machines

MDPI

Review

Actuators and Sensors for Application in Agricultural Robots: A Review

Dongbo Xie [1,2], Liang Chen [1,2], Lichao Liu [1,2], Liqing Chen [1,2,*] and Hai Wang [1,3,4,*]

1 College of Engineering, Anhui Agricultural University, Hefei 230036, China
2 Anhui Intelligent Agricultural Machinery Equipment Engineering Laboratory, Hefei 230036, China
3 Discipline of Engineering and Energy, Murdoch University, Perth, WA 6150, Australia
4 Centre for Water, Energy & Waste, Harry Butler Institute, Murdoch University, Perth, WA 6150, Australia
* Correspondence: lqchen@ahau.edu.cn (L.C.); hai.wang@murdoch.edu.au (H.W.)

Abstract: In recent years, with the rapid development of science and technology, agricultural robots have gradually begun to replace humans, to complete various agricultural operations, changing traditional agricultural production methods. Not only is the labor input reduced, but also the production efficiency can be improved, which invariably contributes to the development of smart agriculture. This paper reviews the core technologies used for agricultural robots in non-structural environments. In addition, we review the technological progress of drive systems, control strategies, end-effectors, robotic arms, environmental perception, and other related systems. This research shows that in a non-structured agricultural environment, using cameras and light detection and ranging (LiDAR), as well as ultrasonic and satellite navigation equipment, and by integrating sensing, transmission, control, and operation, different types of actuators can be innovatively designed and developed to drive the advance of agricultural robots, to meet the delicate and complex requirements of agricultural products as operational objects, such that better productivity and standardization of agriculture can be achieved. In summary, agricultural production is developing toward a data-driven, standardized, and unmanned approach, with smart agriculture supported by actuator-driven-based agricultural robots. This paper concludes with a summary of the main existing technologies and challenges in the development of actuators for applications in agricultural robots, and the outlook regarding the primary development directions of agricultural robots in the near future.

Keywords: agricultural robots; actuator; smart agriculture; environmental perception; end-effectors

check for updates

Citation: Xie, D.; Chen, L.; Liu, L.; Chen, L.; Wang, H. Actuators and Sensors for Application in Agricultural Robots: A Review. *Machines* **2022**, *10*, 913. https://doi.org/10.3390/machines10100913

Academic Editor: Dan Zhang

Received: 29 August 2022
Accepted: 2 October 2022
Published: 9 October 2022

1. Introduction

In the last two decades, with the advent of the information age and unmanned farms, agricultural production methods have changed dramatically [1–3]. The development of science and technology has combined agricultural production technology with internet of things (IoT) technology more closely, making smart agriculture one of the mainstream modes of agricultural production [4–6]. In particular, the wide use of agricultural robots has revolutionized the traditional agricultural labor mode, reduced labor intensity, enhanced agricultural production efficiency, and improved agricultural products' production quality, promoting modern agriculture's development [7–9]. Agricultural robots are special robots applied in agricultural production operations and a new type of intelligent agricultural machinery, which can use multi-sensor fusion, automatic control, and other technologies to realize automatic and intelligent production of agricultural equipment, operating in the natural environment [10–12]. Nowadays, agricultural robots are being widely used in many aspects of agricultural production, completely or partially replacing or assisting people in agricultural production, improving agricultural production efficiency, and enhancing production safety performance [13–15]. According to the robot's working space, they can be divided into indoor and outdoor robots. On the one hand, indoor robots are mainly used in greenhouses and other similar scenarios, including indoor harvesting robots, fruit and vegetable grafting robots, flower cutting robots, transplanting robots, and greenhouse automation control systems. On the other hand, outdoor robots can be applied in large-scale farmland, pasture, and other environments, mainly unmanned aerial vehicle (UAV), harvesting and tractors, nursery work robots, spraying and weeding robots, and fruit harvesting robots [16–20]. In terms of the agricultural production process, the agricultural robots include seeding, planting, harvesting, weeding, and pesticide application-based robots. Moreover, in the agricultural management category, they can be divided into harvesting, collection, and management robots; field mapping robots; dairy farm management robots; soil management robots; irrigation management robots; trimming and management robots; weather tracking and forecast management platforms; and inventory management platforms [21–25].

Agricultural robots have actuation components (drive systems, controller, robotic arm, end-effector), environmental perception (radar, camera), and other auxiliary components [26]. The working performance of agricultural robots depends not only on the working performance of the components, but also on the coordination ability between the systems. As shown in Figure 1, this paper uses a picking robot in agriculture as an example, introduces the hardware components of the robot, and explains its composition and logical architecture. This paper first classifies actuator systems, according to their drive components, control systems, and environmental perception, and second analyzes their application in agricultural production, taking into account different operating environments.

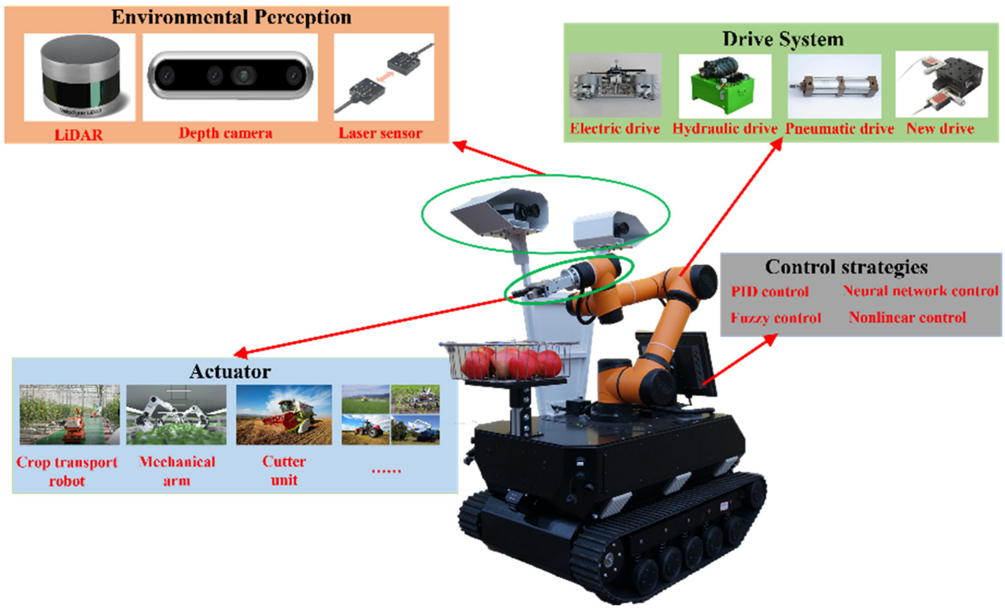


Figure 1. Robot hardware composition of a forest mapping robot, as an example.

The drive system, as the main component of the robot, can be classified into electric, hydraulic, and pneumatic types, based on the different applications of agricultural robots [27]. With the use of specialized sensors, including machine vision, laser-based devices, and inertial devices, actuators (hydraulic cylinders, linear and rotary motors, etc.) play an essential role in enabling the agricultural robots to execute different tasks via the help of electronic devices (embedded computers, industrial computers, and programmable logic controller) [28–30]. An agricultural robot end-effector's most important function is the flexibility to handle the work object, comparably to human arms and fingers [31,32]. At present, a wide variety of end devices have been developed, with fingers, attractors, needles, spray nozzles, scissors, and robotic arms, to grip, cut, attach, or press into crops to effectively perform all biological production processes, which include picking, harvesting, spraying, sowing, transplanting, shaping, primary processing, shearing, and milking [33–35]. In addition, the mechanical part of the end-effector is determined by both the biological properties and the operation of the target object. For the end-effector to perform such flexible operations, it is necessary to determine the characteristics of the target object, including the basic physical characteristics, such as the size, mass, and shape of the target object; mechanical characteristics, such as compression characteristics, friction characteristics, and cutting resistance; and to measure the acoustic characteristics and electrical characteristics, if necessary. In addition, mastering biological growth is also an indispensable element in the design of end-effectors [36–38]. Research results show that, as the selection of materials, the size of the end device, the control algorithm, and the accuracy have been significantly improved, the end execution has exhibited better flexibility and higher controllability.

