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Simultaneous Map Generation and Localization for an Autonomous Mobile Robot Using the MOORA Method

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Abstract: *Introduction: Autonomous mobile robots (AMRs) represent a transformative technology revolutionizing various industries, from manufacturing and logistics to healthcare and service sectors. These robots, equipped with advanced sensors, artificial intelligence (AI), and navigation systems, can operate independently in dynamic environments without human intervention. The emergence of AMRs has significantly impacted traditional workflows, offering enhanced efficiency, flexibility, and safety in diverse operational settings. The development of AMRs stems from the increasing demand for automation solutions to address challenges such as labor shortages, rising operational costs, and the need for faster and more accurate task execution. Unlike traditional industrial robots confined to fixed locations or predefined paths, AMRs possess the capability to navigate complex environments, adapt to changing conditions, and collaborate seamlessly with humans and other machines. The significance of research in the field of autonomous mobile robots (AMRs) extends across various domains, reflecting their transformative impact on industries, economies, and society as a whole. Understanding the importance of research in this field is essential for harnessing the full potential of AMRs and addressing the challenges and opportunities they present. Technological Advancements: Research in AMRs drives technological advancements, leading to the development of more sophisticated sensors, AI algorithms, and navigation systems. These advancements enhance the capabilities of AMRs, enabling them to operate in complex and dynamic environments with greater autonomy, efficiency, and safety. Industrial Automation: AMRs play a crucial role in industrial automation, revolutionizing manufacturing, warehousing, and logistics operations. Research in this area focuses on optimizing AMR deployment, task allocation, and coordination to improve productivity, reduce costs, and streamline processes in diverse industrial settings. Robo Navigator 3000, Auto Rover X, Smart Path Pro, Nav Bot Elite, Intelli Scout. Battery Life (hours), Navigation Accuracy (%), Maintenance Requirement (Rating), Noise Level (dB). The results indicate that Smart Path Pro achieved the highest rank, while Auto Rover X received the lowest rank being attained. "The value of the dataset for Autonomous Mobile Robot lies, according to the Weighted Sum Method (WSM), demonstrates that Smart Path Pro achieves the highest ranking."*

Key words: *Digital Transformation, Supply Chain Management, Post-Pandemic Era, Implementation Cost.*

