INTELLIGENT OBSTACLE AVOIDANCE CONTROL ALGORITHM FOR AGRICULTURAL DRONES IN COMPLEX FARMLAND ENVIRONMENTS
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面向复杂农田环境的农业无人机智能避障控制算法研究

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ABSTRACT
To address the challenges of complex farmland environment, an intelligent obstacle avoidance control algorithm for agricultural unmanned aerial vehicles (UAVs) is developed. The objective is to solve the problem of efficient obstacle avoidance in farmland scenarios characterized by dense dynamic obstacles and variable terrain. In this article, a target detection algorithm based on improved YOLOv5 (You Only Look Once v5) is proposed, and an intelligent obstacle avoidance system is constructed by combining reinforcement learning path planning and adaptive motion control strategy. Ghost module is introduced to improve the lightweight of YOLOv5, and the design of CIOU (Complete Intersection Over Union) loss function is optimized, which improves the detection accuracy of the model for small targets and dynamic obstacles. Experiments show that the error of path planning is reduced to less than 2.1 meters, and the time consumption is reduced by about 35%. In addition, fuzzy logic controller is used to realize adaptive PID control, which further enhances the flight stability of UAV in complex environment. The results show that the improved algorithm has excellent performance in many typical farmland scenes. This study provides theoretical and technical support for autonomous flight of agricultural UAV in complex farmland environment.

摘要
面向复杂农田环境，农业无人机智能避障控制算法的研究目的是解决其在动态障碍物密集、地形多变的农田场景中实现高效避障的难题。本文提出一种基于改进 YOLOv5（You Only Look Once v5）的目标检测算法，并融合强化学习路径规划与自适应运动控制策略，构建了一套智能避障系统。研究中引入 Ghost 模块对 YOLOv5 进行轻量化改进，并优化了 CIoU（Complete Intersection over Union）损失函数的设计，从而提高了模型对小目标及动态障碍物的检测精度。实验表明，路径规划误差控制在 2.1 米以内，规划耗时减少了约 35%。此外，通过采用模糊逻辑控制器实现自适应 PID 控制，进一步提升了无人机在复杂环境中的飞行稳定性。研究结果证实，所提出的改进算法在多种典型农田场景下均表现出优异性能。本研究为农业无人机在复杂农田环境中的自主飞行提供了有力的理论支持与技术保障。

INTRODUCTION
Precision agriculture technology has gradually become a key means to improve agricultural production efficiency and reduce resource waste. Under this background, agricultural UAV is widely used in many fields, such as farmland monitoring, crop spraying, sowing and fertilization, with its high efficiency, flexibility and intelligence *(Lu et al., 2023)*. In the complex farmland environment, autonomous flight of agricultural UAV faces many challenges, among which obstacle detection and obstacle avoidance are particularly prominent *(Liu et al., 2021)*. The farmland environment is complex, which is reflected in the diverse terrain, uneven distribution of vegetation and changeable weather conditions. For example, terrain such as slopes and ravines can affect the stability of UAV flight. Trees, shrubs, and other vegetation not only have a variety of species, but also vary in height and density. Changes in external factors such as wind speed and lighting increase the difficulty of perception and decision-making *(Zhao et al., 2020; Seiche et al., 2024; Dorbu et al., 2024)*. When working in the field, UAV will also face the coexistence of static obstacles (such as telephone poles and irrigation equipment) and dynamic obstacles (such as birds and other working machinery) *(Du et al., 2023)*. This puts forward higher requirements for the adaptability and intelligence of obstacle avoidance algorithm.