With the development of automatic navigation and sensor monitoring technology, more and more actuator-based agricultural robots use navigation and intelligent monitoring technology as important auxiliary technologies in their design [39,40]. However, Hiremath et al. [41] pointed out that the global navigation satellite system (GNSS) is not accurate enough for some tasks, and navigation may fail when the signal is interrupted [42–46]. Therefore, machine vision, as the most widespread information source for agricultural robots, has the characteristics of rich perception information, complete information acquisition, and direct information recognition. However, the accuracy and reliability of the information perceived by machine vision are susceptible to environmental factors, such as natural light and the randomness and diversity of operating objects, which restrict the development of agricultural robots [47]. In recent years, LiDAR has been increasingly used in mobile robot navigation, because of its advantages, such as a high measurement accuracy and the ability to provide a large amount of distance information at a high frequency. During the operation of agricultural robots, LiDAR is mainly used for obstacle avoidance, e.g., in the orchard environment, the positional information of fruit trees obtained by LiDAR scanning can be used as navigation information to realize the navigation of mobile robots [48]. Nowadays, agricultural robots mainly use machine vision, spectral imaging, structured light localization, auxiliary light source, and other related technologies, integrated to improve their recognition, localization accuracy, and precision. However, limited by the traditional agricultural cultivation modes, information recognition is still ineffective for features such as target occlusion, variable posture, and similar color schemes. Therefore, at this stage, operational information acquisition, analysis, and sensing, as well as the servo control of actuators and end-effectors of agricultural robots, will be future research hotspots in the field of intelligent agricultural robots.

This paper provides an overview of the application of actuators and sensors in agricultural robots. The paper is organized as follows. Section 2 provides a comprehensive review of the core technologies of actuation components, including various actuator-based drive systems and control strategies. Section 3 summarizes the application of end-effectors in agricultural robots, based on different application scenarios. Section 4 introduces the sensors, auxiliary technologies, and systems of agricultural robots, such as environmental awareness and information fusion. Section 5 provides a general discussion of the review. Finally, there are the conclusions and outlooks of the paper.

2. Executive Components

As agricultural robots mostly operate in agricultural fields or greenhouses, many uncontrollable natural factors exist, and the growth of crops is constantly changing. In such a complex environment, agricultural robots need to realize mobile operation and precise control actions, such as fertilization and spraying, which correspondingly entail high technical requirements for developing agricultural robots [49]. In addition to fully considering the working requirements of the robot, such as the working speed, drive stability, drive torque, maximum handling weight, accuracy requirements, etc., it is also necessary to consider whether sufficient acceleration can be provided to meet the operational requirements under large load conditions of inertia. Generally, agricultural robots' drive systems can be divided into the following parts, according to the energy conversion mode: electric, hydraulic, pneumatic, and new drive devices, as shown in Figure 2. Therefore, research on drive control methods is key to the stable operation of agricultural robots in non-structured environments. Collating the appropriate hardware and matching an appropriate control strategy will become essential in implementing reliable drive control, against the uncertainties of field operations. Currently, the main control technologies commonly used in agricultural robots are classical control, fuzzy control, variable structure control method, feedback linearization and back-stepping control designs, chaos control, and wavelet theory-based control.

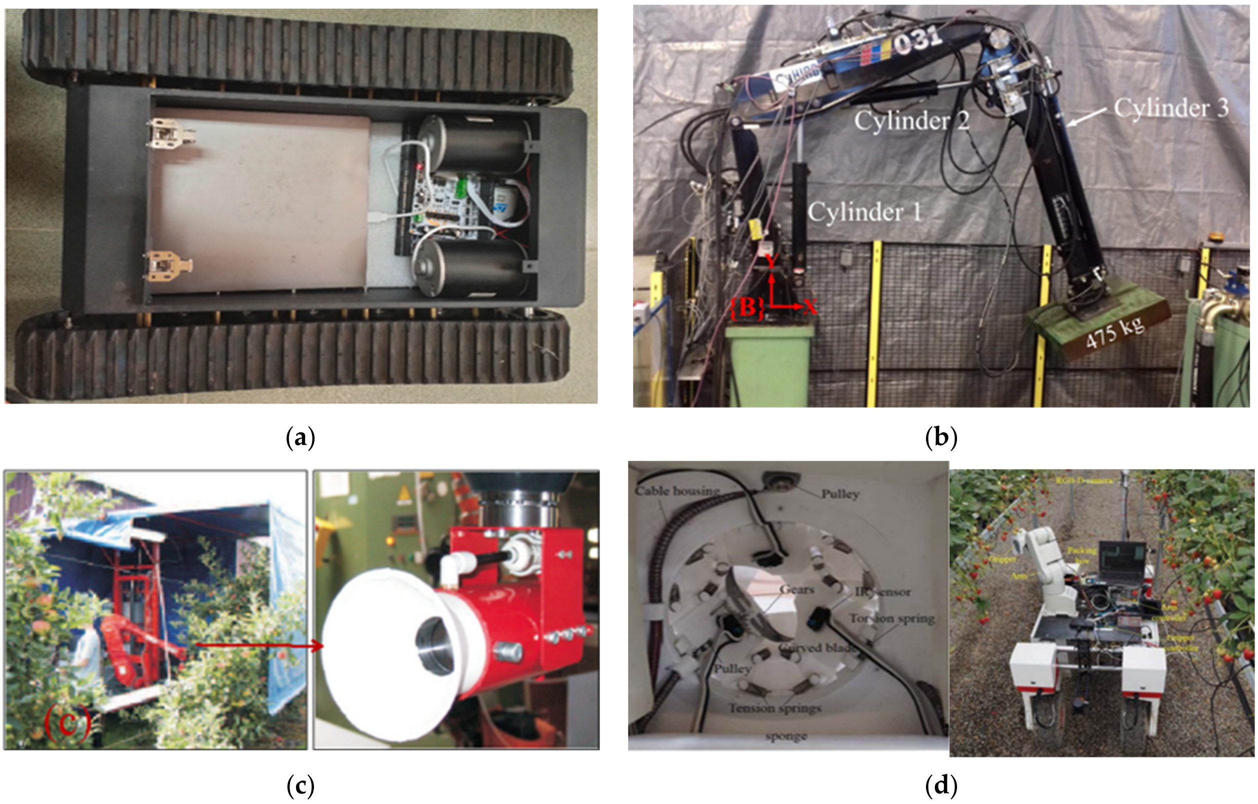


Figure 2. Drive methods for agricultural robots. (**a**) Electric drive robot experimental platform [50]. (**b**) Hydraulic-driven robot arm [51]. (**c**) Vacuum funnel-shaped apple gripper [52]. (**d**) Cable-driven manipulators for strawberry picking robots [53].

In the subsequent sections, various actuator-based motion systems in agricultural robots are described, and the related control techniques are discussed.

