Advances in Research and Application of Harvesting Robots for Protected Agriculture in Japan and Implications for China (Postprint)

Authors: Huang Zichen, SUGIYAMA Saki

Date: 2023-02-17T00:00:00+00:00

Abstract

Intelligent equipment for protected agriculture constitutes an essential guarantee for stable, high-quality, and efficient production in protected agriculture. Japan' s intelligent harvesting equipment has accumulated nearly four decades of research and development experience, offering valuable inspiration and reference. This paper reviews the research and application progress of protected agriculture harvesting robots in Japan, analyzes the harvesting technologies of ten types of protected agriculture harvesting robots based on the integration of agricultural machinery and agronomy—including Solanaceae (tomato, eggplant, green pepper), Cucurbitaceae (cucumber, melon fruits), asparagus, and strawberry—and provides a detailed comparison of the design concepts, advantages, and disadvantages of successive generations of harvesting robots for several vegetables such as tomato and strawberry. It analyzes the scientific challenges confronting protected agriculture harvesting robots and their corresponding solutions, and summarizes future development trends along with their implications for China. This paper can serve as a reference for accelerating the smart, intelligent, and industrialized development of protected agriculture harvesting robots in China.

Full Text

Preamble

Research Progress and Enlightenment of Japanese Harvesting Robot in Facility Agriculture

HUANG Zichen1*, SUGIYAMA Saki2

1. Graduate School of Agriculture, Kyoto University, Kyoto, Japan
2. School of Literature, Zhejiang University, Hangzhou, Zhejiang, China

Abstract: Intelligent equipment for facility agriculture is essential for ensuring stable, high-quality, and efficient production. Japan has nearly four decades of research and development experience in intelligent harvesting equipment, offering valuable insights and reference points. This paper reviews the research progress and application of harvesting robots in Japanese facility agriculture, analyzing harvesting technologies for solanaceous crops (tomato, eggplant, green pepper), cucurbits (cucumber, melon), asparagus, and strawberry based on the integration of agricultural machinery and agronomy. The paper provides a detailed comparison of design concepts, advantages, and limitations across successive generations of tomato and strawberry harvesting robots. It examines the scientific challenges facing facility agriculture harvesting robots and their solutions, and summarizes future development trends and implications for China. This work can provide reference for accelerating the development of intelligent, smart, and industrialized harvesting robots in China' s facility agriculture.

Keywords: facility agriculture; Japan; harvesting robot; unmanned/less-manned system; fruit and vegetable identification; end effector

Citation format: HUANG Zichen, SUGIYAMA Saki. Research progress and enlightenment of Japanese harvesting robot in facility agriculture[J]. Smart Agriculture (Chinese and English), 2022, 4(2): 135-149.

HUANG Zichen, SUGIYAMA Saki. Research progress and enlightenment of Japanese harvesting robot in facility agriculture[J]. Smart Agriculture, 2022, 4(2): 135-149. (in Chinese with English abstract)

1 Introduction

Japan, located in East Asia, shares numerous similarities with China in crop cultivation, including large-scale field agriculture in Hokkaido, intensive rice paddies, facility agriculture, and even tropical agriculture. Facility agriculture equipment can be categorized into seedling pre-treatment equipment, seeding equipment, grafting equipment, transplanting equipment, environmental control equipment, crop adjustment and pollination equipment, plant protection equipment, and crop harvesting equipment. Facility agriculture intelligent harvesting equipment refers to automated and intelligent agricultural machinery that performs picking and harvesting operations under facility agriculture conditions, ensuring stable, high-quality production.

In recent years, Japan has introduced multiple funding and subsidy measures to promote the development of intelligent equipment for facility agriculture. These include the "Agricultural Modernization Fund," "Agricultural, Forestry, and Fisheries Facilities Fund," and "New Business Development Fund." Specifically, the Ministry of Agriculture, Forestry and Fisheries (MAFF, equivalent to China' s Ministry of Agriculture and Rural Affairs) offers the "Agricultural, Forestry, and Fisheries Facilities Fund" with financing terms of up to 20 years at an annual interest rate of approximately 0.20%, covering up to 80% of equipment costs [2]. In terms of subsidies, Japan has launched programs such as the

"Comprehensive Support Grant for Strengthening Agriculture and Developing Leaders" (Japanese: 強い農業・担い手づくり総合支援交付金), which provides subsidies of up to 50% for facility agriculture construction and intelligent equipment introduction [3]. For example, MAFF subsidies for installing Global Navigation Satellite System (GNSS) base stations and introducing automatic steering systems for agricultural tractors can cover up to 50% of costs [4]. In sales, a lease-to-own model is supported, where equipment is provided free of charge initially, with subsequent commissions determined by the workload of the agricultural equipment [3]. To promote industry-academia collaboration and advance the commercialization and product development of smart agriculture, the government has established the "Smart Agriculture New Service Creation Platform," comprising over 4,000 agricultural machinery manufacturers, leasing companies, insurance firms, and research institutions [5].

Japanese research on facility agriculture harvesting robots spans more than 40 years. This paper first introduces the development history of Japanese agricultural robots, detailing the research progress and underlying principles of facility agriculture robots. By integrating Japan' s current agricultural production status with advanced research technologies, the paper proposes development trends for next-generation facility agriculture robots, whose relevant achievements and applications can provide inspiration for China' s facility agriculture harvesting robot development.

2 Development History of Agricultural Robots

According to 2018 data from Japan' s Ministry of Agriculture, Forestry and Fisheries, the total planted area of facility agriculture in Japan is approximately 421,643 km^2, with about 67% dedicated to vegetables, 11% to fruit trees, and the remainder to rice seedling cultivation, flowers, and livestock [6]. Facility agriculture is dominated by greenhouses, with a small number of plant factories. Horticultural crops such as vegetables, fruit trees, and flowers account for approximately 40% of Japan' s total agricultural output. These products constitute a major expenditure in food consumption and require year-round stable supply through facility agriculture. Additionally, high-quality fruits can be sold as gifts, increasing the added value of horticultural crops and making them an important factor in attracting young people to agricultural production.

Facility agriculture robots and field agriculture robots both belong to the category of agricultural robots. The history of Japanese agricultural robot development can be summarized in four stages [7], as shown in [Figure 1: see original paper]. The Agri-robot I stage began in the 1980s, when mature industrial robots were adapted to perform automated operations in facility agriculture. The representative product of this stage was the grafting robot [8], which, after initial R&D, saw substantial corporate participation and product development in later stages [9]. The second stage, Agri-robot II, began around 1992, building on earlier research that introduced industrial robots for harvesting operations [10]. However, industrial robots could not adequately address the specific requirements of facility agriculture production processes, necessitating R&D tailored to specific operating conditions combined with agronomic requirements. During this stage, numerous harvesting robots were successfully developed and tested, replacing labor-intensive manual harvesting operations.