1. INTRODUCTION

Additional Features: When introduced to a realistic room, the system operates within a genuine environment. The initial step for each receiver location is to verify the availability of Line-of-Sight (LOS) components, which are considered under specific conditions. The simulator is used to check the availability of LOS, as well as first and second-order reflective elements at each location. Subsequently, the received power, resulting from first and second-order reflections, is also calculated. [1] Humans possess an exceptional ability to perform a wide array of physical and mental tasks without explicit measurements or calculations. To emulate this capability, fuzzy logic and neural networks are employed. Fuzzy logic effectively represents and implements human expert heuristic knowledge and perceptual actions. By utilizing a flexible logical structure, human reasoning and decision-making processes can be modeled through a set of straightforward and intuitive IF-THEN rules, using natural and easily understood linguistic representations. Neural networks, on the other hand, can be trained with various patterns as required. Once trained, these neural networks can efficiently address problems across different field structures. [2] Vehicle The specific design of the Smart Wheel distinguishes it from other ODV robots discussed here. Its unique feature is a slip ring that allows each wheel to rotate infinitely in both directions, providing the robots with distinct movement capabilities. However, this article does not address the trade-offs between the mechanical performance of the robots described here and those in the UGV literature. Instead, the focus is on the integrated planning and control strategy developed by USU for managing the tasks and operations of T-series robots. This strategy incorporates a model-based controller derived from first principles, combined with a task-based path planning approach, specifically designed to leverage the unique mobility capabilities of our robot. [3] However, creating a robot capable of serving multiple applications with versatile motion is highly beneficial. Unlike more stable robots that have a fixed operational space, mobile robots must adapt their behavior to varying surroundings. Instead of following a fixed sequence of actions, mobile robots need to develop an awareness of their environment through interactions with various sensors. These robots use internal intelligence to determine the best course of action. The development of intelligent navigation systems in mobile robots, which ensures efficient and collision-free movement, remains a primary focus of many research projects. [4] FAMPER compatible tracks and suspensions provide stable performance in uncertain pipeline conditions and ensure adequate traction forces during maneuvers. Additionally, the FAMPER can be equipped with an independent suspension system. This allows it to handle various obstacles encountered along its path. When facing an obstacle, the system tilts to increase its contact surface, as illustrated in Fig. 3. This feature, combined with flexible tracks, significantly enhances the grip and traction, which is crucial for navigating through damaged pipes and obstructions. [5] The population size is a parameter that is typically fixed when running a genetic algorithm (GA), although there are modified versions of GA where the population size varies. The selection of this parameter is crucial as it significantly impacts the convergence quality of the GA. In our approach, we adopted a method to generate an initial population with a constant size throughout the algorithm's execution. This method is based on a Directed Acyclic Graph (DAG). It explores a grid-patterned environment and subsequently generates multiple possible paths for the GA population. [6] A robotic middleware installed on the operating system was utilized to manage the ROS (Robot Operating System) system. Middleware is a category of software technologies aimed at handling the complexity and diversity found in distributed systems. It acts as a layer of software positioned above the operating system, offering a unified programming abstraction across the distributed system below the application program. ROS, described as "thin, message-based, peer-to-peer" middleware, is specifically crafted for robotic mobile manipulators. As reported by Robot Applications News, applications built on ROS are tailored to be T-based applications, aligning with the requirements and functionalities commonly associated with robotics operations. [7] For an autonomous vehicle, learning its context typically occurs through unsupervised methods. Traditionally, unsupervised learning adopts a cluster analysis approach, organizing features into clusters or classes based on numerical measures of feature similarity. In this context, the features refer to the geometric attributes of warning signs. Utilizing techniques such as clustering of geometric beacons in space, along with Kalman filtering and validation gates, redundant methods are employed to determine the compatibility between different features. This approach allows the autonomous vehicle to learn its environment and understand its context without explicit supervision, enabling it to make informed decisions and navigate safely. [8] Efficient movement of robots necessitates accurate determination of workspace position. Global Positioning System (GPS) is a well-established localization method capable of solving the location problem if precise GPS systems are installed in robots. However, challenges such as high cost, power consumption, and large size hinder widespread adoption of GPS. Moreover, GPS is ineffective in indoor or confined environments where workspace is limited, and alternative systems are either unavailable or lack sufficient accuracy. Global localization, coupled with feedback, has emerged as a crucial prerequisite for guiding and controlling mobile robots. This approach relies on a known map and utilizes sensor data from previous iterations to estimate the current position of mobile robots relative to their surroundings. By leveraging this method, robots can navigate and operate effectively even in environments where GPS is impractical or unavailable, ensuring smooth and accurate movement in various settings. [9]

