Research Progress on Path Planning Algorithms for Unmanned Ground Vehicles

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Abstract. This paper systematically reviews the research progress of UGV off-road path planning algorithms in the past five years, classifying them into three categories: traditional search and physical model improvement algorithms, perception-based and geometric sampling planning algorithms, and deep reinforcement learning algorithms. Moreover, the existing algorithms have received more research attention in terms of search strategies and UGV travel energy consumption prediction.Studies have shown that although traditional physical algorithms have advantages in interpretability, DRL algorithms perform well in adaptability. However, the robustness of existing methods in extreme environments still needs to be improved. Finally, this paper looks forward to the future development direction of algorithms, pointing out that the integration of physical models for high-dimensional terrain construction, etc. will be the key to autonomous off-road navigation.

Keywords: Unmanned ground vehicles(UGV), Path planning, Unstructured terrain, Deep reinforcement learning(DRL)

1 Introduction

Currently, as human exploration of the outer space domain continues to deepen, and the demand for emergency rescue in more extreme environments is increasing, many working scenarios pose severe challenges for human entry and operation, such as harsh environments like high radiation and oxygen deficiency. The UGV are widely used in such areas that are difficult for humans to access. They can not only replace humans to complete tasks, but also improve overall efficiency through autonomous operation [1-3]. Moreover, they can keep humans away from the threats of dangerous environments. However, the working environment of UGV usually implies highly complex and unstructured terrain conditions as well as obstacles that are difficult to predict in advance [4-7], which poses significant challenges for the movement of UGV. Therefore, how to enable UGV to fully utilize existing sensor technologies and machine learning algorithms to achieve autonomous route planning, obstacle avoidance, and enhance their ability to pass through has become a key issue that needs to be urgently addressed at present. The planning of UGV for complex existing terrains has shifted from the simple recognition of temporary obstacles by single sensors to a comprehensive path planning. Moreover, almost all algorithms take into account the terrain conditions and the difficulties encountered by the vehicles during their movement. The existing planning algorithms can be classified into traditional search and physical model improvement algorithms, perception-based and geometric sampling planning algorithms. The traditional search and physical model improvement

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algorithms utilize the existing mature shortest path planning algorithms, integrate data such as terrain elevation, and consider the vehicle's ability to pass through to plan the optimal path [8, 9]. Deep reinforcement learning algorithms involve handing over high-dimensional sensor data to the agent, and allowing it to learn driving strategies within this framework. They also apply different optimal strategies in the planning process [7, 10, 11], aiming to enhance the planning capabilities of the algorithm when the modeling accuracy is poor. The perception-based and geometric sampling planning algorithms focus on addressing the uncertainty of sensor perception and the geometric constraints in 3D environments. They usually utilize sampling algorithms and sensors to conduct rapid exploration in complex environments, concentrating on the passability of vehicle geometry and real-time exploration [4, 5].

Accordingly, this paper comprehensively consolidates the development landscape of path planning algorithms during the preceding half-decade, and further assesses the pros and cons of current approaches. Based on the summarized advantages and disadvantages, it provides reference directions for future path planning algorithms.

2 Introduction to Path Planning for UGV

2.1 Introduction to the Problem of Path Planning

In the path planning of UGV, the UGV will utilize sensors to find a trajectory from the starting point (which is sometimes the current position of the UGV) to the destination point, taking into account terrain elevation differences and obstacles. Unlike autonomous vehicles on paved roads, the planning of UGV in rough terrains is not merely a geometric obstacle avoidance issue, but rather a coupled optimization problem with numerous constraints [8, 12]. In the unstructured terrain where UGV are planned to operate, there are usually three constraints to be considered. These constraints mainly involve geometric aspects, dynamic aspects, and the balance between energy and efficiency. Additionally, based on the existing limitations of the vehicles (such as their own energy sources, power limitations, and geometric limitations), the optimal route planning is made.

In the path planning problem, unlike self-driving cars on paved roads, UGV need to fully consider the influence of the surrounding environment on themselves during path planning and movement. This is also a key difficulty in the path planning of UGV.Vehicles need to take into account the complex and unstructured terrain, which usually poses difficulties for the vehicle's movement [13]. They also need to consider the interaction between the terrain and the UGV, which usually affects the vehicle's own energy consumption performance and power requirements. Moreover, the terrain also has an impact on the vehicle itself. For example, the vibration on gravel roads can cause vibrations to the sensors themselves and the equipment on board, which usually interferes with the normal operation of the sensors and introduces noise, causing problems for path planning [7, 9, 10].

