

Review

A Review of Intelligent Perception Technologies and Their Applications in Agricultural AGVs for Agricultural 5.0

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Abstract

Agriculture 5.0 represents a breakthrough transformation from Agriculture 4.0, addressing the needs for safety, sustainability, and resilience in human–robot collaboration in agriculture. By integrating technologies such as artificial intelligence, digital twins, and big data, it achieves breakthroughs in three areas: perception, cognition, and execution. As carriers of agricultural technology, agricultural automated guided vehicles (AGVs) are an indispensable part of agricultural activities and play a crucial role in agricultural production. In the actual operation of AGVs, intelligent perception is a core technological prerequisite for enabling the communication and interaction among machines, humans, and the environment. However, due to the complexity and variability of agricultural environments, intelligent perception technology remains a highly challenging task. While existing reviews have focused on isolated aspects of agricultural automation, a comprehensive synthesis of intelligent perception technologies for agricultural AGVs within the holistic, human-centric framework of Agriculture 5.0 is notably lacking. This review bridges this gap by systematically analyzing and comprehensively reviewing recent advances in intelligent perception for agricultural AGVs, covering multi-sensor technologies, visual perception and target recognition, positioning and navigation algorithms, as well as applications such as path planning, multi-robot coordination, and human–robot collaboration. Furthermore, this paper delves into the potential challenges and future development trends of intelligent perception technology in the context of Agriculture 5.0, highlighting the transformative potential of these technologies in promoting multimodal fusion and addressing safety issues in human–robot collaboration. In the context of Agriculture 5.0, with the continuous advancement of intelligent perception technologies and the ongoing improvement of agricultural intelligent equipment, a human-centered, highly sustainable, resilient, data-driven agricultural production system will ultimately be formed in the future.

Keywords: agriculture 5.0; agricultural AGVs; intelligent perception; multimodal fusion; human–robot collaboration



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1. Introduction

With the growth of the global population and the reduction of arable land resources, agricultural automation has become a crucial pathway to address labor shortages and to improve production efficiency [1]. In recent years, concepts such as digital twins [2], big data [3], cyber physical systems (CPS) [4], and cloud computing [5] have been continuously proposed, while related technologies, including artificial intelligence [6], information communication [7], robotics [8], and drones [9], have been steadily advancing. The age of Agriculture 4.0 is on the horizon. In the Agriculture 4.0 environment, robots can analyze

data in real time, build highly automated and unmanned production systems, achieve crop growth monitoring [10], pest and disease early warning [11], yield prediction [12], and drive intelligent devices to perform precision operations [13], realizing deeper levels of intelligent and unmanned management.

However, Agriculture 4.0, in its pursuit of full automation, seeks to minimize human intervention as much as possible, thereby neglecting the core role of humans. In the production process, the role of humans is irreplaceable. Humans are responsible for setting production goals, making final decisions in sudden crises, and determining the boundaries of technological application. At the same time, robots require humans to teach them how to perform complex, non-standardized new tasks.

Yet, the introduction of the Industry 5.0 [14] concept has opened up new perspectives. Through human monitoring instructions and empirical predictions, combined with the robots' high-strength, high-precision, and repetitive actions, a human-centered approach to human–robot collaboration is achieved, offering significant possibilities for the transition from Agriculture 4.0 to Agriculture 5.0. In the context of Agriculture 5.0, human-centricity is defined by the design of collaborative robots that augment—rather than replace—the physical and cognitive capabilities of an aging agricultural workforce. This paradigm is underpinned by two core pillars: sustainability and resilience. Sustainability is achieved through the precision application of inputs to minimize ecological degradation, while resilience denotes the system's capacity to withstand climatic extremes and market instabilities.

As a core component of intelligent agricultural equipment [15], automated guided vehicles (AGVs) have shown great potential in material transport, crop monitoring, precision spraying [16], and harvesting [17]. Technological advancements have enabled a leapfrog development in agricultural AGV technology [18], expanding their application scenarios from simple standardized greenhouses to complex and variable real-world farmland environments. When operating in actual farmland conditions, intelligent perception technology plays a vital role [19].

However, there are currently few review papers specifically focusing on the intelligent perception technologies and applications of agricultural AGVs. Given these issues, it is necessary to address the following questions: (1) What are the key components and classifications of agricultural AGVs? (2) What are the current popular devices and algorithms for intelligent sensing technologies? (3) What are the main application areas of intelligent sensing technologies? (4) What are the major challenges and future development trends for intelligent sensing in the context of Agriculture 5.0?

To answer these questions through this review, this paper adopts a comprehensive methodological framework aimed at analyzing the technological evolution, application scenarios, and research methods of robotic intelligent sensing for Agriculture 5.0, thereby providing a theoretical framework and references for future trends in agricultural automation research. We focused on retrieving studies from internationally authoritative scientific databases to ensure the comprehensiveness and quality of the selected literature. The databases used include Web of Science, IEEE Xplore, MDPI, and Science Direct. Regarding the literature selection, we limited the search period to publications from 2016 to 2026 to ensure the inclusion of contemporary and methodologically relevant studies. To improve retrieval effectiveness, we used keywords such as “Agriculture 5.0”, “sensors”, “agricultural visual perception”, “agricultural navigation planning”, “multi-robot cooperation in agriculture”, and “human-robot collaboration in agriculture”.

As illustrated in Figure 1, Section 2 introduces the background knowledge on agricultural AGVs and Agriculture 5.0 based on the relevant literature; Section 3 provides a literature review of intelligent sensing technologies, including sensor types, visual per-

ception, and navigation technologies; Section 4 reviews the applications of intelligent sensing, covering path planning, multi-robot coordination, and human–robot collaboration; Section 5 analyzes major challenges and future development trends; Finally, Section 6 summarizes the main conclusions of this study.

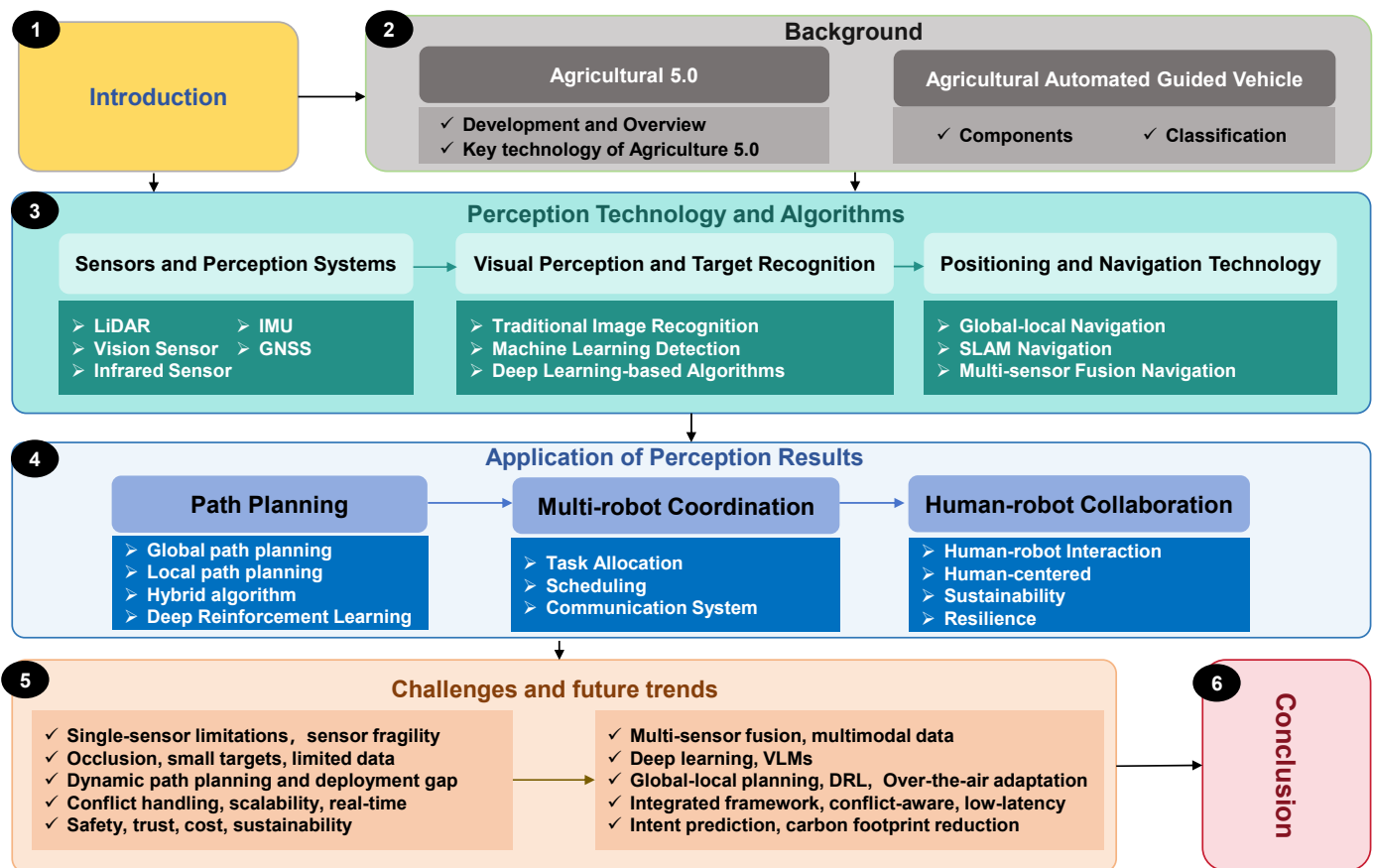


Figure 1. An overview of this review.

2. Background

2.1. Agricultural 5.0

2.1.1. Development and Overview

The evolution from Agriculture 1.0 to Agriculture 5.0 reflects humanity’s continuous efforts to transcend technological limitations, as well as the ongoing adjustment of the relationship between human civilization and nature (Figure 2). Agriculture 1.0 relied on traditional methods, like crop rotation, composting, and seed selection using hand tools and animal power. The shift to Agriculture 2.0 brought steam engines, tractors, combine harvesters, and early chemical inputs, boosting efficiency and yields. However, this mechanized, large-scale model caused high energy use, pollution, and ecological damage. Later, information and automation technologies gave rise to precision agriculture [20]. The integration of global satellite systems [21] and remote sensing technologies [22] enabled precise agricultural production and management, greatly enhancing labor productivity and resource utilization, which became the distinctive hallmark of Agriculture 3.0. More recently, the convergence of the Internet of Things [23], digital twins, artificial intelligence, and robotics has given birth to “Agriculture 4.0”. Agriculture 4.0 represents a higher stage of modern agriculture following traditional agriculture, mechanized agriculture, and automated agriculture [24]. Relying on next-generation information technologies, such as the Internet of Things and big data, Agriculture 4.0 drives a fundamental transforma-

tion of agricultural production from experience-driven to data-driven, and from extensive management to precise and intelligent management [25].

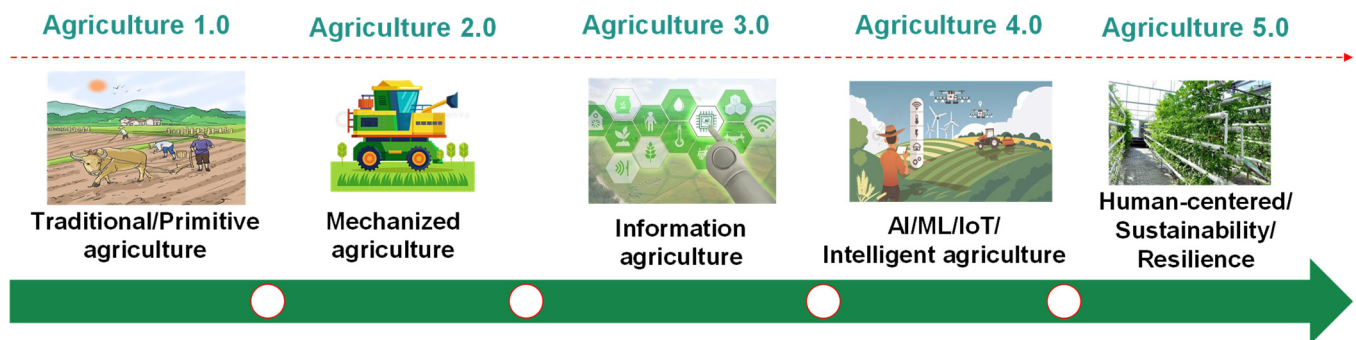


Figure 2. The evolution from Agriculture 1.0 to Agriculture 5.0.

The concept of Industry 5.0 was formally proposed by the European Commission, and its theoretical foundation consists of three core pillars: human-centricity, sustainability, and resilience [26]. Building on Industry 5.0, Agriculture 5.0 is a next-generation agricultural development paradigm following Agriculture 4.0. It deeply integrates cutting-edge technologies, such as artificial intelligence, 6G [27], blockchain, and quantum computing, to form a human-centric, highly sustainable, and resilient data-driven agricultural production system [28]. Human-centricity emphasizes that technology should serve people, not replace them, prioritizing trust, safety, openness, and inclusiveness, enhancing workers' creativity and decision-making capabilities, and achieving human–robot collaboration. Sustainability requires promoting a circular economy, reducing resource dependence and waste emissions, and improving energy efficiency [29]. Resilience refers to enhancing the adaptability of production systems to external shocks, requiring a high degree of flexibility in supply chains [30].

The goal of Agriculture 5.0 is to create a manufacturing environment that is both efficient and aligned with human values and social needs, to promote a circular economy, to improve energy efficiency, and to establish resilient production systems capable of withstanding various shocks [31].

2.1.2. Key Technology of Agriculture 5.0

To achieve the above goals, the key technologies of Agriculture 5.0 are discussed from three dimensions: the perception level, the cognition level, and the execution level, as illustrated in Figure 3.

At the perception level, by fusing data from various sensors, satellites, and remote sensing information, intelligent sensing is used for crop growth monitoring, pest and disease identification, and soil and moisture status analysis [32]. This ensures extremely efficient resource utilization, ecological environment protection, and economic sustainability. At the cognition level, digital twins, large language models, and deep learning are employed to construct early warning systems, enabling rapid response and recovery, and enhancing adaptability to shocks. At the execution level, greater attention is paid to farmer welfare [33]. Farmers and operators use mobile terminals, voice interaction systems, and mobile apps to understand data, receive decision recommendations, or issue commands. Augmented reality interfaces interact with robotic systems, reducing long hours of high-intensity labor while ensuring human safety, ultimately forming a human–robot collaborative production model.

