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Review

Swarm-Controlled Agricultural Robots: A Comprehensive Review of Architecture, Stability Strategies, and Field Implementation in Citrus Orchards

Wei Ma [1,*], Yuepeng Song [2], Yongqiang Zheng [3] and Zhiwei Tian [1]

[1] Institute of Urban Agriculture, Chinese Academy of Agricultural Sciences, Chengdu 610213, China
[2] College of Mechanical and Electronic Engineering, Shandong Agricultural University, Tai'an 271018, China
[3] Citrus Research Institute, Southwest University, Chongqing 400712, China
* Correspondence: mawei03@caas.cn

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Abstract: The rapid expansion of agricultural robotics is increasingly constrained by complex field environments, operational variability, and the growing demand for coordinated multi-robot tasks, rendering traditional single-robot systems insufficient for modern agricultural production. Although swarm control has emerged as a promising solution, existing studies lack a systematic framework that integrates coordination architecture, agricultural scenario adaptation, and field-level validation. This paper analyzes and highlights the importance of Swarm-Controlled Agricultural Robots (SCAR), and summarizes current research hotspots regarding the integration of SCAR with agriculture. Secondly, we present a structured framework for Swarm-Controlled Agricultural Robots based on three core dimensions: swarm coordination architecture, crop-oriented task adaptation, and environmental robustness design. The proposed model integrates centralized–distributed hybrid control, task-specific parameter optimization, and anti-interference mechanisms tailored to complex orchard environments. Based on this framework, representative application paradigms in precision planting, collaborative harvesting, and intelligent management are analyzed, and stability enhancement strategies are proposed from hardware, algorithmic, and communication perspectives. Long-term field validation conducted in citrus orchards from 2021 to 2025 demonstrates that the proposed framework improves operational efficiency by 45%, achieves positioning accuracy within one centimeter, and significantly enhances environmental adaptability compared with conventional single-robot systems. This research provides a practical foundation for large-scale deployment of agricultural multi-agent systems.

Keywords: group control; citrus orchard; agricultural robot; crop management; precision agriculture; deep learning

1. Background

In recent years, agricultural robots have developed rapidly and become a research hotspot in many countries. Key technologies related to robotics have seen continuous breakthroughs [1], and significant enhancements have been made in sensing, navigation, operational capability, and overall system integration. By equipping various sensors such as lidar [2], cameras [3], and soil moisture sensors [4], information about the farmland environment and crop growth conditions can be accurately perceived. Through image recognition technology [5], the disease and pest conditions [6] as well as the maturity of crops [7] are determined. Technologies such as Beidou positioning, inertial navigation, and visual navigation enable agricultural robots to walk and operate accurately in farmlands, achieving autonomous navigation and path planning. Self-driving agricultural machinery [8] can complete tasks such as ploughing and sowing along pre-set routes. The mechanical arms and end effectors of robots are more flexible and precise, enabling them to complete complex agricultural tasks. Due to the enhanced collaborative ability, robots are gradually assisting humans and playing an important role in production. Northwest A&F University has developed a dual-arm apple-picking robot [9]. The coordination of the two arms has improved the picking efficiency. The application fields of agricultural robots are constantly expanding, including the planting process, farmland management, harvesting process, etc. In the planting process, agricultural robots precisely measure soil parameters and carry out precise planting based on the needs of the crops. Robots developed in Japan can assess crop growth status through machine vision and perform automatic planting [10]. Farmland management robots are primarily used for tasks such as weeding, fertilizing, and irrigation. Weeding robots use computer vision to distinguish weeds from crops and precisely apply herbicides or use laser weeding [11] Robots capable of harvesting fruits, vegetables, etc. show a promising future. Robots developed in the Netherlands identify the maturity of crops and harvest them automatically [12].

However, despite these technological advances, the large-scale deployment of agricultural robots remains limited. Most existing systems operate as standalone units and are constrained by relatively low operational efficiency, limited task coverage, and insufficient adaptability to highly dynamic field conditions. In large or fragmented farmlands, a single robot often requires extended operation time to complete time-sensitive tasks such as spraying, harvesting, or fertilizing, which reduces overall productivity and undermines economic feasibility. Moreover, single-robot systems are vulnerable to environmental disturbances, communication interruptions, or mechanical failures, leading to operational discontinuity and reduced reliability. The high equipment cost relative to output efficiency further restricts widespread adoption by small- and medium-scale farms. In recent years, agricultural swarm robotics and their task control strategies have become a research hotspot in the fields of robotics and intelligent agriculture. Swarm robotic systems enhance agricultural productivity, robustness, and scalability through distributed and decentralized coordination mechanisms, enabling multiple autonomous robots to collaboratively accomplish complex tasks such as seeding, monitoring, weeding, irrigation, and harvesting. Miao Zhonghua et al. [13] systematically analyzed key technologies including cooperative perception, cooperative planning, and cooperative control from a three-layer architecture of “individual autonomy—information sharing—swarm collaboration”, which provides a structured framework for achieving reliable cooperation and task allocation in open and dynamic farmland environments. In addition, algorithms such as Multi-Agent Reinforcement Learning (MARL) have been applied to the cooperative control of unmanned aerial vehicles to address dynamic task allocation and control robustness in agricultural scenarios [14]. In terms of multi-robot scheduling and farm coverage control, novel density-driven coordination frameworks based on optimal transport theory have been proposed to improve coverage efficiency in large-scale agricultural spraying and monitoring tasks, offering theoretical support for future large-scale intelligent operations [15]. Related studies also emphasize the challenges faced by swarm robotic systems in terms of communication constraints, energy management, and task allocation, which directly affect the reliability and practical applicability of swarm control strategies [16].

