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A Bibliographic and Qualitative Analysis on Navigation Concepts of Mobile Robots

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ABSTRACT: With the advent of robots in human life, such as self-driving cars and unnamed aerial vehicles, developing effective methods to improve the performance of these autonomous systems has become one of the most attractive research areas in recent years. One of the most fundamental challenges of mobile robots is applying and developing an appropriate and effective navigation strategy. The concept of navigation deals with subjects such as finding the current position in the environment, planning appropriate actions to reach the target, and controlling the actuators to track the desired actions. Therefore, the concept of navigation has different aspects, and the promotion of these aspects leads to the development of good guidance for autonomous robot systems. The first step in developing the navigation unit is identifying the related and correlated areas. This article performs a bibliographic analysis on the development rate, finding sources, and high-occurrence keywords. The required data are obtained from the Scopus database between 2015 and 2025. The most frequent keywords in the last eight years specify the most effective and relevant areas in the concept of navigation. Then, by qualitatively examining the most important keywords, the current position, challenges, and progress are determined.

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1- Introduction

In recent years, the field of robotics has achieved remarkable progress due to its wide range of capabilities and applications. Robots are now extensively employed in factories, laboratories, warehouses, and many other environments, where they can either collaborate with humans or operate autonomously. Many of these systems are able to make decisions and perform tasks without human intervention. Owing to their diverse applications in both industrial and non-industrial domains, robots have consistently been a central focus of research and development.

Among the various types of robots, wheeled mobile robots (WMRs) represent one of the most widely used categories. Their structural simplicity, adaptability, and efficiency make them suitable for diverse environments and operating conditions.

WMRs have been applied in numerous fields, including surveillance, planetary exploration, patrolling, emergency rescue, reconnaissance, petrochemical industries, industrial automation, construction, entertainment, museum guidance, personal assistance, extreme environment interventions, transportation, and medical care, among others. According to previous studies, navigation is a fundamental element in the design and functionality of mobile robots [1]. The navigation process typically consists of three main components.

The first is localization, which identifies the robot's position and orientation using sensors and cameras. In more complex environments, particularly dynamic or unknown ones, localization also involves generating maps of the surroundings. The second component is path planning, where a collision-free trajectory is determined based on the robot's current position, target location, and the presence of obstacles [2].

The third component is motion control, which ensures that the robot can effectively follow the planned path [3]. Therefore, the navigation unit integrates essential subsystems such as localization [1], [4], sensor fusion and vision systems [5], [6], path planning [2], [7], and motion tracking control [3], [8]. Localization addresses the fundamental question, "Where am I?", while sensor fusion techniques are used to reduce accumulated errors caused by internal sensors [9].

The choice of path-planning method strongly depends on the type of environment. Although path planning in static environments is generally straightforward, achieving reliable and collision-free navigation in dynamic and unknown environments remains a major challenge in recent years [10], [11]. The efficiency of any navigation strategy is directly influenced by the accuracy of environmental information [12]. At the motion control level, kinematic and dynamic constraints of mobile robots must be considered.

These constraints are typically classified into holonomic and non-holonomic categories. Kinematic analysis focuses on the robot's position and orientation, whereas dynamic analysis also considers forces and torques, providing a more realistic framework for practical implementation. Selecting

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an appropriate control approach thus depends on how the robot's system is modeled and interpreted. This review aims to highlight critical aspects of navigation in wheeled mobile robots, focusing on key concepts, algorithms, and technical considerations. In particular, the study seeks to identify the strengths and limitations of existing approaches.

A bibliometric analysis is also conducted to examine publication trends, citation patterns, and keyword evolution in this field. Such an approach helps uncover the most influential research directions, identify emerging hotspots, and reveal promising areas for future investigation.

Accordingly, the remainder of this article is structured as follows. Section II presents a bibliometric review to trace the progression and orientation of published works on mobile robot navigation. Section III provides a qualitative analysis of the most frequently used keywords, highlighting fundamental issues and research priorities in this domain.

2- Quantitative Analysis

This section presents a bibliometric analysis of mobile robot navigation. The bibliographic data were collected on December 23, 2024, from two major databases: Web of Science (WoS) and Scopus. According to [13], WoS offers a reliable dataset; however, Scopus provides broader coverage and richer document collections for bibliometric studies (FIG. 1). To ensure accuracy and efficiency, the database search was performed using meaningful keyword combinations. Specifically, the query "mobile robot" AND ("navigation" OR "localization") was applied in both WoS and Scopus.

As shown in FIG. 1, Scopus was selected as the reference database for this study, containing 103,634 documents. To focus on recent developments, only works published between 2015 and 2024 were considered, excluding documents before 2015 and those indexed in 2025. Consequently, the final dataset was limited to 54,212 documents. FIG. 1 illustrates the document selection process following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram.

The publication trend is presented in FIG. 2, which demonstrates the continuous growth of studies in the field of navigation. The increasing number of documents reflects the growing research activities, discussions, and demand for further developments. Since 2000, the publication rate

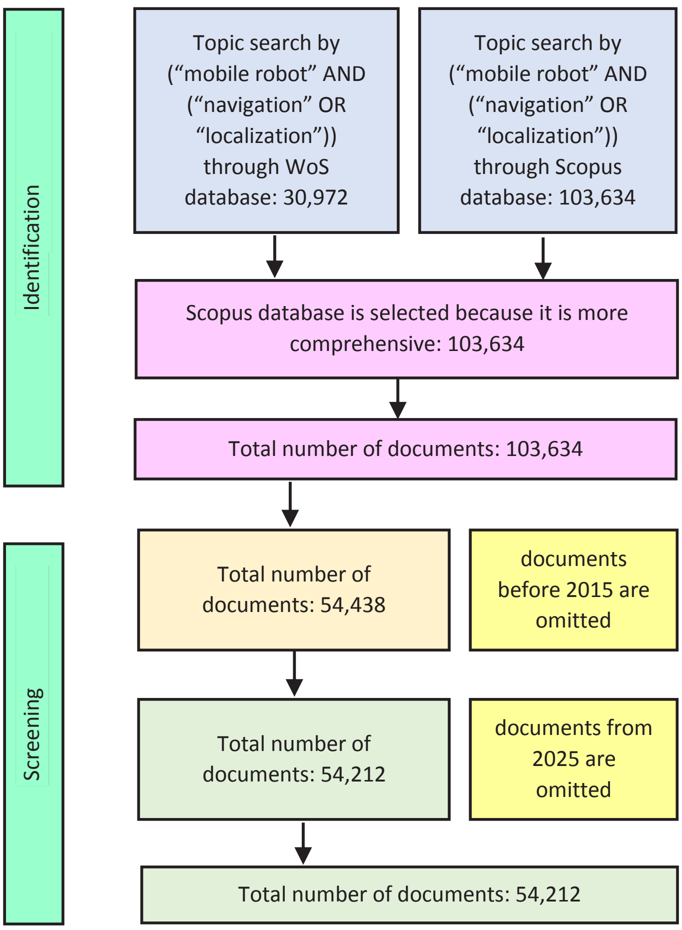

Fig. 1. The PRISMA diagram for the quantitative analysis of the navigation concept for mobile robots.

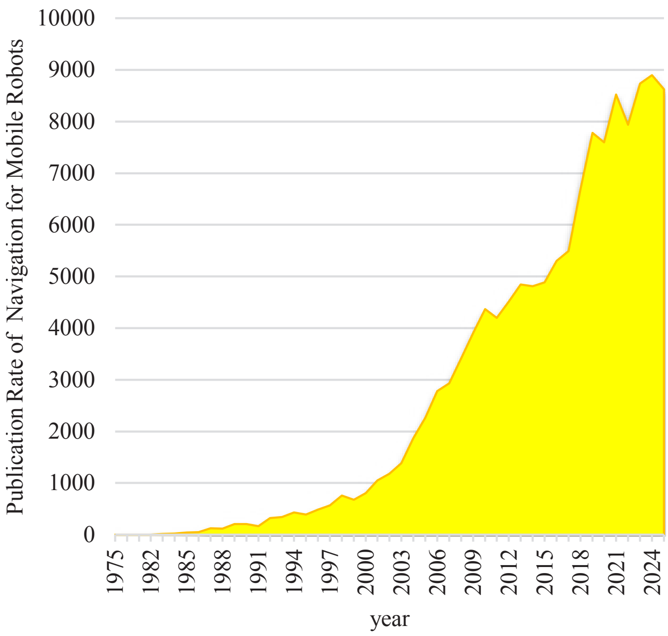

Fig. 2. The annual number of publications on the subject of navigation for mobile robots from 2015 to 2025.

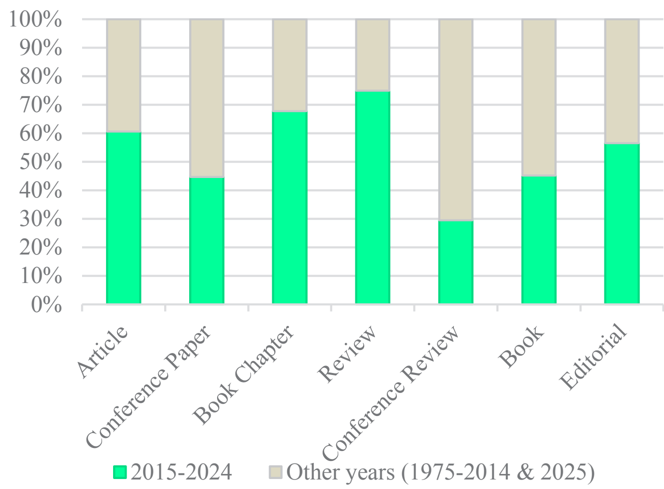

Fig. 3. Type of documents, Blue: From 1975 to 2025, Red: From 2015 to 2024.

has risen significantly, driven by expanding resources and institutional support. An analysis of the most active countries reveals the global distribution of research capacity.

