

## PATH PLANNING FOR GRAIN HARVESTERS BASED ON THE VS-IRRT ALGORITHM

## / 基于 VS-IRRT 算法下谷物收割机路径规划

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DOI: <https://doi.org/10.35633/inmateh-77-49>**Keywords:** harvester; path planning; VS-IRRT algorithm; autonomous navigation; visual servo**ABSTRACT**

To address the problems of slow path planning speed, high path cost, and visual positioning errors encountered by grain harvesters during field operations, this study proposes an improved rapidly-exploring random tree algorithm integrated with visual servoing (VS-IRRT). By employing visual servoing technology to acquire environmental information in real time, the algorithm enables accurate positioning and attitude correction of the harvester. On this basis, heuristic sampling strategies and a path optimization function are introduced to enhance node expansion efficiency and accelerate the convergence of the search tree. To further reduce path cost, a path evaluation model incorporating environmental feature costs is established, which comprehensively considers terrain complexity, crop distribution density, and the machine's turning radius. This model dynamically adjusts the search direction and improves path smoothness. Simulation and field navigation experiment results indicate that the VS-IRRT algorithm reduces path planning time by approximately 32% compared to the traditional RRT algorithm, decreases the average yaw error by 42%, reduces the path curvature variation rate by 33%, and lowers turning frequency by 21%. The algorithm also maintains high robustness and planning accuracy under visual noise and positioning disturbances. Overall, this study provides an effective path planning approach and technical support for autonomous navigation and efficient operation of grain harvesters in complex agricultural environments.

**摘要**

针对谷物收割机在田间工作过程中存在的路径规划速度慢、路径成本高以及视觉定位误差等问题,提出结合视觉伺服的改进随机快速搜索树算法 (Improved rapidly-exploring random tree with visual servoing, VS-IRRT) 过视觉伺服技术实时获取作业环境信息,实现收割机的精准定位与姿态修正;在此基础上,引入启发式采样策略和路径优化函数,提高随机快速搜索树的节点扩展效率与收敛速度。为降低路径成本,设计基于环境特征代价的路径评估模型,综合考虑地形复杂度、作物分布密度及机器转向半径等因素,动态调整搜索方向并优化路径平滑性。仿真与田间的导航试验结果表明,VS-IRRT 算法在路径规划时间上较传统 RRT 缩短约 32%,平均偏差航误差降低 42%,路径曲率变化率降低 33%,转向次数减少 21%。且在存在视觉噪声与定位偏差的情况下仍能保持较高的鲁棒性与规划精度。该研究为谷物收割机在复杂农田环境下的自主导航与高效作业提供了有效的路径规划方法与技术支撑。

**INTRODUCTION**

Grain harvesters are among the most critical agricultural machinery in modern farming. They not only significantly reduce manual labor intensity and shorten harvesting cycles, but also effectively minimize grain loss rates, ensuring efficient and stable grain production (Lin et al, 2025; Yue et al., 2024; Chen, et al., 2025a). However, due to complex farmland environments and uneven crop distribution, grain harvesters still face challenges such as inefficient path planning, high operational costs, and insufficient positioning accuracy during operations.

Traditional path planning methods primarily include A\* algorithm based on grid maps, Dijkstra algorithm for graph search, and Bezier curve and B-spline path planning using curve fitting (Zhang et al.; 2021, Silva et al., 2024). While these methods can generate optimal paths in regular, static environments, they exhibit the following limitations when applied to dynamic, unstructured agricultural scenarios: (1) High computational

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complexity that hinders real-time implementation; (2) Failure to account for mechanical kinematic constraints, resulting in paths unsuitable for actual harvester operations; (3) Insufficient integration with environmental perception data, making it difficult to handle field-specific challenges like uneven crop distribution and random obstacle emergence.

In recent years, Rapid-Exploring Random Tree (RRT) and their improved algorithms have been widely adopted in mobile robotics and autonomous driving due to their rapid search capabilities and adaptability to high-dimensional spaces. For example, by introducing a path reconnection mechanism using the RRT \* algorithm, path search can be achieved in the asymptotic optimal sense, which has been widely used in navigation systems for autonomous vehicles and drones (Wang et al., 2018). Visual SLAM can also be combined with RRT algorithm to achieve autonomous path planning in complex outdoor environments (Xun et al., 2023). Additionally, international researchers have explored deep learning-based perception and sampling strategy optimization. Examples include using convolutional neural networks to predict environmental cost distributions that guide RRT sampling directions, thereby significantly improving path quality and planning efficiency. Other studies combined Global Navigation Satellite System (GNSS), LiDAR, and visual sensors (Shen et al., 2025; Hu et al., 2025; Eiffert et al., 2022) to precisely identify field obstacles and crop row spacing, subsequently optimizing harvester trajectories (Xie and Hong, 2024; Wang et al., 2025). However, most of these methods rely on high-precision sensors or offline planning, demonstrating insufficient real-time performance and visual servo-based positioning accuracy. They fail to meet operational demands in complex field environments and often exhibit deviations between planned paths and actual working scenarios due to inadequate visual positioning support.