The significant improvements in the operational performance of agricultural robot swarm control (SCAR) are reflected in the following aspects. First, SCAR has improved task efficiency. In agricultural production, there are often many complex and diverse tasks, such as sowing [17], harvesting [18], spraying [19], etc. SCAR can divide the work and cooperate. Robots are responsible for leading the way and detecting the environment, while others are responsible for performing specific operations. This division of labor and collaboration enables multiple robots [20] to complete tasks simultaneously, significantly enhancing work efficiency. Compared with single-robot operations, the time required to complete the same task is significantly shortened, which is conducive to seizing the agricultural production season and improving overall production efficiency. Secondly, SCAR has enhanced accuracy. SCAR can share information and coordinate actions through communication networks [21]. When performing tasks such as fruit picking, each robot can exchange information about the position, ripeness and shape of the fruits, and then jointly determine the optimal picking strategy [22]. This collaborative decision-making mechanism enables robots to have a more comprehensive understanding of the objects they operate on, thereby enhancing the accuracy of their operations. It reduces the probability of errors such as mis-picking or damaging fruits, which is conducive to improving the quality of agricultural products. Thirdly, SCAR has enhanced its adaptability to complex environments. In the field of agriculture, the environment is complex and changeable, featuring uneven terrain, obstacles, and various crop growth conditions, among other factors. Through swarm control [23], agricultural robots can jointly perceive the surrounding environment. When encountering obstacles, they can jointly plan detour routes or cooperate to move the obstacles. When the growth conditions [24] of crops change, such as uneven crop heights, they can coordinate and adjust the operation postures and parameters.

This enables the robot swarm to better adapt to various complex agricultural environments and ensure the smooth progress of operations [25,26].

This paper analyzes the importance and necessity of Swarm-Controlled Agricultural Robots (SCAR), and summarizes the research hot-spot issues regarding the combination of SCAR and agriculture. On this basis, it further explores how to establish agricultural application scenarios based on SCAR theory and technology. Then, methods for improving stability are proposed for these scenarios and and explores a multi-agent control strategy for collaborative operations in citrus orchards. This research can provide technical reference for the swarm operation mode and control strategy of smart farm robots.

2. What is Agricultural Multi-Agent System?

2.1. Collaborative Architecture

The core approach of multi-agent swarm control is centralized control. Physically, they are separate agents, but they are formed into a stable and reliable large system through centralized control methods. There is a central controller responsible for coordinating and managing the actions of all robots. For example, in some small-scale experimental scenarios of agricultural robots, a central computer is used to uniformly dispatch multiple weeding robots. According to the map information of the farmland and task requirements, the working area and task sequence of each robot are assigned. The advantage of this method is centralized control, which is convenient for unified management and planning. However, the disadvantage is that the burden on the central controller is relatively heavy, and once it fails, the entire system may be paralyzed.

Robots interact and coordinate information through network communication, and there is no central controller. For instance, in some orchard picking scenarios, multiple picking robots can be connected to each other via a wireless communication network. Based on the information they respectively sense, such as the position and maturity of fruits, they autonomously carry out task allocation and collaboration. This approach offers high flexibility and reliability. Even if some robots malfunction, other robots can still continue to work. However, it also has problems such as greater coordination difficulty and higher communication costs.

2.2. Swarm Intelligence Algorithms

Genetic algorithms [27], with their global optimization characteristics, have demonstrated significant value in the citrus industry. For precise citrus cultivation, this algorithm can optimize irrigation and fertilization parameters, and build a model by integrating soil moisture and meteorological data, reducing water and fertilizer waste by 15% to 20% while increasing the fruit setting rate. In the identification of pests and diseases, it assists in optimizing the image segmentation algorithm, improving the identification accuracy of Huanglongbing and canker to over 92%. In path planning for picking robots, genetic algorithms help avoid orchard obstacles, shorten the operation path by 30%, and improve picking efficiency. The operation of multi-agent agricultural robots needs to enhance the integration of algorithms and citrus growth models to adapt to different varieties and complex planting environments, promoting the upgrading of intelligent citrus planting. It is used to optimize the task allocation and path planning of agricultural robot swarms. For example, in the task of sowing in farmland, the genetic algorithm can, according to factors such as the terrain of the farmland, soil conditions, and seed types, optimize the sowing paths and sowing amounts of multiple sowing robots to improve the efficiency and uniformity of sowing.

