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SURVEY

A Review on Dual-Arm Manipulation in Agriculture

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ABSTRACT This article systematically reviews the literature on major components (application, platform, and control mechanism) of dual-arm robots in agriculture. To achieve an insightful and transparent review, four research perspectives (RPs) were defined from the perspective of the dual-arm component: tasks, platforms, controls, and future directions. Following the RPs, the structure and flow of this review are derived. By highlighting the RPs, this review article aims to identify the current research state and gaps in dual-arm agricultural robots. In this phase, the characteristics and challenges of agricultural tasks, meaningful platform design in terms of mobility, adaptability, and performance, cutting-edge sensing technologies, and advanced control strategies are also indexed. Based on these, promising future directions have been suggested for advances such as tactile guidance and scene understanding. This study will help related researchers gain scalable and improvable insights into dual-arm agricultural robots in dealing with practical challenges. The insights generated from this analysis could be utilized in the agricultural automation industry, helping to respond promptly to the growing needs of sustainable and innovative agriculture.

INDEX TERMS Review, agricultural automation, dual-arm robot, bimanual, goal-coordinated, scene understanding.

I. INTRODUCTION

Over the past decades, advances in the automation of tasks with simple complexity have been significant. Human-like robots have recently gained attention for tasks with higher complexity [1]. Traditional robotic approaches often require extensive workspace redesigns. However, human-like robots can operate within unmodified environments and interact seamlessly. These humanoid robots are expected to mimic human behaviors and manipulate objects.

However, these applications present new challenges, particularly in control and perception, which are less prominent in systems with a single manipulator [2]. Furthermore, the unique characteristics of such tasks necessitate more sophisticated system integration [3], high-level planning and reasoning capabilities [4], and advanced control methodologies [5]. For instance, dual-arm teleoperation, which closely resembles human operations, has been effectively employed in extreme environments (e.g., space exploration, and the handling of hazardous materials) [6], [7]. In addition to teleoperation [8], human-like robots are increasingly being deployed in diverse fields, including domestic applications [9], [10], manufacturing [11], logistics [12], and agriculture [13].

As shown in Fig. 1, dual-arm robots are particularly effective at tasks requiring coordination between the two arms. Among these applications, agricultural scenarios pose some of the most significant challenges due to factors such as target occlusion and difficulty in accessing objects in unstructured, dense environments with varying degrees of stiffness [14]. The limitations of single-arm studies make

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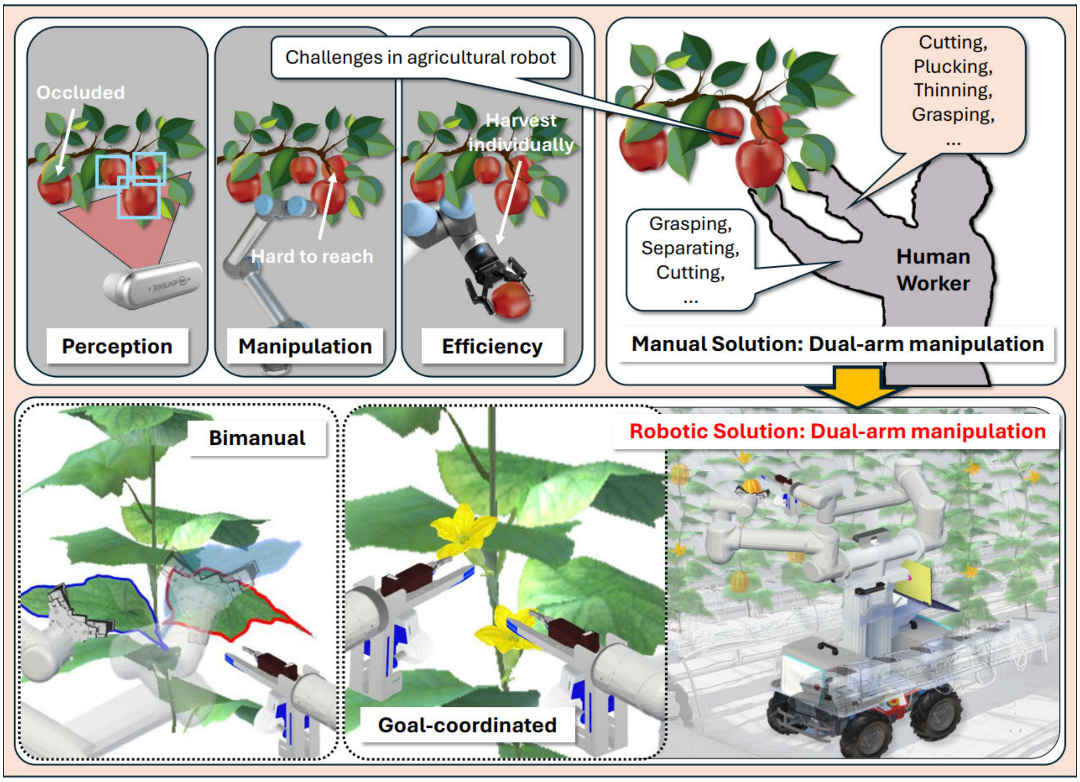


FIGURE 1. Concept of a dual-arm agricultural robot that can perform tasks similar to human actions.

them often ineffective under dynamic conditions. For example, [15] reported that the fruit growth direction and target occlusion constrain the effectiveness of single-arm robots for harvesting tasks. To address these challenges, researchers have focused on enhancing the motion planning of single-arm systems [16] and developing methods to reconstruct or predict occluded portions of fruits [17], [18]. However, fully integrated robotic systems ready for real-world deployment are rare. The robotics community categorizes these uniquely demanding tasks as coordinated and bimanual, emphasizing the suitability of dual-arm robots for such scenarios [2].

Table 1 presents the hierarchy of dual-arm manipulation proposed by [19]. Within this hierarchy, tasks in agricultural environments are categorized into coordinated and bimanual categories.

- Goal-coordinated: Each manipulator of the dual-arm robot performs independent and identical task sequences, including simultaneous harvesting [20], [21].
- Bimanual: When fruits are difficult to access, one arm can control tree branches while the other arm performs harvesting, mimicking human actions [22]. Similarly, one arm can clear obstructing leaves from occluded fruits to expose the pedicel, thereby improving perception and enabling precise cutting [23].

Despite these advances, research into dual-arm agricultural robots remains at an early stage of development [24], [25]. Because of several environmental factors and task-specific challenges that increase the complexity of perception, control, and decision-making [26], [27], agricultural robots must have adaptability and robustness. These challenges highlight the need for practical development to effectively deploy dual-arm robots in real-world agricultural settings.

Figs. 2 and 3 depict the keyword co-occurrence networks for "agricultural robot" and "dual-arm agricultural robot," respectively. These networks reveal the frequency and relationships of keywords. Here, the size of the circle indicates the frequency, and the relationship between keywords is represented by a link. The agricultural robot network has a high density of keywords and reflects a wide range of studies focusing on practical challenges such as obstacle detection and uncertainty. By contrast, the network density of dual-arm agricultural robots is relatively low, and fewer terms are discussed. This identifiable difference indicates that research on dual-arm robots is still in its early stages, and in-depth exploration is limited.

This lack leads to a need for an investigation of existing systems, the current state, challenges, and future perspectives. Further, to advance the field, the examination of task-specific requirements, hardware design, control systems, and practical applications is also required. This paper reviews the state-of-the-art dual-arm platforms, their applications, control mechanisms, and future research priorities.

A. REVIEW PROTOCOL

Before conducting the systematic review, a review protocol was established following [28]. The review began by defining the research perspectives. ScienceDirect, Scopus, Web of Science, Springer Link, Wiley, and Google Scholar were

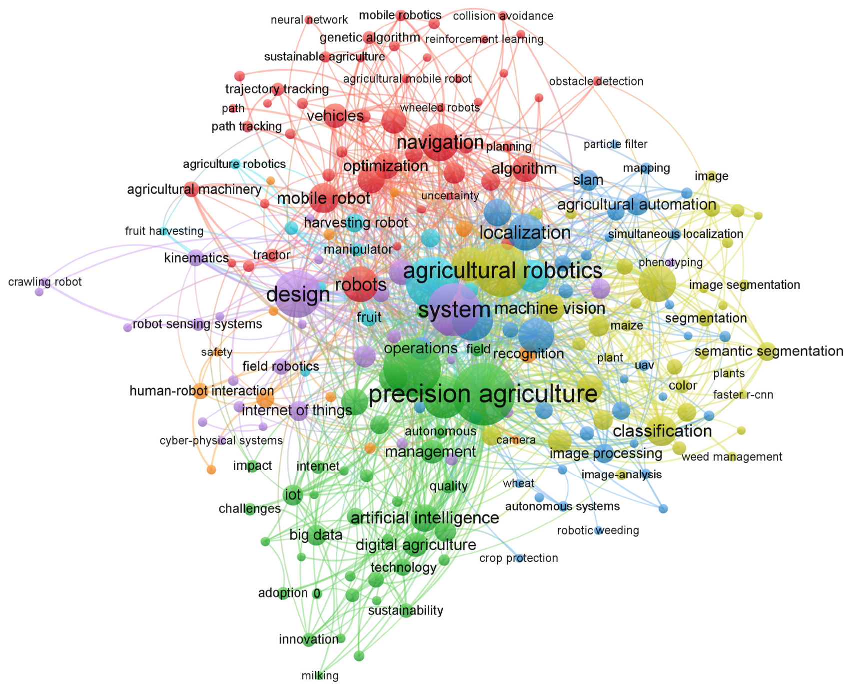


FIGURE 2. Keyword co-occurrence network on "agricultural robot."

