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Human-Centered Robotic System for Agricultural Applications: Design, Development, and Field Evaluation

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Abstract: This paper introduce advancements in agricultural robotics in response to the increasing demand for automation in agriculture. Our research aims to develop humancentered agricultural robotic systems designed to enhance efficiency, sustainability, and user experience across diverse farming environments. We focus on essential applications where human labor and experience significantly impact performance, addressing four primary robotic systems, i.e., harvesting robots, intelligent spraying robots, autonomous driving robots for greenhouse operations, and multirobot systems, as a method to expand functionality and improve performance. Each system is designed to operate in unstructured agricultural environments, adapting to specific needs. The harvesting robots address the laborintensive demands of crop collection, while intelligent spraying robots improve precision in pesticide application. Autonomous driving robots ensure reliable navigation within controlled environments, and multirobot systems enhance operational efficiency through optimized collaboration. Through these contributions, this study offers insights into the future of agricultural robotics, emphasizing the transformative potential of integrated, experience-driven intelligent solutions that complement and support human labor in digital agriculture.

Keywords: agricultural robot; harvesting robot; multirobot systems; autonomous driving; intelligent spraying

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1. Introduction

As the world's population grows and food demand increases, there is a growing need for more efficient and productive agriculture practices [1,2]. However, the aging of the farming population and the trend toward urbanization is making it more difficult to meet this demand [3,4]. To address this challenge, the use of robotics in agriculture is becoming increasingly popular, since it can automate various tasks and eventually help reduce the physical demands of farming [5–8]. For example, unmanned aerial vehicles (UAVs) can cover large fields autonomously and be used for tasks such as crop monitoring and mapping [9,10]. Autonomous tractors can perform labor-intensive tasks such as planting, tilling, and harvesting by navigating the field without direct instruction from a human operator [11]. Apart from these, robotic systems equipped with artificial intelligence and big data analytics have a high potential to enhance the current agriculture industry [12–14].

However, to achieve the full potential of robotics in agriculture, research and development efforts must be focused on every step of the agricultural process, from growing and producing crops to processing and distributing them to consumers [15]. Also, the developed system must be flexible and adaptable to support a wide range of agricultural processes, environments, and tasks [16,17]. In that context, the robotic systems must be designed for allowing for the quick application of original technologies and seamlessly for ensuring a close connection between different technologies [18]. Additionally, unmanned systems that can coexist with farmers are required as reducing labor requirements and allowing for a smooth integration of technology into existing agricultural practices [19].

However, most of the robotic systems currently developed for agriculture have not yet reached a level suitable for commercialization. This is primarily because these systems either do not align with the practical needs of agricultural workers or are prohibitively expensive due to high initial development costs. A key factor behind this misalignment is the lack of trust in the productivity and reliability of these systems, which are often highly dependent on the expertise and experience of agricultural workers [20,21]. Consequently, there is a domain knowledge gap between agricultural practitioners and robotics developers. To address this gap, researchers must focus on aligning system development with the real-world demands and insights of agricultural experts. Therefore, we aim to bridge this gap by designing robotic systems that emulate human behavior. This approach, which we define as human-centered agricultural robotics, focuses on integrating human-like actions into the system. A detailed description of this system is provided in the subsequent subsection.

The structure of this paper is as follows. We present our currently developed agricultural systems incorporating features of fast, seamless, unmanned, and coexistence, which are essential for robotics in agriculture. Among various robotic systems that differ in their purpose and size, we introduce them by considering the range of their workspace. The robotic manipulator for harvesting fruits in the greenhouse is presented with their hardware systems and human-centered harvesting policy considering the manual process. Then, the workspace of the harvesting robot is extended to arable land by designing a cabbage harvester. An intelligent spraying system is another good example of a robotic system focusing on a specific task. By incorporating autonomous driving technology, the workspace of the harvesting and spraying system is extended to the entire farming environment, not only restricted to the workspace of the effectors. Lastly, the multirobot systems are introduced as the solution to expand the simultaneous range of robot motion and increase efficiency.

2. Harvesting Robots

2.1. Harvesting Robots for Greenhouses

The intensifying labor shortage in rural areas and high labor cost have led to an increasing demand for automation in agriculture. A potential solution is to use robots to perform various tasks such as seeding, spraying, fertilizing, irrigation, and harvesting. The development of robots for agriculture application is a research hotspot at present. The development of harvesting robots is of particular interest, as harvesting is a labor-intensive task that requires considerable human resources [22]. Several researches have attempted to develop robots for harvesting fruits and vegetables, such as a sweet pepper robot for harvesting sweet pepper fruit in greenhouses and an autonomous robot for picking strawberries in polytunnels [23]. These robots can navigate their environments and efficiently perform tasks to reduce labor costs and improve the efficiency of agricultural operations [24]. Notably, to commercialize harvest robots, they must match or exceed the efficiency and speed of human workers. In this context, a key challenge for developing effective harvesting robots is to enhance their work efficiency.

One key idea for improving work efficiency is to develop a harvesting system inspired by how human operators perform. The human approach is shown in Figure 1. Therefore, this study developed a human-centered robot system by considering the manual harvesting process for improving work efficiency. The developed harvesting robots consist of perception (i.e., detecting and harvest ordering), visual servoing (i.e., approaching), and end-effector (i.e., grasping and cutting) systems [25]. Because the performance of each component is directly related to work efficiency, the design was performed considering unstructured environments. The designed end-effector consists of cutting, grasping, and transporting modules, as shown in Figure 2, with detailed descriptions of each module provided in [26]. Among them, the transporting module is structured to enable transport simultaneously with harvesting. However, since it is mounted at the lower part, it may frequently collide with crops due to the movements of end-effector. Therefore, the transporting module is designed to maintain its posture, adapting to changes in the tilt angle, (α) in the y-z plane and (β) in the x-z plane, ensuring stability throughout operation.