The third stage, Agri-robot III, emerged as agricultural robots entered a new phase. This stage saw the development of fruit and vegetable grading systems, exemplified by the citrus sorting and grading system developed by Shibuya Seiko and Omi Measuring Instruments, which could individually grade and select fruits and vegetables based on appearance and sugar content. The fourth stage, Agri-robot IV, began around 2013. With the development of high-precision satellite navigation systems, Artificial Intelligence (AI), Internet of Things (IoT), and Information and Communication Technology (ICT), smart agriculture began to be gradually promoted and applied. Real-Time Kinematic (RTK) technology combined with GNSS achieves positioning accuracy of 2 cm, enabling agricultural robots to perform high-precision field operations when adequate satellite signals are available. Major agricultural machinery companies such as Kubota Corporation [13], Yanmar Holdings [14], and Iseki Agricultural Machinery [15] have developed and marketed unmanned or less-manned intelligent agricultural equipment for field agriculture robots. IoT and ICT enable farmers to monitor field agricultural robot operations remotely. For example, Yanmar Holdings' Smart Assist system [16] monitors field agricultural robot operations and improves efficiency by transmitting operational information from agricultural machinery equipped with Global Positioning System (GPS) antennas and communication terminals, achieving visualization of agricultural production management through location information and data analysis. Farmers can monitor robot operations and crop conditions via mobile terminals.

Currently, Japan' s agricultural robots in the first, third, and fourth stages have automated and intelligent equipment deployed in agricultural production. However, harvesting robots in the second stage have not been widely promoted. With the successful commercialization of field agriculture robots, an increasing number of Japanese researchers and enterprises have prioritized facility agriculture harvesting robots as a key area for R&D and commercialization.

[Figure 1: see original paper] The development history of Japanese agricultural robots

According to 2018 data from Japan's Ministry of Agriculture, Forestry and Fisheries [17] (Table 1), the top ten fruits and vegetables by greenhouse cultivation area in Japan are tomato, spinach, strawberry, cucumber, melon, watermelon, green onion, cherry tomato, asparagus, and eggplant. Due to standardized cultivation and minimal individual variation, spinach and green onion are suitable for mechanized harvesting products. For example, Kubota Corporation and Yanmar Holdings have launched spinach harvester SPH400 [18] and green onion harvester HL10 [19], respectively. This paper categorizes and introduces fruit and vegetable robots, with tomato, cherry tomato, eggplant, and green pepper grouped together as solanaceous crops with similar cultivation patterns; cucumber, melon, and watermelon grouped as cucurbits; and asparagus and strawberry selected for analysis due to their significant cultivation area.

3 Harvesting Robot Technology for Major Facility-Grown Crops

3.1 Solanaceous Crop Harvesting Robots

3.1.1 Tomato Harvesting Robots Japanese tomatoes are cultivated in two main patterns: ridge cultivation and elevated cultivation. The former is often preferred by ordinary farmers due to lower costs, while the latter, with its higher degree of standardization, is more conducive to intelligent agricultural harvesting equipment operations. Major research teams for tomato harvesting robots are distributed across Kyoto University, Tokyo University, Ritsumeikan University, and Panasonic Corporation.

Tomato harvesting robots primarily consist of five modules: autonomous mobile system, robotic arm, end effector, image processing, and harvesting decision-making [20]. The mobile system design depends on the greenhouse operating environment, with three main types: wheeled [21], tracked [22], and rail-based [23]. [Figure 2: see original paper] shows a typical tomato cultivation greenhouse with a rail system. Since tomatoes are planted on elevated seedbeds, harvesting tomatoes at height requires mobile work platforms and rails to ensure safe and stable harvesting operations.

Differences in robotic arms mainly involve the Degree of Freedom (DOF). Higher DOF enables more complex harvesting postures. Takuya et al. [20] proposed a modular design system for tomato harvesting robots based on the Robot Operating System (ROS), developing different operational modes. Through comparative testing of various harvesting sub-modules, harvesting a tomato using a 3-DOF manipulator took 29 seconds, 14 seconds faster than a 6-DOF manipulator. Most research has adopted mature industrial robotic arms to shorten development cycles [21,22].

Tomatoes are thin-skinned and fragile, requiring robotic arms and end effectors to avoid obstacles such as leaves, stems, and unripe tomatoes during harvesting. Common end effectors include suction, shear, and rotary types. The suction type consists of a suction mechanism and cutting mechanism that can separate target fruits from tomato clusters, with the cutting mechanism severing the peduncle before the tomato enters a tray through the suction channel [24,25]. The shear type places a cutting mechanism parallel above the gripping mechanism, cutting the fruit stem while gripping it [26,27]. Cherry tomatoes are often harvested in clusters due to high fruit density per plant, making shear-type end effectors suitable for both regular and cherry tomato harvesting. The rotary-type end effector grasps the tomato and rotates it, separating the fruit from the peduncle through pulling. This end effector takes approximately 23 seconds per tomato, with half the time spent in the pulling process [21]. The three main end effector types are shown in Table 2 .

In image processing and harvesting decision-making, early computer processing limitations prevented adequate consideration of obstacles. In the 1980s, Kyoto University developed Japan' s first tomato harvesting robot [10], which obtained 3D position information by moving the camera for two image inputs to complete stereo photography. This research validated the feasibility of tomato harvesting robots and revealed the technical principles of tomato localization based on color information. Kondo et al. [26] collaboratively developed a cherry tomato cluster harvesting robot that identified cherry tomatoes by recognizing and extracting spectral reflectance in the visible light range, using binocular vision technology to determine picking points for each cluster. After each harvest, the robot updated the position of the next target fruit based on newly acquired images and robotic hand position, achieving a 70% success rate with this vision feedback control method.

Ikeda et al. [28] improved image processing algorithms by proposing a method based on tomato morphological features and image segmentation technology to provide obstacle-avoidance routes for robotic arms. Using low-cost commercial products is a requirement for harvesting robot commercialization. While early research used expensive hyperspectral sensors to distinguish tomatoes from stems and leaves, recent studies have focused on using low-cost color cameras or RGBD (Red, Green, Blue, and Depth) cameras to provide point cloud maps for tomato harvesting. RGBD cameras provide not only traditional color images but also calibrated depth images where pixel values represent the distance from the camera to the object, enabling acquisition of fruit shape, size, and position information while helping vision systems distinguish fruits from backgrounds [29].

Fujinaga et al. [30] used point cloud maps from RGBD cameras to successfully differentiate stems, peduncles, unripe tomatoes, and ripe tomatoes, achieving approximately 60% recognition success with a recognition time of 1.0 ± 0.2 seconds in pre-experiments. Yoshida et al. [31] used point cloud maps to identify tomatoes and detect cutting points on tomato peduncles in farm settings, reducing single picking point recognition time to about 0.4 seconds and increasing harvesting success rate to over 90% [32]. Additionally, Yoshida et al. [22,31] reconstructed tomato volumetric pixels by building segmentation voxel layers to identify ripe tomatoes and harvesting cutting points. Tokyo University developed a dual-arm tomato harvesting robot based on dual RGBD cameras [33], with a head-mounted RGBD camera providing approximate tomato location information and arm-mounted RGBD cameras determining spatial position information of multiple tomatoes from close range and multiple angles to identify correct peduncle cutting coordinates and sequence.

