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Path Planning Methods for Agricultural Intelligent Robots

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Abstract. With the rapid progress in smart agriculture, agricultural intelligent robots have been used in many stages of agricultural production, such as field operations, harvesting fruits and vegetables, and plant cultivation within facilities, which make them an important device to improve the efficiency of agricultural production and facilitate the modernization process of agriculture. As the key technology that supports the autonomous operation of agricultural intelligent robots, path planning is crucial in terms of their security, efficiency, and coverage rate. In this paper, the authors conduct a comprehensive review on the mechanisms, technologies, and applications of path planning for agricultural intelligent robots, trace back its development history from single robot autonomy to multi-robot collaboration, analyze its current challenges, and forecast the future direction. This study is expected to provide useful references for the relevant studies and engineering implementations of path planning for agricultural intelligent robots.

Keywords: Agricultural robot, path planning, multi-sensor fusion, multi-robot cooperation, environment modeling

1. Introduction

Along with the quick incorporation of artificial intelligence into the agricultural industry, the worldwide trend of rural revitalization has led to the application of agricultural intelligent robots along the entire chain of agriculture-related processes, from planting to plant protection, harvesting, and transportation. These robots serve as indispensable means to cope with the insufficient labor force in the countryside and optimize agricultural activities. Self-navigation in complex agricultural environment brings various simultaneous demands such as robust obstacle avoidance, extensive coverage area, and crop safety. Therefore, path planning becomes a crucial factor constraining real-world applications.

Path planning is an important problem in the field of robotics. Its main task is to find a feasible route that allows the robot to move safely from the starting point to the target point in the task space without colliding with its surroundings, under certain constraints. However, three persistent challenges exist in this field: first, single path planning methods often lack generality and flexibility; second, in complex environments, sensor performance can be affected by variations in illumination and physical obstacles; and third, there is a lack of effective solutions for multi-robot task coordination.

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2. Research status of key mechanisms for path planning of agricultural robots

Path planning implementation for agricultural robotics is highly reliant on necessary hardware components such as localization, perception, and motion implementation systems whose effectiveness determines the implementation results of path-planning techniques. In dealing with the difficulties posed by complex agricultural settings, numerous research activities have been conducted in recent times by both academia and industry players to create solutions geared toward such scenarios.

2.1. Localization and navigation mechanism

Localization and navigation mechanism is the basic component for path planning in autonomous farming robots, responsible for obtaining pose information of the robot. For complicated field environments, current research tends to use sensor fusion algorithms to achieve high-precision localization and environmental adaptability. Zheng Lu et al. proposed a GNSS + IMU + LiDAR fusion localization method applied in large field applications [1]. Using unscented Kalman filter algorithm, they achieved decimeter-level absolute localization using GNSS while relative pose estimation based on LiDAR offered local dynamic compensation, thus providing absolute localization and local compensation together to effectively reduce damage to crops. Cornell University proposed a vision-LiDAR SLAM algorithm to cope with unstructured environments with dense occlusions in hillsides orchards [2]. Through visible light images and LiDAR point clouds, they accomplished real-time classification and modeling of fruit trees, trunks, weeds, etc., significantly improving obstacle avoidance capability. As can be seen from the above discussion, open-field localization requires GNSS/IMU for global positioning and LiDAR for local compensation, whereas hilly orchard localization requires vision-LiDAR fusion SLAM and semantic modeling.

2.2. Environment perception and target recognition mechanism

The environmental perception technology and target recognition mechanism are very important factors that determine the ability of the agricultural robot to effectively acquire the environment information and make intelligent decisions, with the perceptual reliability and recognition accuracy affecting the adaptability of path planning. In addition, Hu Guangrui et al. proposed a multi-modal perception system combining LiDAR and vision for orchard management. The system utilizes point cloud clustering and image semantic segmentation technology to perform accurate classification and three-dimensional reconstruction of fruit trees, tree branches, and moving obstacles. Its recognition rate of obstacles is up to 96.8% and the system provides high-precision environmental maps for path planning [3]. Li et al. solved the problem of distinguishing between crops and weeds in field environments by constructing the system integrating hyperspectral imaging technology and machine vision. Based on the use of deep learning techniques for pixel-level segmentation, the system can effectively solve the problems of misclassification of targets with similar color tones [4].