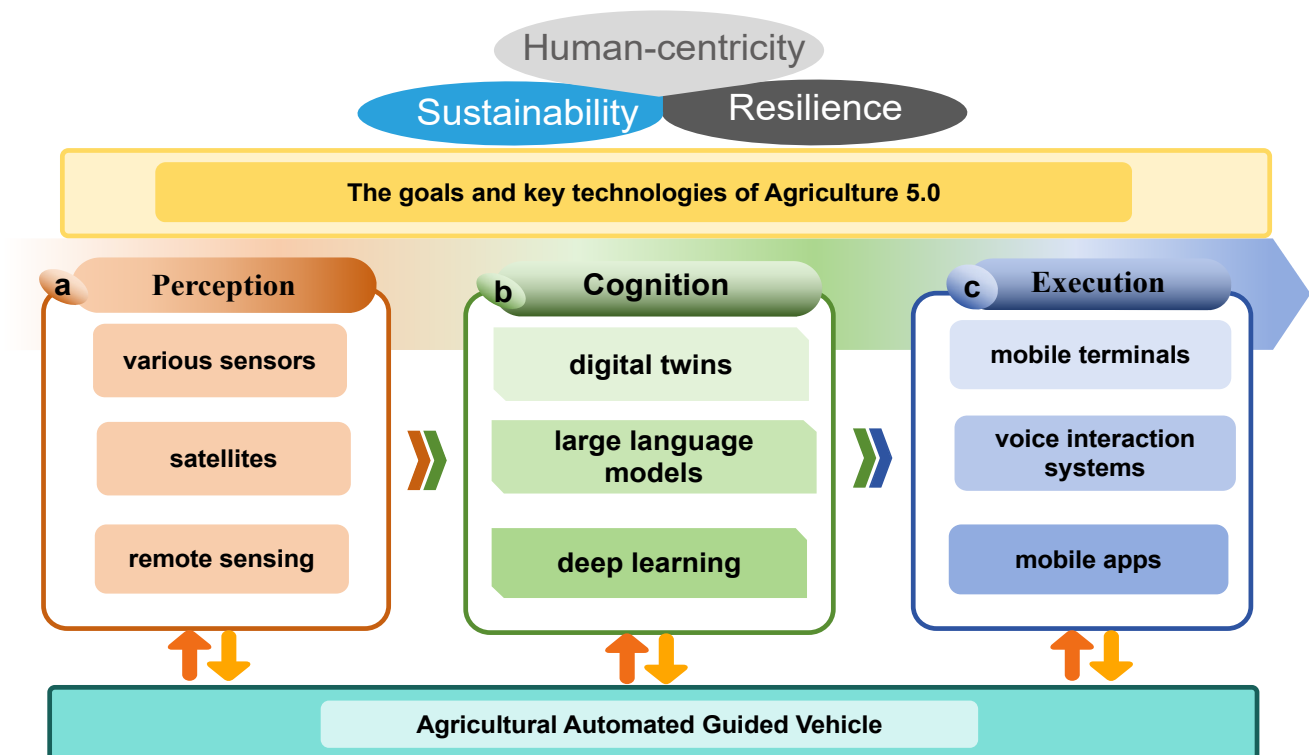


Figure 3. The goals and key technologies of Agriculture 5.0.

The realization of all these technologies ultimately relies on the participation of agricultural AGVs, which are an integral part of the human–robot–environment collaborative system. Agricultural AGVs are equipped with intelligent sensors, enabling the effective perception of the surrounding environment and the transmission of key data information to terminals. By collaborating with cloud platforms, they enable remote monitoring and simulation prediction, while humans can make real-time strategy adjustments through human–computer interaction interfaces. Agricultural AGVs can also collaborate with other agricultural machinery or humans to perform complex tasks, such as picking, grafting, and sorting, thereby improving efficiency and reducing labor intensity. Thus, to achieve the goals of Agriculture 5.0, the presence of agricultural AGVs is indispensable.

2.2. Agricultural Automated Guided Vehicles

2.2.1. Components

The composition of agricultural AGVs is complex and sophisticated, mainly consisting of the following parts: chassis drive system, control and computing system, energy and management system, communication and interaction system, operation execution system, and intelligent perception system [34], as shown in Figure 4.

- **Chassis and Drive System:** This system adopts an Ackermann steering geometry, featuring front-wheel steering and rear-wheel drive, which provides excellent high-speed stability. Alternative configurations include a tracked chassis [35], which provide better off-road adaptability.
- **Control and Computing System:** This system is typically composed of high-performance industrial-grade ARM or x86 processors, running a real-time operating system (RTOS) or ROS 2 framework (framework commonly adopted in agricultural AGV control and computing systems includes ROS, as well as InsightOS, FarmBot OS, and FreeRTOS), responsible for processing all information, making decisions, and coordinating the operation of various components.

- **Energy and Management System:** This system is primarily based on lithium batteries and automatic charging, providing power to the AGV and maintaining its endurance.
- **Communication and Interaction System:** This system includes touch screens, wireless modules, or control panels, enabling information exchange between the robot and other robots or operators.
- **Operation Execution System:** This system comprises robotic arms and end effectors [36], which are customized according to different tasks, such as shears for picking, forks or lifting platforms for transporting, and spray nozzles for spraying.
- **Intelligent Perception System:** This system uses various sensors to perceive the external environment, cope with complex and variable agricultural conditions, and achieve autonomous navigation and safe obstacle avoidance [37].

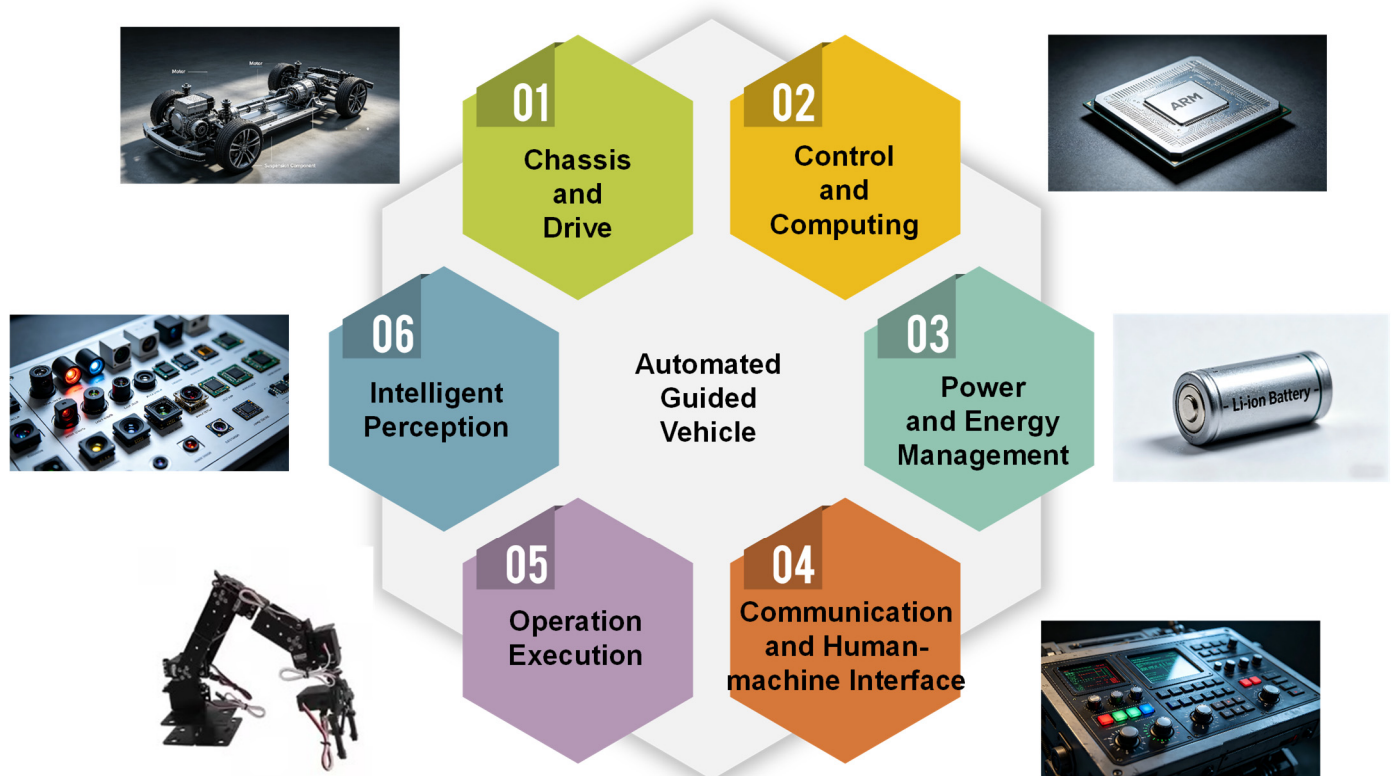


Figure 4. The composition of the agricultural AGV.

2.2.2. Classification

According to different tasks, i.e., different functions, automated guided vehicles can be divided into the following four categories: transport type, operation type, harvesting type, and multifunctional type. Table 1 shows the categories of automated guided vehicles [8]:

- **Transport type:** The actuators mainly include cargo hoppers, towing devices, or lifting platforms, such as unmanned transport vehicles and intelligent carriers. Lajunen et al. used Autonomie software to model and simulate conventional diesel, parallel/series hybrid, fuel cell hybrid, and pure electric tractors, evaluating their functionalities [38].
- **Operation type:** Equipped with spray booms and nozzles, or weeding blades, such as spraying robots [39] and weeding robots [40]. Tan et al. designed a greenhouse strawberry spraying robot that integrates 3D LiDAR and ultrasonic tag technology to meet autonomous spraying operation requirements [41], while Yang et al. developed an electric tracked weeding robot that uses a color camera and YOLOv8s AI model to

identify crop rows, and adjusts the motor differential speed via PID control to achieve autonomous navigation [42].

- **Harvesting type:** Harvesting robots equipped with robotic arms, end effectors, or grippers. Ji et al. proposed an apple harvesting robot capable of identifying branches in complex backgrounds [43], while Takuya Fujinaga developed a tomato harvesting robot for use in plant factories, analyzing the factors affecting harvesting success rates to improve tomato picking efficiency [44].
- **Multifunctional type:** Versatile and equipped with two or more types of actuators. Poojari et al. designed and analyzed a solar-powered multifunctional agricultural robot for cotton cultivation, featuring functions such as seeding, soil moisture and nutrient detection, and plant health identification [45], while Cui et al. designed an electric four-wheel drive, four-wheel steering field management robot platform that supports four steering modes—Ackermann, four-wheel, crab, and zero-radius turning—with adjustable track width, and capable of meeting operational requirements, such as spraying, weeding, and information collection [46].

In summary, agricultural AGVs are not merely industrial transport vehicles used in factories, but rather intelligent agricultural equipment with autonomous mobility capabilities. While retaining their inherent attributes and functions, they are equipped with additional agricultural implements and components to adapt to diverse agricultural environments and to accomplish a wider range of agricultural tasks. Meanwhile, multi-functional types are gradually becoming mainstream. For example, solar-powered multi-functional cotton robots and four-wheel-steering field management robots both feature reconfigurable chassis and modular actuator designs, enabling them to flexibly switch between operations in row-crop fields and orchards. This transition implies that modern agricultural AGVs are progressively decoupling hardware platforms from specific field types, instead relying on robust intelligent perception systems to cope with varying terrain roughness, crop heights, and GNSS availability. Compared with single-purpose agricultural robots, they will exhibit a high degree of flexibility and environmental adaptability.

Table 1. Categories of Automated Guided Vehicles.

Type	Name	Actuator	Operating Environment	Main Advantages	Reference
Transport	Alternative powertrain tractor	Towing device or lifting platform	Agricultural fields, road transport	Evaluates energy consumption of various powertrains; fuel cell and electric options reduce emissions and energy use.	[38]
	Greenhouse strawberry spraying robot	Spray boom and nozzles	Strawberry greenhouse	Solves “long corridor” positioning issues; reduces average positioning error by 32% compared to cartographer; high navigation accuracy.	[41]
	EV crawler-type weeding robot	Weeding blade	Organic onion field	High-precision crop row recognition (AI); autonomous navigation with lateral deviation of ± 2.3 cm, outperforming manual operation.	[42]

Table 1. Cont.

Type	Name	Actuator	Operating Environment	Main Advantages	Reference
Harvesting	Apple branch segmentation robot	Manipulator, end-effector, or gripper	Apple orchard	Segments branches under varying illumination with 94% success rate; enhances contrast for small gray-level differences.	[43]
	Tomato harvesting robot	Manipulator, end-effector, or gripper and seeder	Plant factory	Quantifies “ease of harvesting” via logistic regression; autonomously selects approach direction; improves success rate from 56% to 92%.	[44]
Multifunction	Solar-powered multifunctional cotton robot	Manipulator, end-effector or gripper	Cotton field	Seed sowing, soil moisture/NPK detection, plant health monitoring; increases productivity by 30%; cost-effective.	[45]
	Field management robot	Spray boom and nozzles and weeding blade	Field crops	Four steering modes (Ackermann, crab, zero-radius); adjustable wheel-track; high tracking accuracy (avg error 20.75 mm in crab mode).	[46]

3. Perception Technology and Algorithms

3.1. Sensors and Perception Systems

Sensors serve as the sensory organs of agricultural AGVs, enabling them to perceive information about their surrounding environment. A variety of sensors, each with its own specific role, support agricultural AGVs in completing various operational tasks. In the actual operation of AGVs, the main types of sensors include LiDAR, vision sensors, infrared sensors, and IMUs, complemented by the GNSS positioning and navigation system. The collaboration of these diverse sensors equips AGVs with comprehensive environmental perception capabilities, laying a solid foundation for subsequent decision-making, control, and autonomous operation.

3.1.1. LiDAR

The core application of LiDAR in agriculture lies in endowing traditional agricultural production equipment with the ability to accurately perceive their environment [47]. By emitting laser beams and measuring the reflected signals, it can rapidly acquire high-precision 3D information about farmland, crops, and terrain [48]. As an active sensor, LiDAR maintains stable performance despite variations in lighting, enabling reliable operation during night or low-visibility periods [49]. Nevertheless, in real-world agricultural settings, including greenhouses, orchards, and open fields, its effectiveness is constrained by factors such as occlusion, reflective surfaces, and adverse weather. Thus, rather than acting as a standalone solution, LiDAR serves as a critical component within a multi-sensor perception system. When fused with complementary sensors, it contributes significantly

to the robust environmental awareness required for Agriculture 5.0, supporting precision operations, autonomous navigation, and human–robot collaboration.

The advances in the application of LiDAR for detection and navigation in agriculture are as follows. In orchard environments, LiDAR demonstrates high resistance to illumination variations; however, when encountering missing vegetation or highly irregular canopy shapes, the peaks of the point cloud histogram become flattened, leading to offsets in row center position estimation. Nehme et al. proposed a Hough transform-based structure tracking method with online regression modeling, achieving real-time grapevine row identification with a root mean square error (RMSE) of 0.107 m [50]. In open-field agricultural environments, the quality of LiDAR point cloud data during acquisition is severely affected by dust and adverse weather conditions. Guan et al. improved PointPillars by a multi-pooling encoding module (MPE), depthwise separable convolution blocks (DSB), and a parameter-free simple attention module (SimAM), enabling multi-scale feature fusion and a lightweight design that reduces computational cost while maintaining accuracy in resource-constrained farmland [51]. Qin et al. enhanced Voxel R-CNN by incorporating focal sparse convolution into the 3D backbone, dynamically weighting features to improve extraction from sparse LiDAR point clouds [52].