However, RGBD camera applications currently face interference from strong natural light in greenhouses, though this limitation is expected to diminish with technological advancement. Harvesting robot vision systems can also generate growth state distribution maps for unripe tomatoes [35] while operating, quantifying spatial distribution of tomatoes in greenhouses to guide future harvesting operations and achieve multi-functional capabilities.

Since 2013, Japan has annually hosted the Tomato Harvesting Robot Competition [36-38], rotating among Kyushu Institute of Technology, West Japan Institute of Technology, and Nagasaki Prefectural University. In the competition, robots must autonomously move to harvesting points and complete three phases: Phase 1 involves approaching a tomato fruit (without harvesting); Phase 2 requires harvesting a single tomato from a cluster; and Phase 3 involves harvesting tomatoes from actual plants. The total competition time, including movement within each phase, is limited to 10 minutes [21]. This competition not only incentivizes research teams to invest in tomato harvesting robots but also stimulates student interest in agricultural robots and validates robot performance under near-natural conditions.

These harvesting robot developments often utilize the Robot Operating System and commercial robotic arms [39] with custom-designed end effectors. Panasonic Corporation [23] has developed and commercially sold a tomato picking robot ([Figure 3: see original paper]) priced at approximately 300,000 RMB, with a picking speed of about 6 seconds per tomato. Although 3 seconds slower than manual picking, its vision and lighting systems enable 24-hour operation, compensating for lower efficiency. The vision system can also assess maturity and external quality based on tomato color. With total annual working hours of approximately 160,000 hours in a single greenhouse, of which 35,000-60,000 hours are spent on picking, this robot can reduce manual labor by about 20% and has been successfully deployed in multiple greenhouses.

Due to large planting areas and long harvesting periods, tomatoes have attracted numerous research institutions and led to commercial products. University research primarily focuses on using new consumer-grade depth cameras, such as Intel Realsense series, to identify harvesting points in tomato clusters by establishing spatial models. Enterprises focus on optimizing the five modules of harvesting robots to reduce costs while maintaining efficiency, making them more affordable for farmers.

3.1.2 Eggplant Harvesting Robots Annual labor for eggplant production in a single Japanese greenhouse totals approximately 200 hours, with harvesting accounting for about 40% of this time [40]. To ensure taste quality, Japanese eggplant harvesting uses size as the standard, with length generally not exceeding 13 cm. Eggplant harvesting robots can make intelligent harvesting decisions based on growth patterns, market trends, and variety characteristics. Hayashi et al. [40] developed an eggplant harvesting robot prototype using inclined planting patterns to facilitate easier differentiation from stems and leaves. To achieve damage-free harvesting, the team also designed a soft end effector [41] that can adjust grip shape according to eggplant size while maintaining a gripping force of approximately 0.7 N. After grasping, the peduncle is cut by a shearing mechanism at the arm tip, achieving a 62.5% success rate, with failures primarily due to vision system limitations.

Eggplant cultivation area is only 1/7 that of tomatoes. Due to similar elevated cultivation patterns with tomatoes and green peppers, recent Japanese harvesting robots have potential for multi-crop harvesting, following a similar development trend to tomato harvesting robots.

3.1.3 Green Pepper Harvesting Robots The green pepper harvesting season lasts approximately 9 months annually, requiring vertical space operations in greenhouses that impose significant physical strain on farmers through repeated squatting and standing. AGRIST Co., Ltd. has launched two green pepper picking robots based on RGBD cameras and AI technology [42]. The first model, released in 2021, weighs 16 kg and harvests about 40 kg of green peppers daily. The initial system price is approximately 100,000 RMB ([Figure 4: see original paper]), with additional fees collected as 10% of monthly sales revenue. The robot moves along rails suspended between ridges ([FIGURE:4(a)]) and uses deep convolutional neural networks to differentiate green peppers from stems and leaves ([FIGURE:4(b)]), achieving a harvesting efficiency of 2 fruits per minute. Harvested peppers are temporarily stored beneath the robot ([FIGURE:4(c)]) and delivered to storage trays when positioned above preset containers ([FIGURE:4(d)]). The 2022 model added IoT technology modules supporting 5G communication, enabling remote control, night harvesting, pest detection, and allowing farmers to tag green peppers via applications to improve deep neural network recognition accuracy.

Japanese green pepper harvesting robots, represented by startup AGRIST Co., Ltd., achieve a daily harvest of 40 kg and can operate 24 hours year-round. Through commercial deployment in actual production, the robots are continuously optimized. Additionally, their large vertical operating range provides potential for harvesting other vertically distributed vegetables.

3.2 Cucurbit Harvesting Robots

3.2.1 Cucumber Harvesting Robots Cucumber is the most widely cultivated cucurbit in Japan. Due to similar coloration between cucumbers and stems/leaves, visual identification is a major R&D challenge. Cucumber harvesting robot design represents a typical case of agricultural machinery-agronomy integration. Cucumbers are priced by quantity, command high prices, and grow rapidly, requiring daily harvesting to maintain commercial value.

Researchers developed a cucumber harvesting robot consisting of a vision sensor, 6-DOF robotic arm, end effector, and mobile device. To simplify robot control, a cultivation method called "slope cultivation" was designed to facilitate fruit-leaf separation [43,44]. This method tilts the traditional cultivation pattern and presses stems and leaves with support rods ([Figure 5: see original paper]), with experiments showing a 65° trellis angle is optimal for robot operation. Based on machinery-agronomy integration, Shimane University' s Fujiura et al. [45] developed a vision system consisting of three mirror-reflection sensors, a 3D vision sensor, and a computer. During robot movement, cucumbers can be detected via photoelectric sensors without 3D vision scanning. The mirror-reflection sensor enables preliminary rapid detection, after which the 3D vision sensor scans only the near field for harvesting recognition. The left side of [Figure 5: see original paper] illustrates the working principle: an infrared laser beam (5 mW power, 830 nm wavelength) from a laser diode is split into three beams using semi-transparent mirrors in the middle and lower sections and a total reflection mirror in the upper section. Reflected light from the crop surface is focused by lenses onto photodiodes in each sensor, with signals sent to the computer via analog-to-digital converters. To distinguish reflected light from sunlight, the laser beam is emitted at 10 kHz frequency. When the beam passes through a cucumber' s center, specular reflection from the cucumber skin produces an amplified photodiode output signal, enabling detection of cucumber waveforms and approximate location determination. The robot then uses 3D vision sensors to obtain 3D image data. During processing, cucumber pixels are extracted using 3D images and photoelectric voltage, with thinner upper portions identified as peduncles and other objects classified as stems, leaves, or poles.