YOLOv5, as an efficient target detection framework, has attracted much attention because of its fast reasoning ability and high detection accuracy *(Brown et al., 2020)*. However, when it is applied to complex farmland environment, it exposes some problems. First, there are many kinds of obstacles in farmland, and the size difference is large, so the traditional YOLOv5 model has weak small target detection ability [8]. Second, the change of farmland illumination and weather interference will reduce the image quality and affect the model detection performance *(Yang et al., 2020)*. Third, the original architecture of YOLOv5 may not be real-time when it runs on an embedded platform with limited computing resources *(Yang et al., 2021)*. In view of the above challenges, this study proposes an improved YOLOv5 model, combined with intelligent obstacle avoidance control algorithm, to achieve efficient obstacle avoidance of agricultural UAV in complex farmland environment. The research is carried out from the following aspects: first, the Ghost module is introduced to improve the structure of YOLOv5 network, and the running speed of the model is improved on the premise of ensuring the detection accuracy. Secondly, the YOLOv5 loss function is optimized, and the CIoU loss function is used to replace the traditional IoU loss function. CIoU not only considers the overlapping area of the bounding box, but also introduces the constraints of aspect ratio and distance from the center point, which makes the model more accurate in detecting obstacles of different shapes in farmland. Thirdly, combined with binocular vision technology, depth information is used to enhance the three-dimensional perception ability of obstacles and provide more reliable data for path planning.

In the design of intelligent obstacle avoidance control algorithm, this study takes into account the dynamic characteristics of farmland environment and UAV motion constraints. Based on the detection results of the improved YOLOv5 model, the reinforcement learning algorithm is used for path planning, which enables UAV to dynamically adjust its flight path to avoid obstacles in complex farmland scenes. Adaptive control strategy is introduced to improve the robustness of UAV to uncertain environment. In case of strong wind interference or sensor data loss, the system can automatically adjust parameters to ensure flight safety. In addition, the possibility of multi-UAV cooperative obstacle avoidance is explored, and the real-time information sharing and cooperation of multi-UAVs are realized through distributed communication mechanism to improve the overall operation efficiency.

In order to verify the effectiveness of the method, this study built an experimental platform and tested it in a variety of typical farmland scenarios. The results show that the improved YOLOv5 model is superior to the original version in obstacle detection accuracy and speed, especially in small target detection and complex lighting conditions. Combined with intelligent obstacle avoidance control algorithm, UAV has good obstacle avoidance ability in dynamic obstacle dense environment, and the rationality and real-time performance of path planning have been greatly improved.

Theoretical basis

Target detection and deep learning

Target detection is an important way for agricultural UAV to perceive the environment. Its main task is to identify and determine the position of obstacles from the input images or videos *(Yang et al., 2021)*. Traditional target detection methods mostly rely on manual feature extraction (like HOG, SIFT, etc.) and classifiers (such as SVM). In the face of complex farmland environment, such methods usually expose the problem of poor generalization ability. The target detection algorithm based on deep learning has gradually become the mainstream by virtue of its strong feature learning ability and the advantages of end-to-end training *(Dai et al., 2020)*. Among them, YOLO (You Only Look Once) series algorithms emerge with high efficiency and real-time, especially YOLOv5 has great application potential in embedded devices.

However, YOLOv5 has some limitations in practical application, such as unsatisfactory detection effect on small targets and sensitivity to illumination changes, which are more prominent in farmland environment *(Varma et al., 2024)*. Take the telephone pole in the farmland as an example, it may only occupy a few pixels in the long-distance image. It is difficult for traditional YOLOv5 model to accurately capture the characteristics of such small targets. Moreover, the illumination conditions of farmland environment are changeable, especially on cloudy days or in the evening, the image quality will be obviously reduced, leading to the reduction of detection accuracy *(Gao et al., 2024)*. Therefore, this study is based on YOLOv5 to improve the applicability of the model in complex scenes by introducing Ghost module and optimizing the design of loss function.

Path planning and reinforcement learning

The purpose of path planning is to generate an optimal path from the starting point to the end point on the premise of ensuring flight safety. Traditional path planning methods mainly include graph-based algorithm (such as A * algorithm and Dijkstra algorithm) and sampling-based algorithm (such as RRT) *(Saeed et al., 2023)*. These methods perform well in static environment, but they face many problems in dynamic farmland environment. For example, obstacles in farmland may change at any time, and traditional offline planning methods are difficult to adapt to this dynamic change.