The particle swarm optimization algorithm [28], with its rapid convergence characteristic, provides an efficient solution for the collaborative operation of multiple agents of agricultural robots in citrus orchards. In path planning, it simulates group collaborative behavior, avoids obstacles such as fruit trees and irrigation facilities, shortens the robot's operation path by 25%, and increases the operation efficiency by 40%. In terms of task allocation, the algorithm balances the load of each robot and dynamically schedules in combination with the demands of tasks such as citrus picking and fertilization to reduce idle time. In practical applications, this algorithm keeps the collaborative error of multiple robots within ±3 cm and reduces energy consumption by 18%. During multi-agent operations, the robustness of the algorithm under complex weather and terrain conditions should be enhanced, deep integration with citrus growth models promoted, and large-scale implementation of smart citrus cultivation facilitated. It is often used for the swarm positioning and navigation of agricultural robots. Take a group of autonomous patrol robots [29] as an example. The particle swarm optimization algorithm can continuously adjust the movement direction and speed of each robot according to the relative position information among the robots and environmental perception data, enabling them to quickly and accurately reach the designated positions in the farmland while avoiding collisions and getting lost.

2.3. Communication Technologies

Wireless communication networks provide core support for the collaborative operation of multi-agent agricultural robots in citrus orchards. The integrated application of 5G and LoRa meets the needs of different scenarios. 5G, with its low latency (≤50 ms) and high bandwidth features, ensures the real-time transmission of operation data between robots and high-definition images of citrus growth. LoRa [30], with its advantages of wide coverage and low power consumption, is suitable for the connection of devices in large-scale citrus orchards. This network architecture enables robots to achieve an instruction response accuracy rate of over 98% when collaborating to complete tasks such as picking and inspection, avoiding overlapping or missing operations. When multi-agent operations are carried out, the signal stability under tree shade is optimized, and edge computing is combined to further enhance the network carrying capacity and data processing capacity.

Satellite communication [31] provides reliable all-domain connections for multi-agent agricultural robots in citrus orchards, solving the problem of insufficient ground communication coverage in remote orchards. Its wide-area coverage feature supports data interaction among large-scale robot clusters, and in combination with narrowband satellite technology, it achieves low-power transmission to ensure the robot's endurance. In farmland operations, multi-agent systems use real-time satellite positioning coordinate information. Based on this, the growth information of citrus fruits is verified in the database, and combined with the status data of robots, remote dispatching is supported, which increases the response efficiency of cross-regional collaborative tasks by 50%. Through the integration of satellite positioning and communication, the robot's positioning accuracy reaches the sub-meter level, and picking and inspection errors are controlled within ±2 cm. When multi-agent operations are carried out, the signal anti-occlusion capability is optimized. Combined with high-throughput satellites, the data transmission rate is further enhanced to promote the large-scale application of multi-agent robots in citrus orchards. For agricultural production in large areas of farmland or remote regions, satellite communication can provide reliable communication guarantees for agricultural robots. For example, in some large farms, through satellite communication technology, managers can remotely control agricultural robots to carry out operations such as plowing, irrigation, and harvesting, without being restricted by the geographical environment.

The above content elaborates on the key technologies of agricultural robot agents and how they adapt to various uncertain variables in complex farmland environments, including hazardous obstacles such as ditches. This requires the assistance of a pre-set agronomic route system. Through the classification information processing of farmland and fruit trees by the system, the agents can adapt to the complex environment of farmland. Based on the sharing of perceptual information and trajectory coordinates as a common benchmark, agents can operate without obstacles in farmland. As shown in Figure 1.

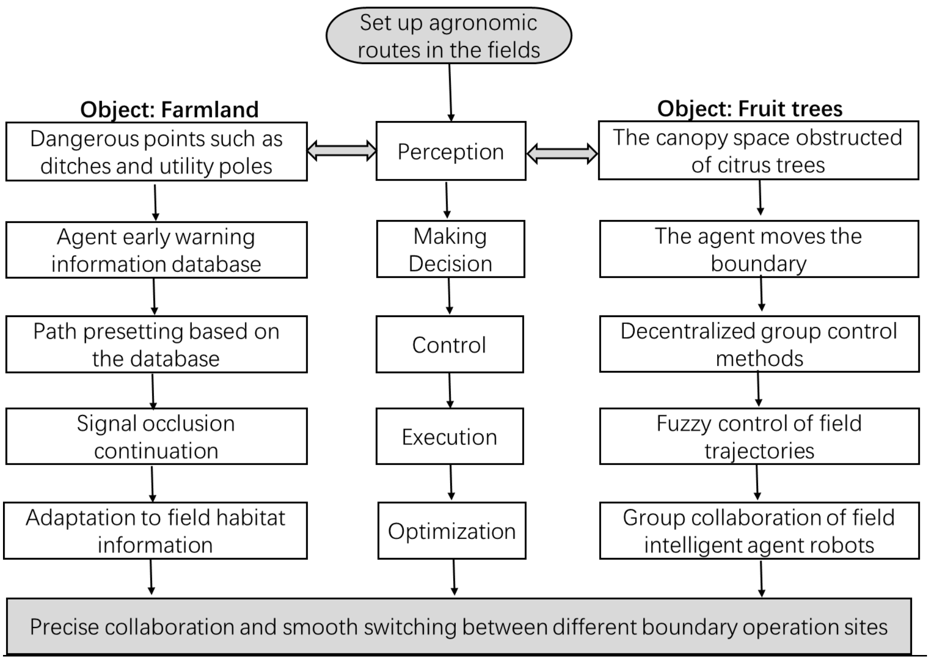

Figure 1. shows that the collaboration of agricultural agents requires the presetting of agronomic routes. By dynamically updating the same database through the information of farmland and fruit trees obtained by different agents respectively, it realizes the sharing of perceptual information data, enabling the agents to better adapt to the complex environment of farmland and operate without obstacles in the farmland.