2.1. Drive System

2.1.1. Electrical Transmission Systems

In the non-structured farmland environment, the road conditions for agricultural vehicles are complex, and vehicle stability control has become a vital issue for intelligent driving. The most commonly used driving system in agricultural robots is an electrical transmission system, characterized by easy realization of high-precision computer control, good environmental adaptability, easy maintenance, and good reliability. Electrical drives generate forces and moments using various electric motors to drive actuators, directly or through mechanical transmission, to obtain different robot motions [54]. As the intermediate energy conversion process is eliminated, a higher efficiency, ease of use, and less consumption can be achieved, compared to hydraulic and pneumatic drives. Based on the characteristics of the independent control torque response of a distributed electric four-wheel-drive agricultural vehicle, Zhou et al. [55] proposed a coordinated and stable control using an improved adaptive predictive model, to realize the intelligentization of agricultural logistics. In agricultural robot mobile platform design, direct current (DC) motor motion is preferably used, because of its good starting and speed regulation characteristics, smooth speed regulation range, strong overload capacity, and the low effect of electromagnetic interference. Control of a DC motor is limited by the control method and pulse width modulation (PWM) control method. Chen et al. [56,57] designed a self-propelled crawler plant protection robot based on a DC brushless motor and a DC brushless motor driver bottom control board, as shown in the c component of Table 1. The plant protection machinery comprised five parts: a bottom drive system, communication system, self-propelled system, pesticide application system, and monitoring system. The whole robot was compactly designed to meet the space requirements of operating in the middle of the narrow spacing of the maize canopy of 600 mm. Zhang et al. [58] designed a crawler-type intelligent gum-cutting mobile platform based on DC motors with sensors including LiDAR and a gyroscope, which had a good capability in woods with different plant and row spacings. To quickly and accurately fit the navigation path of a greenhouse cucumber picking robot, Chen et al. [50] developed a greenhouse cucumber picking robot based on the characteristics of a servo motor combined with a machine vision system. It is worth noting that alternating current (AC) motors are often used in agricultural robots due to their low cost, high reliability, and simple motor speed control, resulting in better applications in agricultural engineering. For example, Jones et al. [59] used brushless AC motors to control the front wheel steering of a kiwi mobile robot platform based on the Ackermann steering system. Guevara et al. [60] used two AC motors to drive two rubber tracks in the design of an autonomous mobile robot for scanning agricultural environments. In contrast to the continuous rotation of a DC motor, when the current is turned on, a stepper motor rotates one angle forward for each electrical pulse signal input. Therefore, the stepper motor can be rotated to the desired angle by inputting an electrical pulse signal equivalent to the desired angle, and positional control can be achieved by combining this with an angle sensor; thus, stepper motors are also widely used in the field of agricultural robots. For example, Xiong et al. [34] developed a low-cost dual-arm system for autonomous strawberry harvesting robots based on stepper motors. To improve the adaptability of a transplanting device to different transplanting trays, Shao et al. [61] developed an adaptive transplanting device for transplanting rice seedlings, which achieved a continuous transplanting action by driving the seedling conveying device with a stepper motor, to improve its transplanting efficiency. This research outcome provided a new method for transplanting rice seedlings.

2.1.2. Hydraulic Drive Systems

The application of hydraulic technology has effectively increased the degree of automation and enhanced the popularization of agricultural machinery. The application of hydraulic technology is multifaceted, providing various types of technical support for agricultural machinery, such as adjustment, power, and assistance. The hydraulic drive converts hydraulic energy into mechanical energy, such as linear motion, rotation, and shaking. Compared to pneumatic drive systems, hydraulic devices can provide a higher pressure value and a larger torque force output; therefore, the device's size can be smaller and more suitable for agricultural robots. Hydraulic drives include hydraulic cylinders for linear motion, hydraulic motors for rotary motion, and rocking motors for rocking motion, which form a hydraulic control system, together with oil tanks, oil pumps, control valves, and control circuits [51]. Wang et al. [62] expounded and analyzed the development of electro-hydraulic suspension control technology from the two aspects of an electro-hydraulic control strategy and a sliding mode control strategy. More importantly, a new concept of integrating cutting-edge technologies, such as big data, fusion control, and artificial intelligence, was proposed, to develop hydraulic-based automated tractors. Li et al. [63] designed a hydraulically driven remote-controlled orbital mobile transport robot for mountain orchards, to solve the problems of inflexible steering, a complex structure, and poor stability of traditional transport vehicles in mountain orchards without grid coverage, as shown in Figure 3. Agricultural robots are also used to lift heavy agricultural products such as watermelons or cabbage [64]. Yang et al. [65] designed an electro-hydraulic servo controller, based on a hydraulic drive auxiliary wheel structure for the problem of complex turning at the front of an unmanned tractor. The designed electro-hydraulic system can realize auxiliary wheel automatic steering, lifting, and driving, as shown in Figure 4. However, agricultural robots often work outdoors and are vulnerable to vibration, sunshine, rainfall, and other factors [66]. Therefore, daily maintenance of hydraulic systems for agricultural robots is essential. Common faults of hydraulic system include four aspects: insufficient power of the hydraulic system, an unstable hydraulic driving process, leakage of the hydraulic system or damage to components, and too high temperature of the hydraulic system.

Figure 3. Mountain orchard transporter [63].

Figure 4. Auxiliary wheel tractor [65].

2.1.3. Pneumatic Actuator

A pneumatic actuator converts air pressure energy into mechanical energy such as linear work, ash transfer, and shaking. Pneumatic actuators include pneumatic motors and shaking pneumatic actuators, which form a pneumatic control system with air tanks, air compressors, or vacuum pumps, as well as control valves and control circuits. In agricultural robots, pneumatic actuators are used for grasping light crops or opening and closing manipulators. In the arm of a tomato harvesting robot, a pneumatic driver similar to an artificial muscle is used to form a pneumatic control system with an air tank, air compressor or vacuum pump, control valve, and control circuit, which is used to convert the air pressure energy into mechanical energy, such as linear motion, rotation, and shaking. Chen et al. [67] designed a pneumatic suction clamp integrated spherical fruit lossless picking manipulator, as shown in Figure 5. Not only were the two actions of the suction cup (pulling back and clamping claw closing) realized, sequential movement driven by a single active cylinder was completed, and the relevant structural parameters of the manipulator were obtained. Mata et al. [68] developed an underactuated multi-finger flexible manipulator, where the bending joint adopted an asymmetric-bellow flexible pneumatic actuator, to realize the smart grasping of various geometries. Using air has the advantages of being clean and safe, small machine size, and simple maintenance, but it is challenging to achieve accurate position and speed control, due to the compressibility of air. Jiang et al. [69] developed a needle-like end-effector for transplanting plant seedlings based on pneumatic actuation, tested its effectiveness, and determined the damage to the root ball. Gao et al. [70] proposed a pneumatic finger end-effector for a cherry tomato picking robot that was pneumatically controlled and capable of continuously and stably harvesting tomato fruit by combining clamping and rotation, with excellent adaptability to intensive operating environments, and which was field tested in a commercial greenhouse, as shown in Figure 6. The results indicated that determining the position of the fruit bunches relative to the stem plays a vital role in harvesting success. Enhancing the end-effector's adaptability, recognizing the fruit bunches' attitude, and improving the positioning accuracy are key research directions to improve robot harvesting performance.

Figure 5. Tomato picking end-effector based on non-destructive pneumatic clamping control [67].

Figure 6. Greenhouse harvesting robot [70].

