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ADVANCES IN PATH PLANNING AND OBSTACLE AVOIDANCE FOR AUTONOMOUS MOBILE ROBOTS

Abstract

This article delivers an extensive review of path planning and obstacle avoidance methods in mobile robotics, covering their theoretical principles, algorithmic progress, and real-world applications. Path planning techniques are grouped into four main categories—classical, sampling-based, optimization-oriented, and learning-based – each discussed in terms of advantages, shortcomings, and suitability for diverse operational contexts. Obstacle avoidance is analyzed through reactive, predictive, and learning-focused approaches, with particular attention to sensor technologies and real-time decision-making. The paper also considers integrated navigation systems that merge global and local planning, utilize layered control structures, and operate on embedded platforms to ensure safe and efficient mobility in complex, dynamic environments. Practical examples, such as the ROS Navigation Stack, autonomous delivery systems, and robotic cleaners, illustrate real-world implementations. Additionally, the article highlights persistent challenges and open research directions, including planning under uncertainty, real-time adaptability, socially aware navigation, coordination of multiple robots, and transfer learning for generalization. The discussion is reinforced with figures and tables comparing algorithmic trade-offs and system designs. Overall, the review provides researchers and practitioners with a structured taxonomy, comparative analysis, and forward-looking perspectives to support the creation of more reliable, adaptive, and intelligent navigation systems for future autonomous robots.

Keywords: mobile robotics, path planning, obstacle avoidance, autonomous navigation, artificial intelligence, robot control.

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АВТОНОМДЫ МОБИЛЬДІ РОБОТТАР ҮШІН ЖОЛДЫ ЖОСПАРЛАУ ЖӘНЕ КЕДЕРГІЛЕРДЕН ҚҰТЫЛУ ӘДІСТЕРІНДЕГІ ЖЕТІСТІКТЕР

Аңдатпа

Бұл мақалада мобильді робототехникадағы жолды жоспарлау мен кедергілерден айналып өту әдістеріне кең шолу жасалады. Зерттеуде олардың теориялық негіздері, алгоритмдік жетістіктері және практикалық қолданулары қарастырылады. Жолды жоспарлау әдістері төрт негізгі санатқа бөлінген — классикалық, үлгіге негізделген, оңтайландыруға бағытталған және оқытуға негізделген тәсілдер. Әрбір топ артықшылықтары, шектеулері және әртүрлі ортада қолдану мүмкіндіктері тұрғысынан талданады. Кедергілерден құтылу тәсілдері реактивті, болжамдық және оқытуға негізделген бағыттармен сипатталады, мұнда сенсорлық технологиялар мен нақты уақыттағы шешім қабылдауға ерекше назар аударылады. Сонымен қатар, мақалада жаһандық және жергілікті жоспарлауды үйлестіретін, иерархиялық басқару құрылымдарын пайдаланатын және кірістірілген платформаларда жұмыс істейтін интеграцияланған навигациялық жүйелер қарастырылады. Практикалық мысалдар ретінде ROS Navigation Stack, автономды жеткізу жүйелері және робот шаңсорғыштары келтірілген. Сондай-ақ мақалада белгісіздік жағдайындағы жоспарлау, нақты уақыттағы бейімделу, әлеуметтік бағытталған навигация, көп роботты үйлестіру және жалпылауға арналған трансферлік оқыту секілді ашық зерттеу мәселелері атап өтіледі. Шолу алгоритмдік айырбас пен жүйелік архитектураларды салыстыратын суреттер мен кестелермен толықтырылған. Жалпы алғанда, бұл жұмыс зерттеушілер мен мамандарға сенімді, бейімделгіш және интеллектуалды навигациялық жүйелерді құруға арналған құрылымдық таксономияны, салыстырмалы талдауды және болашаққа бағытталған ұсыныстарды ұсынады.

Түйін сөздер: мобильді робототехника, траекторияны жоспарлау, кедергілерден айналып өту, автономды навигация, жасанды интеллект, роботтарды басқару.

