's application, operating environment (indoor or outdoor), and specific tasks. Examples include biopotential sensors, motion encoders, force and pressure sensors, and ultrasonic distance sensors. Overall, perception equips robots with the ability to sense, interpret, and respond to their surroundings, enabling intelligent and effective interaction with the environment [32].

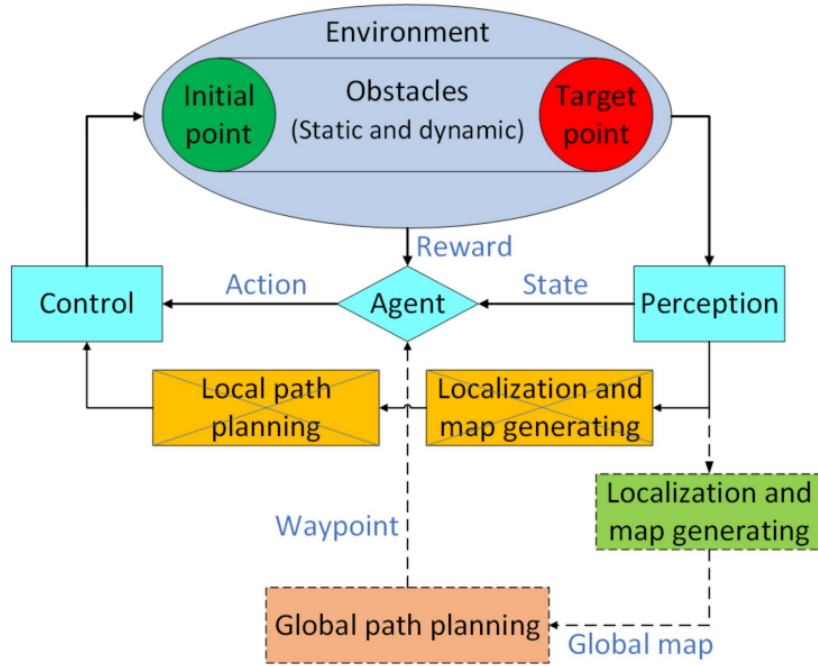


Figure 4: DRL-based navigation system inspired by [33].

4 Mobile Base Applications

4.1 Industrial and Logistics

Handling Robots

Mobile robots are used in manufacturing industries to automate tasks and improve efficiency. They can transport materials, tools, and parts within factories, reducing labor costs and increasing production[34]. Stationary handling robots, such as robotic arms and industrial robots, are used for object manipulation, welding, painting, and assembly[3].

Automated Warehouses

Mobile robots are employed in warehouses to automate the movement of goods. They assist in order fulfillment, packaging, and shipping, enhancing speed and accuracy in order processing[34].

Example: Amazon’s Kiva robots automate shelf transport in warehouses.

4.2 Scientific Exploration

Planetary Exploration

Mobile robots, such as rovers, are utilized for exploring planets and other celestial bodies. They

collect data on surface conditions, atmosphere, and geology, contributing to our understanding of the solar system.

Example: NASA’s Curiosity rover explored the Martian surface.

Oceanographic

Mobile robots explore oceans and underwater environments. They gather data on water temperature, salinity, and marine life, advancing our knowledge of ocean ecosystems[34]. The humanoid underwater robot Ocean-one can retrieve objects with human-like dexterity[3].

4.3 Health and Assistance

Assistance Robots

Mobile robots provide support for elderly or disabled individuals[34]. They assist with tasks such as mobility, shopping, and medication management, improving their quality of life[34][3].

Robotic Surgery

Mobile robots aid surgeons in performing medical procedures. They offer greater precision and dexterity than human hands, thereby reducing the risk of complications[34].

Example: The Pepper robot assists elderly people in Japan with daily tasks.

4.4 Security and Defense

Surveillance and Reconnaissance

Mobile robots are deployed for monitoring and reconnaissance in various environments. Equipped with cameras, sensors, and other technologies, they collect and transmit environmental data to human operators[3][34].

Operations in Hazardous Areas

Mobile robots are used in high-risk environments such as fire scenes, hazardous material sites, and disaster-stricken areas[3]. They assist in tasks like locating survivors, extinguishing fires, and containing dangerous substances[34]. The Atlas robot is specifically designed for search and rescue missions in conditions where human survival is impossible[3]. **Example:** The PackBot robot is used by military forces for bomb disposal.

5 Conclusion

Mobile bases have significantly advanced autonomous robotics by improving mobility, adaptability, and functionality across various environments. This work presented a structured overview of mobile base types: wheeled, legged, hybrid, aerial, and aquatic. Highlighting their operational principles and suitable applications.