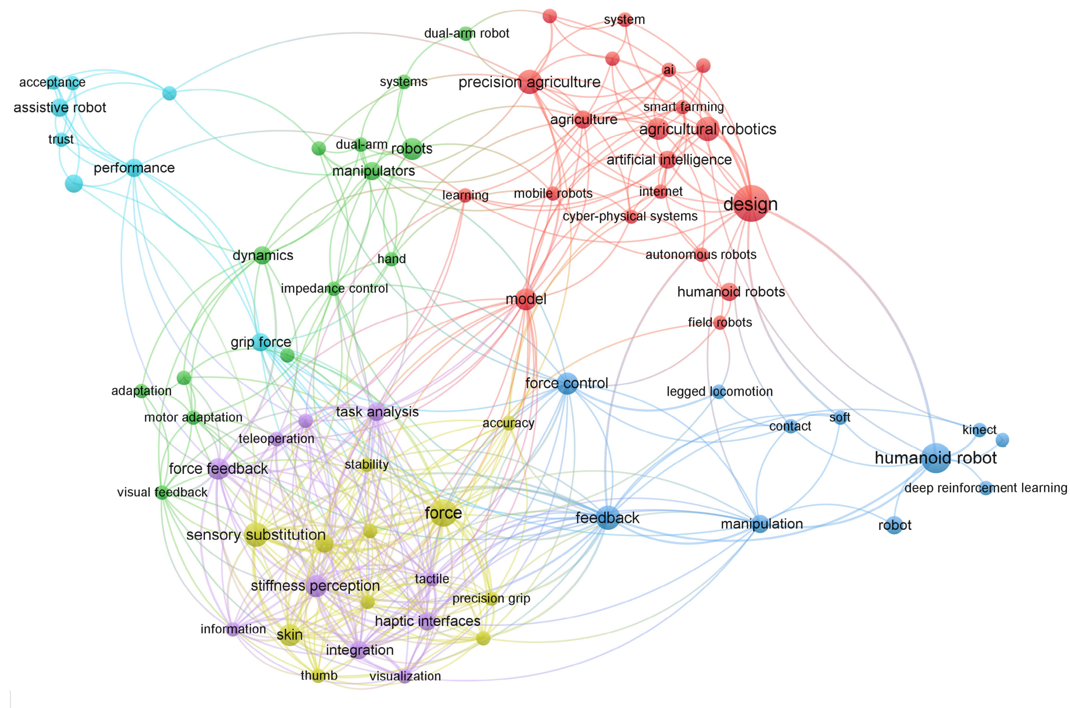


FIGURE 3. Keyword co-occurrence network on "dual-arm agricultural robot."

employed as databases. Relevant studies were identified and filtered using predefined exclusion criteria. The review process was divided into three key stages: planning the review, conducting the review, and reporting the findings.

TABLE 1. Hierarchy of dual arm manipulation [19].

Dual-arm manipulation		
Un-coordinated	Coordinated	
	Goal-coordinated	Bimanual
Example: The left arm is palletizing parts while the right arm is welding an unrelated seam.	Example: Both arms are palletizing parts into the same box.	Example: Both arms are lifting and moving the same box full of parts.

In the planning phase, research perspectives were defined as per the scope of this article. In this phase, we defined publication type, search strings, and selection criteria. The second phase focused on executing the review process. Publications were identified through systematic searches of selected databases. Author details, publication year, publication type, and information aligned with the research perspectives (e.g., title, keyword, abstract) were extracted as publication data. After this, the data were synthesized to provide a comprehensive overview of the existing literature. The final phase was documenting the main findings to conclude the review. Reporting the results and addressing the research perspectives established in the first phase were included in this phase.

B. RESEARCH PERSPECTIVES

This article aims to provide insights into agricultural tasks, dual-arm platforms, and control mechanisms. The studies have been analyzed across the following four research perspectives (RPs):

1) RP1: What tasks have been addressed in the literature for dual-arm platform operations?
2) RP2: Which dual-arm platforms have been used in the agricultural tasks literature?
3) RP3: How have dual-arm platforms been controlled for agricultural task execution?
4) RP4: What challenges still remain in agricultural tasks that use dual-arm platforms?

II. AGRICULTURAL TASKS

To obtain meaningful insights, defining the range of the application field is necessary. Characterizing agricultural tasks is considered important, and understanding these tasks helps address current challenges.

This section provides a detailed review of the specific agricultural tasks performed by dual-arm robots. Following the strategy outlined in Table 1, the key characteristics of agricultural tasks and execution methods are identified. Compared to the single-arm robot, the challenges in integrating recent technologies into dual-arm robotic systems are also examined.

A. PRUNING

Pruning involves trimming plants by removing overgrown branches to maintain their structure, enhance yield and growth, and reduce the risk of diseases [29], [30]. A manipulator designed for pruning must possess sufficient degrees of freedom (DoF) to reach branches with appropriate positioning and orientation, identify which branches or fruits to remove, and employ an end-effector capable of performing precise cuts [31]. Fig. 4 illustrates common methods of robotic pruning. Fig. 4(a) shows a method primarily aimed at adjusting the morphology of plants [32], while Fig. 4(b) illustrates a method aimed at increasing tree growth and reducing disease risk by managing branch density [33]. In the branch density adjustment process, leaves and stems are considered target objects for cutting. The distinct difference between these two methods is the decision-making process for branch removal. The density-adjustment method must perceive most branches and determine the cutting points. By contrast, the morphology-adjustment method considers fewer factors when deciding. However, regarding pruning objectives, branch density adjustment should be prioritized over morphology adjustment [34].

However, adjusting branch density presents two main challenges: perception and control. Both challenges stem from overlapping branches and irregular growth patterns. Perception is often hindered by overlapping branches, which impede the identification of the appropriate pruning point. Similarly, control challenges arise due to irregular growth patterns, which can lead to kinematic singularities or infeasible motion planning. These challenges can be effectively addressed through bimanual operations (e.g., grasping and cutting). The representative study of this section, depending on the type of base platform, is provided in Fig. 5.

Reference [13] proposed a pruning platform capable of responding to occluded branches. To address the motion constraints of dual arms, this system uses a recursive Gibbs-Appell formulation for dynamic modeling. Further, the non-holonomic constraints associated with high-tree pruning applications are effectively handled. In more recent studies, [35] and [36] proposed dual-arm robots for selective pruning with a focus on adjusting branch density. Reference [36] proposed a lightweight dual-arm cooperative manipulator for leaf sampling that uses an ornithopter robot. Although leaf sampling was the primary application in this study, the task shared significant similarities with pruning, as it involves cutting leaves and branches. This onboard dual-arm manipulator, weighing 94.1 g, mimics the operations of human fingers and incorporates two heterogeneous grippers: a scissors-type gripper and a collection gripper. Based on the input derived from a stereo camera, the inverse kinematics of the dual-arm system coordinates the movements of both grippers to achieve precise positioning. The lightweight

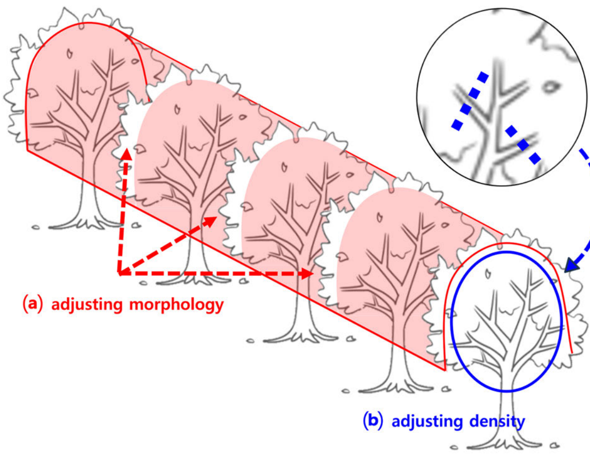
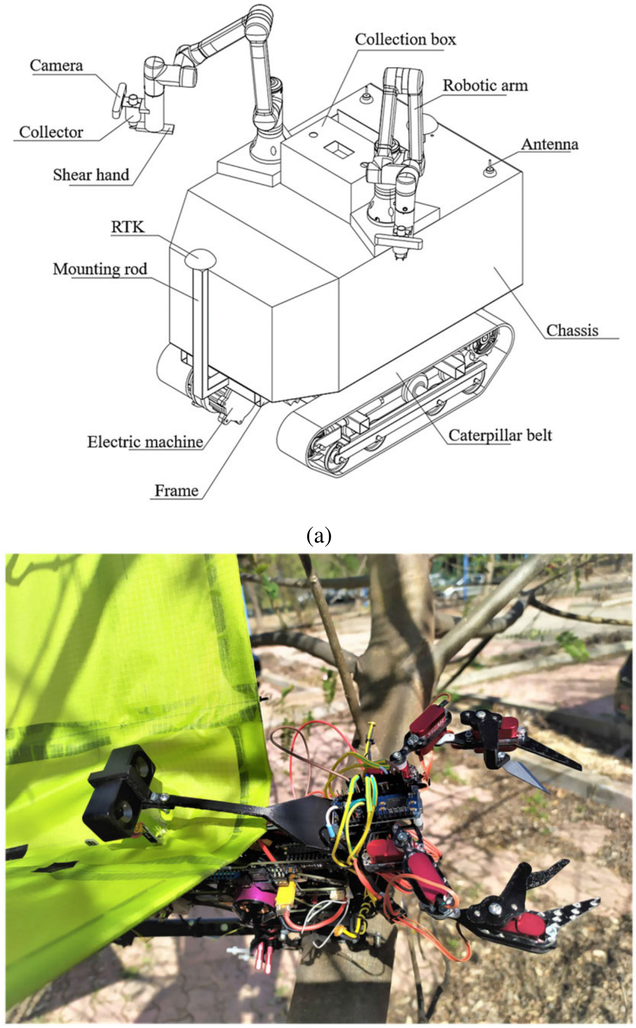


FIGURE 4. Typical methods of robotic pruning: (a) morphology adjustment and (b) density adjustment.



(a)

(b)

FIGURE 5. Different types of pruning robots: (a) UGV type [35] and (b) UAV type [36].

design of the dual-arm manipulator allows the robot system to perch on stems, enabling manipulation tasks to be performed from this perched position.

Reference [35] developed a dual-arm mobile manipulator that leverages deep learning and computer vision to optimize the tea-picking process. A sophisticated vision system was employed with precise tea bud localization for targeted picking. Further, a control module for guiding the robot during the picking phase was integrated.

B. FRUIT THINNING AND HARVESTING

In a dynamic agricultural environment, robotic fruit thinning and harvesting based on single-arm robots often encounter challenges such as occlusion [37], motion planning difficulties [38], and reduced operational efficiency [39]. As depicted in Fig. 1, human workers overcome these challenges using coordinated two-arm actions. By adopting a similar manual strategy, robotic systems can also address these challenges effectively.