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ДОСТИЖЕНИЯ В ОБЛАСТИ ПЛАНИРОВАНИЯ ПУТИ И ИЗБЕЖАНИЯ ПРЕПЯТСТВИЙ ДЛЯ АВТОНОМНЫХ МОБИЛЬНЫХ РОБОТОВ

Аннотация

В статье представлен развернутый обзор методов планирования пути и обхода препятствий в мобильной робототехнике, включающий их теоретические основы, алгоритмические достижения и практическое применение. Техники планирования пути сгруппированы в четыре основные категории — классические, основанные на выборке, оптимизационные и обучающиеся. Каждая группа рассмотрена с точки зрения преимуществ, ограничений и применимости в различных условиях эксплуатации. Методы обхода препятствий классифицированы на реактивные, предсказательные и основанные на обучении, с особым акцентом на сенсорные технологии и принятие решений в реальном времени. Также рассматриваются интегрированные системы навигации, которые совмещают глобальное и локальное планирование, используют иерархические структуры управления и работают на встроенных платформах для обеспечения безопасной и эффективной мобильности в сложных динамических средах. Практические примеры включают ROS Navigation Stack, автономные системы доставки и роботизированные пылесосы. Кроме того, выделяются актуальные проблемы и открытые направления исследований, включая планирование в условиях неопределенности, адаптацию в реальном времени, социально-ориентированную навигацию, координацию множества роботов и трансферное обучение для обобщения. Обзор сопровождается иллюстрациями и таблицами, сравнивающими алгоритмические компромиссы и архитектурные решения. В целом, работа предоставляет исследователям и практикам структурированную таксономию, сравнительный анализ и перспективные направления для создания более надежных, адаптивных и интеллектуальных навигационных систем будущих автономных роботов.

Ключевые слова: мобильная робототехника, планирование траектории, избегание препятствий, автономная навигация, искусственный интеллект, управление роботами.

Introduction

The growing reliance on autonomous technologies in areas such as warehouse logistics, last-mile delivery, planetary exploration, and urban transportation has underscored the critical role of reliable path planning and obstacle avoidance in mobile robotics. These two functions form the foundation of robotic navigation, enabling safe and efficient operation in complex and dynamic environments without direct human control [1]. Path planning focuses on generating feasible and, ideally, optimal routes from a starting point to a destination while considering environmental constraints, robot dynamics, and task requirements. Obstacle avoidance, on the other hand, addresses the real-time adaptation of robot trajectories to static and moving obstacles that may not have been accounted for during the initial planning phase [2]. Over the past decades, numerous solutions have been developed, ranging from classical deterministic algorithms to sampling-based approaches, optimization-driven strategies, and more recently, data-centric methods such as reinforcement learning and deep neural networks [3]. Each category presents its own balance of computational cost, adaptability, and scalability across diverse applications. Despite this progress, there remains a lack of systematic synthesis that simultaneously categorizes these methods, evaluates their trade-offs, and highlights their suitability for specific environments and robotic platforms. This gap motivates the present study.

The purpose of this paper is to conduct a structured and critical survey of path planning and obstacle avoidance techniques for autonomous mobile robots.

Specifically, the study investigates:

- the theoretical principles and algorithmic strategies underlying different approaches;

- their practical performance in real-world robotic systems;
- open challenges and unresolved issues in dynamic, uncertain, and socially constrained environments.

The central premise of this study is that no single method can universally address all navigation scenarios; instead, hybrid and adaptive frameworks are required. By testing this hypothesis through comparative analysis of existing literature, this paper aims to provide researchers and practitioners with a taxonomy, evaluation framework, and forward-looking perspectives for designing more robust and intelligent navigation systems [4].

Research Methodology

This study was conducted between 2021 and 2025 through a systematic review of peer-reviewed journal articles, conference proceedings, and preprints indexed in databases such as IEEE Xplore, ScienceDirect, SpringerLink, and arXiv. The inclusion criteria focused on works that explicitly addressed path planning, obstacle avoidance, or integrated navigation frameworks in the context of autonomous mobile robots. Both theoretical developments and experimental evaluations were considered.