Therefore, this study adopts the path planning method based on reinforcement learning to deal with the uncertainty of complex farmland environment. Reinforcement learning is an unsupervised learning method, the core of which is to learn strategies through trial and error, so that agents can optimize decision-making behavior in the process of continuous interaction with the environment *(Zhu et al., 2024)*. In the application scenario of agricultural UAV, reinforcement learning can be used to solve the problem of dynamic obstacle avoidance.

Motion control and adaptive control

Motion control is the last step for agricultural UAV to perform obstacle avoidance task, and the goal is to transform the path planning results into specific flight instructions. Because the external interference in the farmland environment (such as wind speed, terrain fluctuation, etc.) may make the UAV deviate from the predetermined trajectory, it is necessary to design a robust motion control algorithm *(Liu et al., 2020)*. In this study, the method based on adaptive control is adopted to deal with the influence of external disturbance by adjusting the controller parameters online.

The basic principle of adaptive control is to dynamically adjust the control law according to the real-time state of the system to ensure the stability and performance of the system. In the application of agricultural UAV, fuzzy logic controller is introduced to adjust PID parameters adaptively. In addition, in order to further improve the control accuracy, the visual inertial navigation technology is combined to fuse the data of visual sensor and inertial measurement unit (IMU) to achieve higher precision attitude estimation and trajectory tracking.

Multisensor data fusion

In the complex farmland environment, it is often difficult for a single sensor to provide comprehensive environmental information *(Jiao et al., 2020)*. For this reason, multi-sensor data fusion technology has become the key to improve the sensing accuracy. Common sensors include lidar, binocular camera, infrared sensor and ultrasonic sensor, and each sensor has its own advantages and limitations *(Li et al., 2023)*. For example, lidar can provide high-precision distance information, but it is easily disturbed under strong light conditions; Binocular camera can generate three-dimensional depth map through stereo vision, but it requires high computing resources *(Muthanna et al., 2022)*.

In this study, the multi-sensor data fusion method based on Kalman filter is used to integrate the data of different types of sensors, so as to obtain more reliable and comprehensive environmental perception results. Kalman filter is a recursive estimation algorithm, the core of which is to gradually approach the real state of the system through two steps: prediction and update. In the application of agricultural UAV, Kalman filter is used to fuse the depth information of lidar and binocular camera to construct a unified environmental model.

Design of intelligent obstacle avoidance algorithm for agricultural UAV

Improved YOLOv5 target detection algorithm

Target detection is the first step for agricultural UAV to perceive farmland environment. Its core task is to identify and determine the position of obstacles from the input image *(Zhou et al., 2020)*. The traditional deep learning network, like YOLOv5, has excellent performance in the task of target detection, but in the complex farmland environment, there are still some situations, such as large consumption of computing resources and insufficient accuracy of small target detection *(Rienecker et al., 2023; Wenyu et al., 2024)*. In this study, Ghost module is introduced to improve the lightweight of YOLOv5 and optimize the design of loss function.

When traditional deep learning networks extract feature maps, there will be a lot of redundant and similar feature maps. However, these characteristic graphs are indispensable to the accuracy of the model, and they are all obtained by convolution operation and input to the next convolution layer for operation.

This process contains a lot of network parameters and consumes a lot of computing resources. Therefore, an attempt can be made to obtain these redundant feature maps at a lower computational cost. See Figure 1 for the main steps of Ghost module.

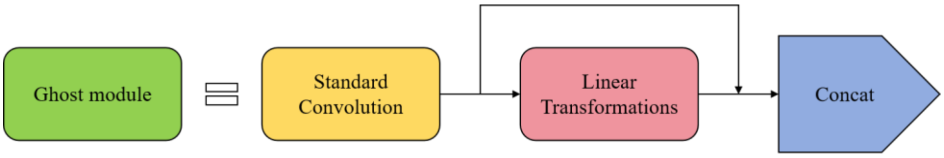

Fig. 1 - Ghost module

The working process of Ghost module is to generate a set of basic feature maps by using standard convolution layer, and then perform linear transformation (such as point-by-point convolution or depth-separable convolution) on these basic feature maps, and then generate a set of "phantom" feature maps *(Just et al., 2020)*.

