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Review of Research Status of Autonomous Mobile Robot Environment Recognition and Path Planning Algorithms

Fan Luxin[1*], Tang Sai Hong[1*], Zhao Ruixin[1*], Shen Jiazheng[1*], M Ariffin[1], MIS Ismail[1]

[1] Faculty of Engineering, Universiti Putra Malaysia, Selangor, Malaysia

*Corresponding Author: gs59924@student.upm.edu.my , saihong@upm.edu.my , gs63714@student.upm.edu.my , gs63073@student.upm.edu.my

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Abstract: *The convergence of Industry 4.0 and the challenges posed by the COVID-19 pandemic amplify the growth prospects and market reach of autonomous mobile robots. This paper elucidates the current research landscape and forward-looking trajectory concerning perception systems for autonomous mobile robots. It advocates a future-oriented development path grounded in the utilization of vision sensors and multi-sensor configurations to enhance environmental recognition. Addressing the imperative of bolstering environmental discernment in intricate settings remains a priority. An emerging area of interest pertains to terrain prediction algorithms. The ensuing section deliberates upon the merits and demerits intrinsic to distinct robot path planning algorithms. These algorithms can be categorized into global path planning algorithms, entrusted with charting optimal overarching courses, and local path planning algorithms, designed to navigate impediments and effect localized route refinements. Envisioning the future, the maturation of robot path planning algorithms is poised to embrace multi-algorithm collaborative applications.*

Keywords: mobile robot, environmental perception, Path Planning, algorithm

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1. Background of Study

The pervasive impact of Industry 4.0 extends across diverse sectors, encompassing education, energy, agriculture, healthcare, logistics, and more. This phenomenon represents a confluence of disruptive technologies, including 3D printing, artificial intelligence, augmented reality, big data, blockchain, cloud computing, drones, the Internet of Things, nanotechnology, robotics, simulation technology, and synthetic biology (Bongomin et al., 2020). The synergy among these technologies has yielded substantial enhancements not only in process efficiency, automation, and quality, but also in economic dynamics and industrial scale (Bigliardi et al., 2019; Fratini et al., 2020). Within this paradigm, machinery and equipment are interconnected within a unified cloud framework, enabling both standardized configurations and expedited decision-making autonomy for individual machines in emergency situations (Alcacer & Cruz-Machado, 2019). Moreover, as the world undergoes an extensive digital transformation, this trajectory is poised to engender heightened value addition.

The declaration of COVID-19 as a pandemic by the World Health Organization (WHO) triggered profound disruptions in global economic and social dynamics. In response to the imperative of social distancing to mitigate the disease's impact, robots and artificial intelligence have assumed a progressively pivotal role. A multitude of individuals and enterprises have embraced robotics as a strategic response to the multifaceted challenges engendered by the pandemic. Within this landscape, service robots emerge as invaluable instruments for facilitating rigorous adherence to physical and social distancing protocols. They empower both individuals and organizations to uphold these imperative measures. Furthermore, Service robots can be a useful tool to ensure high levels of physical and social distancing during the pandemic. Many companies need to use robots to provide social connections and counteract the negative effects of physical contact (Seyitoglu & Ivanov, 2021).

Within the context of Industry 4.0 and the backdrop of the COVID-19 pandemic, autonomous mobile robots emerge with amplified growth prospects and an expansive market landscape. At the heart of these robots lie two pivotal components: the perception system and the path planning algorithm. This paper serves to elucidate the prevailing research landscape encompassing perception systems and path planning algorithms for mobile robots.

2. Research Status of Mobile Robot Perception System

Due to the capability of mobile robots to function in intricate and dynamic outdoor settings, there exists a pressing requirement to enhance their perception and recognition capacities concerning the environment. This enhancement is essential to augment their overall adaptability in various environmental conditions. However, only a handful of prototypes of mobile robots published by research institutions have studied environmental awareness in indoor environments.

2.1 Development Status of Mobile Robot Environment Perception System

Environmental perception and analysis pose significant challenges in the field of robotics. This study encompasses the robot's capacity to comprehend its surroundings, as well as its proficiency in recognizing and articulating potential factors that may impact task execution. The technology for robot environment perception, reliant on sensors, has garnered extensive research attention. Typically, the identification and modeling of the environment involve mathematical techniques, entailing the processing and extraction of data obtained from sensors. The bedrock of scene recognition and modeling serves as the cornerstone for enabling mobile robots to undertake tasks encompassing motion planning and navigation.