2.3. Motion control and actuation mechanism

Motion control and actuation mechanism play essential roles in executing the planned trajectory into practical action in agricultural robot applications, where the control accuracy and dynamics determine the quality of the operation. In order to cope with complicated terrains and environments,

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researchers nowadays pay more attention to the development of adaptive control algorithms for specific scenarios. For instance, Liu Zhijie et al. developed a novel path tracking control algorithm based on a virtual radar sensor model for small crawler tractors in orchards, where experiments were performed at 0.36 m/s and achieved a maximal improvement in terms of lateral deviation by 15.73% compared to a fuzzy control algorithm [5]. Furthermore, Tanaka et al. designed a robust motion execution mechanism, adaptive fuzzy PID for small greenhouse robots [6]. With the help of adapting the parameters in control in time according to the passage width and minimum radius of curvature in greenhouses, the system greatly improves the heading angle control and realizes accurate trajectory tracking. Based on these results, different motion scenarios have different needs on motion control, and motion control strategies are needed to be selected appropriately accordingly.

3. Current status of research on key path planning technologies

Progress in basic technologies such as path planning is crucial for achieving autonomous operation in agricultural robots. Environmental modeling provides a systematic depiction of the environment, which can facilitate planning; global path planning deals with large-scale path search, while local path planning helps with obstacle avoidance; finally, intelligent optimization algorithms provide systematic ways to solve problems with many restrictions. These technologies are interlinked and collectively determine the safety and efficiency of robotic operations.

3.1. Environment modeling and map construction techniques

Environment modeling is evolving from geometric maps toward semantic and spatiotemporal maps, and an appropriate map representation should be selected according to the characteristics of the specific scenario. Environment modeling and map construction are essential technologies used to convert sensor information into the form of structured environment representations. In this context, the complex structure, dynamics, and semantic attributes of agricultural environments create additional difficulties.

Early approaches primarily depended on geometric and grid maps. Geometric maps generate navigation references by extracting geometric features such as tree rows. Geometric maps have low computation overhead and can achieve good real-time performance. However, they cannot represent the shapes of obstacles and environmental regions. It is best suited for homogeneous orchards with regular tree rows and few obstacles. The occupancy of the environment is divided into grids in grid maps. Its data structure is simple and easy to update. It can only distinguish obstacles' existence and cannot recognize semantics. Besides, grid maps require large space when the resolution is increased. It can model the traversable areas in farmland and perform simple obstacle avoidance tasks.

Semantic maps assign categories to each region by combining deep learning-based semantic segmentation technology and occupancy grid. Semantic maps enable semantic understanding of the environment and intelligent decision-making. It requires accurate annotation and heavy computations. An efficient AgriPath method designed by Yang et al. realizes real-time weed detection, thus being suitable for precision target recognition tasks in applications such as plant protection robots for weed spray [7].

The spatiotemporally coupled map takes advantage of time dimensionality to realize dynamic changes like crop growth and branch sway. Spatiotemporally coupled map models the dynamic environment and has high computational overheads and low update frequency. The method named PAg-NeRF designed by Smitt et al. can reconstruct the scene in the three-dimensional space from sparse temporal image sequences and is useful for long-term operations in facility agriculture or orchard environment [8].

The environment modeling develops from geometric maps to semantic and spatiotemporally coupled maps, so different map representations should be adopted for different tasks.

3.2. Global path planning algorithms

However, it is still the most important technology for autonomous navigation in agriculture robotic devices. Based on its different functional requirements, there are three progressive hierarchical planning technologies including shortest point-to-point path planning, full-coverage path planning, and multi-objective path optimization.

For point-to-point path planning, the A* algorithm works efficiently in static farmland environment; however, due to path update delay caused by dynamic environment, it may cause potential collision problems. Wang Yuchao et al. proposed an optimized A* algorithm integrating with fuzzy dynamic window approach. An obstacle density coefficient was used to improve the heuristic function and Bezier curve to optimize path smoothness. It greatly reduced the distance error and heading angle in greenhouse orchards [9].

In the full-coverage path planning technology, there is a need to cover all areas of the operational environment with balanced coverage rate and path length. In order to cope with the problem caused by complex topography in hill regions, Zhou Longgang et al. utilized the Floyd algorithm, the improved genetic algorithm, and terrain cost map together and applied adaptive crossover and mutation operators in this study, thus optimizing path in the simulation [10].