3.1.2. Vision Sensor

Vision sensors are widely used in the field of agricultural perception. They can simulate human vision to capture color and texture information, as well as some depth data. Furthermore, they can calculate three-dimensional spatial information and obtain high-precision depth maps through binocular or multi-ocular vision, making them core enablers of precision agriculture and automated operations, visual recognition technology is the foundation for achieving agricultural automation [53].

Ghazal et al. systematically reviewed the applications of computer vision technology in smart agriculture and precision agriculture, with a focus on the methods for constructing vision-guided intelligent systems throughout the digital life cycle of crops [54]. The study centered on core tasks, such as crop growth monitoring, disease and pest identification, yield prediction, and quality control, achieved through technologies like RGB, multispectral [55], hyperspectral [56], and thermal imaging. Innovatively, it proposed a complete digital agriculture technology framework encompassing image acquisition, stitching, analysis, decision-making, and planning, emphasizing the key role of vegetation indices in a crop health assessment. Sun et al. proposed a soft visual–tactile sensor named Insight, which achieves the high-precision perception of three-dimensional contact force distribution by combining photometric stereo vision with structured light technology. The sensor features a hybrid structure design comprising a single-layer elastomer and a rigid skeleton, with an integrated monocular camera inside. It uses an LED ring light source and a collimator to generate a cone-shaped light projection, capturing minute surface deformations, offering a potential solution for high-resolution tactile sensing in agricultural robots [57]. Khan et al. proposed a UAV-assisted framework for crop pest and disease detection using an improved YOLOv5s model, which achieved 96.0% average precision, 93.0% average recall, and 95.0% mAP on UAV-captured visual sensor data [58].

In the context of Agriculture 5.0, human–robot collaboration is of paramount importance, and no single vision sensor can universally satisfy all HRC requirements. In controlled greenhouse environments, stereo cameras with active infrared projectors are often preferred. In outdoor fields with significant natural light fluctuations, depth cameras are particularly susceptible to direct sunlight, which can overwhelm the infrared projector or produce invalid depth maps; thus, polarized-light cameras are more suitable. In open orchards, thermal-infrared or multispectral cameras can complement RGB sensors to mitigate

illumination variations. Selecting appropriate cameras for different agricultural scenarios can further improve recognition accuracy.

3.1.3. Infrared Sensor

The application of infrared sensors in agriculture has developed into a systematic technological cluster [59]. Their core value lies in the ability to detect various types of information, ranging from molecular vibrations to the surface temperatures of objects, in a non-contact and non-destructive manner. This enables the rapid assessment of the maturity, moisture content, and nutritional components of grains, fruits, and vegetables [60]. Additionally, by monitoring changes in canopy temperature, they can identify stresses such as drought or salinity before visible symptoms appear in crops, providing crucial data support for precision agriculture [61].

Dvorak et al. focused on the application of thermal infrared array sensors in human presence detection systems for highly automated agricultural machinery. Using two sensor models, the TPAM 166 L3.9 and the AMG8833, tests were conducted on a heated anthropomorphic dummy and a standard model compliant with ISO 18497. By comparing two sets of experiments conducted in 2007 and 2024, the capability of low-cost thermal infrared array sensors to detect human presence was validated [62]. Sivakumar et al. systematically reviewed the multi-dimensional applications and technological evolution of thermal infrared remote sensing in agriculture. By capturing surface thermal radiation in the 3–14 μm wave band, thermal infrared remote sensing enables 11 core functions: crop water stress assessment, soil moisture detection, irrigation scheduling optimization, evapotranspiration monitoring, drought stress analysis, pest and disease detection, soil property mapping, crop maturity assessment, yield prediction, subsurface drainage system localization, and residue cover analysis [63].

3.1.4. IMU

The application of the inertial measurement unit (IMU) in agricultural perception has evolved from a simple auxiliary sensor to a core component in multi-sensor fusion systems [64]. Its core value lies in providing high-frequency attitude, angular velocity, and acceleration information, while correcting errors caused by terrain undulations and rapid movements of agricultural machinery, making it a key enabling technology for achieving high-precision positioning and stable control in agricultural machinery.

Addressing the challenges of autonomous navigation for agricultural mobile robots in unstructured orchard environments, Shamshiri et al. proposed a modular perception system based on CAN bus communication to assist existing IMU and GPS navigation. This system improves measurement errors in IMU and GPS, enabling the robot to achieve real-time obstacle avoidance in environments with dense undergrowth and random obstacles [65]. To mitigate collision risks posed by obstacles such as trees and utility poles in farmland, Bhuta et al. developed a plug-and-play perception module. By fusing IMU data with RGB-D camera depth data, it generates LiDAR-like point cloud data. This module effectively detects obstacles within a range of 1.8 m to 4 m, achieves an obstacle avoidance distance of up to 4 m, and consumes only 40% of processor resources, enabling efficient obstacle detection [66].

3.1.5. GNSS

The application of global navigation satellite systems (GNSS) [67] in agricultural perception has evolved from a simple positioning tool into a cornerstone within multi-sensor fusion systems. Providing an absolute geospatial reference for various mobile platforms in farmland environments is a prerequisite for achieving centimeter-level precision operations and navigation control. However, the accuracy of standard GNSS single-point

positioning is only to meter-level, which cannot meet the practical demands of precision agriculture. Therefore, it is necessary to explore the potential of core technologies for achieving centimeter-level positioning [68].

Soitinaho et al. conducted field experiments in an alfalfa field using cylindrical buckets as test objects. Information was acquired through dual 2D LiDAR sensors and an integrated RTK-GNSS/IMU device. By comparing the results with ground truth values obtained from static RTK-GPS measurements, the positioning accuracy of the system was validated [69]. Izere et al. used Pix4D software to process UAV RGB images to generate digital surface models (DSMs) and digital terrain models (DTMs). Canopy height was calculated using the differential method. By comparing the performance of three methods (conventional GNSS+GCP, RTK-GNSS+GCP, and RTK-GNSS without GCP) on triticale, maize, and soybean crops, it was found that RTK-GNSS technology can achieve centimeter-level positioning accuracy. Furthermore, the method without ground control points (GCP) demonstrated a performance comparable to traditional GCP methods in plant height estimation, evaluating the positioning accuracy of RTK-GNSS technology in agricultural UAVs and its application potential in crop height estimation [70].

3.1.6. Multi-Sensor Fusion

Although a single sensor can solve most problems for agricultural robots or AGVs, there are still many limitations. Therefore, achieving multi-sensor fusion has become a mainstream approach. Rakun and Popič proposed an optimization algorithm and completed its practical deployment to address the requirements for accuracy, efficiency, and crop protection in the autonomous navigation of agricultural robots. By integrating LiDAR and IMU sensor data, combined with multi-stage filtering and a finite state machine control architecture, 3D point cloud environmental modeling and precise path tracking were achieved. This work validated the enhancing effect of sensor fusion, data filtering, and control strategy optimization on the autonomous navigation performance of agricultural robots [71]. Brickner et al. proposed a hierarchical classification framework based on multi-source satellite data fusion and machine learning. By employing phenological feature extraction and an expert-driven feature selection strategy, the framework effectively addressed the challenge of monitoring differences in crop development along an aridity gradient, revealing the correlation between wheat phenology and climatic gradients. This approach was used to dynamically monitor changes in agricultural land use in arid regions [72].

Multi-sensor fusion can be implemented at three levels: data level, feature level, and decision level, among which feature-level fusion is the most commonly adopted due to its balanced trade-off between efficiency and accuracy. Practical deployment must address spatiotemporal synchronization and spatial calibration among heterogeneous sensors, while coping with engineering challenges, such as limited onboard computational resources, sensor degradation, dynamic non-Gaussian noise, and frequent recalibration maintenance. The system architecture can be classified into centralized, distributed, and federated configurations. In the future, driven by the demand for multi-source sensor fusion [73], numerous challenges in agricultural intelligent perception—such as achieving semantic-level perception and localization of targets, addressing the environmental susceptibility of vision sensors, compensating for motion distortion and vibration interference, resolving GNSS signal dropout and drift, and achieving spatiotemporal alignment of multi-scale information—will be addressed one by one, as shown in Figure 5. This will greatly contribute to our progress towards Agriculture 5.0.

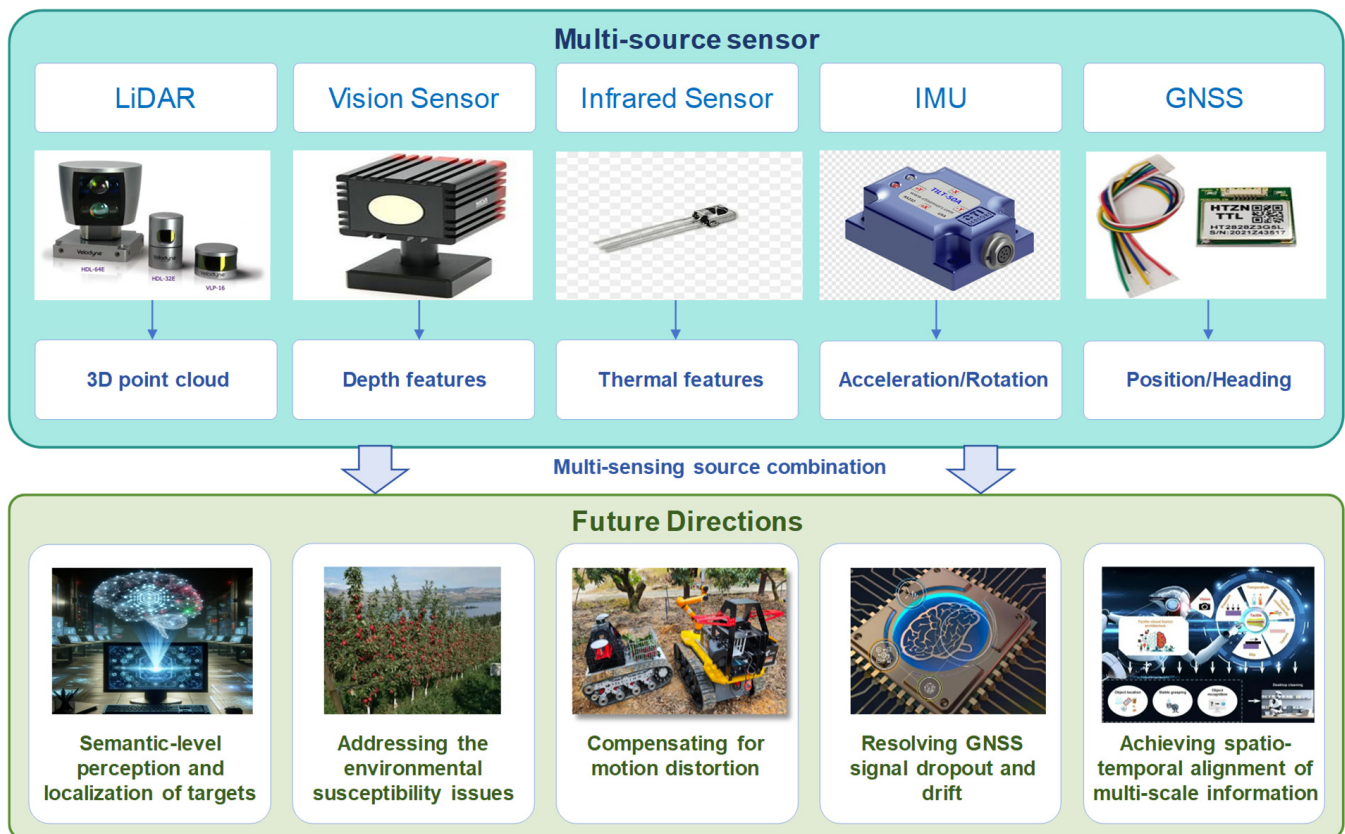


Figure 5. Multi-sensing source combination for future directions.

3.2. Visual Perception and Target Recognition

The development process of visual perception and object detection is shown in Figure 6. Early traditional visual detection techniques mainly relied on basic features of agricultural crops, as these features had significant differences. As the requirements for image detection accuracy continued to increase, people began to incorporate machine learning methods for detection. However, the feature engineering in these methods was heavily dependent on manual work and struggled to leverage massive amounts of data. In recent years, to overcome the limitations of traditional object detection methods, deep learning algorithms have risen strongly. Leveraging automatic feature extraction and powerful nonlinear fitting capabilities, they can significantly improve detection accuracy and speed.

3.2.1. Traditional Image Recognition Algorithms

Most crops usually possess stable and distinctive characteristics, among which color features and geometric shape features are two key indicators for selective crop detection.

Regarding color features, Yu et al. proposed a laboratory-customized autonomous apple harvesting robot named LABOR, which adopts an architecture combining a dual-arm operation system with a binocular vision system, focusing mainly on binocular vision-based apple recognition and localization, as well as dual-arm collaborative picking operations, aiming to address the issues of insufficient flexibility and low harvesting efficiency in traditional agricultural robots [74]. Ratprakhon et al. developed an automatic color evaluation method for mango quality based on a charge-coupled device (CCD) camera and a computer vision system, overcoming the limitation of traditional colorimeters and spectrophotometers that can only measure local areas. By performing a pixel-level analysis to fully characterize fruit color distribution, and by converting the RGB color space to the HSI color system combined with the Natural Color System (NCS) for color coding, precise quantification of mango peel and pulp ripeness was achieved [75].

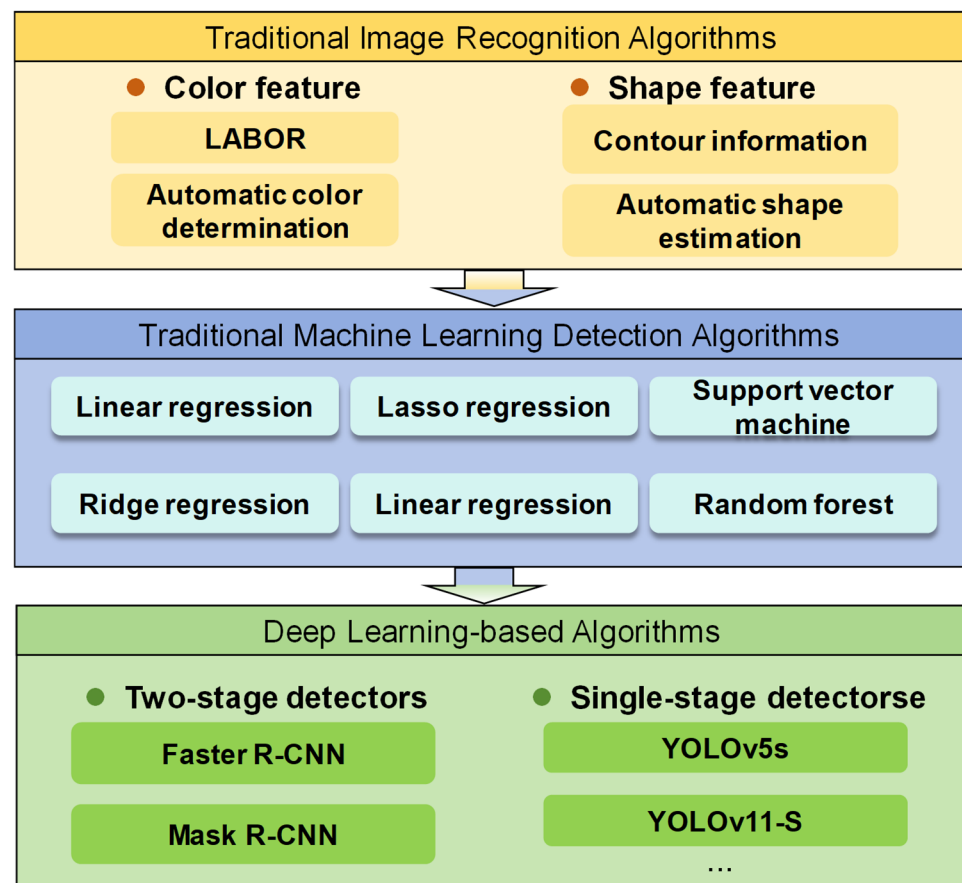


Figure 6. The development process of visual perception and object detection.

