# Development status and trend of agricultural robot technology

Yucheng Jin[1], Jizhan Liu[1*], Zhujie Xu[1], Shouqi Yuan[1], Pingping Li[2], Jizhang Wang[1]

(1. *Key Laboratory of Modern Agricultural Equipment and Technology, Ministry of Education, Jiangsu University, Zhenjiang 212013, Jiangsu, China*;
2. *College of Biology and the Environment, Nanjing Forestry University, Nanjing 210042, China*)

**Abstract:** In the face of the contradiction between the increasing demand for agricultural products and the sharp reduction of agricultural resources and labor force, agricultural robot technology is developing explosively on the basis of decades of technical and industrial exploration. In view of the complexity and particularity of the development of agricultural robot technology, it is of great value to summarize its development characteristics and make reasonable judgments on its development trend. In this paper, the type of agricultural robot systems was first discussed. From the classification of agricultural robot systems, the development of main types of monitoring robots, non-selective and selective working robots for crop farming, livestock and poultry farming and aquaculture were introduced in detail. Then the scientific research, core technology, and commercialization of different types of agricultural robots were summarized. It is believed that navigation in complex agricultural environments, damage-free robot-crop interaction, and agronomy-robot fusion have high scientific value and significance to promote the revolutionary advances in agricultural robot technology. The characteristics of inter-discipline between agricultural robot technology and new materials, artificial intelligence, bionics, agronomy are research focus. The fast damage-free operation, autonomous navigation for complex environments, target detection for complex backgrounds, and special design for agricultural robots are considered to be the key technology of agricultural robot development, and the development path is given. Finally, robot-crop interaction simulation, big data support, and artificial intelligence are regarded as paths to realize the breakthrough of key agricultural robot technologies. The summary and prospect of this paper are of positive significance to promote the overall development of agricultural robot technology.

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## 1 Introduction

Today, with a global population of 7594 million, 430 000 people are still born every day. At the same time, the demand for agricultural products continues to increase as living standards rise. Correspondingly, the world's arable land and other agricultural production resources are shrinking. With fewer agricultural resources to carry a huge pressure of larger and higher demand for food, it is objectively required to fully release the potential of agricultural production with modern technology. Meanwhile, the aging of the population and the sharp decline of the agricultural population objectively require more intelligent and even unmanned ways to ensure agricultural production. Agricultural activities still rely heavily on human labor, because agricultural tasks are considered "hard work" and low profitability, youngsters are looking for job opportunities in urban regions, so farmers are looking for new ways to automate their farms and thus recover any losses[1]. As a representative way and an inevitable trend of agricultural intelligence and modernization, agricultural robot technology is embracing unprecedented development opportunities today.

The development of agricultural robot technology is the inevitable requirement of agriculture from the 1.0 era to the 4.0 era, and its fundamental task is not only to solve the problem of less labor, precision, safety, comfort and green operation which is difficult to realize with traditional agricultural machinery and equipment but also to fill the blank fields that many traditional types of agricultural machinery cannot do. Although there are still many cases in which robots are not as fast as humans, agriculture is currently developing robotic systems to work in the field and help producers with tedious tasks, pushing agricultural systems to the new concept of Agriculture 5.0[2].

However, the development of agricultural robots has a special complexity. Firstly, it has a high degree of inter-discipline. Based on the high integrity of mechanical - electronic - information - control of robot technology itself, biometric and statistics are further integrated into their own to the fragility, growth, and individual differences of biological objects. Secondly, as a new technology, the development of agricultural robots depends on the complicated research chain among basic data, basic models, key technologies, and equipment development. Thirdly, compared with the traditional agricultural machinery which matches the mechanical manufacturing chain with a few electronic components and meters, the agricultural robot industry chain is more complex. At present, there is still a great distance between the current development level of agricultural robots and the actual demand for agricultural

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**Biographies: Yucheng Jin**, PhD candidate, Associate Professor, research interest: agricultural robot technology, Email: Mike2004@126.com; **Zhujie Xu**, Master candidate, research interest: agricultural robot technology, Email: 1119050967@qq.com; **Shouqi Yuan**, PhD, Professor, research interest: agricultural engineering, Email: shouqiy@ujs.edu.cn; **Pingping Li**, PhD, Professor, research interest: agricultural engineering, Email: lipingping@njfu.edu.cn; **Jizhang Wang**, PhD, Associate Professor, research interest: agricultural informatization, Email: whxh@ujs.edu.cn.
***Corresponding author: Jizhan Liu**, PhD, Professor, research interest: agricultural robot technology. Key Laboratory of Modern Agricultural Equipment and Technology, Ministry of Education, Jiangsu University, No.301, Xuefu Road, Zhenjiang 212013, China. Tel: +86-13861392051, Email: liujizhan@163.com.

production. It is of positive significance to the development of agricultural robot technology and industry to summarize its development characteristics under the conditions of the new times and make reasonable judgments on its development trend and direction.

## 2 Development of agricultural robot systems

### 2.1 Types of agricultural robot systems

At present, there are different domain definitions and classification methods of agricultural robots. As shown in Table 1, agricultural robot technology has been studied and applied widely in planting, livestock and poultry farming, aquaculture. In crop farming, agricultural robots for phenotyping[3,4], monitoring, mapping, crop managing, environment control, etc., are available. Similarly, in livestock and poultry farming and aquaculture, agricultural robots can perform functions of phenotyping[3], monitoring, managing, environment control, etc. For crop farming, the research and development of agricultural robots have covered open field production, semi-closed greenhouses production and fully enclosed plant factory production, as well as every task of tillaging, grafting[5,6], planting, fertilizing, pollination, spraying, harvesting, grading, etc. The robotic solutions can also be categorized into airborne, earthbound, and aquiclude solutions[7]. If combining the operation implementation mode and the technical level, the agricultural robots can be divided into two categories: the non-selective working robots and the selective working robots. Non-selective working robots do not distinguish the target individual in working. On the contrary, selective working robots need to realize the selective operation of individual agricultural targets through the identification, positioning, and diagnosis of them based on machine vision or other sensing technologies.

**Table 1 Classification of agricultural robot systems**

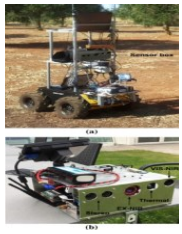
| Aspect | Type |
|---|---|
| Type of industry | Crop farming, livestock and poultry farming, aquaculture |
| Function | Phenotyping, monitoring, mapping, object handling, environment cleaning, health protection, etc. |
| Intelligent level | Remote-control, man-robot collaboration, full autonomous |
| Working mode | Selective, non-selective |
| Mobility | Stationary, mobile |
| Space | Aerial, ground, aquiclude |

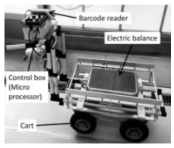
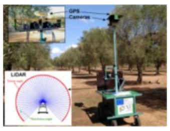
### 2.2 Development of agricultural monitoring robots

#### 2.2.1 Monitoring robots in crop farming

In agricultural production, monitoring plays a vital role which is the foundation of achieving precision agriculture. The distance between crops and satellites is considerable, typically around 700 km, and deeper insights are reachable when sensors remain closer to the targets; for aircraft systems, the distance to land can be around 100 m; when monitoring platforms operate from the ground, the distance from the sensors to the target crop diminishes to less than 2 m[2,8]. As these vehicles move near the crop, the data acquired increase in accuracy, and resolutions of one or more samples per meter are feasible[2]. Today, UAVs have been adopted widely in crop farming monitoring, ground robotic vehicles are also developed rapidly for different scenarios of soil moisture, pH, fertility monitoring and climate conditions monitoring, crop plant diseases and insect pests monitoring, growth and yield monitoring, etc. (Table 2)

