agriculture

Review

Research Progress on Autonomous Operation Technology for Agricultural Equipment in Large Fields

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Abstract: Agriculture is a labor-intensive industry. However, with the demographic shift toward an aging population, agriculture is increasingly confronted with a labor shortage. The technology for autonomous operation of agricultural equipment in large fields can improve productivity and reduce labor intensity, which can help alleviate the impact of population aging on agriculture. Nevertheless, significant challenges persist in the practical application of this technology, particularly concerning adaptability, operational precision, and efficiency. This review seeks to systematically explore the advancements in unmanned agricultural operations, with a focus on onboard environmental sensing, full-coverage path planning, and autonomous operational control technologies. Additionally, this review discusses the challenges and future directions of key technologies for the autonomous operation of agricultural equipment in large fields. This review aspires to serve as a foundational reference for the development of autonomous operation technologies for large-scale agricultural equipment.

Keywords: agricultural equipment; autonomous operation; environmental sensing; complete-coverage path planning

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1. Introduction

Agriculture is a typical labor-intensive industry that relies heavily on labor [1]. With the aging of the population, the agriculture in countries where smallholder farming is the prevalent form of agriculture has been severely affected. These effects are more severe in countries such as China, where smallholder farmers predominate. Compared to 1990, about 4 million hectares of cropland were abandoned in China in 2019 [2]. In the future, the aging population in China is expected to accelerate further, necessitating urgent measures to reduce agriculture's heavy reliance on manual labor [3–5]. To cope with the status quo of smallholder agriculture, new agricultural models have been encouraged by the Chinese government, mainly including family farms, new rural cooperatives, and large-scale farms. The new model is conducive to promoting modern agriculture towards an intelligent and scaled agricultural production model [6,7]. The technology of autonomous operation of agricultural equipment in large fields can be adapted to new modes of agricultural production, which is an important method to improve productivity and reduce labor intensity, and it helps to alleviate the impact of population aging on agricultural production [8–13]. The key technologies for autonomous operation of large-scale agricultural equipment mainly include onboard environmental sensing technology, complete-coverage path-planning technology and autonomous operation control technology, as shown in Figure 1.

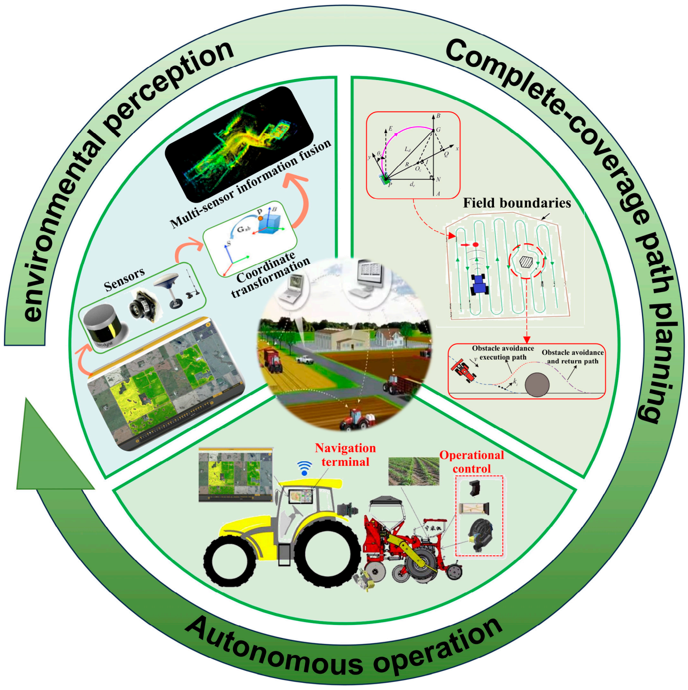

Figure 1. Schematic diagram of the key technology for autonomous operation of agricultural equipment in large fields. This figure illustrates the comprehensive workflow, from multi-sensor environmental data acquisition to complete-coverage path planning, culminating in the autonomous operation of agricultural machinery. Collectively, these factors influence the overall effectiveness of autonomous operations in large-scale agricultural machinery.

Onboard environmental sensing technology is the primary condition for agricultural machines to achieve unmanned operations [14], and it is also the key to ensuring the safe and efficient operation of unmanned agricultural machines in complex and variable unstructured farmland environments. Despite the remarkable advancements achieved in unmanned farm machinery, its practical application continues to confront numerous challenges, stemming from the intricacies and variability of the farmland environment. For example, a single sensor is often utilized to gather environmental information during unmanned operation processes such as cultivation, management, and harvesting [15]. However, a single sensor can only obtain one-sided information when sensing the environment, and there are problems, such as insufficient autonomous sensing ability and poor environmental adaptability. Agricultural machines equipped with multiple environment-aware sensors have improved stability and reliability in unmanned operations, but the application of multi-sensor information fusion algorithms still faces challenges [16]. Hence, analyzing the data characteristics of sensors employed in environmental sensing technologies, while fully leveraging the redundancy and complementary aspects of multi-sensor data, is crucial for developing stable and reliable environmental sensing systems.

The key to realizing the unmanned operation of agricultural equipment lies in the complete-coverage path-planning technology. For different operational tasks and farmland environments, the goal is often to minimize operational costs and cover a wide range of operations [17]. Path-planning technology is employed to devise the optimal driving path for achieving efficient and precise farmland operations. Path-planning techniques are typically categorized into global path planning and local path planning [18,19]. Global path planning aims to plan the optimal path in the whole operation area to maximize the coverage and minimize the costs. Local path planning focuses on responding to real-time changes in the environment, ensuring that agricultural machinery can safely and efficiently accomplish operational tasks in a dynamic environment. At this stage, the main problems faced by path-planning technology include operational efficiency, operational plot coverage, operational safety, and other aspects. Despite significant advancements in path-planning technology, it still faces numerous challenges and requires further research and improvement. Enhancing its adaptability to complex environments, real-time responsiveness, and multi-objective optimization is essential to meet the demands of modern agricultural production.

Autonomous operation control technology is the core for enabling the unmanned operation of agricultural equipment, encompassing two key aspects: motion control and operational control [20–22]. Motion control primarily enhances path-tracking accuracy through speed control and steering control. Operation control addresses the specific tasks performed by agricultural machinery in various operations, such as seeding, fertilizing, spraying, and harvesting [23,24]. Motion control and operation control technologies complement each other to ensure that intelligent farm machinery can efficiently and accurately complete operational tasks in the complex and changing farmland environment. In farmland environments, where there are errors in existence due to factors such as undulating terrain and changes in soil type, it is frequently challenging for motion control methodologies to accurately adhere to a predetermined path. Moreover, operational control is essential for enhancing the autonomous operational capabilities of agricultural machinery, achieving fully unmanned operations, and advancing agriculture towards intelligence and precision. Although some common control methods can mitigate motion control errors and improve the intelligence of operational control, there is still a need for some better methods to improve motion control and operational control effectiveness.