2.1.4. New Driving Device

With the development of robotics technology, new types of actuators using new working principles have emerged, such as magnetostrictive actuators, piezoelectric actuators, electrostatic actuators, shape memory alloy actuators, ultrasonic actuators, artificial muscles, and optical actuators [71,72]. To realize the automatic harvesting of strawberries, Xiong et al. [53] developed a non-contact gripper based on a cable drive and perception ability, where the actuator could store multiple strawberries simultaneously, reducing the manipulator's driving time. However, the harvest success rate of the gripper was not high when it picked in dense or occluded areas of strawberries. Tawk et al. [73] designed a 3D tendon-driven soft gripper, producing linear travel upon activation, which included soft fingers and suction cups that can be operated individually or simultaneously, to grasp specific objects. Elmoughni et al. [74] used advanced computerized knitting to manufacture seamless pneumatic knitting actuators with a combination of weaving parameters to achieve an anisotropic, fully knitted actuator structure. This actuator can also be used to assist in the gripping motion of agricultural robots. In addition, although a titanium-nickel memory alloy flexible clamping mechanism was developed for the flexible clamping of seedlings, this clamping mechanism has not been widely used, because of its complicated structure, delicate manufacturing requirements, high cost, and poor reliability.

Among the drive methods for agricultural robots, a motor drive can achieve precise control according to the set parameters, and with the support of high-precision sensors and computer technology, the control accuracy can far exceed other control methods. However, with a DC servo motor drive, the brushes wear quickly and can form sparks; while stepper motor drives are mostly open-loop control, but they are mostly connected to the reduction device, and a direct drive is more complicated. A hydraulic drive can easily achieve load control, speed control, direction control, centralized control, remote control, and automatic control, but the need for an additional hydraulic source in flexible operations necessitates constant attention to the temperature of the hydraulic pump and solenoid valve, to avoid liquid leakage, causing pollution of the agricultural environment. A pneumatic drive has a simple structure and good adaptability, but they have a low output force, poor stability, low control accuracy, layout difficulties in controlling the speed and accuracy, and other defects. In an unstructured environment, there are significant differences in weather conditions, plant locations, and production methods, and this essential uncertainty puts higher demands on the flexibility and adaptability of agricultural robots. The robustness of the drive systems is essential in the working process of agricultural robots. Therefore, future drive systems of agricultural robots should focus on the following: (1) Drive mode diversification, with the integration of electromechanical and drive-control technology, with one drive mode as the main and other drive modes as auxiliaries, to overcome the problem of the insufficient reliability of work with a single drive mode. (2) With the help of sensors, artificial intelligence and other technologies, drive mode intelligence will be changed from manually operated or semi-automatic, to fully autonomous intelligent drives. (3) Energy-saving drive modes, with the help of new materials and new principles for new drives, such as magnetostriction drives, piezoelectric drives, etc., to reduce the energy consumption of agricultural robots, and to enhance the safety attributes of green agriculture. In addition, agricultural robots also need to combine the specificity of their operating environment and the complexity of the operating object, to choose an appropriate drive method, and at the same time need to use more effective control strategies to make up for the defects of the drive system.

2.2. Control Strategy

High-performance control strategies are necessary, to ensure an excellent operational performance of agricultural robots, including actuators and end-effectors (to be introduced later). The whole control process can generally be described as follows: the movement path is planned according to the desired trajectory, the actuators of the robots are controlled to avoid obstacles and to reach the target position, and finally, the end-effectors are manipulated to complete the flexible operation, with the help of sensors. In addition, due to the complex and changeable operation environments of agricultural robots, the precise navigation and control of agricultural robots' motion has become very important [75]. The automatic navigation of agricultural robots refers to the deviation between the actual position of the robot and the expected path (including lateral deviation and heading angle), to determine the steering angle of the chassis, so that the robot can move according to a predetermined route. Automatic navigation technology mainly includes environmental perception, path planning, vehicle model establishment, and steering control. The current agricultural vehicle models include kinematics and vehicle dynamics [76–78]. The major control methodologies adopted in agricultural robots consist of classical control, intelligent control, including fuzzy control, and nonlinear control, as shown in Table 1.

Table 1. Comparison of control strategies.

Control Strategy	Advantage	Disadvantage	Application Situation
Proportional, integral, differential (PID) control method	Simple to use, flexible, and easy to adjust	The adjustment accuracy is not high, and not precise enough	 a: Automatica-following agricultural robots [79]
Fuzzy control method	Strong robustness and fault tolerance	Lack of systematicness, low control precision and dynamic quality	 b: Autonomous mobile agricultural robot [80]
Sliding mode control method	Fast response, excellent tracking, strong robustness against external disturbances and parametric uncertainties	The discontinuous switching characteristics can cause chattering in the system.	 c: Self-propelled crawler plant protection robot [56]

2.2.1. PID Control

PID control, as the typical classic control method, is widely used in process control and motion control because of its simple algorithm, good robustness, and high reliability, and it has also been widely used in autonomous vehicles [81,82]. The PID algorithm constitutes the control deviation according to the given value and the actual output value of the system. PID control is performed using a linear combination of three components to control the controlled object. However, when disturbances and measurement noises exist in the control system, the control performance will be affected, such as poor system accuracy, long response time, and low stability, resulting in the control system not realizing the ideal control accuracy. Thus, various improved PID control methods have emerged, including fuzzy PID combined with intelligent control, neural network PID, etc. For example, Jia et al. [83] proposed an intelligent PID controller to solve the problem of controller oversaturation, where an improved adaptive Kalman filter algorithm was developed to explore a reliable navigation system for agricultural robots in complex agricultural operating environments. Mousakazemi et al. [84] introduced a genetic algorithm in the PID parameter adjustment by obtaining the optimized values of three control gains via different objective functions.

2.2.2. Fuzzy Control

When farmland operating machinery (i.e., agricultural robot) is operating in a field environment, due to the poor ground conditions of the farmland, the interaction process between tires and the ground is complicated. Moreover, considering that different moving speeds have a great effect on models of the frequency domain, the direct use of robot models should be avoided in the control, since it is difficult to establish a reasonable and accurate model [85]. Thus, many experts and scholars have designed fuzzy control techniques to analyze the collected fuzzy signals, to select the commands, and achieve the corresponding control target. Fuzzy reasoning makes correct decisions about the real-time state of the system, as it does not require an accurate mathematical model of the system and can be robust and adaptive to changes in the system parameters. Moreover, fuzzy control not only simplifies the work of the system designer and the computer, but also gives correct information about how the system operates in the real world; thus, it is often used for the path planning of mobile agricultural robots [86]. In the navigation area, the fuzzy control technique is primarily used for collecting and analyzing information, which can ensure the stable operation of robots, mainly when the received signals are incomplete or weak. Currently, fuzzy control has been combined with sensor-based navigation, to improve the incremental learning of new environments, to minimize the angular uncertainty and radial uncertainty in the environment, such that, not only can an optimal perception of the environment be obtained, but also the robot is able to manage certain dead-angle situations. For example, Zavlangas et al. [87] used the distance and angle between a mobile robot and an obstacle to establish fuzzy logic rules for real-time path planning. Pradhan et al. [88] proposed a rule-based neuro-fuzzy hybrid control technique in an unknown environment, which combined the repulsive influence related to the distance between the robot and a nearby obstacle and the robot's interaction with the target, to determine the steering angle of the robot. Thus, a fuzzy controller can detect obstacles around the robot and make the correct obstacle avoidance decisions.