**Table 2 Monitoring robots in crop farming**

| Task | Platform | Navigation sensor | Monitoring sensor | Appearance example | Reference |
|---|---|---|---|---|---|
| Soil monitoring | Bonirob multi-purpose field robot platform | GPS, Remote-control | Penetrometer app |  | [8] |
| Soil and crop growth monitoring | Ground 4-wheeled vehicle | Stereo camera, GPS | Fluorescence, infrared thermography |  | [9] |
| Soil monitoring | All-terrain vehicle | -- | 2 visual cameras, VIS–NIR sensor, thermal camera, IMU |  | [10] |
| Soiland climate monitoring | 4-wheeled vehicle | -- | Soil moisture level sensor, weather station |  | [11] |
| Crop growth monitoring | High clearance swather | RTK-GPS | 4 ultrasonic sensors, 2 crop circle sensors, 2 infrared thermometers, 2 RGB cameras |  | [12] |
| Crop and environment monitoring | 4-wheeled small tank | Teleoperated, solar sensor | Infrared camera, 2 laser scanner, temperature and humidity sensor |  | [13] |

| Task | Platform | Navigation sensor | Monitoring sensor | Appearance example | Reference |
|---|---|---|---|---|---|
| Crop monitoring | 4WD Electric Monster Truck | Laser range finder, IMU, GPS | Infrared camera, RGB camera |  | [14] |
| Plant growth monitoring | -- | -- | Colour zoom camera, RGB color sensors |  | [15] |
| Yield monitoring | 4-Wheel Cart | Barcode reader | Electronic balance |  | [16] |
| Plant health monitoring | 5-Wheel 6-chassis | Ultrasonic sensor | RGB camera, NIR camera |  | [17] |
| Plant growth and health monitoring | tracked binscarrier | -- | 2 Lidars, 6 crop sensors |  | [18,19] |
| Plant growth monitoring | 4-wheel frame | 2 cameras (front-back) | -- |  | [20] |
| Plant health monitoring | 4-wheeled vehicles | GPS and IMU,stereo camera and the 3D Lidar | 3D scanner (using a 2D laser attached to the arm) |  | [21] |
| Crop disease detection | 4-wheel vehicle | 2D laser LiDAR,GPS,IMU | 2 digital single-lens reflex cameras, multispectral camera, hyperspectral system, thermal camera |  | [22] |
| Pests and diseases | A frame with four fat-bike wheels | Remote-controlled | A multispectral camera, three DSLR cameras, a hyperspectral imaging system, a thermal camera |  | [23] |

Scholz et al.[8] developed an automatic soil penetrometer, which was integrated into an autonomous mobile robot named Bonirob, field measurements have been performed by using the robot in two modes: a "manual mode", where the user controls the system via a remote control panel, and an "automatic mode" where the robot acts completely automatic. The European Union VineRobot project involves eight partner groups from the wine-making countries of France, Italy, Germany, and Spain, have developed an autonomous robot that will measure vineyard parameters (vegetative growth, grape yield, grape composition, and soil moisture) on-the-go in a non-invasive way to help winemaking decisions[9,10]. The follow-up VineScout project funding from the European Union's Seventh Programme VineScout is working to develop an autonomous vineyard monitoring robot that can help wine producers measure key vineyard parameters, including water availability, vine leaf/canopy temperature, and variations in plant vigor. Control of plagues, fungi, and other threats are recurrent tasks in winery[24]. The GRAPE project, founded by the Echord++ program from European Commission, has developed the monitoring robot that is consisted of the automatic pheromone dispenser distribution for matting disruption in vineyards using an autonomous ground robot equipped with a robotic arm[21]. To realize row crop navigation for crop scouting, Austin Schmitz proposed an unmanned ground vehicle structure with reconfigurable parallel and linear configurations to accomplish both inter-row maneuvering and moving from one row to the next (Figure 1)[25].

Satellites must be integrated by UAV and unmanned platforms to construct multi-sensorial systems that operate at different spatial scales (where), temporal (when), and spectral (what), to increase the spatial and also spectral resolution[26]. The Flourish project, funded by the European Community's Horizon 2020 program, is developing an adaptable robotic solution for precision farming[27]. Combining the aerial survey capabilities of a small autonomous multi-copter Unmanned Aerial Vehicle (UAV) with a multi-purpose agricultural

Unmanned Ground Vehicle (UGV) (Figure 2), the system will be able to survey the field from the air, perform a targeted intervention on the ground, and provide detailed information for decision support, all with minimal user intervention[27].

a. Parallel configuration b. Linear configuration

Figure 1 Autonomous parallel-linear ground vehicle for row crop scouting[25]

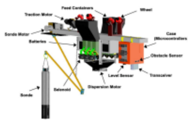
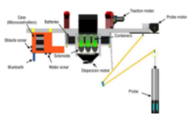
Figure 2 Unmanned ground vehicle Bonirob, carrying an unmanned aerial vehicle[27]

Although robotic monitoring technology is developing so rapidly, and so many types of sensors are integrated to get big data, accurate and efficient autonomous monitoring remains a challenge. Taking early crop disease monitoring as an example, for farmers, it is hoped that robots can detect diseases in certain leave or fruit rather than canopy groups in real-time without any operation. It is a very difficult task, involving autonomous crop target panoramic information acquisition, disease location locking and disease type diagnosis based on multi-information fusion, and so on. It is necessary to further improve the friendliness of big data to farmers and to give direct decisions to end-users.

2.2.2 Monitoring robots in livestock and poultry farming and aquaculture

Poultry houses require daily monitoring to ensure animal health and proper house operation[28]. Maintaining the health and welfare status of livestock at optimal levels has traditionally been a main concern of farmers, and more recently, consumers[28]. Today more and more are engaged in the development of robotic monitoring in livestock and poultry farming (Table 3). The air quality inside a livestock building is more and more taken seriously by both farmers and researchers[29]. Sub-optimal air quality not only could influence the productivity of farm animals, as well as the health and well-being of livestock and workers, but also will affect the healthy and sustainable development of the livestock and poultry industry[30]. As the indoor environmental parameters distribution in livestock and poultry buildings is inhomogeneity, they needed to be monitored frequently, flexibly, freely[30]. Therefore, robotic monitoring is highly represented. The robot was developed by Qi et al.[30] used an off-the-shelf vehicle installed with a 9 DOF MEMS IMU sensor, and measurement sensors (temperature, relative humidity, and dust sensors) were fixed. In livestock and poultry farming, the outbreaks of various diseases and epidemics will bring huge losses. In order to tackle these diseases, it is necessary to implement farm scientific technology for the monitoring of health to reduce production costs[31]. Today, wearable devices such as foot earrings

**Table 3 Monitoring robots in livestock and poultry farming and aquaculture**

| Function | Platform | Navigation sensor | Monitoring sensor | Appearance example | Reference |
|---|---|---|---|---|---|
| Air quality monitoring | 4-wheel vehicle chassis | IMU sensor | Temperature sensor, relative humidity sensor, dust sensor |  | [30] |
| Health monitoring | Milking robot | -- | 6 strain gages, laser distance sensor |  | [32] |
| Health monitoring | Milking robot | -- | 3 strain gauge scales, 3 web cameras | -- | [33] |
| Bunk monitoring | Clearpath Robotics | RTK GNSS, multi-layer lidar | Bunk scanner |  | [34] |
| Water quality monitoring | Four-wheel chassis | Monorail, sonar | Water quality sonde |  | [35] |
| Water quality monitoring | Casing with main frame and side plates | BDS/INS | Temperature sensor, pH sensor, dissolved oxygen sensor |  | [36] |
| Feeding and water monitoring | Four-wheel chassis | Monorail, sonar | Physicochemical sensors |  | [37] |

and ear clips have been widely used in the health monitoring of animals and chickens. By contrast, integrating an automatic cow health measurement system into a milking robot is more feasible and low-cost in dairy[32,33]. With the system developed by Pastell et al.[32,33], the information about the leg weight of cows is measured with four balance platforms and the respiration rate is extracted from the data of a laser distance sensor pointing at the cow's side. Each measurement begins when the robot starts milking and ends when the milking ends, and the total weight and the number of kicks with each leg are calculated[32,33]. The data can be used for automatic detection of leg problems and the symptoms of heat stress can probably be detected as increased respiration rate[32]. Assessment of feed remaining in bunks (calling) is a critically important job at a beef feedlot[33]. Supported by the Australian Government, MLA (Meat & Livestock Australia Limited) developed a bunk calling robot named BunkBot, which could provide highly repeatable (precise) and accurate feed remaining predictions during the validation experiment in a commercial feedlot environment[34].