In conclusion, onboard environmental sensing technology, complete-coverage path-planning technology, and autonomous operation control technology are the key technologies for the unmanned operation of agricultural equipment in large fields. This paper focuses on analyzing the current research status of these three components. Currently, numerous scholars have conducted extensive studies on these three components. However, intelligent agricultural machines, designed for unmanned operations in large fields, are rapidly advancing, but progress overall is uneven. This uneven progress hinders scholars from accurately pinpointing the direction of key technology development in this field. Therefore, it is crucial to systematically summarize the research progress on the key technology of unmanned field operations for large agricultural equipment. The main objective of this paper is to review and analyze representative literature on the key technology of the unmanned field operation of large-scale agricultural equipment, providing a reference for the development of unmanned field operation technology for large agricultural machinery.

2. Onboard Environmental Sensing Technology

Onboard environmental sensing technology is primarily employed to address the complexities and dynamic nature of the operational environment by utilizing localization systems and sensory devices mounted on agricultural machinery. The operational state of the machinery is then continuously adjusted in real time, informed by the data on the terrain, obstacles, and other environmental factors [25,26]. Subsequently, the system swiftly modifies the machine's operational status in response to real-time data inputs. Compared to onboard sensing tasks for road vehicles, farmland lacks distinctive structured features, making it essential to create environment models of typical farmland elements using sensor data for unmanned farm machinary operations. Key sensory elements in farmland comprise information on farmland boundaries, crop rows, and obstacles within the farmland (as illustrated in Figure 2). Currently, the onboard environmental sensing tasks of intelligent agricultural equipment in unstructured farmland environments are mainly focused on localization data acquisition, farmland boundary detection, navigation line extraction, and obstacle detection [27–30]. The main methods are vision and radar detection, which are committed to improving the robustness of the sensing system and enhancing the autopilot and autonomous operation performance of the agricultural equipment.

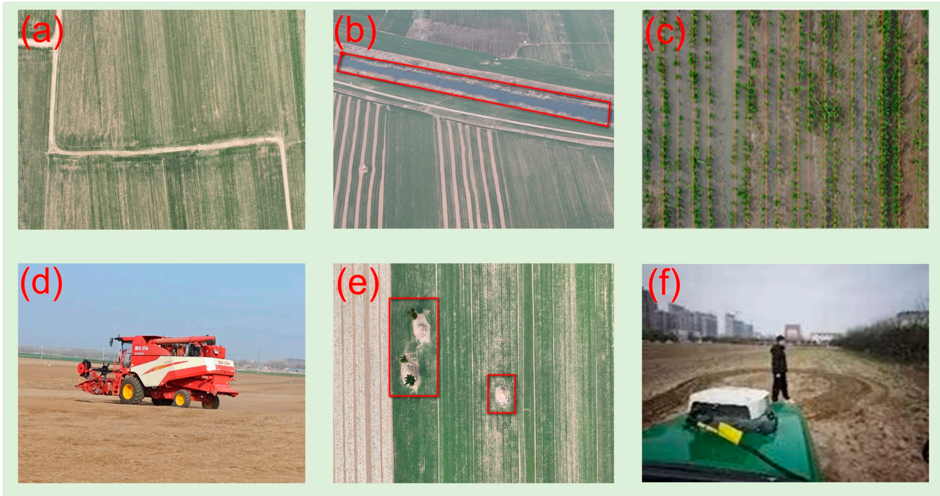

Figure 2. Typical perceptual elements in farmland: (**a**) farm boundary; (**b**) ditch; (**c**) crop row; (**d**) operating farm machinery; (**e**) stationary obstacle; (**f**) person.

The acquisition of precise positioning data is the fundamental prerequisite for enabling the navigation operations of agricultural machinery. The Global Navigation Satellite System (GNSS) has emerged as a universally recognized and widely adopted technology for tracking and positioning agricultural machinery, providing crucial data, such as heading, speed, and time [31]. The GNSS encompasses multiple satellite positioning systems, including GPS, BDS, GLONASS, and Galileo, rather than referring to a singular satellite system [32,33]. While the GNSS can achieve positioning accuracy within a range of a few meters to several meters in open environments, the autonomous navigation of agricultural machinery demands centimeter-level precision, rendering typical GNSS accuracy insufficient for such applications [34–36]. Real-Time Kinematic (RTK) is a differential technique, used for the real-time processing of carrier-phase observations from two measurement stations, encompassing both traditional and network RTK [37,38]. The RTK system, an enhancement technology built upon standard GNSS, significantly improves positioning accuracy from meters to centimeters via differential algorithms, thereby offering essential spatial data support for the implementation of precision agriculture [39]. In recent years, extensive research efforts have been undertaken by scholars to advance navigation and localization techniques grounded in GNSS technology. Yue et al. [40] designed an automatic navigation system for a tracked orchard sprayer based on GNSS technology. The navigation operation accuracy was improved by compensating the effect of machine vibration on the localization data. Kaivosoja et al. [41] developed a GNSS error simulator to simulate the positioning error and positioning reliability of GNSS in various typical agricultural scenarios. Lee et al. [42] designed a dual antenna to receive localization information so that the harvester can obtain the current direction even under stationary working conditions. Although RTK-GNSS achieves high positioning accuracy in open environments, farmland conditions are often complex and variable, with frequent challenges, such as signal occlusion, multipath effects, and environmental obstacles, which can compromise positioning accuracy [43–45]. Consequently, multi-sensor information fusion technology is being progressively integrated into agricultural machinery navigation, harnessing complementary advantages to enhance overall localization performance. Jing et al. [46] designed an automatic navigation grading system for GNSS/INS, which utilized adaptive square root Kalman filtering to fuse the data from GNSS and INS to improve the operational efficiency of grading machines. Li et al. [47] fused GNSS positioning equipment and an inertial measurement unit based on a fuzzy adaptive finite impulse response Kalman filter algorithm to enable high positioning accuracy and the stability of agricultural implements. Xu et al. [48] proposed a backpropagation neural network-based GNSS/INS/OD/NHC adaptive combined navigation method considering vehicle motion, which fully considered the relationship between forward speed, heading angular velocity, and lateral velocity. A review of the literature reveals that multi-sensor fusion localization can leverage data from additional sensors to ensure system stability and continuity in the event of sensor failure. However, practical applications of multi-sensor fusion localization continue to face challenges, including the complexity of data fusion algorithms and time synchronization issues among sensors.