Between 2015 and 2024, the top five contributors were China, the United States, India, Germany, and Japan. In terms of disciplinary contributions, Computer Science, Engineering, Mathematics, Physics and Astronomy, and Materials Science emerged as the leading fields publishing documents related to mobile robot navigation. Identifying these active domains is important for fostering interdisciplinary collaboration, which can help address limitations and enhance the quality of research outcomes.

Finally, the types of published documents are summarized in Fig. 3, providing insight into the distribution of articles, conference papers, reviews, and other document categories.

Keyword analysis provides valuable insights into research interests, emerging challenges, and potential application areas in the field. Table 1 presents the most frequently used keywords identified in this study.

The analysis reveals that navigation is closely associated

Table 1. Occurrence of top keywords for mobile robots' navigation from 2015 to 2024.

#	Keyword	Occurrence	#	Keyword	Occurrence
1	Robots	10,367	11	Cameras	2,612
2	Mobile Robots	9,217	12	Agricultural Robots	2,607
3	Robotics	8,913	13	Mapping	2,559
4	Navigation	6,927	14	Computer Vision	2,496
5	Motion Planning	5,654	15	Deep Learning	2,483
6	Robot Programming	4,958	16	Collision Avoidance	2,458
7	Intelligent Robots	2,941	17	Antennas	2,453
8	Controllers	2,848	18	Reinforcement Learning	2,018
9	Path Planning	2,708	19	Vehicles	2,010
10	Indoor Positioning Systems	2,615	20	Optimization	1,799

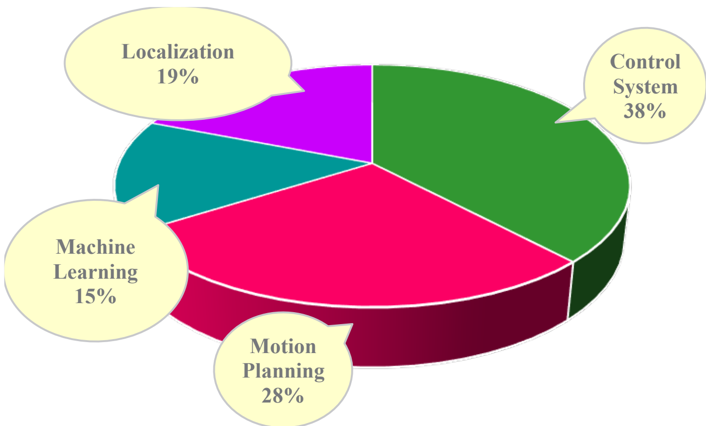

Fig. 4. The share of the top 4 keywords in the concept of mobile robot navigation.

with several related concepts, including robot types, path planning, machine learning, and motion tracking control. This indicates that the development of effective navigation methods requires comprehensive knowledge and integration of these interconnected domains.

Overall, the keyword analysis underscores the interdisciplinary nature of mobile robot navigation and highlights the importance of combining techniques from multiple research fields to address current challenges and advance future developments. Furthermore, FIG. 4 illustrates the relative contribution of each major research field related to mobile robot navigation, highlighting the interdisciplinary nature of the topic.

Fig. 5 illustrates the percentage growth of documents published in the top 10 sources over the past seven years. The analysis indicates that journals such as IEEE Access, IEEE Robotics and Automation Letters, and Robotics and Autonomous Systems have shown a steady increase in publications related to mobile robot navigation during the last three years. This trend suggests that these journals are becoming prominent outlets for research in this domain, making them particularly relevant for scholars aiming to disseminate their work on mobile robot navigation.

3- Qualitative Analysis

3- 1- Types of Robots

Robots are developed to enhance human performance, simplify complex tasks, and reduce operational risks. Their design and structure are determined by their intended purpose and mission. In this article, robots are categorized as illustrated

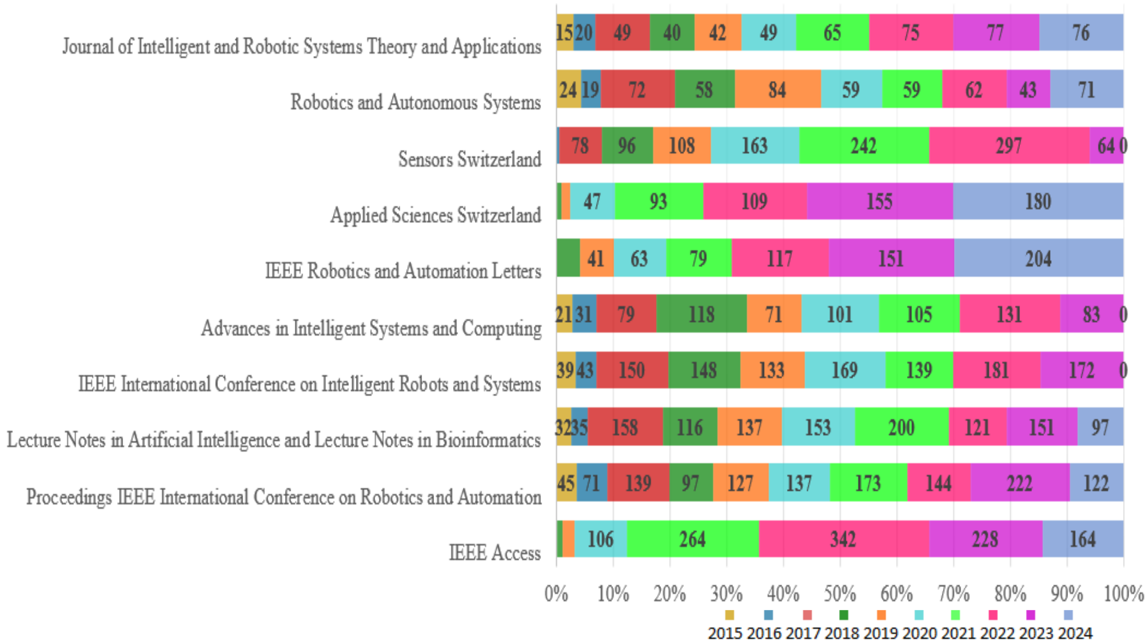

Fig. 5. Published documents in the top 10 sources between 2015 and 2025.

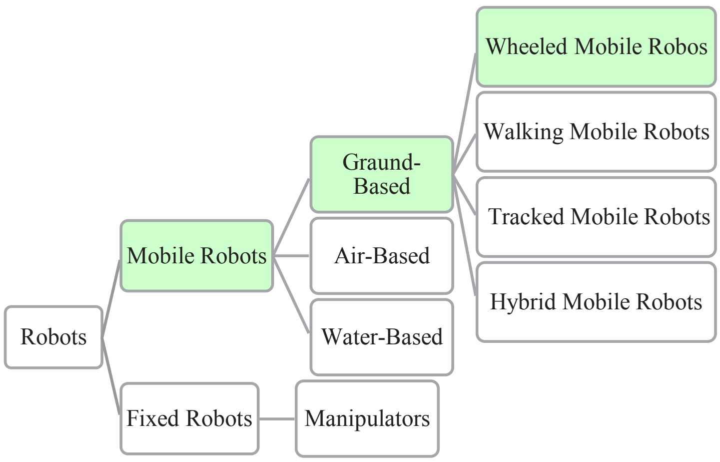

Fig. 6. Types of robot structures.

in Fig. 6.

Ground robots are the most widely employed type. They include domestic, security, environmental exploration (e.g., disaster response and wildlife monitoring), industrial, and medical robots. Industrial and medical robots are generally classified as fixed manipulators, while mobile ground robots are designed for more dynamic and versatile tasks. Among them, wheeled mobile robots (WMRs) are one of the most influential categories, offering diverse designs, tasks, and sizes depending on application requirements. The most notable types include differential-drive robots, autonomous vehicles, omnidirectional WMRs, and synchro-drive robots. The number and type of wheels significantly affect a robot's kinematic and dynamic properties, as well as its maneuverability. Typically, four types of wheels are employed: fixed standard wheels, castor wheels, Swedish wheels, and spherical wheels.

According to [14], [15], three wheels are sufficient to ensure stability, although two-wheeled configurations are also feasible. Two- and three-wheeled robots offer advantages such as simpler design, lower complexity, ease of control, and guaranteed stability [16]. Tracked mobile robots are primarily employed for exploration tasks due to their robust wheel structure. Legged robots, on the other hand, provide better energy efficiency, stability, and mobility compared with wheeled robots [17]. However, they are generally more expensive and complex, with kinematic and dynamic stability being their primary challenge. These robots can be designed with one or multiple legs. Hybrid robots are developed for specific purposes, such as mobile manipulators equipped with arms [18] or water-based robots with multiple legs [19]. Water-based and aerial robots also constitute common categories of robots. Another important distinction lies between unmanned robots and autonomous robots. Unmanned robots are typically remotely controlled by human operators, while autonomous robots operate without direct human intervention [20].

In this study, the focus is on wheeled mobile robots. Accordingly, the following sections address key issues related to their design and operation.

3- 1- 1- Sensors for Wheeled Mobile Robots

Wheeled mobile robots require sensors tailored to their operational environment and task complexity. One of their major challenges is achieving autonomy, which is partially addressed through the integration of diverse sensors. Generally, WMRs rely on sensors for three primary purposes: localization, environmental perception, and motion control. Sensors and cameras are used to gather different types of information, and their interpretation varies depending on the application. For navigation, robots typically employ both internal sensors (e.g., position sensors, encoders, accelerometers) and external sensors (e.g., sonars, laser sensors, ultrasonic sensors, and proximity sensors) [21], [22]. These systems enhance accuracy, reduce accumulated errors, and enrich the data required for reliable navigation [23].