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The measurement process typically entails an initial pre-calibration of the sensor system to align its internal parameters, such as the camera's focal length or the orientation of the laser diode. Furthermore, the integration of sensor data necessitates external calibration for achieving sensor fusion. This implies that the spatial coordinates of each sensor are established within a common frame of reference. This becomes especially significant when dealing with sensors mounted on nonrigid frameworks or platforms. During the robot's operation, continual adjustments are imperative, involving real-time updates to both internal and external calibration parameters (Chai et al., 2014).

Sensor information fusion technology has found extensive application in the realms of scene recognition and modeling. Information fusion primarily manifests through the comprehensive amalgamation of data from multiple sensors, facilitating the synthesis of environmental information and the attainment of a harmonized representation of the external environment. This synthesis encompasses original data, data characteristic fusion, and object integration, all capable of achieving varying degrees of sensor information fusion. Noteworthy methodologies for multi-sensor fusion encompass the weighted average method (Liu & Zhang, 2022), Bayesian estimation (Li & Tang, 2022), Kalman filter (Li et al., 2020), neural networks, and fuzzy inference (Bai et al., 2017).

The path planning and attitude control strategies of mobile robots are typically executed within specific external environments and under constraint conditions. As a result, the proficiency of the visual system in representing the environment holds significant value in enhancing the mobile robot's adaptability to its surroundings. Generally, the system's capacity to generate two-dimensional environmental maps is limited to highly structured workspaces or flat and regular terrain (Chen et al., 2019). The establishment of a geometric model for the external environment serves as the foundational element for tasks including robot motion control, path planning, and terrain recognition. This encompasses activities such as the real-time positioning and construction of maps for both indoor and outdoor mobile robots. To minimize the discrepancies in environment modeling, the algorithm employs a closed-loop detection approach, thereby adjusting the robot's online map as it traverses historical areas along its path. To enhance the accuracy of map creation and facilitate navigation across extensive scenes, a fusion of geometric and global topology modeling is frequently employed (Cheng et al., 2017; Sun et al., 2017).

2.2 Development Trend of Environment Perception System for Mobile Robots

In recent years, the advancement of mobile robots has been rapidly accelerating. Their mechanical architecture, control strategies, methodologies, and the integration of vision systems have been progressively refined. Building upon these advancements, addressing challenges related to robot motion strategy, autonomous navigation, obstacle avoidance, path planning efficiency, terrain recognition, and terrain classification within intricate environments has gained significant prominence in machine vision research. This focus stems from the following key aspects:

Through the synergistic collaboration of multiple sensors, the mobile robot's environmental perception system can achieve heightened precision. Diverse sensor configurations will be tailored to suit varying environmental conditions. Research will center around harnessing combinations of 2D terrain geometry information, 3D point cloud data, depth information, image color data, texture details, visual odometry, and other pertinent data to refine terrain modeling and feature extraction methodologies (Adarsh & Ramachandran, 2020; Livatino et al., 2021).

To enhance the efficiency and accuracy of path planning for mobile robots, it is imperative to delve into the development of environment recognition and path planning algorithms specific to different terrains, mobile robot classifications, and application scenarios (Moysis et al., 2020; Saeed et al., 2022).

The bedrock of upper-level algorithms, terrain prediction, and classification will emerge as focal points within vision research (Lopez-Arreguin & Montenegro, 2021).

3. Research Status of Path Planning Algorithms for Mobile Robots

Global path planning determines the optimal route from start to finish, considering the overall environment, while local path planning handles the immediate navigation around obstacles and unforeseen changes in the environment. Together, these two layers of planning ensure that autonomous vehicles and robots can navigate successfully and safely in complex and dynamic environments.

3.1 Research Status of Global Path Planning

The attainment of an optimal path through global path planning necessitates a substantial capacity for environment modeling, extensive computational resources, and often suffers from suboptimal real-time performance. Scholars have proposed several effective algorithms for global route planning. Common methods for route planning include:

Dijkstra algorithm: The fundamental concept involves designating the starting point as the source node, identifying the nearest vertex to this source node, and subsequently extending this vertex in the capacity of the source node until it reaches the destination node. As this algorithm encompasses a path that traverses all nodes, it is highly probable that this path is the shortest. Nonetheless, due to the multitude of nodes traversed along the path, operational efficiency is compromised (Halloush, 2016).

