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Exploring Autonomous Mobile Robot Technologies for Indoor Cleaning: Path Planning, Obstacle Avoidance, and Sensor Integration

Nandan B J*[1], Dr. Vishwanath Koti [2]

Department of Mechanical Engineering, Ramaiah Institute of Technology, Bengaluru-54

Corresponding Author: Nandan B J

Abstract: - *Autonomous mobile robots (AMRs) are changing the way industries like logistics, healthcare, and home cleaning operate, driving efficiency while reducing the need for human labor. A major challenge for AMRs is path planning—finding the best route to navigate their environment while balancing factors like safety, energy use, and time. This task becomes even more complex in dynamic environments, where unforeseen obstacles or changing conditions can require real-time adjustments. In this review, we dive into the different path planning strategies, from global planning to local and multi-objective optimization methods. We also look at how technologies like SLAM, LiDAR, and ultrasonic sensors are helping AMRs navigate more effectively. Finally, we highlight emerging trends and discuss the key challenges that still need to be addressed to improve AMR performance and adaptability in real-world environments.*

1. Introduction

In recent years, mobile robots have become a game-changer across industries like manufacturing, agriculture, and education. The COVID-19 pandemic only accelerated this shift, particularly in sectors like healthcare, security, and food industries, where autonomous systems help reduce the need for human interaction and curb the spread of the virus [1][35]. Unlike traditional automated guided vehicles, Autonomous Mobile Robots (AMRs) are designed to navigate their surroundings independently, without relying on centralized control. This makes them not only more efficient but also more adaptable to varying environments [2][35].

A crucial aspect of any AMR is its ability to plan its path efficiently. Path planning involves determining the best route based on several factors, like time, energy use, and ensuring full coverage of the area. AMR path planning is typically divided into two categories: global path planning, where the robot has complete knowledge of its environment (ideal for static spaces), and local path planning, which uses real-time sensor data to adapt to dynamic or unknown environments. One of the standout features of AMRs is their ability to adjust and recalculate their path whenever unexpected obstacles arise, ensuring smooth, continuous operation while minimizing disruptions.

Technologies like SLAM (Simultaneous Localization and Mapping), LiDAR, and ultrasonic sensors are game-changers in this context. They allow AMRs to "see" and understand their surroundings, helping them avoid obstacles in real-time. These sensors work together to build a map of the environment, making the robot's navigation more precise and efficient. As AMRs expand into more unpredictable environments—like cleaning homes or responding to disasters—they need to be equipped with robust strategies that let them not only avoid obstacles but also adapt to changing conditions.

In this review, we dive into the various path planning techniques that help AMRs navigate these challenges, exploring everything from classical methods to newer multi-objective optimization strategies. We'll also look at the technologies that support AMRs, such as SLAM, LiDAR, and sensor fusion, and how they work together to enhance performance in complex real-world environments. The structure of the paper is as follows: Section 2 discusses path planning strategies; Section 3 focuses on obstacle avoidance techniques; Section 4 covers SLAM-based navigation; Section 5 looks at IoT integration; Section 6 delves into motor control and power management;

Section 7 reviews docking mechanisms; Section 8 addresses real-world deployment challenges; and Section 9 wraps up with future research directions.

2. Path Planning Strategies for AMRs

Path planning is a crucial component for the efficient operation of Autonomous Mobile Robots (AMRs) in various dynamic environments, such as cleaning robots and delivery systems. It involves determining the optimal route based on performance factors like safety, energy efficiency, and coverage.

2.1 Global and Local Path Planning

Global path planning is used in static environments where the robot has full knowledge of the surroundings, allowing for pre-planning. A widely used algorithm is A*, which combines Dijkstra's algorithm and greedy best-first search to determine the shortest path. This method is effective in grid-based environments like warehouses, where obstacles are known beforehand [3]. However, in dynamic environments, local path planning becomes necessary, allowing the robot to adjust its path in real-time using onboard sensor data. Key algorithms for local path planning include Rapidly Exploring Random Trees (RRT), which excels in high-dimensional spaces, and Probabilistic Roadmap Methods (PRM), effective in unstructured environments [4]. Figure 1, shows the decision-making process for global vs local path planning.