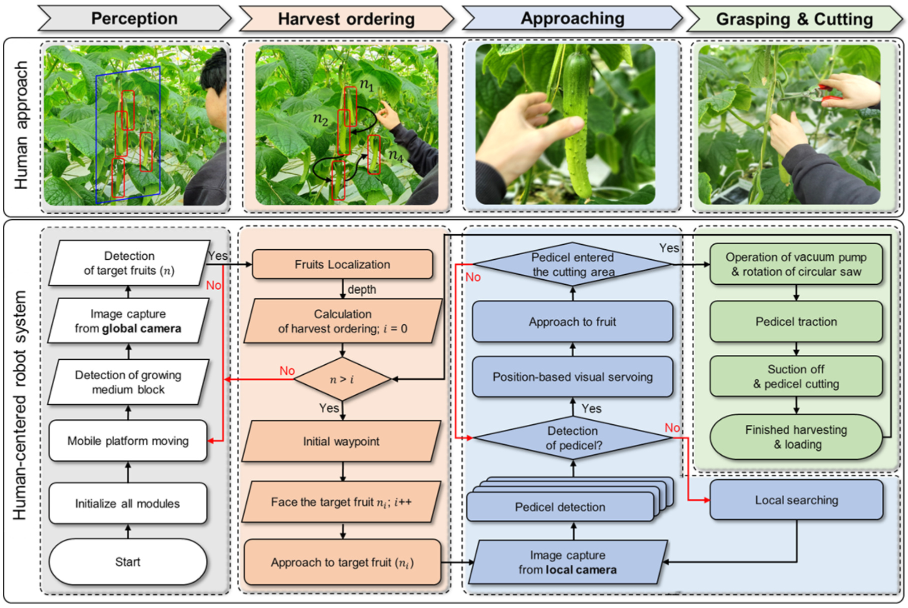

Figure 1. Harvesting process: human approach and human-centered robot system [25].

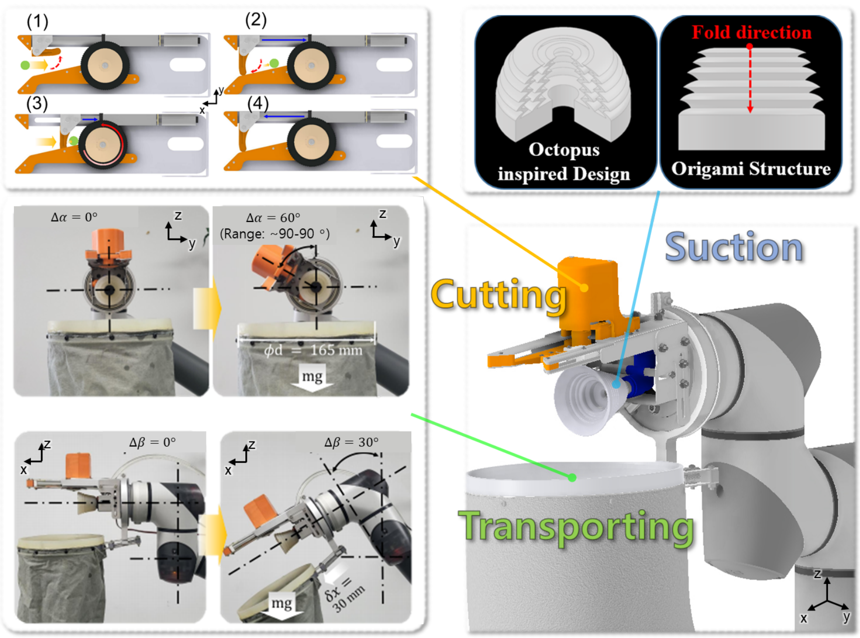

Figure 2. Fruit harvesting robot end-effector [26].

The efficiency of harvesting robots depends on their ability to accurately recognize fruits and plan safe paths while considering obstacles. Typically, Convolutional Neural Network (CNN)-based deep learning techniques are used to detect fruits. However, obtaining a sufficiently large open dataset for training a 2D detection model can be challenging. To address this problem, we proposed a method that uses YOLOv3 with data augmentation using RandAugment (RA) to simulate the effect of having a larger dataset. In addition, we used a real-time 3D localization method that combines the 2D detection results with information from an infrared (IR) stereo sensor. By using the bounding box determined by the 2D detection network, we filtered out unnecessary 3D point data obtained from the IR sensor and estimated the 3D position of the crops as the center position of the filtered data. Figure 3 presents the procedure for determining the 3D position of the crops, along with an experimental demonstration of measuring the localization accuracy. During the experiment, a sample tomato was moved along given trajectories while the camera captured images at 30 Hz from a fixed position. We achieved an average 3D localization error of 7 mm, demonstrating the effectiveness of our approach.

Harvesting robots face various obstacles such as stems, leaves, and target fruits, making it challenging to navigate safely. To address this problem, we classified obstacles according to their criticality and represented them with probabilities. For example, small leaves surrounding the target fruits were given a low value for their criticality, indicating that the robot could pass through them without damaging the plant. We used this probability in a sampling-based path planning algorithm, which biased new samples toward low-criticality regions to increase the number of valid nodes and reduce the cost of the final path. Instead of using collision detection, we added criticality to the process of computing the cost, which reduced the computation time while avoiding obstacles. This approach also allowed us to create paths passing through low-criticality obstacles, increasing the success rate of path creation. Figure 4 illustrates how the robot can reach the target position by passing through a leaf covering it.

However, in greenhouses, fruit rows are typically narrow. This makes it difficult to secure sufficient workspace when using a conventional hand-eye type manipulator. To solve this problem, this study designed a harvesting method based on identifying the fruit location with a global camera and harvest ordering. While approaching the stem, data from a local camera (hand-eye) were used to ensure a precise approach visual servoing was incorporated to respond to position changes caused by collisions with leaves and stems. Finally, the harvesting was performed by grasping and cutting the fruit with the end-effector. The experiment was conducted from 2019 to 2023, including field testing for each module. The experimental crop for this study was cucumbers, and system success was evaluated by categorizing each operation into perception, approaching, and grasping and cutting. Experiment were conducted at three distinct locations, with a total of 265 cucumbers targeted for harvesting, yielding 150 successful harvests [25].

At the first site, the system achieved a 56.3% success rate, with 98 detections, 82 successful entries, and 63 cuts out of 112 attempts. At the second site, a success rate of 50.9% was recorded, comprising 35 detections, 29 entries, and 27 cuts out of 53 trials. The third site reported the highest success rate at 60.0%, with 89 detections, 63 entries, and 60 cuts out of 100 attempts. Overall, the system demonstrated a success rate between 50.9% and 60.0% across all sites, resulting in an average success rate of 56.6%. Additionally, 4.7% of harvested cucumbers experienced damage, with seven damaged cucumbers in total. These findings suggest variable system performance across different environments, indicating a need for further optimization to improve consistency in diverse field conditions.