2.2 The basic principle of path planning

In the path planning of UGV, a complete topographic map of the surrounding area is usually required. Usually, the vehicle will obtain the 2.5D elevation map information of the local terrain in advance, or combine RGB images and LiDAR point clouds to construct a map with semantic labels to distinguish the types of obstacles [5, 10, 12, 13]. In the planning process, it is also necessary to obtain the physical parameters of the UGV itself, such as the vehicle width, wheelbase, turning radius, suspension height, driving torque and power, to construct the vehicle dynamics and kinematics models. These physical characteristics should be taken into account during the planning process [7, 8, 11]. After the algorithm model planning is completed, different cost functions are constructed for different application scenarios in the candidate path options to select the optimal path. The cost function usually comprehensively considers factors such as distance, risk, energy consumption, and smoothness that affect the planning process, and different weight coefficients are assigned in advance to change according to the tasks executed by the UGV and the required environment, thereby planning different optimal routes.

3 Existing path planning algorithms

3.1 Traditional search and physical model improvement algorithms

Traditional search and physical model improvement algorithms plan the shortest path based on the obtained images, and the representative algorithms are A* algorithm and Dijkstra algorithm. However, unlike the traditional method of finding the shortest path based on the image, in the path planning of UGV, the existing research no longer focuses on finding the path with the shortest geometric distance. Instead, it introduces an appropriate cost function. By introducing the estimation of possible dangers and difficult-to-pass sections on the path by the vehicle, this is usually achieved through multi-dimensional maps rather than traditional two-dimensional images. It often contains detailed semantic information of the terrain and different types of ground are usually described by mechanical formulas to reflect the influence of the terrain on the vehicle. This thereby allows conventional path-finding algorithms to enhance the environmental adaptability of UGV when operating in unstructured terrain.

Bai et al. [12] proposed a multi-dimensional grid map, which not only contains ordinary two-dimensional data but also includes information such as elevation in the terrain, surface properties of the road, and risk areas . In the A* algorithm, by fully considering the impact of terrain on the progress of UGV, three different functions are designed to adapt to path planning requirements in different scenarios. The comparison and applicable scenarios of the three heuristic functions are shown in Table 1. The 24-neighbor algorithm is also used to smooth the planned path, avoiding the path unevenness issues caused by traditional 4-zone and 8-zone planning. A detailed demonstration diagram of the neighborhood planning algorithm is shown in Figure 1 [12].

Table 1. Comparison and application scenarios of three heuristic functions

Mode name	Mode selection tendency	Suggested application scenarios
Time priority	Minimize travel time	Scenarios with strict time requirements such as disaster rescue
Safety priority	Minimize the total risk of the driving path	The vehicle itself is relatively expensive, or it is difficult for humans to manually correct the overturned area of the UGV to ensure its safety

Stability priority	Minimize the change in slope	Minimize the jolt level of vehicles along the UGV's path, applicable to scenarios where the vehicles have numerous sensors.

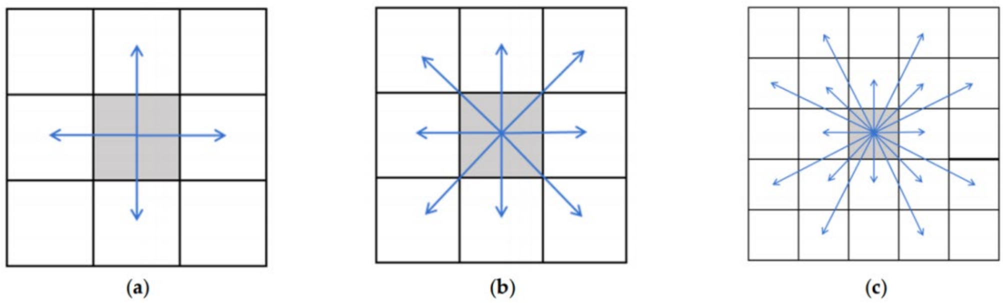

Fig. 1. Schematic diagram of three domain algorithms

In Figure 1, Figure (a) represents the 4-region planning in the planning algorithm, Figure (b) represents the 8-region planning in the planning algorithm, and Figure (c) represents the 24-domain algorithm in the planning algorithm, which has a significant advantage in path planning.