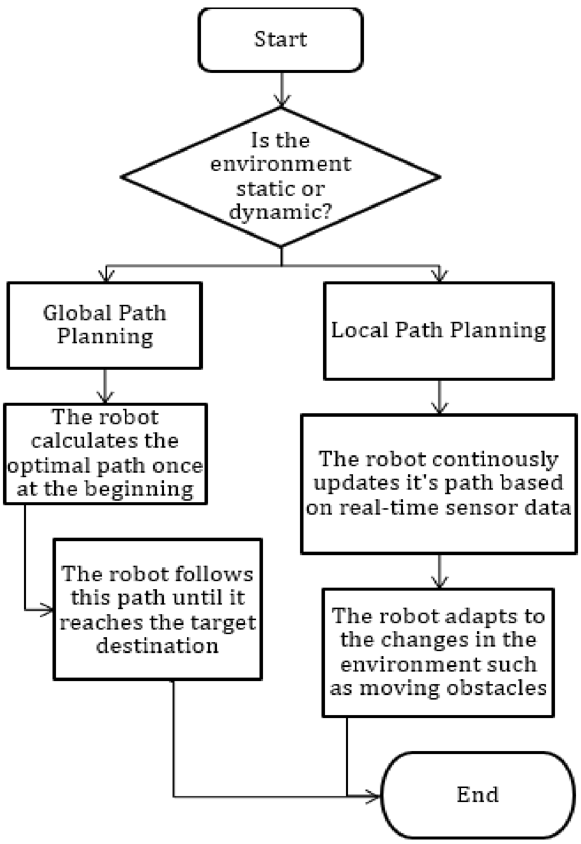

Fig. 1. Path Planning Flowchart

2.2 Multi-Objective Path Planning

MOPP tackles the challenge of optimizing multiple, often conflicting objectives, such as minimizing travel time, reducing energy consumption, and ensuring complete coverage. Giang et al. (2024) proposed the BWave framework, which optimizes robot motion by balancing energy efficiency and coverage, crucial for long-duration autonomous tasks like cleaning. Additionally, Dhouib's (2023) method addresses the trade-off between energy and travel time, adapting in real time to obstacles and battery levels, which is particularly valuable in dynamic environments [5][6]. As demand grows for more energy-efficient robots, integrating machine learning into MOPP will enable adaptive optimization based on environmental feedback and past experiences.

Algorithm	Pros	Cons	Use cases
A*	Optimal solution in static environments	Computationally expensive in large search spaces	Static environments, grid-based maps
RRT	Efficient for high-dimensional spaces, good for dynamic obstacles	Not optimal for static, narrow spaces	Dynamic environments, robot motion planning
ACO	Good for solving coverage problems in unstructured environments	Coverage slowly and computationally expensive for large-scale problems	Multi-robot systems, coverage problems

Table.1: Overview of Path Planning Algorithms

2.3 Complete Coverage Path Planning

CCPP ensures that AMRs can cover an entire area without leaving any spots uncleaned. In cleaning robots, this is critical for efficient operation. Lee et al. (2009) introduced multi-robot systems for large-scale cleaning, dividing the area into sub-regions to reduce cleaning time and ensure redundancy in case a robot malfunctions. Similarly, Liu et al. (2008) presented a dynamic algorithm that adapts to obstacles like furniture or human movement in unstructured environments. The integration of ROS-based systems, as discussed by Zhao et al. (2024), enables real-time adjustments, ensuring no area is missed while navigating dynamic obstacles like humans and furniture [7][8][9].

The strategies for path planning in Autonomous Mobile Robots (AMRs) have evolved to meet the challenges of navigating through both static and dynamic environments. While global path planning remains effective for static environments, local path planning algorithms like RRT and PRM are better suited for dynamic environments where real-time adjustments are necessary. Moreover, multi-objective path planning and complete coverage path planning are essential for ensuring that robots can operate efficiently while covering large areas and optimizing resources. Future research should continue to refine these methods, incorporating machine learning and advanced algorithms to further improve the efficiency and adaptability of AMRs in increasingly complex environments.

3. Obstacle Avoidance in Dynamic Environments

AMRs face significant challenges in dynamic environments, especially when navigating through spaces with moving obstacles like pedestrians or vehicles. Effective navigation in such settings requires a seamless integration of real-time sensing, decision-making algorithms, and control systems. This section reviews key techniques for obstacle avoidance, emphasizing the role of sensors, real-time algorithms, and dynamic obstacle handling.

3.1 Role of Sensors in Obstacle Detection

Sensors are essential for AMRs to navigate dynamically, providing critical data for obstacle detection. LiDAR, ultrasonic, and visual sensors are commonly used, with LiDAR being particularly valuable due to its precision and long-range capabilities. It operates effectively in low-light or cluttered environments, offering consistent measurements regardless of object color or lighting conditions [10]. Mysami et al. (2024) highlight the importance of sensor fusion, combining LiDAR with ultrasonic sensors for improved obstacle detection in large, dynamic spaces. Sensor fusion techniques enhance the AMR's ability to navigate and avoid obstacles in continuously changing environments, improving navigation accuracy [12].