Field boundary detection and navigation line extraction are important foundations for the autonomous operation capability of agricultural machinery. Currently, the methods of farmland boundary detection by onboard sensing systems of agricultural machines are mainly based on sensors such as mono/binocular vision and LiDAR. Hong et al. [48] designed a field boundary recognition and ranging method based on a binocular vision approach. Multi-feature fusion and split-tree algorithms were applied for cost calculation and cost aggregation respectively. Using the multi-scale cost aggregation framework, the linkage of matching costs at different scales was established to enhance the reliability in weak texture regions. Then, the interference elimination method based on point-cloud continuity was designed according to land cultivation and crop growth. Adaptive extraction for point-cloud boundary is realized, and accurate ridge boundary lines are identified, which improves the stereo-matching accuracy and speed of farmland images. Wang et al. [49] designed the detection method of non-regular headland boundary lines based on machine vision technology; this method provides a baseline for the automatic navigation and turning of agricultural equipment at the boundary of the farmland to achieve the whole autonomous navigation operation of agricultural machinery. Li et al. [50] proposed a machine vision-based headland boundary detection method for paddy fields, which introduced depth information, in addition to RGB images, to improve its detection accuracy. A deep learning network combining a convolutional neural network and a recurrent neural network was constructed for headland semantic segmentation. Meanwhile, an interactive attention module is proposed to fuse the complementary information in RGB-D images adaptively. In addition, the image preprocessing technique and the proposed distance-based clustering algorithm for boundary points are applied to the headland segmentation mask to obtain the boundary line of the farmland. This process provides technical support for the automatic turning strategy of the agricultural machine. There often exists some highly non-uniform vegetation at the field boundaries [51], which leads to difficulties in extracting the field boundaries. Although the point-cloud data acquired by LiDAR at the field boundary has irregular height characteristics, the data still have certain linear characteristics [52–54]. Therefore, strengthening the linear features of the point-cloud data becomes an important method for improving the accuracy of boundary extraction by LiDAR sensors.

Navigational line extraction is also crucial for improving the autonomous operation of agricultural machinery. Hou et al. [55] proposed a lightweight path recognition model based on the U-Net model, which solves the problem of poor accuracy and real-time performance of the method for recognizing navigation paths for fruits between ridges. The model can also improve the real-time navigation and accuracy requirements. Gong et al. [56] effectively extracted navigation lines based on the composite localization points of corn and stems and solved the problem regarding the difficult extraction of navigation lines in corn fields with weed interference. Diao et al. [57] proposed an algorithm for the extraction of navigation lines of corn-spraying robots based on an improved YOLOv8s network. The algorithm addressed the low accuracy of navigation line extraction for corn-spraying robots in a complex farmland environment and improved the accuracy of the autopilot feature. In addition, LiDAR is an important sensor for navigation line extraction. For example, it can be used for crop row identification and navigation line extraction within regions of interest in the LiDAR scanning area using the least squares method [58,59]. In addition, Wang et al. [60] designed a navigation-line extraction method for an autonomous spraying machine in an orchard based on LiDAR. Liu et al. [61] et al. proposed a tree row recognition and navigation method based on the fusion of least squares and support vector machines.

Using the least squares fitting method, combined with the SVM algorithm, to identify tree rows, the centerline between rows in the orchard is predicted, which improves the accuracy of the autonomous navigation of orchard equipment for the orchard environment.

Currently, farmland boundary detection and navigation line extraction are mostly based on visual schemes, mainly image grayscale processing, image segmentation, navigation line extraction, navigation line tracking, and other steps. The focus is on solving the effect of natural illumination on the robustness of the detection system. The commonly used methods for farmland boundary and navigation line extraction research are shown in Table 1.

Table 1. Characterization and application of commonly used sensors for field boundary and navigation line extraction.

Method	Sensor Type	Characteristics	Sensing Task
Vision Sensors	Monocular Camera	Monocular cameras are low cost and provide rich image information, but lack depth data and are susceptible to environmental influences.	Farmland boundary detection, navigation line extraction
	Binocular Camera	Binocular cameras can provide rich image information and highly reliable depth information, but the configuration and calibration are more complicated; the computation is large, and parallax calculation depends on computing resources.	Farmland boundary detection, navigation line extraction
	RGB-D Camera	RGB-D camera can provide an RGB map and a depth map, and the calculation amount is small. However, the measurement range is narrow, the noise level is high, the field of view is small, and it is easily interfered with by daylight.	Farmland boundary detection
Radar Sensor	Lidar	LIDAR is highly accurate, stable, and reliable. However, it has a high cost, is susceptible to dust interference with the limited detection range, and cannot recognize color and texture in farmland boundary identification and navigation line extraction.	Navigation line extraction

Obstacle detection is an important method to improve the level of autonomous operation of farm machinery in large fields and to ensure safe operation. Currently, the research on field obstacle detection based on the onboard sensing system of agricultural machinery mainly includes methods based on vision detection, LiDAR detection, millimeter-wave radar detection, and multi-sensor fusion detection [62], as shown in Figure 3.

In terms of visual detection, Li et al. [63] proposed a method based on a deep neural network to detect obstacles such as people, concrete pillars, and utility poles in the orchard environment. Their method can provide a basis for intelligent orchard robots to detect obstacles automatically and distinguish traversable and non-traversable areas for obstacle avoidance. Furthermore, Xue et al. [64] improved the YOLOv5s algorithm based on the k-means clustering algorithm and CIoU loss function to improve the detection speed of obstacles in farmlands. The algorithm also has reliable detection accuracy for small-target obstacles. Xu et al. [65] detected moving obstacles in panoramic images based on panoramic camera vision and the Lucas–Kanade optical flow algorithm. This method has good transient and detection results for dynamic obstacle detection. Du et al. [66] introduced spatial attention and deformable convolution into the Mask R-CNN model to construct a segmentation algorithm for unstructured farmland obstacles. The model can control the detection speed while still maintaining a reliable model detection accuracy. Deep learning models perform well in image processing and feature extraction. Deep learning methods have become some of the most widely used techniques in visual obstacle detection. Representative research methods mainly include YOLO, Faster R-CNN, U-Net, and RetinaNet. Deep learning models can automatically learn and extract complex features in images, greatly improving the accuracy and robustness of obstacle detection.

The commonly used camera types and features when using deep learning methods for obstacle detection are shown in Table 2.