To address these challenges, this paper proposes an improved rapidly-exploring random tree algorithm integrated with visual servoing (VS-IRRT). By integrating visual servoing technology, the system achieves precise positioning and attitude correction for combine harvesters during operations. The proposed approach incorporates heuristic sampling strategies and path optimization functions to improve path planning efficiency and trajectory smoothness, thereby enhancing autonomous navigation and operational capabilities of grain harvesters in complex agricultural environments.

## MATERIALS AND METHODS

### Space environment modeling

#### Spatial characteristics of farmland operation

The working environment of grain harvesters is a typical semi-structured space characterized by uneven row spacing, undulating terrain, and randomly distributed obstacles. To achieve efficient path planning, the farmland environment needs to be abstracted into a mathematical model suitable for algorithmic operations. The farmland space can be represented as a three-dimensional plane (Fig. 1), defined as:

$$E = (X, Y, O, C) \quad (1)$$

where:

$X$  and  $Y$ — represent the coordinate boundary of farmland operation area, m;

$O$  — Collection of obstacles, such as field boundaries, ridges, trees or temporary obstacles;

$C$  — Crop distribution and terrain cost information, which is used to guide path sampling and planning.

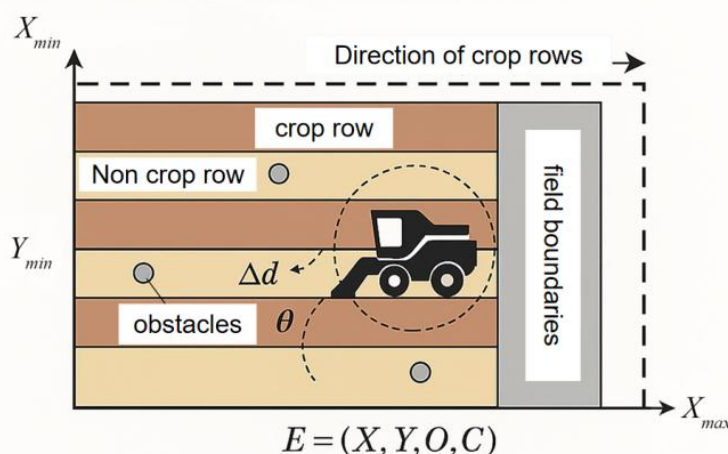


Fig. 1 - Characteristics of farmland operation space

### Visual servo perception and map construction

The vision servo system acquires crop row spacing, boundary lines, and obstacle information through front-end cameras and image processing. By fusing GNSS and IMU data for positioning, it generates real-time environmental maps using a grid occupancy model. This model discretizes farmland into grids of specified sizes  $\Delta d$ , with each grid recording accessibility probability and environmental value (Huo et al., 2024).

(1) Occupancy probability  $P_{occ}$ : According to visual detection and sensor data, it is determined whether the grid is passable, impassable or unknown;

(2) Environmental surrogate value  $C_{env}$ : used to guide path optimization by comprehensively considering factors such as crop density, terrain slope and distance of obstacles;

(3) Dynamic status label: dynamically mark the temporary obstacles and support local path re-planning.

Finally, the vision servo perception and map construction module generates a high-resolution and real-time updated farmland operation environment map as the calculation basis of the VS-IRRT algorithm path planning.

### Composition of VS-IRRT algorithm

To address challenges in field operations such as slow path planning speed, high path cost, and visual positioning errors in grain harvesters, this paper proposes an improved rapidly-exploring random tree algorithm integrated with visual servoing (VS-IRRT). The proposed system consists of three core components: (1) a visual servo-based perception and localization module, (2) an enhanced RRT path planning module, and (3) a path optimization and execution module.

The visual servo perception and positioning module utilizes front-end cameras, GNSS receivers, and IMU sensors to acquire environmental information and pose data. This paper selects the Basler acA1920-40gc high-definition Gigabit network camera and Trimble BD940 GNSS module for capturing agricultural operation environment images. Additionally, the Xsens MTi-300 inertial measurement unit is employed in conjunction with Kalman filtering for short-term high-precision attitude estimation.

The algorithm is partially implemented on an Industrial Control Computer (IPC) with Advantech IPC-610H hardware platform. The system features an Intel Core i7-9700 CPU (3.0 GHz, 8-core), 16 GB of RAM, and NVIDIA GeForce RTX 2060 GPU with 6 GB of video memory. Developed using the ROS (Robot Operating System) framework, the algorithm utilizes C++ to implement core path planning algorithms and Python for visual servoing and data fusion processing (Yan et al., 2025).