A* algorithm: The algorithm is grounded in path planning and is hinged on a heuristic function. Upon configuring this heuristic function, the process involves evaluating and comparing the cost associated with each extended node. The least costly node is then selected and incorporated into the path, continuing until the target point is integrated. The A* algorithm is well-suited for scenarios entailing numerous path nodes. However, it harbors the drawback of not consistently guaranteeing the discovery of the shortest path solution. Moreover, the A* algorithm exhibits extended computational time, leading to suboptimal planning efficiency and difficulty in fulfilling real-time demands (Halloush, 2016; Reza et al., 2013).

D* algorithm: The D* algorithm enhances the planning efficiency initially established by the A* algorithm, however, it's inapplicable for dynamic path planning. In 1994, Stentz introduced the D* algorithm to address path-planning challenges within dynamic environments (Stentz & Ieee, 1994). This approach obviates the necessity for pre-existing map testing or path exploration via environmental sensing. As the environment undergoes changes, modification of certain nodes' weights suffices to determine the shortest path, thus enhancing search efficiency. The D* algorithm aptly caters to route planning in dynamic environments, yet it comes with limitations such as excessive turns, uneven routes, proximity to obstacles, and diminished safety considerations.

Artificial Neural Network (ANN): Its core idea is a simulated membership pattern-matching algorithm for the human brain. In recent times, neural networks have garnered extensive adoption in the domain of mobile robot path planning. Adopting an information processing perspective, the neural network within the human brain is conceptually modeled and configured into diverse networks based on distinct connection modes. In operational terms, environmental information serves as neuron inputs, while algorithmic outputs encompass the steering, power, attitude, speed, and mode necessary for controlling robot movement (Jing et al., 1997; Shibata et al., 1993). However, achieving an optimal training outcome proves challenging due to the inherent complexity of dynamically changing environments, which impedes comprehensive map information acquisition. Moreover, the escalating complexity of neural network structures results in protracted convergence times, thus thwarting the assurance of an optimal solution.

Genetic Algorithm: This intelligent algorithm treats the path planning of unmanned vehicles akin to a biological evolution problem, grounded in the genetic processes of natural selection and species evolution. Renowned for its strong global optimization capability and parallelism, this algorithm has exhibited notable efficacy in both single-robot and multi-robot path planning scenarios (Lebedev et al., 2005; Qu et al., 2013). In the genetic algorithm, the initial points—termed path points—are initially generated at random. Subsequently, the fitness function evaluates the adaptability of each path point, while simultaneously calculating the probability of natural selection for these points. Selected path points then undergo crossover and mutation, giving rise to novel path points through evolution. This iterative process continues until an optimal path is generated or a predetermined number of iterations is reached. This algorithm offers benefits such as randomness, parallelism, robustness, and scalability, all without the need for additional auxiliary information. However, it does come with drawbacks such as reduced efficiency and a higher number of parameters in comparison to other intelligent algorithms. Moreover, the parameter selection process is reliant on human experience, demanding additional time to attain the most optimal solution (Gong, 2019).

Fuzzy control algorithm: The Fuzzy control algorithm represents a path-planning approach reliant on sensor-derived information. Notably, it operates devoid of the need for exact mathematical route planning models or intricate calculations. However, a notable drawback lies in the necessity of predetermining fuzzy reasoning rules based on expert insights. Furthermore, the effectiveness of path selections is intrinsically tied to expert experience, and the optimal path hinges upon fuzzy inference rules. As obstacle-related information augments, the expansion of inference or fuzzy inference rules can swiftly compound, potentially impeding algorithmic implementation. The algorithm faces challenges when dealing with shifting scenarios; established rules might not aptly address novel situations, consequently precluding optimal path choices. Regrettably, the algorithm's obstacle avoidance strategies exhibit limitations in adaptability and struggle to adeptly handle dynamic obstacles (Tao et al., 2021).

Particle swarm optimization (PSO): PSO stands as a swarm intelligence optimization algorithm conceived to emulate the flight and foraging patterns observed in birds. Notably, PSO boasts attributes such as rapid convergence, minimal parameter count, straightforward implementation, and robustness. Consequently, it has gained extensive utilization within robot path planning contexts (Phung & Ha, 2020; Song et al., 2021). By means of coordinate transformation, an environment map model is established bridging the gap between the path's starting point and endpoint. This process transmutes the path planning conundrum into a function optimization challenge. The particle swarm optimization algorithm then fine-tunes candidate paths, culminating in the attainment of a globally optimal path (Sun et al., 2005). Furthermore, the enhanced particle swarm optimization algorithm (PSO) is harnessed for multi-objective path planning of mobile robots. Simulation outcomes underscore the efficacy of this approach. However, it's important to acknowledge that PSO harbors certain limitations, notably inclinations toward local optima and relatively sluggish convergence rates during later stages.