Addressing these challenges often requires alternative approaches. As one approach, when fruits are occluded by obstacles such as leaves or branches, one robotic arm can be designated to hold or clear the obstacle, thereby improving perception (see the bimanual strategy in Table 1) [23], [40]. In crops that grow in clusters, obstacles may include other non-target fruits, introducing additional complexity. These scenarios may require a high-level decision-making model, such as harvest ordering, for effective task sequencing (discussed further in Section IV-B). As another approach, to maximize efficiency, both arms can be deployed simultaneously for harvesting, using identical end-effectors to execute goal-coordinated actions (refer to the goal-coordinated strategy in Table 1) [20]. A summary of this section is presented in Fig. 6.

Reference [41] proposed a dual-arm harvesting robot for tomato picking. A mobile platform, dual-arm manipulators, and a stereo camera comprise the system. The robot was equipped with two task-specific end-effectors: a cutting gripper and a vacuum gripper, which enabled grasping and detachment. Reference [21] proposed a dual-arm-based pear and apple harvesting robot. In the proposed system, the harvesting sequence consisted of fruit detection, localization, information integration, inverse kinematics, and path planning. This study focused on fruit detection under challenging outdoor conditions (e.g., occlusion, varying light intensities). Reference [23] proposed a dual-arm robotic system for automating grape harvesting in cluttered vineyards. In their study, one arm detected and cut the grape stem, while the other arm manipulated the grape to improve stem visibility for cutting. This system solved occlusion by synchronized bimanual manipulation. The effectiveness was validated in laboratory and field experiments.

C. TRANSPORTATION

Transportation remains a labor-intensive task in agriculture. In agriculture, transportation often involves handling

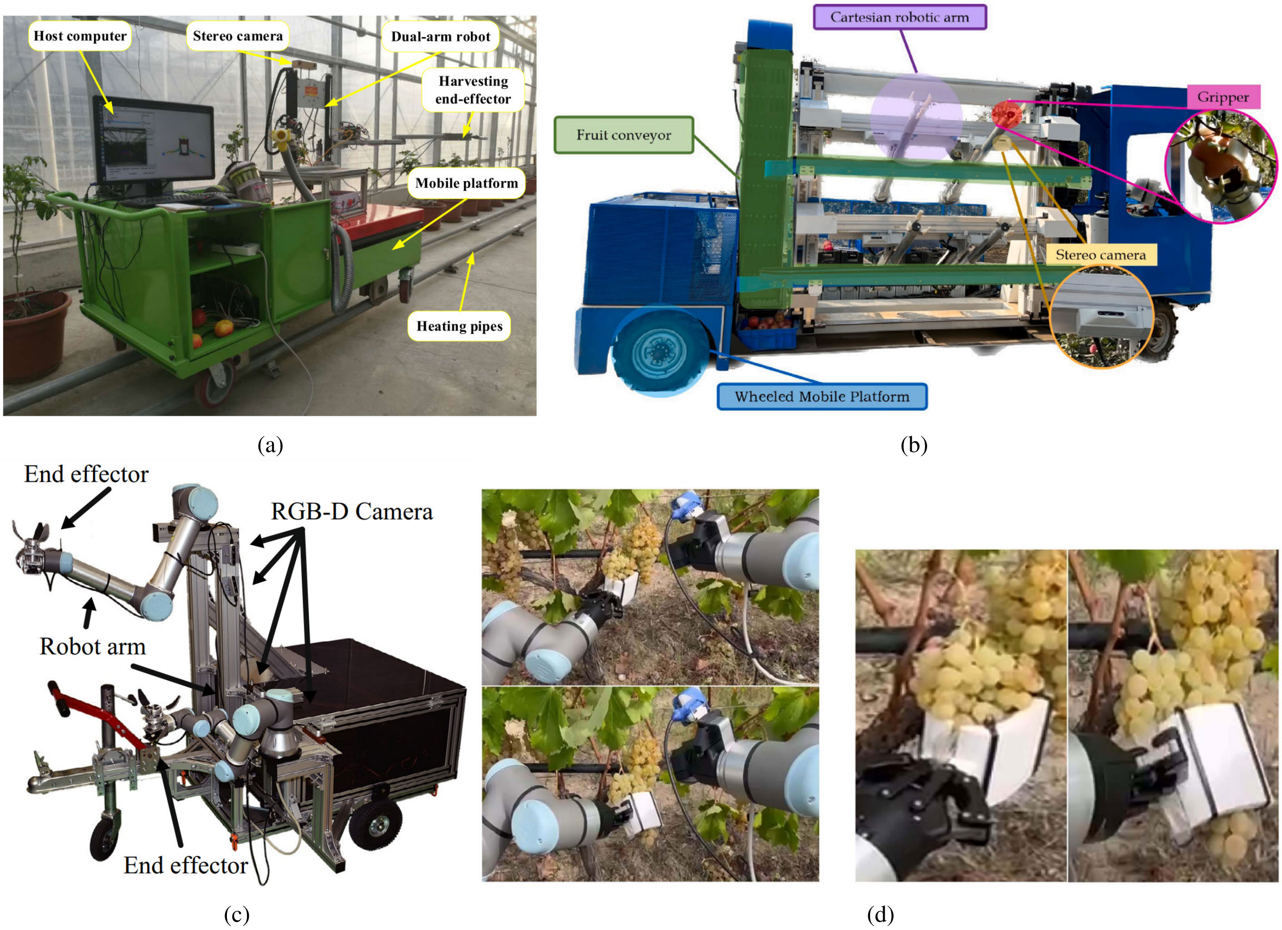


FIGURE 6. **Different types of harvesting robots: (a) [41], (b) [20], (c) [21], (d) [23].**

irregularly shaped [42], fragile [43], [44], or densely packed objects [45], which adds complexity to the task. As shown in Fig. 7, a major challenge in these tasks arises from shifts in the center of mass when moving boxes containing multiple objects, which may potentially compromise stability and handling precision [46]. Single-arm robotic platforms frequently employ advanced control strategies, such as sliding mode control [47] or Zero Moment Point (ZMP) control [48], to address these issues by maintaining balance during object handling. However, the restricted payload capacity and reduced handling versatility are limitations of single-arm robots often noted in the robotics community.

Dual-arm robotic systems enhance the capability to manage shifts in the mass moment and distribute loads [50], [51]. During complex transportation tasks, the bimanual actions of two manipulators improve stability. In agricultural applications, these systems must also address the unique challenge of handling delicate products such as fruits and vegetables [49], which requires precise force control mechanisms and the integration of soft grippers to prevent damage to sensitive surfaces while maintaining a secure grip [52], [53].

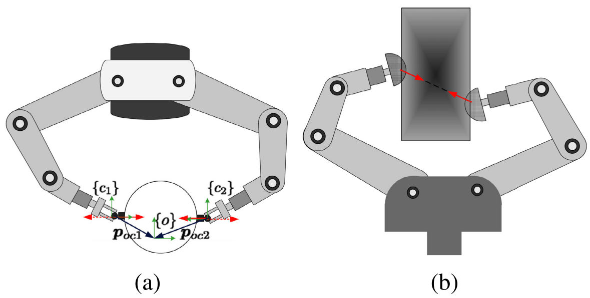


FIGURE 7. **Modeling of dual-arm manipulation for transportation [2]: (a) bimanual manipulation with two rigid grippers and (b) bimanual manipulation with two soft grippers.**

The restricted payload capacity and reduced handling versatility of single-arm robots are solved by distributing loads between two arms. Reference [54] developed a dual-arm logistics platform capable of navigating and operating in uneven agricultural environments. Complementing this, [55] presented a whiffletree mechanism designed to maintain stable load distribution, even when positional inconsistencies occur. Experimental results demonstrated that two UR5

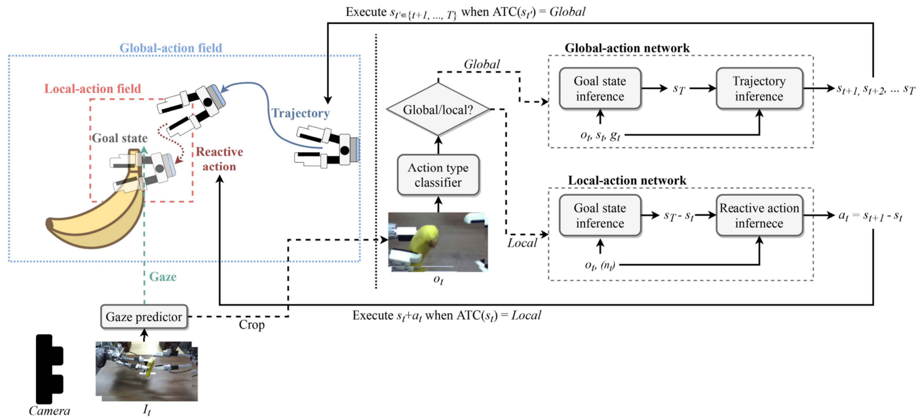


FIGURE 8. Bimanual transportation considering the delicacy of agricultural products [49].

robotic arms working in tandem were able to reposition a 7 kg load–surpassing the lifting capacity of a single arm.

Reference [49] introduced a deep imitation learning system to enable dual-arm robots to handle delicate and deformable objects, as shown in Fig. 8. In this study, to structure the robot's motion and trajectory, a dual-network architecture comprising global and local networks was applied. The global network manages high-level motion planning, and the local network provides fine control during interactions with fragile objects. The delicate object (e.g., banana-peeling scenario) was manipulated effectively by coordinating the transitions between these two networks.

D. OTHERS

Although spraying, seeding, pollination, monitoring, and sampling are essential agricultural tasks, they typically do not require intensive dual-arm cooperation because these tasks are relatively unaffected by challenges such as occlusion, motion planning, and singularity. However, efficiency remains a critical concern. Coordinating multiple robotic arms to perform the same task simultaneously is an effective approach to improving robotic throughput. This section reviews several case studies to stimulate discussion on simultaneous dual-arm task execution.

Reference [56] developed a pesticide sprayer robot, SprayRo, to address multiple farming processes. The authors developed a dual-arm agricultural platform by incorporating the platform controller, nutrient sprayer, and sensor system equipped with two nozzles. To enhance user accessibility, the authors also developed a dedicated application for the dual-arm platform.

Reference [57] proposed a mobile dual PR arm agricultural robot comprising four main subsystems: a digging module, a seed planting module, a watering module, and an inline motion module. The dual PR robotic manipulator performed the digging and soil-covering tasks entirely, operating based on kinematic synthesis using Denavit-Hartenberg modeling.