Path tracking and optimization control are executed by PLC and electro-hydraulic proportional control system. The whole machine adopts Siemens S7-1200 PLC to be responsible for path tracking and execution control signal output, and selects Danfoss PVG 32 electro-hydraulic proportional valve to realize the adjustment of harvester steering Angle by combining control signal.

### Improve the RRT path planning module

#### Design of environmental cost function

(1) Basic form of cost function

In the path planning process of grain harvesters, environmental complexity directly impacts the feasibility and operational efficiency of route generation. To address this, this paper develops an environment-aware comprehensive cost function within the VS-IRRT algorithm. This cost function guides sampling point generation, path expansion direction selection, and final route optimization. Specifically, an environment-based comprehensive cost function ( $F_{cost}$ ) is constructed, which holistically incorporates terrain complexity, crop density, and obstacle distance factors, and is defined as:

$$F_{cost} = \alpha \cdot L + \beta \cdot \theta + \gamma \cdot E_{env} + \delta \cdot S_{safe} \quad (2)$$

where:  $L$ —Path length cost, used to measure the total distance of the path. The shorter the path, the lower the cost, m;

$\theta$ —Turning cost, which represents the cumulative size of turning angles in the path, and is used to limit the adverse effects of frequent turning on the stability and energy consumption of the harvester; °;

$E_{env}$ —environmental characteristic cost, reflecting the influence of crop density, terrain complexity (slope) and obstacle distribution on the path;

$S_{safe}$ —safety cost, used to measure the distance between path nodes and obstacles and boundaries to ensure the safety of harvester operation, m;

$\alpha, \beta, \gamma, \delta$  - The weight coefficient is determined by experiment and optimization according to the characteristics and priorities of the operation scenario (Russello et al., 2022).

In grain harvesting operations, paths should prioritize extending along crop rows to enhance efficiency and prevent missed fields. The system employs visual servoing to acquire crop row position data and introduces a crop density cost ( $C_{crop}$ ) for path guidance. When a sampling point falls within the crop row area, its contribution value is calculated as the product of a proportional coefficient  $k_1$  and the perpendicular distance ( $d_{row}$ ) from the sampling point to the nearest crop row centerline. If the sampling point enters non-harvesting zones, its contribution value is set to infinity, ensuring forced avoidance during path optimization.

In grain harvesting operations, the path should preferably extend along the crop row direction to improve harvesting efficiency and avoid crop omission. This paper obtains the crop row position through visual servo and defines the crop density cost ( $C_{crop}$ ):

$$C_{crop} = \begin{cases} k_1 \cdot d_{row} & , d_{row} > 0 \\ \infty & , d_{row} \leq 0 \end{cases} \quad (3)$$

where:

$k_1$  —is the proportion coefficient, which ensures that the sampling points are concentrated near the crop row and avoids crossing the row or entering the non-operation area;

$d_{row}$  —the vertical distance from the nearest crop row centerline, m;

$\infty$ —indicates that the value is infinite, that is, the path cannot pass through the point.

#### (2) The safety cost of obstacle distance

In order to avoid collisions, path nodes need to keep  $d_{safe}$  a safe distance  $S_{safe}$  from obstacles. The safety cost function is defined as shown in Equation (4) (Wang et al., 2024):

$$S_{safe} = \begin{cases} k_2 \cdot \left(\frac{1}{d_{obs}}\right) & , d_{obs} > d_{safe} \\ \infty & , d_{obs} \leq d_{safe} \end{cases} \quad (4)$$

where:

$d_{obs}$  —the distance between the node and the nearest obstacle. When the path approaches the obstacle, the price rises sharply, so as to guide the path to avoid dangerous areas; m;

$d_{safe}$  —Preset safety distance threshold, when  $d_{obs} \leq d_{safe}$ , collision risk is considered to exist, m.

In hilly or uneven terrain, path planning should avoid long distance and high slope driving to reduce energy consumption and skidding risk. Therefore, this chapter proposes the slope cost  $C_{slope}$  expression as shown in Equation (5):

$$C_{slope} = k_3 \cdot \tan(\varphi) \quad (5)$$

where:

$\varphi$ —Slope Angle of the path section, °;

$k_3$ — is the weight coefficient. The higher the slope, the higher the cost, and the path is encouraged to choose a flat area.

#### (3) The cost of complexity of steering

Considering the restriction of the minimum turning radius  $R_{min}$  of the harvester on the feasibility of the path, this paper introduces the steering Angle cost:

$$C_{\theta} = k_4 \cdot \sum |\Delta\theta| \quad (6)$$

where:

$\Delta\theta$  —The change of steering angle between consecutive path segments. By limiting the accumulation of steering angles, a smoother and more executable path is generated, °.

Ultimately, the VS-IRRT algorithm evaluates candidate paths through a comprehensive cost function ( $F_{cost}$ ) during each node expansion, prioritizing nodes with the lowest overall cost for tree expansion. By integrating these various cost constraints, the algorithm generates optimal routes that balance shortest path optimization, driving stability, obstacle avoidance safety, and operational efficiency.