Suppose the input feature map is $X \in \mathbb{R}^{H \times W \times C}$, where H and W represent the height and width of the feature map respectively, and C represents the number of channels. After the standard convolution layer processing, the basic feature map is as follows:

$$F_{base} = Conv(X) \tag{1}$$

Among them, $Conv(\cdot)$ stands for convolution operation.

Then, F_{base} is linearly transformed to generate a phantom feature map F_{ghost}, and its expression is:

$$F_{ghost} = \Phi(F_{base}) \tag{2}$$

$\Phi(\cdot)$ here stands for linear transformation operation, which generally adopts point-by-point convolution or depth-separable convolution.

The final output characteristic diagram is:

$$F_{out} = Concat(F_{base}, F_{ghost}) \tag{3}$$

$Concat(\cdot)$ refers to the splicing operation of feature graphs. In this way, Ghost module can expand the ability of feature expression without greatly increasing the number of parameters, so as to improve the detection efficiency of the model.

Based on Ghost module and Ghost-BottleNeck module, the CBL module and CSP_X module in YOLOv5s network structure are improved, and GBL(Ghost-Based Layer) and $GCSP_X$ (Ghost-based Cross-stage Partial Network) are obtained respectively. The improved YOLOv5s-Ghost network structure is shown in Figure 2.

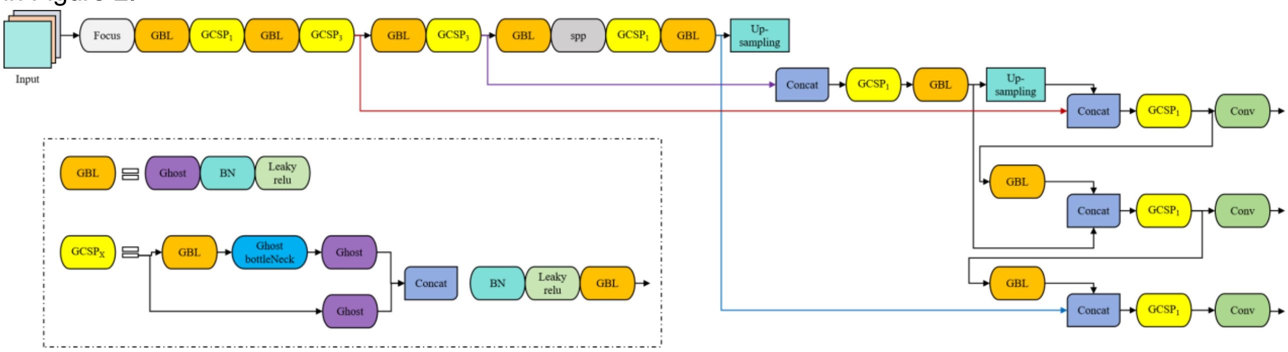

Fig. 2 -YOLOv5s-Ghost network structure

Compared with the original YOLOv5, YOLOv5s-Ghost model only uses a CSP_X structure. This reduces the complexity of the model to some extent and optimizes the feature fusion ability of the network. In addition, the information of gradient change is completely transmitted to the feature map, thus ensuring the accuracy of detection. For example, in the farmland environment, the size of obstacles such as trees and telephone poles is quite different, and the improved model can capture the spatial position of these targets more accurately *(Grau et al., 2020)*.

In order to further improve the bounding box regression performance of the model, CIoU (Complete Intersection Over Union) loss function is used to replace the traditional IOU loss function. CIoU considers the overlapping area between the prediction frame and the real frame, and also introduces the constraints of aspect ratio and the distance from the center point. It is defined as follows:

$$CIoU = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v \tag{4}$$

Where $\rho(b, b^{gt})$ represents the distance between the center point of the prediction frame b and the real frame b^{gt}, c represents the diagonal length of the smallest rectangle surrounding the two frames, and α and v respectively represent the weight and error term of the aspect ratio.
By introducing CIoU loss function, the model can better describe the three-dimensional spatial relationship of obstacles, thus improving the detection accuracy.