Regarding geometric dimensions and shape, Lin et al. proposed a novel fruit detection method based on contour information in natural environments, using a combined framework of partial shape matching and probabilistic Hough transform to achieve universal detection of six types of fruits: citrus, tomato, pumpkin, bitter melon, luffa, and mango. This method addresses the shortcomings of traditional color feature-based detection methods under varying illumination and low-contrast scenarios [76]. Oo and Aung designed a computer vision-based method for the automatic estimation and classification of strawberry shape and size, innovatively employing “right kite” and “simple kite” geometric models to fit the two-dimensional image features of strawberry fruit. By extracting fruit boundary pixels and calculating geometric parameters, high-precision measurements of strawberry diameter, length, and top angle were achieved [77].

When recognition is performed using color features, the color of the crop itself must be relatively distinct. Nevertheless, detection techniques are often susceptible to environmental variations, including illumination changes, shadows, and occlusions. Furthermore, a high degree of similarity in color between the crop and its background presents an additional formidable challenge to detection [78]. Although shape features are less influenced by environmental factors, individual size variations can also increase detection difficulty.

3.2.2. Traditional Machine Learning Detection Algorithms

Research on computer vision and machine learning algorithms are widely used in crop growth monitoring and decision-making in precision agriculture [79]. Fu et al. proposed a rapid estimation method for corn leaf area index (LAI) called VisLAI, based on computer vision and UAV remote sensing technology. They compared six different machine learning algorithms (linear regression, ridge regression, Lasso regression, linear regression, support

vector machine, and random forest) as well as a visual algorithm using color space conversion and threshold segmentation techniques for predicting the LAI in corn at different growth stages, and analyzed the advantages and disadvantages of these algorithms. The analysis concluded that VisLAI outperforms traditional models at all growth stages [80].

Machine learning algorithms also play a significant role in classification problems. Tseng et al. focused on rice seedling detection using UAV imagery and proposed a machine learning solution based on transfer learning. Compared with the traditional HOG-SVM method, the improvement in classification accuracy was not significant. However, in object detection tasks, this solution achieved an average precision far exceeding that of traditional machine learning algorithms, exposing the accuracy limitations of traditional machine learning algorithms and demonstrating the absolute superiority of deep learning algorithms in object detection [81].

3.2.3. Deep Learning-Based Algorithms

In recent years, agricultural object detection algorithms have mainly developed along two technical routes: two-stage detectors and single-stage detectors [82]. Table 2 shows a comparison between the major deep learning-based algorithms.

Two-stage detectors (such as Faster R-CNN [83], Mask R-CNN [84]) first generate candidate regions and then perform classification and regression. They offer obvious advantages in accuracy but are relatively slow. Bai et al. proposed an improved detection model based on Faster R-CNN, using ResNet50 as the backbone network, introducing a feature pyramid network (FPN) for multi-scale feature fusion, and applying ROI Align to optimize the positioning accuracy of candidate boxes, effectively overcoming the performance bottlenecks of traditional models under complex illumination and multi-scale obstacle detection [85]. To address the severe occlusion, overlap, and shape variation of sweet potato leaves in the field, Wang et al. introduced a convolutional block attention module (CBAM) to improve Faster R-CNN for enhanced feature extraction, and adopted distance-IoU non-maximum suppression (DIoU-NMS) to refine detection results [86]. Fang et al. improved the Mask R-CNN architecture by using a hybrid ResNet–DenseNet backbone to boost feature extraction, combined with a ZED2i stereo camera to capture apple images in complex orchard environments, effectively solving the localization difficulties caused by uneven illumination, leaf occlusion, and fruit overlap [87]. Lyu et al. also proposed a non-contact measurement method for melon fruit diameter based on an improved Mask R-CNN algorithm, which employs a ResNet50 backbone together with a CPCA channel prior convolutional attention mechanism and a bidirectional feature fusion pyramid network, while introducing a self-attention mechanism in the mask branch and using dice loss to optimize the segmentation accuracy, thereby efficiently measuring fruit maturity [88].

Single-stage detectors (such as the YOLO series) directly predict bounding boxes and categories [89], and they dominate agricultural scenarios that demand strict real-time performance. Zhu et al. proposed a lightweight object detection algorithm YOLO-VDS based on an improved YOLOv5s, incorporating the IRBC3 module and the ECA attention mechanism, which significantly reduces model complexity while maintaining detection accuracy, effectively solving missed and false detections in dense strawberry clusters [90]. Zhang et al. designed an efficient object detection algorithm named Seedling-YOLO based on an improved YOLOv7-tiny, using the ELAN_P backbone module, introducing the CARAFE upsampling operator and the CA attention mechanism to improve the planting quality inspection of broccoli seedlings [91].

To solve the problem of pineapple fruit detection in complex agricultural scenes captured by UAVs, Lin et al. introduced the coordinate attention mechanism into YOLOv8 to enhance feature extraction, integrated the BiFPN network for multi-scale feature fusion,

and finally adopted the RT-DETR detection head combined with a self-attention mechanism to optimize target localization [92]. Hou et al. proposed an optimized YOLOv8n model, designing a parallel bottleneck module (PBN), introducing an efficient multi-scale attention mechanism (EMA) into the spatial pyramid pooling fast module (SPPF), and replacing the upsampling method with bilinear interpolation upsampling (BLIU) to balance detection speed and accuracy while preserving features and their fusion [93].

Yang et al. optimized the YOLOv11-S architecture, adopting a MobileNetV4 depthwise separable convolutional backbone, Focus operation for $4\times$ downsampling, and a hybrid local-channel attention mechanism, constructing the ASD-YOLO model with only 9.5 MB parameters, achieving high accuracy, high speed, and small error [94]. Ma et al. proposed an improved joint detection model YOLO-TRS based on YOLO11n. By introducing the C3k2-DS module and the CAA attention mechanism, the model adapts to challenges such as stem–leaf occlusion, fruit overlap, and difficulty in peduncle localization during field tomato harvesting [95].

Table 2. Comparison between major deep learning-based algorithms.

Target	Reference Model	Regarding the Issue	Improvement Methods	Performance Index	Reference
Farmland obstacles	Faster R-CNN	Insufficient detection accuracy in complex farmland environments, poor multi-scale feature fusion, inaccurate candidate box localization	ResNet50 backbone, FPN for multi-scale feature fusion, ROI Align for better localization	Precision 91.6%, Recall 89.7%, mAP 93.8%	[85]
Sweet potato leaves	Faster R-CNN	Dense leaves, severe occlusion, overlapping, and shape variation in natural scenes causing missed and false detections	CBAM attention module, DIoU-NMS to replace NMS	mAP 95.7% ($\uparrow 2.9\%$ over baseline)	[86]
Apple	Mask R-CNN	Insufficient fruit positioning accuracy in complex orchards; occlusion and overlapping affecting recognition	ResNet–DenseNet hybrid backbone, removed classification branch, binocular vision + template matching	Positioning accuracy 99.61%, picking success 94.3%	[87]
Melon fruit	Mask R-CNN	Low manual measurement efficiency, high subjective error; traditional vision methods sensitive to lighting and background	ResNet50 + CPCA attention, bidirectional FPN, self-attention in mask branch, Dice Loss	Detection P 94.2%, segmentation P 92.7%; horizontal error 7.1%, vertical 7.6%	[88]

Table 2. Cont.

Target	Reference Model	Regarding the Issue	Improvement Methods	Performance Index	Reference
Strawberry	YOLOv5s	Lack of detection for different growth stages; occlusion and background interference in natural environments causing missed/false detections	IRBC3 module (inverted residual), ECA attention	mAP@0.5 81.9%, params 5.3 M, FPS 37.1	[90]
Broccoli	YOLOv7-tiny	Root balls similar to soil, occlusion by leaves, missed hills resembling background, small target detection difficulty	ELAN_P module (partial convolution), CARAFE upsampling, CA attention	mAP@0.5 94.3%, params 4.98 M, FPS 29.7	[91]
Pineapple	YOLOv8	Fruit occluded by leaf crowns, complex background, dense small targets leading to poor detection	P2 small-target layer + BiFPN, Coordinate Attention, RT-DETR head, Focaler-CIoU	mAP@0.5 62.0% (6.6% over baseline)	[92]
Small-target pests	YOLOv8n	Weak features of small pests in complex environments, easy to miss; difficulty balancing accuracy and speed	PBN module (parallel bottleneck), SPPF-EMA attention, bilinear interpolation upsampling	mAP@0.5 96.6%, mAP@0.5:95 81.7%	[93]
Pepper seeds	YOLOv11-S	High-throughput industrial sorting; difficulty balancing algorithm precision and real-time performance, poor hardware–software coordination	MobileNetV4 backbone, Focus operation, MLCA attention, pulse feedback correction, fuzzy grading	mAP 96.5%, params 9.5 M, GFLOPs 17.7, latency 5.5 ms	[94]
Tomato	YOLOv11n	Stem–leaf occlusion, fruit overlap, difficulty in stem localization, affecting harvesting robot performance	C3k2-DS module (dynamic snake convolution), CAA attention	Precision 89.9%, Recall 91.5%, mAP 94.8%	[95]

It can be seen that algorithms such as Faster R-CNN, Mask R-CNN, and YOLO have been widely used for object detection in fruits, vegetables, and other crops, and have achieved good results. How to further improve deep learning algorithms, as well as feature extraction and fusion methods, to adapt them to the visual detection of multiple crops, will become a key technology for realizing Agriculture 5.0.

While the aforementioned object detection algorithms have achieved remarkable performance in crop and obstacle identification, the paradigm of Agriculture 5.0 demands a fundamental shift in the role of visual perception, from task-oriented automation to human-centric collaboration. In human–robot collaboration (HRC) scenarios, visual perception is no longer merely required to detect static objects or crops; it must interpret human presence,

posture, action, and intention in real time, such as real-time human pose estimation and action recognition, safety-centric perception metrics and trust, enabling robots to proactively coordinate with human workers to finish tasks well.

3.3. Positioning and Navigation Technology

The current agricultural positioning technologies are mainly classified into four categories: global navigation, local navigation, SLAM navigation, and multi-sensor fusion navigation, with each mode forming differentiated solutions tailored to specific scenario requirements.

3.3.1. Global Navigation and Local Navigation

Global navigation involves finding an optimal or feasible macro-path from a starting point to a destination within a known, static map environment. It does not consider real-time obstacles but only relies on inherent information on the map, such as GNSS. Local navigation, on the other hand, dynamically plans a short, safe, smooth, and collision-free trajectory during movement based on real-time surrounding environmental information perceived by sensors (cameras, LiDAR, ultrasonic). It handles unforeseen situations that global planning cannot anticipate [96].

The effectiveness of global navigation and local navigation is not determined by the algorithms themselves, but rather by the physical environment of the agricultural scenario. In open fields with unobstructed sky views, GNSS can provide centimeter-level positioning accuracy, making global navigation the primary means of guidance, while local navigation serves only as a supplementary layer for obstacle avoidance. In orchards and vineyards, canopy occlusion and multipath effects severely degrade GNSS signals, significantly reducing the accuracy of global navigation; consequently, local navigation methods, such as LiDAR-based structure tracking, become indispensable for real-time inter-row correction. In enclosed or semi-enclosed facilities, such as greenhouses and plant factories, metallic frameworks and covering materials completely block GNSS signals, creating a GPS-denied environment where global navigation fails entirely. In such cases, localization and path tracking can only rely on local navigation solutions based on visual SLAM, LiDAR SLAM, or UWB fused with wheel odometry and IMU.

Regarding global navigation, Maldaner et al. proposed a statistical evaluation framework. By constructing a standardized testing platform, a systematic exploration of static and dynamic testing methods for GNSS receivers in agriculture was conducted. A comparative analysis of 10 GNSS receivers with different accuracy levels was performed, focusing on quantifying the relationship between the number of test repetitions and statistical power [97]. Zhu et al. proposed a quasi-global soil moisture retrieval method based on a stacked fusion model. By integrating three algorithms—Gradient Boosting Decision Tree, eXtreme Gradient Boosting, and Random Forest—a multi-layer stacked model was constructed. This method utilizes spaceborne CYGNSS data combined with machine learning techniques to achieve soil moisture monitoring with high spatial and temporal resolution, effectively improving the accuracy and robustness of soil moisture retrieval [98]. However, global navigation is often limited by screen size, typically only displaying the top few core entrances and unable to present the full breadth and depth of the site. As a concept within a closed system, it struggles to handle cross-system and cross-platform jump requirements. When the user's information needs exceed the current system boundaries, it suffers from high failure rates.

For local navigation, such as autonomous navigation of agricultural robots in vineyards, Nehme et al. proposed a LiDAR-based method as a low-cost alternative to GNSS systems. This approach overcomes the limitations of traditional GNSS navigation systems

which, despite achieving centimeter-level accuracy, require time-consuming pre-surveying and high costs, significantly reducing task preparation time and expenses [50].

3.3.2. SLAM Navigation

SLAM navigation, simultaneous localization and mapping, is currently one of the most widely applied core technologies in the field of autonomous navigation for mobile agricultural robots [99]. It enables agricultural equipment operating in unknown environments to gradually construct a local map of the surrounding area while moving, and simultaneously rely on the constructed map to estimate its real-time position within that environment. This perfectly addresses the need for autonomous positioning and navigation in scenarios where a pre-existing global environmental map is unavailable and stable GNSS signals cannot be obtained. It is particularly well-suited for agricultural operation scenarios where traditional navigation technologies struggle to function effectively, such as scattered plots in hilly and mountainous terrain and densely planted forest areas in orchards.

From a technical roadmap perspective, SLAM navigation currently applied in agriculture is mainly categorized into two directions: LiDAR SLAM based on LiDAR sensors and Visual SLAM based on vision sensors.

Laser SLAM, leveraging the characteristics of LiDAR, such as high ranging accuracy, strong stability, and minimal impact from lighting variations, has become one of the mainstream solutions for agricultural SLAM navigation [100].