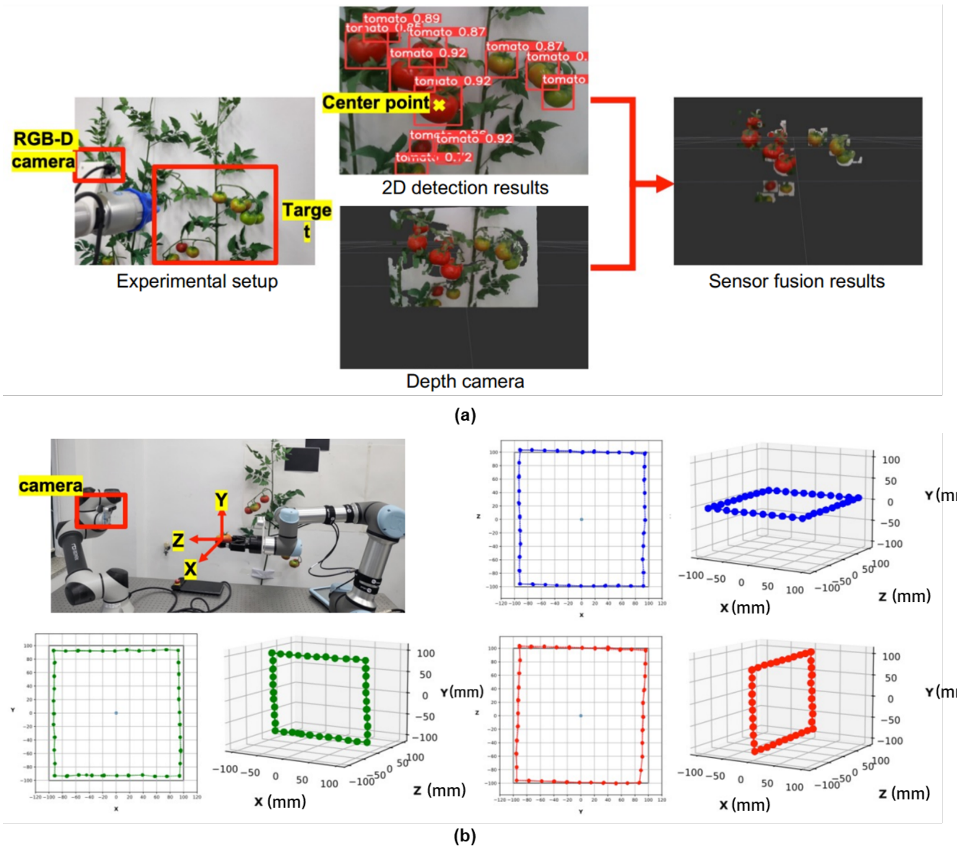

Figure 3. Three-dimensional localization of the target fruit; (**a**) the procedure of localizing fruits by fusing 2D detection results and depth information. (**b**) experimental demonstration of measuring the localization accuracy.

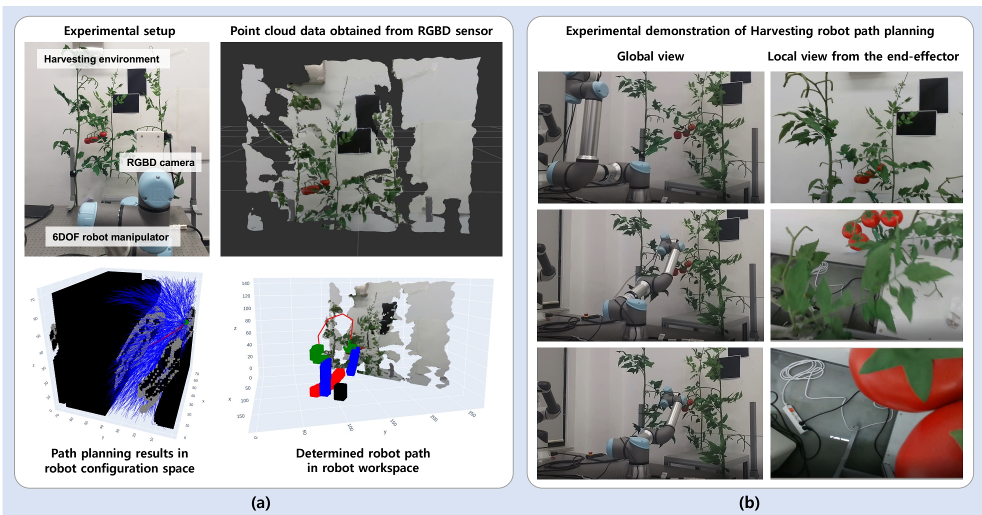

Figure 4. Obstacle-class-dependent-probability-based path planning for tomato harvesting robot; (**a**) experimental setup determining the safe path using the point cloud data and (**b**) experimental demonstration of the harvesting robot following the determined path, with views from the global and the end-effector cameras.

2.2. Harvesting Robot for Arable Farming

While numerous studies focus on the autonomous operation of tractors and combines, these machines generally rely on environments optimized for ease of operation. However, real-world conditions are rarely unstructured, leading to frequent operational inaccuracies in automated tasks. To address these challenges, the development of harvesting robots for arable farming is essential. Here, harvesting robots for arable farming refer to robots specifically designed to autonomously harvest field crops, facilitating automation in diverse open-field cultivation environments.

For example, Korean cabbage is a major food crop that is labor-intensive to harvest. The use of a harvesting robot could improve efficiency, reduce costs, and improve working conditions for farmers in arable farming. The main issue in developing a cabbage harvester for Korean cabbage cultivation is the difficulty in accurately cutting the cabbages without damaging them. This scenario is shown in Figure 5a: owing to the unique structure of Korean cabbages (stems and roots located inside the head), it is necessary to control the attitude of the cutting blade to ensure cutting within the optimal range. However, the environment of arable land is irregular, which renders it challenging to control the attitudes. This problem is applicable to not only Korean cabbage but also other arable crops. In the existing harvesters, such as walking-type, tractor-attached, and crawler combine models, it is challenging to control the attitude of the cutting device, which affects the accuracy of cutting. To accomplish the task, the cutting device needs to move flexibly like a robot arm.