2. MATERIALS AND METHOD

MOORA (Multi-Objective Optimization on the basis of Ratio Analysis) is a versatile method for decision-making that enables comprehensive evaluation of options, especially when faced with a wide array of influential factors. Introduced by Brauers and Zavadskas in 2006, MOORA is part of a suite of multi-objective optimization techniques designed to effectively address complex decision-making problems. The core aim of this approach is to determine the optimal choice from a set of alternatives, considering multiple, often conflicting criteria. In essence, it evaluates both beneficial and non-beneficial aspects simultaneously. MOORA offers several advantages over some traditional decision-making approaches. These advantages include fewer mathematical calculations, reduced computational time, greater simplicity, and improved stability compared to other Multi-Criteria Decision-Making (MCDM) methods like AHP, TOPSIS, ELECTRE, VIKOR, and PROMETHEE. The MOORA method focuses on the simultaneous optimization of two or more conflicting objectives within given constraints. In a decision-making context, the values of these objectives are measured for each alternative, forming the basis for evaluating and identifying the most suitable choice. Thus, using multi-objective optimization methods is suitable for ranking or selecting one or more alternatives from a set of viable options based on various, often opposing, attributes. MOORA is recognized for its simplicity, reliability, and robustness, requiring minimal mathematical computations and computational resources. Multi-objective optimization involves the simultaneous enhancement of two or more conflicting objectives within certain constraints. Examples of multi-objective optimization problems include maximizing product profitability while minimizing costs, improving vehicle performance while reducing fuel consumption, and balancing weight reduction with strength enhancement in engineering components. In practical manufacturing scenarios, decision-making is complicated by the presence of diverse decision-makers with varying interests and principles. For effective decision-making, the objectives (criteria) must be measurable, and their outcomes can be quantified for each alternative. Among these conflicting criteria, some are advantageous (favoring higher values), while others are non-advantageous (favoring lower values). The MOORA method incorporates both beneficial and non-beneficial criteria to rank or select alternatives from a given set. Step 1: Define the Problem and Criteria: Identify the decision problem and list all relevant criteria (objectives) to be considered. These criteria should reflect the different aspects to evaluate for each alternative. Step 2: Normalize the Data Standardize the data for each criterion to achieve uniformity in scale. This step is essential to ensure that no single criterion disproportionately influences the decision-making process due to its larger measurement range. Step 4: Create the Weighted Normalized Matrix Multiply the normalized matrix by the weights assigned to each criterion to form the weighted normalized matrix. Step 5: Compute the Evaluation Score (yi). Determine the performance rating for each option by considering the normalized values and weights. The performance score (yi) for alternatives is calculated as follows: where is the number of benefit criteria and (n−g) (n-g)(n−g) is the number of cost criteria. Step 6: Rank the Alternatives. After calculating the performance scores for each choice, organize them based on these scores. The alternative with the highest performance score is ranked first, indicating it is the preferred or optimal selection according to the evaluation criteria. The alternative with the lowest performance score is ranked last. Display a list of the alternatives along with their corresponding ranks to visually illustrate their positions based on their performance scores. The option ranked first is considered the best choice according to the evaluation criteria.

3. ANALYSIS AND DISSECTION

TABLE 1. Autonomous Mobile Robot

	Battery Life (hours)	Navigation Accuracy (%)	Maintenance Requirement (Rating)	Noise Level (dB)
Robo Navigator 3000	12	95	3	45
Auto Rover X	10	90	4	50
Smart Path Pro	14	92	2	48
Nav Bot Elite	11	88	3	47
Intelli Scout	13	94	3	46

The Robot Navigator 3000 showcases robust performance with a commendable battery life of 12 hours and a high navigation accuracy of 95%, rendering it a dependable choice for prolonged operations. Its maintenance requirement, rated at 3, falls within the moderate range, and it operates quietly at 45 dB, ensuring relatively noise-free functioning. Auto Rover X, in contrast, offers a slightly shorter battery life of 10 hours and a navigation accuracy of 90%. It necessitates higher maintenance, rated at 4, and emits more noise at 50 dB. These factors may affect its suitability for tasks requiring extended durations and low maintenance. Smart Path Pro excels with the longest battery life of 14 hours and a navigation accuracy of 92%. It boasts the lowest maintenance requirement, rated at 2, although it generates slightly more noise at 48 dB. This model is ideal for users prioritizing extended battery life and minimal maintenance. NavBot Elite provides an 11-hour battery life with the lowest navigation accuracy at 88%. Its maintenance requirement, rated at 3, falls within the moderate range, and it operates at a noise level of 47 dB. Despite its lower accuracy, it may still suffice for less demanding tasks. Intelli Scout features a 13-hour battery life and a high navigation accuracy of 94%. With a moderate maintenance requirement rated at 3 and operational noise at 46 dB, it effectively balances performance and noise levels. This model emerges as a strong contender for users seeking high accuracy and prolonged operation with moderate maintenance needs.