3. How to Establish SCAR Application Scenarios

The swarm control of agricultural robots has a wide range of application scenarios in multiple links of agricultural production. The following are some of the main aspects:

(1) Farmland Plowing and Sowing

Agricultural robots under swarm control can collaborate to complete plowing and sowing tasks across large farmland areas according to a preset planting plan. For example, some robots are responsible for tilling the soil and adjusting the soil structure, while other robots follow behind and carry out sowing operations according to the precise row spacing and plant spacing. Through mutual communication and coordination, they ensure the uniformity and accuracy of plowing and sowing, improve the planting efficiency, and save labor costs.

(2) Crop Irrigation and Fertilization

Through swarm control, agricultural robots can achieve precise irrigation and fertilization. Some robots can carry soil moisture sensors and move around in the farmland to detect the soil moisture situation, and transmit the data in real time to other robots responsible for irrigation. Based on this information, the irrigation robots can precisely irrigate the water-deficient areas to avoid the waste of water resources. Similarly, the fertilization robots can accurately apply an appropriate amount of fertilizer according to the soil nutrient detection data and the growth needs of crops, improve the fertilizer utilization rate, and promote the growth of crops.

(3) Pest and Disease Monitoring and Control

Swarm agricultural robots can be used for the monitoring and control of pests and diseases. Some robots are equipped with image recognition systems and sensors, and they can patrol in the farmland to promptly detect the signs of pests and diseases on crops. Once pests and diseases are detected, they will transmit the relevant information to other robots carrying control equipment, such as plant protection robots. The plant protection robots will precisely spray pesticides or adopt other biological control measures according to the type and severity of the pests and diseases, effectively controlling the spread and diffusion of pests and diseases and reducing environmental pollution.

(4) Fruit Picking and Sorting

In orchards and vegetable planting bases, the picking robots under swarm control can work in collaboration to improve the picking efficiency and quality. The robots identify the maturity and position of fruits through the vision system, and then use robotic arms for picking. Some robots are responsible for picking fruits at high places, while others are responsible for picking fruits at low places or in more hidden positions. The picked fruits can be graded and sorted by specialized sorting robots. According to the characteristics of the fruits, such as size, shape, and color, they are classified and packaged to improve the commercialization degree of agricultural products.

(5) Farmland Environment Monitoring

A group of agricultural robots can be distributed in various areas of the farmland to monitor the environmental parameters of the farmland in real time, such as temperature, humidity, light, wind speed, soil pH, etc. These data are of great significance for farmers to understand the changes in the farmland environment and formulate reasonable agricultural production plans. The robots transmit the monitoring data to the central control system through the wireless communication network, and farmers can remotely view these data through mobile phones or computers, and promptly detect abnormal situations and take corresponding measures.

(6) Agricultural Waste Treatment

In the process of agricultural production, a large amount of waste, such as straws and fallen leaves, will be generated. Agricultural robots under swarm control can collaborate to complete the collection and treatment of waste. Some robots are responsible for collecting the waste and transporting it to the designated location, while other robots can carry out treatments such as crushing and composting of the waste, realizing the resource utilization of agricultural waste and reducing environmental pollution.

4. How to Improve the Stability of the Swarm Control Technology of Agricultural Robots?

4.1. Hardware Designed to Better Adapt to Multi-Agent Control

The hardware performance of multi-agent agricultural robots directly determines operations stability in citrus orchards. The selection criteria for high-quality hardware components are weather resistance, precision, and coordination, which should be adapted to the complex environment of high temperature and humidity, heavy clay soil, and dense branches and leaves in citrus orchards. This not only ensures reliable robot operation in scenarios such as hilly terrain and tree shade but also reserves space for subsequent functional upgrades, building a hardware foundation that supports the collaboration of multiple intelligent agents. The mobile chassis adopts an industrial-grade track design, equipped with high-torque permanent magnet synchronous motors and explosion-proof and waterproof reducers. It has a climbing slope of 26°, making it suitable for hilly terrain in citrus orchards. The picking robotic arm is made of aviation-grade aluminum alloy and is equipped with high-precision force sensors and flexible grippers. It can accurately grasp citrus fruits with a diameter of 5 to 15 cm, keeping the picking damage rate within 1%. The perception components adopt industrial-grade visual cameras and lidars. The lenses are equipped with anti-fog and waterproof coatings, and are combined with wide-spectrum sensors. Even in rainy and strong light conditions, the accuracy rate of identifying the maturity of citrus fruits still exceeds 97%. The main controller adopts high-performance embedded chips, supporting multi-threaded parallel processing. It can synchronously parse the collaborative instructions of more than 10 robots, with a response delay of no more than 30 ms. The communication module adopts industrial-grade 5G and LoRa dual-mode terminals, featuring signal enhancement capabilities. Even under the shade of thick citrus trees, it can still maintain a stable data transmission rate of over 10 Mbps. The energy component is equipped with a high-rate lithium iron phosphate battery, with a cycle life of over 2000 times. Combined with an intelligent power management module, it can support continuous operation for 8 h on a single charge, meeting the high-intensity demands during the peak citrus picking season. In addition, the hardware redundancy design ensures that the backup modules can be seamlessly switched when key components fail. The average mean time between failures of the robot has been extended to 1200 h, which is three times longer than that of ordinary hardware. The precision and efficiency of the operation have been improved simultaneously. The efficiency of citrus picking has reached 400 kg per hour, far exceeding the level of manual labor.