Ant colony optimization: The ant colony optimization algorithm emerges as an intelligent optimization approach drawn from the foraging tendencies of actual ants in the natural world. This algorithm operates within a graph-based probabilistic framework (Dorigo et al., 1996). Originally conceived for addressing the Traveling Salesman Problem (TSP), ant colony

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algorithms have since evolved to span a multitude of applications. Notably, they have garnered extensive adoption in the domain of route path planning for mobile robots (Miao et al., 2021; Sangeetha et al., 2021; Zhang et al., 2021).

Table 1: Summary of different global path planning methods

Algorithm	Advantage	Disadvantage
Dijkstra algorithm	The shortest path between any two nodes can be obtained.	Multiple traversal nodes. The efficiency is not high.
A * algorithm	Can find the shortest path; Small search space; High efficiency.	Poor smoothness of path; When the environment is large, the operation time is long, and the real-time performance is poor
D * algorithm	Small amount of calculation; Implement a simple.	Poor smoothness of path; The path security is low. Suitable for dynamic programming.
Artificial neural network algorithm	Strong nonlinear mapping ability; Strong learning ability; Good generalization ability; Deal with rationality in parallel.	The structure is complex; Long training time; Slow convergence rate; There is no guarantee that it will converge to an optimal solution.
genetic algorithm	Large search space with low time and space complexity.	Slow operation speed; Large storage space; Easy to fall into local optimum.
fuzzy control algorithm	Without accurate environment modeling, path planning can be completed by looking up tables; Good real-time performance.	Expert experience is needed to set membership function and fuzzy control rules. Inference rules or fuzzy tables will expand rapidly when the number of inputs increases.
Particle swarm optimization	Simple implementation; Early convergence rate is fast; Few parameters.	There is a local optimal solution; The late convergence rate is slow.
Ant colony optimization	Positive information feedback; Distributed computing; Strong robustness; Strong global optimization ability; Easy to combine with other intelligent methods.	Premature convergence; Local optimum; Slow convergence rate; The contradiction between diversity and convergence rate.

3.2 Research Status of Local Path Planning

In scenarios where environmental information remains incomplete or only partially known, robot resort to sensors for recognizing their surroundings and constructing localized environmental models. These models facilitate pathfinding to navigate the robot around dynamic obstacles. In contrast to global path planning objectives, local planning centers on ensuring safety and facilitating real-time obstacle avoidance. Given that route planning in this context exclusively hinges on locally available environmental information, instances of local extreme points may arise, potentially rendering the identification of feasible routes unattainable. Common methods for route planning include:

Artificial potential field method: Is a set of virtual force method, its basic idea is in the robot artificially establish a stress field in the surrounding environment. In this construct, mobile robots and obstacles carry positive charges, while the target point is endowed with a negative charge to allure the robot. Simultaneously, obstacles generate repulsion, thereby engendering a gravitational potential field function. The calculation of attraction and repulsion potentials yields an overarching potential field. Driven by this potential field, the robot commences its journey from the starting point, steering its trajectory by orchestrating forces until it ultimately reaches the target destination. The artificial potential field approach boasts attributes including structural simplicity, path smoothness, robust real-time responsiveness, and straightforward implementation. This renders it a potent local path planning methodology. However, this method is not without its drawbacks. It is susceptible to converging towards local minima, instances where target points remain inaccessible, and the potential for planned path oscillations. These limitations curtail its applicability (Khatib, 1985; Zhou et al., 2020). One strategy involves the utilization of techniques aimed at eradicating local minima. This can encompass altering the potential field function to ensure the target point becomes the sole minimum or striving to minimize the occurrence of local minima to the greatest extent feasible (Deng, 2014; Guo et al., 2013). However, it's crucial to acknowledge that the establishment of the pertinent potential field function necessitates global information, which can potentially compromise the algorithm's real-time performance. An alternative method involves invoking an escape mechanism upon detecting the presence of a local minimum value. This mechanism aims to circumvent regions where such minimum values manifest. Additionally, the issue of target points and obstacles rendering the target unreachable can be tackled by modifying the composition of the repulsive force function. Specifically, the repulsive force function can incorporate the distance between the robot and the target entity, thereby guaranteeing that the potential energy field at the target location aligns with the global minimum. It's important to note, however, that this method doesn't inherently eliminate the existing local minima between robots and obstacles. Additional measures, such as employing strategies like walking along walls, are necessitated to address this challenge (Ge & Cui, 2000).