To ensure comprehensive coverage, we applied a keyword-based search strategy combining terms such as *"mobile robots", "path planning", "obstacle avoidance", "reinforcement learning", "sampling-based planning" and "navigation frameworks."* After initial screening, 120 publications were shortlisted, of which 48 were selected for detailed comparative analysis. The selected studies span applications in indoor service robots, outdoor delivery platforms, warehouse automation, and multi-robot coordination. The methodology adopted for analysis involved categorizing techniques into four major families (classical, sampling-based, optimization-based, and learning-based) and evaluating them against performance metrics such as completeness, optimality, computational cost, scalability, and adaptability to dynamic environments. Benchmark datasets, simulation environments (Gazebo, KITTI, ScanNet), and reported real-world deployments were considered as evidence for assessing algorithmic performance. This section provides a comprehensive classification of path planning techniques employed in mobile robotics, highlighting the evolution from rule-based to learning-driven approaches. These techniques are organized into four primary categories: classical, sampling-based, optimization-based, and learning-based methods. Each category addresses specific challenges in robot navigation, such as computational complexity, environmental uncertainty, and adaptability to dynamic conditions. The categorization also reflects the trade-offs between completeness, optimality, and real-time feasibility, which are critical when selecting an appropriate planning strategy for a given application. Figure 1 presents a taxonomy of these techniques, offering a visual overview of their relationships, algorithmic representatives, and operational characteristics.

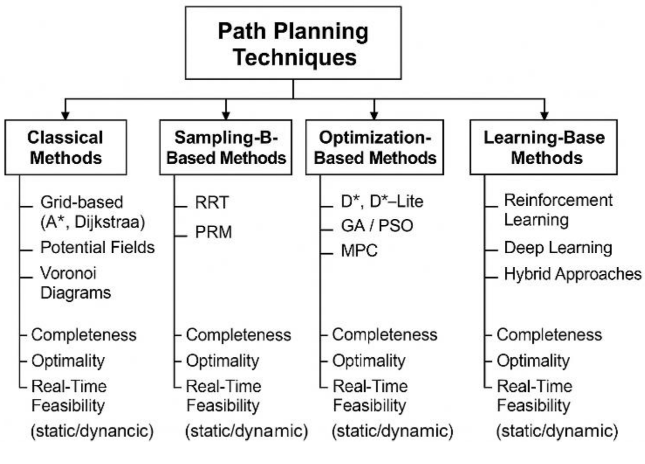

Figure 1. Taxonomy of Path Planning Techniques in Mobile Robotics

PRM, in contrast, constructs a roadmap by randomly sampling nodes and connecting collision-free edges, suitable for multi-query problems [5]. These methods do not guarantee completeness but are probabilistically complete, meaning the probability of finding a path increases with computation time. Optimization-based planners model the path planning task as a cost minimization problem. D and D-Lite** are incremental search algorithms that dynamically update paths in changing environments, making them suitable for real-time applications [6].

This is effective in dynamic or partially known environments but demands extensive training. Deep learning-based methods learn mappings from sensory inputs to actions or trajectories, facilitating end-to-end planning in complex domains. Hybrid systems combine learned models with classical planners to enhance generalization and safety. However, these approaches often lack interpretability and may struggle with generalization beyond trained scenarios, highlighting the need for robust validation frameworks.

Results of the Study

The analysis confirmed the initial hypothesis that no single algorithmic family universally satisfies all requirements of mobile robot navigation. Classical methods (e.g., A*, Dijkstra) remain reliable for structured and static environments but show poor scalability. Sampling-based planners (e.g., RRT, PRM) are highly effective in high-dimensional spaces but can produce suboptimal paths. Optimization-based approaches (e.g., D*, MPC) provide strong adaptability and near-optimal solutions but at significant computational expense. Learning-based methods, particularly reinforcement learning and deep neural networks, demonstrate flexibility in unstructured or dynamic environments but lack interpretability and require extensive training resources.