From the analysis above, it can be found that both traditional point-to-point and full-coverage planning focus more on path length. However, in addition to this criterion, energy consumption, soil compactness, and other indicators should be taken into consideration in practice. Therefore, multi-objective path planning becomes another hot topic. With the improved whale optimization algorithm, Yang et al. proposed the AgriPath framework for balancing the dynamic path planning of length, smoothness, and planning time in dynamic farmland [7].

Overall, it shows the evolution process of global path planning from traditional technology towards multi-objective dynamic optimization to fulfill the needs of practical function requirements.

3.3. Local path planning and dynamic obstacle avoidance techniques

Local path planning makes up for the unpredictable dynamic changes in the environment by making local modifications to the global path according to perceptual information in real-time, guaranteeing safe obstacle avoidance while moving. The advantage of DWA lies in that it realizes real-time obstacle avoidance by sampling and evaluating the velocity space. The advantages of DWA include easy computation and quick response. Nevertheless, the adaptability to dynamic environment of DWA is still weak. In order to solve this problem, Wang Yuchao et al. applied fuzzy logic control into DWA, creating a new algorithm named fuzzy dynamic window approach (FDWA), where weights of evaluation function are dynamically modified using fuzzy rule, hence significantly increasing the success rate of passing through densely planted tree rows in greenhouses [9]. Therefore, FDWA can handle the dense obstacles but with static environments better.

However, the algorithm TEB optimizes the global path in a secondary way by establishing spatiotemporal elastic band, allowing longitudinal and lateral deviations to be explicitly controlled while the path is very smooth. Lan Wangjiao et al. developed an improved version of TEB using the key points of Bezier-smoothed path as local targets, resulting in shortened path length and fewer

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turning points [11]. TEB is quite applicable for narrow and windy environments. Local path planning is designed for unpredictable dynamic changes in the environment by making local modifications to the global path using perceptual information.

Additionally, the model predictive control (MPC) performs well in precise path tracking due to its ability of state prediction under dynamic constraints. The NDOB-ENMPC proposed by Shen Yue et al. successfully integrates the disturbance observer with the extended-state MPC to suppress the external interference and improve the accuracy of path following [12]. The MPC is very useful in environments with large terrain variations and strict precision requirements.

3.4. Intelligent optimization algorithms

Swarm intelligence optimization algorithms draw inspiration from biological natural processes to provide useful means for solving constrained path planning problems. Among various approaches, genetic algorithm, ant colony optimization, and particle swarm optimization represent three typical optimization techniques and possess corresponding strengths and weaknesses based on different agricultural applications.

Genetic algorithms use selection, crossover, and mutation as the principles to optimize paths according to natural biological evolution process, which possesses outstanding global optimization property and can be easily parallelized but is easy to converge prematurely. Zhang Chicheng et al. combined the simulated annealing strategy into the genetic algorithm, thus overcoming the issue of premature convergence and reducing both total path length and computation cost significantly [13].

Ant colony optimization uses the principle of positive feedback based on pheromone trails to explore paths. Due to its ability of parallel computing, it is applicable to dynamic environment. However, its converging velocity is rather slow, and there is the issue of stagnation in ant colony optimization. Guo et al. proposed a hybrid approach based on genetic and ant colony optimization for safflower harvesting trajectory planning with an adaptive volatilization rate and pheromone bounding strategy, thus considerably saving time spent on agricultural fields [14].

Particle swarm optimization obtains fast convergence result by virtue of collaboration and communication among individuals. Its simplicity lies in using fewer parameters and ease of implementation, but it fails in terms of poor local search property and being easy to converge prematurely. Hilli et al. built a distance-risk double objective function model in a quasi-dynamic condition and used particle swarm optimization algorithm to obtain the optimal path, hence proving its effectiveness in the dynamic environment [15].

In this regard, it can be argued that genetic algorithm can be applied to static multi-objective optimization, while ant colony optimization suits dynamic path searching. Particle swarm optimization performs well in cases requiring real-time computation.