2.2.3. Nonlinear Control

With the rapid development of robotics, agricultural robots are carrying out more considerable and heavy tasks, which has prompted the development of agricultural wheeled robotic multi-body systems, towards flexible robots with a higher complexity and degree of freedom. This requires optimizing the modeling methods of complex agricultural wheeled robots, to improve their efficiency and accuracy [89]. In the path tracking control of agricultural robots, the modeling accuracy can be affected by strong coupling and nonlinearity, and traditional inverse kinematic algorithms can no longer meet the requirements of high-precision operations. Therefore, nonlinear controllers have also been introduced to solve the inherent unmodeled dynamics, uncertainty, and disturbances [90]. To address these problems, controllers operating in uncertain environments must constantly adapt to changing conditions, to avoid steady-state errors, output oscillations, and even instability of closed-loop systems. The authors of [91] proposed a moving horizon estimation (MHE)-based nonlinear model predictive control (NMPC) framework for the control of agricultural robots. In addition, sliding mode variable structure control has been widely used, due to its insensitivity to disturbances [92]. To address the problem whereby tracked plant protection robots can significantly deviate from the expected path when operating in soft, sticky soil and complex environments (e.g., mid to late corn cultivation), Li et al. [56] developed a sliding mode variable structure algorithm-based path tracking control for tracked robots. Tu et al. [54] developed a four-wheel steering (4WS) and four-wheel-drive (4WD) agricultural robot mobility platform, based on a robust controller with back-stepping sliding mode control. The research results demonstrated the strong capability and robustness of the sliding mode controller in controlling a non-holonomic system with high degrees of freedom.

3. Application Scenarios in Agriculture

In the face of complex working scenarios, agricultural robots cannot accomplish their tasks by relying solely on drive systems and control strategies. Therefore, combining dexterous end-effectors and robotic arms is necessary to achieve precise operation. The end-effector, the other crucial actuating component, plays an essential role in the gentle handling of the operating objects. An actuator mechanism designed to enable this gentle operation of the end-effector is shown in Table 2. It is necessary to master the biological growth conditions, which is an indispensable element when designing an end-effector. First of all, it is necessary to determine the characteristics of the object, including the basic physical characteristics, such as the size, weight, and shape of the object, as well as the mechanical characteristics, such as the compression characteristics, friction characteristics, and cutting resistance [93]. In addition, an end-effector is greatly affected by machine vision and robotic arms. Since the position detected using machine vision has a certain error, the expansion and rotation of the robot arm will have a deflection or gap, such that the end-effector cannot reach the correct position due to this effect. Therefore, the end-effector needs to have the function of absorbing these errors. In addition, the end-effector, mainly driven by a motor or air pressure, can have other drawbacks, such as a poor stability of output force, low control accuracy, and complex layout, which are unsuitable for picking fruit with while maintaining quality. However, a hydraulic-driven end-effector exhibits the advantages of a large power/mass ratio, compact structure, high stability, and fast response. A hydraulic drive system based on force perception can accurately output an appropriate operating force, according to the working environment, and is especially suitable for picking fruits with a large volume and high quality. In short, the end-effector of agricultural robots must not only deal with the individual differences of organisms, but also have robustness against the errors of other mechanisms [94].

3.1. End-Effector Applications in Agricultural Robots

An end-effector equivalent to a human hand is a robotic part that can directly act on the work object. It is generally installed at the front end of a robotic arm, to perform various tasks. Tools are first installed on the end-effector of agricultural robots, such that different tasks can be completed by changing the end-effector, according to the type of work [100]. When designing and manufacturing the end-effector for an agricultural robot, it is necessary to fully grasp the object's physical properties and explore how to complete the task. The end-effector does not need to imitate hands for the operation, as long as the same effect is obtained. According to different operational objects, this paper gives examples of a clamping mechanism, cutting mechanism, absorbing mechanism, pressing mechanism, and disc weeding knife, to describe the application of end-effectors in agricultural robots, as shown in Table 3.

Table 2. Examples of end-effector applications in the field of agricultural robotics.

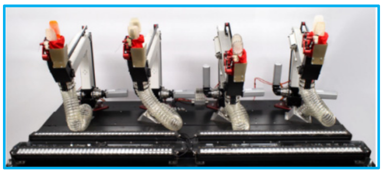
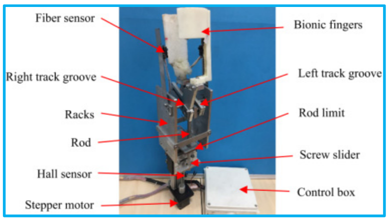
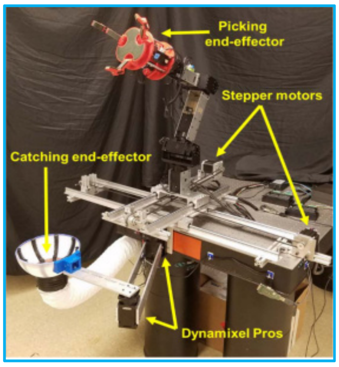
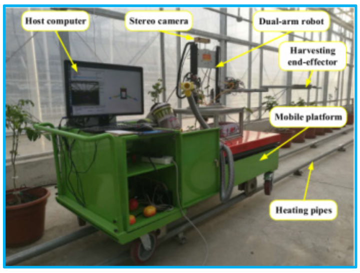
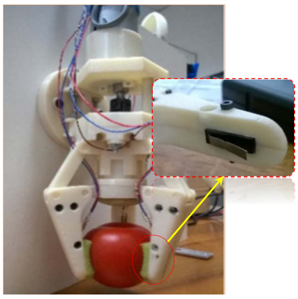
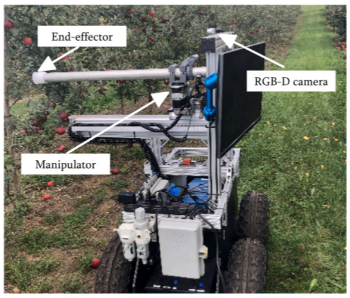
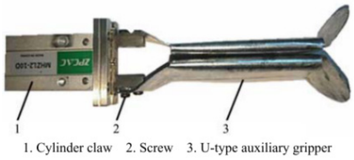
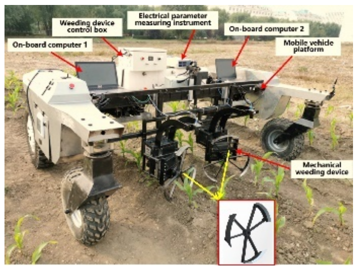
Actuator	Mobile Platform	Detection Sensor	Job Object	Degree of Freedom	Schematic Diagram	References
Grippers	/	A pair of color cameras	Kiwifruit	4-bar linkage		[95]
Self-designed gripper	4-wheel electric vehicle	Kinect	Kiwifruit	UR5 6-DoF jointed		[96]
Three-finger piking, catching	/	/	Apple	6-DOF jointed arm + x − y displacement (picking), 2-DOF planer jointed (catching)		[97]
Saw cutting type, suction type	Railed mobile platform	Bumblebee2 stereo camera	Tomato	3-DOF SCARA-like		[98]
Kinova Gripper KG-3	/	RGB camera 3D depth camera	Aubergine	Kinova MICOTM 6-DoF jointed		[99]

Table 3. Examples of dexterous end-effectors and robotic arms.

Object	Drive System	End-Effector	Appearance Example	Reference
Tomato	Electric	Clamping mechanism		[101]
Flowers	Electric	Cut-off mechanism		[78]
Apple	Pneumatic	Absorption mechanism		[102]
Plug seedling	Pneumatic	Press-in mechanism		[61]
Weeding	Electric	Disc weeding knife		[103]

3.1.1. Clamping Mechanism

Agricultural robots have various application characteristics, such as the season of operation, the complexity of the operating environment, the delicacy and complexity of the operating objects, and the specificity of the objects, that entail various demands for application in agriculture. A clamping mechanism is usually flexible according to the sequence of clamping and separating actions, characterized by the gripper grabbing the fruit and then disconnecting the fruit from the stem through a corresponding mechanism or action. According to the harvesting operational requirements, a reaper must achieve a certain weight, shape, center of gravity, size tolerance, and surface condition, as well as function in a small harvesting space or when part of the fruit obscured by branches and leaves [104]. The main purpose of the design is to improve the fruit picking success rate and reduce the fruit damage, such as with holding, cutting, twisting, and so on. In addition, for delicate, small bunches of fruits (i.e., grapes), for which direct clamping is very difficult and may cause damage to the fruit, clamping of the fruit stalk can be used, but this method is not suitable for fruits and vegetables with a weak connection between the fruit and the stalk. However, to provide a stable and efficient picking process, the end-effector can be equipped with some ancillary mechanisms, such as suction cups, putts, and sensors, to provide accurate pick-and-roll and damage reduction.