Recent consumer-grade RGBD cameras or Lidar can acquire depth images at low cost [46], making image acquisition systems more lightweight and efficient when combined with Fujiura et al.' s recognition algorithms.

The cucumber harvesting robot system exemplifies machinery-agronomy integration, using slope cultivation to distribute cucumbers and stems/leaves in different spaces, mirror-reflection sensors for preliminary rapid detection, and 3D images to determine harvesting cutting points.

3.2.2 Melon Harvesting Robots For large cucurbits like melons and watermelons, the end effector requires at least 10 kg load capacity, resulting in limited research on harvesting robots with more focus on harvesting end effectors. Hokkaido University' s Roshanianfard [47] developed a manipulator for harvesting melons, watermelons, and pumpkins, evaluating eight parameters including workspace, system resolution, harvestable area, accuracy, repeatability, harvest success rate, cycle time, and damage rate. Results showed 92% grasping success and 0% damage rate, with final system harvest area and length of 0.286 m^2 and 0.8 m, respectively, meeting melon harvesting requirements. However, as the manipulator requires tractor rear-mounting, its application is limited in greenhouses.

3.3 Asparagus Harvesting Robots

As a high-profit vegetable, asparagus production has been expanding in Japan, but harvesting requires prolonged bending labor with high labor costs. Asparagus grows approximately 10 cm daily and requires daily harvesting. Since asparagus and its parent plant are both green, harvesting requires size identification, typically using 2D laser radar for visual identification. Sakai et al. [48] developed asparagus harvesting robots based on laser radar and robotic arms, achieving 75% detection success with 2-second laser scanning and 2.4-second harvesting time [49]. Funami et al. [50] improved harvesting decision algorithms to enable arms to bypass non-target asparagus, achieving over 95% decision success when non-target asparagus density is below 25 plants/m^2. As laser radar technology is color-independent, it has potential application for white asparagus.

Inaho Co., Ltd. launched a compact asparagus harvesting robot in 2022 ([Figure 6: see original paper]) [51], using customized medical robotic arms, tracked self-propelled systems, and AI identification for harvestable asparagus, with harvesting efficiency of about 12 seconds per spear. Its IoT module supports mobile phone remote control, and the lease-to-own sales model reduces initial costs with fees based on harvesting volume.

3.4 Strawberry Harvesting Robots

Strawberry cultivation involves longer working hours compared to other fruits and vegetables, with a harvesting period of about 5 months (total harvesting time approximately 5,000 h/ha) [52]. In Japan, strawberries are relatively expensive, with individual berries costing about 8 RMB in supermarkets, making farmers more receptive to equipment investment for high-quality production [53]. A questionnaire survey [54] revealed that 69.4% of farmers prefer human-robot collaborative operation (robots harvest most strawberries while humans handle difficult cases), while only 16.8% want fully robotic harvesting. About 80% of farmers want harvesting robot prices under $30,000 (approximately 200,000 RMB). Kyoto University’ s Kondo team [53-56] has developed multiple strawberry harvesting robots with different operational methods.

Table 3 Comparison of Four Generations of Strawberry Harvesting Robots

Generation	Robotic Hand Harvesting Method	End Effector	Advantages	Disadvantages
1st [54]	Bottom-up suction	Suction-type end effector	High success rate	Cannot identify unripe strawberries
2nd [55]	Top-down grasping	Gripping mechanism	High success rate	Mis-harvests adjacent unripe strawberries

Generation	Robotic Hand Harvesting Method	End Effector	Advantages	Disadvantages
3rd [53]	Individual strawberry harvesting and grading	Suction head with dual grippers	High-density, efficient	Large, bulky
4th [56]	Systematic solution	Integrated system	All-day operation, quality grading	Large, bulky, expensive

The first-generation strawberry harvesting robot was developed for elevated strawberries [54,57,58], consisting of a 5-DOF robotic arm, pneumatic end effector, CCD camera vision sensor, and four-wheel mobile device. Strawberries hang from planting beds suspended from greenhouse ceilings, eliminating obstacle avoidance needs. The end effector uses vacuum suction for bottom-up picking. After peduncle cutting, fruits remain in the suction head and are transported to trays by the robotic arm. Limit switches on the suction head enable stopping without external depth sensors. While achieving 100% experimental success, strong suction sometimes harvested adjacent unripe fruits. From a machinery-agronomy perspective, peduncle length control could reduce unripe fruit harvesting.

The second-generation robot targeted ridge-cultivated strawberries [59], moving above ridges for harvesting. While achieving near-100% harvesting rates like the first generation, it also harvested unripe strawberries. The third-generation robot addressed this with a redesigned end effector, machine vision system, and mobile device for 24-hour operation [53]. The end effector has three DOF, with a suction head connected to an air cylinder and two gripping mechanisms that can grasp fruits and rotate-cut peduncles according to inclination. The vision system comprises three identical color cameras: side cameras calculate 3D fruit positions while the center camera identifies fruit and peduncle details. The 3-DOF robotic arm can also place harvested strawberries into corresponding tray positions [52]. Prototype tests showed 38% success, with low rates attributed to stereo matching errors and fruit/peduncle identification errors. The robot also embedded a strawberry grading system for direct post-harvest quality assessment. After algorithm improvements, three months of experiments in real strawberry greenhouses harvested 667 out of 879 strawberries, achieving 76% success [60].

The fourth-generation robot improved upon the third generation, jointly developed by Kyoto University, the National Agriculture and Food Research Organization (similar to the Chinese Academy of Agricultural Sciences), and Shibuya Seiko Co., targeting all strawberries in standard greenhouses for all-weather harvesting. To increase yield, Hayashi et al. [61] designed a high-density strawberry cultivation greenhouse with high space utilization. The movable bench-based high-density planting system measures 16.0 m ×9.2 m, consisting of 2 longitudinal conveying units, 2 lateral conveying units, 2 nutrient supply units, 1 pesticide sprayer, 62 planting benches, and 1 control unit. The longitudinal mechanism combines rod rotation and sliding motion, with a 67-second cycle time for benches to return to initial positions. This method achieves planting density of 16.0-20.0 plants/m^{2}, approximately 2-2.5 times conventional methods. Harvesting tests in a 48 m ×6 m high-density greenhouse showed harvesting success rates of 54.9% and work efficiency of 102.5 m/h [62]. After algorithm improvements, success rates reached 58.6% at night and 62.4% during daytime [63].