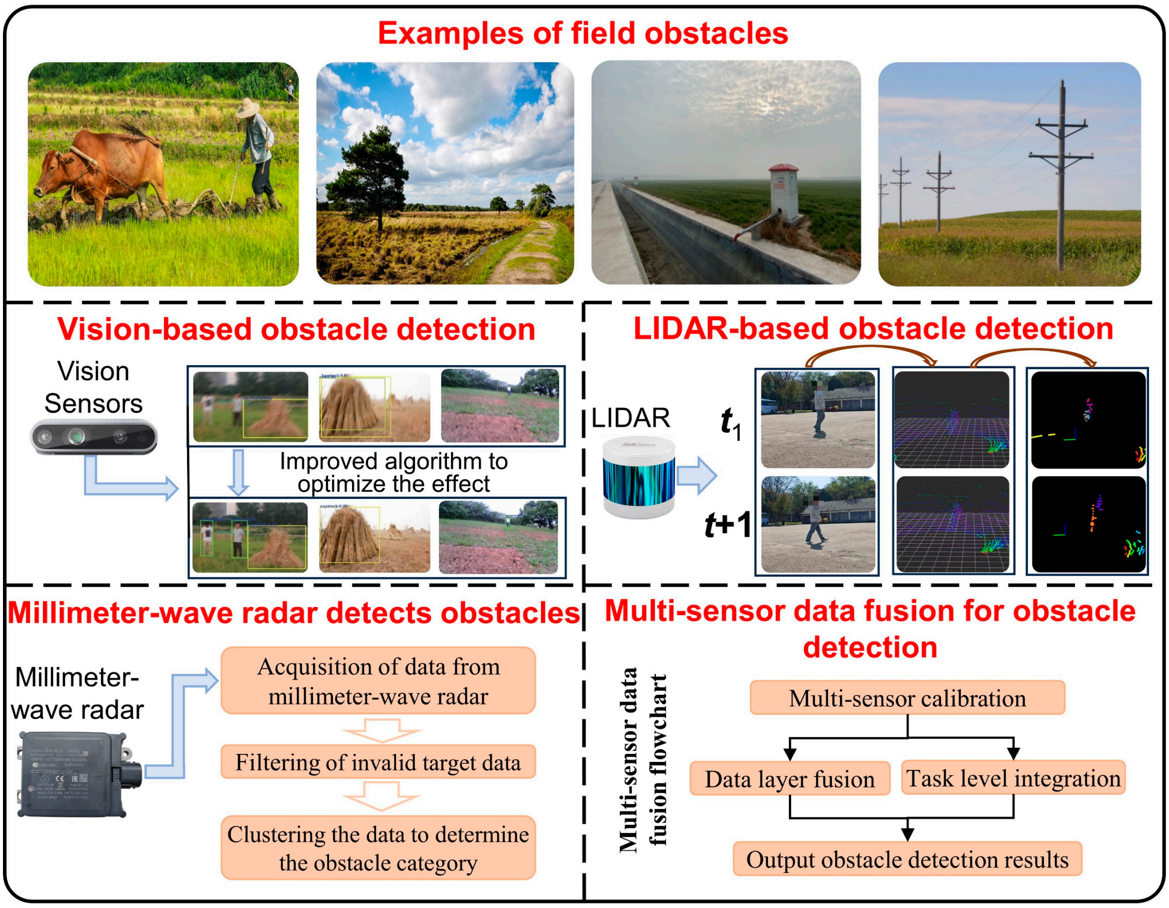

Figure 3. Methods for detecting obstacles in agricultural fields.

Table 2. Deep learning of camera types and characteristics commonly used in obstacle detection.

Camera Type	Features	Advantages	Common Cameras
RGB Cameras	A standard color camera that captures images in the red, green, and blue color channels.	RGB cameras provide rich color and texture information that helps distinguish between different types of obstacles, are low cost, and are easy to integrate and deploy.	Logitech C920, Sony Alpha Series (Logitech, Lausanne, Switzerland)
Depth Camera	In addition to capturing RGB images, it also acquires depth information for each pixel.	Combining depth information and RGB images improves the accuracy and reliability of obstacle detection, providing more precise obstacle localization, especially in complex environments.	Intel RealSense (Intel, Santa Clara, CA, USA), Microsoft Kinect 360 (Microsoft 360, Washington, DC, USA)
Stereo Camera	Captures stereo images through two cameras and uses parallax to calculate depth information.	Provides high-precision depth perception for fine obstacle detection tasks and is more reliable than a single depth camera in terms of detection accuracy and range.	ZED Series (ZED Series, San Francisco, America), Bumblebee2 (Teledyne FLIR, Washington, DC, USA)
Panoramic Camera	Capable of capturing images or videos with a 360-degree field of view.	In obstacle detection, it provides a comprehensive view of the environment, reduces blind spots, and improves the coverage and accuracy of obstacle detection.	Ricoh Theta (RICOH, Tōkyō, Japan), Insta360 Pro (insta360, Shenzhen, China)

In terms of obstacle detection by LiDAR and millimeter-wave radar, Shang et al. [67] proposed a 3D laser point-cloud method for detecting field obstacles based on Euclidean clustering. First, the voxel down-sampling method and RANSAC algorithm are utilized to filter the point cloud and differentiate between ground and above-ground objects. Then, the obstacles are recognized based on the Euclidean clustering frame of the K-D tree, which achieves the detection of agricultural implements, haystacks, field ridges, short houses, and trees on both sides of the field road. T. Wang et al. [68] proposed an adaptive method for the real-time 3D detection of obstacles for a single sub-domain based on the semantic–geometric–intensity fusion strategy. The inaccurate 3D detection of obstacles in the absence of many samples is addressed, and the experimental results demonstrate the high accuracy and efficiency of the proposed method in performing obstacle detection. Using a millimeter-wave radar for farmland obstacle detection has the problem of high computation because of the presence of many invalid targets in the output data. Therefore, Xue et al. [69] addressed this issue by filtering out empty targets, pseudo-targets, and non-threatening data based on the invalid target filtering method. The above literature uses LiDAR or millimeter-wave radar as the detection sensor, which achieves better detection results. However, there is still the problem of high computation, which leads to low detection efficiency and is not easy to deploy.