These findings validate the working hypothesis: hybrid and adaptive frameworks, which combine complementary strengths of different paradigms, are essential for robust real-world deployment. Comparative results are summarized in Table 1, which highlights the trade-offs across completeness, optimality, real-time feasibility, and adaptability.

Table 1. Comparative analysis of path planning techniques

Method Category	*Completeness*	*Optimality*	*Computation Time*	*Scalability*	*Adaptability to Dynamic Environments*
Classical (e.g., A, Dijkstra)*	*High*	*High*	*High (for large maps)*	*Low*	*Low*
Potential Fields	*Low*	*Low (local minima)*	*Low*	*Medium*	*Medium*
Voronoi Diagrams	*High*	*Medium*	*Medium*	*Low*	*Low*
RRT / PRM	*Probabilistic*	*Low to Medium*	*Low*	*High*	*Medium*
*D, D-Lite***	*High*	*Medium*	*Medium*	*Medium*	*High*
GA / PSO	*Medium*	*Medium to High*	*Medium to High*	*Medium*	*Medium*
Model Predictive Control (MPC)	*High*	*High*	*High*	*Medium*	*High*
Reinforcement Learning	*Variable*	*Variable*	*High (training)*	*High*	*High*
Deep Learning	*Variable*	*Variable*	*Low (inference)*	*High*	*High*
Hybrid Systems	*Medium to High*	*Medium to High*	*Medium*	*High*	*High*

In summary, the landscape of path planning techniques in mobile robotics is rich and diverse, with each category offering distinct advantages depending on the task requirements and environmental complexity. From deterministic classical methods to adaptive learning-based strategies, the choice of algorithm must balance factors such as efficiency, reliability, and scalability. This classification not only aids in understanding existing approaches but also provides a foundation for developing hybrid systems that leverage the strengths of multiple paradigms for enhanced navigation performance.

This section explores the diverse range of techniques used for obstacle detection and avoidance, a critical capability for ensuring safe and reliable navigation in mobile robotics. As robots operate in increasingly complex and dynamic environments, the ability to perceive, interpret, and respond to obstacles in real time has become essential. This chapter categorizes obstacle avoidance strategies into sensor-based perception systems, reactive mechanisms, predictive modeling approaches, and learning-based frameworks. Each category offers unique advantages depending on the application context, environmental uncertainty, and computational constraints. Figure 2 illustrates a high-level overview of these strategies, showing the flow from sensor inputs through various decision-making layers to motion planning outputs.

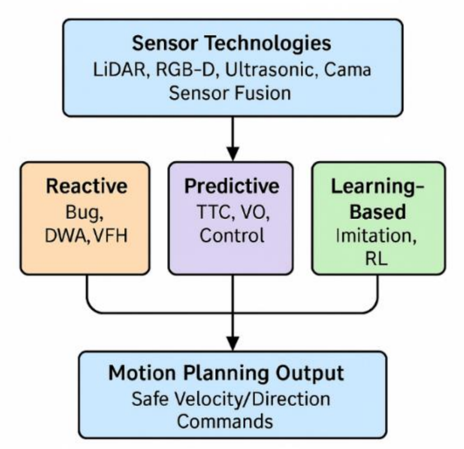

Figure 2. Pipeline representation of obstacle detection and avoidance strategies in mobile robotics.

Effective obstacle detection in mobile robotics relies heavily on sensor technologies. LiDAR provides high-resolution 3D point clouds, enabling accurate distance measurements in structured and unstructured environments [7]. Ultrasonic sensors are low-cost and ideal for short-range detection but suffer from poor angular resolution [8]. Vision-based systems, particularly those powered by convolutional neural networks, can recognize object types and locations [9]. Sensor fusion integrates data from multiple modalities to improve perception robustness, often using techniques such as Kalman filtering or Bayesian inference [10], enhancing obstacle recognition in dynamic and cluttered scenes. Reactive techniques generate immediate responses to sensed obstacles without global planning. Bug algorithms follow wall-following or boundary-tracing strategies, enabling basic navigation around obstacles but can be inefficient [11]. The Dynamic Window Approach (DWA) computes a robot's velocity commands within a feasible dynamic window by optimizing a cost function:

$$\begin{aligned} G(u,w) &= \alpha \cdot heading(v,w) \\ &+ \beta \cdot clearance(v,w) \\ &- \gamma \cdot velocity(v,w) \end{aligned} \tag{1}$$