Hayashi analyzed strawberry harvesting failure cases [52], primarily caused by image recognition failures due to overlapping unripe strawberries or stems/leaves covering ripe fruits. Harvesting success relates to flower/fruit thinning methods; natural cluster growth easily causes overlap, affecting vision system peduncle localization. Considering various strawberry cultivation patterns have harvesting robot development cases, subsequent R&D focuses on algorithmic improvements to enhance ripe strawberry recognition, such as deep neural network-based image processing algorithms that significantly improve recognition success in complex environments, surpassing traditional systems by identifying ripe strawberries even when occluded [64]. For multi-functionality, Tsubota et al. [65] integrated RGBD cameras with near-infrared spectrometers on harvesting robots to measure sugar content during harvesting for direct post-harvest grading.

The fourth-generation strawberry harvesting robot system, combined with movable benches for high-density cultivation, has been sold by Shibuya Seiko Co. since 2014 at approximately 300,000 RMB [66]. High planting density enables land savings and high-yield production, with 8,000 strawberry plants cultivable in a 1,000 m^{2} greenhouse. The company also optimized post-harvest handling, enabling precise strawberry placement in tray cells and automatic tray replacement. However, the system' s drawbacks include bulky, expensive equipment [67] and sluggish sales since launch [68]. The design concept of one robot handling entire high-density greenhouse harvesting requires sufficient load capacity for storing harvested strawberries, resulting in bulky equipment with movement speed of only 0.19 m/s. Traditional harvesting robots' large size and heavy load requirements create high costs and mobility challenges in greenhouses, with industrial robotic arms representing a significant cost proportion in some systems.

Recently, Huang et al. [69,70] proposed a new operational mode: distributed collaborative robot systems ([Figure 7: see original paper]). This system mimics field agricultural robot operation, with multiple harvesting robots working simultaneously in one greenhouse. Since individual robots don' t handle entire greenhouse operations, they can be smaller and periodically deposit harvested strawberries in large trays at ridge ends. Implementation requires centimeterlevel indoor positioning systems providing real-time location information for multiple robots, currently in early R&D stages. Developed sound-based systems provide 1.58° direction measurement accuracy [69,71], while wireless modules provide approximately 5 cm positioning accuracy [67].

3.5 Scientific Challenges and Solutions

Over 40 years, Japan has developed facility agriculture harvesting robots for various typical fruits and vegetables. Scientific challenges and solutions in typical harvesting robot design primarily focus on two aspects:

(1) Fruit and vegetable identification. Vision systems must determine harvesting points, but stems, leaves, and non-target fruits interfere with target harvesting cut points. The persistent solution is slope cultivation patterns that simplify operating environments through machinery-agronomy integration. The main factor limiting harvesting success is fruit/vegetable overlap and occlusion. For strawberry harvesting robots, machinery-agronomy integration can use flower/fruit thinning or chemical growth regulators to control stem length, vertically separating ripe and unripe strawberries. Vision algorithm improvements can address occlusion through deep convolutional neural networks or RGBD camera point cloud technology to reconstruct spatial information for correct harvesting point determination.

(2) End effectors. Rigid components may damage fragile fruit/vegetable surfaces during harvesting. End effector design must consider both versatility and specific shape/weight parameters for particular crops, requiring flexible end effectors. Numerous solutions exist beyond those mentioned for tomato harvesting robots, including soft robotic hands [41], pressure sensors for force feedback [47], and biomimetic mechanical hands [72].

4 Future Trends and Implications

4.1 Future Development Trends

Over the past decade, reduced hardware costs, emerging technologies, and various entrepreneurship support programs have ushered in a new peak in Japanese facility harvesting robot development. Current Japanese harvesting robot development concepts emphasize: simplifying operating environments through machinery-agronomy integration, using widely commercialized vision systems to reduce costs, and employing AI technologies represented by deep neural networks as accelerators for joint enterprise R&D targeting consumer markets. Harvesting robot development shows the following trends:

(1) New operational modes. Addressing bottlenecks, small and lightweight harvesting robots represent an important trend and characteristic of recent Japanese startup developments. Internationally, numerous small, lightweight harvesting robots with excellent performance and commercial potential have emerged. For example, China Agricultural University’ s Yu et al. [73] developed a ridge-cultivated strawberry harvesting robot with deep learning network recognition success reaching 94%. Belgium’ s KU Leuven and a startup collaborated on a lightweight strawberry picking robot [74] using Ultra-Wide Band (UWB) modules with 10 cm precision for autonomous greenhouse movement. Norway’ s Life Sciences University’ s Xiong et al. [75] developed an elevated strawberry harvesting robot weighing 120 kg with over 60% harvesting success. For improved efficiency, dual-arm simultaneous harvesting is also a development trend. Additionally, drone technology shows potential for indoor fruit/vegetable harvesting [76]. Compared to traditional ground-based platforms, drones offer faster movement and vertical operation advantages. Israel’ s Tevel Aerobotics Technologies mounted robotic arms on quadcopters for fruit harvesting, though drone platforms impose strict weight requirements on end effectors [77], and wind fields limit application scope.

(2) New technology applications. AI algorithms have developed rapidly in recent years, significantly impacting harvesting robots due to their speed and performance surpassing traditional fruit/vegetable recognition systems [64]. Fusion algorithms combining point clouds and deep learning can reduce fruit/vegetable recognition time to milliseconds for harvesting decision-making [78,79]. Point cloud and SLAM (Simultaneous Localization and Mapping) fusion technology can reconstruct spatial distribution of fruits/vegetables through multi-angle point cloud mapping, determining appropriate harvesting sequence and picking points even with complex crop overlap [80]. With improved chip computing power, large-volume point cloud data technology is no longer limited by computing constraints, helping computers understand spatial relationships of harvesting targets [81]. In materials, carbon fiber composites can reduce weight while maintaining strength for miniaturization. In end effectors, biomimetic and soft robotics technologies can significantly improve performance [82]. With IoT and communication technology development, mobile phone control and monitoring make harvesting robots more convenient to use.

(3) Multi-functionality. Multi-functionality is another important trend, including multi-crop use and multi-function integration. Multi-crop use enables single robots to harvest multiple fruit/vegetable types for year-round operation. Multi-function integration allows single robots to complete harvesting, grading, packaging, and other functions. For night operation, additional light sources are needed for identification, such as UV light for fruit/vegetable recognition and quality detection [83]. Adding UV light sources to existing systems enables fluorescence-based quality detection systems for grading [83] or maturity judgment [84] during harvesting.

4.2 Implications for China

Japanese harvesting robot R&D peaked in the 1990s, emphasizing machinery-agronomy integration to simplify operating environments. Recent R&D focuses on research institution-enterprise collaboration, yet many achievements haven' t achieved successful commercialization. Despite support from agricultural cooperative financing, government subsidies, and low-interest bank loans, farmers' willingness to purchase and use harvesting robots remains low. With the application of unmanned field farms, unmanned facility farms have become an important R&D direction. Reviewing Japanese facility agriculture harvesting robot development provides the following implications for China' s relevant research and industry:

(1) Enhance government support and build standardized greenhouses and demonstration facilities. Establish robust subsidy systems for facility agriculture intelligent equipment including harvesting robots, incorporating them into agricultural machinery purchase subsidies. Encourage banks to offer low-interest loans for facility agriculture intelligent equipment. Japan' s relatively standardized facility agriculture dimensions are 50 m ×10 m [52], with rails between ridges enabling different intelligent equipment to operate. Standardized greenhouses enable developed harvesting robots to work across different facilities, reducing costs. On this basis, establish harvesting robot demonstration projects that introduce R&D robots into actual greenhouse conditions to improve performance and promote development.