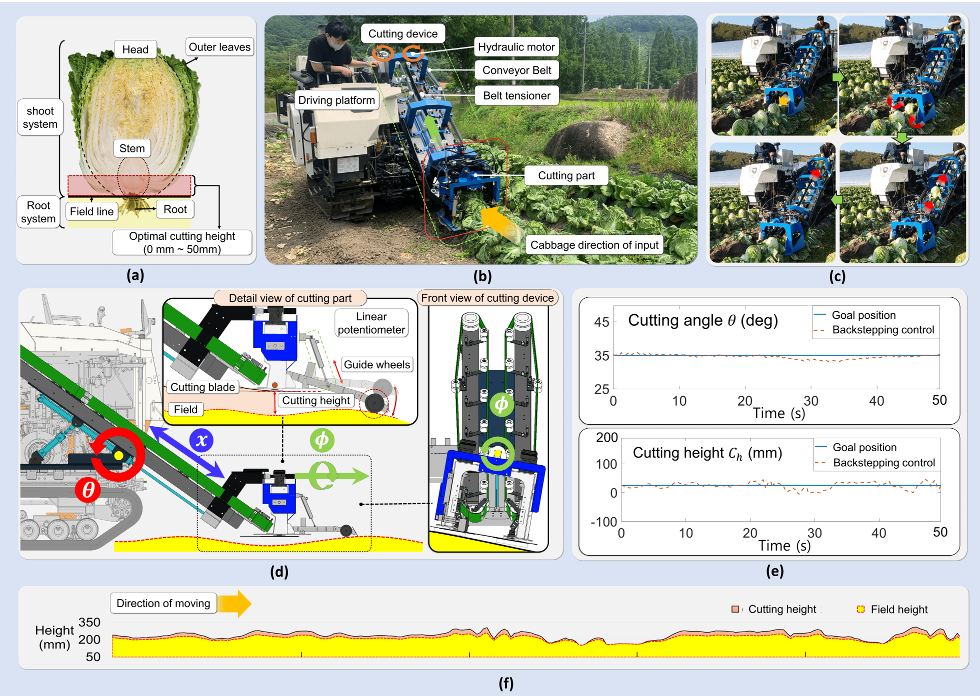

Figure 5. Korean cabbage harvester [27]; (**a**) structure of a Korean cabbage, (**b**) harvesting process of the developed harvester, (**c**) attitude control system of the cutting device, (**d**) verification of goal position following, and (**e**,**f**) harvesting of Korean cabbage using an attitude control system.

As shown in Figure 5b, a novel harvester developed considering the structure of Korean cabbages can improve the farmers' efficiency and working conditions [27]. The attitude (e.g., orientation and balance) can be controlled while the harvester moves through fields and handles the cabbages (Figure 5c).

- Roll angle (ϕ): level of the cutting blades;
- Pitch angle (θ): angle of the cutting device;
- Cutting height (C_h): cutting position of the cutting device.

As shown in Figure 5d, the control system is composed of three main components: roll angle control (ϕ), pitch angle control (θ), and cutting-position height control (C_h). Roll angle control ensures that the cutting blade remains level with the slope of the field. Pitch angle control maintains a constant angle for the cutting device. Cutting-position height control adjusts the height of the cutting blade based on data from a linear potentiometer, which measures the height between the ground and blade. The controller can rapidly and accurately control the attitude of the Korean cabbage harvester to ensure accurate cutting in irregular field conditions. This study applied the backstepping control algorithm to the hydraulic system of the attitude control system. The control system was designed to maintain a specific position for the blade to ensure accurate cutting. The controller performance was evaluated through field experiments in real-world, unstructured cabbage fields.

Specifically, the performance of the proposed system was tested in a domestic cabbage field. The experiment was conducted in 2022–2023. The results showed that the controller could maintain the correct position of the cutting blade and improve the harvestering accuracy (Figure 5e,f). The performance of the Korean cabbage harvester was evaluated through an average cutting quality assessment based on field experiments. In these tests, a total of 60 cabbage heads were harvested, with each cutting surface quality scored to capture the precision and effectiveness of the harvester's cutting mechanism. A score of three was awarded when the cabbage was cut precisely at the optimal position, requiring no additional trimming. If minor trimming was necessary, a score of two was given, while slight head damage due to excessive cutting height resulted in a score of one. Cabbages that were severely damaged, rendering them unsuitable for further use, received a score of zero. The results showed an average cutting quality score of 2.57 out of a possible 3.00, indicating an overall performance rate of 85.7%. The attitude maintenance performance of the controller was compared using a PID controller, with the metrics being the root mean square error (RMSE) and average absolute error (MAE). The RMSEs for the pitch angle (θ) and cutting height were 0.73° and 11.20 mm, respectively, and the MAEs were 0.53° and 8.97 mm. These results highlighted that the backstepping control-based system can improve the position and cutting accuracy of the cutting devices of Korean cabbage harvester, even in unstructured field conditions.

3. Intelligent Spraying

Pesticide application is an important agricultural task to enhance the productivity and quality of cultivated crops, and thereby, food supply worldwide [28]. This task is typically accomplished through extensive spraying to mitigate the probability of pest occurrence and address the associated unstructured environments. Notably, this method may expose workers to harmful substances and lead to soil changes and economic losses owing to the indiscriminate use of pesticides. Another key problem is unintended area spray drift, which may result in loss of productivity owing to damage to crops in other fields. These problems can be overcome by developing an intelligent spraying control system that sprays appropriate amounts of pesticides in a perceptive manner (by detecting trees or spray drift) to enhance the stability and economic benefits for farmers [29,30].

The intelligent spraying control system distinguishes itself from traditional indiscriminate mechanical pest control by drawing inspiration from human manual spraying practices. Humans selectively apply treatment only to areas that require it, based on their acquired knowledge and experience. This selective approach stems from the desire to utilize limited resources efficiently. Specifically, humans identify necessary areas, avoid unnecessary treatments in non-target locations, and determine the appropriate quantity of treatment to be applied. By integrating this decision-making process into an intelligent system, we can develop spraying robots that emulate human-like operational strategies. The developed intelligent spraying system of platform, perception, and control system are shown in Figure 6. This system combines a mobile platform that is equipped with an intelligent spraying module for control and perception. The module includes a 300 L pesticide tank, computational PC, and spray boom with eight nozzles. Two RGB-D cameras are attached to the frame (one on each side of the platform), and data are transmitted between the PC and cameras.

The intelligent spraying system recognizes trees and environments using deep learning-based semantic segmentation [31]. Training was performed by labeling five classes in the dataset: two for a fruit tree (leaf + branch + trunk and fruit) and three for the background

(ground, sky, and pipe). The dataset (2000 images) was acquired over 2 years (2019–2020) from pear orchards using Intel RealSense D435 cameras. The image dataset was built using images from various time zones, in which the light intensity and shadow differed depending on the position of the sun. Training and testing were performed using datasets from commonly used models (U-Net, SegNet, ICNet, and DeepLab v3). The SegNet model was noted to correspond to the highest accuracy. In general, orchards consist of many rows of trees, and the background also involves trees. The trees in the background could be detected, and therefore, fusion with depth data was incorporated to recognize the target object. This approach could prevent the background trees from being segmented and ensure that only the trees to be sprayed were segmented.

Furthermore, 3D information of the tree (i.e., the distance and area), as the control input of the proposed pulse-width modulation (PWM)-based controller, was obtained in real time, and the nozzle was controlled [32]. Proportional solenoid valves were controlled using a PWM controller for determining the flow rate. The unintended pressure at the nozzle tip was not considered, and thus, the theoretically modeled flow rate and actual spray volume were expected to differ. Moreover, because variable flow control involves strong non-linearity, the control input was required to be carefully designed. This study attempted to design the control input based on preliminary experiments and used the results to model the flow rate, according to Equation (1). The flow rate was controlled in real time by the flow rate control unit [32]:

$$V_{pwm} = \begin{cases} 75\% & if \quad d_c \leq 0.9(m) \\ K_p \times A_p \times d_c + C_v\% & else \end{cases} \quad (1)$$

where K_p is the proportional constant, A_p is the fruit area, d_c is the distance between the sprayer and camera, and C_v is the dead zone depending on the valve dynamic characteristics. According to these dynamic characteristics, the proportional valve did not open at a duty cycle of less than 75%. This value was adjusted to ensure that the pesticide was sprayed according to the distance at the appropriate time. At small distances, all fruit trees were sufficiently covered, and the proportional gain was optimized to ensure that all the areas could be sprayed at the given spraying distances. Specifically, the gain value was set as 0.8 based on the results of the preliminary experiments.