In addressing the challenges of multi-obstacle avoidance and path planning in complex agricultural environments, autonomous navigation positioning and mapping using laser SLAM plays a crucial role. Lv et al. constructed a high-precision 3D point cloud map using laser SLAM technology and developed the R-TEB local planning algorithm, as shown in Figure 7. By introducing curvature optimization constraints, velocity smoothing constraints, and global path deviation constraints, this approach solves issues like trajectory jitter and high energy consumption found in traditional TEB algorithms within sparse point cloud environments, achieving centimeter-level positioning and dynamic environmental perception [101]. Schmitz et al. proposed an online mapping and autonomous trajectory execution system based on SLAM, integrating LiDAR sensors for real-time environmental mapping and positioning. By combining this with vehicle odometry data, the system improves computational efficiency and accuracy, providing a highly maneuverable autonomous platform solution for agricultural robots [102]. Xu et al. proposed a multi-level loop closure detection strategy based on RS-SC fusion, combining a fast rough search using radius search with fine matching via scan context. An NDT-ICP joint optimization algorithm was employed to effectively reduce cumulative errors, significantly enhancing detection efficiency and accuracy [103]. To address the problem of positioning error accumulation caused by weak GNSS signals and similar environmental features, Qu et al. proposed a LiDAR-SLAM system based on the ROS framework. This system achieves coordinate system transformation and kinematic modeling through a URDF model, constructing a navigation system that includes both global and local cost maps [104].

Visual SLAM, leveraging the advantages of low sensor cost and rich environmental information acquisition, is gradually being applied in agricultural operation scenarios [105]. In addition to completing positioning and navigation tasks, it can simultaneously perform extra operational tasks, such as crop identification, weed detection, and fruit counting, achieving multi-purpose use with a single sensor.

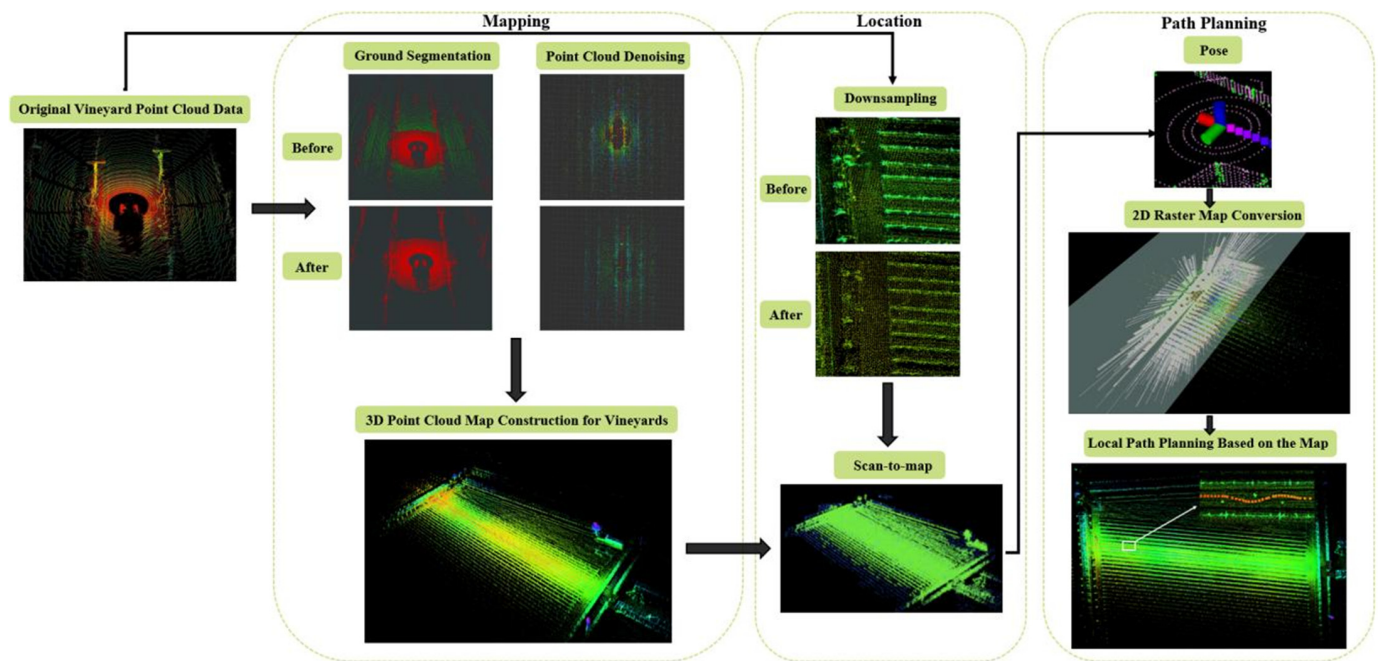


Figure 7. SLAM System and Autonomous Navigation Schematic Diagram [101].

However, acquiring high-quality images with Visual SLAM poses a significant challenge in complex agricultural scenes characterized by low light, haze, occlusion, and interference. Xinjung Wang addressed this by integrating an RGB-D camera with the ORB-SLAM2 framework and incorporated a dynamic feature point removal algorithm using the YOLOv4 tiny network. Depth images were used to elevate 2D feature points to 3D space, the PnP algorithm optimized camera pose estimation, and cumulative errors were reduced through local bundle adjustment and global graph optimization, ultimately constructing a dense 3D map suitable for complex operational scenes [106]. Islam et al. established a real-time stereo Visual SLAM system named AGRI-SLAM. This system integrates an image dehazing and enhancement algorithm based on an atmospheric scattering model, a multimodal feature extraction strategy combining ORB point features and LSD line features, and a complete SLAM framework encompassing image enhancement, tracking, local mapping, and loop closure detection, specifically enhancing image integration for agricultural environments [107]. Wang et al. integrated the lightweight semantic segmentation network BiSeNetV2 into the ORB-SLAM3 system to construct a point cloud map containing both geometric and semantic information. The system employs a two-stage filtering strategy to remove noise and utilizes OctoMap for efficient storage, solving the challenge of managing large-scale point cloud data and enabling efficient acquisition of tomato plant phenotypic traits [108]. To address issues of unclear obstacle recognition and environmental understanding, Chen et al. constructed a dual-thread architecture integrating a semantic segmentation network and a SLAM system. Semantic information was mapped onto the point cloud map through probabilistic data association. A lightweight semantic segmentation network was designed, employing an asymmetric encoder–decoder structure and multi-scale convolution kernels to achieve navigation assistance with centimeter-level positioning accuracy [109]. Yang et al. designed a 2HR feature detection network, integrating the K-Means clustering algorithm into the L2-Net framework. A lightweight YOLOv8n model was integrated for real-time detection and removal of dynamic region feature points. A shared matching Siamese network was proposed, employing a dual-branch feature fusion strategy and a similarity optimization algorithm to improve feature matching accuracy,

overcoming the two major challenges in dynamic scenes: insufficient feature reliability and severe dynamic interference [110].

3.3.3. Multi-Sensor Fusion Navigation

In response to various challenges encountered in different agricultural environments, many research teams have sought solutions through multi-sensor fusion for positioning and navigation [111].

In orchard environments, Wang et al. integrated LiDAR, vision, and inertial sensors, using YOLO-world for 2D object detection and FAST-SAM to generate pixel-level instance masks. Multi-view semantic information was then projected onto a 3D point cloud using a Bayesian fusion framework. This approach addresses the problems of traditional point cloud maps lacking semantic information and vision methods being susceptible to lighting variations in agricultural scenes [112]. Su et al. developed a complete navigation system, including hardware architecture and software algorithms, using a tracked agricultural platform as a carrier and integrating a 2D LiDAR, a dynamic electronic compass, and an encoder. The DBSCAN-ratio-threshold method was used to process LiDAR point cloud data to identify trunk cluster centers, which were then coordinate-matched with a pre-constructed fruit tree distribution map. Combined with an extended Kalman filter for platform pose estimation, this solves the problem of decreased positioning accuracy in orchard environments caused by tree canopy occlusion experienced by traditional GNSS navigation [113].

In greenhouse environments, Yan et al. constructed a loosely coupled framework based on an extended Kalman filter by integrating measurement data from wheel odometry, an IMU, and visual-inertial odometry. Concurrently, an improved ORB-SLAM2 algorithm was employed to generate dense 3D point cloud maps in real-time. This addresses the challenges of autonomous navigation for agricultural robots in unstructured, dynamic, and GPS-denied greenhouse environments [114]. Cheng et al. designed a positioning algorithm optimized based on NLOS (non-line-of-sight) confidence. By introducing a laser rangefinder to calibrate UWB coordinates and fusing IMU, odometry, and LiDAR data with an extended Kalman filter, minimal lateral and heading deviations were achieved, mitigating the impact of non-line-of-sight propagation on UWB positioning accuracy [115].

Furthermore, Guan et al. constructed a tightly coupled factor graph optimization framework by integrating 3D LiDAR, IMU, and a visual fiducial marker system. Centimeter-level absolute pose information provided by AprilTags was used to correct systematic drift in the LiDAR-inertial odometry, while also addressing the issue of accumulated positioning errors caused by weak GNSS signals and similar environmental features in greenhouses and orchards [116]. To tackle the problem of insufficient positioning accuracy due to GNSS signals being susceptible to noise interference in automatic agricultural machinery navigation, Li et al. proposed introducing a quaternion method to resolve nonlinear issues caused by attitude angles. A fuzzy inference system was employed to enhance adaptive adjustment capability against abnormal noise, and a forgetting factor was introduced to reduce the system's reliance on historical statistical information, thereby enabling rapid tracking of abrupt signal changes [117].

Against the backdrop of the deep integration of agricultural mechanization and intelligence, positioning and navigation technologies are continuously evolving from single-sensing methods toward multi-source collaboration and scenario adaptability. Various navigation technologies do not replace one another but complement each other across different operational stages and scenarios, collectively building the foundational capability for agricultural equipment in environmental perception, precise positioning, and autonomous decision-making. As agricultural systems accelerate their transition toward Agriculture 5.0,

increasingly higher demands are being placed on positioning and navigation technologies. It is foreseeable that, with continued breakthroughs in sensors, computing platforms, and intelligent algorithms, positioning and navigation technologies will play an even more fundamental and driving role within the Agriculture 5.0 framework, propelling agricultural production toward a comprehensive transformation—from experience-driven to model-driven, from single-point operations to systematic collaboration, and from automated execution to autonomous decision-making.

4. Application of Perception Results

4.1. Path Planning

Mobile robots play an increasingly vital role in people’s production and daily life. Therefore, research on the autonomy and intelligence of mobile robot path planning holds significant importance [118]. Table 3 shows a comparison between the major path planning algorithms.

Table 3. Comparison between the major path planning algorithms.

Type	Fundamental	Applicable Scene	Advantage	Disadvantage
Global path planning	A* algorithm RRT, genetic algorithm, ant colony optimization, particle swarm optimization	Known static environment with complete map information	Can find global optimal or near-optimal path; pre-planned path ensures safety; good for structured environments	Cannot handle dynamic obstacles; high computational cost for large maps; depends on accurate map modeling
Local path planning	Dynamic Window Approach (DWA), artificial potential field (APF), Time Elastic Band (TEB)	Unknown or dynamic environment, real-time obstacle avoidance	Real-time response; adapts to moving obstacles; no need for global map	Prone to local minima; may produce non-smooth paths; cannot guarantee global optimality
Hybrid algorithm	A* + DWA, ACO + DWA, GA + ACO, RRT + APF, PSO + GA/SA	Complex environments with both static and dynamic obstacles	Combines global optimality with dynamic obstacle avoidance; improves path smoothness and robustness	Increased algorithm complexity; more parameters to tune; may have higher computational overhead
Deep Reinforcement Learning	DQN, DDQN, DDPG, TD3, PPO, etc.	Unknown or dynamic environments, mapless navigation	Learns from interaction; adapts to changing conditions; handles high-dimensional state/action spaces	Long training time; requires many episodes; unstable convergence; sensitive to hyperparameters

4.1.1. Global Path Planning

(1) A*algorithm

The A* path planning algorithm is a heuristic search algorithm widely used in graph search and path optimization. It was proposed in 1968 by Hart et al. [119]. By combining actual cost with estimated cost, it skillfully balances the breadth-first exploration of Dijkstra’s algorithm and the directional exploration of greedy best-first search. Through the concise formula $f(n) = g(n) + h(n)$, it achieves the ability to quickly find optimal paths in complex environments. While ensuring the shortest path is found, it significantly improves

search efficiency. It is a heuristic path search method that possesses both accuracy and efficiency [119].

But the traditional A* path planning algorithm suffers from low search efficiency and an imbalance between actual cost and predicted cost. Consequently, many research teams have improved the algorithm for practical applications. Zhang et al. proposed an improved A* algorithm for path planning in radioactive environments of nuclear facilities. By introducing predicted cost as a heuristic function and designing a weighting scheme to balance actual and predicted costs, the improved algorithm reduced the cumulative radiation dose, the number of execution points, and the computation time [120]. Ou et al. proposed an improved A* algorithm based on grid maps, incorporating a path smoothing strategy and a safety protection mechanism. By checking for obstacles between two path nodes to eliminate redundant points and minimum corner points, the algorithm effectively enhanced path smoothness and avoided wear [121].

However, extending graph-search-based techniques to high-dimensional spaces poses significant challenges; therefore, this method is more suitable for path planning in two-dimensional spaces. As the planning dimension increases, it suffers from the curse of dimensionality.

(2) RRT algorithm

The core idea of the rapidly-exploring random tree (RRT) algorithm is to guide the growth of a tree through random sampling, thereby avoiding the massive computational cost of finely modeling the entire space. Like rapidly growing vines, it spreads randomly and exploratively until it touches the target point, quickly finding a feasible path in unknown or complex high-dimensional spaces [122].

In various complex agricultural scenarios, the practical effectiveness of path planning is strongly constrained by agronomic requirements, field geometry, operational efficiency, and the different postures and heights of crops. To improve the planning efficiency and path quality of the traditional RRT algorithm in complex environments, the GD-RRT algorithm introduces a Gaussian mixture probability distribution model and a dynamic depth strategy. It adaptively adjusts sampling distribution, step size, and sampling strategy based on collision detection results and environmental complexity. Compared with traditional RRT, GD-RRT reduces average path cost by 15% and planning time by 67.04% in 2D maps, while achieving a 100% obstacle avoidance success rate for robotic arms in 3D simulations with an average planning time of 263.4 ms [123]. Traditional RRT suffers from high randomness and insufficient memory during node expansion, limiting mobile robot performance. To address this, GD-RRT adopts a Gaussian mixture model and dynamic depth strategy, adaptively tuning sampling and step size based on collision feedback and environmental complexity—cutting path cost by 15% and planning time by 67.04% in 2D, and achieving 100% 3D obstacle avoidance for robotic arms at 263.4 ms average. For dense agricultural obstacles, Zhu et al.'s team enhanced P-RRT* with bidirectional dynamic structure and greedy strategy, plus adaptive interpolation and hybrid trajectory optimization. The resulting BDIP-RRT reduces path length by 2.72% and computation time by 63.16%, generating smooth trajectories with high-order derivative continuity and rapid convergence under 10-s disturbances, offering a practical solution for forest and dense environments [124]. To overcome the uneven sampling, redundant paths, and excessive nodes of traditional RRT, a Halton sequence-based Rapidly-exploring Random Tree path planning algorithm (HB-RRT) incorporates a goal-directed strategy, a candidate sampling pool, and multi-level planning. Compared with standard RRT and heuristic RRT*, it reduces path length by 27.94% and 6.87%, and cuts planning time by 91.66% and 85.39%, respectively. Furthermore, it yields smoother linear and angular velocity profiles, reducing mechanical load and enhancing overall robot efficiency [125].