### Node expansion and reconnection optimization

Traditional RRT algorithms generate excessive redundant nodes during node expansion and produce infrequently optimized paths with lengthy, high-turnover routes. To address these issues, this study introduces node expansion optimization and reconnection optimization (Rewire) strategies within the VS-IRRT framework. Specifically, during expansion processes, new nodes are prioritized to expand along target directions or low-cost regions, thereby reducing redundant expansions and path redundancy (Lian *et al.*, 2024). For each expansion iteration, the system calculates directional vectors  $\vec{d}_{goal}$  from current nodes ( $n_{near}$ ) to target nodes ( $n_{goal}$ ),  $\vec{d}_{goal}$  then applies weighted expansion directions based on environmental cost functions:

$$\vec{d}_{exp} = \omega_1 \cdot \vec{d}_{goal} + \omega_2 \cdot \vec{d}_{low-cost} \quad (7)$$

$\vec{d}_{exp}$ —The node expansion direction vector, which represents the final search direction of the current node during expansion, m;

$\vec{d}_{goal}$ —The direction vector from the current node to the target node, m;

$\vec{d}_{low-cost}$ —The direction vector pointing to the region with low value of environmental cost function, m;

$\omega_1, \omega_2$ —Weight factor, which enables the path to avoid high cost areas while approaching the target.

### Path feasibility screening based on kinematic constraints

In practical operations, grain harvesters face kinematic constraints including vehicle dimensions, steering radius, speed, and acceleration. Therefore, path planning must not only ensure global accessibility but also needs to meet the kinematic feasibility of the harvester. To address this, this chapter introduces a path feasibility screening mechanism based on kinematic constraints within the VS-IRRT algorithm. The harvesters utilize a fully hydraulic steering system, with their steering limited by the minimum turning radius ( $R_{min}$ ). During the node expansion and optimization processes of path planning, it is essential to ensure that the path curvature meets the following requirements:

$$R = \frac{v^2}{a} \geq R_{min} \quad (8)$$

where:  $v$ — harvester speed, m/s;

$A$ —centripetal acceleration, m/s<sup>2</sup>.

$R_{min}$ —minimum turning radius allowed by harvester, m.

If the curvature radius of the newly expanded path segment is less than  $R_{min}$ , the segment should be discarded and the extended nodes resampled (Chen *et al.*, 2025b) to prevent abrupt turns that the harvester cannot complete. During node expansion, the curvature radius is calculated based on the geometric relationship with adjacent path segments. If  $R < R_{min}$ , the node is directly rejected or its expansion direction is adjusted to meet curvature constraints. Additionally, considering the physical limitations of the harvester's steering mechanism, the steering angle change  $\Delta\theta$  between adjacent nodes in the path should satisfy:

$$|\Delta\theta| \leq \theta_{max} \quad (9)$$

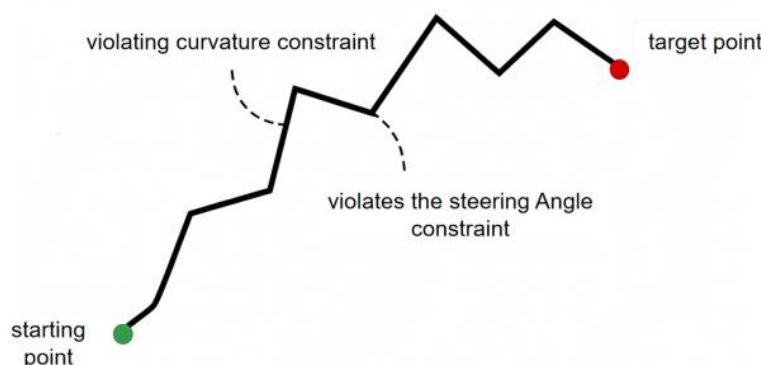


Fig. 2 - Schematic diagram of route feasibility screening



In the formula,  $\theta_{max}$  represents the maximum steering angle limit of the harvester. During path generation and reconnection processes, the steering angle is monitored in real-time. For paths exceeding  $\theta_{max}$ , smooth adjustments or resampling are applied to ensure path continuity, as illustrated in Fig. 2. The path connects the starting point to the target point, but contains two types of segments that violate the constraints:

(1) Path segment violating curvature constraint: In a certain path segment, the radius of curvature is less than the minimum turning radius of the grain harvester ( $R < R_{min}$ ), and the harvester cannot complete such a sharp turn, so this path segment is deemed to be infeasible.

(2) The path segment that violates the steering Angle constraint: Another path has a steering Angle change of too much ( $\Delta\theta > \theta_{max}$ ), which exceeds the limit Angle of the hydraulic steering system of the harvester. If it is directly executed, it will lead to steering difficulty or operation instability.