3- 1- 2- Visual Sensors

Visual systems play a central role in mobile robot navigation. Commonly used devices include RGB cameras [25], event-based cameras [26], thermal cameras [27], 3D cameras [28], and stereo cameras [29], [30]. RGB cameras provide color information, enabling detailed scene analysis and improving system reliability.

Event-based cameras measure pixel brightness changes asynchronously, encoding time, location, and intensity. They offer high temporal resolution, wide dynamic range, low energy consumption, high bandwidth, and reduced motion blur [31].

Thermal cameras operate in the infrared spectrum, allowing object detection in low-light conditions (e.g., nighttime), though they generally offer lower resolution than RGB cameras [32]. Stereo cameras employ multiple lenses to reduce occlusion and enable accurate depth measurement, thereby improving scene interpretation [33]. 3D cameras capture volumetric information, enabling three-dimensional environmental perception [34]. Visual sensors provide rich information, color perception, and relatively low cost. However, their performance deteriorates in adverse weather conditions (e.g., rain or fog), and they require advanced image-processing software.

3- 1- 3- Laser-Based and Active Sensors

Laser-based sensors, available in both 2D and 3D formats, provide high accuracy and fast processing, with 3D systems offering richer environmental data. Their main drawback is their relatively high cost [35].

Active sensors, such as ultrasonic systems and cameras with integrated illumination, are widely used in autonomous WMRs for obstacle detection and mapping. While they provide reliable information for collision avoidance, they are highly sensitive to lighting conditions, which reduces their effectiveness in extreme environments.

3- 1- 4- Sensor Fusion

To overcome the limitations of individual sensors, sensor fusion is widely applied in mobile robot navigation. Fusion techniques integrate data from multiple sensors to reduce uncertainty, increase accuracy, and improve overall system reliability. Additional benefits include extended spatial and temporal coverage, enhanced resolution, and reduced system complexity [5].

The most powerful fusion methods include maximum likelihood estimation, Kalman filtering, and particle filtering [35], each of which offers distinct strengths depending on the application context.

3- 2- Concept and Approaches of Localization

The first step in operating wheeled mobile robots in known or unknown environments is finding the current location. The problem of localization can be divided into three parts: 1) position tracking, which has the most studies (55%), 2) global positioning/localization is in the second place (26%), and 3) kidnapped robots (19%) [36]. Wheeled mobile robots employ internal sensors to track their movements in the environment. Due to measurement and accumulation errors, it is necessary to use information from external sensors to determine their position relative to the map. According to [37], the most effective positioning methods are odometry, although it is the most straightforward way. However, the problem is positional drift due to slipping wheels [38]. Inertial navigation does not depend on the environmental conditions or view of the environment; however, its exact implementation is costly [39].

Magnetic compasses are resistant to environmental and Earth's magnetic field effects. Nevertheless, they are usually deflected by the Earth's magnetic field near power lines or steel structures [40]. Active beacons and global positioning systems are always available, but their accuracy is low, and the efficiency decreases in closed environments [41]. Landmark navigations are usually easily recognizable, but most of them are in fixed and specified positions. In the next step, the localization algorithm must specify the robot's position on the map. The accuracy of the map is entirely related to the task and the accuracy required for the wheeled mobile robot. In some applications, the map needs to be updated, or even a map of the environment must be created. Therefore, localization methods can be divided into two categories based on a predetermined map: 1) probabilistic approaches and 2) autonomous map building. There are three common perspectives for implementing probability-based localization [37]:

- ***Markov localization:*** The current position is estimated based on the robot's previous positions and odometer (prediction phase). Then, by combining information from the external sensors with the estimated current position, which is obtained by the internal sensors, the robot's current position is modified (perception phase). The capabilities of this approach can be appropriate to solve three problems 1) localization, 2) the ability to run from an unknown position, and 3) the ability to track multiple points by the robot. This method needs to describe the space discretely to update the probability of possible situations. Nevertheless, limited memory is required due to the description of discrete space [42], [43]. Moreover, this technique can use any probability distribution function to display the robot's position [44].
- ***Kalman Filter (KF) localization:*** This technique only uses the Gaussian probability distribution function to estimate the position [37]. In the prediction phase, an estimate of the motion model is obtained along with the measurement uncertainty of the internal sensors (Gaussian error). Then, in the perception phase, the assessments are updated based on the weighted average, leading to an increase in the estimate's accuracy. This approach is based on a sensor fusion approach that can effectively solve the problem of position tracking [36]. The limitation of this method is that the initial position of the tracking needs to be known. This method can also be implemented in the continuous world [45]. The KF is developed for linear systems. However, many systems are nonlinear. Hence, the Extended Kalman filter (EKF) was introduced to overcome the problem of nonlinearity. In the EKF, the system is linearized around the operating point. Comparing the KF and the EKF [49] shows that the EKF is more efficient than the KF in estimating the robot's position. In this trend, the Unscented Kalman Filter (UKF) was developed, which uses an unscented transform for linearization. To update the perspective on multi-sensor fusion and sensor comparisons in mobile-robot localization, a recent comprehensive review is also available [181]. A review study provides a comparison based on the practical data between the EKF and UKF, which shows that the EKF works as well as the UKF for the localization aim of the mobile robot [50].
- ***Monte Carlo Localization (MCL):*** This approach is also known as Particle Filter (PF) localization [46], which selects a set of possible positions from the total set of possible positions to construct the robot belief. This method reduces the number of updates and thus the reduction in complexity. A specific PF is introduced by combining the Markov chain Monte Carlo sampling technique and the Differential Evolution method to minimize a fitness function online. It can apply effective localization in conditions such as dynamic and unmodeled obstacles [47]. Reference [48] introduces a new Markov Vision-based localization approach for challenges in visual conditions and complex roadways.

For more information on probabilistic approaches, recent studies, challenges, and developments, the reader may refer to [51]. Due to the dynamics of the environment in many applications, the idea of autonomous map building has received much attention. The wheeled mobile robot localizes itself in three stages: "starting exploration from a random location", "identifying the environment through sensors", and "making a map based on information received from the surroundings" [52]. Since the quality and accuracy of the map depend on identifying the environment, the type and manner of fusion of the information received from the sensors are influential.

With the development of visual systems, the possibility of accessing rich data has been provided, and has taken a big step in developing autonomous map-building strategies [53]. A concept called Simultaneous Localization and Mapping (SLAM) has been proposed to create a map automatically by the wheeled mobile robot. Creating a map has advantages such as the possibility of path planning, limiting the estimating error of the position of the robot, and dead-reckoning (limiting the error using a loop closure [54]) [55]. Initially, the SLAM problem was introduced as probabilistic formulations and was developed based on the KFs and PFs [56] and [57]. The first SLAM was formulated based on EKF, which used an extended vector including robot pose and the position of all environment features [36]. The "Robocentric Map Joining algorithm" was introduced to overcome the uncertainty of the vehicle movement and sensor model conditions in the implementation of the EKF-SLAM, which is a concept based on creating a sequence of independent local maps by robot-centered representation in each regional map [58]. On the other hand, the UKF-SLAM approach has advantages such as increasing the accuracy of state estimation, reducing the effects of linearization, and proper estimation of variance and mean linearity as compared with the EKF-SLAM approach. However, its disadvantages include cubic computational complexity in the number of states and inconsistency of the state estimates. The introduction of SLAM based on Observability-Constrained UKF (OC-UKF) reduced calculations' complexity and increased accuracy of the state estimates [59]. Ref. [60] presented a comparison between the EKF and UKF based on the results. These two filters perform relatively well in reconstructing the robot's position because the nonlinearities of the model are not severe enough to highlight the fundamental differences. Fast localization and mapping (FastSLAM) is based on particle filtering and has been considered in many articles. However, two important problems of particle filters are "impoverishment" and "degeneracy".

Evolutionary methods such as Particle Swarm Optimization (PSO) and bat-inspired optimization are used to improve these problems. To overcome the impoverishment problem due to particle depletion in the resampling phase in FastSLAM, an improved PSO-based resampling method was proposed for the pose convergence of the particle set instead of rejection and replication. In fact, utilizing the improved PSO-based resampling method leads to better accuracy than the standard FastSLAM [61]. Currently, the concept of SLAM is significantly improved by computer vision, signal processing, geometry, graph theory, optimization, probabilistic estimation, and system integration, sensor calibration [62]. By introducing a predictive model-based SLAM framework using the control switching mechanism, the concepts of "increasing performance by reducing SLAM uncertainty" and "area coverage work" in obtaining a collision-free path were satisfied. In fact, the graph topology approximates the original problem to a constrained nonlinear least-squares problem, leading to reduced SLAM uncertainty. Moreover, a sequential quadratic programming method addresses the area coverage task [63].

A brain-robot interface (BRI) based on a control system is proposed in [64], where a combination of RGB-D (to gain rich information), optical flow (to track feature points in real-time accurately), and deep learning (for object-detection purposes and to reduce localization error) is performed. It has been presented to achieve navigation and control of a wheeled mobile robot in unknown environments. For comprehensive information on SLAM, especially vision-based SLAM, the reader may refer to [62]. Moreover, [65] reviews wheeled mobile robots' solutions, challenges, and applications in dynamic human-presence environments. A recent trend review on autonomous mobile-robot path planning provides an updated overview of search, sampling-, and curve-based methods [66]. A turning-points-based method for generating smooth paths in known environments with stationary obstacles is proposed in [67]. An open-access version is also available [68].