Where v and w are linear and angular velocities [12]. Vector Field Histogram (VFH) builds histograms from obstacle densities to find safe navigation directions [13]. Reactive methods are fast and simple but often lack global awareness.

Predictive and Model-Based Approaches

Model-based methods incorporate future state predictions to avoid collisions proactively. The Time-to-Collision (TTC) metric estimates the remaining time before impact with an obstacle based on relative velocity:

$$TTC = \frac{d}{|v_{rel}|} \tag{2}$$

Here d represents the distance to the obstacle and v_{rel} is the relative velocity between the robot and the obstacle [14]. These predictive methods are particularly effective in dynamic environments where obstacle movements can be estimated with reasonable accuracy. However, their success depends heavily on precise modeling of system dynamics and often entails significant computational cost.

Reinforcement learning (RL) enables robots to discover navigation policies through trial-and-error interaction with the environment, where safe and efficient movements are reinforced with positive rewards [15]. These methods perform particularly well in unstructured or unfamiliar settings and demonstrate the ability to generalize across new scenarios. Nonetheless, they typically demand substantial training data or prolonged simulation runs, and their lack of formal safety guarantees restricts their application in domains where reliability and safety are critical.

The evaluation of obstacle avoidance methods requires standardized benchmarks and clearly defined metrics. Common indicators include navigation safety (e.g., the frequency of collisions along a trajectory), real-time responsiveness (such as reaction time to moving obstacles), and computational demand (CPU/GPU usage during execution) [7, 11]. Publicly available benchmarks, including Gazebo simulations, TurtleBot field trials, and datasets like KITTI and ScanNet, provide structured environments for consistent and fair comparisons across algorithms. Beyond these, additional performance measures are increasingly emphasized, such as robustness to sensor noise, adaptability to unexpected environmental changes, and energy efficiency – factors that are especially critical for real-time embedded systems and resource-constrained robotic platforms.

This section examines the integration of path planning and obstacle avoidance into unified navigation frameworks capable of functioning effectively in real-world environments. Unlike standalone algorithms, integrated systems synchronize global path planning with local obstacle avoidance, while respecting the constraints of real-time processing and hardware limitations. Such integration allows robots to maintain consistent and reliable performance across a wide range of conditions, from structured indoor spaces to highly dynamic outdoor scenarios.

The typical design follows a hierarchical control architecture, consisting of strategic, tactical, and reactive layers. The strategic layer manages mission-level decisions, the tactical layer generates feasible paths, and the reactive layer ensures immediate responses to unforeseen obstacles. Figure 3 provides a schematic overview of this layered architecture, showing the information flow from raw sensor inputs through planning modules to final motion commands, and highlighting practical implementations across different robotic platforms.

Contemporary robotic navigation frameworks often integrate global and local planning to achieve a balance between long-term trajectory optimality and short-term adaptability. The global planner generates an initial path based on environmental maps, while the local planner continuously refines this trajectory to accommodate dynamic obstacles and sudden environmental changes. This two-tiered approach improves system robustness, making it possible to operate effectively in uncertain or partially known environments [16].

A common example of such integration is the use of A* for global trajectory generation, combined with Dynamic Window Approach (DWA) or Timed Elastic Band (TEB) for local path adjustments.