Reference [58] introduced Stickbug, a six-armed pollination robot. Stickbug employed a kiwi drive mechanism for manoeuvring, six manipulators for parallel execution, a detection model and classifier, and a felt-tip end-effector for contact-based pollination.

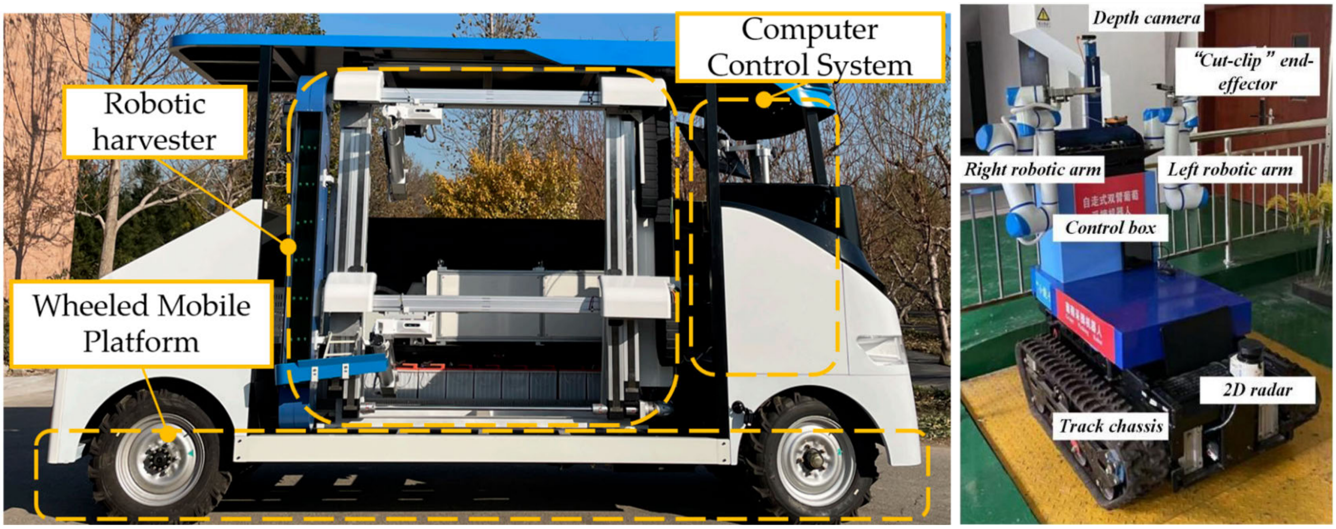
III. AGRICULTURAL PLATFORMS

This section presents an overview of the base platforms used in agricultural tasks, including Unpiloted Ground Vehicles (UGVs), Unpiloted Aerial Vehicles (UAVs), and dual-arm manipulators. Various gripper designs and their associated sensors, which are essential for effective operation across these platform categories, are analyzed. Furthermore, the features, advantages, and limitations of the dual-arm platform component regarding mobility, payload, and adaptability are examined, as well as the importance of aligning the platform with the specific requirements of agricultural applications. A summary of the key insights and comparisons is provided in Tables 2-3.

A. BASE PLATFORM

The base platforms are mobility-focused systems that support task efficiency, stability, and task-specific requirements. In agricultural environments, the most commonly used UGV and UAV base platforms are selected.

UGVs are robots designed for planar motion and are characterized by extended operational time, high payload capacity, and stability, making them suitable for most industrial applications. As shown in Fig. 9, UGVs are typically classified into tracked and wheeled types based on their driving structure, and the selection is determined by the operational environment and driving conditions [35], [60]. Although most previous studies have focused on wheeled UGVs, [59] proposed a monocular vision-based dual-arm robot for fruit harvesting that employs a tracked UGV system. Unlike previous wheeled designs, the tracked base in [59] was selected precisely because it can negotiate loose soil while carrying the dual arms and an additional harvest bin, a load level that wheeled harvesters in similar studies [35], [60] could not stably support. This highlights a classic mobility-versus-payload trade-off between the two chassis types.



(a) (b)

FIGURE 9. Different driving structures of UGVs: (a) tracked UGV [59], (b) wheeled UGV [60].

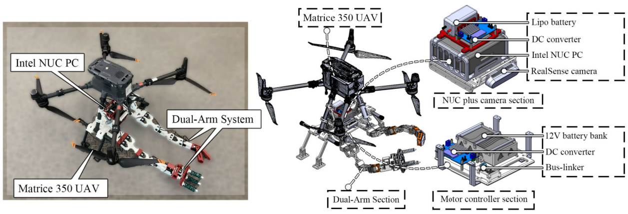


FIGURE 10. Dual-arm aerial manipulator for harvesting avocado [61].

Although research on tracked platforms is limited, they were selected for their superior mobility and payload capacity in open-field agricultural environments compared to wheeled platforms. Previous studies have focused on wheeled platforms because they are adaptable to various soil conditions. Although issues such as slippage and soil compaction during field operations are critical in agricultural applications, these mechanical aspects are beyond the scope of this paper.

Compared to UGVs, UAVs provide enhanced mobility, offer broader operational ranges, and increase flexibility through three-dimensional motion. However, short operational times, low payload capacity, and limited stability restrict practical use. For instance, [36] and [62] proposed UAV systems equipped with dual-arm manipulators for leaf sampling. They developed and attached a lightweight manipulator weighing 94.1 g to an ornithopter UAV platform with a payload capacity of 500 g. Likewise, Fig.10 shows the UAV-based avocado harvester of [61], which operates a 5.36kg manipulator at the edge of the vehicle's capacity. Collectively, these studies confirm that UAVs reach canopies inaccessible to ground robots, yet their arm-to-airframe mass ratio remains an order of magnitude below that of UGVs, revealing an energy-density bottleneck that must be overcome for heavier tasks.

UGVs, particularly wheeled configurations, dominate tasks that require long duty cycles and heavy tooling, whereas UAVs excel at canopy-level access but remain limited by payload (< 6 kg) and flight time (< 15 min). Platform choice therefore depends on whether vertical reach or endurance is the primary mission driver (Table 2).

B. DUAL-ARM ROBOTS

Owing to the hierarchical structure of the manipulator composed of links and joints, the robot can execute both linear and nonlinear trajectories. The types and combinations of links and joints determine the manipulator's DoF and configuration, and these configurations define the number of independent motion directions that a robot can control. In dense and unstructured environments, robots with high DoF can achieve complex motion and trajectory planning. However, kinematic inefficiencies and unnecessary link movements must be considered as the structure becomes more complicated. These challenges can be compounded in dual-arm robot systems, where additional complications, such as self-collision (discussed further in Section IV-A), can occur. Therefore, selecting an appropriate DoF and structure based on the task requirements is necessary for efficient and effective robot design.

Anthropomorphic manipulators, which resemble the human arm, remain the dominant choice because their 6–7 DoF chains can weave around foliage and irregular trellises [22], [27]. This agility makes them the first option for cluttered orchard scenarios (Tables 2–3), but it also results in more complex inverse kinematics and a higher risk of self-collision.

Cartesian systems offer the opposite trade-off. By replacing rotary chains with orthogonal linear slides, the designs in [20], [31], [67], and [71] reduced planning time and virtually

TABLE 2. Overview of agricultural tasks and associated robotic platforms#1.

Task	Object	Platform	Gripper Homo/Hetero	Control hierarchy	Sensors	Technical challenge	Validation environment	Ref.
Harvesting	Tomato	6DOF manipulator (2) Wheeled UGV (1)	Homo	Goal-coordinated	Camera	Motion planning	Laboratory	[16]
Transportation	N/A	7DOF manipulator (2)	Hetero	Bimanual	Force/torque	Grasping	Laboratory	[12]
Harvesting	Orange	7DOF manipulator (2) Wheeled UGV (1)	Hetero	Bimanual	Camera	Cooperative control	Laboratory	[22]
Harvesting	Kiwifruit	6DOF manipulator (2)	Homo	Goal-coordinated	Camera	Localization Motion planning	Laboratory	[63]
Transportation	Box	6DOF manipulator (2) Wheeled UGV (1)	Homo	Bimanual	Force/torque Haptic	Grasping	Laboratory	[3]
Harvesting	Apple	4DOF manipulator (2) Wheeled UGV (1)	Homo	Goal-coordinated	Camera	Ordering	Field	[60]
Harvesting	Grape	6DOF manipulator (2) Tracked UGV (1)	Homo	Goal-coordinated	Camera LiDAR	Localization Motion planning	Laboratory Field	[59]
Harvesting	Grape	6DOF manipulator (2) Wheeled UGV (1)	Homo	Goal-coordinated	Camera	Localization Motion planning	Field	[64]
Harvesting	Apple	6DOF manipulator (2) Wheeled UGV (1)	Hetero	Goal-coordinated	Camera	Motion planning	Laboratory	[65] [66]
Spraying	N/A	Sprayer (2) Wheeled UGV (1)	Homo	Goal-coordinated	Proximity	Platform	N/A	[56]
Transportation	Banana	6DOF manipulator (2)	Homo	Bimanual	Force/torque Camera	Grasping	Laboratory	[49]
Transportation	Box	6DOF manipulator (2)	Homo	Bimanual	Force/torque	Cooperative control	Laboratory	[55]
Pruning	Branch	3DOF manipulator (2) Wheeled UGV (1)	Homo	Goal-coordinated	N/A	Platform Motion planning	Simulation	[13]
Harvesting	Apple	4DOF manipulator (2) Wheeled UGV (1)	Homo	Goal-coordinated	Camera Laser	Ordering	Field	[67]
Harvesting	Apple	3DOF manipulator (4) Wheeled UGV (1)	Homo	Goal-coordinated	Camera	Localization Ordering	Field	[20]
Harvesting	Tomato	7DOF manipulator (2) Wheeled UGV (1)	Homo	Goal-coordinated	Camera	Localization Motion planning	Simulation	[26]
Harvesting	Tomato	3DOF manipulator (2) Wheeled UGV (1)	Hetero	Bimanual	Camera	Localization	Field	[41]

TABLE 3. Overview of agricultural tasks and associated robotic platforms#2.