To control the gripping force of agricultural robots, Russo et al. [101] proposed a new horticultural product gripper that firmly grips medium-sized horticultural products without damage, based on the requirements and characteristics of horticultural product gripping. Tian et al. [105] designed a sliding sensor with piezoelectric resistance, using an adaptive neuro-fuzzy inference system controller to adjust the gripping force of the agricultural robot in real-time, and a subtractive clustering method to simplify the fuzzy rules. The experimental results showed that the sliding signal could be effectively extracted, regardless of the variation of the normal gripping force, and the gripping pressure of tomatoes and apples was successfully controlled. Roshanianfard et al. [106] developed an end-effector with a unique harvesting method, based on the characteristics of pumpkins. The end-effector was a five-fingered anthropomorphic hand that used an electric drive and internal impact to achieve the grasping function. Hou et al. [36] designed a bionic human finger soft grasping mechanism for a tomato picking robot, using computed tomography (CT) to obtain the internal structure of the finger and defining smooth contact mechanic indices to characterize the softness of the finger region during the light grasping of tomatoes. The research results provided evidence for how the mechanics and structure of human fingers quantitatively affect the soft contact mechanics behavior during light grasping, which in turn can be used to develop robotic fingers with different degrees of softness, to meet different fruit picking requirements.

3.1.2. Cut-Off Mechanism

Among the operations performed by agricultural robots, a cut-off mechanism is required for harvesting, pruning, fruit picking, weeding, and shearing. Agricultural robots in cut-off operations need to control their cut-off force. Note that too small a cut-off force cannot cut off the work object, while an overlarge force can have a large margin for operation, but will increase the weight and size at the end of the actuator. Moreover, it will become a burden on the robot arm and mobile mechanism. To select the best cutting force, it is necessary to fully investigate the cutting characteristics of the work object, i.e., shape, size, etc. Reliable and robust systems for detecting and harvesting fruits and vegetables in non-structural environments are essential for harvesting robots. Zhang et al. [78] designed a novel gripper that can simultaneously grip and cut the peduncle of a crop, without touching the flesh. Experiments on a robot were conducted to evaluate the effectiveness of the proposed harvesting system.

3.1.3. Absorption Mechanism

A robot must hold the fruit or stalk for operation when it harvests large fruits. When the fruit is too small or the surface is too soft to be held, it is brought to the end-effector using attractive force. Agricultural robots often need to use soft material absorption mechanisms to hold the work object. Typical absorption mechanisms include suction cups, which use a vacuum pump to adsorb the object. One feature of these absorption cups is that the absorption force can be changed by simply adjusting the pressure of the vacuum pump, and the number of absorption cups can be changed to correspond to various situations, regardless of the size and shape of the object; as long as the work object has a flat part. Kurpaska et al. [107] developed a strawberry harvesting robot end-effector based on an integrated pneumatic suction cup structure for strawberry fruit harvesting. Experiments were conducted using three suction cup structures and three suction cup surface positions on the strawberry surface, which showed that a pneumatic suction cup scheme is feasible for strawberry harvesting. Moreover, negative pressure suction requires a smooth fruit surface, and vacuum suction nozzle absorption functions with fixed fruit, such as in sweet pepper vacuum absorption [108]. Cavity nesting is a commonly used absorption method for absorption-type end-effectors, which uses a semi-closed cavity with a fixed shape to contain and restrict the fruit. The general cavity nesting method has no driving components, and is usually combined with the separation of fruit without a fixed link. For example, robots that adopt a vacuum absorption end-effector to harvest apples can not only greatly shorten the time required for apple harvest sub-processes, but also have no direct contact with the apple components, such that the mechanical damage caused by apple harvesting can be effectively avoided.

3.1.4. Press-In Mechanism

A press-in mechanism is mainly used as the end-effector for seedling transplantation [109]. During transplanting, the general method is to clamp, enter the pushrod from the drainage hole at the bottom of the tray, and clamp the culture soil with shovels similar to mechanical fingers, and then the robot inserts two needles into the culture soil to transport the seedlings. The front end of the end-effector is equipped with two inclined opposite needles, which are driven by the cylinder to slide instantaneously. The front end is crossed when the needle is inserted into the culture soil at the maximum depth. When the end-effector is lifted in this state, it can be transported together with the entire piece of culture soil and without contacting the seedlings. The culture soil will not spread and fall if the seedlings form a silver bowl. In addition, the end actuator is equipped with a proximity sensor to detect units with insufficient seedlings, without needing contact. Shao et al. [61] developed a multi-adaptive rice transplanting supply device to improve the adaptability of a transplanting supply device to different transplanting trays. The designed end-effector consisted of a cylindrical claw and a U-shaped auxiliary grip, which was used for picking up and dropping the seedlings of various seedling planting devices. The research results could provide a new concept for the mechanized transplanting of vegetables and flowers, but it is not easy to achieve the practical application of high-speed transplanting at this stage.

3.1.5. Other Mechanisms for End-Effectors

Due to the diverse types of agricultural production and complex processes, which lead to a large family of agricultural robots, agricultural robots have various end-effectors to accomplish their operational tasks [110]. To address the problems of the difficulty in using large sprayers in hilly orchards, mechanical damage to fruit trees, and a low deposition rate within the canopy of fruit trees, Bao et al. [111] designed a new remote-controlled cable-driven target spray robot based on a concentric tubular manipulator with six degrees of freedom and using a spring-hinged structure. For weeding problems in the field, mechanical weeding is the most promising weeding method for weed management in organic agriculture. Quan et al. [103] develop a deep learning-based intelligent agricultural robotic weeding system for detecting weeds between crop rows. This intelligent inter-plant mechanical weeding device with a disc-type rotating mechanism operated in the inter-monopoly with an average weeding rate of 85.91%. Pérez-Ruírez et al. [112] designed a weeding component with an end-weeder that was distributed on both sides of the plant and used machine vision to detect the seedlings' position and control the weeder's movement for weeding purposes. Langenkamp et al. [113] developed a weed control device called " tube stamp", which was mounted on a BoniRob robot to eliminate detected weeds. In addition, with the widespread use of information technology, artificial intelligence, and sensing technology in animal husbandry, Yang et al. [114] developed a milking robotic arm suitable for milking robots to realize the cleaning, massaging, and milking of cows, using components such as an integrated image recognition ranging system, milking cluster, milking cleaning line, cluster removal device, and teat cleaning brush. A three-degree-of-freedom motion mechanism enabled the milking robotic arm to complete the milking trajectory within the minimum range of motion, and improve the efficiency of milking.