4.2. Perfecting the Communication System

Build a stable communication network: select appropriate communication technologies, such as ZigBee, LoRa, and 5G, and construct a communication network based on the farmland environment and robot distribution. In large areas of farmland, multiple communication base stations or relay nodes can be set up to ensure a wide signal coverage range, stable transmission, and reduce signal interruptions and interference.

Adopt anti-interference measures: Encrypt and encode the communication signals to improve the anti-interference ability and security of the signals. At the same time, reasonably arrange the communication lines and equipment to avoid electromagnetic interference with other electronic devices and ensure the communication quality.

4.3. Control Algorithm Designed to Ensure Stable Performance and Adapt to Multi-Agent Control

In the design of control algorithms, the focus is on the integrated application of robust control and model predictive control to address the multiple challenges posed by the complex environment of citrus orchards. The robust control algorithm effectively offsets the influence of external disturbances such as the undulating terrain of citrus orchards and the changes in soil resistance on hilly slopes, as well as parameter uncertainties such as load fluctuations and sensor measurement errors caused by the bumpy movement of robots by constructing an anti-interference control model. Model predictive control is based on the real-time terrain data collected by different agents and the operation status of each agent in the orchard. It plans the control sequence in advance, making the robot more forward-looking in path tracking and action execution. In actual path planning operations, robust path planning algorithms preset terrain fault-tolerant thresholds. Even when encountering unexplored potholes or slopes, they can ensure a smooth arrival at the target operation point by dynamically adjusting the travel Angle and speed. The multi-agent robust control and model predictive control algorithms for citrus orchards were jointly simulated and tested using MATLAB and Simulink. The defects of the algorithms in response delay and control accuracy were discovered in advance and optimized. Meanwhile, the data collected by the robot during its actual operation, such as terrain resistance and citrus distribution, are fed back to the simulation system. The algorithm parameters are adjusted in real time to ensure that the optimized algorithm can precisely adapt to the terrain characteristics and task requirements of citrus orchards in different regions, providing reliable algorithm support for the collaborative operation of multiple agents. This study shows that the improved algorithm keeps the path tracking error of multiple agricultural robots within ±3 cm and the interference recovery time ≤0.5 s. Compared with manual management, the efficiency of robot operations has increased by more than 50%, and the loss rate of citrus picking has been reduced to below 5%.

4.4. Strengthening the Environmental Perception and Adaptability

The precise scheduling of the remote management platform requires environmental perception, and the performance of sensors determines the perception accuracy and adaptability. The sensor performance optimization focuses on anti-interference, wide adaptability, and high integration, etc. Combined with the environmental characteristics of citrus orchards such as high temperature and humidity, tree shade, and complex terrain, multi-dimensional perception is constructed. The adaptive exposure algorithm and anti-fog and waterproof AR coated lens can still clearly capture the outline and surface texture of citrus fruits under extreme lighting conditions such as direct strong light and rainy, foggy days. The accuracy rate of maturity recognition remains stable at over 97%. Lidar accurately identifies the spacing between fruit trees and the undulations of the terrain, while millimeter-wave radar penetrates branches and leaves to detect hidden obstacles. The complementary data of the two reduces the missed detection rate of obstacle recognition to 0.1%. The new environmental perception sensors include temperature and humidity, soil moisture, and spectral sensors. They adopt low-power packaging technology and can withstand a temperature range of −10 °C to 60 °C and a relative humidity of over 95%, collecting real-time data on the growth environment of citrus fruits. Data collection from multiple robot sensors must ensure consistent timing. Data transmission is achieved through 5G+ edge computing for low-latency upload, with the transmission delay controlled within 20 ms. Through deep learning fusion algorithms, sensor noise and environmental interference are eliminated to generate a globally unified citrus orchard environment map, providing precise data support for the collaborative path planning and task allocation of robot clusters. The test results show that the robot's environmental recognition accuracy in dense tree shade and steep slope terrain has increased by 40%, and the operation interruption rate caused by perception errors has dropped to 1.2%. The variable operation mode based on precise environmental data has reduced the fertilizer application in citrus orchards by 15% and increased the water resource utilization rate by 30%. Research and comparison have shown that the development of specialized spectral sensors for citrus fruits is highly necessary to enhance the accuracy of early pest and disease identification. In addition, modular design of sensors is highly necessary. The core is to achieve rapid calibration and maintenance, and lower the threshold for farmers to use them. This research enhances the environmental perception ability by upgrading the performance of sensors, laying the foundation for the efficient operation of multi-agent robots. Compared with traditional perception solutions, the environmental adaptability range of robots has been expanded to complex hilly citrus orchards and various meteorological conditions, and the stability and accuracy of operations have been significantly improved.