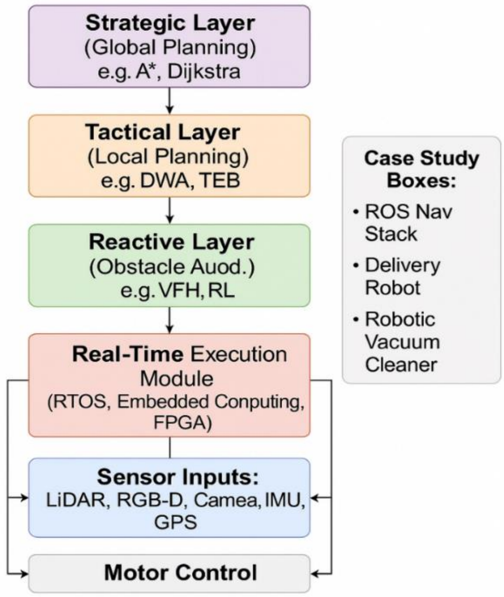

Figure 3. Integrated Path Planning and Obstacle Avoidance Architecture in Mobile Robots

The coordination between these layers is typically governed by a cost function, which balances global efficiency with local responsiveness to ensure safe and efficient navigation:

$$J_{total} = \lambda_g J_{global} + \lambda_l J_{local} \tag{3}$$

Where λ_g and λ_l are weighting factors balancing global and local priorities.

Layered control frameworks organize robotic behavior into distinct levels, enhancing both modularity and system scalability. In a typical configuration, the strategic layer manages mission-level planning, the tactical layer focuses on path generation, and the reactive layer handles real-time obstacle avoidance [17]. This division of responsibilities enables high-level objectives to shape motion goals, while low-level controllers quickly adapt to changes in the environment. Communication between layers is achieved through structured interfaces, ensuring that decisions remain coherent and contextually appropriate. Such hierarchical architectures are widely adopted in both research and industry, as they allow robots to address multiple objectives and process heterogeneous data streams simultaneously, while still upholding real-time safety and maintaining generalizable behavior.

Path planning and obstacle avoidance modules are required to meet strict real-time constraints, particularly when deployed on embedded platforms with limited computational resources. Algorithms must deliver results within fixed execution windows to guarantee timely and safe decision-making. Inevitably, this creates trade-offs between the depth of planning and computational latency, a challenge that is especially pronounced in dynamic environments [18]. To address these limitations, embedded systems often rely on optimized implementations, including pre-computed lookup tables, efficient data structures, and parallelization techniques using GPUs or FPGAs. In addition, real-time operating systems (RTOS) play a crucial role by ensuring deterministic execution and prioritization of critical tasks [19]. Failure to meet these timing requirements may lead to unsafe robot behavior, particularly in high-speed scenarios or applications involving close interaction with humans.

The ROS Navigation Stack serves as a prime example of an open-source, integrated framework that unifies global path planning, local obstacle avoidance, and real-time sensor feedback through a modular node-based architecture [20]. It incorporates costmaps, localization using Adaptive Monte Carlo Localization (AMCL), and a layered planning hierarchy to deliver robust autonomous navigation. Similarly, autonomous delivery robots—such as sidewalk delivery bots—employ comparable architectures but place greater emphasis on interaction with pedestrians, compliance with traffic rules at crosswalks, and cloud-based updates for mapping. In contrast, robotic vacuum cleaners represent highly resource-constrained, embedded implementations, relying on onboard SLAM, simplified reactive planning, and low computational overhead [21]. Collectively, these case studies highlight how integrated navigation systems differ in complexity based on environmental demands and performance objectives, yet consistently follow common architectural principles.

Discussion

A central challenge in robotic navigation lies in planning under uncertainty, where the robot operates without full or precise knowledge of its environment or its own state. Common sources of uncertainty include sensor noise, moving obstacles, localization drift, and incomplete or inaccurate maps [22]. Traditional deterministic algorithms often fail to cope effectively in such scenarios. To address this, probabilistic methods, such as Partially Observable Markov Decision Processes (POMDPs), explicitly account for uncertainty, but they are typically computationally demanding. Current research therefore focuses on developing efficient approximations, risk-aware planning frameworks, and resilient decision-making strategies that balance computational feasibility with reliability. One of the key open problems is the creation of scalable algorithms that can handle uncertainty robustly while guaranteeing safety and task completion, even under ambiguous or incomplete observations.