Hua et al. [8] still adopted the A* algorithm as the basis for path planning, constructing a terrain model within a range of 10 meters by integrating multi-source data differences . They used Bakker's theory to calculate the maximum driving speed and energy consumption of the UGV in real-time under different terrains, quantified the driving cost of the UGV, and integrated it with the A* algorithm to generate a min-mobility cost route (MMCR). The MMCR was then compared with the min-distance route (MDR) and the min-slope route (MSR). The results showed that the MMCR path planning had advantages over the other two algorithms.

The experimental results demonstrate that although the MMCR algorithm lacks a distinct edge over MDR and MSR when considering both the length of the planned trajectory and its average incline, it yields a solution that minimizes both energy consumption and travel time for the unmanned ground vehicle, and consequently outperforms alternatives in optimizing energy usage.

Saad et al. [9] combined the total path distance and total energy consumption by introducing a greedy-like algorithm (improved Dijkstra algorithm) and a composite metric formula, thereby enabling the algorithm to automatically reduce distance and energy consumption when considering. This makes the algorithm studied more suitable for path planning in large-scale topographic maps, and the greedy algorithm makes the path planning speed faster compared to Ant Colony Optimization (ACO), making the algorithm faster in cases with complex data points. This algorithm fully considers the factors of distance and energy by introducing the metric formula. It focuses on solving the trade-off problem between distance and energy consumption. While significantly shortening the path length (up to 17.7%), the increase in route energy consumption is only a small amount compared to the minimum energy consumption algorithm (no more than 3.65%). The algorithm comparison is shown in Table 2 [9].

Table 2. Comparison and application scenarios of three heuristic functions

Route	Length of ACO path planning (m)	Article algorithm path planning length (m)	Energy consumption of ACO path planning (kJ)	Article Algorithm Path Planning Energy Consumption (kJ)	Time for ACO path planning (for 100 iterations as an example) (s)	Article algorithm path planning time (s)
Route1	2388.3	1828.9	296.8	98.5	58	3.42
Route2	1958.7	911	666.7	601.3	33	3.22
Route3	699.6	663.6	68.9	52.8	30	3.43
Route4	558.1	490.9	287.5	279.2	23	3.49

3.2 Perception-based and geometric sampling planning algorithms

The planning algorithm based on perception and geometric sampling is partially consistent with the Traditional search and physical model improvement algorithms. Firstly, through semantic segmentation, a preliminary understanding and segmentation of the surrounding terrain is achieved. However, unlike the Traditional search and physical model improvement algorithms, these algorithms do not typically traverse all the grids to search for possible paths. Instead, they use a completely random rapid exploration method (such as the RRT algorithm) for rough path planning, reducing the difficulty of searching in a high-dimensional space. Subsequently, the algorithm is used to optimize the trajectory and delineate a safe area to meet the dynamic constraints of the vehicle. These algorithms place great emphasis on the smoothness of the path and the geometric continuity.

Wang et al. [4] first constructed three types of grid maps using sensors and extended the RRT algorithm to three-dimensional space, dividing it into global RRT and local RRT to identify frontier points. They then used an optimal target evaluation function to determine the traversability of frontier points and employed the A* algorithm to search for paths. After generating the paths, they used a cubic polynomial spiral to generate sufficiently smooth paths that meet the curvature constraints of the vehicle itself.

Zang et al. [5] divided path planning into integrated traversable area assessment (ITAA) and path planning and path optimization (PPPO). The algorithm first constructed a hierarchical map model on the ITAA layer. Considering the geometric constraints of the vehicle itself and combining with the terrain height information, it evaluated the terrain passability and marked the inaccessible areas at the same time. Then, it conducted a grid-by-grid analysis to score the grid passability and projected the vehicle posture onto the terrain surface for vehicle stability analysis. The PPPO layer was based on the analysis of the ITAA layer to quickly randomly search for the initial path and construct a safe driving corridor. For the generated path, it imposed curvature constraints and safety corridor constraints to smooth the path planning.