Furthermore, preliminary and field experiments were conducted at a real pear orchard. Each control method was evaluated using water-sensitive paper (WSP). The pesticide adhesion rate (Rp) on the WSP was used to validate the spraying performance. The intelligent control system was verified through field experiments conducted in three conditions:

- Control 1: all nozzles open (spraying without applying an intelligent spraying system);
- Control 2: on/off control (spraying while applying an intelligent spraying system);
- Control 3: variable flow rate control (spraying while applying a variable spraying system).

The experiment was conducted in 2020. The experiment results are shown in Figure 7. The performance baseline was control 1, which did not involve a control method (i.e., traditional spraying method). The performance was compared using Rp. The experiment was performed in two trials, with 54 WSPs used on areas to be sprayed (target) and not to be sprayed (non-target). A higher performance meant that the target exhibited a high Rp and the stage exhibited a low Rp. For the target, the Rp values were 56.15% (±17.24%), 68.95% (±21.12%), and 57.33% (±21.73%), with the pesticide usage being 25 L, 19.6 L, and 12.7 L for the different control methods. The performance was satisfactory for all cases because the target Rp was always higher than that of control 1. The Rp values for the non-target cases were 58.80 (±16.83%), 39.37 (±26.54%), and 8.08 (±5.97%). Controls 2 and 3 showed lower Rp than that of control 1. In other words, the undesired area was not sprayed. These results indicated that the proposed method could minimize spraying in areas in which variable control is not desired while optimizing the amount of pesticide used. In addition, the performance could be ensured even in unstructured environments because optimization was conducted based on preliminary experiments.

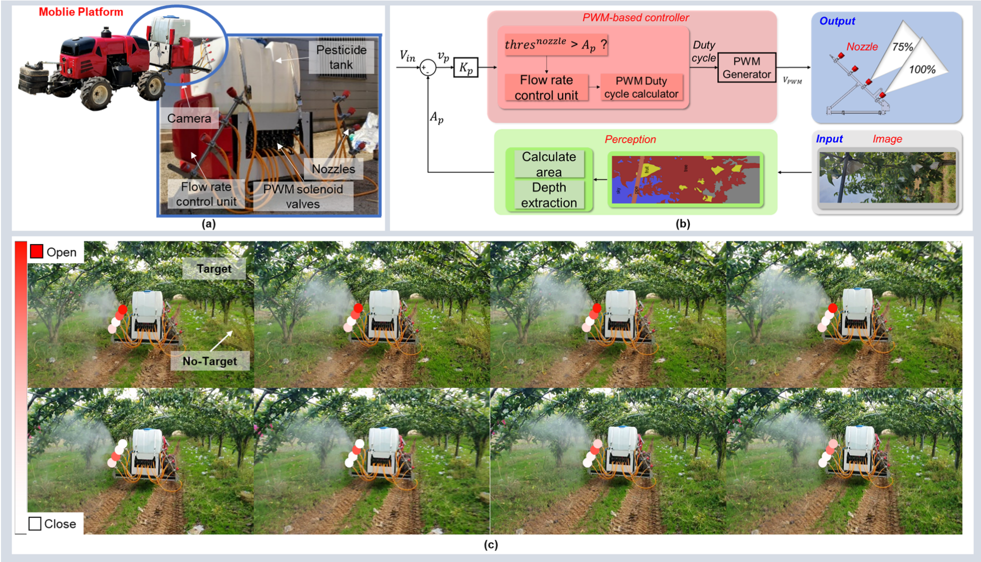

Figure 6. Intelligent spraying system: (**a**) intelligent spraying platform, (**b**) nozzle control diagram, and (**c**) snapshot of spraying; each nozzle has a selective opening according to the target tree.

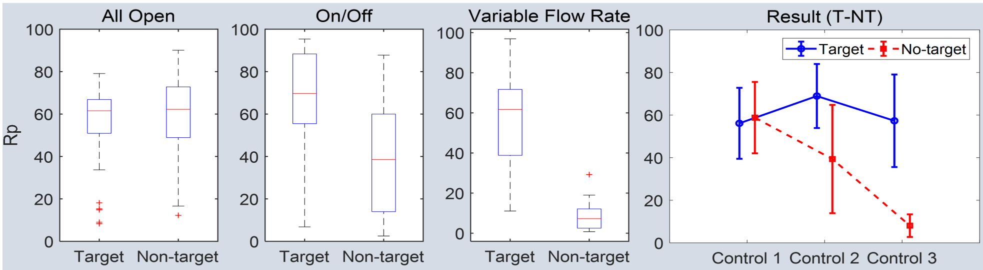

Figure 7. Results of intelligent spraying application in the field (pear orchard).

4. Autonomous Driving Robots for Greenhouse Environments

Autonomous driving technologies are expected to improve the quality of life of farmers and alleviate labor force problems through the introduction of robots. This technologies can be used to seed, spray, harvest, and transport crops in greenhouse work efficiency and functionality. Current greenhouse operations rely primarily on human labor, supplemented by machinery that is strategically arranged to avoid task disruption, leading to logistical challenges when transporting or activating these machines. The presence of numerous workers and structures complicates the integration of robotic systems, as humans are skilled at recognizing each other's activities and navigating around one another to collaborate effectively. By incorporating human attributes such as rapid environmental assessment and efficient resource utilization into robotic systems, operational flexibility and efficiency can be significantly enhanced. Therefore, mobile robotic systems must dynamically identify human workers and other robotic structures as obstacles, allowing for seamless collaboration and effective task execution in agricultural environments.

Simultaneous localization and mapping (SLAM) are important aspects of autonomous driving systems for mobile robots [33]. The autonomous mobile robot can realize path planning to navigate the optimal path from the starting position to the target position without colliding with obstacles in the working environment [34,35]. Path planning can be divided into global path planning, which pertains to the entire movement path, and local path planning, aimed at regenerating paths to obstacles in real time using sensor data. In this context, path planning have to account for the environment of greenhouses, where narrow passageways often accommodate only a single mobile robot [36,37]. Greenhouses commonly deploy various robots for different tasks, introducing both dynamic and static obstacles in the robot's path (Figure 8a). Furthermore, since only one robot can traverse the inner corridors and gates at a time, it is essential to plan paths efficiently to facilitate seamless operation among multirobots.