Aquaculture produces and breeds fish, shrimp, and clams under controlled conditions, physicochemical parameters, such as dissolved oxygen, pH, salinity, and temperature, must be measured in real-time to provide data for carrying out corrective actions and maintaining optimal conditions of production[35]. Considering the diversity and variability of the breeding environments, in order to obtain more comprehensive information, it is often required to install multiple monitoring equipment in more positions, which would greatly increase the procurement and maintenance costs. Compared with measurement equipment installed in fixed positions, the flexibility of the water quality detection robot has obvious advantages[36]. According to Table 3, the robot was designed by Huang et al. used the BDS module for surface navigation and used the water quality detection module, to collect parameters such as the water temperature, pH value, and dissolved oxygen (DO) content of the freshwater aquaculture environment[37]. The robot developed by Fernando travels automatically on a monorail to dispense the food and measure the water parameters[35,37]. Local and remote experiments were performed to show the usefulness of the robot operation via the Internet for intensive cultivation of the freshwater red claw crayfish[35]. Livanos et al.[38] developed a smart autonomous underwater vehicle with intelligent optical navigation to enable automated inspection of aquaculture net-pen cages.

### 2.3 Development of non-selective agricultural working robots

#### 2.3.1 Unmanned agricultural machinery in crop farming

At present, the research and development of various agricultural robot equipment are flourishing and rapidly extends from the laboratory to the enterprise and production. In the field of non-selective agricultural working robots represented by field navigated and unmanned agricultural machinery, the research on GNSS-IMU integrated navigation technology of agricultural machinery systems has become mature, and the agricultural machinery navigation system has been productized. Grass cutting is the most fundamental but tedious task[39,40]. Remote-controlled and autonomous robotic lawn mowers guided by global navigation satellite systems are welcomed[41,42]. More and more robotic lawn mowings are incorporated with GPS, cameras, ultrasonic sensors to have performances of detection and avoidance of obstacles[43]. For in-row spraying, tilling, ditching, etc., in fields, greenhouse, orchards, and vineyards, local navigation with machine vision, Lidar or RGB-D fusion is a research hotspot[44-46]. Liu also developed an autonomous transplanter of strawberry plug seedlings and automatic mobile substrate paver for elevated cultivation navigated with an arc array of photoelectric switches[47-49], and a high-ridge automatic transplanter for strawberry plug seedlings with a profiling walking device[50].

#### 2.3.2 Unmanned agricultural machinery in livestock and poultry farming and aquaculture

High-density livestock and poultry breeding pose a great challenge to environmental security[51]. Disinfection is the most basic, effective, and extensive way of epidemic prevention in the process of livestock and poultry breeding[51]. Due to the high frequency of disinfection, strict operation standards, and poor working conditions, it is of great significance to develop and apply automatic disinfection equipment to ensure the high efficiency and safe production of livestock and poultry breeding[51,52]. A crawler-type disinfection robot that used a sprayer with a gas-liquid extraneous mixture structure was developed[51,52]. It could move along the line marked with the magnet and RFID label on the ground to meet the need for the high-flow and long-range spray[51]. It is also important to maintain clean and dry ground in livestock and poultry house, automatic alley scrapers with a cable or a shuttle drive are effective in pushing manure through slats, robotic slat cleaners without cables can be programmed to scrape the areas in the barn where manure builds up the most[53]. Since there are not only static obstacles, such as the stable but also dynamic obstacles, such as people and livestock, obstacle detection with ultrasonic sensors, etc., is necessary[53,54]. If a robotic slat cleaner encounters people or livestock in the alley, it will shut down or go around[53].

In aquaculture, feeding is the primary factor determining efficiency and cost[55]. In order to address the issues of nonuniform feeding and high labor cost plaguing the process of farming Chinese river crabs, Ruan et al.[56,57] proposed a multifunctional automatic river crab feeding boat based on GPS/INS integrated navigation. Pribadi et al.[58] designed a fish feeder robot based on ArduinoAndroid. Hu et al.[59] proposed a fishpond cleaning robot based on SLAM technology in industrial aquaculture. Kaizu et al.[60] designed a robotic boat for mowing aquatic weeds, which is automatically controlled by the real-time kinematic global navigational satellite system (RTK-GNSS).

#### 2.3.3 Commercial non-selective agricultural working robots

John Deere has developed unmanned deformable tractors (Figure 3a). Kubota company has pioneered the driverless farming machine "SL60A" in Japan, and Russia's Rostov Agricultural Machinery Group's driverless combine harvester will go into production in 2023. In 2018, the Telematics Industry Application Alliance (TIAA) of China organized Jiangsu University and other units to launch the first national full-course unmanned agricultural machinery working demonstration in Xinghua City, Jiangsu Province, China, and then continued to carry out such demonstrations in Jiansanjiang and other areas. Research and development of unmanned agricultural machinery in China has rapidly formed an upsurge. YTO Group Corporation (Figure 3b), FJ Dynamics, ZoomLion Heavy Machinery, etc., have launched unmanned tractors, rice transplanters, harvesters, and other products, and quickly put them into the market and agricultural production.

The unmanned agricultural machinery based on vision, laser radar, and other navigation and combined with the global positioning system has also got the attention paid by the enterprises. An American firm of Rabbit Tractors has developed an autonomous agricultural robot that can run 12 cameras and 4 lidar sensors simultaneously to handle multiple tasks. Clearpath Robotics has developed the Dajeon driverless chassis (Figure 4a). Autonomous

Solutions has developed the Forge agricultural robot platform for vineyard applications. Autonomous Tractor has developed modular driverless tractors. Kinze Manufacturing has developed autonomous tractors and grain trucks (Figure 4b).

Compared with crop farming industries, the environment of livestock and poultry farming buildings is more regular and easier to realize unmanned operation. Milking robots that refer to stationary automatic milking systems have been used widely in dairy farms. Animal feeding robots that auto-drive through the barn produced by Hetwin, Lely, GEA and other companies have been applied for several years (Figure 5a). Ramsta Robotics, Washpower, Kyodo, etc., supply robot cleaners to clean out livestock and poultry houses automatically by spraying water at high pressure. Barn floor cleaning robots are also supplied by Lely, Hetwin, etc. In aquaculture, FFAZ supplies a type of automatic feeding robot that travels on the water surface to deliver precise amounts according to the plan of each enclosure and at designated intervals (Figure 5b). Underwater drones produced by Deep Trekker are used to monitor eating habits and monitor for damage to nets.

a. John Deere b. YTO Group

Figure 3 Unmanned agricultural machineries based on GNSS-IMU combined navigation

a. Clearpath robotics b. Kinze manufacturing

Figure 4 Unmanned agricultural machineries based on other navigation

a. Animal feeding b. Fish feeding

Figure 5 Unmanned feeding machinery in livestock and poultry farming and aquaculture

**2.4 Development of selective agricultural working robots**

2.4.1 Selective harvesting robots

Compared with non-selective working, robotic selective working faces a great challenge in the highly textured agricultural environment[61]. The characteristics of selective working robots are those types of robotic equipment that need to realize the selective operation of individual agricultural targets through the identification, positioning and diagnosis of them based on machine vision and other technologies. Considering the high labor cost of fresh-eating fruit harvesting, harvesting is undoubtedly the earliest and largest research field of agricultural robot technology. Significant progress has been made in decades of research and development, more work is required in order to reduce the cycle-time before it can be commercially viable and improving operational efficiency has become the most concerned issue in R & D[62]. As a result, robotic multi-arm harvesting has been paid more and more attention, it is believed to be able to remarkably improve the harvesting efficiency[63]. In general, robotic multi-arm harvesting can be categorized in parallel operation and cooperation (Table 4).

Williams, Zhang, SEPÚLVEDA, Mu, Chen, Li, and Liu et al.[64-76], have developed multi-arm robots for kiwifruit, tomato and grape harvesting and other high-density fruit respectively. Facing the new demand of the new urban production–leisure integrated industry, different humanoid dual-arm harvesting robots have been developed by Peng, and Chen et al.[69,70], which adopt parallel operation mode with the help of on-head RGB-D cameras and in-hand RGB-D cameras. It is believed to achieve a much higher combined harvesting rate with several arms and end-effectors to work at the same time[61,62]. However, the harvest zones and harvest order planning are the essential and big challenges to realize the multiplication of efficiency[63,66,70-72].