Using LiDAR allows obtaining 3D images and checking conditions that affect the quality of the received information. Moreover, due to the advancement of LiDAR technology, its cost is decreasing. In addition, [69] compares several vision-based and LiDAR-based SLAM algorithms on the NASA UAS (Unmanned Aircraft System) flight test data. Two types of solid-state LiDAR and mechanical LiDAR have been investigated to locate and map simultaneously. According to [70], the localization accuracy of the solid-state LiDAR was lower than that of the mechanical LiDAR in challenging conditions. In conditions of small changes in the field of view and jerking along a straight path, the localization accuracy of solid-state LiDAR was higher than that of the mechanical LiDAR. For wheel-legged robots, an indoor LiDAR-inertial SLAM integrating the kinematic model has been introduced [71]. Another comprehensive survey specifically covers advances in LiDAR odometry [72]. An additional update introduces adaptive-intensity feature extraction within LiDAR-inertial SLAM to enhance robustness [73]. Another continuous-time LiDAR-inertial SLAM framework targeting real-time navigation has been proposed [74]. For highly dynamic legged-robot scenarios, a robust RGB-D-inertial fusion SLAM has been proposed [75]. A comprehensive comparison of localization and SLAM methods, with their respective strengths, weaknesses, and applications, is presented in Appendix A (Table A1).

3- 3- Machine Learning Applications

Machine learning, as a relatively new and rapidly expanding concept, has permeated many aspects of modern technology and is now considered one of the most significant components of robotic research. Figure 7 illustrates the growth in publications related to the application of machine

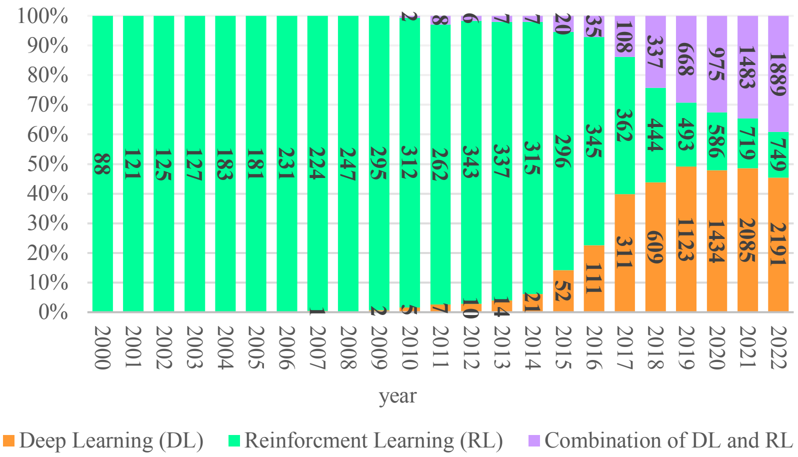

Fig. 7. Annual number and annual contribution of publications in machine learning for wheeled mobile robots' applications.

Table 2. The occurrence of top keywords of machine learning related to wheeled mobile robots

#	Keyword	Occurrence	#	Keyword	Occurrence
1	Deep Learning	3,394	11	Decision Making	656
2	Reinforcement Learning	2,670	12	Object Detection/ Object Recognition	859/ 599
3	Motion Planning	1,820	13	Deep Reinforcement Learning	447
4	Navigation	1,602	14	Image Segmentation	445
5	Computer Vision	1,095	15	Classification	394
6	Deep neural Network	995	16	Feature Extraction	371
7	Path Planning	899	17	Autonomous Driving	354
8	Convolutional Neural Networks	797	18	Support Vector Machines	294
9	Controllers	769	19	Transfer Learning	220
10	Collision Avoidance	674	20	Model Predictive Control	206

learning in wheeled mobile robots. This notable upward trend reflects the fundamental potential of ML in addressing diverse robotic challenges. The top 20 machine learning keywords in robotics for 2024 are listed in TABLE 2, showing the breadth of its applications. Keyword analysis indicates that deep learning and reinforcement learning are the most widely adopted branches within this domain.

According to the Scopus database, the most common robotic platforms employing ML techniques are agricultural robots, unmanned aerial vehicles (UAVs), and industrial robots. Machine learning is typically classified into supervised, unsupervised, and reinforcement learning. Supervised learning is commonly used for classification and regression tasks, whereas unsupervised learning supports clustering, dimensionality reduction, and uncovering latent data structures. As reported in TABLE 2, the majority of research efforts focus on machine vision, navigation, path planning, and control. FIG. 8 presents the categorization of current ML methods based on learning type.

Machine learning has numerous applications across robotics. In machine vision, supervised classification methods play a central role, enhancing environmental perception and navigation efficiency. For example, transformer models have recently been introduced for vision-based robot navigation [76]. In [77], multivariate adaptive regression splines were applied to address challenges in camera-based robot navigation. Similarly, a vision-integrated regression approach was implemented on humanoid robots to overcome the limitations of earlier regression-based methods [78]. Logistic regression has also been employed to predict collisions from acceleration data [79]. The k-nearest neighbor (KNN) algorithm, known for its robustness to nonlinear data [80], has been combined with deep-stacked autoencoders for object detection from sensor data [81]. In [82], Support Vector Machine (SVM)-based classifiers were applied to optimize feature dimensions, improving environmental recognition. Additionally, SVM classifiers have been integrated with decision trees to estimate human upper-body orientation [83]. Bayesian optimization has been further utilized for path planning, enabling reliable navigation using low-cost camera systems [84].

Neural networks have become indispensable for environmental recognition, decision-making, and control in wheeled mobile robots. For instance, the Multi-Layer Perceptron (MLP) network provides near-optimal collision-free path planning, suitable for real-time navigation tasks [86]. A hierarchical sensor fusion technique utilizing an MLP was proposed to improve robot self-localization [87]. Moreover, comparative studies have assessed the performance of fuzzy logic and back-propagation neural networks in navigation tasks such as wall-following [50].

Recent developments highlight the increasing importance of hybrid methods that combine machine learning with traditional control and optimization approaches. These methods leverage the adaptability of ML while ensuring the stability and interpretability of classical models, making them particularly effective for real-time navigation and safety-critical robotics. Nevertheless, several challenges remain, including dependency on large datasets, high computational cost, and limited generalization to dynamic and unstructured environments. Addressing these challenges will require lightweight learning models, efficient training strategies, and robust multi-sensor integration. Looking ahead, machine learning is expected to play a central role in advancing autonomy, adaptability, and robustness in wheeled mobile robots. This trajectory underscores the importance of interdisciplinary collaboration across robotics, artificial intelligence, computer vision, and control engineering.

The comparative study in [50] shows that the overall performance of wheeled mobile robots remains similar when applying fuzzy logic and back-propagation neural networks. However, the back-propagation approach enables the robot to move at a higher speed than the fuzzy logic system. In [88], a comparison between the A* algorithm and the Hopfield neural network for time-optimized path planning was presented. Results demonstrated that A* offered superior performance in terms of efficiency, although the Hopfield network showed potential for reducing execution time under certain conditions, suggesting room for further improvements.

In multi-robot systems, one of the most critical challenges is establishing effective group coordination strategies. Recent studies have explored deep reinforcement learning (DRL)-based approaches for achieving collaborative behaviors in multi-robot environments [89]. Such methods enable adaptive decision-making in dynamic and uncertain conditions. Similarly, Hopfield networks have been applied to model cooperative strategies in multi-agent robotic systems [90].

For motion tracking and control, adaptive control strategies based on the Radial Basis Function (RBF) network have been introduced to handle model uncertainties [91]. These approaches demonstrate robustness in both kinematic [92], [93] and dynamic [94] scenarios, leading to enhanced localization accuracy [95]. Moreover, the integration of learning-based adaptive controllers is increasingly being used to address challenges in real-time environments with noise and disturbances.

With the rapid advancement of processors and computational capabilities, deep learning methods have gained widespread adoption in wheeled mobile robot applications [96–99]. Deep convolutional neural networks, recurrent neural networks, and hybrid architectures are increasingly utilized for tasks such as end-to-end navigation, environment recognition, and real-time path planning. These techniques not only improve robustness and adaptability but also open new avenues for integrating semantic understanding of the environment into navigation pipelines.

Furthermore, a growing trend in recent literature focuses on combining classical optimization-based methods (e.g., A* and Dijkstra) with deep learning models to balance interpretability, optimality, and adaptability. Such hybrid approaches represent a promising research direction, particularly in safety-critical scenarios where both efficiency and reliability are required.

Among the various branches of deep learning, the most significant architectures include autoencoders, deep belief networks (DBNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) [100]. Autoencoders are particularly suitable for handling unlabeled data in unsupervised learning settings. One of their primary advantages is dimensionality reduction through learning compact representations of input data [101].

Furthermore, autoencoders can accelerate training processes by providing effective parameter initialization for recurrent neural networks [102]. DBNs also operate in an unsupervised manner, offering hierarchical feature learning capabilities [103]. For example, an improved SLAM framework combining RGB-D and LiDAR inputs with parallel noise filtering for 2D navigation has been developed, leveraging such architectures [104].

CNNs and DBNs have been widely applied for obstacle detection and collision avoidance [105]. In [106], two high-resolution depth-color cameras (RGB-D and TOF) were integrated, combining high-resolution visual input with low-resolution depth sensing to construct accurate maps. A Fully Convolutional Network (FCN) was further employed for semantic segmentation. Unlike autoencoders and DBNs, CNNs require extensive offline training using large-scale datasets, but they provide powerful advantages, including robust feature extraction and invariance to rotation and translation.