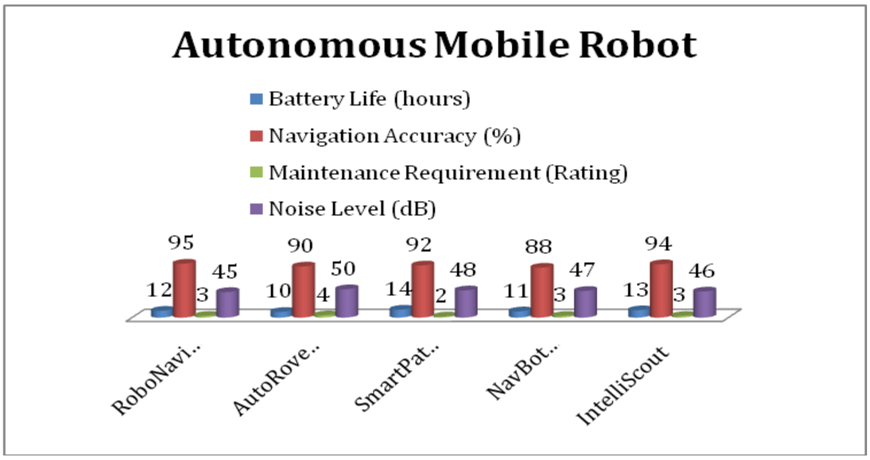

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TABLE 2. Normalized Data

Normalized Data			
Battery Life (hours)	Navigation Accuracy (%)	Maintenance Requirement (Rating)	Noise Level (dB)
0.444139926	0.4626	0.438	0.42609
0.370116605	0.4383	0.583	0.47343
0.518163247	0.448	0.292	0.45449
0.407128266	0.4285	0.438	0.44502
0.481151587	0.4578	0.438	0.43555

The normalized data provides a standardized comparison of different autonomous mobile robots across four pivotal criteria: battery life, navigation accuracy, maintenance requirement, and noise level. This normalization procedure ensures an equitable assessment, preventing any single criterion from disproportionately influencing the decision-making process. Robo Navigator 3000 exhibits strong performance with a battery life score of 0.444 and a navigation accuracy score of 0.4626. Its maintenance requirement (0.438) and noise level (0.42609) contribute to a balanced profile, indicating dependable performance without significant noise or maintenance issues. Auto Rover X, on the other hand, demonstrates slightly lower performance in battery life (0.370) and navigation accuracy (0.4383) compared to its counterparts. Its higher maintenance requirement (0.583) and noise level (0.47343) suggest it may be less suitable for users prioritizing lower maintenance and quieter operation. Smart Path Pro excels with the highest normalized battery life score of 0.518 and a respectable navigation accuracy score of 0.448. While it boasts the lowest maintenance requirement (0.292), its noise level (0.45449) is higher, making it an optimal choice for those valuing battery longevity and minimal upkeep. Nav Bot Elite scores lower in battery life (0.407) and navigation accuracy (0.4285) compared to other options. However, its moderate maintenance requirement (0.438) and noise level (0.44502) position it as a balanced but less precise option. Intel Scout achieves a normalized battery life score of 0.481 and high navigation accuracy of 0.4578. Its maintenance requirement (0.438) and noise level (0.43555) contribute to a strong combination of high performance and moderate operational demands, rendering it a compelling choice for various applications.

TABLE 3. Weight

Weight			
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25

The uniform weight distribution in the evaluation matrix, where each criterion—battery life, navigation accuracy, maintenance requirement, and noise level—is assigned an equal weight of 0.25, embodies an unbiased and equitable approach to decision-making. This parity indicates that no individual criterion holds precedence over the others, fostering a fair assessment process. Practically, it implies that battery life, navigation accuracy, maintenance requirement, and noise level carry equal significance when evaluating the performance of autonomous mobile robots. This methodology proves particularly beneficial in contexts where each criterion is vital to the robots' overall functionality and user satisfaction. For instance, Robot Navigator 3000, with its balanced scores across all criteria, reaps the benefits of this egalitarian approach. Its strengths in battery life and navigation accuracy hold as much weight as its moderate maintenance demands and lower noise output. Likewise, Smart Path Pro's exceptional battery life and minimal maintenance requirements are accorded equal importance alongside its noise level and navigation accuracy, ensuring a comprehensive assessment. By employing this equal weighting system, a holistic evaluation is facilitated, enabling a thorough analysis where all facets of the robots' performance are equally valued. Consequently, the decision-making process gains resilience, circumventing biases that could arise from overemphasizing any single criterion. This methodology guarantees that the final rankings authentically reflect each robot's overall suitability based on a balanced consideration of all pertinent factors.