To harvest fruits by the cooperation of different arms is another selection. Inspired by artificial operation, Liu et al.[73] designed a wolfberry harvesting robot that adopts dual-arm to branch-gripping end-effectors to work together. Joseph et al.[74] designed a dual-arm robot for apple harvesting, results from laboratory studies showed the pick-and-catch coordination resulted in a fifty percent reduction in harvesting cycle time compared to the pick-and-place method. Zhao et al.[75,76] designed a dual-arm robot for harvesting tomato fruits, which used a saw cutting end-effector to cut the stem and the other end-effector to grasp the tomato for avoiding tomato shaking caused by the cutting operation. It is worth noting that the dual-arm cooperation mode puts forward requirements for manipulator configuration, canopy space and cooperation control. Whether it is the reasonable direction of harvesting robot technology development is worth further exploring.

2.4.2 Other selective working robots in crop-farming

In recent years, precision agriculture (PA) is emerging rapidly worldwide. The term Precision Agriculture is described as being “a management strategy that uses electronic information and other technologies to gather, process, and analyze spatial and temporal data for the purpose of guiding targeted actions that improve efficiency, productivity, and sustainability of agricultural operations”[1]. Robotic technology is a powerful tool to realize targeted actions in agriculture, which usually rely on machine vision or other sensing technologies to perform selective or targeted working of seed sowing[77], Seedling sorting/replanting[78], spraying[79,80] weeding[81], pruning[82,83], trimming[60,84-86], flower or fruit thinning[87,88], fruit bagging[87,89,90], de-leafing[91,92], pollination[93-97], bin-handling[98-100], fruit transportation[101,102], fruit grading[103,104], etc. (Table 5).

For pruning, a robotic system must be able to perceive the 3D pose of the branch to be cut, as well as move a cutting implement precisely to a cut point while avoiding obstacles such as other branches or structures[83]. A fully autonomous system must also be able to choose cut points automatically[83]. For trimming, challenges arise to realize the visual servoing control of cutting tools towards the target objects, to represent the correct shape and size of a topiary bush and subsequently deciding where and how much cutting is needed for an overgrown bush[61]. The EU H2020 funded project named TrimBot2020 is trying to investigate the underlying robotics and vision technologies to prototype the next generation of intelligent gardening consumer robots[61,105]. The TrimBot2020 robotic platform is based on a modified version of the commercial Bosch Indigo lawn mower on which a Kinova robotic arm is mounted[61]. The robot platform is equipped with a pentagon-shaped rig of five pairs of stereo cameras and two circular counter rotating sets of knives, one of these will have sharp edges whereas the other will act as an anvil with blunt edges[61]. Compared with trimming, robotic pruning is more difficult, there is still a long way to the practical level.

One urgent challenge facing the agriculture industry is the decline of natural pollinators, the high cost of renting bee colonies and the inadequate pollination[93]. The idea of using robots to aid pollination has been considered for more than a decade[95,96]. There may be two fundamentally different approaches in robotic pollination, the first approach is the use of a ground platform with a manipulator and some sort of end-effector, the second approach is for the robot to fly in the form of a drone or robotic bee imitation[97]. Shi et al.[106] proposed that when the UAV is close to the flowering tomato, the downwash flow blows the pollen from the stamen. Pollen will drift to the pistil under the wind, and then pollination is completed. In the greenhouse experiment, as the height of the flower decreases, the proportion of pollen area in the culture dishes which were placed next to the flower was 0.34%, 0.25%, 0.32%, 0.69%, which preliminarily verified the possibility of the modified drone for pollination. Berman et al.[107] presented a scalable approach to optimizing robot control policies for a target collective

**Table 4 Multi-arm selective fruit harvesting robots**

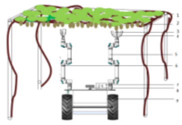
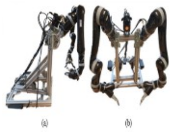
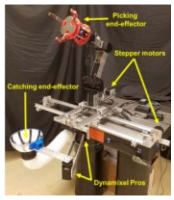
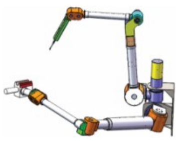
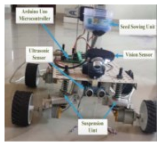
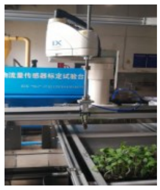
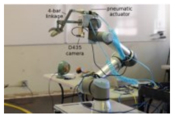
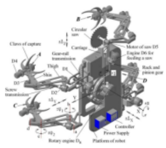
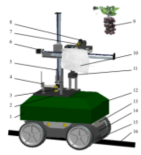
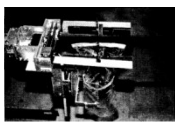
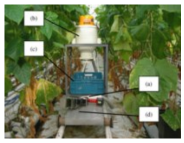
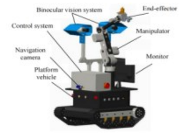
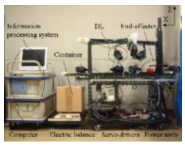
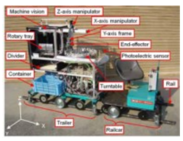
| Object | Category | Platform | Navigation sensors | Manipulator | Detection sensor | End-effector | Appearance example | Reference |
|---|---|---|---|---|---|---|---|---|
| Kiwifruit | Parallel | -- | -- | 4-bar linkage | A pair of color cameras | Grippers |  | [64,65] |
| Kiwifruit | Parallel | 4-wheel electric vehicle | -- | UR5 6-DoF jointed | Kinect | Self-designed gripper |  | [66,67] |
| Aubergine | Parallel | -- | -- | Kinova MICOTM 6-DoF jointed | RGB camera, 3D depth camera | Kinova Gripper KG-3 |  | [68] |
| Tomato | Parallel | VMAX omni-direction mobile moving base | -- | HRP2 humanoid robot, 7-DOF | Xtion (head), Carmine (arm) RGBD sensors | Special scissors |  | [69] |
| Grape | Parallel | Crawler-type vehicle | Lidar, electronic compass | 6-DOF jointed | RealSense D435 | Clip-shear-support integrated end-effector |  | [69] |
| Tomato | Cooperation | Railed mobile platform | -- | 3-DOF SCARA-like | Bumblebee2 stereo camera | Saw cutting type, suction type |  | [75,76] |
| Apple | Cooperation | -- | -- | 6-DOF jointed arm+x-y displacement(picking), 2-dof planer jointed(catching) | | 3 finger piking, catching |  | [74] |
| Wolfberry | Cooperation | -- | -- | 4-DOF jointed (gripping), 6-dof with spherical joint (picking) | -- | Gripper, groove |  | [73] |
| High-density fruit | Parallel | -- | -- | 4-DOF (xyz+rotation) | Realsense D455 depth sensor | -- |  | [63] |

**Table 5 Selective working robots in crop-farming except for harvesting robots**

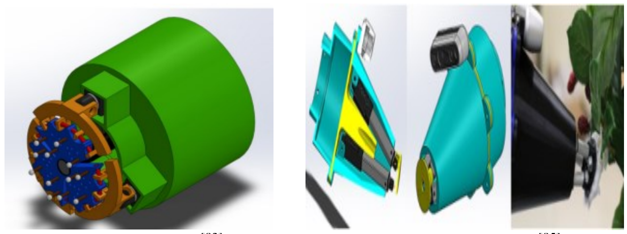
| Task | Platform | Navigation sensor | Detection sensor | Working part | Appearance example | Reference |
|---|---|---|---|---|---|---|
| Seed sowing | 4-wheeled platform | Vision sensor | Ultrasonic sensors and IR sensors | Lead screw and rotating disc |  | [77] |
| Seedling sorting/ replanting | -- | -- | RealSense RGB-D camera | Pneumatic grippers |  | [78] |
| Spraying | Electric 4-wheeled platform | Horizontal Lidar | Vertical lidar | Spraying device with four independent nozzles |   | [79] |
| Spraying | Multifunctional rubber-tracked vehicle | RTK-DGPS GNSS receiver, attitude and AHRS | Stereo camera, sick laser scanner | Smart spraying system |  | [80] |
| Weeding | Crawler-type autonomous caterpillar robot "Phoenix" | IMU, Sick LMS111 2D laser scanner | Sonar sensor pico+100/U | Rotary weeder from humus co. called "humus planet" |  | [81] |
| Pruning | 2 wheel mobile platform from Neobotix | SICK laser scanner | 2 Intel Realse D435i RGBD cameras | A cutting tool with pruning shear |  | [82] |
| Pruning | -- | -- | RealSense D435 RGB-D camera | Pneumatically-actuated four-bar linkage with custom-ground blades |  | [83] |
| Trimming | -- | -- | Stereo camera | Trimming end-effector |  | [61,84] |
| Trimming | Tree trunk walking with 4 legs | Remote control | -- | Circular saw |  | [85] |
| Trimming | Lawn mower | Pentagon-shaped rig of five pairs of stereo cameras | | 2 circular counter-rotating sets of knifes |  | [61,84] |
| Thinning | -- | -- | 3D vision system | Dual-servo rotating brush |  | [88] |
| Bagging | Wheeled mobile platform | magnetic navigation sensor | 2 OK_AC1210 USB cameras | Adding two spring leaves on both sides of the grape bags |  | [89] |
| Bagging | -- | -- | Color TV camera with infrared sensitivity, photo-electric sensor | End-effector with spring plates |  | [87,90] |