(2) Conduct key technology research addressing scientific challenges. Based on China's facility agriculture development status, formulate development plans for harvesting robots, identify main research directions and priorities, adhere to machinery-agronomy integration, and encourage enterprise-research institution collaboration for technology breakthroughs and industrialization. Promote indoor positioning and navigation system development, establishing "indoor GPS" as standardized greenhouse infrastructure. Researchers can combine advanced concepts with enterprise productization technologies to develop facility agriculture harvesting equipment meeting farmer needs. Provide researchers with support in funding, technology transformation, and intellectual property protection.

(3) Strengthen talent cultivation. Optimize talent training mechanisms to develop and reserve talent for facility agriculture intelligent equipment R&D, promoting interdisciplinary composite talent development and building "facility agricultural engineering" discipline groups and comprehensive laboratories. Establish international exchange platforms to promote communication among intelligent harvesting equipment researchers from different countries. Host harvesting robot competitions using simulated and actual greenhouse scenarios to stimulate student interest in agricultural robots.

(4) Innovate sales models and encourage cooperative development. Encourage enterprise lease-to-own models where fees are determined by fruit/vegetable harvest volume, reducing upfront investment costs. Promote cooperative development and encourage cooperatives to use facility agriculture harvesting robots to improve operational efficiency and save labor costs.

References

[1] QI F, LI K, LI S, et al. Development of intelligent equipment for protected horticulture in world and enlightenment to China[J]. Transactions of the CSAE, 2019, 35(2): 183-195.

[2] Agricultural Modernization Fund: Ministry of Agriculture, Forestry and Fisheries[EB/OL]. [2022-04-09]. https://www.maff.go.jp/j/g_{biki}/yusi/06/1_{0603}.html.

[3] Next-Generation Agriculture Support Service[EB/OL]. [2022-04-09]. https://www.maff.go.jp/j/kanbo/smart/nougyousien.html.

[4] About Tax System, Financing, and Subsidies Available for Agricultural Management: Ministry of Agriculture, Forestry and Fisheries[EB/OL]. [2022-04-09]. https://www.maff.go.jp/j/kobetu_{ninaite}/n_{pamph}/zeisei_{hojyo}.html.

[5] Industry-Academia-Government Collaboration Council. Ministry of Agriculture, Forestry and Fisheries "Knowledge" Aggregation and Application Platform[EB/OL]. [2022-04-09]. https://www.knowledge.maff.go.jp/.

[6] Ministry of Agriculture, Forestry and Fisheries. Facility Horticulture[EB/OL]. [2022-02-08]. https://www.maff.go.jp/j/seisan/ryutu/engei/sisetsu/.

[7] KONDO N. Robotics technologies supporting smart agriculture: Plenary speech[R]. Beijing, China: 6th IFAC Conference on Bio-Robotics, 2018.

[8] TORII T. Current status of robot technology in seedling production[J]. Measurement and Control, 1994, 33(10): 843-847.

[9] TOMITA T, WAGASA H. Grafting robot[J]. Measurement and Control, 1998, 37(2): 99-100.

[10] KAWAMURA N, NAMIKAWA K, FUJINAGA T, et al. Research on agricultural robot (Part 1)[J]. Journal of the Japanese Society of Agricultural Machinery, 1984, 46(3): 353-358.

[11] KAWANO S, WATANABE H, IWAMOTO M. Determination of sugar content in intact peaches by near infrared spectroscopy with fiber optics in interactance mode[J]. Engei Gakkai Zasshi, 1992, 61(2): 445-451.

[12] SHIINA T, IJIRI T, MATSUDA I, et al. Determination of brix value and acidity in pineapple fruits by near infrared spectroscopy[J]. Acta Horticulturae, 1993(334): 219-224.

[13] KUBOTA. Agri Robo MR1000A[EB/OL]. [2022-02-08]. https://agriculture.kubota.co.jp/product/tractor/a

[14] YANMAR. Yanmar Smart Agriculture[EB/OL]. [2022-02-08]. https://www.yanmar.com/jp/agri/smart_{a

[15] ISEKI. NEW RTS SERIES RESPA[EB/OL]. [2022-02-08]. https://products.iseki.co.jp/tractor/rts/.

[16] SMARTASSIST[EB/OL]. [2022-04-09]. https://www.yanmar.com/jp/agri/afterservice_{support}/smarta

[17] Ministry of Agriculture, Forestry and Fisheries. Status of Horticultural Facility Installation[EB/OL]. [2022-02-08]. https://www.maff.go.jp/j/seisan/ryutu/engei/sisetsu/haipura/setti_

[18] KUBOTA. Spinach Harvester[EB/OL]. [2022-02-09]. https://agriculture.kubota.co.jp/product/kanren/spi harvester/.

[19] YANMAR. Green Onion Harvester HL10[EB/OL]. [2022-02-10]. https://www.yanmar.com/jp/agri/products/vegetable/vegetable_{harvest}/hl10/index.html.

[20] TAKUYA F, SHINSUKE Y, KAZUO I. System development of tomato harvesting robot based on modular design[C]// 2019 International Workshop on Smart Info-Media Systems in Asia: SS1-1. Tokyo, Japan: The Institute of Electronics, Information and Communication Engineers, 2019.

[21] YAGUCHI H, NAGAHAMA K, HASEGAWA T, et al. Development of an autonomous tomato harvesting robot with rotational plucking gripper[C]// 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems. Piscataway, New York, USA: IEEE, 2016: 652-657.

[22] YOSHIDA T, FUKAO T, HASEGAWA T. A tomato recognition method for harvesting with robots using point clouds[C]// 2019 IEEE/SICE International Symposium on System Integration. Piscataway, New York, USA: IEEE, 2019: 456-461.

[23] PANASONIC NEWSROOM JAPAN. Tomato Harvesting Solution ~AI Solves Agricultural Labor Shortage~ Robot Automatically Harvests Tomatoes[EB/OL]. (2018-05-23) [2022-02-11]. http://news.panasonic.com/jp/stories/2018/57949.html.

[24] LI B, URA T, FUJINAGA T, et al. Development of end-effector for harvesting tomato using suction and cutting mechanism[C]// JSME annual Conference on Robotics and Mechatronics (Robomec). Tokyo, Japan: The Japan Society of Mechanical Engineers, 2017: ID 1A1-D06.