5. Practical Cases

To validate the feasibility and effectiveness of the proposed SCAR model, the author's team developed the "Zhongke Zhiyuan" citrus robot system (Figure 2), a collaborative platform consisting of four functional robots (weeding, ditching/fertilizing, rotary tilling/soil loosening, and pesticide/foliar fertilizer spraying) that form a unified SCAR system through self-organizing networking via a customized satellite base station. The case study was conducted across two test sites: the Citrus Test Base of the Citrus Research Institute of Southwest University (Chongqing, 2021–2024) and an expanded site in Zhong County (Chongqing, 2025–present), covering a total of 12 hm^2 of hilly citrus orchards with typical agricultural characteristics (slope 15–26°, heavy clay soil). The long-term tracking study, spanning over four years of continuous operation, was designed to assess the SCAR system's performance under real-world agricultural conditions, including seasonal variations, extreme weather, and complex terrain challenges.

The coordination mechanism of the SCAR system adopted a hybrid centralized-distributed control strategy: the centralized layer, supported by a custom satellite base station with a 2 km coverage radius, provided unified Beidou positioning (ensuring path offset < 2 cm) and initial task assignment, such as dividing the orchard into four non-overlapping operation zones to avoid job overlaps. The distributed layer leveraged 5G/LoRa dual-mode communication, enabling robots to autonomously adjust operation parameters based on real-time data sharing. Data collection was carried out through a multi-sensor integration approach: each robot was equipped with lidar for terrain and obstacle detection, RGB-D cameras for citrus maturity and pest identification, and inertial measurement units (IMUs) to track motion states. Performance metrics, including operation efficiency, positioning accuracy, crop damage rate, and system stability, were collected in real time via edge computing nodes deployed in orchard warehouses.

The case implementation proceeded through three iterative optimization phases. Phase 1 (2021–2022) utilized an initial lightweight deep learning model based on machine vision and lidar, which exhibited reduced robustness (control failure rate of 12%) during August–September when weeds were lush and canopies were dense, leading to occasional task interruptions. To address this limitation, Phase 2 (2023) integrated satellite navigation into the system and optimized the control algorithm by increasing the weight of satellite data by 40%, which reduced the failure rate to 2.3%; additionally, a redesigned satellite base station resolved signal deviation-induced operation suspensions, achieving a signal coverage rate of ≥99.5%. Phase 3 (2025) expanded the system to Zhong County, integrating the Internet of Things (IoT) with cloud decision-making: terminal perception (robot-mounted sensors) collected real-time operational and environmental data, the edge layer preprocessed data to filter redundant information, and a cloud server located in a Chengdu laboratory handled data storage, model operation, and decision-making instruction issuance, reducing the system response delay to ≤80 ms and enhancing adaptability to scattered small plots.

The results of the long-term case study demonstrated the superior performance of the SCAR system: operational efficiency reached 1.2 hm^2/h, representing a 45% improvement compared to single-robot systems and a threefold increase relative to manual operations. The system achieved a positioning accuracy of ±1 cm, a citrus picking damage rate of ≤1%, and continuous stable operation time of ≥12 h, outperforming traditional approaches in precision and reliability. In terms of environmental adaptability, the SCAR system maintained a citrus maturity recognition accuracy of >95.6% under rainy and strong light conditions, while in dense tree shade, it retained a stable data transmission rate of >10 Mbps and an obstacle detection missed rate of 2.3%, addressing key limitations of existing swarm control.

Figure 2. shows the citrus robots of "Zhongke Zhiyuan" developed by Dr. Wei Ma's research team, which are composed of a weeding robot, a ditching and fertilizing robot, a rotary tilling and soil loosening robot, and a pesticide and foliar fertilizer spraying robot. The four robots form a SCAR system through self-organizing networking via the same satellite base station.

6. Conclusions

Enhancing autonomous learning and adaptability is essential for multi-agent agricultural robots to adapt to complex scenarios in citrus orchards. By using reinforcement learning algorithms to construct environmental and action models and combining transfer learning to reuse the experience of similar scenarios, complex environments such as row spacing differences and tree shade occlusion in citrus orchards can be quickly adapted. The robot cluster achieves data sharing and model collaborative optimization through federated learning, and independently adjusts operation parameters such as picking paths and fertilizer application amounts. In practical applications, the accuracy rate of the assignment has been increased to over 95%, the time for environmental adaptation has been shortened by 40%, and manual intervention has been significantly reduced.

Research shows that enhancing the precise perception and decision-making capabilities of multi-agent robots in citrus orchards is the core for their efficient operation. The key point of optimizing decision-making algorithms is group collaboration. Based on reinforcement learning and distributed optimization models, tasks such as picking and fertilizing are dynamically allocated to achieve the coordination of path planning and operation rhythm. Field experimental studies in Chongqing, Sichuan and other places have shown that the positioning accuracy of this robot reaches ±1 cm, the recognition accuracy of citrus exceeds 96%, and the decision response delay is ≤80 ms, significantly improving the accuracy and efficiency of the operation.