Vision-based methods for obstacle detection are low cost and have advantages in measuring object height and width, as well as in recognition accuracy. They can also provide rich planar information. However, the role of vision distance and ranging accuracy in these methods are not as good as those in a millimeter-wave radar. Moreover, these methods are easily affected by light and weather [70]. LiDAR can obtain accurate position data while not being affected by light conditions. However, when a large amount of dust exists in the farmland environment, features such as shape and texture information of the obstacles are more difficult to obtain. Single sensors are still deficient in terms of reliability, robustness, and accuracy in obstacle detection. Multi-sensor information fusion methods for obstacle detection synthesize heterogeneous information from different sensors and have their respective advantages. Hence, applying these methods has become the main trend in obstacle detection. Lv et al. [71] designed a decision-level fusion algorithm by combining the advantages of millimeter-wave radar in range and speed measurement and the advantages of the camera in type recognition and lateral localization. After calibrating the outer parameters of the millimeter-wave radars and the inner and outer parameters of cameras, the obstacle detection test was conducted in a ROS environment. Comparative experiments with sensor fusion algorithms showed that the detection accuracy of the decision-level fusion algorithm was 95.19%, which is higher than that of feature-level and data-level fusion by 4.38% and 6.63%, respectively. Cai. [72] realized the temporal and spatial fusion of vision and millimeter-wave radars based on a fusion detection technology for a vision–millimeter-wave radar. The task of detecting obstacle dimensions in the visual depth map was accomplished using the effective target selected by the millimeter-wave radar as the seed point. The problem of detecting the spatial location and dimensional information of obstacles in front of agricultural machines was solved. Kragh et al. [73] used conditional random fields to fuse LiDAR and camera sensing probabilistically with semantic segmentation and combined appearance-based and geometric detection methods. Finally, a multimodal fusion algorithm was applied to achieve obstacle detection in agriculture with moving ground vehicles. Multi-sensor fusion sensing technology has shown great advantages in farmland obstacle detection and will be gradually applied to farmland obstacle detection in the future. The farmland environment is complex and variable, and a single sensor is prone to blind spots or insufficient information in obstacle detection. Multi-sensor fusion can comprehensively utilize the advantages of different sensors to make up for the shortcomings of a single sensor. The core of fusion technology is to solve the problem of the fusion of heterogeneous data information from different sensors. By fusing data from multiple sensors, such as RGB cameras, depth cameras, and LIDAR, more comprehensive and precise environmental information can be obtained to improve the accuracy and reliability of obstacle detection.

3. Complete-Coverage Path-Planning Technology

Based on farmland information, operation types and sensory data, complete-coverage path-planning technology plans optimal paths and commands the underlying modules to deal with complex farmland environments effectively. Currently, the task of farm machine path planning in unstructured farmland environments mainly focuses on global path planning and local path planning, with the goal of improving operational efficiency, operational farmland coverage, and operational safety to adapt to the complex and changing operational environments in different farmlands and fields [74]. The classification of common path-planning algorithms in path-planning technology and their range of applications is presented in Table 3. To perform specific agricultural tasks such as deep loosening, targeting, ridging, rotary ploughing, seeding, and applying pesticides, when operating unmanned vehicles in a field, large agricultural equipment often follows a path comprising straight lines and turns. Unlike standard roads, agricultural fields generally have irregular shapes (depicted in Figure 4). Achieving smooth path trajectories and velocity continuum is challenging when relying solely on a combination of straight lines and turns for complete-coverage path planning. Therefore, in recent years, researchers have proposed numerous algorithms to address complete-coverage path-planning problems in agricultural fields. In this chapter, the representative algorithms for complete-coverage path-planning technology are classified into two categories: classical path-planning algorithms and bionics-based path-planning algorithms.

Table 3. Classification and application scope of common path-planning algorithms.

Classification	Common Algorithms	Common Application Areas
Algorithms based on graph search	Dijkstra, A *, D *	Global path planning
Algorithm based on sampling	RRT	Global path planning
Algorithms based on artificial potential fields	Artificial potential field method	Local path planning
Algorithms based on curve fitting	Arcs and straight lines, polynomial curves, spline curves, Bessel curves, differential flatness	Local path planning
Algorithms based on numerical optimization	Describing and solving planning problems using objective functions and constraints	Local path planning
Intelligent algorithms based on bionics	Genetic algorithms, particle swarm optimization algorithms, ant colony algorithms	Global path planning, local path planning

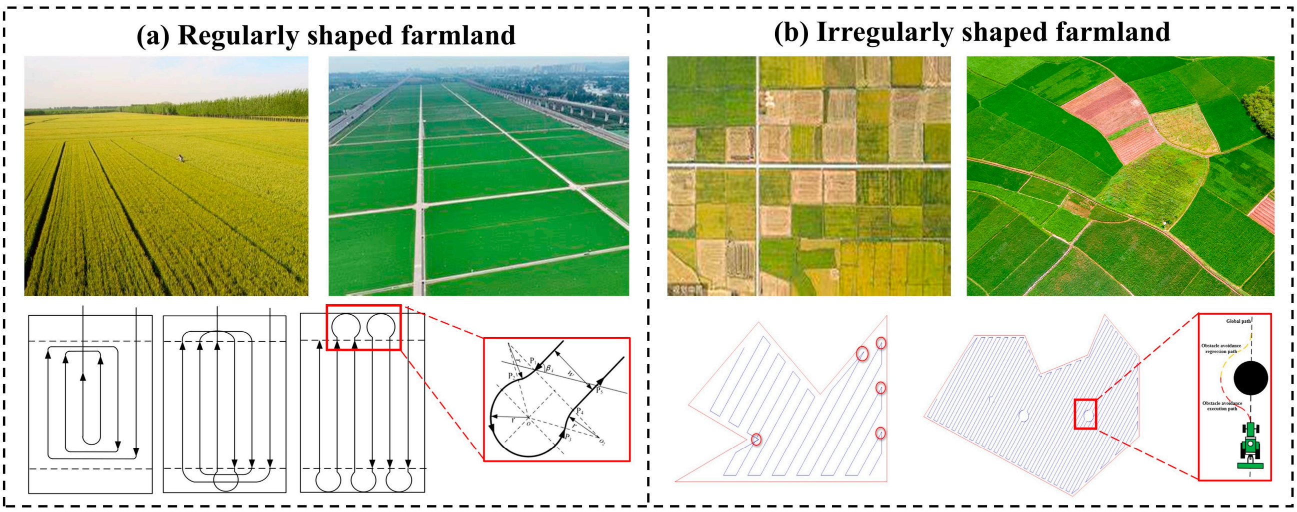

Figure 4. Shapes of typical regular and irregular fields.

3.1. Classical Path-Planning Algorithm

Global path planning is to plan an optimal operation path to carry out the operation by combining the positioning information after determining the operation plot. Local path planning integrates the real-time information obtained from the intelligent farm machinery vehicle-mounted sensing system, performs real-time path planning, and adjusts the operational status. The main classical path-planning algorithms currently applied are search-based global path-planning algorithms, sampling-based global path-planning algorithms, artificial potential field-based local path-planning algorithms, local path-planning algorithms based on curve fitting (arcs and straight lines, polynomial curves, spline curves, Bezier curves, and differential flatness), and numerical optimization-based local path-planning algorithms.