[25] FUJINAGA T, YASUKAWA S, ISHII K. Development and evaluation of a tomato fruit suction cutting device[C]// 2021 IEEE/SICE International Symposium on System Integration. Piscataway, New York, USA: IEEE, 2021: 628-633.

[26] KONDO N, NISHITSUJI Y, LING P P, et al. Visual feedback guided robotic cherry tomato harvesting[J]. Transactions of the ASAE, 1996, 39(6): 2331-2338.

[27] KONDO N, YATA K, IIDA M, et al. Development of an end-effector for a tomato cluster harvesting robot[J]. Engineering in Agriculture, Environment and Food, 2010, 3(1): 20-24.

[28] IKEDA T, FUKUZAKI R, SATO M, et al. Tomato recognition for harvesting robots considering overlapping leaves and stems[J]. Journal of Robotics and Mechatronics, 2021, 33(6): 1274-1283.

[29] URAMOTO S, SUZUKI H, KUWAHARA A, et al. Tomato recognition algorithm and grasping mechanism for automation of tomato harvesting in facility cultivation[J]. Journal of Signal Processing, 2021, 25(4): 163-170.

[30] FUJINAGA T, YASUKAWA S, ISHII K. Evaluation of tomato fruit harvestability for robotic harvesting[C]// 2021 IEEE/SICE International Symposium on System Integration. Piscataway, New York, USA: IEEE, 2021: 628-633.

[31] YOSHIDA T, FUKAO T, HASEGAWA T, et al. Fast detection of tomato peduncle using point cloud with a harvesting robot[J]. Journal of Robotics and Mechatronics, 2018, 30(2): 180-186.

[32] YOSHIDA T, FUKAO T, HASEGAWA T, et al. Cutting point detection using a robot with point clouds for tomato harvesting[J]. Journal of Robotics and Mechatronics, 2020, 32(2): 437-444.

[33] CHEN X, CHAUDHARY K, TANAKA Y, et al. Reasoning-based vision recognition for agricultural humanoid robot toward tomato harvesting[C]// 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems. Piscataway, New York, USA: IEEE, 2015: 6487-6494.

[34] YAGUCHI H, HASEGAWA T, NAGAHAMA K, et al. A research of construction method for autonomous tomato harvesting robot focusing on harvesting device and visual recognition[J]. Journal of the Robotics Society of Japan, 2018, 36(10): 693-702.

[35] FUJINAGA T, YASUKAWA S, ISHII K, et al. Tomato growth state map for the automation of monitoring and harvesting[J]. Journal of Robotics and Mechatronics, 2020, 32(6): 1279-1291.

[36] ISHII K, MATSUO T, TAKEMURA Y, et al. Tomato-harvesting-robot competition towards smart agriculture[C]// International Conference on Artificial Life and Robotics. ALife Robotics Corporation Ltd., Oita, Japan: 2021, 26: 1-5.

[37] NAKAMURA G, SAKAGUCHI K, NISHI T, et al. Development of tomato harvesting robot: Development of arm part and examination of image processing system[J]. The Proceedings of JSME annual Conference on Robotics and Mechatronics (Robomec), 2020, 32(6): 1279-1291.

[38] MATSUO T, SONODA T, TAKEMURA Y, et al. Toward smart tomato greenhouse: The fourth tomato harvesting robot competition[J]. Journal of Robotics, Networking and Artificial Life, 2019, 6(2): ID 138.

[39] OGUMA K, HIGUCHI S, IKEDA F, et al. Development of automatic tomato harvesting system using universal vacuum gripper and RGB-D camera[J]. The Proceedings of the International Conference on Motion and Vibration Control, 2020, 15: ID 10050.

[40] HAYASHI S, GANNO K, ISHII Y, et al. Robotic harvesting system for eggplants[J]. Japan Agricultural Research Quarterly, 2002, 36(3): 163-168.

[41] HAYASHI S, GANNO K, ISHII Y, et al. Development of a harvesting end-effector for eggplants[J]. Journal of Society of High Technology in Agriculture, 2001, 13(2): 97-103.

[42] AGRIST CO, LTD. AGRIST Co., Ltd. Developing AI Agricultural Robots[EB/OL]. [2022-02-11]. https://agrist.com/products/robot.

[43] ARIMA S, KONDO N, SHIBANO Y, et al. Studies on cucumber harvesting robot (part I). Investigation of cultivation training and mechanism of manipulator[J]. Journal of the Japanese Society of Agricultural Machinery, 1994, 56(1): 55-64.

[44] SEIICHI A, NAOSHI K, HIROSHI N. Development of robotic system for cucumber harvesting[J]. Japan Agricultural Research Quarterly, 1996, 30(4): 233-238.

[45] FUJIURA T, UEDA K, CHUNG S H, et al. Vision system for cucumber-harvesting robot[J]. IFAC Proceedings Volumes, 2000, 33(29): 61-65.

[46] SYED T N, JIZHAN L, XIN Z, et al. Seedling-lump integrated non-destructive monitoring for automatic transplanting with Intel RealSense depth camera[J]. Artificial Intelligence in Agriculture, 2019, 3: 18-32.

[47] ROSHANIANFARD A, KAMATA T, NOGUCHI N. Performance evaluation of harvesting robot for heavyweight crops[J]. IFAC-PapersOnLine, 2018, 51(17): 88-92.

[48] SAKAI H, SHIIGI T, KONDO N, et al. Accurate position detecting during asparagus spear harvesting using a laser sensor[J]. Engineering in Agriculture, Environment and Food, 2013, 6(3): 105-110.

[49] IRIE N, TAGUCHI N. Asparagus harvesting robot[J]. Journal of Robotics and Mechatronics, 2014, 26(2): 238-245.

[50] FUNAMI Y, KAWAKURA S, TADANO K. Development of a robotic arm for automated harvesting of asparagus[J]. European Journal of Agriculture and Food Sciences, 2020, 2(1): 1-10.

[51] YOSHIDA H. Inaho Launches Commercial Service for Asparagus Automatic Harvesting Robot, First Unit Deployed to Saga Prefecture Farm[EB/OL]. [2022-02-11]. https://jp.techcrunch.com/2019/10/03/inaho-vegetable-harvesting-robot/.

[52] HAYASHI S, SHIGEMATSU K, YAMAMOTO S, et al. Evaluation of a strawberry-harvesting robot in a field test[J]. Biosystems Engineering, 2010, 105(2): 160-171.

[53] SHIIGI T, KURITA M, KONDO N, et al. Strawberry harvesting robot for fruits grown on table top culture[C]// 2008 ASABE Meeting. St. Joseph, USA: American Society of Agricultural and Biological Engineers, 2008.

[54] KONDO N, NINOMIYA K, HAYASHI S, et al. A new challenge of robot for harvesting strawberry grown on table top culture[EB/OL]. [2022-01-30]. http://www.aptech.kais.kyoto-u.ac.jp/e/summary/date/sum3_2.pdf.