4. Typical application scenarios of path planning for agricultural robots

Research on path planning technology for agricultural robots must ultimately serve practical production needs. Different operational scenarios impose distinct requirements on path planning. This section examines the current application status of path planning technologies across four typical agricultural scenarios: field operations, harvesting and picking, facility agriculture and specialized scenarios, and transportation and multi-robot cooperation.

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4.1. Path planning in field operations

Field applications are characterized by large-scope operations such as plowing, sowing, fertilizing, and plant protection. The core idea of path planning under such scenarios is to ensure efficient traversal without any damage to the quality of operation caused by soil compaction. GNSS/IMU technology is usually adopted to achieve centimeter-accuracy global positioning with the aid of local corrections using LiDAR at the edges of the field; thus, absolute positioning and relative compensation become the backbone of this system.

For example, in one instance of plant protection operations conducted in Northeast China, Wang Yuchao et al. adopted the improved A* algorithm along with the fuzzy dynamic window approach (FDWA), where A* provides the shortest path on the global scale map, while FDWA solves problems associated with real-time obstacle detection and collision prevention when turning into headlands and meeting temporary obstacles [9]. On the perceptive level, hyperspectral and visual fusion technologies were used to differentiate between crops and weeds, so the cost map could avoid damaging expensive plants; on the motion control side, sliding mode variable structure control technology was used to deal with possible disturbances caused by the terrain, ensuring centimeter accuracy of lateral deviation from the optimal path. This experiment has proven to improve efficiency by 12%.

4.2. Path planning in the harvesting and picking stage

Path planning in the picking phase demands maximized real-time capability and accurate obstacle avoidance. In addition to navigating to the target plant, the robot must make the optimal decision of the picking sequence and motion trajectory of the robotic arm according to fruit distribution.

Due to the high density of crops and severe occlusion from plants, large-scale combine harvesting operations are confronted with great challenges in path planning. To solve this problem, Zhang Weirong et al. came up with the scheme of extracting navigable paths beneath the canopies using deep learning and Gaussian process regression in the maize field when the plant reaches mid-to-late growth stage [16]. Such an approach successfully tackles the problem of line detection resulting from leaf occlusion, which gives reliable information about the path used for autonomous farming machines in obscured conditions. In the process, multimodal perception is applied to model the environment in terms of canopies and dynamic planning of path ensures real-time obstacle avoidance.

As for apple orchards, a prototype of dual-arm apple harvester robot is designed by Huang et al. By utilizing dual UR manipulators, a collaborative working area was created, and a U-tube optimization algorithm was employed in determining the task allocation and picking sequence to ensure the collision-free collaboration between the arms [17]. Experiments prove the efficiency of the system. All in all, these cases demonstrate that real-time and precision demand of picking calls for the integration of perception-planning-execution system.

4.3. Path planning in facility agriculture and specialized scenarios

The environment characteristics of facility agriculture include narrow space, fixed passageway, lack of GPS signals, and large variations in lighting. In the greenhouse and polytunnel environment, the key challenge is precise positioning and dense obstacle avoidance. While in hilly or mountainous environments, undulating terrain and blocking signal are both problems.

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In the environment of greenhouse lacking satellite signals, visual and LiDAR SLAM will become a key technology for localization. Li et al. proposed using depth cameras to realize centimeter-level positioning in the greenhouse environment under the ORB-SLAM2 framework, supplying reliable information for the subsequent path planning task. This kind of multi-sensor fusion architecture can achieve high precision in positioning without GNSS [18].

Terrain undulations will sharply increase tracking errors when conventional control algorithm is used in hilly or mountainous operations. Dai Fancheng et al. put forward the application of model predictive control in hilly or mountainous areas. A slope steering model was developed in this paper that allowed average path tracking error reaching 0.039 m on a slope angle of 15°. Such an extension of the anti-disturbance control algorithm to sloped area allows pre-compensation of disturbance caused by undulating terrains through state prediction [19].

As a result of its unique nature, elevated strawberry planting has the particular requirement on path planning. Developed in the Beijing Academy of Agriculture and Forestry Sciences' Intelligent Equipment Technology Research Center, "Roucai" picking robot uses a four-wheel differential steering system to achieve flexible, pivot and oblique-motion operation, coupled with AI algorithms, autonomous picking-path planning is enabled.