### Field test

To validate the effectiveness and adaptability of the proposed VS-IRRT algorithm in real agricultural environments, this study conducted path planning and autonomous navigation experiments in actual field scenarios. The results were compared with traditional RRT algorithms. The system was equipped with a CAN bus interface and a full hydraulic steering system, utilizing a Basler acA1920-40gc industrial camera (40 fps) to capture images of crop rows and obstacles. The control system employed an Advantech IPC-610H industrial computer (Intel i7-9700 processor, 16 GB RAM) to execute the VS-IRRT algorithm, while a Siemens S7-1200 PLC managed path tracking and hydraulic steering control (Mwitta and Rains, 2024).

### Test design and method

The experimental plot measures 60 meters in length and 35 meters in width, featuring four parallel crop rows spaced 0.6 meters apart – mirroring standard grain cultivation patterns. The terrain exhibits gentle undulations with natural obstacles including stones, field ridges, and temporarily placed farming tools, creating a 5-10 cm elevation variation across the surface. This design incorporates small depressions and field ridge boundaries to simulate real-world agricultural environments. The system employs the VS-IRRT algorithm for path planning and navigation execution, incorporating path optimization and visual servo-based correction mechanisms. It is compared with traditional RRT algorithms for path planning and autonomous navigation implementation.

During the trial, the grain harvester utilized Global Navigation Satellite System (GNSS) and visual servoing to complete field environment scanning, generating a grid map with crop row and obstacle positions annotated. The system then employed traditional RRT and VS-IRRT algorithms for global path planning, creating operational routes from start to finish. During path execution, the harvester autonomously navigated along the planned route, where the VS-IRRT algorithm combined real-time pose correction through visual servoing to enhance navigation accuracy. The trial recorded actual travel trajectories via GNSS and vision systems, measuring yaw errors, path execution time, and operational stability (Yuan et al., 2025; Ahmadi et al., 2022; Sangeetha et al., 2021). Post-trial analysis compared both algorithms in path planning time, path length, average yaw error, path smoothness, and operational efficiency. The evaluation methods for different metrics are detailed below (Liu et al., 2025).

#### (1) Path planning time

It refers to the total time from the completion of environmental mapping to path planning until the generation of executable paths, and the calculation method is shown in Equation (10):

$$T_{plan} = t_{end} - t_{start} \quad (10)$$

where:  $t_{start}$ —Path planning start time;

$t_{end}$ —Path generation completion time.

#### (2) Average yaw error

It refers to the average deviation between the actual travel trajectory of the harvester and the planned path in the horizontal direction, which mainly measures the path tracking accuracy:

$$L_{path} = \sum_{i=1}^{n-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \quad (11)$$

where:  $x_i, y_i$ — are the coordinates of path nodes;

$n$ —Number of path nodes.

### (3) Path smoothness

The continuity and smoothness of the path are measured by the rate of change of path curvature. The path with high smoothness has fewer turns, which is conducive to reducing the load of hydraulic steering system and improving operation stability. The calculation formula is shown in Equation (12):

$$S_{curv} = \frac{1}{n-2} \sum_{i=2}^{n-1} |\theta_{i+1} - \theta_i| \quad (12)$$

where:  $\theta_i$ —is the turning Angle of the path node.