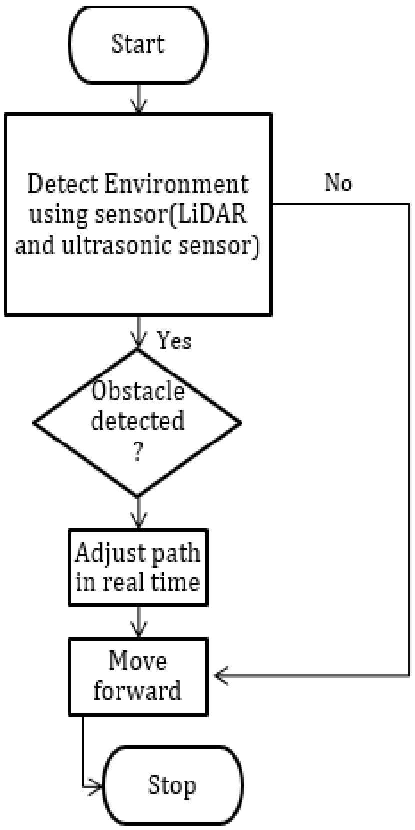

Fig 2: Obstacle Avoidance Flowchart

3.2 Real-Time Obstacle Avoidance Algorithms

For AMRs, real-time obstacle avoidance is crucial, especially in unpredictable environments. Manikandan and Kaliyaperumal (2022) propose a hybrid approach using the Velocity Obstacle (VO) algorithm and Markov Decision Process (MDP), enabling real-time decision-making and trajectory adjustments in crowded environments [12]. This hybrid strategy improves the robot's collision avoidance capabilities while maintaining its target path. Similarly, Abdulov et al. (2018) explore communication-based collision avoidance, where robots share obstacle data with nearby robots. This collaborative strategy enhances overall efficiency by allowing robots to avoid collisions not only using their own sensors but also by leveraging data from surrounding robots [13].

3.3 Dynamic Obstacle Handling

Handling dynamic obstacles, especially those with unpredictable movements, is a challenge for AMRs. Gharajeh and Jond (2022) introduce an Adaptive Neuro-Fuzzy Inference System (ANFIS) that combines fuzzy logic and neural networks to manage dynamic obstacles in real-time. By using ultrasonic sensors to detect obstacle distance, ANFIS computes a steering angle to help the robot avoid collisions and follow an optimal path in cluttered environments [11]. Additionally, Abdulov et al. (2018) demonstrate how the VO algorithm, integrated with communication systems, allows AMRs to predict and avoid potential collisions with moving obstacles by sharing environmental data with other robots [13].

4. SLAM-based Navigation for AMRs

Simultaneous Localization and Mapping (SLAM) is vital for Autonomous Mobile Robots (AMRs), allowing them to build accurate maps of unknown environments and localize themselves within those maps. This capability is essential for navigating dynamic, unstructured environments without relying on pre-existing maps. SLAM has evolved significantly, with advancements improving accuracy, computational efficiency, and real-time performance, particularly for AMRs in various environments, from indoor spaces to large-scale applications.

Originally introduced by Smith, Self, and Cheeseman in 1990, SLAM revolutionized robotics by enabling autonomous navigation without external maps or infrastructure [17]. The system estimates the robot's position and simultaneously constructs a map, which is essential for effective path planning, obstacle avoidance, and decision-making [16]. Recent advancements have expanded SLAM's applicability, integrating sensors like LiDAR, cameras, and IMUs to enhance robustness and adaptability across diverse environments [15].

4.1 SLAM Algorithms

SLAM algorithms can be categorized based on their core principles and sensor types, with grid-based and graph-based SLAM being the primary approaches.

4.1.1 Grid-based SLAM

GMapping, a widely used grid-based SLAM algorithm, is particularly effective for 2D indoor mapping. It combines laser scanner data with odometry to create real-time occupancy grid maps, allowing the robot to navigate efficiently in predictable indoor environments [16].

4.1.2 Graph-based SLAM

Cartographer, developed by Google, represents a more advanced approach capable of generating both 2D and 3D maps. It uses data from multiple sensors, such as LiDAR, IMUs, and RGB-D cameras, to optimize map accuracy and consistency. This graph-based method makes it suitable for large-scale and outdoor environments, offering high adaptability in dynamic and challenging spaces [15][17][18]. Table 2, compares various SLAM algorithms in terms of accuracy, computational efficiency and sensor requirements.