3.3 Deep reinforcement learning

Deep Reinforcement Learning (DRL) algorithms, through end-to-end or hierarchical learning methods, enable machine learning algorithms to continuously learn and optimize their path selection strategies from multi-dimensional sensor map data (including images, elevation, and other information). They focus on solving planning problems in off-road environments where there is no very precise terrain elevation data, improving the robustness of path planning and the terrain generalization ability of machine learning algorithms. By setting up a reward function, the agent can decide how to choose the path on its own, without using traditional mechanical formulas to try to describe the impact of the environment on the vehicle.

Hu et al. [7] developed a simulation-to-reality (Sim-to-Real) framework, which allows datasets trained within a simulated environment to be directly applied to real-world scenarios . By integrating the A3C (Asynchronous Advantage Actor-Critic) network into their approach, the authors incorporated three randomization strategies—terrain slope fluctuation, robot motion disturbance, and robot pose deviation—to estimate discrepancies and narrow the divergence between 3D simulated terrains and real-world environments. Furthermore, within the DRL module dedicated to path planning, a hybrid network architecture combining convolutional neural networks (CNNs) and long short-term memory (LSTM) networks was adopted, alongside a tailored reward function designed to support trajectory generation.

Li et al. [10] focused more on the navigation of UGV in unknown off-road environments without prior maps . Therefore, they abandoned the traditional deep reinforcement learning method in the form driven by goals and instead utilized dynamic calculation of "leading points" ahead to provide real-time guidance and control for the UGV, solving the problems of low learning efficiency and difficulty in finding the optimal path of traditional deep learning algorithms. The authors designed a new heuristic function to plan the leading points, and introduced a multi-head attention module in the DRL network to aggregate historical observation sequences for reference. They also designed a new reward function to constrain the path of the DRL module from six dimensions. The results showed that the innovative LMAW algorithm proposed by Zhijian.L et al. successfully maintained a success rate of over 90% on new maps that were not involved in training, and the algorithm demonstrated good robustness in noise processing.

Li et al. [11] first calculated the energy consumption of UGV on different slopes by establishing an energy cost model. They initially employed an improved D* Lite algorithm for global planning, and then introduced a global-local collaborative mechanism for local path planning during vehicle operation . The local path planning utilized a DRL-DWA hierarchical planning framework to facilitate rapid search space exploration and adapt to environmental changes. Congduan et al. also considered the scenario of multiple UGV formation, specifically optimized the algorithm for multiple UGV teams, and established a Leader-Follower model, making the algorithm perform excellently in the case of multiple UGV formation.

4 Limitations of the current algorithms

By integrating the three algorithms, it can be observed that although the path planning algorithm based on traditional search has strong interpretability, introducing these complex high-precision physical models in complex terrains leads to high computational costs for high-resolution maps and in complex environments. Moreover, the physical models have insufficient adaptability when UGV encounter unknown terrains and different soil compositions. DRL typically has strong adaptive capabilities, but the inherent characteristics of DRL make the interpretability of its algorithm poor. During path generation, it may violate the kinematic constraints such as the vehicle's turning radius and suspension height, resulting in difficulties in troubleshooting when the algorithm fails. Furthermore, DRL simplifies the interaction between the vehicle and the environment, which leads to the insufficient response ability of the trained agent in considering environmental factors and responding to emergencies. Most of the algorithms are trained for static environments and do not consider the dynamic changes of terrain such as landslides, collapses, and floods, or the loss of performance due to battery depletion. The quantification of uncertainty is also insufficient, and the response ability when facing errors in terrain modeling and semantic segmentation is also inadequate.

Therefore, future algorithms can solve the aforementioned problems by integrating algorithms. For instance, a rough planning can be conducted using traditional search algorithms, and then DRL can be employed in local planning to enable vehicles to have sufficient response capabilities in local emergencies. Moreover, higher-dimensional maps can be constructed in terrain modeling to reduce the pressure on subsequent algorithm estimations. In Sim-to-Real migration at the DRL level, introducing more uncertainties and more intense factors and simplifying the task objectives can enable the algorithms to converge quickly and conduct real-time evaluation of the feasibility of DRL-generated results. Additionally, during global and local path planning, by referring to the geometric and dynamic characteristics of the vehicle, safe corridors can be generated to solve the problem of unclear boundaries in unstructured terrains, making the planned paths more refined.