3.2. Robot Arms Applied in Agricultural Robots

The main role of a robotic arm is to manipulate the end-effector to the target position. There are many types of human-robotic arms for industrial robots, such as the horizontal multi-joint type used in assembly line product assembly operations, the vertical multi-joint type in welding and painting, and the cylindrical coordinate type in crating operations. Similarly, many kinds of robotic arms also exist for agricultural robots, as shown in Figure 7, and where the object's size, quality, and cultivation method are the main factors affecting the robotic arm construction. For example, Liu et al. [115] designed a wolfberry harvesting robot that used dual arms with branch grasping end-effectors to work in concert. The TrimBot 2020 robot platform, based on a commercial Bosch Indigo mower, was developed and fitted with a six-degree-of-freedom robotic arm for shrub pruning and rose pruning [116]. Mohamed et al. [117] implemented a flexible robotic arm that used agonist-antagonist actuators connected to a joint by a flexible tendon for tomato harvesting. By acquiring the scenario RGB map and depth map through Kinect V2 fixed on the side of the robotic arm, Wang et al. [118] performed image segmentation and 3D localization of the fruit stems of litchi, planned an obstacle avoidance harvesting path online based on the RRT (rapidly-exploring random trees) algorithm, and implemented fruit branch shearing and clamping using a cylinder-driven end, to achieve efficient and stable litchi bunch harvesting. In pest control, Obert et al. [119] developed a robot that detected the onset area for target spraying, and an online disease assessment model based on machine vision ensured that the spot spraying area was minimized. You et al. [120] designed a branch skeleton analysis algorithm for a cherry pruning robot, and the correct rate of branch reconstruction based on semantic guidance exceeded 70%, which could effectively support the robot pruning decisions. To improve harvesting speed, many selective harvesting robot design solutions chose multi-arm parallel technology [121]. Zhao et al. [122] proposed a modular dual-arm robot concept for tomato harvesting, to improve the efficiency of tomato harvesting robots in unstructured environments, and tested a dual-arm frame for tomato harvesting, consisting of two three-degree-of-freedom manipulators and two different types of end-effector. Spanish AGROBOT Robotics [123] developed a strawberry harvesting robot for high-monopoly and rack cultivation that employed 24 robotic arms arranged on six linear module units, each with a short-view integrated color and infrared depth sensor and image processing unit, to determine the ripeness of the strawberries to be harvested, and which used stem-breaking clamping to harvest the strawberries to avoid damage. However, since a dual-arm cooperative mode imposes higher requirements on the manipulator configuration, canopy space, and collaborative control [124,125], further exploration is needed of whether dual-arm harvesting robots are the optimal future direction of harvesting robotics development.

Agricultural robots require the end-effector and the robot arm to be able to replicate each other entirely when they perform flexible operations. In short, the end-effector of agricultural robots should be able to not only cope with the individual differences of organisms, but also have the robustness to cope with the errors of other mechanisms. Thus, in the future, the research on end-effectors and robotic arms of agricultural robots will focus on the following: (3) addressing the complexity of the operation object and the problem of flexible operation, by studying the damage mechanism of crops, using new materials, developing efficient control strategies, and planning the motion path of the end-effector and robotic arm, and eventually achieving efficient and flexible operation. (2) Based on the structure of the mobile chassis of agricultural robots, according to the operation range of the mobile platform, end-effectors and robotic arms will be developed to adjust to their operational environment. (3) establishing a universal end-effector and robotic arm, and adjusting the operation path and the size of the driving force adaptively, according to the different operation objects detected by the vision sensor, to realize low-loss operation of the end-effector and robotic arm.

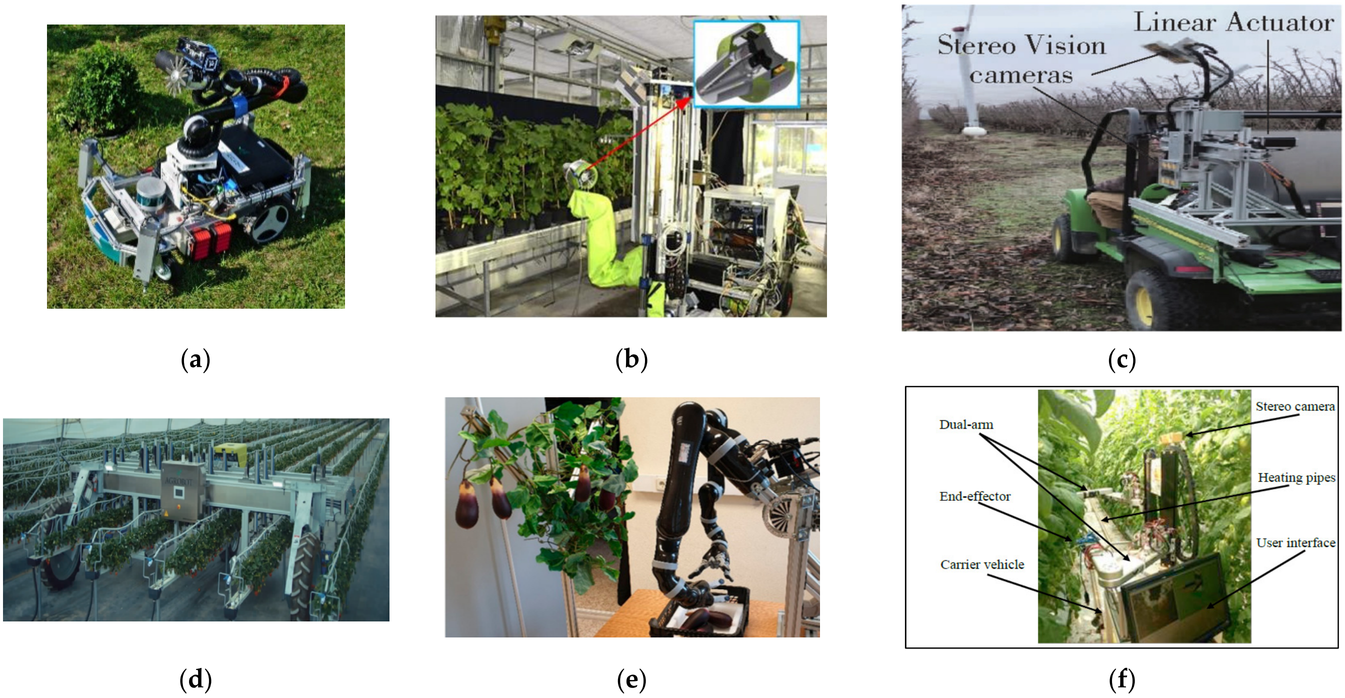


Figure 7. Robotic arms in an agricultural robot. (**a**) Mechanical arm structure of a mowing robot [116]. (**b**) Spot spraying robot with disease area detection [119]. (**c**) Cherry pruning robot [120]. (**d**) Strawberry harvesting robot [123]. (**e**) Dual-arm manipulator harvesting eggplants [121]. (**f**) Dual-arm tomato harvesting robots [122].

4. Assistive Technologies and Systems

Although actuators are the major driving components of agricultural robots, some assistive systems are also necessary, to ensure the robots operate appropriately, with high performance, i.e., environmental perception. To solve the problems of the autonomous walking of actuator-based agricultural robots and the sensing of environmental information to drive end-effectors, agricultural robots use depth cameras, LiDAR, and ultrasonic and other sensors to obtain various data about the soil, crops, climate and other agricultural environment factors, and cooperate with autonomous positioning and path planning technologies to realize autonomous map building, positioning, and navigation functions. However, it is essential for agricultural robots to recognize subtle differences in color, shape, and size of similar products [126], as the objects of work are crops with different shapes and types during field operations. Machine vision technology is more objective and standardized than human eyes in recognizing crops or other agricultural products. Therefore, machine vision is often used in the navigation of agricultural robots, in addition to in the grading of agricultural product's quality, and the detection and control of pests, diseases, and weeds in agricultural fields, as well as in automatic agricultural harvesting systems [127,128]. Thus, machine vision has become the main external sensing technique for the front-end sensing components of agricultural robots to obtain external information sources.

Below, we will discuss environmental perception and information fusion.