Path planning in dynamic environments requires robots to continuously adapt to moving obstacles, evolving terrain conditions, and shifting goals. Planners must compute safe and feasible trajectories within strict time limits, often with only partial knowledge of future events [23]. Existing approaches include dynamic re-planning methods such as D* and Timed Elastic Band (TEB), reactive control policies, and predictive modeling frameworks. Nevertheless, maintaining both low latency and trajectory optimality remains a persistent trade-off. The challenge lies in striking a balance between computational efficiency and responsiveness, especially on resource-constrained embedded platforms. Open research directions include the design of lightweight predictive models for motion pattern estimation, the integration of temporal reasoning mechanisms, and methods that ensure stability when obstacles exhibit non-deterministic or adversarial behaviors.

As robots become more common in human-populated spaces, navigation systems must account for human behavior and social conventions. Human-aware navigation requires predicting pedestrian trajectories, maintaining comfortable interpersonal distances, and following socially appropriate behaviors such as yielding or queueing [24]. Ignoring these aspects can result in unsafe, awkward, or disruptive interactions. Current methods leverage crowd simulation models, intent prediction algorithms, and reinforcement learning trained on human demonstrations. Despite these advances, significant challenges remain in developing systems that incorporate cultural sensitivity, contextual reasoning, and interpretability. Future progress will likely involve closer integration of robotics and cognitive science, enabling robots to achieve socially compliant and context-aware navigation in shared environments.

The results underscore three major insights. First, while deterministic methods remain important for their interpretability and guarantees, they cannot address uncertainty and dynamic changes effectively. Second, data-driven approaches, though powerful, raise challenges of safety validation, generalization, and computational demand. Third, integrated architectures – combining global planning with local obstacle avoidance – are emerging as the most practical solutions for real-world robots.

These conclusions align with prior surveys [1,3,5], which similarly argue for hybridization as the future of mobile navigation. However, this study contributes a more detailed taxonomy that not only categorizes algorithms but also evaluates their operational trade-offs in terms of scalability, uncertainty handling, and social compliance.

Looking ahead, future research should prioritize:

- Uncertainty-aware planning through probabilistic reasoning and robust decision-making.
- Human-aware navigation, ensuring safety and social acceptance in pedestrian-rich environments.
- Sim-to-real transfer, allowing learning-based models trained in simulation to generalize reliably in deployment.
- Resource-efficient implementations, particularly for embedded platforms with limited computation.

Conclusion

This survey has provided an extensive examination of path planning and obstacle avoidance techniques in mobile robotics, tracing their evolution, categorization, and integration into practical robotic systems. Classical approaches, such as grid-based searches and potential fields, deliver deterministic and interpretable outcomes, while sampling-based methods like RRT and PRM address scalability in high-dimensional configuration spaces. Optimization-driven techniques and learning-based models expand the design space further, enabling robots to achieve adaptive and resilient navigation in complex, dynamic settings.

For obstacle avoidance, strategies span from reactive mechanisms to predictive models and data-driven frameworks, each offering distinct trade-offs in terms of responsiveness, computational efficiency, and safety. Integrated navigation frameworks, exemplified by the ROS Navigation Stack and various commercial robotic systems, demonstrate how global planning, local control, and real-time sensor fusion can be harmonized into cohesive, deployable solutions.

Despite notable progress, multiple open challenges remain unresolved—particularly in handling uncertainty, achieving robust generalization across domains, ensuring human-aware and socially compliant navigation, and coordinating multi-robot systems at scale. Advances in deep learning, edge computing, and high-fidelity simulation are rapidly pushing the frontiers of autonomous navigation, yet the need persists for systems that are transparent, adaptive, computationally efficient, and safety-assured. Future research must therefore focus on creating planning and avoidance frameworks capable of operating reliably in unpredictable, unstructured environments, while also scaling across diverse robotic platforms and maintaining the trust and safety required for widespread adoption.

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