[55] KONDO N, MONTA M, HISAEDA K. Harvesting robot for strawberry grown on annual hill top. Part 2. Manufacture of the second prototype robot and fundamental harvesting experiment[J]. Shokubutsu Kojo Gakkaishi, 2001, 13(4): 231-236.

[56] The Capability of “Agricultural Harvesting Robot” that Picks Only Ripe Fruit: Nikkei Business Electronic Edition[EB/OL]. [2022-02-09]. https://business.nikkei.com/atcl/report/15/226265/093000057/?SS=imgview&FD=1428315772.

[57] KONDO N. Strawberry harvesting robot[J]. Journal of the Society of Mechanical Engineers, 2000, 103(976): 18-21.

[58] ARIMA S, KONDO N, YAGI Y, et al. Harvesting robot for strawberry grown on table top culture[J]. Journal of Society of High Technology in Agriculture, 2001, 13(3): 159-166.

[59] KONDO N, MONTA M, HISAEDA K. Harvesting robot for strawberry grown on annual hill top. Part 2. Manufacture of the second prototype robot and fundamental harvesting experiment[J]. Shokubutsu Kojo Gakkaishi, 2001, 13(4): 231-236.

[60] RAJENDRA P, KONDO N, NINOMIYA K, et al. Machine vision algorithm for robots to harvest strawberries in tabletop culture greenhouses[J]. Engineering in Agriculture, Environment and Food, 2009, 2(1): 24-30.

[61] HAYASHI S, SAITO S, IWASAKI Y, et al. Development of circulating-type movable bench system for strawberry cultivation: MAFF[J]. Japan Agricultural Research Quarterly, 2011, 45(3): 285-293.

[62] HAYASHI S, YAMAMOTO S, SAITO S, et al. Field operation of a movable strawberry-harvesting robot using a travel platform[J]. Japan Agricultural Research Quarterly, 2014, 48(3): 307-316.

[63] HAYASHI S, YAMAMOTO S, TSUBOTA S, et al. Development and practical application of stationary strawberry-harvesting robot integrated with movable bench system[J]. Journal of Japanese Society of Agricultural Machinery, 2017, 79(5): 415-425.

[64] HABARAGAMUWA H, OGAWA Y, SUZUKI T, et al. Detecting greenhouse strawberries (mature and immature), using deep convolutional neural network[J]. Engineering in Agriculture, Environment and Food, 2018, 11(3): 127-138.

[65] TSUBOTA S, TEJIMA T, YAMAMOTO S, et al. Development of sugar content measurement technology using stationary strawberry harvesting robot[J]. Plant Environment Engineering, 2019, 31(1): 31-41.

[66] Plant Factory & Agriculture Business Online. NARO and Shibuya Seiko Develop Stationary Strawberry Harvesting Robot Capable of Daytime Harvesting[EB/OL]. (2013-06-13) [2022-02-11]. https://innoplex.org/archives/15423.

[67] HUANG Z, SHIIGI T, TSAY L W J, et al. A sound-based positioning system with centimeter accuracy for mobile robots in a greenhouse using frequency shift compensation[J]. Computers and Electronics in Agriculture, 2021, 187: ID 106235.

[68] NEWSWITCH. Agricultural Robots: Evolving Functions but Slow Popularization?[EB/OL]. (2016-04-16) [2022-02-11]. https://newswitch.jp/p/4343.

[69] HUANG Z, FUKUDA H, JACKY T LWAI, et al. Greenhouse based orientation measurement system using spread spectrum sound[J]. IFAC-PapersOnLine, 2018, 51(17): 108-111.

[70] HUANG Z, JACKY T LWAI, ZHAO X, et al. Noise tolerance evaluation of spread spectrum sound-based positioning system for a quadcopter in a greenhouse[J]. IFAC-PapersOnLine, 2019, 52(30): 239-242.

[71] HUANG Z, JACKY T L W, ZHAO X, et al. Position and orientation measurement system using spread spectrum sound for greenhouse robots[J]. Biosystems Engineering, 2020, 198: 50-62.

[72] HOU Z, LI Z, FADIJI T, et al. Soft grasping mechanism of human fingers for tomato-picking bionic robots[J]. Computers and Electronics in Agriculture, 2021, 182: ID 106010.

[73] YU Y, ZHANG K, LIU H, et al. Real-time visual localization of the picking points for a ridge-planting strawberry harvesting robot[J]. IEEE Access, 2020, 8: 114116-114126.

[74] DE PRETER A, ANTHONIS J, DE BAERDEMAEKER J. Development of a robot for harvesting strawberries[J]. IFAC-PapersOnLine, 2018, 51(17): 14-19.

[75] XIONG Y, GE Y, GRIMSTAD L, et al. An autonomous strawberry-harvesting robot: Design, development, integration, and field evaluation[J]. Journal of Field Robotics, 2020, 37(2): 202-224.

[76] ASLAN M F, DURDU A, SABANCI K, et al. A comprehensive survey of the recent studies with UAV for precision agriculture in open fields and greenhouses[J]. Applied Sciences, 2022, 12(3): ID 1047.

[77] BOGUE R. Fruit picking robots: Has their time come?[J]. Industrial Robot, 2020, 47(2): 141-145.

[78] VITZRABIN E, EDAN Y. Adaptive thresholding with fusion using a RGBD sensor for red sweet-pepper detection[J]. Biosystems Engineering, 2016, 146: 45-56.

[79] FU L, GAO F, WU J, et al. Application of consumer RGB-D cameras for fruit detection and localization in field: A critical review[J]. Computers and Electronics in Agriculture, 2020, 177: ID 105687.

[80] LI Y, ZHANG P, YUAN J, et al. Visual positioning and harvesting path optimization of white asparagus harvesting robot[J]. Smart Agriculture, 2020, 2(4): 65-78.

[81] KOUNALAKIS N, KALYKAKIS E, PETTAS M, et al. Development of a tomato harvesting robot: Peduncle recognition and approaching[C]// 2021

3rd International Congress on Human-Computer Interaction, Optimization and Robotic Applications. Piscataway, New York, USA: IEEE, 2021: 1-6.

[82] WANG G, YU Y, FENG Q. Design of end-effector for tomato robotic harvesting[J]. IFAC-PapersOnLine, 2016, 49(16): 190-193.

[83] HUANG Z, OMWANGE K A, TSAY L W J, et al. UV excited fluorescence image-based non-destructive method for early detection of strawberry (Fragaria ×ananassa) spoilage[J]. Food Chemistry, 2022, 368: ID 130776.

[84] NIE S, RIZA D FAL, OGAWA Y, et al. Potential of a double lighting imaging system for characterization of "Hayward" kiwifruit harvest indices[J]. Postharvest Biology and Technology, 2020, 162: ID 111113.