## RESULTS AND ANALYSIS

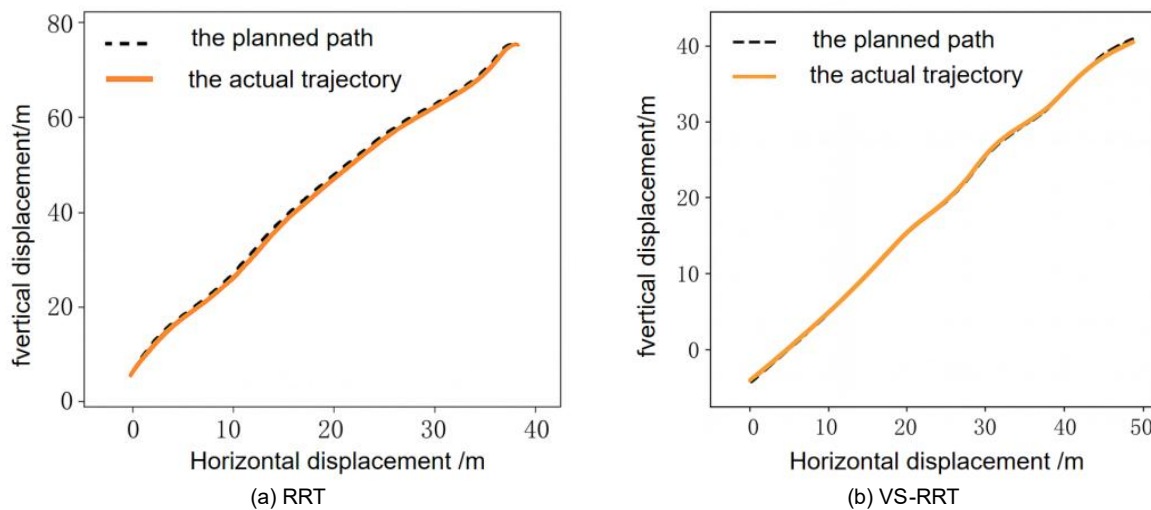
### Path planning time

This study conducted comparative experiments on path planning time between traditional RRT and VS-IRRT algorithms. The experiments were performed under identical field conditions (length 60 m, width 35 m, 4 crop rows, slight terrain undulations, and natural obstacles). Each algorithm was tested 10 times, with parameters including average planning time, path length, and node count recorded. Results in Table 1 show that VS-IRRT achieved a path planning efficiency of 4.02 seconds, demonstrating approximately 32% reduction in average time compared to RRT, while decreasing node count by 27% and path length by 18.5%. This improvement primarily stems from the algorithm's environment-cost-based heuristic sampling and node reconnection optimization strategies. The environment-cost-based heuristic sampling reduces unnecessary searches, enhances path convergence speed through node expansion and reconnection optimization, and the kinematic constraint screening method proposed in Section 2.2.3 improves path feasibility. These combined approaches effectively minimize redundant searches and nodes, thereby enhancing search efficiency and generating shorter, smoother paths.

**Table 1**

**Comparison of path planning times**

| Algorithm type | Average planning time/s | Average path length/m | Average number of nodes/total |
|----------------|-------------------------|-----------------------|-------------------------------|
| tradition RRT  | 5.92                    | 62.8                  | 154                           |
| VS-RRT         | 4.02                    | 51.2                  | 112                           |



**Fig. 3 - Comparison of RRT and VS-IRRT path trajectories**

### Average yaw error

The path execution performance of RRT and VS-IRRT is illustrated in Fig. 3. As shown in Fig. 3(a), the actual trajectory in the RRT algorithm deviates significantly from the planned path, particularly at path transitions where substantial yaw errors occur. This indicates that traditional RRT suffers from high path tracking errors during navigation execution, primarily due to insufficient path smoothing, frequent sharp turns, and the absence of visual servo correction, which leads to cumulative positioning errors. In contrast, the VS-IRRT results (Fig.3 (b)) demonstrate high alignment between the actual trajectory and the planned path with markedly reduced yaw errors. Notably, it maintains consistent performance even on sections with significant curvature changes.

This improvement can be attributed to two key factors: first, the environment-cost-based heuristic sampling strategy reduces unnecessary expansions, making the planned path more aligned with the main direction of the operational area; second, real-time visual servo correction continuously compensates for pose deviations during navigation, effectively preventing cumulative yaw errors caused by GNSS inaccuracies and terrain disturbances.

### Path smoothness

This study quantifies path smoothness by calculating the average change in turning angles across adjacent path segments. The comparison between RRT and VS-IRRT algorithms based on curvature rate variations is presented in Table 2. Results demonstrate that VS-IRRT achieves a curvature rate of only 3.15 °/m, a 33% reduction from traditional RRT's 4.72 °/m, while decreasing turn count by approximately 21% and minimizing maximum turning angles by 20%. The enhanced path smoothness primarily stems from implementing minimum turning radius constraints during expansion, which prevents excessively curved segments. Combined with node reconnection optimization, this approach improves local path structures by eliminating redundant nodes and shortening paths, thereby reducing the frequency of abrupt turns.

**Table 2**

| Comparison of path smoothness |                                        |                                        |                            |
|-------------------------------|----------------------------------------|----------------------------------------|----------------------------|
| Algorithm type                | Average curvature rate of change (°/m) | No. of turns (revolutions per section) | Maximum steering Angle (°) |
| tradition RRT                 | 4.72                                   | 14                                     | 28.3                       |
| VS-IRRT                       | 3.15                                   | 11                                     | 22.6                       |

## CONCLUSIONS

This study addresses key challenges in the field operation of grain harvesters, including low path planning efficiency, high path cost, and visual positioning errors. To overcome these limitations, an improved rapidly-exploring random tree algorithm integrated with visual servoing (VS-IRRT) is proposed. The system achieves real-time environmental perception and pose correction through visual servo feedback, while introducing heuristic sampling, node reconnection optimization, and kinematic constraint filtering into the RRT framework. The main conclusions are as follows:

(1) Field test results show that the average path planning time of VS-IRRT algorithm is 4.02 s, which is 32% shorter than the traditional RRT, and the number of nodes is reduced by 27%. In the field environment with terrain undulation, natural obstacles and positioning noise, VS-IRRT can still maintain high navigation accuracy and path feasibility.