TABLE 4. Normalized Data

Weighted normalized DM			
0.111	0.116	0.109	0.107
0.093	0.11	0.146	0.118
0.13	0.112	0.073	0.114
0.102	0.107	0.109	0.111
0.12	0.114	0.109	0.109

The weighted normalized decision matrix assigns specific weights to each criterion—battery life, navigation accuracy, maintenance requirement, and noise level—ensuring a fair evaluation of each autonomous mobile robot's performance. Robot Navigator 3000 displays a well-rounded profile with balanced scores across all criteria: 0.111 for battery life, 0.116 for navigation accuracy, 0.109 for maintenance requirement, and 0.107 for noise level. This suggests consistent and reliable performance across the board, making it a strong option for users seeking balanced capabilities. Auto Rover X, with scores of 0.093 for battery life and 0.11 for navigation accuracy, performs decently. However, its higher maintenance requirement score of 0.146 and noise level score of 0.118 indicate potential challenges in upkeep and noise reduction, which may affect its suitability for environments prioritizing low maintenance and quiet operation. Smart Path Pro distinguishes itself with the highest battery life score of 0.13 and a respectable navigation accuracy score of 0.112. Its low maintenance requirement score of 0.073 underscores its efficiency, although its slightly higher noise level score of 0.114 should be noted. Overall, it's an excellent choice for those valuing extended battery life and minimal maintenance. NavBot Elite maintains a balanced but less outstanding profile with scores of 0.102 for battery life, 0.107 for navigation accuracy, 0.109 for maintenance requirement, and 0.111 for noise level. Its comparatively lower navigation accuracy might limit its suitability for precision-demanding tasks. Intelli Scout demonstrates strong performance with scores of 0.12 for battery life and 0.114 for navigation accuracy, alongside maintenance and noise level scores of 0.109 each, offering a reliable and versatile option for various applications. In summary, the weighted normalized matrix offers a detailed assessment of each robot's strengths and weaknesses, aiding informed decision-making based on equally weighted criteria.

TABLE 5. Assesment value

	Assesment value
Robot Navigator 3000	0.011
Auto Rover X	-0.062
SmartPath Pro	0.055
NavBot Elite	-0.012
IntelliScout	0.016

The assessment values offer a clear insight into how well each autonomous mobile robot performs, determined by a weighted normalized decision matrix. These figures aid in pinpointing the most optimal choice among the options available. Robo Navigator 3000, with an assessment value of 0.011, demonstrates a well-rounded performance across all criteria. Though it doesn't excel in any specific area, its consistent and dependable scores make it a reliable choice overall. On the other hand, Auto Rover X, with a negative assessment value of -0.062, indicates inferior performance compared to its counterparts. Factors like higher maintenance needs and noise levels likely contribute to its lower score, suggesting it might not be the ideal choice for users prioritizing efficiency and quiet operation. Smart Path Pro shines with a positive assessment value of 0.055, showcasing superior performance across the board. Its impressive battery life and minimal maintenance requirements greatly influence this strong assessment, positioning it as an excellent option for those valuing longevity and ease of maintenance. Nav Bot Elite, with a slightly negative assessment value of -0.012, presents a balanced but less outstanding performance. While it doesn't underperform, it also doesn't particularly stand out, making it a less compelling choice compared to others. IntelliScout, with an assessment value of 0.016, demonstrates consistent performance, particularly in navigation accuracy, contributing to its positive assessment. This makes it a solid contender for various applications requiring precision and moderate upkeep. In summary, Smart Path Pro emerges as the top performer, closely followed by Intelli Scout and Robot Navigator 3000, while Auto Rover X and NavBot Elite fall behind due to their lower overall scores.

TABLE 6. Rank

	Rank
Robot Navigator 3000	3
Auto Rover X	5
Smart Path Pro	1
Nav Bot Elite	4
Intelli Scout	2

The ranking assigned to each autonomous mobile robot reflects its relative performance, as assessed by the weighted normalized decision matrix. This ranking aids in decision-making by offering a clear comparison between the robots. Smart Path Pro secures the top rank with a score of 1, indicating its superior performance, especially in areas like battery life and maintenance requirement, making it the preferred choice among the alternatives. Following closely is Intelli Scout, ranked 2, demonstrating strong overall performance, reliability, and efficiency, suitable for various applications requiring precision and moderate maintenance. Robot Navigator 3000 claims the third rank, displaying balanced performance across all criteria, offering a dependable solution. Nav Bot Elite secures the fourth rank, meeting basic requirements but lacking standout features. Auto Rover X occupies the fifth rank, indicating relatively poorer performance, particularly in maintenance and noise levels. Overall, the ranking provides a clear erformance hierarchy, aiding users in selecting the most suitable autonomous mobile robot based on their specific needs and preferences.