Shen et al. [75] proposed a primitive optimization strategy to correct the inter-row path points based on the tree row position information. This strategy is a response to the traditional A * algorithm's problem of path point offsets that are not suitable for direct substitution optimization. Xu et al. [76] designed an improved A * algorithm that reduces the number of turns in global path planning and improves path stationarity and operational efficiency. The RRT algorithm is slow to search when used for global path planning, and when the number of iterations is small, the feasibility of the planned global path is poor. Feng et al. [77] added global random sampling and key area sampling strategies to the RRT algorithm to improve the global search capability and the effect of optimal paths. Kong et al. [78] proposed an improved A * path-planning algorithm based on multi-constraint Bessel curves. The approach combines robot kinematic constraints with Bézier curves to smooth the turning paths of the A * algorithm, integrating multiple objectives, such as minimum turn radius and continuous curvature, to achieve global path planning. The literature [79,80] addresses the problem that traditional artificial potential field methods tend to fall into local minima and suffer from goal unreachability during path planning, by introducing an annealing algorithm and obstacle repulsive potential field function method to avoid the falling into local optimum and unreachable goal phenomena. Boryga et al. [81] proposed a path-planning method based on polynomial transition curves to plan the trajectory of a machine turning in a field by using polynomial transition curves to reduce the working and non-working distances and to improve the efficiency and energy utilization of the machine. In addition to the above methods, the method of improving the local path-planning algorithm by utilizing the circular arc tangent law has been well applied to tracked harvesters (shown in Figure 5). The improvement reduces the frequency of steering control of tracked harvesters, which in turn improves driving stability and operational efficiency [82–86]. There is no essential difference between global path planning and local path planning [87]. To adapt to the farmland operational environment, current optimization strategies employed by research scholars to enhance algorithms typically include path-planning algorithms that minimize time and distance costs; algorithms that accommodate various shapes, sizes, and locations of obstacles; and algorithms that impose constraints on the speed and energy consumption of agricultural machinery. By summarizing the published literature, we find that global path-planning algorithms can be used for local path planning after improvement, and local path-planning algorithms can be used for global path planning after optimization. Therefore, focusing on integrating global path-planning algorithms with local path-planning algorithms can enhance the realization of complete-coverage path planning.

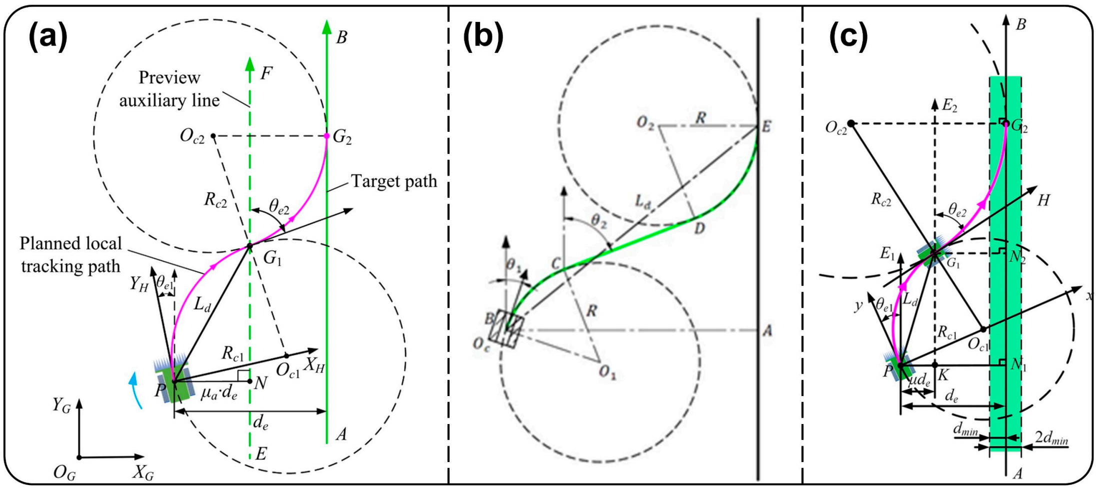

Figure 5. A localized path-planning method based on the arc tangent method. (**a**) Schematic representation of the improved pure pursuit model using the two-segment tangent method. (**b**) Schematic diagram of three-tangent localized path planning. (**c**) Schematic of adaptive localized path planning.

3.2. Bionics-Based Path-Planning Algorithms

The main bionics-based path-planning algorithms are the genetic algorithm (GA), the particle swarm optimization algorithm (PSO), and ant colony algorithm (ACO) [87]. A genetic algorithm-based path-planning optimization algorithm is a heuristic search optimization algorithm designed to find the optimal path by simulating natural selection and genetic mechanisms [88–90]. The path-planning optimization algorithm, based on a genetic algorithm, can effectively search the complex path space to find the best path solution that satisfies the specific optimization objective, which is especially suitable for generating better paths in field environments with complex terrain and many obstacles. The particle swarm optimization algorithm is an evolutionary computational technique initially developed as a simplified model inspired by the coordinated flocking behavior of birds in flight [91]. The process of path planning based on the particle swarm optimization algorithm can be regarded as the process of finding the optimal position of many particles in the solution space. The ant colony algorithm is designed to simulate the foraging behavior of ants in nature. When applied to path planning, the algorithm utilizes a pheromone update mechanism for path searching. Ants leave pheromones on the path, and other ants choose the path based on the pheromone concentration, thus gradually finding the optimal path. The above three algorithms are all group intelligence algorithms (pseudo-code comparisons are shown in Table 4) that solve optimization problems by simulating the behavior of organisms in nature or the behavior of groups.

Table 4. Pseudo-code comparison of bionics-based path-planning algorithms.

Step	**GA**	**PSO**	**ACO**
Initialization	Initialize population	Initialize particles	Initialize ants
Fitness Eval.	Evaluate fitness	Evaluate fitness	Evaluate fitness
Selection	Roulette wheel selection	N/A	Select next node based on probability
Crossover	Single-point crossover	N/A	N/A
Mutation	Swap mutation	N/A	N/A
Update Ind.	Replace individual	Update velocity and position	Update pheromone
Update Best	Find best individual	Update global best	Find global best path
Iteration Loop	Repeat for max generations	Repeat for max iterations	Repeat for max iterations
Return Result	Return best individual	Return global best	Return global best path

N/A means this item is empty.