Wheeled robots remain efficient for structured terrains, while legged and hybrid systems offer greater adaptability to rough environments. Aerial and aquatic platforms extend robot deployment into inaccessible domains. Advances in control from PID to ASMC, MPC, and DRL enable more robust and adaptive behavior under uncertainty. Complementary navigation algorithms (e.g., A*, RRT) and perception systems (e.g., SLAM, LiDAR, vision) enhance autonomy and environmental awareness.

These technologies have enabled applications in logistics, exploration, healthcare, and hazardous environments. Looking ahead, future research will likely focus on energy efficiency, swarm coordination, human-robot inter-

action, and bio-inspired designs to further expand the capabilities of autonomous robotic platforms.

References

- [1] A. Stefek, T. Van Pham, V. Krivanek, and K. L. Pham, "Energy comparison of controllers used for a differential drive wheeled mobile robot," *IEEE Access*, vol. 8, pp. 170915–170927, 2020.
- [2] M. F. Silva and J. Tenreiro Machado, "A historical perspective of legged robots," *Journal of Vibration and Control*, vol. 13, no. 9-10, pp. 1447–1486, 2007.
- [3] F. Rubio, F. Valero, and C. Llopis-Albert, "A review of mobile robots: Concepts, methods, theoretical framework, and applications," *International Journal of Advanced Robotic Systems*, vol. 16, no. 2, 2019.
- [4] M. B. Alatise and G. P. Hancke, "A review on challenges of autonomous mobile robot and sensor fusion methods," *IEEE Access*, vol. 8, pp. 39830–39846, 2020.
- [5] X.-B. Jin, T.-L. Su, J.-L. Kong, Y.-T. Bai, B.-B. Miao, and C. Dou, "State-of-the-art mobile intelligence: Enabling robots to move like humans by estimating mobility with artificial intelligence," *Applied Sciences*, vol. 8, no. 3, p. 379, 2018.
- [6] L. P. Ramalepa and R. S. Jamisola Jr, "A review on cooperative robotic arms with mobile or drones bases," *International Journal of Automation and Computing*, vol. 18, no. 4, pp. 536–555, 2021.
- [7] K. Kanjanawanishkul, "Omnidirectional wheeled mobile robots: wheel types and practical applications," *International Journal of Advanced Mechatronic Systems*, vol. 6, no. 6, pp. 289–302, 2015.
- [8] E. Garcia, M. A. Jimenez, P. G. De Santos, and M. Armada, "The evolution of robotics research," *IEEE Robotics & Automation Magazine*, vol. 14, no. 1, pp. 90–103, 2007.