Applications of CNNs span image and video recognition [105–107], classification [110], semantic segmentation [111], [112], and even recommender systems [113]. Building on these capabilities, the Robot with Artificial Intelligence-based Cognition (RAICO) system integrated CNN-based perception to achieve reliable object recognition with efficient inference speed [114]. RNNs differ in that their neuron connections are directional, enabling the use of internal memory to process sequential data, which is critical for tasks requiring temporal dependencies, such as trajectory prediction. For more details on RNN architectures and their applications, readers are referred to [115].

The third major branch of machine learning, reinforcement learning (RL), has gained significant traction in robotic navigation, particularly for path planning and control strategies [116–119]. A recent review emphasizes the role of deep reinforcement learning (DRL) in enabling multimodal perception integration and real-time decision-making [120]. For instance, DRL-based self-exploration methods that fuse LiDAR and camera data have been demonstrated [121], with subsequent official corrections published to refine prior results [122]. Classical Q-learning has been successfully applied to obtain feasible paths in structured environments [123–125]. However, its performance is limited by the curse of dimensionality in complex state-action spaces, making collision-free navigation challenging. The Dyna Q-learning variant improves path quality by integrating planning with learning, yet the dimensional constraints of the Q-table persist. To address these limitations, model-based RL approaches have been introduced, offering accelerated learning and improved generalization in navigation tasks [126]. To extend RL into continuous state-action spaces, integration with deep

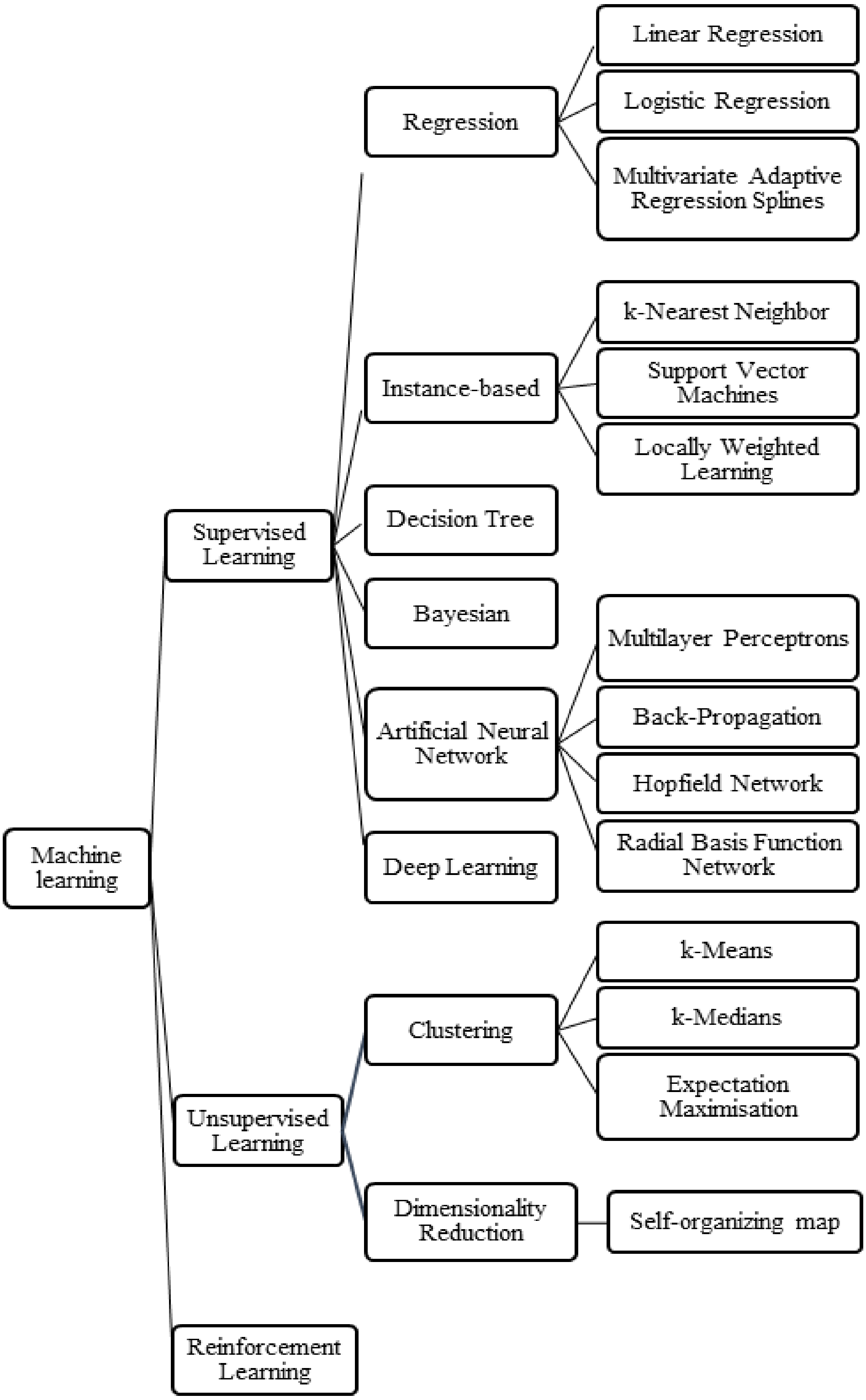

Fig. 8. Well-known methods in machine learning for wheeled mobile robot applications.

learning has been pursued [127–129]. In these hybrid models, deep networks are employed for feature extraction and function approximation, resulting in improved path quality and adaptability [130], [131]. DRL has also been utilized to design advanced controllers capable of handling nonlinear dynamics and uncertainties [132], [133]. Beyond traditional architectures, graph neural networks (GNNs) have recently been applied to model spatial relationships and support navigation in complex topologies [134]. Complementing these advances, explainable AI techniques have been proposed to increase the transparency of decision-making in DRL-based navigation systems [135], addressing concerns of interpretability and trust in autonomous systems.

To provide a more comprehensive perspective, a comparative analysis of the most prominent machine learning approaches applied to wheeled mobile robots is included in Appendix B (Table B1). This extended table summarizes the main applications, strengths, weaknesses, and key references of traditional machine learning, deep learning, reinforcement learning, hybrid approaches, and explainable AI methods. The insights highlight trade-offs between interpretability, adaptability, and computational efficiency, serving as a useful reference for future research directions.

3- 4- Planning Phase

Path planning is a fundamental problem in mobile robotics and refers to determining a sequence of points that guide the robot from its current or initial position to the desired target location. One of the primary requirements of path planning is ensuring collision-free motion, which involves avoiding both static and dynamic obstacles. Depending on the type of environment and the specific task of the wheeled mobile robot, an appropriate path-planning strategy must be selected. Environments are typically categorized based on two criteria:

- Information availability: known versus unknown environments.
- Dynamics: static environments (with fixed objects) versus dynamic environments (with moving agents).

In static and fully known environments, motion planning can be performed offline, where the path is computed before execution. In contrast, when the environment contains unknown regions or dynamic agents, the robot requires online (real-time) planning to continually re-evaluate and generate safe trajectories in response to new information. From a computational perspective, online methods are generally less complex than offline global planners, allowing real-time path generation even with limited onboard processing power. Global path planning thus refers to the offline determination of a complete path before execution, while local path planning focuses on dynamically adjusting the trajectory based on continuously updated sensor data from the robot's surroundings. In the literature, multiple terminologies are used:

- Path planning typically refers to the geometric computation of a feasible path without considering time or dynamics.
- Trajectory planning incorporates kinematic and dynamic constraints of the actuators, ensuring feasible motion along the planned path.
- The integration of path and trajectory planning is generally termed motion planning.
- Motion tracking represents a related concept where the robot (follower) continuously adjusts its trajectory to follow another agent (leader).

Several optimization criteria have been proposed to improve motion planning strategies. Common objectives include minimizing travel time, reducing energy consumption or actuator effort, limiting jerk (for smoother motion), and combining multiple objectives into hybrid criteria [136]. Furthermore, in human-populated environments, crowd-aware path-planning frameworks have been introduced to enhance safety and social compliance, enabling robots to navigate smoothly while avoiding discomfort or risk to pedestrians [137].

So far, various methods have been proposed for the motion planning of wheeled mobile robots. TABLE 3 lists some crucial characteristics of the main motion planning methods. Another up-to-date survey categorizes and compares mobile-robot path-planning methods [143]. The classical methods of path planning are typically offline and require environment modeling. However, increasing the dimensions of the environment increases the complexity of calculations. Sample-based methods have been very successful, and many efforts have improved them. One of the most significant features of the sample-based methods is guaranteeing at least one successful path [144]. A joint path-planning and path-tracking framework for static and dynamic environments has also been proposed [145]. A comprehensive survey on coverage path planning in dynamic environments is provided in [146].

The Rapidly Random Tree (RRT) method cannot yield an optimal path. Then, the RRT* method was developed that produces an optimal path. However, the RRT* requires more memory than RRT [147]. The RRT* Fixed Nodes (RRT* FN) method was introduced in [148], where the problem of RRT* was solved, but could only be implemented for known and fixed environments. It was also shown that the RRT* method can generate a shorter path than the proposed RRT* FN method.

For more information on RRT and the developed strategies, [149] provides a comprehensive and valuable review. Grid-based methods can design high-quality paths.

The Dijkstra method can create the optimal path in terms of minimum distance, but it decreases its efficiency due to a large number of nodes [150]. The A* method is employed in many fields due to its completeness, optimality, and remarkable performance. Still, this method is also not very efficient due to the large number of nodes. The A* search method was introduced for dealing with efficient node searching that, in addition to creating an optimal path, requires less memory to store nodes [151]. An enhanced A* with staged heuristics and artificial potential fields for complex environments is presented in [152].