All three of the above algorithms possess global search capabilities and advantages in parallel processing [92,93], enabling them to find optimal solutions in complex spaces. A comparison of the effectiveness of bionics-based path-planning algorithms when applied to path planning for farm machinery used in large fields is shown in Table 5. However, they also suffer from complex parameter tuning, unstable convergence speed, and decreased efficiency in high-dimensional spaces. The adaptability to specific problems and the interpretability of the results also need further improvement and research. Therefore, to suit the agricultural field operational environment, current optimization strategies employed by research scholars to enhance algorithms typically encompass path-planning algorithms that minimize time and distance costs, algorithms adaptable to various shapes, sizes, and locations of obstacles, and algorithms imposing constraints on the speed and energy consumption of agricultural machinery. In dynamic environments, various real-time planning algorithms are chosen to navigate constraints such as moving targets and adapting effectively to diverse operating environments. Zhou et al. [94] proposed a traversal path-planning method by combining the Floyd algorithm with an improved genetic algorithm. The traversal path problem when agricultural equipment traverses multiple plots is adapted. Xu et al. [95] considered the kinematic model of agricultural machinery, defined the paths that satisfy the kinematic model through parametric equations, and solved the initial paths using an analytical method. Meanwhile, an improved real-time path-planning algorithm for a parametric kinematic model of agricultural machinery is proposed based on the particle swarm optimization algorithm. Zhao et al. [96] proposed a path-planning method based on an improved bio-neurodynamic approach to enhance the path-planning capability of arbitrarily shaped differential-drive agricultural robots. Through several experiments in narrow and complex environments, the method was proven to have a better path-planning ability. Zhang et al. [97] compared the hyper volume estimation algorithm, the grid-based evolutionary algorithm, the turning point-driven evolutionary algorithm, and the non-dominated sorting genetic algorithm to assess their effectiveness in path planning. Their goal was to shorten the total path of agricultural machinery operation and reduce the total turning angle. Then, they proposed a multi-objective evolutionary algorithm-based path-planning method for agricultural mobile robots. Wu et al. [98] proposed an improved adaptive ant colony optimization algorithm by introducing a heuristic mechanism for directional information, an adaptive pseudo-random transfer rule, and an unevenly distributed pheromone approach, in conjunction with the traditional ant colony algorithm. The method improves the superiority of the ant colony optimization algorithm in terms of convergence speed and global optimal solution search capability.

Table 5. Comparison of bionics-based path-planning algorithms.

Algorithm Category	Global Search Ability	Convergence Speed	Computational Complexity	Adaptability	Scalability
Genetic algorithm	★★★★	★★	★★★★	★★★★	★★★
Particle swarm optimization	★★★★	★★★★★	★★★	★★★	★★★★
Ant colony algorithm	★★★★★	★★★	★★★★	★★★★	★★★★

★ represents the degree.

Currently, significant research progress has been made in applying complete-coverage path-planning techniques in unstructured farmland environments. This research primarily focuses on traditional algorithms (such as the A * algorithm, Dijkstra's algorithm, geometric methods, dynamic window approaches, etc.) and population intelligence algorithms (including the ant colony optimization algorithm, the genetic algorithm, the particle swarm optimization algorithm, etc.). By addressing global path planning and local path-planning issues, operational efficiency, farmland coverage, and operational safety have been enhanced.

4. Autonomous Operation Control Technology

Autonomous operation control technology is mainly based on the upper computer-specified commands to control the movement and operation of intelligent agricultural equipment. Taking the combined harvester shown in Figure 6 as an example, the autonomous operation control system consists of a navigation sensor unit, a user interface unit, a height sensor for the cutting table, an angle sensor, a tracking control unit, and a hydraulic actuator unit. Currently, common research in motion control primarily focuses on navigation tracking control. Research in operation control primarily focuses on equipment controlling for tasks such as ploughing, planting, management, and harvesting operations. Autonomous operation control is committed to improving the ability of self-driving farm equipment to cope with complex farmland environments and to solving the uncertainty problem brought abought by the low feedback and large inertia of farm machinery in operation control.

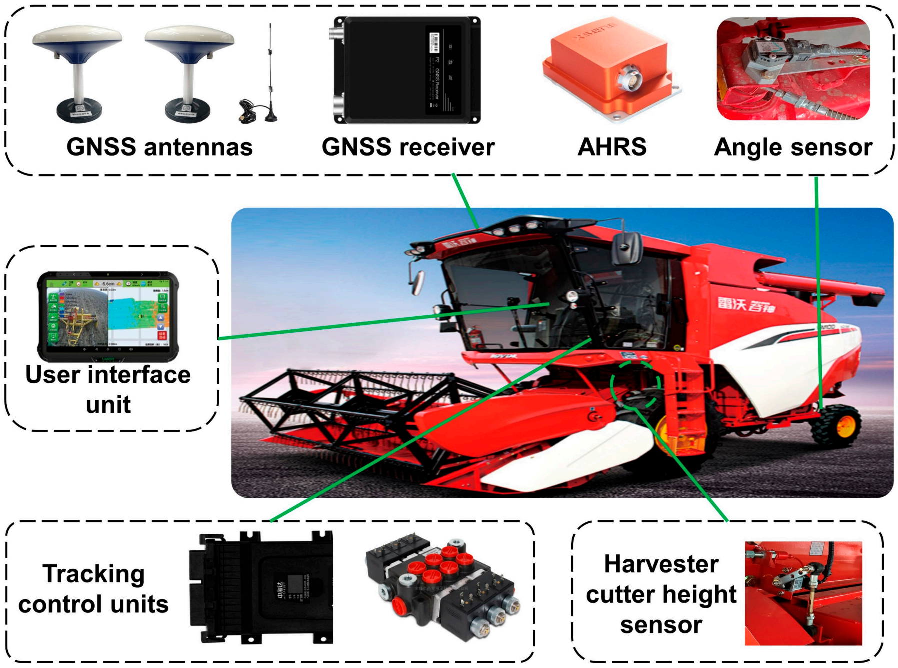

Figure 6. Autonomous operation control system and components for combine harvesters.

Motion control is the basis of autonomous operation control, and domestic and international research on the motion control of intelligent agricultural machines mainly includes PID control methods, fuzzy control methods, model predictive control methods, optimal control methods, and so on. For instance, to address the nonlinear characteristics of the tractor's longitudinal driveline system, Wang et al. [99] linearized the tractor's longitudinal dynamics model using an inverse modelling approach and designed a sliding-mode variable-structure controller to mitigate the impact of external disturbances on acceleration. Miao et al. [100] decoupled the control system into longitudinal and transverse motion control and designed a velocity controller based on the PID control algorithm. Wang et al. [101] designed a large-angle steering control algorithm based on the instantaneous center of rotation of the tracked vehicle for the steering characteristics of tracked agricultural machines based on unilateral braking. It enables the tracked vehicle to steer directly to the target heading. Navigation path tracking is the core technology to realize automatic navigation, and it is also the current research hotspot in motion control. In recent years, research scholars have applied model-free intelligent control methods (e.g., reinforcement learning, particle swarm optimization, neural networks, etc.) to navigation path tracking and obtained better results. Shan et al. [102] designed a reinforcement learning model to integrate the PID controller with the PP controller to handle the tracking error and obtain better path tracking accuracy. Zhang et al. [103] proposed a two-depth Q-network-based vehicle path tracking control method for mobile robots to achieve the accurate tracking of straight paths and smooth transitions between polygonal trajectories. This method considers driving speed and steering rate constraints to better approximate real-world scenarios.