Task	Object	Platform	Gripper Homo/Hetero	Control hierarchy	Sensors	Technical challenge	Validation environment	Ref.
Harvesting	Avocado	4DOF manipulator (2) UAV (1)	Hetero	Bimanual	Camera	Localization Motion planning	Laboratory	[61]
Pruning	Leaf	2DOF manipulator (2) UAV (1)	Hetero	Bimanual	Camera	Platform Localization	Laboratory Field	[36]
Harvesting	Grape	6DOF manipulator (2) Tracked UGV (1)	Homo	Bimanual	LiDAR Camera Compass	Platform	Laboratory	[68]
Seeding	N/A	2DOF manipulator (2) Wheeled UGV (1)	Homo	Goal-coordinated	Moisture	Platform	Simulation	[57]
Harvesting	Eggplant	6DOF manipulator (2)	Homo	Goal-coordinated	Camera	Localization Motion planning	Laboratory	[69]
Pollination	Flower	4DOF manipulator (6) Wheeled UGV (1)	Homo	Goal-coordinated	LiDAR Camera	Localization	Field	[58]
Harvesting	Grape	6DOF manipulator (2) Wheeled UGV (1)	Hetero	Bimanual	Camera	Cooperative control	Laboratory Field	[23] [40]
Pruning	Leaf	7DOF manipulator (2) Wheeled UGV (1)	Hetero	N/A	LiDAR Camera	Localization	Laboratory	[70]
Harvesting	Strawberry	6DOF manipulator (2) Wheeled UGV (1)	N/A	N/A	LiDAR Camera	Localization	Field	[27]
Harvesting	Strawberry	6DOF manipulator (2) Wheeled UGV (1)	N/A	N/A	LiDAR Camera	Localization	Field	[27]
Transportation	N/A	3DOF manipulator (2) Wheeled UGV (1)	N/A	N/A	Photo- -electric	Platform	N/A	[54]
Pruning	Leaf	6DOF manipulator (2) Tracked UGV (1)	Homo	N/A	GPS Camera	Platform Localization	Field	[35]
Harvesting	Strawberry	5DOF manipulator (2) Wheeled UGV (1)	Homo	Goal-coordinated	LiDAR Camera	Localization Motion planning	Field	[71]
Harvesting	Apple	6DOF manipulator (2) Wheeled UGV (1)	Homo	Goal-coordinated	Camera	Localization Motion planning	Field	[21]
Harvesting	Apple	6DOF manipulator (2) Wheeled UGV (1)	Hetero	N/A	Camera	Localization Motion planning	Laboratory	[25]
Harvesting	Tomato	3DOF manipulator (2) Wheeled UGV (1)	Hetero	Bimanual	Camera	Platform	Field	[72]

eliminated self-collision, albeit at the cost of a larger footprint and motion limited to box-shaped workspaces. These studies show that when the crop rows are straight and the canopy height is uniform, simplicity can outweigh dexterity.

SCARA-style arms sit between the two extremes. The height-controlled indoor robots in [41], [54], and [72] achieved high-speed, repetitive picking on flat benches because their planar kinematics provide stiffness and accuracy. The drawback is that they require carefully leveled and regulated environments and cannot reach around obstacles.

Anthropomorphic arms maximize reach in unstructured orchards, Cartesian gantries favour straight-row tasks that tolerate larger hardware, and SCARA units excel on flat, indoor lines. Configuration choice should therefore follow task geometry rather than a one-size-fits-all rule (Fig. 11).

C. GRIPPERS

Grippers are a fundamental component of agricultural robots, and their design requires meticulous attention to detail and strict precision. The specifications of grippers, including size, force, torque, and stiffness, must be tailored to the specific requirements of each task. These considerations are critical for both single-arm and dual-arm agricultural robots. In dual-arm robots, using two grippers raises an additional question: *should the pair be heterogeneous or homogeneous?* As shown in Figs. 12 and 13, the answer usually follows the control strategy. In a bimanual control strategy, where the two arms perform different subtasks toward a common goal, heterogeneous end-effectors are typical. In a goal-coordinated strategy, where both arms perform the same task in parallel, homogeneous grippers are preferred. Across the 33 papers surveyed, only 10 adopted heterogeneous designs, indicating that role-divided tooling is still an open design space (Tables 2–3).

1) HETEROGENEOUS GRIPPERS FOR BIMANUAL CONTROL

The bimanual control strategy executes physically unrelated tasks simultaneously to achieve common objectives. Reference [57] developed a mobile dual prismatic-revolute arm agricultural robot to perform heterogeneous tasks, with one arm dedicated to soil digging and the other to soil-covering tasks. In [23], two functionally different grippers were used in dual-arm grape harvesting systems: grasping and cutting. References [41] and [72] proposed a bimanual control concept for tomato harvesting that integrated heterogeneous end-effectors. This system features two types of end-effectors: a cutting device for fruit separation and a vacuum cup for gripping the target tomato. These examples show a clear pattern: when the workflow requires role differentiation (e.g., hold + cut), heterogeneous grippers reduce cycle time by eliminating tool changes but at the cost of added mechanical complexity.

2) HOMOGENEOUS GRIPPERS FOR GOAL-COORDINATED CONTROL

The goal-coordinated strategy deploys identical grippers so that both arms can work in separate zones concurrently. [56] demonstrated a low-cost dual-arm sprayer, while [69] equipped each arm with three-finger grippers for eggplant harvesting. In [21], fruit is gripped below the stem and detached by rotation, removing the need for a dedicated cutter. Reference [59] designed a curved cut-clip finger specifically for grape stems, and [67] introduced a soft silicone vacuum gripper for gentle detachment. Homogeneous designs simplify maintenance and control but may limit flexibility when tasks demand asymmetric forces or distinct tool geometries.

Heterogeneous end-effectors shine when tasks require complementary roles (hold + cut, dig + cover soil), whereas homogeneous pairs excel in high-throughput, symmetric operations. Selecting between them thus hinges on whether task role diversity or parallel throughput is the primary performance driver.

D. SENSORS

Sensors underlie perception, planning, and feedback, but in a dual-arm setting their chief value is in synchronizing two independent manipulators. This section reviews the literature on sensor applications in dual-arm agricultural robots. Further, the following paragraphs explain how each sensor type can more directly improve coordinated bimanual manipulation.

LiDAR sensors are often used to improve operational mobility, such as terrain analysis [59], 3D mapping [68], and the acquisition of detailed spatial data [64], [70]. These sensors are sometimes used in advanced sensing applications. In particular, spraying pattern analysis systems using high-resolution LiDAR sensors have been developed to minimize spray drift [73], [74]. Likewise, LiDAR enables accurate crop condition assessment and resource allocation optimization in precision agriculture by leveraging high-resolution and high-precision spatial data capabilities.

Stereo RGB-D, multispectral, or infrared cameras are typically mounted on the wrist or arranged around the chassis to provide eye-in-hand or multi-view feedback. Reference [41] integrated a binocular stereo pair with a dual-arm tomato harvester so that one arm could hold foliage aside while the other located and cut the fruit, achieving 96% detection accuracy and an 87.5% harvest success rate. Reference [21] placed four Intel RealSense D435 RGB-D cameras at different heights on a dual-arm apple–pear robot. The upper arm harvested fruit above shoulder level while the lower arm handled lower branches, with the multi-camera layout minimizing blind spots behind leaves.

Several recent studies fuse LiDAR structure with camera semantics; [75] reported that combining the two modalities improves object delineation in cluttered scenes, a benefit that is particularly useful when both arms must reach into occluded canopy regions.

Infrared (IR) proximity sensors supply millimetre-scale range data during the final centimetres of approach, allowing the two wrists to decelerate together and avoid bruising the

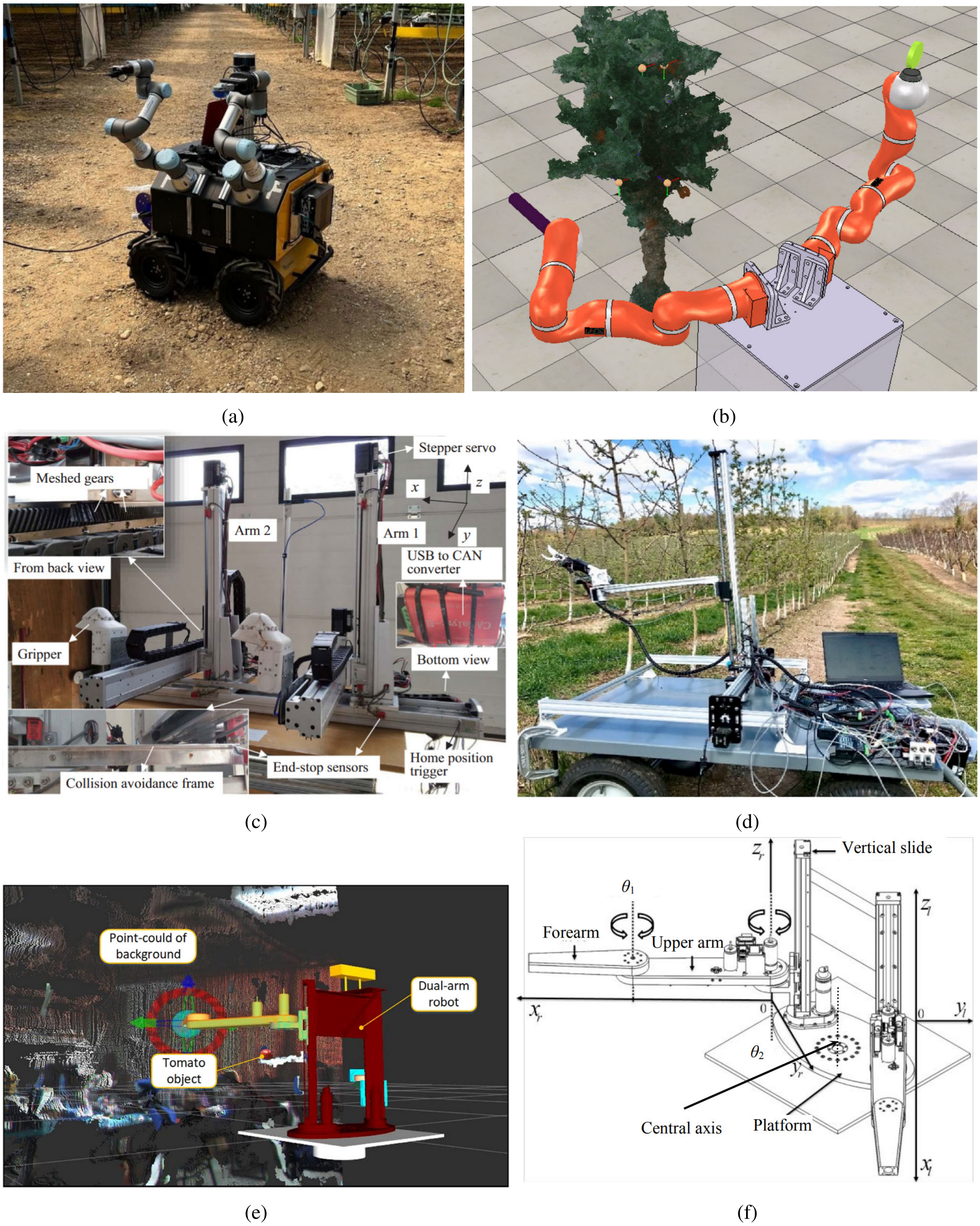


FIGURE 11. Various harvesting robots: anthropomorphic: (a) [27], (b) [22]; Cartesian: (c) [71], (d) [31]; SCARA: (e) [41] and (f) [72].