4.4. Transportation and multi-robot cooperation applications

With the increasing size of the farms, using only a single robot cannot meet the demands of efficiency. As such, multi-robot cooperation and planning of their traveling paths are important issues in the current studies.

Material transportation in the farm requires solving the dynamic docking problem between harvester and vehicle for transporting grains. To optimize the scheduling problem caused by maize grain harvesting and conveying, a study introduced a cooperative solution of multiple-robot systems through Markov decision process and unloading threshold optimization, which shortened the time and cost required [20]. In other words, multi-robot cooperation and global planning of tasks and local trajectory optimization met the needs of agriculture production.

Besides the integrated harvesting and transporting system where picking and transportation were merged in one machine, another example was Fruit-Link designed by a student group at Southwest Forestry University. Multi-robots cooperation SLAM technology allowed Fruit-Link to perform in-orchard real-time positioning and map construction: the role of the robot for fruit transport was taken up by another robot once the picking was completed. In facility environment, however, there was a problem of robots having to travel along narrow cultivating beds, where traditional global path planning had trouble dealing with the constraints. Takuya proposed a lightweight strategy for navigating based purely on LiDAR data that allowed keeping a constant distance and an angle of attack between the robot and the cultivation bed; with errors in distance and angle of ±0.05 m and ±5° respectively, the robot was able to move precisely [21]. Such a strategy may be used to control transport robots locally after global path planning.

To conclude, multi-robot coordination evolves from centralized decision making towards distribution one, whereas navigation strategies in facilities help solve the last mile problem of transport robots.

5. Conclusion

This paper has systematically reviewed the key mechanisms, core technologies, and typical application scenarios of path planning for agricultural intelligent robots, tracing the technological evolution from single-machine autonomy to swarm intelligence. Despite continuous algorithmic optimization and considerable progress, several bottlenecks remain. First, perceptual robustness in complex environments is still inadequate: variable illumination and occlusion degrade recognition accuracy, while semantic and spatiotemporal map construction relies heavily on high-quality annotated data and imposes substantial computational loads. Second, dynamic response capability is weak, as global planning suffers from update delays and local planning struggles to achieve real-time smoothness when dealing with dense obstacles and rough terrain. Third, multi-robot cooperation mechanisms are not yet fully developed, with task allocation and conflict resolution still largely dependent on centralized scheduling; breakthroughs in distributed decision-making and collision-free dual-arm planning are urgently needed. Fourth, cross-scenario generalization and all-weather operation remain limited, because the adhesion, dustproofing, waterproofing, and endurance of current chassis platforms on hilly slopes still cannot meet the demands of intensive field work.

The following research efforts could help resolve these bottlenecks. Firstly, an integrated multimodal perception module is to be established with vision fusion, LiDAR, hyperspectral imaging, and IMU, along with lightweight semantic SLAM combined with dynamic reconstruction based on neural radiance field; in tandem, extensive agricultural vision models across various crops, illuminations, and occlusions are to be designed to reinforce semantic segmentation and object detection capability. Secondly, dynamically adaptive global-local cooperative decision-making algorithms are to be improved with local replanning and reinforcement learning to continuously adjust the weight of evaluation functions in real time and achieve multiple objectives such as optimal path length, smoothness, energy consumption, and timely obstacle avoidance. Thirdly, swarm intelligence and multi-robot scheduling algorithms are to be improved through global digital twin-based map and market-oriented task scheduling, as well as lightweight LiDAR feedback control in facility corridors to make harvest-transport cooperation smoother. Hardware-wise, biomimetic flexible end-effector with tactile/force sensing, along with chassis kinematic optimization and composite control algorithm, will enhance slope tracking accuracy and further decrease the damage rate during harvesting. In addition, scenario generalization and weather adaptability are to be promoted by integrating a comprehensive library of parameters concerning crops, terrain, and climate and applying transfer learning techniques for rapid deployment across greenhouses, open fields, and orchards, while the high protection and energy density of chassis platform with adaptive attitude control will ensure operations in adverse conditions of rain, fog, bright sunlight, and mountainous slopes. With continuous development of the perception-decision-control system, path planning for agricultural robots will become more precise, efficient, and generalized, which will lay down the technical basis for the transformation of intelligent agriculture from autonomous single robots to swarm intelligence.

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