Operation control is a direct part of ensuring the quality of an unmanned operation of field agricultural equipment. Domestic and international research on unmanned operation control of field agricultural equipment primarily focuses on equipment controlling for ploughing, harvesting, sowing, and levelling operations. Wang et al. [104] developed a tillage speed and slip ratio switching control system for wheeled electric tractors, which can effectively control the speed and slip ratio under different tillage resistance, and has better results in terms of tillage efficiency and tillage depth stability. To solve the problem of a low level of automated control of the cutting platform height, Tan et al. [105] designed a harvester cutting platform height adaptive system based on PID control technology and tested the impact of activating the adaptive system at different forward speeds and operating modes on the operating effect. The results show that the system meets the harvester's operational needs by adjusting the height of the cutting platform. Xue et al. [106] designed a high-precision sowing depth control system for wheat planters based on fuzzy PID control technology using real-time sowing depth as the feedback input, which ensured the stability and consistency of sowing depth. Jing et al. [107] designed an adaptive PID navigation control method considering the side-slip estimation to enhance the operational stability of the unmanned farm grader, considering the side-slip phenomenon that occurs during operation. At present, the research on motion control and operation control for intelligent agricultural machinery and equipment has yielded significant results.

5. Conclusions and Prospection

5.1. Conclusions

Agricultural equipment achieves the perception of the complex and changing operating environment around it by carrying onboard environmental sensing sensors. It carries out autonomous path planning and navigation according to the preset operation tasks and map information and carries out the operation control of the operation equipment, thus realizing the unmanned operation of large-scale agricultural equipment. To improve the level of environmental sensing, path planning, and autonomous operation control of large-scale agricultural equipment, researchers have carried out many studies. This review systematically examines the progress of key technologies for the unmanned operation of field agricultural equipment from three aspects: onboard environmental sensing technology, coverage path-planning technology, and autonomous operation control technology. Although the unmanned operation technology of field agricultural equipment has a wide range of application prospects, it still faces a series of challenges and problems in practical application. The challenges of robustness of environment perception, practicality of path-planning methods, and efficiency of autonomous operation control methods need to be further improved. Through the systematic review, the key conclusions are drawn as follows:

(1) Single-sensor onboard environmental sensing methods are no longer adequate to meet the demands of unmanned operations. Traditional vision methods are affected by environmental factors such as light and weather, resulting in insufficient stability and accuracy under complex farmland conditions. Although LiDAR can provide high precision distance information, it is susceptible to errors when interfered with by particulate matter in agricultural fields. Therefore, the advantages of multiple sensors, such as vision, LiDAR, and millimeter-wave radar, should be combined. Their characteristics in information acquisition and environmental adaptability can be comprehensively utilized to enhance the accuracy and robustness of farmland boundary detection, navigation line extraction, and obstacle detection.

(2) Classical complete-coverage path-planning algorithms such as A * and Dijkstra are suitable for planning in static environments but can result in unsmooth and inefficient

paths in complex farmlands. The introduction of methods based on artificial potential fields, sampling, and curve fitting can improve the accuracy and adaptability of path planning. In addition, intelligent bionics-based algorithms, such as the genetic algorithm, particle swarm optimization, and the ant colony algorithm, which optimize path selection by simulating biological behavior, have certain advantages in finding the globally optimal path in complex environments. Although complete-coverage path-planning techniques have been well developed, the related algorithms are deficient in accuracy and timeliness when dealing with terrain changes and the real-time requirements of dynamic farmland environments.

(3) Research on motion control focuses on speed, steering, and navigation tracking, using PID, fuzzy control, model prediction, optimal control, and other methods. Operational control encompasses scenarios such as ploughing, harvesting, seeding, and grading operations, primarily enhancing operational quality and efficiency through PID adaptive systems and fuzzy control techniques. While these research methods have significantly enhanced the unmanned operation capabilities of large-scale agricultural equipment, they still inadequately address the low feedback and high inertia issues encountered by medium- to large-size agricultural machinery during field operations. Autonomous operation systems exhibit poor robustness under varying ground conditions, significant disparities in tracking control performance, and limited adaptive capabilities to different ground conditions.

5.2. Prospection

Large-scale fields are the primary production zones for food crops, and the research on agricultural equipment for these vast terrains is a critical issue that demands urgent attention in advancing large-scale agriculture. The autonomous operation of agricultural machinery in large farmland areas is a pivotal strategy to enhance production efficiency, reduce labor intensity, and mitigate the impact of an aging population on agriculture. A comprehensive overview of the research progress on key technologies for the autonomous operation of large-scale farmland machinery will facilitate the systematic advancement of agricultural equipment in these vast areas. Regarding onboard environmental sensing technology, multi-sensor fusion sensing technology has demonstrated significant advantages in environmental sensing. However, existing research still faces the following shortcomings: the complexity of data fusion algorithms results in inadequate real-time performance, interference, and signal inconsistency among sensors. These issues negatively impact perception accuracy, and there is poor adaptability to harsh environments. Therefore, future research can focus on the following two aspects: first, optimizing data fusion strategies and algorithms to enhance real-time and processing efficiency, to ensure rapid response in complex farmland environments; second, improving sensor anti-interference capability and signal consistency, adopting advanced calibration and compensation techniques to enhance sensing accuracy and adaptability to harsh environments.

In terms of complete-coverage path-planning technology, current research mainly focuses on single-field complete-coverage route planning technology. Existing research has improved the real-time and adaptive nature of path planning by improving the relevant algorithms, thus increasing operational efficiency, farmland coverage, and operational safety. However, there have been relatively few studies on complete-coverage path planning for multiple fields. To further enhance the efficiency of unmanned operations for large-scale agricultural equipment, future research should prioritize the following aspects: First, develop efficient path-planning algorithms applicable to multi-field environments to ensure a smooth transition and path optimization between different farmlands. Second, with the gradual realization of intelligent operation of agricultural machinery, the limitations of single-machine agricultural operations are gradually becoming evident. Research should focus on developing multi-machine intelligent scheduling and task allocation systems tailored to diverse operational requirements across multiple fields, optimizing operation sequencing and resource allocation. Leveraging the collective intelligence of groups of agricultural machines can significantly enhance overall agricultural production efficiency.

In terms of autonomous operational control technology, navigation accuracy and operational quality have become critical factors in the effectiveness of operational systems. Therefore, further research should investigate the variations in motion trajectories of field agricultural equipment under different ground conditions and implement targeted compensatory control measures to enhance the robustness, adaptability, and operational accuracy of autonomous operation control systems.

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