(2) The path curvature generated by VS-IRRT has a rate of change of 3.15 °/m, which is 33% lower than RRT, with a reduction of 21% in steering cycles and 20% decrease in maximum steering angle. By applying the minimum turning radius constraint, the system generates smooth paths that conform to the kinematic characteristics of the harvester, thereby reducing the impact of sharp turns on the hydraulic steering system and improving operational stability. This study has established a comprehensive research framework encompassing theoretical modeling, algorithm implementation, and field validation, laying a solid foundation for future integration of VS-IRRT algorithms into harvester control systems and multi-machine collaborative testing.

(3) Although the VS-IRRT algorithm exhibits exceptional performance in terms of path planning efficiency, smoothness, and navigation accuracy, it still presents certain limitations. The experimental scope and terrain complexity in this study are still constrained, with a lack of validation in large-scale farmland or extreme environments. Furthermore, the weight parameters in the cost function were mainly optimized via empirical approaches and small-scale experiments, lacking universal optimization strategies suitable for diverse crop types and terrain conditions. Therefore, future research should concentrate on multi-scenario, multi-crop, and large-scale operational environments for experimental validation. Furthermore, exploring more adaptive weight adjustment strategies for the cost function will improve the algorithm's versatility and robustness.

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## REFERENCES

- [1] Ahmadi, A., Halstead, M., McCool, C. (2022). Towards autonomous visual navigation in arable fields. *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Vol. 2022, pp.6585-6592. <https://doi.org/10.1109/IROS47612.2022.9981299>
- [2] Chen, W., Chi, W., Ji, S., Ye, H., Liu, J., Jia, Y., & Cheng, J. (2025a). A survey of autonomous robots and multi-robot navigation: Perception, planning and collaboration. *Biomimetic Intelligence and Robotics*, Vol. 5(2), 100203. <https://doi.org/10.1016/j.birob.2024.100203>
- [3] Chen, Z., Chen, Y., Li, H., Wang, P. (2025b). Design and control algorithm of a motion sensing-based fruit harvesting robot. *Frontiers of Agricultural Science & Engineering*, Vol. 12(2), pp. 190-207. <https://doi.org/10.15302/j-fase-2024588>
- [4] Eiffert, S., Wallace, N.D., Kong, H., Pirmarzashti, N., Sukkarieh, S. (2022). Resource and response aware path planning for long-term autonomy of ground robots in agriculture. *Field Robotics*, Vol. 2, pp. 1-33. <https://doi.org/10.55417/fr.2022001>
- [5] Hu, M.Y., Zhang, K., Yu, K.J., Yue, C.T., & Liang, J. (2025). Review of Multi-machine Coordination and Task Allocation in Agricultural Machinery (农机多机协同与任务分配研究综述). *Tractor & Farm Transporter*, Vol. 52(04), pp. 9-14. (In Chinese)
- [6] Huo, F., Zhu, S., Dong, H., & Ren, W. (2024). A New Approach to Smooth Path Planning of Ackerman Mobile Robot based on Improved ACO Algorithm and B-Spline Curves. *Robotics and Autonomous Systems*, Vol. 175, 104655. <https://doi.org/10.1016/j.robot.2024.104655>
- [7] Lian, J., Hui, G., Ma, L., Zhu, T., Wu, X., Heidari, A. A., & Chen, H. (2024). Parrot Optimizer: Algorithm and Applications to Medical Problems. *Computers in Biology and Medicine*, Vol. 172, 108064. <https://doi.org/10.1016/j.compbiomed.2024.108064>
- [8] Lin, Y.P., Yan, G.Y., Wang, T., Bai, T., Tang, S., Chen, J.J., Zhang, B.L. (2025). Development and testing of an intelligent tobacco leaf harvesting robot based on machine vision. *INMATEH-Agricultural Engineering*. Vol.75(1), pp. 600-609. <https://doi.org/10.35633/inmateh-75-51>
- [9] Liu, T.H., Lai, J.S., Sun, W.L., Chen, J.P., Liang, Z.Z., Liu, S.Y., & Chen, S.Y. (2025). Navigation Path Planning of Pineapple Planting Field Based on Jump Point Optimized Ant Colony Algorithm (基于跳点优化蚁群算法的菠萝田间导航路径规划). *Transactions of the Chinese Society for Agricultural Machinery*, Vol. 56(04), pp. 387-396. <http://dx.doi.org/10.6041/j.issn.1000-1298.2025.04.036> (In Chinese)
- [10] Mwitwa, C., Rains, G. C. (2024). The integration of GPS and visual navigation for autonomous navigation of an Ackerman steering mobile robot in cotton fields. *Frontiers in Robotics and AI*, Vol. 11, pp. 1359887-1359887. <https://doi.org/10.3389/frobt.2024.1359887>
- [11] Russello, H., Tol, R.v.d., R., & Kootstra, G. (2022). T-Leap: Occlusion-robust pose estimation of walking cows using temporal information. *Computers and Electronics in Agriculture*, Vol. 192, 106559. <https://doi.org/10.1016/j.compag.2021.106559>
- [12] Sangeetha, V., Krishankumar, R., Ravichandran, K. S., Cavallaro, F., Kar, S., Pamucar, D. and Mardani, A. (2021). A fuzzy gain-based dynamic ant colony optimization for path planning in dynamic environments. *Symmetry*, Vol. 13(2), 280. <https://doi.org/10.3390/sym13020280>
- [13] Shen, X.Y., Tao, Z.R., Wang, Y.D., Zhang, T.Z., Liu, Y.H., Wang, X.X., Yang, J., Li, Z.W., Chen, L., Wang, K.F., & Wang, F.Y. (2025). Key Problems of Embodied Intelligence Research: Autonomous Perception, Action, and Evolution (具身智能研究的关键问题：自主感知、行动与进化). *Acta Automatica Sinica*, Vol. 51(1), pp. 43-71. <https://doi.org/10.16383/j.aas.c240364> (In Chinese)
- [14] Silva, R. D., Cielniak, G., Gao J. (2024). Vision based crop row navigation under varying field conditions in arable fields. *Computers and Electronics in Agriculture*, Vol. 217, 108581. <https://doi.org/10.1016/j.compag.2023.108581>
- [15] Wang, D., Zhang, B., Zhou, J., Xiong, Y., Liu, L., & Tan, Q. (2024). Three-Dimensional Mapping and Immersive Human-Robot Interfacing Utilize Kinect-Style Depth Cameras and Virtual Reality for Agricultural Mobile Robots. *Journal of Field Robotics*, Vol. 41(7), pp. 2413-2426. <https://doi.org/10.1002/rob.22294>
- [16] Wang, W., Zuo, L., & Xu, X. (2018). A Learning-based multi-RRT approach for robot path planning in narrow passages. *Journal of Intelligent and Robotic Systems*, Vol. 90, pp. 81-100. <https://doi.org/10.1007/s10846-017-0641-3>