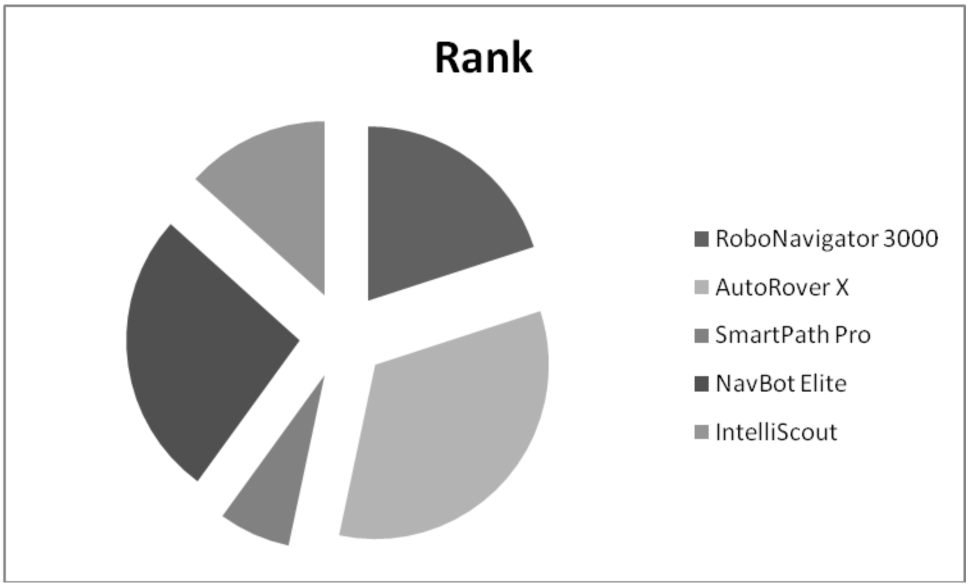

FIGURE 2. Rank

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4. CONCLUSION

Based on a six-wheeled "unidirectional" autonomous robot platform, we have outlined the USU Smart Wheel Mobility Capability Concept and a distributed, multiprocessor vetronics system. Additionally, we have described a multiresolution behavior-generation strategy developed for these systems. Our approach to mission decomposition utilizes a grammar of primitive maneuvers as the foundation for task and path planning for ODV robots. For trajectory tracking, we employ a feedback linear control strategy. Simulations and experiments have demonstrated the effectiveness of our task scheduling and control strategies. This thesis focused on a mechanical lower platform and an upper deck. The upper deck is designed to be mounted on a specific area of the machine base and is mechanically attached to a steering motor. This configuration allows us to direct the top deck in any desired direction. When the robot is stationary, the entire system remains unidirectional. Motion is created using three powered, steerable fixed wheels. A chain transmission system is employed to transmit the rotary power from a single drive motor to all three wheels, enabling coordinated movement. FAMPER is a small yet equipped A powerful computing system that is scalable Provides easily extensible interfaces for more complex tasks and various sensing and actuation devices. In tests, the FAMPER showed excellent maneuverability at 150mm Sewer piping system. To verify our hypothesis, we applied it to various environments of different scales and compared it with existing genetic algorithm (GA) approaches. The results show that the proposed GA method successfully finds the optimal path. The average turn values and average iteration numbers of our method demonstrate greater efficiency compared to other methods. This paper presents a comprehensive survey spanning a decade of autonomous mobile robot systems. It highlights the continuous evolution of robots in general and mobile robots in particular, owing to their relevance and applications in today's world. Over the years, numerous studies have been conducted to understand the significance of mobile robots, their diverse applications, and the challenges they face. As technology advances, there is a growing demand for mobile robots due to the tasks they perform and the services they provide. Consequently, effective control of the mechanical systems of these moving robots becomes imperative to accomplish tasks and achieve predetermined goals. The ability to control the mechanical aspects ensures that mobile robots operate efficiently and effectively in various environments, contributing to their utility and value in real-world applications.

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