| Task | Platform | Navigation sensor | Detection sensor | Working part | Appearance example | Reference |
|---|---|---|---|---|---|---|
| De-leafing | Railed vehicle | -- | Near-infrared-based computer vision system | Teeth, two electrodes (thermal cutting) |  | [91] |
| Leaf picking | Railed vehicle | -- | -- | 1 picking rotor with a motor, a pipe, a vacuum cleaner |  | [92] |
| Pollination | ClearPath Robotics® Husky platform | 3D lidar | To-hand camera, in-hand depth camera | 3 linear actuators,1 flexible member,cotton-tipped brushes |  | [93] |
| Pollination | Pedrail type vehicle | Camera and sonar sensors | Binocular vision system | Nozzle |  | [94] |
| Pollination | ClearPath Robotics 4-wheel ground vehicle | -- | Intel RealSense TM D435 depth-camera | 3 linear actuators, 1 flexible plate,a cotton padding |  | [95] |
| Pollination | Autonomous multi-purpose Mobile platform | -- | Cameras, LED light bars | Spray manifolds |  | [95,97] |
| Bin-handling | 4-wheel-independent-steering system(4WIS) | GPS, IMU | -- | Forklift actuated by a scissors-structured lifting mechanism |  | [98] |
| Bin-handling | Wheel-ground engagement system (WGES) | LMS 111 laser scanner | ultrasonic sensors | Bin lifting |  | [99] |
| Bin-handling | 4-wheel-independent-steering system (4WIS). | GPS, Lidar, | RTK, GPS, 2 laser scanners, | Forklift-type bin loading system |  | [100] |
| Transportation | 4-wheel plafform | Ultrasonic sensors | -- | -- |  | [101,102] |
| Grading | -- | -- | 5 progressive scan video cameras | Long-finger gripper |  | [103] |
| Grading | Trunk | -- | Camera | -- |  | [104] |
| Grading | Railed platform | -- | Progressive scan video camera | Rotary tray, flexible gripper |  | [108] |

behavior in a spatially inhomogeneous robotic swarm, which is illustrated with a scenario in which the behaviors of a swarm of robotic bees are optimized for both uniform and nonuniform pollination of a blueberry field, including in the presence of an unknown wind. However, robotic bees require tethered to power and control so are still a long way off being viable pollinators[97]. The ground robotic pollination seems to be more feasible at present, which needs to locate 3D positions of flowers and use physical touching or spraying to finish the pollination. In different researches, detection rates of single flowers may reach 50.0%-93.1%[95-98]. Researchers at West Virginia University (WVU) have recently developed an autonomous robot named "BrambleBee" that can pollinate bramble plants within a greenhouse environment. The first-generation end-effector consists of three linear actuators that push and pull a flexible member on which cotton-tipped brushes are inserted[93] (Figure 6a). The second-generation end-effector uses a flexible plate is attached to the linear servos to allow for off-axis flexibility, which is then coated in cotton padding for transferring pollen[95] (Figure 6b). Experimental results show that the proposed system is able to achieve a 76.9% "pollination" success rate tested with high-fidelity artificial flowers[95].

2.4.3 Selective working robots in livestock and poultry farming

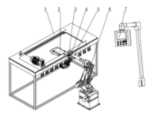
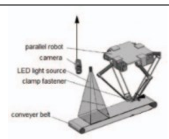
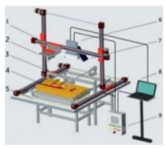
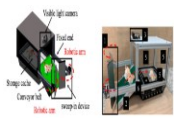
In livestock and poultry farming, selective and targeted management are becoming more and more important, some prototypes in development are listed in Table 6. Automatic milking systems (AMS), when made mobile, give the possibility of milking cows in the field without additional labor[109]. In recent years, intelligent feeding control according to changes in behavior and growth status has gained increasing attention[55]. A lot of evisceration work to separate internal organs from poultry carcass is required in the poultry slaughtering industry, robotic eviscerating can ensure the safety of poultry processing health, improve the production efficiency and reduce labor intensity[110,111]. Infectious hoof disorders are a serious challenge for dairy productions since they cause pain and discomfort in cows and can compromise the competitiveness of dairy farming. Robot scrapers are capable of frequently removing liquid manure from slatted floors and can contribute to improved hygiene of walkways[112].



a. First generation[93] b. Second generation[95]

Figure 6 Pollinating end-effectors of BrambleBee

**Table 6 Selective working robots in livestock and poultry farming**

| Task | Platform | Navigation sensor | Detection sensor | End-effector | Appearance example | Reference |
|---|---|---|---|---|---|---|
| Eviscerating | Workbench | -- | Industrial camera, position sensor | -- |  | [110] |
| Eviscerating | Workbench | -- | Camera | -- |  | [111] |
| Floor eggs picking | 3 driven pneumatic wheels | Laser scanner | Camera | Bent helical spring |  | [113,114] |
| Floor egg picking and grading | 4-wheel chassis | Ultrasonic sensor | Camera | Egg collection channel |  | [115] |
| Floor egg picking and classification | 4-wheel chassis | Ultrasonic sensors | Camera | Modified stretchable spring egg-collecting and sorting mechanism |  | [116,117] |
| Floor eggs picking | 4-wheel chassis | Indoor GPS | Kinect 3D camera | Suction pad |  | [28,114] |
| Half-sheep cutting | Workbench | -- | Azure Kinect | End cutting saw |  | [118] |
| Dead chickens removal | Tracked vehicle | Remote-control | Camera | Sweep-in device |  | [119] |

There is a growing interest in using automatic floor egg collection in the modern animal-friendly loose housing systems adopted for laying hens[113]. Bastiaan, Usher, Chang, et al have developed various prototypes of egg collection robots, some of them can realize egg picking and classification at the same time[28]. Poultrybot is a system in current development for automated floor-egg collection, in experiments, 46% of over 300 eggs were collected successfully[28,113-117]. The system developed by Joffe et al was retrofitted with a Microsoft Kinect 3D camera and a commercially available "indoor GPS" system, and the robust testing of the egg picking algorithms yielded a success rate of 91.6%[28,117].

2.4.4 Commercial selective working robots

Due to the non-structural and individual differences of the agricultural environment and crop object, the selective operation is a great challenge. However, more and more big companies invest in selective operational robot products development, more and more start-ups in this field are emerging and becoming industry stars. Bosch-funded start-up company Deepfield Robotics is the latest company to develop a field vehicle that can distinguish weeds from crops and neatly fish. Robots are used to fertilize the plants efficiently with a nitrogen fertilizer at the base of the crops. TerraSentia is the first robot from EarthSense, which can help crop breeders create new high-yielding crops with less water, chemicals, and other inputs. Harvest Croo Robotics in the United States and AgRobot in Spain are working with up to thirty picking parts based on visual detection, and even completing sorting and packaging simultaneously (Figure 7). The target herbicide spraying robot developed by Blue River Technology in the United States (Figure 8a), the weeding robot developed by F Poulsen Company in Denmark (Figure 8b), and the lettuce thinning robot developed by Vision Robotics in the United States (Figure 8c), etc., carry out synchronous target spraying, weeding or thinning operations respectively with multiple working parts based on real-time visual detection or mapping. However, the large-scale commercialization of agricultural robots and their large-scale application in agricultural production still need time. The lack of supporting agronomy and the technical immaturity in the face of a complex agricultural environment are still the key obstacles.

a. Harvest CROO b. Agrobot

Figure 7 Large strawberry harvesting robot

a. Blue River b. F Poulsen c. Vision Robotics

Figure 8 Large field-managing robots

## 3 Latest scientific and technical research

### 3.1 Scientific research

Agricultural robots take the semi-natural ecosystem as the operating scene, the living body as the object, and the autonomous operation as the goal. They have the typical characteristics of being highly interdisciplinary. In particular, the breakthrough of selective working robot technology has put forward the objective requirements for basic scientific research of related disciplines and interdisciplinary research. On the contrary, the relevant basic research has also greatly enriched and promoted the development of agricultural robot technology.