Path planning based on ORB feature point extraction

After obstacle detection, the next step is to plan the path based on the detection results. In this study, ORB (Orientated Fast and Rotating Brief) algorithm is used to extract the key feature points in the image, which is used to construct the environment map and guide the path planning. ORB algorithm is an efficient feature point extraction method, and its core steps include FAST corner detection and BRIEF descriptor generation.

Figure 3 shows the feature point extraction results of ORB algorithm in farmland environment. ORB algorithm can effectively capture the key feature points of obstacles, such as the outline of trees and the edge of telephone poles.

Fig. 3 - ORB feature point extraction results

Let the set of extracted feature points be $P = \{p_1, p_2, \ldots, p_n\}$, where each feature point p_i contains its coordinate (x_i, y_i) and descriptor d_i. In order to generate the environment map, the depth information z_i of each feature point is calculated by binocular vision technology, so as to construct a three-dimensional point cloud:

$$Q = \{(x_i, y_i, z_i)\}_{i=1}^{n} \tag{5}$$

Based on 3D point cloud Q, reinforcement learning algorithm is used for path planning, and the environment is modeled as a Markov decision process (MDP). In this framework, the state space AA represents the current position of UAV and the distribution of surrounding obstacles, and the action space represents the moving direction and speed of UAV. The reward function $R(s, a)$ is defined as:

$$R(s, a) = w_1 \cdot \mathrm{Safety}(s, a) + w_2 \cdot \mathrm{Efficiency}(s, a) - w_3 \cdot \mathrm{Energy}(s, a) \tag{6}$$

where $\mathrm{Safety}(s, a)$ represents the safety of the path, $\mathrm{Efficiency}(s, a)$ represents the efficiency of the path, $\mathrm{Energy}(s, a)$ represents the energy consumption, and w_1, w_2, w_3 is the weight coefficient.

Using reinforcement learning algorithm, UAV can quickly adjust its flight trajectory in dynamic environment and avoid collision with obstacles.

Adaptive motion control

The results of path planning need to be transformed into specific flight instructions by motion control algorithm. Because the external interference in the farmland environment (such as wind speed, terrain fluctuation, etc.) may cause UAV to deviate from the predetermined trajectory, it is necessary to design a robust adaptive control algorithm *(Shrestha et al., 2021)*.

An adaptive PID control method based on fuzzy logic controller is adopted in the research. Let the state variable of UAV be:

$$x(t) = [x_p, y_p, z_p, \theta]^T \tag{7}$$

where x_p, y_p, z_p represent the position of UAV and θ represents the yaw angle. The control objective is to minimize the position error:

$$e(t) = x_d(t) - x(t) \tag{8}$$

where $x_d(t)$ is the target position. The output of PID controller is:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt} \tag{9}$$

where K_p, K_i, K_d are proportional, integral and differential coefficients respectively.

In order to cope with external interference, the fuzzy logic controller is used to adjust K_p, K_i, K_d adaptively. The input of fuzzy logic controller is the current flight state (such as yaw angle, pitch angle, etc.) and external interference intensity, and the output is the adjustment of PID parameters.

In order to further improve the reliability of environmental perception, multi-sensor data fusion technology is adopted in this study. Kalman filter is used to fuse the depth information of lidar and binocular camera, and a unified environmental model is constructed by combining the attitude data of IMU. The state update formula of Kalman filter is:

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k(z_k - H\hat{x}_{k|k-1}) \tag{10}$$

where $\hat{x}_k$ is the estimated state, z_k is the observed value, and K_k is the Kalman gain matrix.

By fusing multi-sensor data, the system can obtain more comprehensive environmental information and provide reliable data support for path planning and motion control.