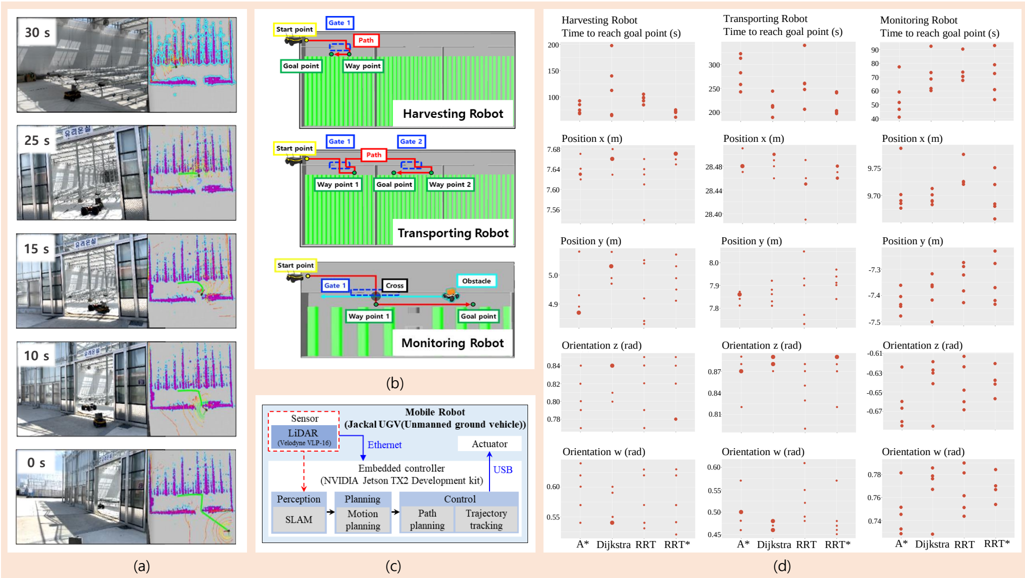

Figure 8. Autonomous driving system; (**a**) autonomous driving experiment in a smart farm, (**b**) scenario of a harvesting robot (short-distance path planning with static obstacles), transporting robot (long-distance path planning with static obstacles), and monitoring robot (path planning with dynamic obstacle), (**c**) hardware architecture, and (**d**) results of field test according to path planning algorithms.

This study compared various global planners and selected path-planning algorithms suitable for greenhouse. Specifically, we compared and analyzed the well-known grid-based Dijkstra and A* algorithms and sampling-based RRT and RRT* algorithms. The experiment involved two types of static scenarios and one type of dynamic scenario, which we assume to include a short-distance harvesting robot and a long-distance transportation robot for the static scenarios, and a monitoring robot for the dynamic scenario (Figure 8b). Field experiments were conducted using the Jackal UGV from Clearpath Robotics equipped with a Velodyne VLP-16. The platform was controlled by a Jetson TX2 (Figure 8c). The SLAM algorithms was the 3D cartographer algorithm combined with the A* algorithm. To ensure a fair comparison of the algorithms' performance, the control parameters were modified, and the velocity was set as 0.5 m/s to minimize position errors in the experimental environment and increase reliability.

The experiment was conducted in 2022. The results of the field experiment for path planning in the greenhouse are shown in Figure 8d. The robots, which are assumed to be a short-distance harvesting robot, long-distance transportation robot, and monitoring robot, reached the goal point with the lowest time when using the RRT* algorithm, Djikstra algorithm, and A* algorithm, respectively. The A* and RRT algorithms exhibited high localization accuracies. The A* algorithm generated the shortest path by relying on the heuristic function; however, it is not always faster than the Dijkstra algorithm. We performed statistical analysis to evaluate the experimental results. In environments such as greenhouses, it is essential to minimize damage to crops, so it is more important to accurately reach the target rather than quickly. The A* algorithm showed high localization accuracy in all cases and is more predictable than the sampling-based algorithm.

The successful implementation and evaluation of the global planner in greenhouse environments offer a basis for expanding this autonomous navigation system to multirobot applications. Multirobot autonomous navigation introduces novel challenges not encountered in single-robot systems: coordination and optimality [38]. These emerging challenges are addressed within the framework of the multiagent pathfinding (MAPF) problem, which has garnered significant attention in the fields of computer science and robotics.

The MAPF problem involves computing a collision-free path for each agent in a discretized environment. The problem assumes $V = v_1, \cdots, v_N$ as the set of N robots, each assigned a start and goal position on a 2D grid W with static obstacles $C \subset W$. Given these assumptions, multiagent pathfinding is defined as a discretized decision-making problem where at each time-step t, the i-th agent takes a control input $\tilde{u}t^i$. The discretized system at time-step t can be represented as a graph $Gt = (V, E_t, W_t)$ consisting of V, the set of agents; $E_t \subseteq V \times V$, the set of edges; and $W_t : E_t \rightarrow \mathbb{R}$, which assigns weights to the edges [39].

We are interested in automating agricultural tasks based on a reliable UGV platform. As described in Figure 9, this system configuration must address two principal challenges inherent in multirobot autonomous navigation. First, coordination among multiple robots is required to ensure collision avoidance. Second, each robot should navigate along an optimal path. A meticulous and rigorous investigation into MAPF algorithms is critical for addressing these challenges and achieving a practical implementation.

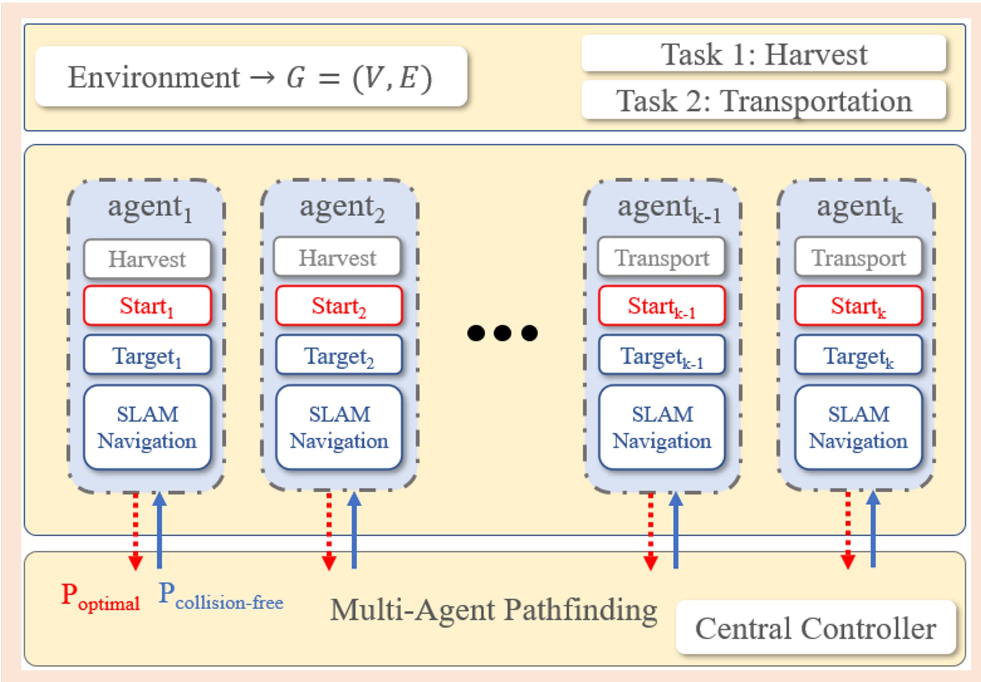

Figure 9. Multi-UGV control architecture.