- [17] Wang, W.J., Chen, Y., Li, T.X., Zhang, Y.Z., & Zhang, H. (2025). RRT\* robotic arm path planning combined with dynamic constrained sampling (结合动态约束采样的 RRT \* 机械臂路径规划). *Communication & Information Technology*, Vol. 4, pp. 36-41. (In Chinese)
- [18] Xie, W., & Hong, X. (2024). Omnidirectional-Sensor-System-Based Texture Noise Correction in Large-Scale 3D Reconstruction. *Sensors*, Vol. 24(1), pp. 78. <https://doi.org/10.3390/s24010078>
- [19] Xun, Y., Li, D.Z., Wang, Y., Huang, X.T., Wang, Z.H., & Yang, Q.H. (2023). Motion Planning of Harvesting Manipulator Based on VS-IRRT Algorithm (基于 VS-IRRT 算法的采摘机械臂路径规划). *Transactions of the Chinese Society for Agricultural Machinery*, Vol. 54(02), pp. 129-138. <http://dx.doi.org/10.6041/j.issn.1000-1298.2023.02.012> (In Chinese)
- [20] Yan, H.F., Li, F.L., Zhu, Y., Li, L., Wu, H.H., & Fang, X.F. (2025). Path Planning Method for Robotic Operation Platforms in Controlled Traffic Farming (受控交通农业模式机器人化作业平台路径规划方法). *Transactions of the Chinese Society for Agricultural Machinery*, Vol. 56(06), pp. 155-166. <http://dx.doi.org/10.6041/j.issn.1000-1298.2025.06.015> (In Chinese)
- [21] Yuan, J., Zhang, Y.G., Jia, E.K.B.K., Zhang, N.N., Liu, C., & Xie, L.W. (2025). Path Planning of Transportation Robots Based on AFD Fusion Algorithm (基于 AFD 融合算法的运输机器人路径规划方法). *Transactions of the Chinese Society for Agricultural Machinery*, Vol. 56(06), pp. 594-607. <http://dx.doi.org/10.6041/j.issn.1000-1298.2025.06.056> (In Chinese)
- [22] Yue, F., Sha, Z., Sun, H., Chen, D., & Liu, J. (2024). Research on the Optimization of TP2 Copper Tube Drawing Process Parameters Based on Particle Swarm Algorithm and Radial Basis Neural Network. *Applied Sciences*, Vol. 14(23), 11203. <http://dx.doi.org/10.3390/app142311203>
- [23] Zhang, Q., Liu, F.P., Jiang, X.P., Xiong, Z., & Xu, C. (2021). Motion planning method and experiments of tomato bunch harvesting manipulator (番茄串收机械臂运动规划方法与试验). *Transactions of the Chinese Society of Agricultural Engineering*, Vol. 37(9), pp. 149-156. <https://dx.doi.org/10.11975/j.issn.1002-6819.2021.09.017> (In Chinese)