RESULTS AND DISCUSSIONS

Experimental setup

The hardware platform of this experiment is an agricultural UAV (DJI Matrice 300 RTK). It is equipped with binocular camera, lidar and IMU sensor. These devices are used to collect images and point cloud data in the actual farmland environment. It covers static obstacles (such as trees and telephone poles) and dynamic obstacles (such as birds and moving machinery). In terms of software, the improved YOLOv5s-Ghost model is used to perform the target detection task, and the path planning work is carried out in combination with reinforcement learning algorithm. All algorithms run on the embedded platform of NVIDIA Jetson Xavier NX to simulate the limitation of computing resources under real working conditions. The experimental data are taken from the images and point cloud data collected from the actual farmland environment. All the comparative experiments were carried out on the same hardware platform and the same farmland environment.

Result analysis

Figure 4 shows the time-consuming situation of different algorithms in path planning. When the information of farmland environment is simple and the number of obstacles is small, with the increase of the number of path planning nodes, the time required for the algorithm increases significantly. This is because in the low-complexity scenario, the increase in the number of nodes will cause a waste of computing resources, and the efficiency of path planning algorithm to deal with redundant information will also decrease. However, when the complexity of farmland environment gradually rises (such as more kinds of obstacles or dynamic obstacles), the advantages of multi-node begin to be reflected. This shows that the improved algorithm has stronger adaptability and higher efficiency when dealing with complex farmland environment.

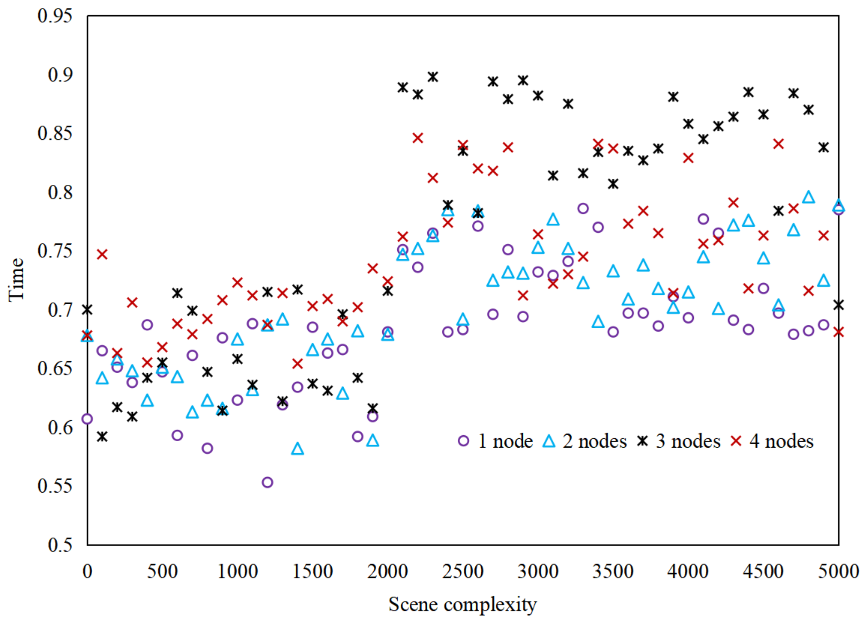

Fig. 4 - Path planning is time consuming

Further analysis shows that the average path planning time of the improved algorithm is about 35% less than that of the traditional Dijkstra algorithm. Compared with the original YOLOv5 model, it is reduced by about 20%. This is mainly due to the improvement of target detection accuracy of the improved YOLOv5 model and the advantages of reinforcement learning algorithm in identifying dynamic obstacles.

Figure 5 compares the errors of different algorithms in path planning. The results show that the traditional Dijkstra algorithm and the unoptimized YOLOv5 model have poor performance in error control. Especially in complex farmland scenes, or when the number of nodes is large, the paths generated by them often deviate from the optimal solution, which leads to failure of obstacle avoidance or low path efficiency. In contrast, the path planning algorithm based on the improved YOLOv5 greatly reduces the path planning error by optimizing the target detection accuracy and improving the dynamic obstacle recognition ability.