Future research will focus on enhancing the navigation capabilities of robotic arms in complex and dynamic obstacle environments, further improving their performance and adaptability in complex scenarios.

(3) GA algorithm

The genetic algorithm (GA) [126] is a nature-inspired algorithm based on Darwin's theory of evolution [127,128].

The traditional genetic algorithm (GA) in path planning is prone to issues such as generating infeasible solutions, premature convergence, and neglecting variable-length chromosomes. To address these problems, Lamini et al. proposed a path planning method for autonomous mobile robots based on an improved genetic algorithm. They designed a novel crossover operator and a multi-objective fitness function, achieving better path planning outcomes by optimizing path length, safety, and energy consumption in static environments [129]. In response to the low efficiency of initial population generation, susceptibility to infeasible paths, and high number of iterations in traditional genetic algorithms for path planning, Ab Wahab et al. optimized the population initialization process using a linear ranking-based gap probability roadmap method and designed a combination of four genetic operators to balance global search and local optimization. This resulted in success rate increases of 156% and 1021.74%, respectively, a 57.02–89.6% reduction in initialization time, making significant contributions to global path planning for mobile robots in static environments [130].

(4) ACO algorithm

The ant colony optimization (ACO) algorithm originates from observing and imitating the foraging behavior of ants in nature, exchanging information through virtual "pheromone" trails [131]. In aquatic environmental monitoring, to address the spatial and human limitations of traditional monitoring methods, an autonomous surface vehicle path planning method based on ant colony optimization and Gaussian processes, named ACO-Path, has been developed. This approach uses Gaussian processes to update pollution concentration and uncertainty maps in real time, dynamically generating exploration and exploitation areas, and employs the ant colony algorithm to optimize the sampling path of the ASV. This overcomes the dual challenges of information collection efficiency and path smoothness in dynamic monitoring of water environments [132]. For emergency scenarios, an improved ant colony optimization algorithm (EPIACO) has been proposed, introducing six innovative mechanisms to optimize shortcomings in such scenarios, such as slow convergence speed and a tendency to fall into local optima [133].

(5) PSO algorithm

The core idea of particle swarm optimization (PSO) is to imagine each possible path or trajectory as a "particle" within the search space. These particles recall the best position they have individually found while also striving to discover the globally best position [134]. When AGVs operate in agricultural environments, they inevitably collide with some crops and fruits. To reduce the interference of obstacles on movement, Gao et al. proposed a path planning method for apple-picking robots based on an improved particle swarm optimization algorithm. This method first extracts three-dimensional point cloud data of the fruit and its surrounding branches, and calculates the fruit's picking direction. Subsequently, a spatial model of the obstacles is established. Finally, the improved particle swarm optimization algorithm is employed to dynamically adjust the obstacle avoidance trajectory of the end-effector in space [135].

Table 4 conducts the advantages and limitations between different global path planning algorithms. Global path planning serves as a critical bridge connecting intelligent perception and autonomous action, endowing perception results with clear goal orientation and practical value. By generating a macroscopic route, it specifies the spatial scope and

key elements that the perception system should focus on, thus completing the transition from understanding environmental states to making spatial behavioral decisions, enabling intelligent systems to perform meaningful, task-oriented movements.

In addition, ROS plays an extremely important role in global path planning, serving as a key bridge connecting global path planning algorithms with physical robots. Its navigation stack enables field validation of algorithms such as A* and RRT in scenarios including greenhouse spray robots and orchard harvesting robots through standardized plugin interfaces. Meanwhile, the simulation environment (Gazebo) and visualization tools (Rviz) provided by ROS allow researchers to conduct reliability tests of planning algorithms in simulated orchard or greenhouse settings, and then seamlessly transfer the validated algorithms to real robots for field operations, significantly shortening the cycle from algorithm development to practical deployment in agricultural fields.

Table 4. Advantages and limitations between different global path planning algorithms.

Algorithms	Description	Feature	Advantages	Limitations	Reference
Improved A* algorithm	A modified A* algorithm for path planning in the radioactive environment of nuclear facilities	Radiation-aware heuristic + adaptive weighting	Lower cumulative dose, faster search	No path smoothing, static field only	[120]
	Improved A* path planning method based on the grid map	Path smoothing + steering cost + adaptive weight	13% less time, 11% fewer nodes	Requires an accurate map	[121]
RRT algorithm	An improved RRT* path planning algorithm combining Gaussian distributed sampling and depth strategy for robotic arm of fruit-picking robot	Gaussian mixture sampling + dynamic depth	100% obstacle avoidance, faster convergence	Parameter tuning needed	[123]
	Fast dynamic P-RRT*-based UAV path planning and trajectory tracking control under dense obstacles	Bidirectional P-RRT* + greedy + prescribed-time control	63% faster planning, smooth trajectory	Complex integration	[124]
	HB-RRT:A path planning algorithm for mobile robots using Halton sequence-based rapidly-exploring random tree	Halton sequence + candidate pool + multi-stage	90% less planning time, high stability	2D only, static environments	[125]
GA algorithm	Genetic algorithm based approach for autonomous mobile robot path planning	Improved crossover (ISA) + multi-objective fitness	Fewer turns, faster convergence	Weights tuning needed	[129]
	Improved genetic algorithm for mobile robot path planning in static environments	Linear rank-based CBPRM + multiple genetic operators	Fewer infeasible paths, higher fitness	Static environments only	[130]

Table 4. Cont.

Algorithms	Description	Feature	Advantages	Limitations	Reference
ACO algorithm	ACO-Path: ACO-based informative path planning with Gaussian processes for water monitoring with a fleet of ASVs	GP-based action zones + explore-then-exploit	Lowest peak error, smoother trajectories	Simple ant system used	[132]
	Emergency path planning based on improved ant colony algorithm	Six improvements (EPIACO): directional heuristic, adaptive evaporation, etc.	13.66% shorter path, 97.96% faster convergence	Many parameters	[133]
PSO algorithm	Apple-picking robot picking path planning algorithm based on improved PSO	Adaptive inertia + learning factors based on swarm center of mass	Faster convergence, 85.93% picking success	Only one branch considered	[135]

4.1.2. Local Path Planning

While global planning [136] can devise a theoretically optimal path, its effectiveness is highly dependent on assumptions such as a static environment, an accurate map, and structured terrain. However, agricultural field environments often present challenges, like dynamic obstacles, map inaccuracies, and unstructured terrains. Therefore, relying solely on global planning cannot guarantee the safe operation of a robot. To address this, local path planning is necessary. Leveraging real-time data from the perception system, it performs fine trajectory adjustment and dynamic obstacle avoidance while adhering to the macro-direction of the global path, thereby ensuring the reliable operation of the robot.

Local path planning includes algorithms such as the dynamic window approach (DWA), time elastic band (TEB), and artificial potential field (APF), among which DWA is the most commonly used. Gong et al. proposed an improved fuzzy-controlled DWA algorithm that optimizes the velocity cost function, introduces a target deviation evaluation function, and uses a fuzzy module to dynamically adjust weight coefficients. Specifically, it increases safety distance by 62.08% and reduces sampling steps by 35.42% in dense obstacle scenarios, while achieving 12.5% and 26.86% improvements respectively in complex environments, enabling adaptive obstacle avoidance and path planning in unknown dynamic settings [137]. To address the detour phenomenon of the traditional DWA algorithm in dense obstacle areas through MATLAB simulation verification, Wang et al. demonstrated that the improved DWA algorithm plans smoother paths in dense obstacle regions [138].

Compared with the DWA algorithm, the TEB algorithm shows significant advantages in path smoothness, velocity stability, and parking accuracy. Duan et al. improved the TEB algorithm by incorporating time information, vehicle kinematic constraints, and dynamic obstacle perception into the planning model, thereby enhancing path smoothness and real-time performance. In single-obstacle scenarios, the velocity fluctuation rate was reduced by 17.73%; in multi-obstacle scenarios, parking planning time was shortened by 44.84%. Moreover, the obstacle avoidance success rate reached 95.40% on the KITTI dataset [139].

Furthermore, the traditional artificial potential field (APF) algorithm avoids local minima by modifying the directions of attractive and repulsive forces, thereby guiding the robot to bypass obstacles and reach the target. However, the traditional APF suffers from issues such as local minima traps, oscillations in narrow passages, and unsmooth paths.

Lin et al. introduced a rotational repulsive force field and improved the potential field direction, combined with real-time feedback from force sensors. The improved method enhances path smoothness by more than 60%, achieving efficient obstacle avoidance and path optimization [140].

In summary, DWA is based on velocity space sampling, and its bottleneck lies in the fixed evaluation function weights that are difficult to adapt to complex environments. Although fuzzy control is introduced to dynamically adjust the weights, which makes the algorithm computationally efficient and highly real-time, its poor look-ahead capability often leads to entrapment in local optima in dense obstacle areas. APF is based on a virtual force field, suffering from local minima and neglect of tool dimensions. Although improvements such as a rotating repulsive force field and modeling the tool as a vector have been proposed to address obstacle avoidance for 3D robotic arms, this method is mathematically concise and yields excellent path smoothness, yet its parameters are sensitive to tuning. TEB transforms path planning into a multi-objective graph optimization problem, focusing on introducing soft constraint penalty functions for Ackermann steering, non-holonomic motion, etc. Despite its higher computational complexity, it provides the most accurate kinematic modeling for unmanned vehicles, achieving the best performance in accuracy and obstacle avoidance success rate, while reducing parking time by approximately 44.84% compared to DWA. Therefore, in practical selection, differential-wheeled robots are better suited to the improved DWA, robotic arms should prefer the enhanced APF, and high-precision unmanned vehicles rely on TEB.

4.1.3. Hybrid Algorithm

Currently, an increasing number of research teams are inclined to fusing two or more algorithms for path planning to circumvent the various limitations that may arise from using a single algorithm and to enhance model generalization. Abhishek et al. innovatively combined the particle swarm optimization algorithm with two different optimization algorithms: PSO-HSA and PSO-GA. By integrating PSO's global exploration capability with HSA's local exploitation ability or GA's genetic operations, this approach achieves collaborative optimization of multiple objectives, including path length, fuel consumption, traversal time, and evasion of enemy radar [141]. Zhang et al. proposed an enhanced dynamic genetic algorithm–ant colony optimization (DGA-ACO) framework, constructing a 2D risk penalty mapping model and a dynamic obstacle avoidance mechanism. It improves the pheromone distribution mechanism of the max-min ant system, introduces adaptive crossover and mutation operators, integrates a hidden Markov model for dynamic obstacle trajectory prediction, and designs a multi-objective fitness function to comprehensively optimize path length, smoothness, safety, and dynamic obstacle avoidance capability [142]. Lu and Da proposed a robot global–local path planning method that integrates an improved ant colony algorithm with the dynamic window approach, optimizing strategies for static and dynamic environments separately. This enhances the global search ability and convergence speed of the ant colony algorithm, improves the obstacle avoidance stability of the dynamic window approach [143]. Guan et al. proposed an improved bidirectional artificial potential field-RRT algorithm (BIAP-RRT*). It features a dynamic target biasing strategy to improve the artificial potential field method and a bidirectional tree growth mechanism, accelerating convergence by directly connecting collision-free node pairs [144].

Specifically addressing AGV motion planning, Wang et al. proposed a solution that integrates an improved A* algorithm with the dynamic window approach, enabling local dynamic obstacle avoidance while following a globally optimal path [145]. Furthermore, for practical crop environments, such as greenhouses and plastic tunnels, a global–local path planning method integrating an improved A* algorithm and a fuzzy dynamic window

algorithm was proposed. By utilizing cubic Bézier curves for path smoothing, the hybrid algorithm reduces the maximum distance deviation by 31.8%, the maximum heading angle deviation by 28.6%, and increases the safety distance by 30% across three types of paths, offering a new approach to problems related to path redundancy and unstable obstacle avoidance [146].

4.1.4. Deep Reinforcement Learning

In recent years, deep reinforcement learning (DRL) has shown great potential in the field of robot path planning due to its powerful environmental perception and policy optimization capabilities. Wen et al. proposed a path planning method based on deep reinforcement learning. By improving the TD3 algorithm and introducing long short-term memory networks and Poisson encoding techniques, it effectively addresses issues such as local optima, obstacle collisions, and inaccurate environmental modeling found in traditional DRL algorithms for path planning, and can be effectively applied in unknown agricultural environments [147]. Zhou et al. proposed an indoor blind-zone-guided autonomous robot path planning method based on deep reinforcement learning. By improving the DDQN algorithm framework, introducing a prioritized experience replay mechanism, and innovatively designing blockage and blind corner mechanisms, it can effectively enhance the exploration efficiency and coverage of robots in complex greenhouse environments [148]. A deep reinforcement learning solution based on quantum-inspired experience replay was proposed, designing a QiER framework consisting of three stages: quantum initialization, quantum preparation, and quantum measurement. Utilizing the probability amplitude amplification characteristic of qubits to dynamically adjust sample priority during experience replay, this approach is applicable for communication optimization in agricultural robots [149].

4.2. Multi-Robot Coordination

Multi-robot coordination for agricultural AGVs (automated guided vehicles) refers to the use of scheduling algorithms and communication systems to organize multiple types of agricultural robots to work together in completing complex farming tasks, such as tillage, plant protection, harvesting, and transportation. For example, when multiple harvesters are operating in the field and a grain bin is about to reach capacity, the system automatically dispatches the nearest unmanned grain transport vehicle to assist, achieving seamless coordination. This perfectly demonstrates the collaborative approach between harvesting and transport, significantly reducing harvester downtime and improving operational efficiency. This is not just about the automation of individual equipment, but a systemic transformation of the entire farm operation model.

4.2.1. Task Allocation

Task allocation is a prerequisite for multi-robot coordination [150]. To optimize task allocation and to address the challenges related to cost-effectiveness and operational efficiency, exploring high-quality task scheduling and allocation methods is imperative. Guo et al. proposed a collaborative discrete artificial bee colony algorithm (CDABC) by introducing a collaborative follower bee strategy, a dynamic strategy list, and a key robot-based neighborhood operator. Two heuristic initialization methods based on problem knowledge were designed, and the superiority of CDABC in minimizing the makespan indicator was validated, providing a reference for practical applications addressing the complexity of task allocation in the context of Agriculture 5.0 [151].