3.1.1 Continuously deepening research on autonomous chassis and navigation

In agricultural application, the design and control of omnidirectional chassis and wheel-track combined chassis based on soil characteristics and ground mechanics of track slip and slippage is becoming a hot research topic. The navigation in greenhouses, orchards, tea gardens, livestock, poultry houses, and so on for robotic working usually bases on the full perception and understanding of local scene features, which is completely different from the motion-planning navigation in the open field based on satellite signal and global coordinates. The navigation technology based on agricultural scene perception has also been developed from relying on single information of 2D radar, CCD vision to RGB-D fusion. And this vision information is further integrated with obstacle judgement, geographical direction to realize deep understanding and comprehensive planning[120]. In addition, real-time sensing is furtherly being integrated with SLAM, field electronic mapping, IOT monitoring of agricultural conditions, etc. to put forward the deepening of scene-based navigation technology[121,122].

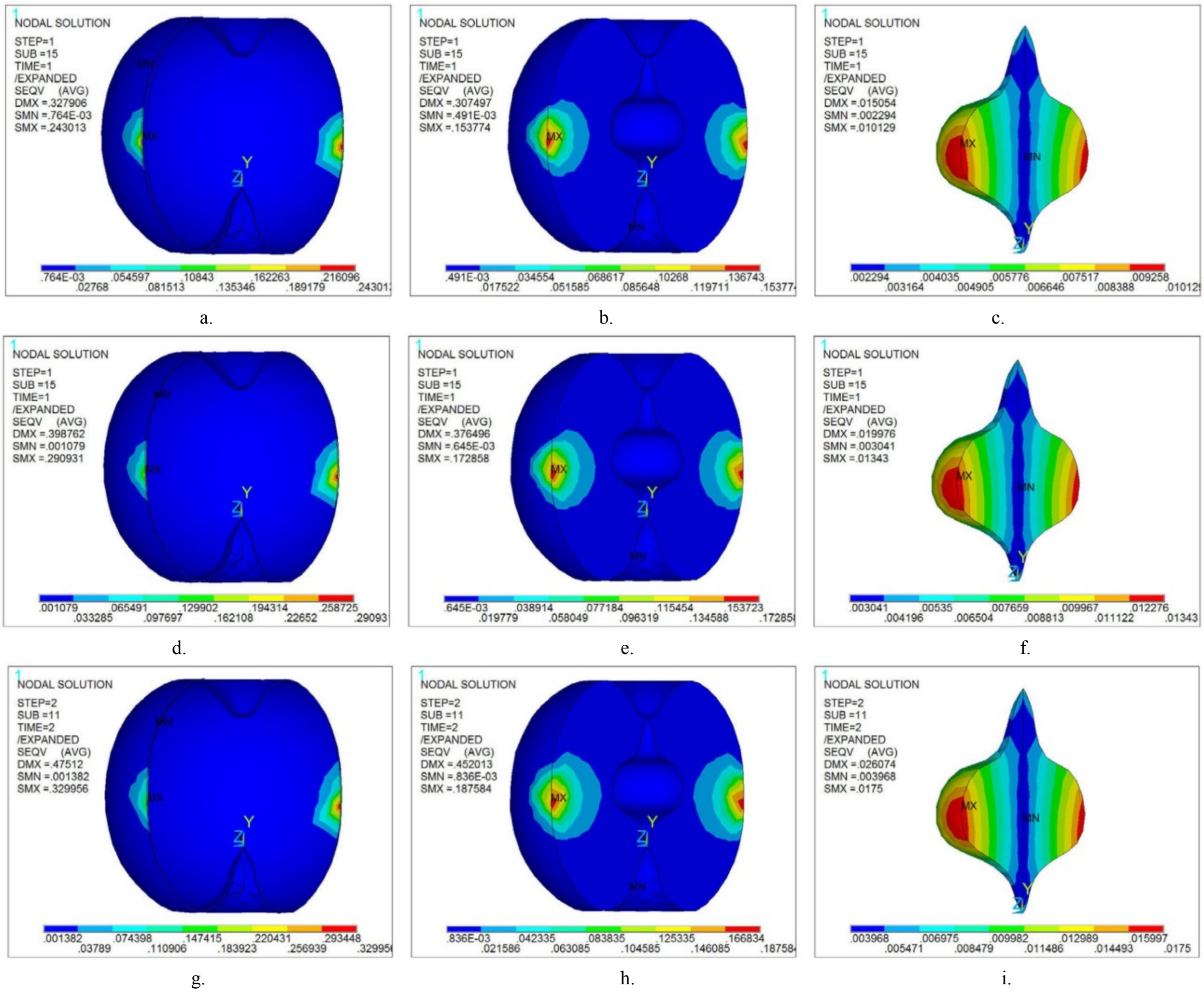
3.1.2 Research on a damage-free robotic operation based on crop properties and robot-crop interaction

Selective harvesting is the largest application field of agricultural robots. An end-effector is the tool that directly interacts with the object and performs the operation task, its structure and principle are greatly different according to the crop, agricultural material properties and canopy structure, and its innovative research and development have also become the most active and productive direction of harvesting robot technology. Nowadays, the structure of chassis, vision system and manipulator are becoming more and more standardized, the end-effector has become the largest difference between different types of harvesting robot equipment.

At the same time, the agriculture robot must adjust the gripping force in real-time rather than exerting a predetermined force[123]. High-efficiency and damage-free are the core requirements of actual production for robotic operation in agriculture, but they are exactly contradictory. The study on the interaction rules of the fragile biological target and robot and behavior characteristics of harvesting robots are of great significance for realizing breakthrough of these requirements. The characterization of the viscoelastic-rheological constitutive models of various fruits has been studied all over the world. Liu[124], Ji[125] (Figure 9), Zhou[126], Li[127], et al., have successively carried out the modeling and simulation study of static gripping and dynamic collision between end-effector and viscoelastic fruit. Liu firstly established the research direction of high-speed damage-free harvesting and found two important characteristics of fast gripping collision: active energy input and constrained contact collision[124,128]. In addition, Xiong[129], Bachche[130], and Liu[131], respectively researched the combined research of mechanical cutting, thermal cutting, laser cutting with the mechanics and heat transfer theory of fruit stem, petiole and weed.

3.1.3 Research on robot design and motion planning for agronomy-robot fusion

The research of agronomic-robot fusion has been paid more and more attention. Zhang et al.[132] and Bac, et al.[133] carried out research on the combination of cultivation pattern, crop canopy geometry, design and path planning of manipulator. Van Hock et al.[134] designed varieties, climate, cultivation technology, light conditions for robot harvesting from the indices of visibility, reachability, grasp ability, and detectability. Bloch et al.[135] presented and demonstrated a methodology for the simultaneous optimal design of robot kinematic and the working environment for robotic harvesting (Figure 10).




Note: a, d, g are shown the maximum stress (SMX) and minimum stress (SMN) of apple skin at the grasping velocities of 0.1 mm/s, 0.5 mm/s, 1 mm/s, respectively; b, e h are shown the maximum stress (SMX) and minimum stress (SMN) of apple flesh at the grasping velocities of 0.1 mm/s, 0.5 mm/s, 1 mm/s, respectively; c, f, i are maximum stress (SMX) and minimum stress (SMN) of apple core at the grasping velocities of 0.1 mm/s, 0.5 mm/s, 1 mm/s, respectively.