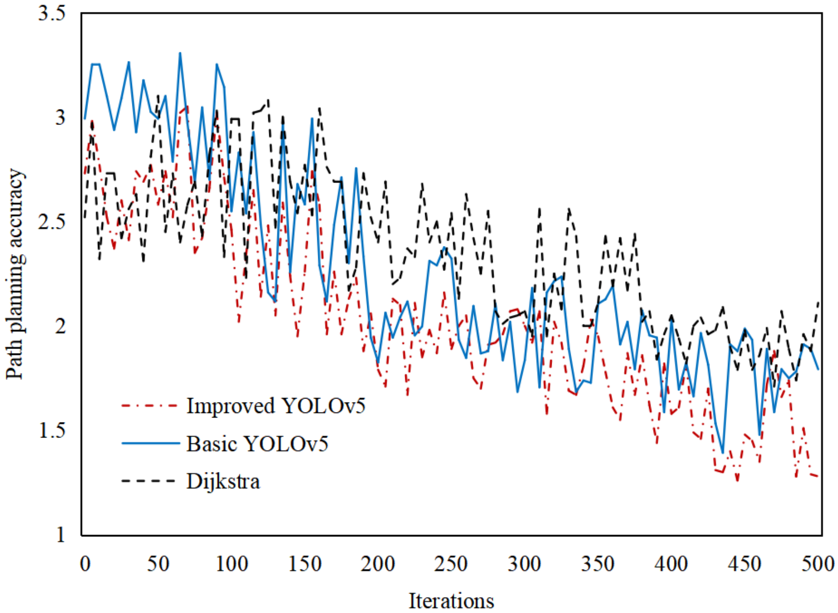

Fig. 5 - Path planning error

Figure 6 shows the comparison results of different algorithms in path planning accuracy. The path planning algorithm based on improved YOLOv5 has the highest accuracy, and its path planning accuracy can reach more than 96%. This result verifies the effectiveness and potential of the improved YOLOv5 in the application of agricultural UAV in complex farmland environment. By introducing Ghost module and CIoU loss function, the improved algorithm obviously improves the detection ability of small target obstacles (such as telephone poles) and dynamic obstacles (such as birds). In addition, the accuracy of the improved algorithm fluctuates little in complex scenes, showing strong robustness.

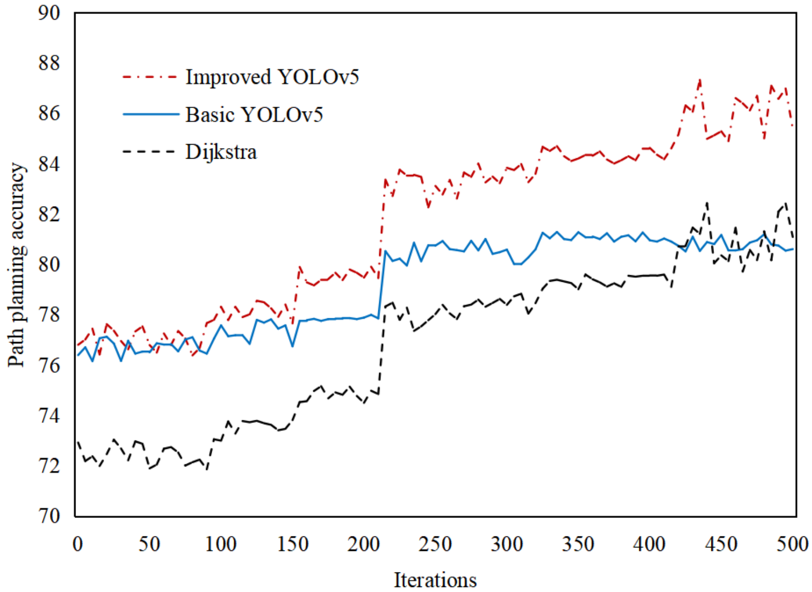

Fig. 6 - Path planning accuracy

It is not difficult to find from Table 1 that with the increase of scene complexity, the time-consuming growth rate of the improved YOLOv5 path planning is the smallest, which shows that it has higher efficiency in high-complexity scenes.