For the agricultural multi-robot task allocation problem, Lu et al. proposed a reinforcement learning-based optimization method, NWC-APONet, which models the AMRTA problem as a multiple traveling salesman problem with node workload constraints (NWC-

MTSP). Node features are extracted via graph neural networks, and task allocation is achieved using an attention mechanism-based policy network [152]. For large-scale agricultural operation tasks, Qin et al. proposed a dual-population optimization algorithm based on an improved non-dominated sorting genetic algorithm II, overcoming the limitations of existing methods in time-sensitive priority scheduling, energy balance, and dynamic response mechanisms [153]. Different from Qin's approach of dynamically adjusting probabilities and ratios using genetic strategies, Lee et al. designed MRTA-RM, which constructs a road network model based on generalized Voronoi diagrams to divide the environment into multiple components. From a broader perspective, robot reallocation is achieved through supply-demand analysis, and task allocation is ultimately executed by a priority flow mechanism [154]. To address the issues of low efficiency, high cost, and insufficient spatial resolution in traditional manual soil sampling, Roberts-Elliott et al. innovatively designed a "Distance/Opportunity Variance" (DOV) bid calculation method by integrating Kriging interpolation variance information. Combined with dynamic sampling strategies and task queue optimization, once a Kriging variance threshold is set, tasks with low information gain can be filtered out, achieving efficient task allocation [155].

4.2.2. Scheduling

The efficient operation of multi-robot coordinated systems relies on a critical issue: how to coordinate the action sequences and resource allocation of multiple agents to complete a set of tasks with spatial-temporal constraints and logical relationships in an optimal or satisfactory manner. This is the multi-robot coordination scheduling problem. As the decision-making core of multi-robot cooperative systems, scheduling directly affects the system's operational efficiency, resource utilization, and task completion quality [156].

Multi-robot coordination scheduling not only involves the timing arrangement and resource allocation found in traditional scheduling problems, but requires consideration of complex factors, such as cooperative constraints among agents and dynamic adaptability. Compared with single-robot scheduling, multi-robot coordination scheduling exhibits exponential growth in problem dimensionality, constraint complexity, and solution difficulty. Particularly in dynamic and uncertain environments, the scheduling system must possess capabilities such as online re-planning, real-time responsiveness, and robust fault tolerance.

Ding et al. focused on addressing the efficiency bottlenecks caused by traditional scheduling algorithms considering only a single objective during task allocation. By constructing a scheduling model with dual objectives—harvesting robot waiting time and the number of transport robots—and achieving collaborative optimization with an improved PSO algorithm, the task execution time was significantly reduced. This approach holds promise for future expansion to multi-crop collaborative harvesting scenarios [157]. Miao et al. proposed a multi-objective iterative greedy algorithm incorporating reinforcement learning, termed Q_DPIG, focusing on balancing the dual objectives of efficiency and economy. By establishing a mixed-integer programming model, it solved the NP-hard problem of robot task allocation and path planning [158]. To address the contradiction between the high-dimensional state space of dynamic multi-robot task scheduling and the demand for real-time performance, Song et al. adopted a distributed DDRL strategy to achieve the parallel processing of task demand generation and robot decision-making execution, effectively alleviating computational pressure [159]. Huang et al. presented a multi-objective optimization solution that balances the makespan and the number of deployed robots by adjusting the number of collaborative robots. A mixed-integer linear programming model and a constraint programming model were constructed, and a hybrid genetic tabu search algorithm was designed to achieve efficient cooperative scheduling [160].

4.2.3. Communication System

Communication serves as the foundation for information exchange and collaboration among multiple robots. In agricultural production, various environmental factors affect the precision operations of agricultural robots. To maintain coordination and cooperation among multiple robots and to gain a comprehensive understanding of the environment during task execution, robots need to interact with each other through information exchange to accomplish assigned tasks more effectively [161]. Communication is exceptionally important for robots; even with only limited communication capabilities, the overall performance of a multi-robot system can be significantly improved [162].

Explicit communication is the most traditional and direct form of communication. Machines send data packets with explicit formats through specific physical channels to inform others of their status, intentions, or instructions. Ünal et al. designed an adaptive multi-robot communication system based on WiFi, encompassing a complete solution, including hardware architecture, data acquisition, communication protocols, and collision avoidance algorithms (Figure 8). The hardware part employs industrial PCs, GPS, and digital compasses to construct a positioning system, achieves spatiotemporal data acquisition via the NMEA 0183 protocol, and establishes a wireless communication network using the IEEE 802.11b/g standard. At the software level, a client-server architecture communication system developed in C# supports multi-threaded concurrent processing, enabling real-time data exchange among robots [163]. Dong et al. proposed a Gaussian mixture model-based efficient mapping system for multi-robot communication, MR-GMMapping. By constructing GMM sub-maps and employing an adaptive model selection strategy, robots can achieve relative localization by transmitting only the GMM sub-maps, reducing the data transmission volume by 98% compared to point cloud maps. This approach is applicable to addressing the data transmission bottleneck in multi-robot systems under communication-constrained agricultural environments [164]. Zhao et al. presented a multi-robot collaborative perception system based on distributed neural radiance field learning, revealing the impact of communication frequency on reconstruction quality. At 100% communication frequency, the multi-agent approach achieves performance comparable to centralized training. When the communication frequency drops to 25%, although the detail blurring increases, the overall structure remains intact. This research provides valuable insights for overcoming the efficiency bottleneck challenges of traditional centralized data transmission in scenarios with limited communication bandwidth [165].

Implicit communication is a more advanced and efficient form of communication. Instead of directly sending data packets containing complete intentions, robots alter the environmental state or exhibit observable behaviors, allowing other robots to interpret their intentions through their own sensors (vision, LiDAR, force sensing, etc.). Das et al. proposed a multi-robot communication system based on passive action recognition, MRoCS, which mimics the waggle dance behavior of honeybees. It utilizes the autonomous movements of drones to form geometric patterns, which are recognized by computer vision algorithms to achieve information transmission. Its advantage lies in operating without reliance on wireless channels, offering greater anti-interference capability and security, effectively addressing the limitations of traditional communication in complex environments [166].

Explicit communication, carried via radio waves, Bluetooth, or dedicated data links, is highly dependent on network connections and is susceptible to interference and attacks. Implicit communication relies on high-performance perception algorithms and is susceptible to factors like lighting conditions and line-of-sight occlusion during sensor operation. Clearly, in practical multi-robot coordinated systems, relying on a single type of communication is often insufficient; the combination of explicit and implicit communication

has become an inevitable trend. Explicit communication ensures precise task assignment and consistency of the global state, while implicit communication endows multi-robot systems with the ability to respond quickly, naturally, and with low overhead in dynamic environments. The combination of the two is essential to build multi-robot coordinated systems that are both controllable and highly autonomous, empowering communication and interaction in the complex scenarios of Agriculture 5.0.

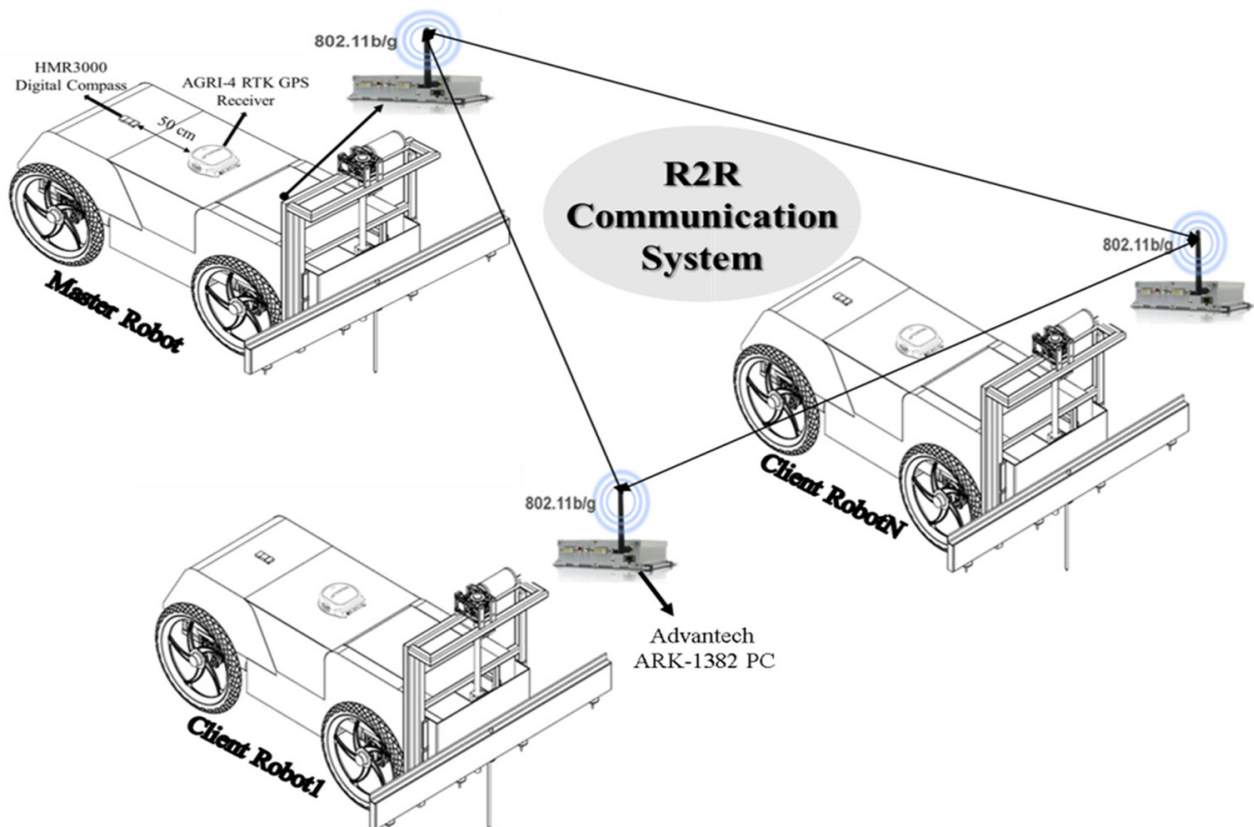


Figure 8. Whole architecture of the wireless R2R communication system [163].

Under the synergistic and progressive support of task allocation, scheduling algorithms, and communication systems, robots will be better able to accomplish their own tasks, as shown in Figure 9. Agricultural multi-robot coordination is advancing from simple mechanical cooperation toward systematic collaboration characterized by full-process coverage, multi-agent participation, and dynamic responsiveness. This evolutionary trajectory aligns closely with the core principles of Agriculture 5.0. In multi-robot coordination scenarios, scheduling no longer solely pursues locally optimal efficiency; rather, it must achieve dynamic gaming and adaptive optimization among spatiotemporal constraints, energy consumption balancing, task priorities, and global resource allocation. Communication, in turn, ceases to be merely a conduit for data transmission and instead becomes the collaborative substrate for constructing distributed intelligence. This enables multi-machine systems to realize cross-platform collaborative operations and dynamic resource matching across complex agricultural tasks, such as harvesting, plant protection, and transportation. Within the smart agricultural ecosystem envisioned by Agriculture 5.0, multi-machine coordination will serve as the pivotal nexus connecting the digital realm with physical field operations, thereby providing robust support for the development of an efficient and sustainable modern agricultural system.

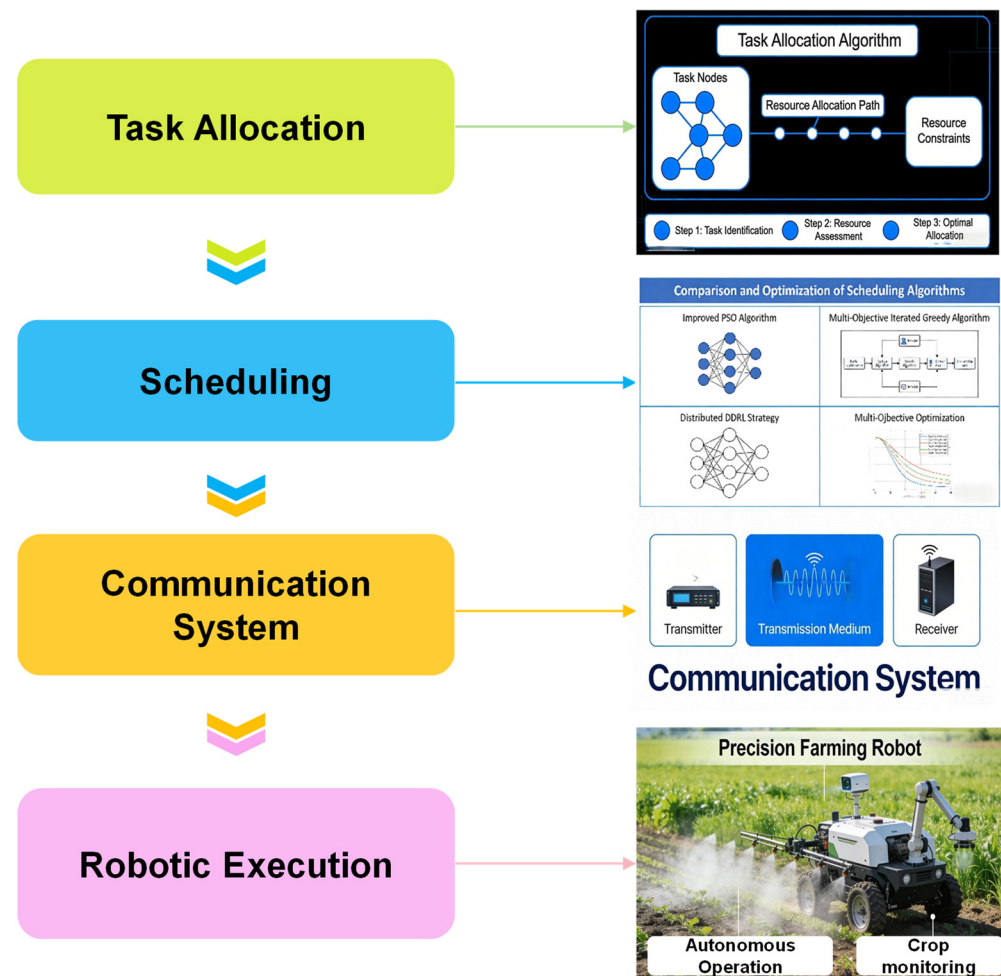


Figure 9. Multi-robot coordinated execution framework.

4.3. Human–Robot Collaboration

Human–Robot Collaboration (HRC) is not only one of the most central technical features of Agriculture 5.0, but the primary pathway to realizing its “human-centric” value goal. HRC aims to enable humans and robots to work together in shared workspaces to jointly accomplish tasks. HRC emphasizes that humans and robots complement each other: humans provide flexibility, judgment, and experiential knowledge, while robots offer precision, repeatability, and endurance. In the context of Agriculture 5.0, HRC is not about replacing humans, but about enhancing the efficiency, adaptability, and sustainability of the overall system through “human-machine synergy”. Human–robot collaboration is of great significance to Agriculture 5.0, and intelligent perception is an indispensable part of this collaboration [167]. Figure 10 shows the composition of Human–Robot Collaboration.

4.3.1. Human–Robot Interaction

Human–robot interaction is the foundation of human–robot collaboration and plays a decisive role in natural communication [168]. Moysiadis et al. innovatively introduced dynamic gestures into agricultural robot control, constructing a human–robot interaction framework integrating OpenPose pose estimation, LSTM sequence classification, and ROS system integration. By converting dynamic human gestures captured by a depth camera into specific actions of an unmanned ground vehicle, efficient collaboration in orchard scenarios was achieved [169]. Addressing issues of safe navigation, intent communication, and user acceptance in complex outdoor agricultural environments, Baxter et al. used pilot experiments to explore interaction patterns between human pickers and the autonomous

transport robot Thorvald. The results confirmed the appropriateness and safety of the robot's behavior [170].