- [9] A. Brunete, A. Ranganath, S. Segovia, J. P. De Frutos, M. Hernando, and E. Gambao, "Current trends in reconfigurable modular robots design," *International Journal of Advanced Robotic Systems*, vol. 14, no. 3, 2017.
- [10] O. Hachour, "Path planning of autonomous mobile robot," *International journal of systems applications, engineering & development*, vol. 2, no. 4, pp. 178–190, 2008.
- [11] M. J. Mohamed and M. Abbas, "Design a fuzzy pid controller for trajectory tracking of mobile robot," *Engineering and Technology Journal*, vol. 36, no. 1A, pp. 100–110, 2018.
- [12] A. Barsan, "Position control of a mobile robot through pid controller," *Acta Universitatis Cibiniensis. Technical Series*, vol. 71, no. 1, pp. 14–20, 2019.
- [13] I. Carlucho, M. De Paula, S. A. Villar, and G. G. Acosta, "Incremental q-learning strategy for adaptive pid control of mobile robots," *Expert Systems with Applications*, vol. 80, pp. 183–199, 2017.
- [14] A. K. Khalaji, "Pid-based target tracking control of a tractor-trailer mobile robot," *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, vol. 233, no. 13, pp. 4776–4787, 2019.
- [15] N. Abbas, Z. Abbas, and X. Liu, "Adaptive recursive sliding mode control (arsmc)-based uav control for future smart cities," *Applied Sciences*, vol. 13, no. 11, p. 6790, 2023.
- [16] K. Lee, D.-Y. Im, B. Kwak, Y.-J. Ryoo, *et al.*, "Design of fuzzy-pid controller for path tracking of mobile robot with differential drive," *International Journal of Fuzzy Logic and Intelligent Systems*, vol. 18, no. 3, pp. 220–228, 2018.
- [17] T. D. Tran, T. T. Nguyen, V. T. Duong, H. H. Nguyen, and T. T. Nguyen, "Parameter-adaptive event-triggered sliding mode control for a mobile robot," *Robotics*, vol. 11, no. 4, p. 78, 2022.
- [18] B. B. Mevo, M. R. Saad, and R. Fareh, "Adaptive sliding mode control of wheeled mobile robot with nonlinear model and uncertainties," in *2018 IEEE Canadian Conference on Electrical & Computer Engineering (CCECE)*, pp. 1–5, IEEE, 2018.
- [19] O. A. Choudhry, M. Wasim, A. Ali, M. A. Choudhry, and J. Iqbal, "Modelling and robust controller design for an underactuated self-balancing robot with uncertain parameter estimation," *Plos One*, vol. 18, no. 8, 2023.
- [20] G. Farias, G. Garcia, G. Montenegro, E. Fabregas, S. Dormido-Canto, and S. Dormido, "Reinforcement learning for position control problem of a mobile robot," *IEEE Access*, vol. 8, pp. 152941–152951, 2020.
- [21] K. Zhu and T. Zhang, "Deep reinforcement learning based mobile robot navigation: A review," *Tsinghua Science and Technology*, vol. 26, no. 5, pp. 674–691, 2021.
- [22] N. H. Yung and C. Ye, "An intelligent mobile vehicle navigator based on fuzzy logic and reinforcement learning," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 29, no. 2, pp. 314–321, 1999.
- [23] C. Wang, X. Liu, X. Yang, F. Hu, A. Jiang, and C. Yang, "Trajectory tracking of an omni-directional wheeled mobile robot using a model predictive control strategy," *Applied Sciences*, vol. 8, no. 2, p. 231, 2018.
- [24] K. Zhang, J. Wang, X. Xin, X. Li, C. Sun, J. Huang, and W. Kong, "A survey on learning-based model predictive control: Toward path tracking control of mobile platforms," *Applied Sciences*, vol. 12, no. 4, p. 1995, 2022.
- [25] D. Rachmawati and L. Gustin, "Analysis of dijkstra's algorithm and a* algorithm in shortest path problem," in *Journal of Physics: Conference Series*, vol. 1566, p. 012061, IOP Publishing, 2020.

- [26] A. E. Mirino *et al.*, “Best routes selection using dijkstra and floyd-warshall algorithm,” in *2017 11th International Conference on Information & Communication Technology and System (ICTS)*, pp. 155–158, IEEE, 2017.
- [27] D. Connell and H. Manh La, “Extended rapidly exploring random tree-based dynamic path planning and replanning for mobile robots,” *International Journal of Advanced Robotic Systems*, vol. 15, no. 3, 2018.
- [28] L. Wang, X. Yang, Z. Chen, and B. Wang, “Application of the improved rapidly exploring random tree algorithm to an insect-like mobile robot in a narrow environment,” *Biomimetics*, vol. 8, no. 4, p. 374, 2023.
- [29] Y. Sun, C. Zhang, and C. Liu, “Collision-free and dynamically feasible trajectory planning for omnidirectional mobile robots using a novel b-spline based rapidly exploring random tree,” *International Journal of Advanced Robotic Systems*, vol. 18, no. 3, 2021.
- [30] B. Alsadik and S. Karam, “The simultaneous localization and mapping (slam): An overview,” *Surveying and geospatial engineering journal*, vol. 1, no. 2, pp. 1–12, 2021.
- [31] S. Zheng, J. Wang, C. Rizos, W. Ding, and A. El-Mowafy, “Simultaneous localization and mapping (slam) for autonomous driving: Concept and analysis,” *Remote Sensing*, vol. 15, no. 4, p. 1156, 2023.
- [32] M. A. Niloy, A. Shama, R. K. Chakraborty, M. J. Ryan, F. R. Badal, Z. Tasneem, M. H. Ahamed, S. I. Moyeen, S. K. Das, M. F. Ali, *et al.*, “Critical design and control issues of indoor autonomous mobile robots: A review,” *IEEE Access*, vol. 9, 2021.
- [33] R. Raj and A. Kos, “Intelligent mobile robot navigation in unknown and complex environment using reinforcement learning technique,” *Scientific Reports*, vol. 14, no. 1, p. 22852, 2024.
- [34] R. Raj and A. Kos, “A comprehensive study of mobile robot: History, developments, applications, and future research perspectives,” *Applied Sciences*, vol. 12, no. 14, p. 6951, 2022.