Figure 9 Apple gripping stress distribution[125]

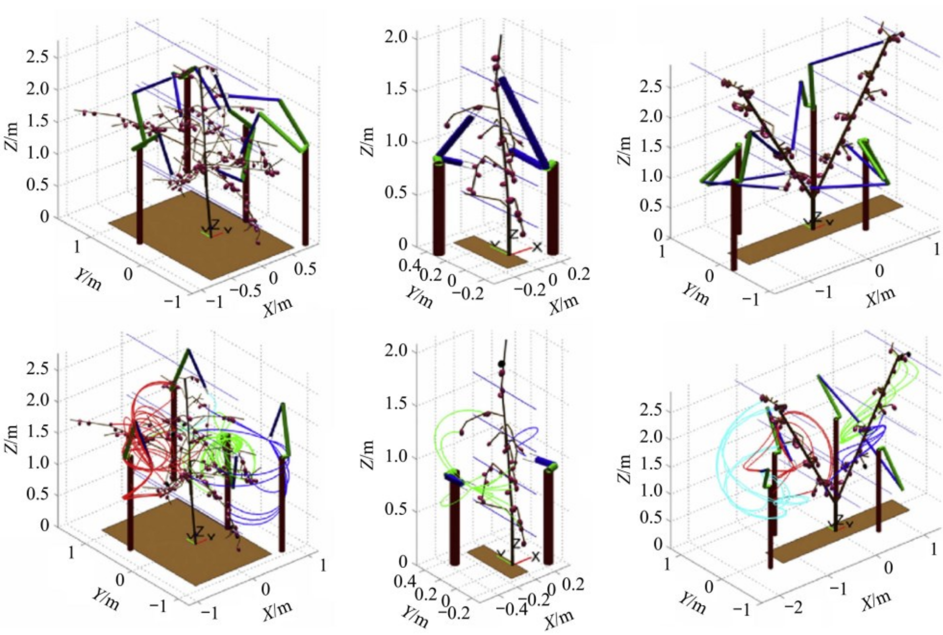



Figure 10 Optimal robots for different tree shapes[135]

### 3.2 Technical research

It can be found that virtual design technology, modular reconfigurable technology, bionic technology, etc. have been applied in the design of the whole machine and key components of agricultural robots. Especially, the innovative design of end-effector has become the concentrated application field of different kinds of new materials, new structures, and new technologies.

3.2.1 Virtual robot-crop interaction technology

Robot-crop interaction simulation can get rid of the limitations of the growing season, time and money costs of prototype development and experiments, and greatly accelerate the design, analysis and planning of the robot. Unlike the virtual and simulation design of traditional mechanical systems, virtual working simulation of agricultural robots relative to virtual fruit and vegetable targets in virtual scenes such as orchards has been continuously applied in robot research and development. A key step toward the acceleration of robotics is the choice of simulation software, middleware operating systems, and virtual environment platforms, and there is a long list of academic and professional simulation platforms that can be adapted and used for agricultural robots[136]. Mahmud et al.[137] have carried out the design and planning of mobile robots under the virtual greenhouse crop environment. Zou et al.[138] have carried out a simulation study on robotic harvesting in a virtual tree canopy environment.

3.2.2 Robot reconfigurable technology

A reconfigurable robot can change its configuration according to the change of task or environment. Grimstad et al.[139] have developed the Thorvald II Robot, a reconfigurable multi-modularization agricultural mobile robot with power supply, drive, control, suspension, and detection. The EU Crops project has funded the research and development of modular reconfigurable agricultural robots which can realize the application of target spraying and harvesting tasks respectively[140]. Levin et al.[141] have further established the design framework of a highly modular reconfigurable harvesting arm. Based on different tree shapes, different harvesting arm configurations can be reconstructed through the modular design of direct action, revolute joints, end-effectors, and connectors.

3.2.3 Soft agricultural robot technology

This research has become a hot topic and has great potential advantages in flexible and adaptive operations in agriculture. Mohamed et al.[142] have developed a soft robotic arm that used agonist-antagonist actuators connected to the joints via flexible tendons for tomato harvesting. Using elastic silica gel as material, Bartlett et al. have designed a soft robotic hand with a pneumatic network as an actuator[143]. Devi et al. have developed an underactuated multi-finger soft robotic hand, whose bending joints adopted asymmetric bellow flexible pneumatic actuator (ABFPA), which could realize the dexterous grip of various geometric shapes[144]. Excell et al. have developed a six-finger soft picker, which can gently grasp fruits and vegetables according to their shapes[145]. Shea has applied a soft hand made of electroactive polymer actuator (EAP) to the gripping of tender fruits, showing the characteristics of fast and flexible[146] (Figure 11). Nishida et al.[147] have developed a universal gripper using magnetorheological fluid (MR).

3.2.4 Bionic design technology for agricultural robots

Bionics design uses biological structure and functional principles to develop relevant equipment[148], which is expected to provide an important opportunity for the development of agricultural robot technology. The joint and configuration design of six-legged agricultural robots has been carried out by Zhang[149], Rong[150] and Zhang[151]. Huang et al.[152] have designed a bio-inspired snake bone-armed robot for agricultural irrigation application. Li et al.[153] have proposed an inchworm-like hook claw soft gripper actuated by shape memory alloy (SMA) spring. Quan[154] has designed a multifunctional dragonfly claw-form bio-mimetic end-effector. Deng et al.[155] have developed a bionic non-destructive handheld suction apple picker by combining handpicking action and octopus adsorption principle (Figure 12). Robotic bees for crop pollination promise to solve the growing problems of pollination quality caused by relying on natural bees[156] (Figure 13).

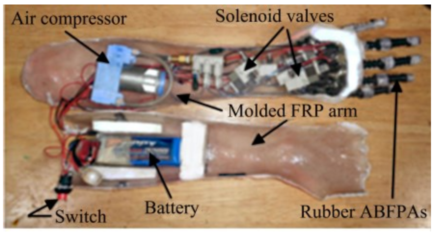


Figure 11 Multi-finger, multi-joint soft hand[146]

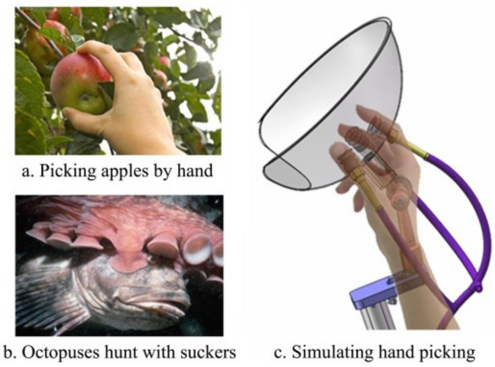
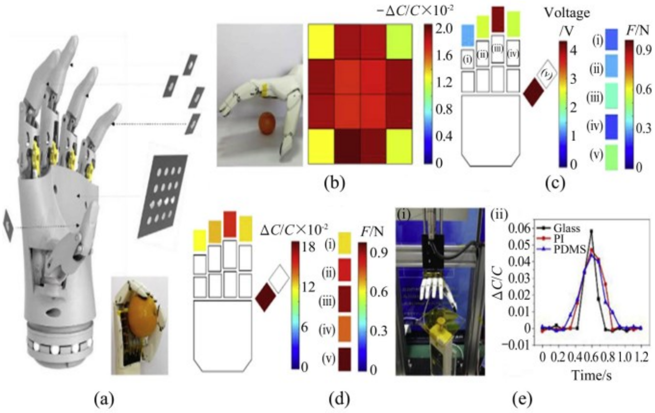


Figure 12 Bionic apple picking device[155]


Figure 13 Robotic bee pollination[156]

3.2.5 Perception and understanding of decision-making techniques

It is the core of agricultural robots to realize the performance of autonomous working, and a lot of continuous research has been carried out in this field, which has strongly promoted the progress of this technology. As a long-term technical bottleneck of agricultural robot technology to the actual production, the rapid upgrading of hardware provides major support for the breakthrough of the technology: from black-and-white CCD to color CCD, binocular-vision to highly integrated RGB-D camera supported by many source programs, high-speed GPU, and cloud-edge-terminal fusion computing system. At the same time, recognition and positioning technology methods are also developed from the traditional color image segmentation to multi-feature fusion and deep learning of deep image, RGB-D image. A major breakthrough is expected to make in visual recognition and positioning technology. The research based on combination sensing technologies of lidar, RGB-D, spectrum and UWB on fruit and vegetable target recognition and orchard navigation has been deepening[157-160]. The complex sense of touch and force based on piezoelectric film and electronic skin is greatly improving the ability to grasp delicate fruit and vegetable targets accurately and flexibly[161,162] (Figure 14). At the same time, multi-information fusion, cross-media perception, deep learning, agricultural big data, cloud-edge-terminal fusion computing, multi-unit network cooperation, 5G communication and other technologies are promoting agricultural robots to achieve a leap from individually limited autonomous intelligence to unlimited full-process, full-chain, full-unmanned monitoring-working agriculture[163,164] (Figures 15 and 16).