SLAM Algorithm	Accuracy	Computational Efficiency	Sensor requirements
Cartographer	High	Medium	LiDAR + IMU
Hector SLAM	Medium	High	LiDAR
Graph-based SLAM	High	Medium to low	Camera + LiDAR

Table 2: Comparison of Different SLAM Algorithms

4.2 Sensor Integration in SLAM

Sensor fusion is critical for enhancing the performance of SLAM systems. By combining LiDAR, cameras, and IMUs, SLAM systems achieve improved environmental perception, especially in dynamic environments. LiDAR-based SLAM, such as LOAM and LIO-SAM, is widely used for detailed 3D mapping and precise localization, excelling in environments requiring high spatial accuracy [17]. Visual SLAM systems, like ORB-SLAM, use cameras to build maps and estimate the robot's pose, making them ideal for environments where LiDAR data is either unavailable or too costly. RGB-D SLAM systems, which combine RGB cameras with depth sensors, offer a balance between performance and cost, making them suitable for a wide range of applications [15].

Integrating IMUs into SLAM systems enhances localization by providing additional motion data, which is particularly useful in environments where LiDAR or visual data may be compromised by factors like lighting. IMUs help correct drift and improve map consistency, ensuring more accurate navigation [15].

5. IoT Integration in AMRs

The integration of Internet of Things (IoT) in Autonomous Mobile Robots (AMRs) has become a critical aspect of their development, enabling enhanced real-time monitoring, remote control, and efficient task management. IoT technologies allow AMRs to communicate with other devices, share data, and optimize their operations by leveraging real-time information. This section reviews several studies that explore IoT applications in AMRs, particularly in relation to energy management, wireless communication, and resource tracking.

5.1 Remote Control and Monitoring

IoT plays a vital role in the remote control and monitoring of AMRs, enabling efficient operation and performance tracking. Vamsi et al. (2021) [24] developed a ROS-based autonomous disinfectant robot for hospital environments, integrating IoT to collect real-time data and enable remote control of the robot's status and battery levels. This allows for efficient task execution in human-filled environments, reducing direct human interaction [23]. Similarly, Anggraeni et al. (2018) developed a multi-robot communication platform using ROS for managing multiple AMRs within factory settings. The system allows for seamless task coordination, data sharing, and obstacle avoidance, enhancing the collaborative capabilities of AMRs in large-scale operations [22].

5.2 Battery and resource Management

Battery management is critical for the autonomous operation of AMRs. Siqueira et al. (2016) propose a fuzzy logic system to optimize recharging decisions by evaluating the robot’s energy level, target distance, and proximity to the nearest charging station. This IoT-enabled system ensures that the robot recharges only when necessary, extending its operational lifespan and optimizing energy use [21].

5.3 Data Collection and Feedback

IoT significantly enhances data collection and feedback systems for AMRs. Deepa et al. (2021) developed an IoT-enabled ROBOVAC cleaning robot that collects real-time data from various sensors, including ultrasonic sensors for obstacle detection. This data is transmitted to a central system for analysis, enabling the robot to adjust its cleaning tasks, re-route, or return to the charging station based on sensor feedback [23]. By integrating IoT technology, AMRs can adapt to environmental changes and maintain optimal performance without human oversight.

Moving forward, the continued development of IoT systems, sensor fusion, and intelligent algorithms will further optimize the capabilities of AMRs, making them a valuable asset in various applications across industries. Table 3, summarizes IoT integration in AMRs.

Features	Description
Sensor Data Collection	Collects real-time data for navigation and obstacle avoidance.
Energy Management	Enables remote monitoring and task scheduling through IoT platforms.
Remote Control	Enables remote monitoring and task scheduling through IoT platforms.

Table 3: IoT Integration in AMRs

6. Motor Control and Power Management in AMRs

Motor control and power management are vital for ensuring AMRs’ efficiency, maneuverability, and autonomy. Proper motor control guarantees optimal path execution, while effective power management extends the robot’s operational time by utilizing available energy efficiently.

Tarao et al. (2020) proposed an autonomous mobile robot using in-wheel motors integrated directly into the wheels, eliminating gears, reducing mechanical complexity, and improving energy efficiency. These motors are ideal for compact designs and enable better maneuverability in confined spaces and uneven surfaces. However, brushless motors require adaptive control systems to handle their sensitivity to disturbances, and PI controllers can enhance their performance in dynamic environments [25].

Singh et al. (2023) developed a hybrid path planning algorithm combining the Firefly Algorithm (FA) with the Three Path Method (TPM) to optimize motor control. This hybrid method improves both path length and computational efficiency, ensuring motor performance adapts dynamically to avoid collisions and optimize energy consumption in real-time. Their system minimizes energy waste, adjusting motor speed based on path complexity and obstacle presence [26].