We evaluated search-based algorithms, specifically conflict-based search (CBS) and enhanced conflict-based search (ECBS), alongside a rule-based algorithm, push and rotate (PAR), as representative decoupled approaches for the MAPF problem. The experiment, conducted in 2022, involved a multirobot system (MRS) with 10, 15, and 20 robots navigating an environment modeled after the agricultural environment. The PAR algorithm achieved the highest success rate, which is a traditional performance metric. Also, the results reveal that the ECBS algorithm showed a high success rate in a limited set of scenarios. Specifically, for the MRS configurations with 10 and 15 robots, the ECBS algorithm demonstrated strong performance. The experimental results were statistically analyzed, confirming that the path differences among the three algorithms were not statistically significant. In other words, the travel distances calculated by the three algorithms in typical agricultural environments show negligible differences. This finding further underscores the importance of success rate as a function of computation time.

We are currently developing an algorithm that enables robots to follow near-optimal paths while accounting for the priorities of heterogeneous tasks in agricultural environments [40]. This algorithm is being employed in field evaluations in orchards to facilitate the efficient execution of agricultural tasks using heterogeneous robots.

5. Multirobot Systems

Agricultural robots can enhance productivity and reduce the working time of farmers [41,42]. However, agricultural robots still face limitations in unstructured, unknown, and expansive agricultural environments, where efforts have primarily focused on enhancing the performance of individual robots [43–45]. As the capabilities of single robots continue to improve, there is a growing need for research that advances performance from a comprehensive task-oriented perspective. MRS has emerged as promising framework to increase the task efficiency in agriculture domains [46,47]. MRS is highly an advantage such as reliability owing to characteristics (i.e., flexibility) to cope with tasks even if a certain robot fails. In addition, MRS exhibit a higher operational efficiency than a single robot system. In particular, cooperation among MRS maximizes their work efficiency, and thus, MRS represent a key future arable farming technology [48–50].

Before integrating applications, we focused on the modeling, control, and implementation of multirobot systems, specifically targeting cooperation among heterogeneous field robots [51]. Traditional approaches to multirobot systems often rely on time-based control frameworks, which present practical limitations. For instance, unexpected events like robot malfunctions or collisions with obstacles may prevent the generation of effective control commands. These challenges are common in the dynamic, unstructured environments of agriculture, necessitating an alternative control approach. Therefore, this study developed a hybrid system-based control architecture considering the eligible events for heterogeneous field robot cooperation. Several researches have experimentally demonstrated that hybrid systems combined with continuous-time-based dynamics at a low-level and discrete-event-based dynamics at a high level can efficiently control large-scale dynamic systems such as heterogeneous field robots.

The control architecture and modeling methods of the hybrid system are shown in Figure 10. In plant modeling, formal methods such as automata and Petri net are typically used to model discrete event dynamics. These studies developed hybrid automata models that incorporate continuous-time dynamics into deterministic automata [52,53]. The hybrid automata models contain the states of heterogeneous robots, transition functions between states, events, and initial and marked states. The overall plant model is computed by synthesizing each hybrid model of the designed heterogeneous robots in parallel. The plant state (e.g., robot pose and mission) and event (e.g., sensor information and collision) are transmitted to the controller through the information channel. The hybrid automaton $\mathcal{G}_h$ is a tuple consisting of the following elements [52]:

$$\mathcal{G}_h = (\mathcal{E}, \mathcal{X}, \Omega, \mathcal{U}, \mathcal{F}, \phi, Inv, Guard, \rho, \mathcal{E}_0, \mathcal{X}_0) \quad (2)$$

where $\mathcal{E}$ is the set of discrete states, $\mathcal{X}$ is the set of continuous states, Ω is the set of events, $\mathcal{U}$ is the set of admissible controls, $\mathcal{F}$ is the vector field of $\mathcal{G}_h$ ($\mathcal{F} : \mathcal{E} \times \mathcal{X} \times \mathcal{U} \to \mathcal{X}$), ϕ is the discrete state transition function of $\mathcal{G}_h$ ($\phi : \mathcal{E} \times \mathcal{X} \times \Omega \to \mathcal{E}$), Inv is the set defining an invariant condition ($Inv \subseteq \mathcal{E} \times \mathcal{X}$), $Guard$ is the set defining a guard condition ($Guard \subseteq \Omega \times \mathcal{E} \times \mathcal{X}$), ρ is the reset function ($\rho : \Omega \times \mathcal{E} \times \mathcal{X} \to \mathcal{E} \times \mathcal{X}$), $\mathcal{E}_0$ is the initial discrete state, and $\mathcal{X}_0$ is the initial continuous state.

The proposed control system for the cooperation of heterogeneous field robots consists of a high-level controller based on supervisory control theory and a conventional control theory-based low-level controller. The high-level controller transmits the control command to the lower level based on the policy representing that each robot follows the desired behavior. To develop control policies, we designed behavior specifications modeled in hybrid automata. For example, a specification refers to a desired behavior in which obstacle avoidance control is input to the system instead of motion control of the heterogeneous robot in a state of obstacle avoidance or in which formation control is activated for heterogeneous robots in the cooperation mode. The developed policy-based control approach can control heterogeneous field robots by operating a low-level controller through a control interface consisting of a mapping function that generates a signal.

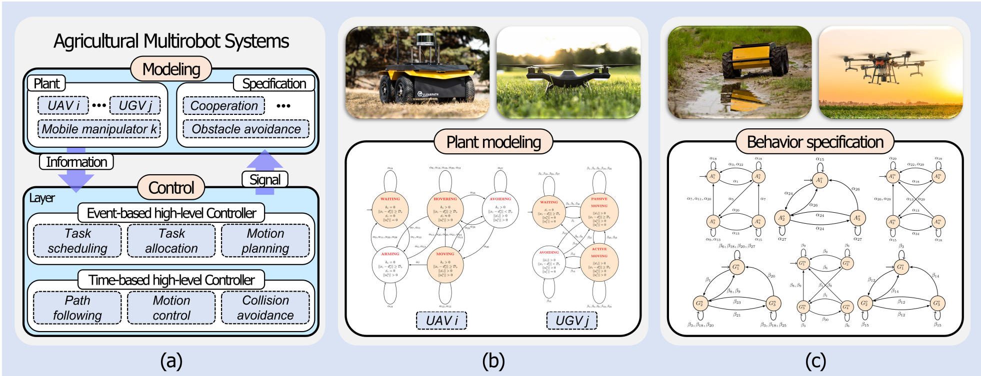

Figure 10. Hybrid system for a multirobot system: (**a**) framework, (**b**) plant modeling, and (**c**) control objective modeling.