Note: (a) The integration of the sensor array in a bionic hand; (b) 3D shape mapping of an orange; (c) Open circuit voltage outputs of the fingertip sensor units during light grasping of the orange, the forces on each fingertip simultaneously measured by commercial thin-film sensors are shown on the right side; (d) Capacitance changes of fingertip sensors units during grasping the orange with higher pressure, simultaneous force measurements by commercial thin-film sensors are shown on the right side; (e) Hardness measurements using the E-skin on the bionic hand, experiment setup, (i) and capacitance changes as the bionic hand touched and retracted from three types of surfaces (ii).

Figure 14 Electronic skin[162]

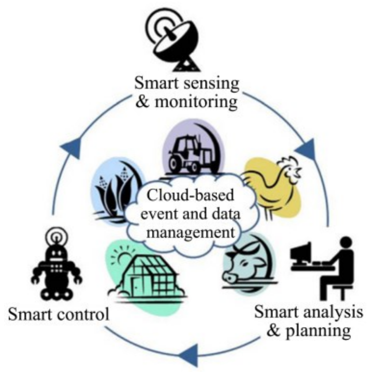



Figure 15 Intelligent agricultural monitoring-robotic working[163]

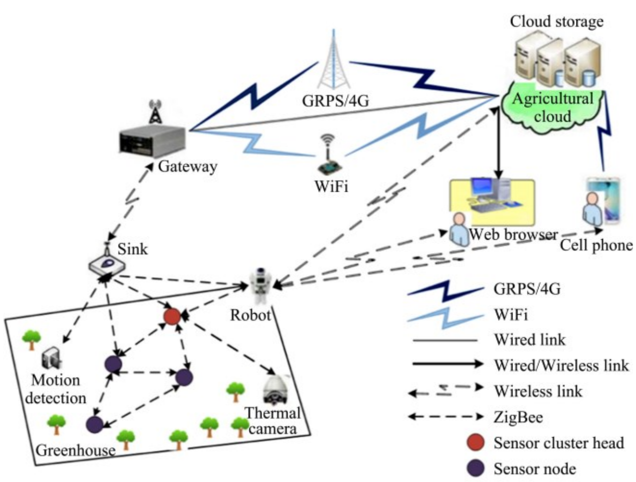



Figure 16 Agricultural cyber-physical fusion[164]

## 4 Development of key agricultural robot technology

### 4.1 Key technologies for agricultural robots

4.1.1 Fast damage-free operation technology

In either crop farming or livestock and poultry farming and aquaculture, autonomous operations for soil, water body and production facilities with water, fertilizer, or pesticide tend to be easier to implement. On the contrary, it is important and difficult to plant and harvest living crops, and catch animals, collect eggs or fish without damage. At the same time, fast or even high-speed operation makes the problem of damage more prominent, speedy damage-free operation is still a huge bottleneck of agricultural robots.

The realization of speedy damage-free operation, on the one hand, is largely determined by the innovative design of the end-effector supported by a new sensing method, new flexible material, new transmission structure. On the other hand, it depends on the effective dynamic soft gripping control and coordinated control of arm (manipulator)-hand (end-effector)-eye (vision) based on the mechanical-physiological properties of fruit-stem, etc.

4.1.2 Autonomous navigation technology for complex environment

The agricultural environment is regarded as a semi-natural environment, which has many random and seasonal components. For autonomous navigation under the conditions of open field, tea garden, orchard, vineyard, greenhouse, livestock and poultry, or water surface, there are great differences in scene features, navigation objectives and requirements, and information sources. At present, the navigation is mainly divided into global navigation based on world coordinates and local navigation based on scene perception, and there is also a huge difference between indoor and outdoor navigation. Global navigation based on satellite signals has been widely used in agricultural machinery operation, but the local navigation in so complicated and different agricultural scene is still a certain distance from production. Furtherly, according to the actual production needs, global-local, indoor-outdoor integrated navigation in more environments is becoming the focus and key.

4.1.3 Target detection technology for complex backgrounds

Vision technology is the core of agricultural robot technology, and undoubtedly, it is also the biggest bottleneck in the application and promotion of agricultural robot technology so far. Harvesting robots need to guarantee the fruit of the reliable detection and positioning of target fruit in complex dense canopy, weeding robot needs to distinguish between crops and weeds reliably within the complex soil backgrounds. Compare with industrial applications, all the above backgrounds are unstructured, highly random and changeable. Until today, these visual tasks are still a huge challenge. Traditional image segmentation technology relying on color difference features has been proved its huge limitations. Be competent for such a complex task, different features from depth image, thermal image, spectral image, etc, may be helpful to fuse with RGB image. The breakthrough of target detection technology for complex backgrounds needs to realize the important breakthrough of multi-information fusion technology and image processing algorithm under the guarantee of rapid upgrading of vision hardware (sensors, chips).

4.1.4 Special design technology for agricultural robots

Today, for the design of traditional industrial robots, there are typical methods, standards, and tools. However, the working environment, object, and task of agricultural robots are so different from those of industrial robots, their design is also more complicated than and much different from the existing technology of industrial robots. Therefore, it is the objective need of the development of technology and industry to establish the special design system of agricultural robots through the joint efforts of academia and the industry. Today, there has been a good academic exploration, but the special design methods, design techniques, design tools still need to be established.

**4.2 Path to realize the breakthrough of key technologies**

4.2.1 Modelling and virtual simulation of robot-crop interaction

At present, great progress has been made in the 3D modeling and virtual simulation of agricultural robots, as well as in the virtual simulation and analysis of robot-crop integration. However, the existing simulation of robot crop interaction is still limited to size matching and operation observation, and the soft handling simulation of end-effector to fruit target is not integrated with the whole robot and working environment. One day virtual reality will be integrated with mechanical-physical physiological-interaction of robot-crop, with visual detectability and hand-arm maneuverability, with crop phenotypes and robot digital design. Virtual reality based on deep robot-crop interaction will promote the research of design, navigation, perception and fast damage-free operation control of agricultural robots.

4.2.2 Comprehensive support of big data

Today, agricultural robots have moved forward from single machine optimization to big data supported design, perception control and collaboration. By establishing database and systematic data mining methods of knowledge big data, agricultural big data, industry chain big data, the design, manufacturing, sensing and control optimization, the application will be greatly accelerated. Construction and reasoning of agricultural robot technology efficacy map based on patent knowledge graph will realize the rapid digital design for the specific environment, objects and tasks and reduce the challenge and risk of innovative design. Industrial chain big data will connect the upstream and downstream relationship of the agricultural robots industry, and provide strong support for the special modularization and small-batch customization of agricultural robots. Big data of patrol inspection and internet of things (IoT) of agricultural production will realize continuous training of models and algorithms, and make it possible for agricultural robots to realize robust autonomous operation without intervention in the whole process.

4.2.3 Comprehensive support of artificial intelligence

Today, artificial intelligence has been fully integrated into all fields of production and life. From different types of equipment of mobile phones, automobiles, public transportation, engineering vehicles to different fields of entertainment, tourism, shopping, education and manufacturing, artificial intelligence is playing a more and more important role. The rapid development of key technologies of driverless with artificial intelligence as the core, vision and key components of solid-state lidar, supercomputing chips will inject strong power into the development of agricultural robot technology. Agricultural robot technology will be fully supported and empowered by artificial intelligence, supported by 5G communication technology and large computing power chip technology. Agricultural robots can perform big data acquisition and autonomous operation tasks in agricultural scenes, while artificial intelligence can enhance the fusion and understanding ability of big data and the interaction ability of robots. Through deep learning, cloud edge fusion computing, adaptive learning, cross-media computing, etc., agricultural robot technology will accelerate its performance improvement and continuously shorten its R & D cycle. Artificial intelligence in combination with agriculture robots will make a great breakthrough in agriculture.

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