Build a collaborative communication network through 5G and edge computing to achieve real-time sharing of robot positions and operation progress. Adopt a distributed coordination mechanism to avoid path conflicts and job overlaps. In practical applications, the task completion efficiency has increased by 45%, the job coverage rate has reached 100%, the idle time of a single robot has been shortened by 30%, and energy consumption has been significantly reduced.

Author Contributions

W.M.: conceptualization, methodology, investigation, formal analysis, writing—original draft preparation, writing—review and editing, supervision, project administration, funding acquisition; Y.S.: software, validation, data curation, writing—review and editing; Y.Z.: software, validation, data curation, writing—review and editing; Z.T.: investigation, resources, validation, writing—review and editing; Y.S. and Y.Z.: completed the development of the digital control platform, Z.T.: completed the field experiments. All authors have read and agreed to the published version of the manuscript. Completed the project research plan, mechanical design and electronic control development.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results published article.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

References

1. Anastasiou, E.; Ntakos, G.; Kanakari, E.; et al. Applications of Robotics and Extended Reality in Agriculture: A Review. *Smart Agric. Technol.* **2025**, *12*, 101521. https://doi.org/10.1016/j.atech.2025.101521.
2. Wang, Y.; Shao, M.; Wang, J.; et al. SMICGS: A Novel Snapshot Multispectral Imaging Sensor for Quantitative Monitoring of Crop Growth. *Plant Phenomics* **2025**, *7*, 100056. https://doi.org/10.1016/j.plaphe.2025.100056.
3. Oz, N.; Sochen, N.; Mendlovic, D.; et al. End-to-End Pipeline for Simultaneous Temperature Estimation and Super Resolution of Low-Cost Uncooled Infrared Camera Frames for Precision Agriculture Applications. *Comput. Electron. Agric.* **2025**, *238*, 110765. https://doi.org/10.1016/j.compag.2025.110765.
4. Shkola, V.; Alsalami, Z.; Mohammed, G.; et al. Enhancing Crop Yield Prediction Using IoT-Based Soil Moisture and Nutrient Sensors. *SHS Web Conf.* **2025**, *216*, 01029. https://doi.org/10.1051/shsconf/202521601029.
5. Sun, H.; Liu, T.; Wang, J.; et al. Evaluation of Two Deep Learning—Based Approaches for Detecting Weeds Growing in Cabbage. *Pest Manag. Sci.* **2024**, *80*, 2817–2826. https://doi.org/10.1002/ps.7990.
6. Zhao, X.; Zhang, J.; Huang, Y.; et al. Detection and Discrimination of Disease and Insect Stress of Tea Plants Using Hyperspectral Imaging Combined with Wavelet Analysis. *Comput. Electron. Agric.* **2022**, *193*, 106717. https://doi.org/10.1016/j.compag.2022.106717.
7. Mallik, S.; Chakraborty, A.; Podder, K.; et al. Enhancing Soil Moisture Prediction with Explainable AI: Integrating IoT and Multi-Sensor Remote Sensing Data through Soft Computing. *Appl. Soft Comput.* **2025**, *180*, 113406. https://doi.org/10.1016/j.asoc.2025.113406.