Table 3. Well-known methods for motion planning of wheeled mobile robots, C: Classic, S: Sample-based, G: Grid-based, A: Artificial intelligent, D: Directional approach, M: Machine learning

#	Method	Algorithm	Path planning		Problems
			Global	Local	
1	Visibility graph	C	*		-High temporal complexity [138]
2	Voronoi graph	C	*		-Mutational site [139]
3	Tangent graph	C	*		-High possibility of collision
4	Cell Decomposition Approach	C	*		-Assignment of the borders [140]
5	Topological method	C	*		-Environment with sparse obstacles, -Difficult re-modification
6	Probabilistic roadmap	S	*		-Narrow passage problem [141]
7	Rapidly exploring random trees	S	*		-Not results in the shortest path [142]
8	Dijkstra Algorithm	G	*		-Discrete environment
9	A* Algorithm	G	*	*	-Discrete environment
10	D* Algorithm	G	*	*	-Discrete environment
11	Neural network	A	*	*	-Complexity of adjusting weights
12	Fuzzy logic	A	*	*	-Definition of rules
13	Genetic algorithm	E	*	*	-Incline to premature convergence -Low convergence speed and high temporal complexity in the final stage
14	Ant colony optimization	E	*	*	-Incline to premature convergence, -Low convergence speed and high temporal complexity in the early stage
15	Particle swarm optimization	E	*	*	-Local minima
16	Artificial potential field	D	*	*	-Local minima -Low convergence speed and high temporal complexity in the final stage
17	Rolling windows	-	*	*	-The optimal path is not guaranteed, -Local minima
18	Reinforcement learning	M	*	*	-Limitation of the Q-table's dimension, -Possibility of collision due to improper definition of states, -Limitation on applicable actions
19	Deep learning	M	*	*	-Temporal complexity in real-time planning, - Proper network training

The D* algorithm can create a shorter optimal path than the A* and deal well with unknown or unpredictable threats. However, its weakness is the possibility of failure when the motion target is uncertain153]]. Neural networks, despite their complexity, have always been considered in motion planning. The input information acquired from the sensors is fed to the neural network to adjust the weights to optimize the cost function. One of the most important features of neural networks is their constant adaptability to the environment. The online learning of the neural networks for motion planning can only be implemented in some situations and for particular structures of the networks. The modified pulse-coupled neural network model presents a real-time and optimal motion planning method in dynamic environments [154]. In [155], by introducing a novel dynamic neural network, an efficient method for obtaining real-time and collision-free motion has been proposed without the need for any process of learning and estimating collisions at any stage of the movement, based only on neural connections within the network. Moreover, the stability of the network has been proved by qualitative analysis and the Lyapunov approach [156]. Using the motion-planning algorithm based on incremental sampling as a near-optimal rapid random tree exploration, the effect of nonlinear kinematic and dynamic constraints on the motion was investigated in [157], where a neural network is employed to predict the cost function. One of the most important advantages of fuzzy systems is the model-free solving approach, which significantly reduces the computational complexity of the planning unit. Combining the neural network with a fuzzy system creates an adaptive neuro-fuzzy inference system (e.g., ANFIS) that can approximate nonlinear functions as a universal estimator for motion planning [158]. In recent years, evolutionary algorithms have been the subject of the most significant studies related to motion planning [136]. The purpose of these algorithms is multi-objective optimization. However, it has disadvantages, such as getting trapped in the local minima and not guaranteeing the optimal global solution.

The most widely used method among the evolutionary algorithms is the Genetic Algorithm (GA). The GA is the most effective method in motion planning that was developed with an improved crossover operator to prevent premature convergence. In addition, finding a better path can increase the convergence speed [159]. The Ant Colony algorithm, which is another type of evolutionary algorithm, was introduced for the wheeled mobile robot in [160], where the algorithm converges rapidly even in complex environments according to simulations [161]. The PSO was first introduced in [162]. In this method, finding the optimal solution is not guaranteed. However, the Conventional PSO was introduced in [163] to find the optimal path in non-convex environments with the help of the random sampling method [164]. The adaptive PSO algorithm was presented in [165] to create an online path. The simulations show that this method can better avoid collisions with obstacles and reach the goal faster than the conventional PSO. The main purpose of the "nature-inspired algorithms" is to solve a constraint optimization problem. However, most of these methods are not able to find the global optimal solution. In [166], a hybrid method using the FA and GA was presented to design a global path for wheeled mobile robots. The FA part finds the local optimal solution, which is the subject of selection, crossover, and mutation operations in the GA that finds the global optimal response. The results indicate that the calculation ability and the reaction speed of the mobile robot have been improved [167]. The Artificial Potential Field (AFP) method is one of the most popular path design methods.

To overcome the local minima, [168] introduced a novel concept named "black-hole force". Then, the problem was solved by adjusting the repulsive force parameters [169], [170]. In [171], by using ANFIS, it was shown that the robot is never caught in local minima. Reinforcement Learning (RL) is one of the remarkable approaches for learning and finding an appropriate path. The classical Q-learning allows learning without the need for a previous model of the environment. However, it has disadvantages such as limitations in the number of states and actions, slow convergence to the optimal solution, and a proper definition of the reward function. Therefore, to increase the efficiency of the classical Q-learning in known and unknown environments, the APF method has been used to improve the convergence rate of the classical approach to the optimal solution. Furthermore, to check the performance and effectiveness of the proposed method, the parameters of the path length, smoothness of the path, and learning time were considered. The results of this method showed better performance than the classical Q-learning [172]. In [173] and [174], RL and APF have been used to obtain a suitable motion and overcome local minima in the potential field. For motion planning purposes, deep learning is used to approximate functions. New benchmarking frameworks for comparing RL algorithms in mobile robot navigation have been developed [175]. In [176], to improve the definition of the reward function in the classical QL, the structure of the reward function is generalized using environmental spatiotemporal information and the structure of the operating environment so that each member of the group avoids other wheeled mobile robots or dynamic objects. Also, in [177], the Adaptive APF (A-APF) method was introduced, which solved the local minima problem by adjusting the virtual obstacle's repulsive force parameters using the model reference adaptive system method. Then, improved Q-learning (IQL) was introduced to solve the lack of generalization of experience between states and the long time to gain experience problems. This led to an increase in convergence speed to the optimal action. The A-APF method was then utilized as a supervisor of the IQL to ensure the collision avoidance of static and dynamic obstacles in unknown environments. Safe reinforcement learning approaches for reducing collisions in unknown environments have been proposed [178]. In [179], an efficient method for exploring a wheeled mobile robot in an unknown environment using deep reinforcement learning was presented. Due to the unpredictable structure of the environment for exploration and rescue operations, deep learning has also been used to extract suitable features for path planning and frontier exploration, and thus helps approximate a function to access the optimal policy [180].

The dynamic window method (DWA) controls the wheeled mobile robot's motion using the optimal speed in real-time by transforming the path-planning problem into a constrained optimization problem of the velocity space. This method is considered an effective method for local planning. The most important disadvantages of this method are "insufficiency of evaluation functions" and "absence of a weight selection algorithm for evaluation functions". To solve these two problems, two new evaluation functions were introduced to consider more complex situations and improve the robot's behavior in complex environments. Then, the Q-learning was used to adjust the DWA parameters adaptively based on the structure of the unknown environment [181]. A combination of the path planning and SLAM has also been proposed to improve the navigation quality. The dueling deep Q-learning algorithm created a collision-free path by a fully convolutional neural network for obstacle reorganization [182]. The 2D representation obtained from the environment is based on FastSLAM. Deep Reinforcement Learning method has been employed to find the shortest path by considering the motion constraints of the vehicle in simulations and in real-world applications [183]. Deep learning has been used in [184] to avoid collisions and to determine a suitable control input for the actuators. In this work, the required sample set is obtained by using the potential field and the ant colony algorithm [185]. With an asynchronous deep reinforcement learning method, the path planning (without hand-designed features and prior representation) was performed to move the robot in an unknown and dynamic environment, and only with limited horizon capability [186]. Most existing methods are based on understanding the interactions between the robot and the surrounding environment. However, understanding the interactions between the environmental factors can provide meaningful information to the behavior design unit. In [187], using a decentralized structured RNN network with coarse-grained local maps (LM-SRNN), robot-human interactions were modeled through spatiotemporal graphs. Moreover, the human-human interactions were modeled through coarse-grained local maps that enable safe movement in crowded environments. By using RGB frames as the input, it was shown in [188] that it is possible to plan a safe path and to estimate the position on the map. Since deep Q-learning can only consider state-space continuously (continuous space) and the number of actions that can be performed is limited (discrete space), this approach is mainly used to create a meaningful and better understanding of the environment. Methods such as the asynchronous advantage actor-critic algorithm [189] and soft actor-critic [190] have been used to achieve a continuous state-action space, which has led to a smoother and more efficient path. Since real environments are usually unknown and/or dynamic, [191] presented a comprehensive review of two categories of classical (e.g., APF and Roadmap) and heuristic (e.g., GA, PSO, and Fuzzy Logic) algorithms that can be applied in dynamic environments. Bio-inspired algorithms for mobile robot path planning have also been developed [192]. Hybrid swarm intelligence and graph-based algorithms have also been proposed [193]. It also presented the general advantages and disadvantages of each method by examining the criteria of "path planning in cluttered areas", "detection and tracking of moving targets", "prediction of the direction of moving objects", and "effect of the speed of obstacles in decision-making". Ref. [194] provides the "random tree*" algorithm with real-time exploration for obstacle avoidance to detect 3D objects. Then, the output of the path-design unit is considered as the input of the model prediction controller to achieve safe movements. Table 4 shows the top 10 popular methods for path planning from 2015 to 2024 according to the Scopus dataset. A recent special issue focusing on mobile-robot navigation—including perception, localization, and SLAM—has been organized as well [195]. A detailed comparison of the main motion planning methods for wheeled mobile robots, including their advantages, limitations, and key references, is provided in Appendix C (Table C1).