fruit. Inertial-measurement units (IMUs) on each arm record acceleration and angular velocity, filtering out base vibration and keeping the manipulators dynamically aligned as they work in parallel [71]. Finally, tactile arrays on the gripper surfaces measure normal force and detect the onset of slip; if one side loosens, the controller can immediately redistribute the load to its partner (see Section IV-C). In short, IR refines distance, IMUs stabilize motion, and tactile sensing closes the force loop, enabling gentle bimanual contact that pure vision or LiDAR alone cannot guarantee.

LiDAR provides both arms with a shared geometric map, cameras supply the semantic cues needed for fruit or branch recognition, and tactile or IR feedback closes the force loop. Used together, these sensors allow a dual-arm robot to carry

FIGURE 12. Heterogeneous end-effectors: using the bimanual control strategy [69].

FIGURE 13. Homogeneous end-effectors: using the goal-coordinated control strategy [23].

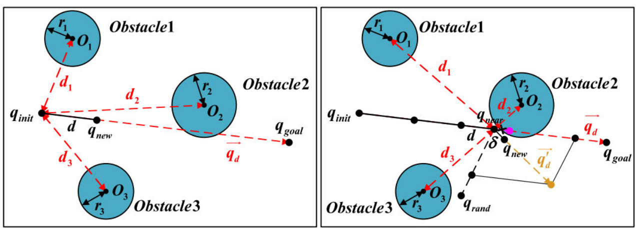


FIGURE 14. Determination of the dynamic step in the EDDS-bi-rapidly-exploring random trees algorithm [65].

out tightly coordinated agricultural tasks such as grape-cluster harvesting, selective branch pruning, and two-arm bin loading—applications that go beyond the reach of a single-arm pick-and-place system.

IV. CONTROLS

A. MOTION PLANNING

Motion planning generates collision-free trajectories that guide both arms to a goal while avoiding obstacles and, crucially, self-collision between links, which becomes a greater risk when two manipulators share a confined canopy. Recent dual-arm studies address this challenge in three complementary ways.

First, workspace-partition methods shrink the search space. Reference [69] divided the reachable volume into sub-zones and added approach-direction constraints; the narrower zones reduced the number of inverse-kinematic branches that had to be tested. Reference [63] applied a brainstorm optimizer based on a multi–traveling-salesman formulation to assign zones to each arm and defined bounding regions whose distance thresholds guaranteed that the arms could not collide, while also reducing the number of inverse-kinematic branches that had to be explored.

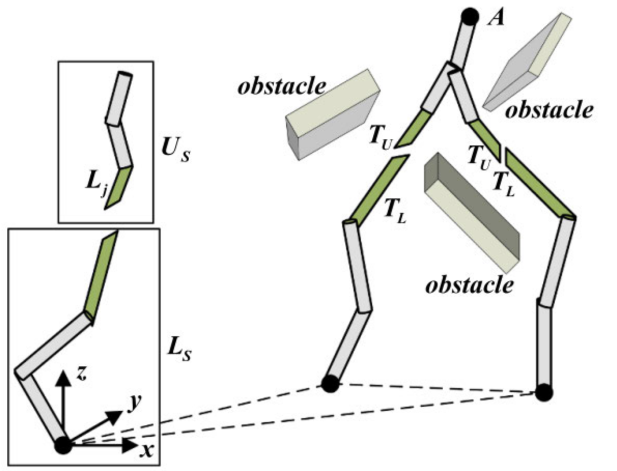


FIGURE 15. Two-step division-merge mechanism which proposed by [66].

Second, constraint-hierarchy planners keep all zones active but resolve priorities at each control step. Reference [40] stacked joint limits, self-collision margins, and moving-obstacle constraints in a quadratic-program cascade; the robot always found a feasible motion, though at a higher computation cost than the partition approach.

Third, adaptive-sampling planners improve exploration efficiency. As shown in Fig.14, [65] proposed the EDDS bi-RRT sampler, which rotates the tree-growth direction when a node encounters an obstacle and halves the step size if the search stagnates. Integrated into a 17-DoF humanoid, EDDS produced paths with roughly one-third fewer nodes than classic bi-RRT. The same group's division–merge inverse kinematics [66] solved each arm's sub-chain analytically and then merged the poses, eliminating iterative solvers from the inner loop (Fig.15).

Partition strategies excel when crop rows allow clear zone division; constraint hierarchies guarantee feasibility in clutter but increase computation time; adaptive sampling remains robust in unstructured orchards yet still depends on fast collision checking. Combining these approaches, for example by seeding EDDS with partition-based waypoints, is a promising step toward millisecond-level dual-arm replanning in the field.

B. HARVEST ORDERING

Low-level optimizations (e.g., operational speed) improve individual sub-task steps (e.g., approach, pick, and place), but the sequence in which two arms harvest multiple fruits often dominates overall cycle time. Recent dual-arm work frames harvest ordering as either a time-logic coordination problem or a task-sequence assignment problem.

As shown in Fig. 16, [20] modeled two practical constraints, laser scanner interference and overlapping suction lines, and encoded them as temporal rules. Alternating scan cycles removed sensor conflict, while a central vacuum

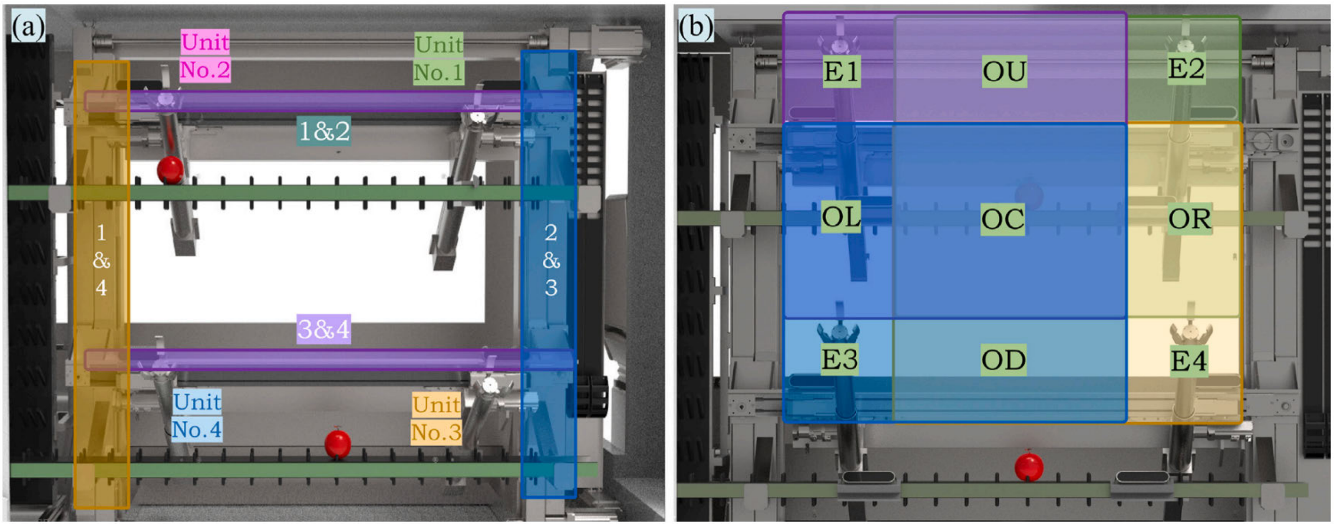


FIGURE 16. Schematic of the proposed multi-arm robot structure and workspace:(a) Illustration of shared strokes: the upper and lower arms access a common area formed by zones OL, OC, and OR through shared guides 1&4 and 2&3. Similarly, guides 1&2 and 3&4 provide access to a shared region comprising zones OU, OC, and OD for units 1 and 2, as well as 3 and 4, (b) Workspace zones: E1-E4 (exclusive areas) and OU, OL, OD, OR, OC (common areas). [20].

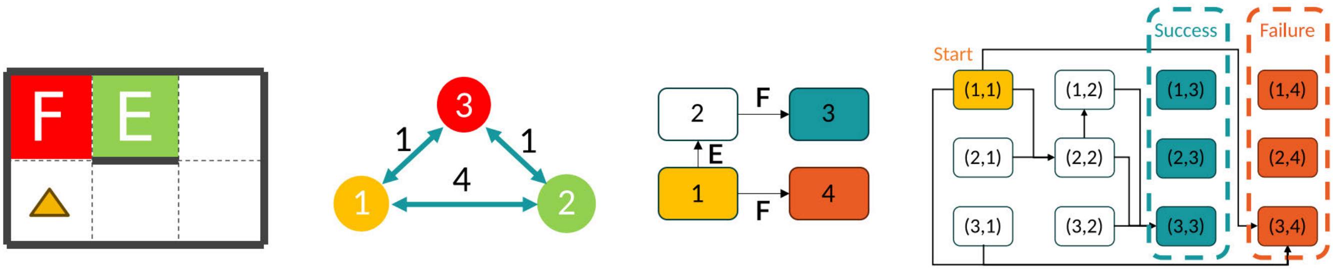


FIGURE 17. Fire extinguishing mechanism for harvest order: the red zone represents a fire area inaccessible without a fire extinguisher, and the green zone indicates the location of the extinguisher. A person, represented by a yellow triangle, begins at position "1," retrieves the extinguisher from "2," and proceeds to position "3" to extinguish the fire [67].

prevented the arms from working in the same zone simultaneously. Experiments showed a meaningful idle-time reduction compared with naïve simultaneous planning.