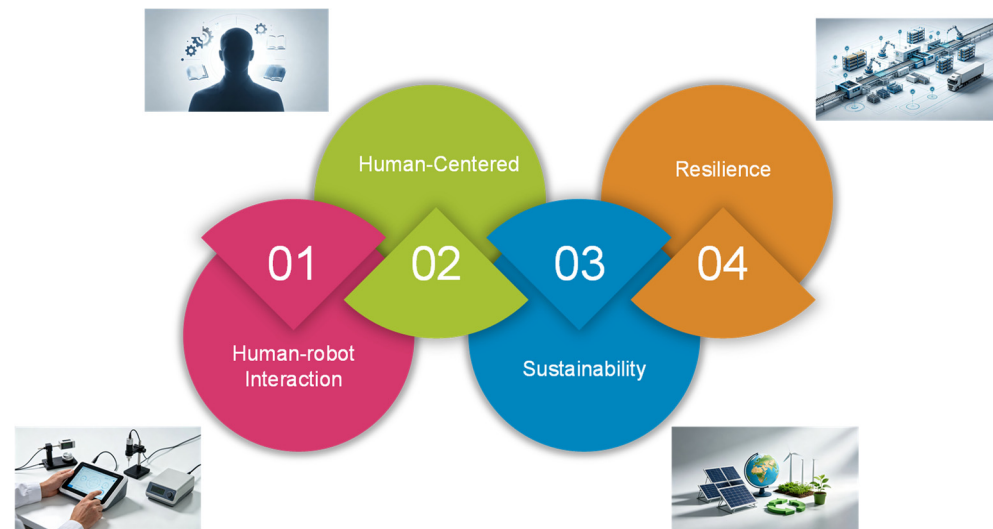


Figure 10. Composition of Human–robot Collaboration.

Perceptual systems are widely used in human–robot interaction. Bandi and Thomas integrated YOLOv8-based object detection, human pose estimation, and hand–object unified pose estimation and action recognition (using EfficientNet-B0, adaptive attention fusion, deformable transformer encoder, and cross-attention mechanisms) to achieve real-time, high-precision human–robot interaction perception [171]. Garcia proposed a multimodal framework that integrates visual, auditory, and spatial data, combining advanced algorithms, such as object detection, face recognition, gaze tracking, and speech recognition, to construct a unified user database, enabling accurate identification of and personalized responses to the most actively interacting user [172]. Weng et al. developed a dual-arm mobile robot integrating a visual perception system, combining an OpenPose-based real-time gesture recognition model with YOLOv4 object detection to improve the efficiency and quality of elderly care [173].

4.3.2. Human-Centered

Human–robot collaboration frees humans from repetitive and dangerous tasks, allowing them to focus on high-value activities, such as innovation and decision-making. Collaborative robots handle tasks, like heavy lifting and hazardous welding, while humans are responsible for process design and creative optimization. Thus, the primary and most important goal of human–robot collaboration is to ensure human safety.

Addressing the issues of low efficiency and safety risks in traditional collaborative robots operating in shared workspaces due to a lack of deep understanding of human intent, a dual-modal safety monitoring system integrating visual and tactile perception enables robots to dynamically adjust collaboration strategies based on human intent, improving productivity while ensuring safety [174]. Katsampiris-Salgado et al. integrated an infrared thermal imaging sensor with a depth camera to build a multimodal perception system, combined with a multi-layer LSTM neural network to predict the operator's future trajectory, ensuring safety [175].

Beyond optimizing perception and path planning, collision issues must also be considered. Li et al. emphasized that the selection of safety strategies should match the level of human–robot interaction, focusing on pre-collision and post-collision safety strategies [176]. Liu and Jebelli proposed a novel robot motion planning method, named IAPMP, integrating

a deep learning network with a probabilistic collision detection mechanism. This enables the robot to predict the worker's motion intent in real time and to calculate collision probability, thereby generating collision-free and spatially efficient motion trajectories, reducing the probability of collisions in human–robot collaboration [177].

4.3.3. Sustainability

Human–robot collaboration also plays a crucial role in developing a circular economy [178] and reducing resource consumption and waste. Xia et al. designed a human motion prediction method integrating context and interaction awareness, incorporating object motion trajectories as contextual information and introducing a human–object interaction recognition mechanism. This research studied the improvement of sustainability in human–robot collaboration in the context of Industry 5.0, yielding significant environmental, social, and economic benefits [179]. Shen et al. proposed an optimization framework combining human–robot collaboration with a multi-objective discrete bee algorithm to achieve disassembly line balancing in product recovery and remanufacturing under resource scarcity and environmental pressure, providing theoretical support and practical reference for agricultural automation and green manufacturing [180]. Zhang et al. innovatively integrated human–robot collaboration, selective disassembly modes, and uncertainty handling into the CHRCSDSP framework, combining it with the multi-objective evolutionary algorithm EMOBA to improve the disassembly efficiency of end-of-life products [181].

4.3.4. Resilience

Human–robot collaboration provides a safeguard for value chains and production capabilities against external shocks, combining humans' flexible adaptability with robots' precise and stable execution. This enables production systems to rapidly adapt to market changes and supply chain fluctuations. Yuan et al. proposed a novel human–robot collaborative disassembly method based on a multi-criteria resilience assessment, measuring a system's ability to maintain, absorb, respond, and recover under disturbances through an indicator system encompassing stability, redundancy, efficiency, and adaptability, thereby enhancing the ability to quantify system responses to fault risks in disassembly scenarios [182]. Facing the global manufacturing challenge of a 60% workforce skills gap, especially in contexts of cyclical demand fluctuations and high turnover rates where traditional assembly line balancing methods struggle with the complexity of heterogeneous workforce and robot collaboration, a mixed-integer linear model was proposed to address the assembly line balancing problem with heterogeneous robots and collaborative robots [183]. Buerkle et al. developed a novel human sensor detection system based on mobile electroencephalography (EEG), addressing the two major technical challenges of time delay and noise interference, which can effectively reduce dynamic risks in emergency situations [184].

Human–robot collaboration demonstrates great potential in agricultural environments, significantly improving productivity, reducing worker burdens, and optimizing resource use without complete automation. Although current research is still in its early stages and faces technical, human, social, and other challenges, HRC is regarded as one of the key pathways toward "Agriculture 5.0". Future success depends not only on advances in algorithms and hardware but on human-centric design and the development of ecologically responsible technologies.

5. Challenges and Future Trends

5.1. Existing Challenges

(1) Sensors are the core of perception systems, playing a particularly important role in navigation and localization. However, a single sensor is highly susceptible to the influence of natural agricultural environments [185]. For example, GNSS signals are easily lost or subject to multipath effects in dense crops, leading to a sharp increase in localization errors; LiDAR performs poorly in adverse weather conditions; vision sensors are greatly affected by lighting variations. Apart from the external environment, in closed greenhouses and plant factories, GNSS is fully blocked, rapid lighting shifts destabilize vision, high humidity degrades LiDAR/camera data, and narrow aisles cause non-line-of-sight issues. These compounded factors make general single-sensor solutions highly fragile.

(2) For visual detection, challenges persist in extreme occlusion [186], small target detection, and limited dataset scale and diversity. Under conditions of severe occlusion, similar colors between leaves and fruits, or similar shapes among crops, detection accuracy can significantly decline. When detecting small targets, such as tiny pests, early-stage fruits, or pedicels, missed detections or localization errors remain common. Moreover, most studies use self-built datasets focused on a few crop species, lacking validation across different crops and climatic conditions.

(3) In path planning, dynamic strategy adjustment and algorithm complexity are the two most critical aspects. Although many models perform well in static environments, their real-time path planning capabilities need improvement in more complex dynamic environments. The training process requires substantial time and computational resources, increasing network complexity and computational load. A deeper gap lies in superficial ROS integration with physical hardware. Most algorithms are validated in simulation, ignoring field constraints: low-power computing, sensor synchronization, unreliable wireless, and missing actuator abstractions. This undermines reproducibility and long-term reliability. When navigating or avoiding obstacles on complex terrains, one can also address the challenges by changing the robot's morphology, such as employing bipedal or zoomorphic configurations, to better cope with uneven ground.

(4) Conflict handling in multi-robot coordination is limited, with insufficient scalability and real-time performance. Scheduling and task allocation are often treated separately, leading to deadlocks or collisions. Rescheduling strategies are often impractical in real scenarios, and centralized approaches suffer from long computation times for large-scale problems. Multi-robot coordination also faces practical challenges, such as communication delays and operational costs, which are rarely accounted for in simulation-based studies.

(5) Issues related to safety and trust during human–robot collaboration, as well as economic and sustainability concerns, persist. In shared workspaces, if a robot fails to fully understand or misinterprets human intentions and actions, collisions and injuries can easily occur. This also leads to low levels of human trust in robots, affecting collaboration efficiency. The integrated cost of collaborative robots and their perception systems is high, and technologies such as AI models, digital twins, and edge computing consume substantial energy, which is not conducive to sustainable economic development.

5.2. Future Trends

To address the persistent challenges confronting current intelligent perception systems and their applications, further research should prioritize advancements in universality, accuracy, complexity, and security. Therefore, future trends can evolve around the following aspects.

(1) To improve the adaptability of various sensors under extreme agricultural conditions, multi-sensor fusion is necessary to leverage the strengths of each sensor and

compensate for their respective weaknesses [187]. Deep fusion of LiDAR and vision can integrate color information as early as the point cloud generation stage, while utilizing the short-term high-precision characteristics of the IMU to fill positional gaps. At the same time, GNSS signals can continuously correct the accumulated drift of the IMU. By exploiting the differences in physical properties among different sensors, information complementarity is achieved, thereby improving the overall system accuracy, robustness, and safety. Beyond conventional multi-sensor fusion, vision–language models (VLMs) offer transformative advantages for multimodal perception in precision agriculture through their inherent visual-semantic cross-modal alignment for context-aware reasoning, and their feedback-driven self-correction potential, as demonstrated by strategies like error-probing prompting [188].

(2) To enhance visual detection capability in complex and disturbed environments, it is necessary to leverage deep learning [189] or multimodal data fusion. This includes using multimodal information fusion for detection, employing generative adversarial networks (GANs) for occlusion repair or data augmentation [190], and introducing attention-guided scale-adaptive modules. In addition, VLMs can also be used in visual detection. VLMs enable zero-shot visual detection without annotations, deliver interpretable reasoning, exploit visual-semantic context for robust discrimination, and support self-correction via error-probing prompts addressing the poor generalization and opacity of conventional detectors.

(3) To improve obstacle avoidance stability and path smoothness, and to continuously advance models in terms of path length, planning time, number of turns, and convergence speed, further exploration of global–local planning fusion methods is needed to achieve consistency between global optimal path planning and real-time dynamic obstacle avoidance. Furthermore, bridging the algorithm-deployment gap requires tight ROS 2–digital-twin integration for closed-loop validation under varying conditions. Over-the-air reconfiguration enables rapid adaptation, reducing field trials and strengthening resilience.

(4) To improve multi-robot coordination, a holistic framework of “allocation, scheduling, communication” should be constructed for a given task. An end-to-end framework can be adopted to optimize allocation and paths, and a conflict-aware allocation strategy should be introduced. At the same time, lightweight online learning algorithms should be developed, along with adaptive parameter adjustment mechanisms, to enable real-time rescheduling. Addressing communication latency and operational costs requires a dual approach: deploying edge computing and dual-link communication for low-latency connectivity, while reducing capital and operating expenses through lightweight design and multi-robot coordination.

(5) To enhance the safety, economy, and sustainability of human–robot collaboration, methods such as variable impedance control and safety potential fields can be introduced to predict human motion intentions and to enable adaptive adjustment of robot actions for effective obstacle avoidance. At the same time, the carbon footprint of AI models should be quantified, and model structures should be optimized to reduce computational resource consumption.

6. Conclusions

With continuous technological innovation and development, the application of intelligent perception is expected to become one of the core applications in the future direction of Agriculture 5.0.

From field environmental information perception to autonomous operation of agricultural robots, intelligent perception technology has been deeply integrated into the entire agricultural production process, including seeding, field management, and harvesting, providing solid technical support for reducing costs, increasing efficiency, and improving

both yield and quality. To address the challenges mentioned above, multi-sensor deep fusion, multimodal visual detection combined with the construction of public standardized datasets, adaptive path planning algorithms integrating global and local approaches, end-to-end integrated multi-robot coordination frameworks, and low-energy, safe human–robot collaboration schemes have become recognized development directions within the field. In the future, with the continuous iteration of related technologies, such as artificial intelligence, chip manufacturing, and the Internet of Things, intelligent perception technology will further break through the limitations of scene adaptability and cost, truly transforming traditional agricultural production models, driving agriculture toward a more intelligent and sustainable direction, and injecting continuous momentum into ensuring global food security and promoting agricultural industrial upgrading.

This paper reviews the latest advances and applications of intelligent perception technology for agricultural AGVs. It focuses on various types of sensors, visual detection methods, navigation methods, path planning methods, multi-robot coordination frameworks, and human–robot collaboration. (1) Based on the main types of sensors used in agriculture, they can be divided into four categories: LiDAR, vision sensors, infrared sensors, and others. This paper analyzes their working principles, recent applications, and the advantages of multi-sensor fusion. (2) Visual detection methods can be divided into three categories: traditional image recognition methods, machine learning-based methods, and deep learning-based methods. Image recognition technology relies on the color and shape of crops; although it is computationally simple and has a fast response speed, it has limited applicability. Machine learning-based methods achieve better detection performance than traditional image techniques, but they struggle to effectively handle and control detection accuracy when faced with large amounts of data in actual agricultural settings. Detection using deep learning technology can be divided into two approaches: two-stage and single-stage. These methods enable high-precision visual detection in complex agricultural environments. (3) Agricultural localization technologies are mainly divided into four categories: global navigation, local navigation, SLAM-based navigation, and multi-sensor fusion navigation. SLAM-based navigation can be further subdivided into visual SLAM and LiDAR SLAM. This paper introduces the latest research on different localization methods and their respective application scenarios. (4) Path planning algorithms are mainly divided into the following four types: global path planning, local path planning, hybrid (fusion) algorithm planning, and deep reinforcement learning. This paper analyzes their algorithmic principles, recent applications, advantages, and disadvantages. (5) This paper analyzes the main areas of multi-robot coordination within the framework of “allocation, scheduling, and communication”. Through the synergistic support of task allocation, scheduling algorithms, and communication systems, the collaborative foundation for multi-robot operations in Agriculture 5.0 is realized. (6) Introduce human–robot collaboration from four aspects—human–robot interaction, human-centered, sustainability, and resilience—reflecting the importance of human–robot collaboration for achieving Agriculture 5.0. Finally, this paper also analyzes the potential challenges and future development trends of intelligent perception technology and applications for agricultural AGVs, in order to help readers gain a comprehensive understanding of the latest advances in this field.

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