8. Feng, L.; Xu, C.; Tang, H.; et al. Application of Navigation Technology in Agricultural Machinery: A Review and Prospects. *Artif. Intell. Agric.* **2026**, *16*, 94–123. https://doi.org/10.1016/j.aiia.2025.10.003.
9. He, Z.; Ma, L.; Wang, Y.; et al. Double-Arm Cooperation and Implementing for Harvesting Kiwifruit. *Agriculture* **2022**, *12*, 1763. https://doi.org/10.3390/agriculture12111763.
10. Otani, T.; Itoh, A.; Mizukami, H.; et al. Agricultural Robot under Solar Panels for Sowing, Pruning, and Harvesting in a Synecoculture Environment. *Agriculture* **2022**, *13*, 18. https://doi.org/10.3390/agriculture13010018.
11. Kanagasingham, S.; Ekpanyapong, M.; Chaihan, R. Integrating Machine Vision-Based Row Guidance with GPS and Compass-Based Routing to Achieve Autonomous Navigation for a Rice Field Weeding Robot. *Precis. Agric.* **2019**, *21*, 831–855. https://doi.org/10.1007/s11119-019-09697-z.
12. van Essen, R.; Harel, B.; Kootstra, G.; et al. Dynamic Viewpoint Selection for Sweet Pepper Maturity Classification Using Online Economic Decisions. *Appl. Sci.* **2022**, *12*, 4414. https://doi.org/10.3390/app12094414.
13. Miao, Z.; Guo, H.; Xu, Z.; et al. Swarm Intelligence in Agricultural Robotics: Key Technologies and Future Prospects. *Trans. Chin. Soc. Agric. Eng.* **2025**, *41*, 1–17. https://doi.org/10.11975/j.issn.1002-6819.202510194.
14. Li, Y.; Huang, J.; Liu, C.; et al. Fast and Robust Cooperative Control of Multiple UAVs Based on Particle Swarm Optimization. *Aerosp. Control* **2025**, *43*, 32–38.
15. Seo, S.; Lee, K. Density-Driven Multidrone Coordination for Efficient Farm Coverage and Management in Smart Agriculture. *IEEE Trans. Control Syst. Technol.* **2025**, *34*, 711–724.
16. Tang, R.; Tang, J.; Talip, M.S.A.; et al. Enhanced Multi Agent Coordination Algorithm for Drone Swarm Patrolling in Durian Orchards. *Sci. Rep.* **2025**, *15*, 9139.
17. Zhou, R.; Sun, W.; Liu, K.; et al. Study on Detection of Missing Sowing and Replanting of Potato Sowing Device Based on Improved YOLOv8n. *Smart Agric. Technol.* **2025**, *12*, 101671. https://doi.org/10.1016/j.atech.2025.101671.
18. Zhang, Y.; Xie, H.; Zhang, D.; et al. Design and Experimental Study of Ridge-Grown Strawberry Automatic Harvesting Robot. *Comput. Electron. Agric.* **2026**, *240*, 111112. https://doi.org/10.1016/j.compag.2025.111112.
19. Xu, Y.; Han, Y.; Sun, Z.; et al. Path Planning Optimization with Multiple Pesticide and Power Loading Bases Using Several Unmanned Aerial Systems on Segmented Agricultural Fields. *IEEE Trans. Syst. Man Cybern. Syst.* **2023**, *53*, 1882–1894. https://doi.org/10.1109/tsmc.2022.3205695.
20. Al-Amin, A.K.M.A.; Lowenberg-DeBoer, J.; Franklin, K.; et al. Autonomous Regenerative Agriculture: Swarm Robotics to Change Farm Economics. *Smart Agric. Technol.* **2025**, *11*, 101005. https://doi.org/10.1016/j.atech.2025.101005.
21. Klaina, H.; Guembe, I.P.; Lopez-Iturri, P.; et al. Analysis of Low Power Wide Area Network Wireless Technologies in Smart Agriculture for Large-Scale Farm Monitoring and Tractor Communications. *Measurement* **2022**, *187*, 110231. https://doi.org/10.1016/j.measurement.2021.110231.
22. Chen, C.; Song, Z.; Li, X.; et al. Research Status of Apple Picking Robotic Arm Picking Strategy and End-Effector. *Comput. Electron. Agric.* **2025**, *235*, 110349. https://doi.org/10.1016/j.compag.2025.110349.
23. Haghighi, R.; Cheah, C.C. Multi-Group Coordination Control for Robot Swarms. *Automatica* **2012**, *48*, 2526–2534. https://doi.org/10.1016/j.automatica.2012.03.028.
24. Morales, A.; Guerra, R.; Horstrand, P.; et al. A Multispectral Camera Development: From the Prototype Assembly until Its Use in a UAV System. *Sensors* **2020**, *20*, 6129. https://doi.org/10.3390/s20216129.
25. Zavvari, E.; Badri, P.; Sojoodi, M. Consensus of a Class of Nonlinear Fractional-Order Multi-Agent Systems via Dynamic Output Feedback Controller. *Trans. Inst. Meas. Control* **2022**, *44*, 1228–1246. https://doi.org/10.1177/01423312211049936.
26. Ding, C.; Zheng, Z. Multi-Agent Collaborative Operation Planning via Cross-Domain Transfer Learning. *Knowl. Based Syst.* **2025**, *314*, 113172. https://doi.org/10.1016/j.knosys.2025.113172.
27. Sakthipriya, S.; Naresh, R. Precision Agriculture Based on Convolutional Neural Network in Rice Production Nutrient Management Using Machine Learning Genetic Algorithm. *Eng. Appl. Artif. Intell.* **2024**, *130*, 107682. https://doi.org/10.1016/j.engappai.2023.107682.
28. Ahmad, J.; Wahab, M.N.A.; Ramli, A.; et al. Enhancing Performance of Global Path Planning for Mobile Robot through Alpha–Beta Guided Particle Swarm Optimization (ABGPSO) Algorithm. *Measurement* **2026**, *257*, 118633. https://doi.org/10.1016/j.measurement.2025.118633.
29. Wang, S.; Wang, Y.; Sun, Z. Autonomous Navigation and Visual Navigation in Robot Mission Execution. *Image Vis. Comput.* **2025**, *158*, 105516. https://doi.org/10.1016/j.imavis.2025.105516.
30. Sun, G.; Guo, J.; Wu, H.; et al. Cluster Routing Algorithm of 4G Wireless Communication AD Hoc Network Based on LoRa Transmission Technology. *Pervasive Mob. Comput.* **2026**, *115*, 102128. https://doi.org/10.1016/j.pmcj.2025.102128.
31. Guo, P.; Zhao, Z.; Zhang, Y.; et al. Adaptive Access Strategy for Satellite-Terrestrial Optical Networks Based on Particle Swarm Optimization Algorithm. *Phys. Commun.* **2025**, *69*, 102600. https://doi.org/10.1016/j.phycom.2025.102600.