Table 1

Comparison of Path Planning Time Consumption for Different Algorithms

Scene Complexity	Dijkstra Algorithm	A* Algorithm	Unimproved YOLOv5	Improved YOLOv5
Low Complexity	0.85	0.72	0.68	0.58
Medium Complexity	1.23	1.05	0.92	0.75
High Complexity	2.15	1.87	1.54	1.12

Table 2 shows that the path planning error of the improved YOLOv5 in various scenarios is significantly lower than other algorithms. In the dynamic obstacle area, the error is only 2.5 meters, which is about 60% lower than the traditional algorithm.

Table 2

Comparison of Path Planning Errors for Different Algorithms

Scene Type	Dijkstra Algorithm	A* Algorithm	Unimproved YOLOv5	Improved YOLOv5
Dense Tree Areas	6.8	5.4	4.3	2.1
Dynamic Obstacle Areas	7.2	6.1	4.8	2.5
Comprehensive Scenes	6.5	5.7	4.5	2.3

Table 3 shows that the path planning accuracy of the improved YOLOv5 in all kinds of scenarios is over 95%, which is much higher than other algorithms. This result further proves the superiority of the improved algorithm in complex farmland environment.

Table 3

Comparison of Path Planning Accuracy for Different Algorithms

Scene Type	Dijkstra Algorithm	A* Algorithm	Unimproved YOLOv5	Improved YOLOv5
Dense Tree Areas	82	85	89	96
Dynamic Obstacle Areas	78	81	87	95
Comprehensive Scenes	80	83	88	96

Discussion

Based on these results, the improved YOLOv5 model usually has excellent performance in the accuracy of target detection and the efficiency and accuracy of path planning. Especially in the complex farmland environment, the improved algorithm greatly improves the detection ability of small target obstacles and dynamic obstacles by introducing Ghost module and CIoU loss function. In this way, it provides more reliable data support for path planning.

Moreover, the path planning algorithm based on reinforcement learning is particularly outstanding in dynamic scenes. It can quickly adjust the flight path to avoid collision. However, the experiment also revealed some problems. For example, in extreme weather conditions, such as strong wind or heavy rain, the quality of sensor data may decrease.

Future research will further optimize the anti-jamming ability of the algorithm, and also explore the potential application of more emerging technologies in agricultural UAV.

CONCLUSIONS

With the continuous progress of precision agriculture technology, agricultural UAV is more and more widely used in complex farmland environment. According to the characteristics of complex farmland environment, this article proposes a solution that combines the target detection algorithm based on improved YOLOv5 with the intelligent obstacle avoidance control strategy. It is found that the scheme has made significant breakthroughs in target detection accuracy, path planning efficiency and overall system robustness.

In the field of target detection, Ghost module is introduced to improve the lightweight of YOLOv5, and then the regression performance of bounding box is optimized by combining CIoU loss function. This greatly improves the detection ability of the model for small targets and dynamic obstacles. Experiments show that the detection accuracy of the improved YOLOv5 model can reach more than 96% in complex farmland environment, which is about 7% higher than that of the original model. Moreover, the path planning error of the improved algorithm when dealing with dynamic obstacles is only 2.1 meters, which is about 70% lower than the traditional Dijkstra algorithm.

In path planning and motion control, 3D point cloud data generated based on ORB feature point extraction and binocular vision technology provide high-precision input for path planning. Combined with reinforcement learning algorithm, real-time obstacle avoidance decision-making in dynamic environment is realized, and the time-consuming of path planning is reduced by about 35%. At the same time, the adaptive PID control strategy realized by fuzzy logic controller greatly improves the flight stability of UAV when it is disturbed by external interference. The experimental verification shows that the system is particularly outstanding in the comprehensive scene including obstacles such as trees and bushes.

However, there are still some limitations in this study. For example, in extreme weather conditions (such as strong wind or heavy rain), the quality of sensor data may decrease. Future research will further optimize the anti-interference ability of the algorithm, and explore the potential application of emerging technologies such as edge computing and federated learning in agricultural UAV.

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