Reference [67] partitioned the workspace into fire-extinguisher–style regions and used a Markov decision-process reinforcement learning approach to assign the five motion phases (approach, extension, grasp, retraction, placement) to whichever arm could execute them without conflict (Fig. 17). Grouping phases that could run in parallel yielded a shorter completion time than nearest-fruit heuristics.

Time-logic rules are simple to implement but rely on hand-tuned constraints; sequence-learning methods adapt automatically yet require training data and add computation. A hybrid scheme that uses learning-based ordering seeded with time-logic rules could combine robustness with adaptability and is a promising direction for field trials.

C. TACTILE FEEDBACK CONTROL

Tactile sensors provide contact, friction, and pressure data that vision alone cannot, and thus allow two arms to adapt their forces when manipulating fragile or partly occluded produce [76] (Fig. 18). Although several of the papers cited below use a single manipulator, each technique scales naturally to coordinated bimanual work. For clarity, they are grouped into three strands with notes on the dual-arm implications in every case.

1) CONTACT-TRIGGERED MOTION RECONFIGURATION

Reference [77] placed taxels along a single arm and switched to an alternate joint trajectory as soon as contact was detected, letting the arm slide along an obstacle rather than stop. Reference [78] extended the idea to a redundant mobile base and showed that the same controller formalism accommodates multiple arms by adding self-collision distances to the task-priority stack; dual-arm prototypes therefore inherit millisecond-level reactions with minimal code changes.

2) PREDICTIVE FORCE CONTROL

Classical functional predictive control uses a linear contact model and replans at fixed intervals; it copes with simple pushes but underestimates force peaks on irregular fruit clusters. Reference [79] replaced that model with a neural network that predicts the next contact wrench from recent tactile images. Although demonstrated on one arm, the network runs per gripper and therefore transfers directly to a two-arm layout, where anticipating partner-induced disturbances is even more critical.

3) HUMAN-IN-THE-LOOP INTERFACES

When perception is uncertain, operators can inject expertise through gestures. Reference [80] combined a data glove with an OptiTrack tracker so that the operator could steer a tomato harvester in six degrees of freedom, while embedded tactile sensors streamed real-time contact forces to the controller. This intuitive tactile loop not only warns the operator of incipient slip but also enables the system to modulate grasp force against crop-specific bruise thresholds, providing a transferable safety layer for future dual-arm platforms. Because the interface addresses each wrist independently, it can teleoperate either arm alone or both arms cooperatively, making it a straightforward fallback for coordinated harvesters.

Contact-triggered replanners supply reflex-like reactions, predictive controllers forecast contact dynamics, and gesture overrides bring human insight. All three ingredients are portable to dual-arm robots, yet field deployment still hinges on tactile skins that survive dust, moisture, and temperature swings. Engineering outdoor-rated skins and fusing data-driven force prediction with human gestures are the most immediate steps toward reliable bimanual operation.

D. DUAL-ARM COORDINATION

Early coordinated control drew on the hybrid position–force framework. Reference [81] extended the single-arm formulation of [82] to two manipulators handling one constrained object, separating object motion from internal forces that do not affect the object pose. Their task Jacobian and hand-constraint matrix remain the standard way to specify grasp constraints in agricultural robots that must hold a branch while cutting.

Stability and dynamic coupling were analyzed soon after. Reference [83] introduced the generalized Jacobian to capture interaction between two arms, and [84] proposed object-level impedance control that regulates both motion and internal force. These results underpin recent impedance or admittance controllers that let one arm absorb fruit motion while the other completes a cut.

A survey by [2] showed how the above theories migrated from fixed-base platforms to mobile and humanoid systems. More recently, [23] demonstrated a grape-harvesting robot in which one arm stabilized a cluster and the second arm cut the stem.

Most agricultural prototypes still rely on quasi-static models and low-frequency force sensing, which limits cycle time and makes real-time internal-force regulation difficult in oscillating plants. High-bandwidth six-axis force–torque sensors and fast inverse-dynamics solvers are needed to move beyond "hold and cut" toward tasks such as cooperative carrying of fruit trays.

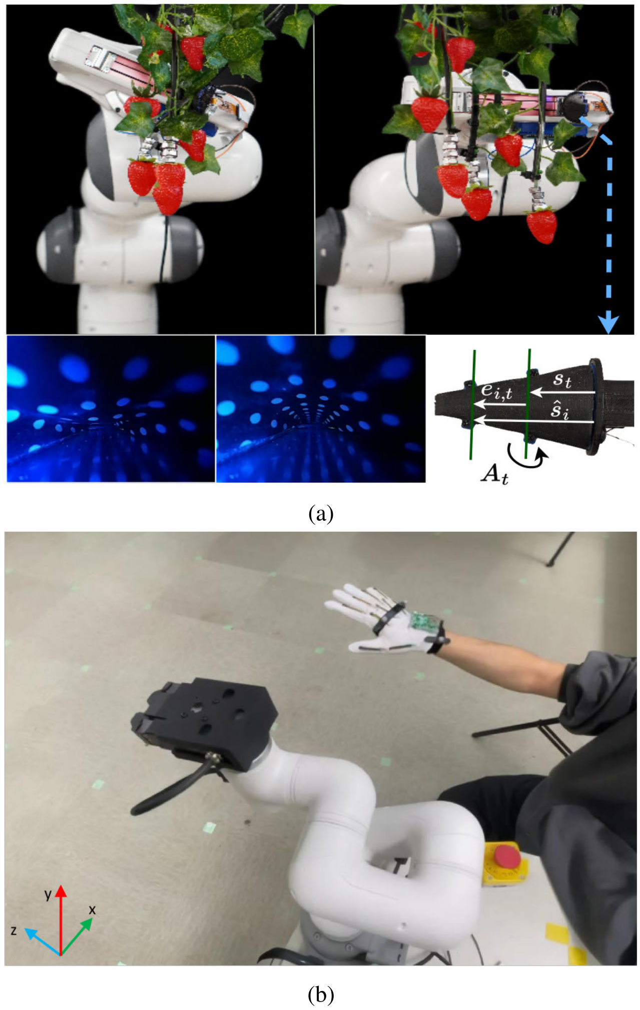


FIGURE 18. Application of tactile feedback control technology in agriculture: (a) [79] and (b) [80].

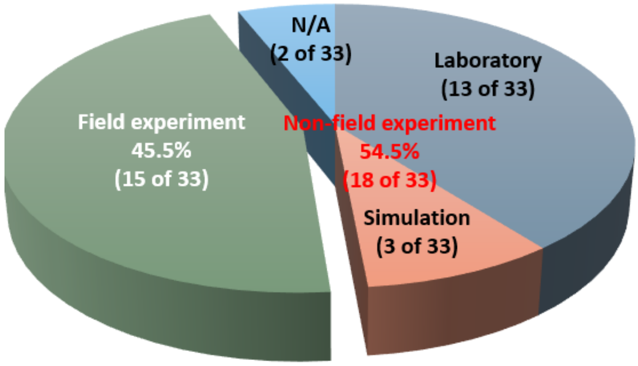
Future work should integrate object-level impedance with vision-based state estimation so that internal force targets adapt to branch stiffness. Large language model planners could issue high-level role assignments ("left arm stabilize, right arm cut") that are then realized by the Yoshikawa object-space controller. Combining these elements will push dual-arm robots from laboratory demos to field-ready, fully coordinated harvesters.

V. CHALLENGES AND FUTURE PERSPECTIVES

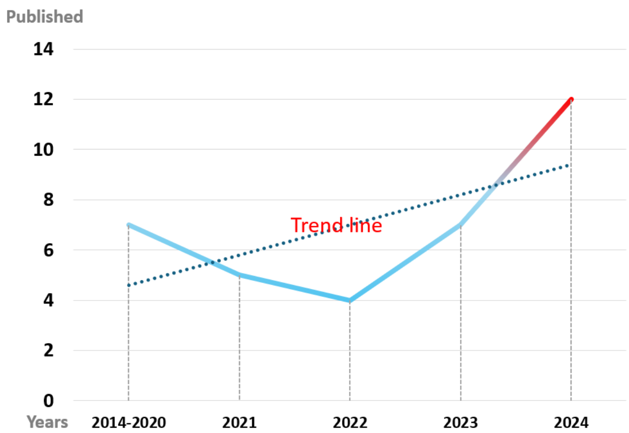
This section aims to establish meaningful insights based on the literature reviewed in the earlier sections. In this section, we discuss the remaining challenges for the defined RPs and respective sections, and the resulting future perspectives.

A. RP1 RELATED

The expansion from the agricultural robotics community to the field is considered important in terms of system design, verification, and deployment. This paper covers the latest



(a)



(b)

FIGURE 19. (a) Proportion chart of validation environment in the recently published dual-arm study, and (b) number of published dual-arm papers by year.

research on dual-arm manipulation in agriculture. However, development and discussion at the current research stage are limited and sparse. Fig.19(a) shows the proportion chart of the validation environments of the reviewed documents. 48.4% of the total was verified only in the laboratory or simulation (16 of 33). This percentage for the studies that presented identifiable validation environments increased to 51.6% (16 of 31). These levels are expected to decline as interest in dual-arm agricultural robots increases (see Fig.19(b)), but this alone is not enough for successful deployment in the field. Future studies should fully identify each task characteristic (e.g., task-performing method (Fig.4 and Fig.7), discussed in Section V-C) and constraints (e.g., occluded area restoration [37]) to cope with the uncertainty of the site.

In particular, the high-level perception and decision framework should be carefully tuned to suit the characteristics of the field and the object and integrated with the robot system. It is believed that perception frameworks such as recognizing object clusters [85], recognizing 3D morphology [86], classifying object characteristics [87], and alleviating environmental constraints [37] can guarantee robust performance.