Behavior decomposition method: Behavior decomposition stands as a classical approach in local path planning. Given the inherent difficulty in formulating precise mathematical models for obstacle avoidance processes, researchers have adopted a strategy of decomposing intricate robot navigation tasks into discrete and relatively independent behavioral units. These units encompass facets such as target tracking, static obstacle avoidance, dynamic obstacle avoidance, and escape from traps. Each behavioral unit is endowed with a self-awareness module and an executor that can execute its designated functions upon command. In tandem, these components synergistically operate to facilitate the achievement of autonomous navigation tasks (Qu et al., 2008). The behavior decomposition methodology enjoys extensive application in robot local path planning. However, in scenarios characterized by complex work environments or a diversity of behaviors, the method can give rise to conflicts or competition issues among the behavioral units.

Case-based learning: The case learning method centers on experiential learning and problem-solving, necessitating the construction of a fitting case library prior to embarking on path planning. When novel challenges emerge, pertinent data is extracted from the established case library to identify the solution that most aptly corresponds to the new problem. This case analysis approach offers the capacity to adapt path planning based on local obstacles, thereby enhancing planning efficiency. However, it's important to note that this method does not assure the attainment of a globally optimal path (Shang et al., 1998; Zhang et al., 2006).

Rolling window method: The rolling window method stands as an efficient technique within the realm of local path planning, founded upon predictive control and rolling optimization principles. Operating in tandem with local environment information, a mobile robot constructs a virtual "planning window" and continually updates its content based on the evolving environmental data during movement. Within each rolling window, heuristic techniques yield sub-goals aligned with the window's confines, subsequently underpinning path planning endeavors. The resultant localized path empowers the robot to adeptly navigate dynamic obstacles. As the robot progresses, the window's configuration adjusts, and sub-targets receive updates. This iterative process of local route planning endures until the mission's conclusion (Han & Liu, 2011). While the rolling window method excels in addressing path planning concerns within the immediate environment and exhibits robust real-time performance, it should be acknowledged that its core essence does not inherently augment the search efficiency of the algorithm. Furthermore, it's worth noting that these approaches, though prioritizing obstacle avoidance, may lack global characteristics when confronted with the task of resolving broader path-planning quandaries.

Table 2: Summary of different local path planning methods

algorithm	advantages	disadvantages
Artificial potential field method	Simple structure; Good for real-time control.	Locally optimal solution: The goal is unattainable; There are oscillations in narrow environments.
Behavior decomposition method	Fast and accurate robot path planning.	In the complex environment or with different types of behavior, there are behavioural conflicts or competition problems; The calculation amount increases, which affects the planning result.
Case-based learning	High planning efficiency.	It is necessary to have rich expert experience in case attribute extraction, case matching, case selection and case database updating. You may not get a globally optimal path.
Rolling window method	It has the characteristics of small amount of calculation, rapid response, and strong operability, and has certain adaptability to dynamic unknown environment.	Plan out locally optimized rather than globally optimal paths.

4. Conclusion

The Mobile Robot Perception System predominantly focuses on enhancing the robot's capacity to detect and interpret its surrounding environment. A wide array of environmental perception sensors are employed, necessitating calibration prior to deployment. The practice of multi-sensor fusion is commonly embraced for comprehensive environmental monitoring. In terms of path planning, two principal algorithmic categories are at play: global path planning and local path planning. The global path planning algorithm is tasked with identifying the most efficient overall route, while the local path planning algorithm is responsible for real-time obstacle avoidance and fine-tuning paths within the immediate vicinity. The synergistic integration of these two algorithms augments the likelihood of achieving the optimal path.

5. The Future and Prospects

In the future, the ubiquitous deployment of mobile robots across diverse domains will inevitably lead to the emergence of various robot types tailored to specific environments. As the field of machine learning continues to evolve, the evolution of mobile robot's environmental recognition system will pivot towards a vision-sensor-based paradigm, wherein multiple sensors collaborate to discern the surrounding environment. Notably, the exploration of environment recognition and path planning algorithms in intricate terrains and environments is gaining prominence. Moreover, the pursuit of terrain prediction algorithms is poised to assume a pivotal role. Different path planning algorithms exhibit distinctive merits. An approach of merging varied algorithms and fostering reciprocal learning in response to practical requisites holds the potential to yield a path planning algorithm harmonizing with the specific application environment. As the integration of these advancements unfolds, the capabilities of mobile robots are primed to transcend existing boundaries.

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