5 Conclusion

This paper reviews the current status of path planning for UGV in complex terrains over the past five years and analyzes the deficiencies. In summary, this paper indicates that current research on UGV is divided into traditional search algorithms and deep reinforcement learning algorithms. In traditional search algorithms, A* or Dijkstra-like algorithms are used for planning and traditional mechanical formulas are employed for prediction. In deep reinforcement learning algorithms, path planning is learned iteratively through the algorithm, and a reward function is reasonably set to make the algorithm's path planning more reasonable and converge faster. Moreover, existing algorithms have been extensively studied in search strategies and energy consumption prediction during UGV travel, but there is less research on deep learning algorithms from simulation to reality (Sim-to-Real) and on temporary decision-making optimization for UGV in dealing with unexpected situations. These findings can provide a good summary and reference for researchers studying existing UGV-related algorithms. In addition, the analysis results can provide directions for existing researchers to better develop UGV path planning algorithms.

Reference

[1] Szrek, J., Zimroz, R., Wodecki, J., Michalak, A., Góralczyk, M., Worsa-Kozak, M.: Application of the infrared thermography and unmanned ground vehicle for rescue action support in underground mine—The amicos project. Remote Sensing. 13(1), 69 (2020)

[2] Fortuna, S., Roncagliolo, P., Graziato, D., Merlo, A., Chiodini, S., Valmorbida, A., Pertile, M.: ROS 2-based autonomous navigation strategy for a lunar rover featuring multiple locomotion modes. Acta Astronautica. (2025)

[3] Dinelli, C., Racette, J., Escarcega, M., Lotero, S., Gordon, J., Montoya, J., ... Hassanalian, M.: Conurations and applications of multi-agent hybrid drone/unmanned ground vehicle for underground environments: A review. Drones. 7(2), 136 (2023)
[4] Wang, L., Qi, Y., He, B., Xu, Y.: An Efficient Autonomous Exploration Framework for UGV in Uneven Off-Road Environments. Drones. 9(7), 490 (2025)
[5] Zang, Z., Gong, X., Zhang, X., Gong, J.: Coordinated Path Planning for Autonomous Ground Vehicles in Off-Road Environments with 3D Rigid Terrain and Obstacles. Knowledge-Based Systems. 114055 (2025)
[6] Carruth, D. W., Walden, C. T., Goodin, C., Fuller, S. C.: Challenges in low infrastructure and off-road automated driving. In: 2022 Fifth International Conference on Connected and Autonomous Driving (MetroCAD), pp. 13–20. IEEE (2022)
[7] Hu, H., Zhang, K., Tan, A. H., Ruan, M., Agia, C., Nejat, G.: A sim-to-real pipeline for deep reinforcement learning for autonomous robot navigation in cluttered rough terrain. IEEE Robotics and Automation Letters. 6(4), 6569–6576 (2021)
[8] Hua, C., Niu, R., Yu, B., Zheng, X., Bai, R., Zhang, S.: A global path planning method for unmanned ground vehicles in off-road environments based on mobility prediction. Machines. 10(5), 375 (2022)
[9] Saad, M., Salameh, A. I., Abdallah, S., El-Moursy, A., Cheng, C. T.: A composite metric routing approach for energy-efficient shortest path planning on natural terrains. Applied Sciences. 11(15), 6939 (2021)
[10] Li, Z., Li, X., Hu, J., Liu, X.: Mapless autonomous navigation for UGV in cluttered off-road environment with the guidance of wayshowers using deep reinforcement learning. Applied Intelligence. 55(4), 254 (2025)
[11] Li, C., Zhang, Y., Song, D., Zhang, N., Chen, L., Yang, J., ... Zhai, X. B.: UGV Formation Path Planning Based on DRL-DWA in Off-Road Environments. Applied Sciences. 15(22), 12212 (2025)
[12] Bai, J., Zhu, W., Liu, S., Xu, L., Wang, X.: Path Planning Method for UGV in Complex Off-Road Environments Based on an Improved A* Algorithm. Sustainability. 17(11), 4805 (2025)
[13] Chen, D., Zhuang, M., Zhong, X., Wu, W., Liu, Q.: RSPMP: Real-time semantic perception and motion planning for autonomous navigation of unmanned ground vehicle in off-road environments. Applied Intelligence. 53(5), 4979–4995 (2023)