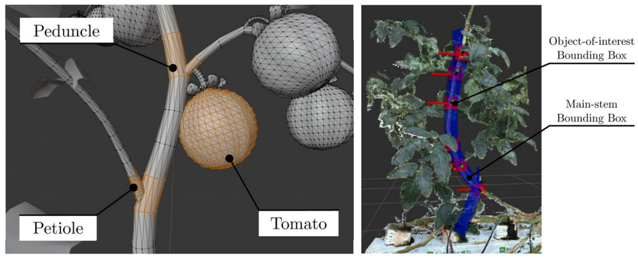


FIGURE 20. Task-relevant plant part searching framework for automating harvesting and de-leafing proposed by [88].

B. RP2

Although dual-arm robotic systems inherently possess structural advantages for coordinated bimanual operations, a review of the selected literature reveals that these advantages have not been fully exploited at the gripper level. Among the 33 reviewed articles, only 10 adopted a heterogeneous gripper configuration. More notably, out of the 11 studies explicitly addressing bimanual manipulation, 4 (36%) still employed homogeneous grippers, wherein both arms were equipped with identical end-effectors.

From these statistics, it is evident that current practices do not fully align with the functional requirements of bimanual operation (which entails role differentiation between the two manipulators). In the current robotic platform, the widespread use of homogeneous gripper configurations limits the potential for such role specialization (e.g., human analogues).

To address this gap, future research should pursue two complementary directions:

- **Functionally distinct gripper design** tailored to specific subtasks—e.g., grasping [89], cutting [90], or pushing [79]. Dedicated end-effectors make it possible to allocate clear roles to each arm.
- **Task-role hierarchical planners** that automatically assign those subtasks to the appropriate manipulator based on its gripper capabilities (see Fig. 20) [88].

C. RP3

Only 11 of the 33 papers we reviewed embedded explicit bimanual coordination; most still mirrored single-arm routines, so the two manipulators moved in parallel rather than in cooperation [20], [67]. Closing that gap requires progress on four tightly linked fronts.

1) TASK-SEMANTIC ROLE ALLOCATION

Geometry-centric planners decide where an end-effector should go but seldom encode *why* it moves. Effective harvesters must first decide which arm stabilizes a branch, which arm cuts, and when roles should swap as occlusions or weight distribution change (task methods in [93], [94]; crop characteristics in [95]). Fig. 21 sketches how a language-model planner could generate such high-level assignments. [91]

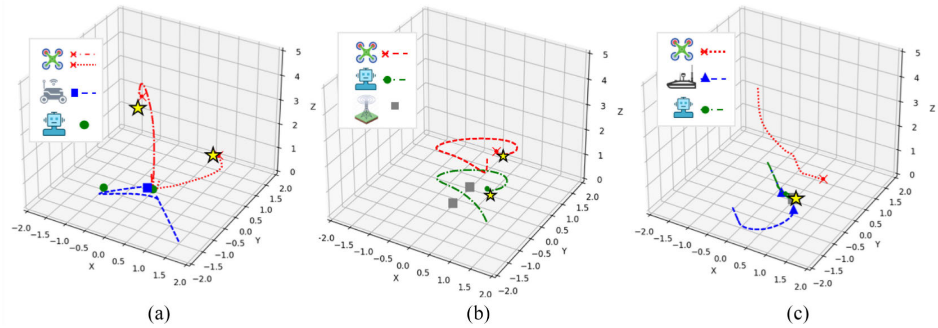


FIGURE 21. The large language model-powered cooperative control framework suitable for various robot capabilities, task characteristics: (a) logistics, (b) inspection, (c) search & rescue. Each case can be compared to the dual-arm's goal-coordinated operation (a, b) and bimanual operation (c) [91].

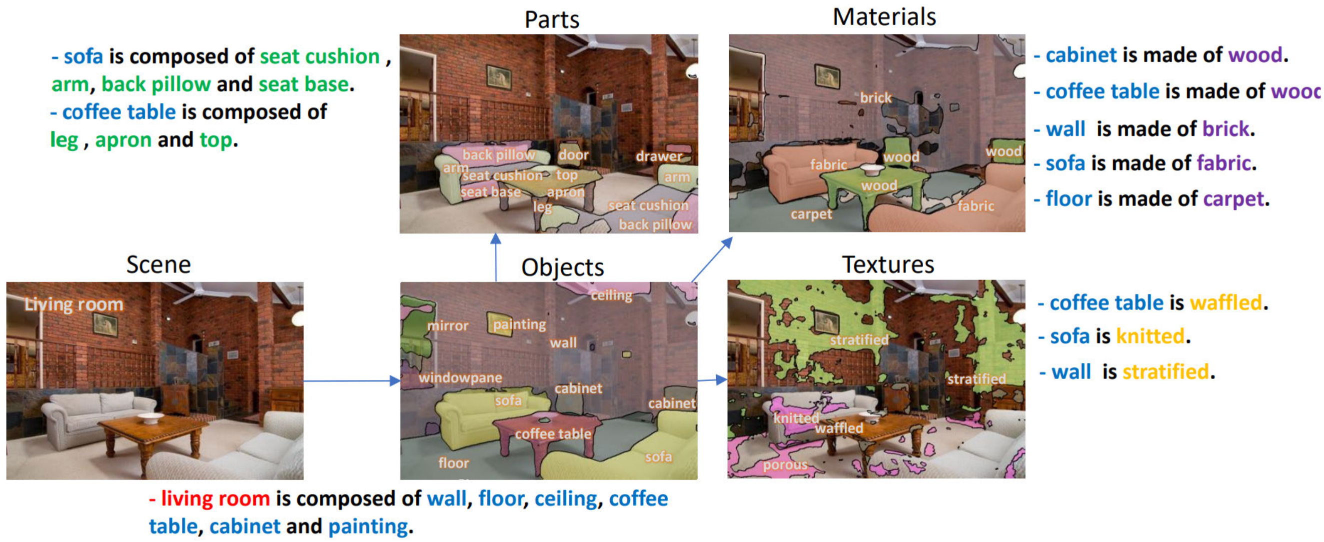


FIGURE 22. Situation awareness and scene understanding for future dual-arm harvesting robots [92].

2) OBJECT-LEVEL FORCE SHARING

Simply mirroring joint torques ignores asymmetric fruit mass and branch stiffness; one gripper then slips while the other carries the load. Extending Yoshikawa's hybrid position–force framework to crops remains an open challenge, because the controller must estimate internal forces in real time and adapt compliance to living-plant variability.

3) MULTIMODAL FEEDBACK FUSION

Vision localizes fruit, but only tactile skins and wrist force–torque sensors can feel slip or bruising. Few systems fuse these streams at the control rate. A pipeline that blends RGB-D perception with kilohertz tactile data would let each arm predict incipient slip and modulate grasp forces before damage occurs.

4) SHARED EVALUATION METRICS

Most studies report isolated success rates, making comparison difficult. Benchmarks such as cycle time per fruit cluster in dense canopy, root-mean-square internal-force error during cooperative cuts, and cumulative bruise ratio would allow the community to quantify gains and focus efforts where they are most needed.

Moving beyond duplicated single-arm loops will require controllers that assign semantic roles, balance forces at the object level, fuse visual and tactile feedback in real time, and report results against common field-oriented metrics. Addressing these intertwined challenges is the next step toward truly cooperative dual-arm field robots.

D. RP4

Dual-arm robots already boost productivity in pruning and harvesting, yet they still falter when tasks require real-time replanning in cluttered, changing orchards. Reaching full autonomy will therefore demand more than bounding-box detection; the system must understand the scene itself—how fruits, leaves, and stems depend on one another—and reason about those relationships before deciding how the two arms should cooperate [92], [96]. Fig. 22 illustrates this need for relational awareness.

Recent work in other fields has shown that images can be converted into scene graphs—language-like structures that list objects and label the spatial or functional ties between them [97]. In agriculture, robots must detect objects such as fruits, leaves, and stems from acquired scenes and infer their positions (e.g., up, down, left, right, near) and attributes (e.g., ripeness, rigidity, and color). Additionally, they must recognize dependent relationships, such as stem–leaf, stem–fruit, and leaf–fruit, to effectively plan tasks. Despite the current limitations of agricultural datasets, building scene-label datasets to pre-train models and fine-tune them for agricultural applications is necessary [98].

Future studies are expected to incorporate human expertise to improve the coordination of dual-arm robots and enable autonomous decision-making. Knowing that one leaf occludes a fruit would allow the planner to assign the left arm to clear foliage while the right arm cuts, or schedule actions to minimize branch oscillation and tool interference. Human know-how can also be folded in through language grounding: an operator might say ''stabilize the branch, then cut here,'' and the robot could translate that instruction into complementary roles for its two arms.

Vision alone cannot guarantee safe or reliable grasping once the robot leaves the lab. Tactile skins detect incipient slip, wrist force–torque sensors report how the load is shared, and fusing these signals with RGB-D data at control-loop speed enables the system to react before fruit damage occurs. Because grasp force can then be clamped just below crop-specific bruise limits—even as lighting, wind, or branch motion change—the same controller is far more likely to remain stable when the platform is deployed outdoors [99].

In short, the path to fully autonomous dual-arm field robots lies in agricultural scene-graph datasets, relation-aware planners that balance forces as well as geometry, and multimodal feedback loops that close the gap between global perception and local interaction.

VI. CONCLUSION

This article reviews dual-arm agricultural robotic systems as a solution to the limitations of single arm designs. The review shows that dual arm systems offer clear advantages in handling uncertainty, occlusion, and task complexity for representative agricultural operations (e.g., pruning, thinning, harvesting, transportation). In particular, simultaneous bimanual manipulation enables dexterous execution in scenarios that demand delicate handling of fragile produce or tightly coordinated motion.

A comprehensive review of dual arm platforms is also provided to inform future development. Base platforms, manipulators, grippers, and sensors shape mobility, task specificity, and execution strategies. Advanced sensing technologies such as computer vision, tactile sensors, and multimodal feedback are identified as key enablers of real time, accurate decision making. Beyond hardware, advanced control mechanisms including motion planning, tactile feedback, and multimodal integration are emphasized as essential for adaptive and precise operation in dynamic agricultural environments.

In summary, this article provides scalable and extensible insights into dual arm agricultural robotics from the perspectives of application, platform, and control. Addressing practical challenges including adaptability, robustness, and cost efficiency highlights constructive directions for future research.

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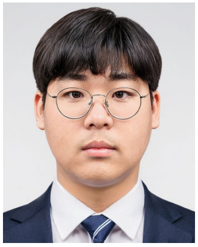

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