Siqueira et al. (2016) proposed a fuzzy logic-based energy management system, enabling the robot to make intelligent recharging decisions based on factors like energy levels and distance to the target or nearest charging station. This system ensures that the robot doesn't waste energy prematurely and operates efficiently in dynamic environments [27].

Anggraeni et al. (2018) highlighted the integration of multi-robot communication in energy management, enabling multiple AMRs to share real-time data on energy consumption and battery levels. This collaborative approach optimizes resource allocation across fleets, improving overall energy efficiency in large-scale operations [28].

7. Docking Mechanisms for AMRs

Docking is crucial for continuous AMR operation, particularly in environments requiring autonomous charging, such as warehouses and security patrols. Zhang et al. (2021) proposed an automatic docking system using LiDAR sensors for autonomous docking, utilizing particle filter positioning for precise alignment and a multi-stage stabilization control method for accurate docking [32]. Similarly, Guangrui et al. (2017) presented a vision-based autonomous docking system using AprilTag markers and ORB-SLAM for 3D pose estimation, achieving a 97.33% success rate in warehouse environments [33].

Ravankar et al. (2015) introduced an Intelligent Docking Station Manager, which dynamically allocates docking stations based on priority, battery levels, and location awareness, ensuring efficient docking even when stations are fully occupied [34].

8. Real-World Challenges in AMR Deployment

8.1 Outdoor Navigation Challenges

Outdoor AMR deployment presents unique challenges such as unpredictable terrain, weather variations, and moving obstacles. Clauer et al. (2021) emphasized integrating robot design with environmental factors to enable AMRs to adapt to changing conditions and navigate effectively in outdoor environments [29]. Path planning and sensor integration are key to ensuring reliable performance in unpredictable outdoor settings.

8.2 Industrial and Factory Environment Challenges

AMRs in industrial settings face challenges like complex factory layouts, moving obstacles, and fluctuating pedestrian traffic. Harapanahalli et al. (2019) argue that adaptive navigation systems that integrate advanced sensing technologies and real-time communication are essential for navigating dynamic factory environments [30]. These systems ensure AMRs can adjust their paths in response to unexpected changes in the environment.

8.3 Safety and Collision Avoidance in Dynamic Environments

Safety is a primary concern in environments shared with humans. Manikandan and Kaliyaperumal (2022) reviewed various collision avoidance strategies, focusing on real-time adjustments to avoid obstacles in crowded environments like hospitals and factories [12]. Abdulov et al. (2018) explored the use of communication-based systems, enabling AMRs to share environmental data, improving navigation and collision avoidance in dynamic environments [13].

8.4 Robustness and Adaptability of Path Planning Systems

AMRs must adapt to unforeseen environmental changes, especially in dynamic settings. Gharajeh and Jond (2022) proposed using Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to handle dynamic obstacles, combining fuzzy logic and neural networks to optimize path planning [11]. LiDAR and camera-based systems further improve adaptability by providing real-time obstacle detection and mapping, even in cluttered environments [10].

8.5 Real-World Case Studies and Application Scenarios

Vamsi et al. (2021) tested AMRs in hospital environments for disinfecting isolation wards, highlighting the importance of dynamic path planning, sensor integration, and real-time decision-making for successful deployment [24]. Similarly, Anggraeni et al. (2018) tested AMRs in industrial environments, demonstrating their ability to adapt to dynamic obstacles and perform tasks autonomously, while noting challenges such as sensor inaccuracies and battery limitations [22].

9. Conclusion

This review has explored the core technologies and challenges surrounding Autonomous Mobile Robots (AMRs), focusing on key areas like path planning, obstacle avoidance, and the integration of systems like SLAM, IoT, and sensor fusion. We discussed how different path planning strategies—global, local, and multi-objective—help AMRs navigate complex, dynamic environments. The integration of technologies like SLAM and IoT has been instrumental in improving the autonomy and adaptability of these robots in real-world applications.

Despite the progress, challenges remain—especially in helping AMRs adapt in real-time, use energy efficiently, and safely navigate environments filled with moving obstacles. Combining AI models with sensor fusion has the potential to take obstacle avoidance and task performance to the next level. As AMRs become more common in industries like healthcare, logistics, and cleaning, the focus of future research should be on improving algorithms, enhancing scalability, and optimizing energy usage to make these robots even more efficient.

AMRs have the ability to reshape industries by making processes faster, more efficient, and reducing the need for human labour. By overcoming current hurdles and harnessing new technologies, the future of AMRs looks promising—creating smarter, safer, and more capable robots that can work seamlessly across different environments.

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