Table 4. The occurrence of the top 10 keywords of path planning methods for wheeled mobile robots

#	Keyword	Occurrence	#	Keyword	Occurrence
1	Reinforcement learning	1,288	6	Artificial potential fields	512
2	Optimization	1,065	7	Fuzzy logic	449
3	Deep learning	939	8	Neural networks	423
4	Particle swarm optimization	573	9	Ant Colony optimization	402
5	Genetic algorithms	559	10	Machine learning	368

3- 5- Motion Tracking Controllers

In the final stage of the navigation architecture, an efficient controller is required to ensure reliable trajectory tracking and stable execution of the path generated by the planning unit. Among the major challenges in the domain of wheeled mobile robots (WMRs) is the design of robust and adaptive tracking controllers that can cope with nonlinear kinematics, dynamic uncertainties, actuator constraints, and real-time environmental disturbances. While the motion-planning unit can be regarded as the behavior design unit, the control system is responsible for translating this planned behavior into executable motion [195]. The control unit receives its inputs from two sources: (i) the motion-planning unit and (ii) surround sensing systems. The primary objective is to minimize the tracking error, defined as the difference between the desired trajectory and the real-time robot state measured by sensors.

Classical and Theory-Based Controllers

Traditional control approaches have been categorized into three broad groups [197]:

- **Global linearization-based control**, which transforms the nonlinear robot dynamics into equivalent linear state-space systems through coordinate transformations.
- **Approximate linearization-based control**, which relies on linearization around local operating points or equilibria.
- **Lyapunov theory-based control methods**, which directly guarantee stability through Lyapunov function construction.

Although these controllers provide theoretical stability guarantees, they often suffer from sensitivity to parameter variations and modeling uncertainties. To address this, adaptive control methods have emerged as one of the most effective solutions for WMRs.

Adaptive and Nonlinear Controllers

Adaptive strategies exploit online parameter estimation to handle time-varying and uncertain dynamics. Methods such as Lyapunov-based adaptive control [198], backstepping re-parameterization [199], and switching control combined with Lyapunov stability theory [200] have shown success in reducing parameter thrust and actuator saturation issues. Novel adaptive feedback controllers have been proposed for WMRs under wheel slip and dynamic constraints [201].

Integration with machine learning has expanded adaptive control capabilities. Neural networks and wavelet networks, with their universal function approximation properties, are able to model nonlinear robot dynamics online and enhance controller robustness [202]. Hybrid NN–PID controllers [194] and recurrent neural network–based optimal controllers [203] have further improved adaptability in unstructured environments.

Sliding-Mode Controllers (SMC)

SMC techniques remain popular for WMR tracking control due to their robustness against model uncertainties and external disturbances. High-frequency switching enables reduced invariant tracking errors [204]. To mitigate chattering and enhance performance, intelligent SMC frameworks combined with radial basis function (RBF) neural networks have been reported [205].

Model Predictive Controllers (MPC)

Model predictive control has gained substantial attention due to its ability to handle multi-constraint optimization problems in real time. By formulating the tracking-error kinematics into finite-horizon quadratic programming (QP) problems, primal–dual neural networks have been utilized to accelerate convergence [176]. Recent works demonstrate the success of MPC in:

- **Tracking and obstacle avoidance** in dynamic environments [208, 209].
- **Robust MPC under parametric uncertainties** [210–212].
- **Integration of deep learning with MPC** for vision-based and data-driven navigation [213, 214].
- **Hybrid global–local planning frameworks coupled with MPC** further ensure adaptability in non-stationary environments [209].

Intelligent and Learning-Based Controllers

The recent paradigm shift in robot control focuses on intelligent, data-driven, and learning-based strategies:

- **Reinforcement learning (RL)** has been employed to optimize control policies directly from interaction data, enabling adaptive behavior in previously unseen environments. Safe RL approaches have been introduced to guarantee collision avoidance under uncertainty.
- **Deep learning–enhanced controllers**, especially when combined with MPC or SMC, have shown remarkable results in high-dimensional state-action spaces.
- **Vision-based and multimodal control architectures**, which integrate RGB-D, LiDAR, and inertial sensors, are paving the way for fully autonomous adaptive control.
- **Explainable AI (XAI) in control** has been explored to enhance transparency and trust in autonomous systems [215].

Future Directions

Despite the progress, open challenges remain in designing controllers that combine robustness, adaptability, real-time efficiency, and explainability. Promising research trends include:

- Nonlinear adaptive control with neural approximation [216].
- Intelligent sliding-mode control with NN-based compensation [217].
- Safe learning-based MPC for navigation in dynamic human–robot interaction scenarios.
- Hierarchical control architectures that unify planning, perception, and control under a common learning-based framework.

For completeness, a comprehensive comparison of the main control strategies applied in wheeled mobile robots is provided in Appendix C (Table C2). This comparative analysis outlines their theoretical foundations, advantages, limitations, and typical application domains. As shown in the table, the choice of control strategy strongly depends on the trade-off between robustness, adaptability, computational complexity, and real-time feasibility. While adaptive and sliding-mode controllers are often preferred for their robustness and stability guarantees, model predictive control and reinforcement learning–based approaches have recently gained increasing attention due to their capability of handling highly dynamic and uncertain environments.

4- Conclusions

This paper presents a qualitative analysis of the navigation of wheeled mobile robots. The number of WoS and Scopus documents was compared, with more documents in the Scopus database from 2015 to the end of 2024. In the bibliographic analysis section, the process of publishing documents indicates the growing demand for research and development in wheeled mobile robot navigation. By examining the most frequent keywords in the concept of navigation, the most effective and important aspects related to it were identified: localization, machine learning, motion planning, and control systems, respectively. Then, in the qualitative analysis, the most widely used types of wheeled mobile robots were reviewed, and wheeled mobile robots were selected as one of the most popular types of robots for reasons such as design, structure, and uncomplicated control in the industry. The concept of localization as the first part of the navigation concept was divided into two categories: probabilistic approaches and autonomous map building based on the presence or absence of knowledge about the environment (map). It is essential and challenging to discuss the type of sensors and the combination of information received from them. Cameras can generate rich details, and to achieve this goal, the concept of computer vision is introduced. By investigating machine learning as the most widely used machine vision method in wheeled mobile robots, deep learning, reinforcement learning, and classic learning were identified to meet decision-making, object recognition, classification, semantics, and collision avoidance goals. Then, for the concept of path planning in the related literature, motion optimization perspectives, types of methods, and their advantages and disadvantages were discussed. The motion-planning unit is known as the decision level to plan appropriate behavior in various environmental conditions. Finally, the control unit was examined at the actuator level. Controller design approaches were divided into three categories based on purpose: global linearization-based control, approximate linearization-based control, and Lyapunov theory-based control. Moreover, adaptive control, neural networks, sliding-mode control, and model predictive control methods were studied as the most popular ones. Finally, the tables that indicate the number of keyword occurrences show researchers' interest in these research backgrounds. This may be due to the possibility of further progress in future studies, greater effectiveness, and better performance. Therefore, the development or combination of the methods mentioned in Tables 1, 2, and 4 is suggested to focus on future research.

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Appendices — Supplementary Comparative Tables on Machine Learning, Navigation, and Localization Methods in Wheeled Mobile Robots

Appendix A. Localization and SLAM Approaches

Table A1. Comparative overview of SLAM methods

Method	Advantages	Limitations	Key References
Odometry	Simple to implement; no need for external infrastructure; works in real time	Accumulated drift due to wheel slip and measurement noise; not reliable over long distances	[37], [38]
Inertial Navigation (IMU-based)	Independent of environment; robust to lighting/texture conditions	High cost; drift accumulates quickly; requires frequent calibration	[39]
Magnetic Compass	Resistant to environmental effects; low cost	Distorted near power lines or steel structures; low precision	[40]
GPS / Beacons	Global availability; robust outdoors	Low accuracy (meter-level); poor performance in indoor/urban canyon environments	[41]
Landmark-based Localization	High accuracy if landmarks are known and fixed; simple detection in structured environments	Limited to pre-mapped landmarks; poor generalization in dynamic/unstructured spaces	[40]
Markov Localization	Handles global localization and multi-hypothesis tracking; robust to noisy sensors	Requires discretization (high memory demand); computational cost grows with environment size	[42], [43], [44]
Kalman Filter (KF)	Efficient for linear Gaussian systems; low computational cost	Assumes linearity; needs known initial position	[36], [45]
Extended Kalman Filter (EKF)	Handles nonlinear models by linearization; widely used in mobile robotics	Approximation errors; sensitive to model inaccuracies; computationally expensive for large maps	[49]
Unscented Kalman Filter (UKF)	Better accuracy than EKF; no explicit linearization; effective in moderate non-linearities	Higher computational complexity (cubic in state dimension); inconsistency in estimates	[50], [59], [60]
Particle Filter (MCL)	Works with arbitrary distributions; robust in dynamic environments; can represent multi-modal beliefs	Computationally expensive with a large state space; particle degeneracy and impoverishment	[46], [47], [48]
FastSLAM (PF-based)	Efficient with large-scale maps; separates robot pose and landmark estimation	Particle depletion; degeneracy; requires resampling improvements	[56], [61]
PSO-/Evolutionary-based SLAM	Reduces particle degeneracy; improves resampling; better pose accuracy	Higher computational overhead; parameter tuning required	[61]
Vision-based SLAM	Rich feature extraction enables loop-closure; scalable with computer vision progress	Sensitive to lighting, occlusion, and dynamic objects	[53], [62], [63]
LiDAR-based SLAM	Accurate 3D environment reconstruction; robust in low-light	Expensive sensors (though prices are dropping); affected by reflective/absorptive surfaces	[69], [70], [72], [73]
LiDAR–Inertial Fusion SLAM	Robust in dynamic environments; combines complementary modalities	Complex integration requires calibration; computationally heavy	[71], [74]
RGB-D / Multimodal SLAM	Rich semantic understanding; supports human–robot interaction and high-level navigation	High computational requirements; limited range of RGB-D sensors	[64], [75]
Graph-based SLAM (Optimization-based)	Reduces SLAM uncertainty via graph optimization; scalable; robust loop closure	Solving large nonlinear least-squares problems requires efficient solvers	[63]

Appendix B. Machine Learning Methods in Robotics

Table B1. Comparative Analysis of Machine Learning Approaches for Wheeled Mobile Robots.