To evaluate the proposed control system for MRS, we applied it to the following agricultural scenarios as shown in Figure 11:

- Application 1: homogeneous robots for tributary mapping;
- Application 2: heterogeneous robots for orchard mapping and monitoring.

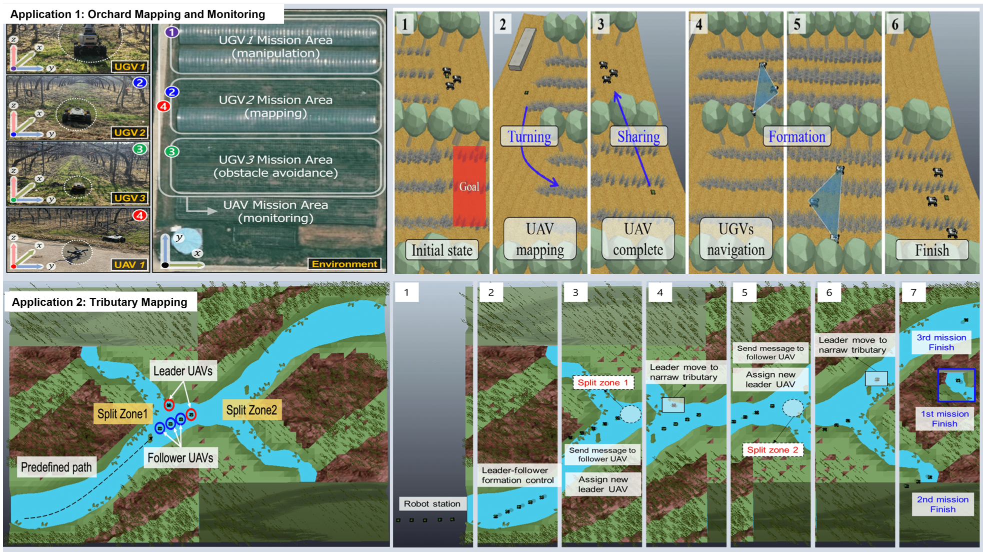

Figure 11. Multirobot system for agricultural application.

5.1. Application 1: Tributary Mapping

This scenario was designed to overcome the mobility limitations of a single UAV for tributary mapping by extending it to multiple UAVs. Because tributaries contain branching points, mapping scenarios must be configured. We designed an environment involving three split tributaries. The experiment was conducted in 2023.

1. Mapping is performed with multiple UAVs in an unknown, unstructured tributary environment;
2. UAVs perform tasks by separating the leader based on leader–follower control at the split zone;
3. The UAVs successfully complete the mission by mapping all tributaries [54].

To evaluate the performance of the developed supervisory controller in branching tributaries, simulations were conducted. The environment includes three divided tributaries with a total of two branching points. In the case of a single UAV, all tributaries must be visited to gather complete environmental data, necessitating repeated exploratory passes. This repetitive exploration critically impacts both operational time and the UAV's limited battery capacity. Assuming an infinite battery capacity, the single UAV took 192 s to cover all tributaries. In the multi-UAV system, the closest UAV to the lead UAV (UAV 1), UAV 2, was newly designated as the leader to perform the task in the second branch. Likewise, in the third branch, UAV 3, the closest to the current leader UAV (UAV 2) assumed the lead role. As a result, the task was efficiently completed by UAVs 1, 3, and 2. Consequently, this multi-UAV system, with newly designated leader groups at each branching point, completed the exploration in the same 192 s, significantly reducing the required operation time.

5.2. Application 2: Orchard Mapping and Monitoring

This scenario was designed to improve the efficiency of agricultural tasks by exploiting the advantages of UAV mobility and unmanned ground vehicle (UGV) accessibility. The detailed experimental scenario is as follows:

1. Allocate a mission to UAV to rapidly sense large areas aerially;
2. Share the map information generated by the flying UAV with the UGVs;
3. Allocate missions to UGVs to perform detailed tasks on the ground;
4. For weak and strong cooperation, the UGVs perform the following tasks:
    - Autonomous navigation with obstacle avoidance;
    - Precise mapping of orchard;
    - Manipulation for crop management;
    - Formation maintenance for transportation.
5. The UAV monitors the UGVs through patrols to successfully complete the overall missions.

The experiment was conducted in 2019–2021. The experimental results showed that each heterogeneous robot reaches the marked state while satisfying the behavioral specifications [52,53]. Here, satisfying behavioral specifications means executing tasks without issues while achieving pre-designed control objectives. The proposed approach can efficiently compute the system model by synthesizing hybrid models and implement the desired control policy based on the design of the behavioral specifications. In other words, hybrid systems offer high scalability and suitability for large-scale, dynamic agricultural environments, as they systematically model, control, and analyze both homogeneous and heterogeneous multirobot systems. This method, facilitating cooperation among heterogeneous field robots, is well-suited to address many existing challenges in agricultural robotics and holds significant potential for future agricultural applications requiring coordinated multirobot collaboration.

6. Conclusions

In this paper, we introduced an agricultural robot system developed by our group to address practical challenges in agriculture, such as productivity, efficiency, and autonomy. Our human-centered agricultural robot system focuses on applications where performance typically depends on the expertise of agricultural workers, aiming to integrate and replicate human experience within robotic systems. In conclusion, this study has presented the development of human-centered robotic systems as essential advancements for digital agriculture. Initially, we introduced a harvesting robot system designed for both greenhouse and arable farming, emphasizing a human-centered approach. Furthermore, we developed an intelligent spraying system, which achieved significant enhancements in productivity and economy, notably reducing pesticide usage by up to 49.2% while ensuring effective target coverage. To further bolster operational autonomy, we implemented an autonomous driving system within greenhouse environments. Each of these systems has been rigorously tested in field trials to confirm their effectiveness in real-world applications. Lastly, we extended our framework to include a multirobot system, aimed at enhancing work efficiency and scalability in complex agricultural settings. These solutions illustrate a pathway towards fully integrated, intelligent automation that complements human expertise and meets operational demands in the agricultural sector. By aligning robotic development with practical, user-driven insights, this research provides a foundation for scalable, high-performance systems that advance the goals of digital agriculture.

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