Method / Algorithm	Key Applications in WMR	Main Advantages	Limitations / Challenges	Key References
Supervised Learning (Regression, Logistic Regression, SVM, KNN, Decision Trees)	Object detection, collision prediction, human orientation estimation, and feature optimization	Simple implementation, interpretable, effective for classification & regression, robust in structured environments	Requires large labeled datasets; limited adaptability in dynamic/unstructured environments	[76]– [83]
Unsupervised Learning (Autoencoders, DBN, Clustering, Dimensionality Reduction)	Feature extraction from sensory data, SLAM enhancement, sensor fusion (RGB-D + LiDAR), anomaly detection	Learns from unlabeled data, dimensionality reduction, useful for sensor fusion, initialization for RNNs	Computationally intensive, limited direct control application, post-processing often required	[100]– [104]
Deep Neural Networks (CNNs, FCN, DBN)	Obstacle detection, semantic segmentation, end-to-end navigation, object recognition	Robust feature extraction, invariance to noise/rotation, strong performance in perception tasks	Requires massive training datasets, high computational demand, prone to overfitting, and low interpretability	[105]– [114]
Recurrent Neural Networks (RNN, LSTM, GRU)	Trajectory prediction, temporal sequence modeling, path tracking	Exploits temporal dependencies, suitable for sequential decision-making	Training instabilities (vanishing gradients), resource-intensive, harder to optimize	[115]
Hybrid ML + Classical Algorithms (A, Dijkstra + DL, Bayesian Optimization, Regression + SLAM)	Optimal path planning, navigation under constraints, and real-time decision support	Combines the interpretability & stability of classical methods with the adaptability of ML; better real-time feasibility	Integration complexity, trade-off between accuracy and speed, is still computationally heavy	[84], [88], [104]
Reinforcement Learning (Q-Learning, Dyna-Q, Model-Based RL)	Policy learning, adaptive obstacle avoidance, navigation in structured/partially unknown environments	Model-free learning, adaptability to dynamics, and APF-enhanced RL improve convergence	Curse of dimensionality, slow convergence, limited generalization	[116]– [126]
Deep Reinforcement Learning (DQN, A3C, SAC, Actor–Critic, GNN-based RL)	Autonomous navigation in unstructured environments, multi-robot coordination, and continuous control	Handles nonlinearities, multimodal fusion (LiDAR + camera), continuous state-action spaces, scalable	Sample inefficiency, safety & stability concerns, high training costs, interpretability issues	[120]– [135]
Neuro-Fuzzy & Hybrid Learning Controllers (RBF Networks, ANFIS, Adaptive Neuro-Controllers)	Adaptive tracking, robust control under uncertainties, and real-time disturbance rejection	Model-free adaptability, robust under noise, combines learning with stability guarantees	Complexity of hybrid models, risk of instability, tuning overhead	[91]– [95]
Explainable AI (XAI) applied to ML & DRL	Enhancing transparency in decision-making, safety-critical navigation, human–robot interaction	Improves trust and interpretability, supports accountability in autonomous systems	Still emerging, may reduce performance in exchange for transparency	[135]

Appendix C. Path Planning and Control Methods

Table C1. Advantages and limitations of the main path planning approaches for wheeled mobile robots

Based Method	Advantages	Limitations	Key References
Dijkstra (Graph-based)	Guarantees the shortest path (optimal in distance); simple and deterministic.	Computationally expensive in large environments; poor scalability.	[150]
A*	Complete, optimal, efficient with heuristics; widely used in robotics.	Requires large memory for node storage; performance decreases in high-dimensional spaces.	[151], [152]
D*	Adaptive to changes in the environment; shorter paths than A*.	May fail when the target is uncertain; higher computational complexity.	[153]
RRT (Sampling-based)	Scalable to high-dimensional spaces; probabilistically complete.	Path is not optimal; random exploration may lead to inefficiency.	[147], [149]
RRT*	Asymptotically optimal; guarantees improved path quality.	High memory usage; slow in large environments.	[147], [148]
RRT* FN	Memory-efficient version of RRT*.	Limited to static and known environments.	[148]
Neural Networks	Adaptive learning from sensor inputs; real-time applicability.	Require extensive training; limited generalization; network complexity.	[154]– [157]
Fuzzy Logic	Model-free; low computational cost; intuitive reasoning.	Limited scalability; less accurate in dynamic environments.	[158]
ANFIS (Neuro-Fuzzy)	Universal approximator; handles nonlinearities; adaptive.	Training complexity requires careful rule design.	[158]
Genetic Algorithm (GA)	Effective in global optimization; avoids local minima (with modifications).	Premature convergence risk; computationally heavy.	[159]
Ant Colony Optimization (ACO)	Fast convergence; efficient in complex environments.	Prone to stagnation; sensitive to parameter tuning.	[160], [161]
Particle Swarm Optimization (PSO)	Simple, efficient, good for multi-objective optimization.	May trap in local minima; cannot guarantee global optimum.	[162]– [165]
Firefly Algorithm (FA) + GA (Hybrid)	Balances global/local search; improves responsiveness.	Increased algorithmic complexity.	[166], [167]
Artificial Potential Field (APF)	Simple and real-time; intuitive design.	Local minima problem; oscillations near obstacles.	[168]– [171]
Q-Learning (Classical RL)	Model-free; adaptive to unknown environments.	Limited by state/action discretization; slow convergence.	[172]– [176]
Improved RL (IQL, Hybrid RL+ APF)	Faster convergence.	Still sensitive to reward function design.	[177]
Improved RL (IQL, Hybrid RL + Adaptive APF)	Faster convergence than [177]; better generalization; avoids local minima; Improved APF; supervisor learning; collision avoidance guaranteed	Requires more computational resources than classical RL	[176]
Deep RL (DQN, A3C, SAC)	Handles continuous state-action spaces; scalable; robust in dynamic environments.	Requires high computational resources; data-hungry.	[178]– [190]

Table C1. Continue

Based Method	Advantages	Limitations	Key References
Dynamic Window Approach (DWA)	Real-time velocity-based optimization; effective in local planning.	Evaluation function limitations; weight selection issues.	[181]
Hybrid SLAM + DRL	Combines mapping with adaptive planning; robust in real-world applications.	High complexity; requires multimodal sensor data.	[182]– [186]
Crowd-Aware / Socially Compliant Planning	Safe navigation in human-populated spaces; considers robot-human interaction.	Complex modeling; requires large datasets.	[137], [187], [188]
Bio-inspired & Hybrid Swarm-Graph Methods	Effective in dynamic and uncertain environments; scalable.	Lack of global optimality guarantees; sensitive to swarm dynamics.	[192], [193]

Table C2. Comparison of major control strategies for wheeled mobile robots

Control Method	Main Idea	Advantages	Limitations	Typical Applications
Adaptive Control	Online parameter estimation and model re-parameterization	Handles parameter uncertainties, ensures stability with Lyapunov/backstepping, suitable for nonlinear models	Sensitive to fast dynamics and noise; tuning complexity	Trajectory tracking under uncertain dynamics, slip compensation
Sliding-Mode Control (SMC)	Discontinuous switching to force system states onto sliding surface	Strong robustness to modeling errors and external disturbances; ensures finite-time convergence	Chattering phenomenon; performance degradation with actuator constraints	Robust tracking in uncertain terrains; disturbance rejection
Model Predictive Control (MPC)	Optimization of control input over a prediction horizon subject to constraints	Explicit handling of input/state constraints, high tracking accuracy, flexible to nonlinear extensions	Computationally expensive; requires accurate models; scalability issues	Obstacle avoidance, dynamic trajectory tracking, hybrid global–local planning
Neural Network–Based Control	Universal function approximation for dynamics and uncertainties	Online learning ability, strong adaptability, nonlinear compensation	Requires large training data; potential stability concerns	Adaptive NN-PID, wavelet networks for slip dynamics, RNN-based optimal control
Reinforcement Learning (RL)–Based Control	Policy learning through interaction with environment using reward functions	Learns directly from data, no need for explicit modeling, adaptable to unknown environments	High sample complexity, reward shaping challenges, limited safety guarantees	Path tracking in dynamic environments, adaptive navigation, safe RL for human–robot interaction
Hybrid Methods (e.g., NN+SMC, MPC+DL, Neuro-Fuzzy)	Combining complementary techniques to balance robustness, adaptability, and efficiency	Exploits strengths of multiple controllers, improved robustness, better generalization	Increased design and computational complexity	Safe navigation in cluttered spaces, multi-objective control (energy, smoothness, accuracy)