4.1. Environmental Perception

Agricultural robots are susceptible to the climate, time, agronomic measures, operating conditions, and other factors. Therefore, exploring environmental perception and path planning is of great importance in improving the autonomy and intelligence of agricultural robots. Environmental perception is essential for agricultural robots, ensuring the safe interaction between robots and people, and between target objects and the surrounding environment [129,130]. Environmental perception collects point clouds or image data through various visual sensors, followed by the analysis and processing using a computer, so that the robot system can obtain different information about objects in the environment. Figure 8 shows an agricultural planting robot with machine vision.

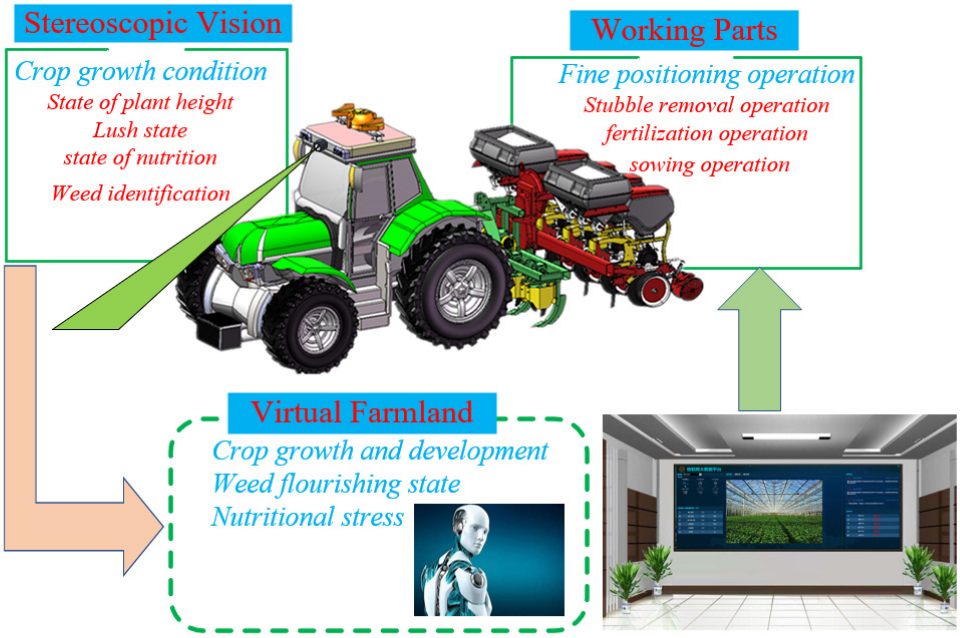


Figure 8. Schematic diagram of robot system with intelligent visual function.

As an external sensor of intelligent agricultural robots, machine vision is the eye of the operating equipment for agricultural robots and the most prominent information source, which has the advantages of rich perceptual information and complete information collection [131]. The first step for agricultural robot operation is to achieve autonomous obstacle avoidance, and the prerequisite for obstacle avoidance is to enable robots to perceive their surrounding environment [132]. In general, various sensors need to be installed to monitor the required field information, which also provide the parameters of the surrounding environment for robots, such as the size, shape, and position of obstacles and targets. At present, there are various obstacle avoidance sensors used in agricultural robots. According to their principles and characteristics, their application scopes in agricultural environments are also different [133]. Cameras and radars are commonly used and will be discussed further below.

4.1.1. Cameras

The visual recognition system of agricultural robots usually includes one or two cameras. Cameras are widely used in agricultural robots because of their low price, easy installation, rich data information, and relatively mature processing algorithms. The main steps include image acquisition, image preprocessing, and obstacle detection. In terms of types, cameras can be divided into monocular, binocular, and RGB-D cameras.

Monocular Camera

In agricultural robots, the information obtained by a single camera is minimal, so it is necessary to add an algorithm to assist in obtaining information [134–136], to determine the distance relationship between each object in the scene and the lens. The commonly used monocular cameras can be divided into the charge-coupled device (CCD) and complementary metal-oxide-semiconductor (CMOS) cameras. Therefore, both cameras are widely used in agricultural robots in different environments [137]. Similarly to machine vision, and based on CMOS image sensor (CIS) cameras, Lyu et al. [138] proposed a free-space recognition technique in an orchard environment, for a developed small agricultural unmanned ground vehicle (UGV), and using a low-cost, lightweight processor. Cubero et al. [139] developed a remote-controlled field robot, RobHortic, equipped with color, multispectral, and hyperspectral cameras, to detect the presence of pests and diseases in gardening. Lei et al. [140] proposed a kernel fuzzy C-means clustering algorithm, to segment the pomegranate fruit images collected by a CCD camera, to improve the applicability and work efficiency of a picking robot. Zhou et al. [141], based on the pinhole imaging principle, established a CCD camera-based testbed, for the automatic sorting of agricultural products, with target classification, localization, and capture.

Binocular Camera

Compared with monocular cameras, binocular cameras are widely used in agricultural robots, due to their low price, high-ranking accuracy, and more mature technology. An intelligent binocular vision system combined with an intelligent algorithm software system can realize image processing, binocular stereo positioning, deep learning algorithms, and visual servoing in a non-structural environment, providing perfect eyes and brains for agricultural robots [118]. To adapt to the complexity and diversity of the environment, binocular cameras are selected as the visual perception sensor of agricultural robots, and convolutional neural networks are used to perceive the surrounding environment [142]. Aiming at cotton field operation management low-speed linear driving conditions, Zhang et al. [143] established a tractor path tracking control system based on binocular vision, using a crop row identification and path planning method. The control system realizes the automatic track tracking control of cotton line operations and meets the agriculture requirements for cotton field operational management. To achieve accurate grape picking in non-structural environments, Yin et al. [144] proposed a method of grape detection and pose estimation based on the Mask-RCNN (regions with CNN features) algorithm, and using low-cost binocular stereo. To improve the applicability of their tomato clustering recognition method, Xiang et al. [145] proposed a tomato clustering recognition algorithm based on binocular stereo vision, which ensured a good real-time performance, to meet the requirements of harvesting robots. The study findings showed that the adaptive vision navigation algorithm for agricultural robots based on binocular vision, originally designed for automatic agricultural robot navigation, could be extended to agricultural IoT systems.

Depth Camera

Depth cameras are also called RGB-D cameras. A depth camera can obtain ordinary 2D RGB images and the depth information of objects in the shooting scene, so it has a wide range of applications in the field of agricultural robots, in the face of the needs of different scenarios. The most commonly used RGB-D camera in the field of agricultural robots is the Kinect V2 depth camera produced by Microsoft, which consists of an infrared (IR) light source, an infrared camera, and an RGB camera [146]. For example, Gu et al. [147] used a convolutional neural network method and a Kinect camera to identify corn rootstocks. After detecting and identifying the obstacle targets, the driving path was obtained, to achieve autonomous obstacle avoidance for a corn interrow collection robot. To improve the picking efficiency of apple picking robots, Tian et al. [105] proposed an optimized image recognition algorithm based on image depth information. The Kinect V2 camera obtains a depth contour map of the target image and gradient field information. The gradient information is projected onto a two-dimensional plane, and the vorticity is formed in a uniform and orderly area, by rotating the gradient vector, the central projection of the target fruit, to achieve rapid positioning of the target fruit. Quan et al. [148] developed a YOLO-V4 model based on the Kinect V2 camera, to locate weeds with a detection speed of up to 17.8 fps. This research result could be used to determine the type and fresh weight of weeds, to match an appropriate dosage of herbicides for real-time spraying, which provides a new concept for optimizing weeding strategies and to reduce the use of herbicides. In addition, the proposed method could be widely applied to the prediction of the fresh weight of crops, which would facilitate the variable and precise operation of herbicide robots in spraying herbicides, for the purpose of supporting crop genetic breeding and improving soil health.

In precision agriculture, another application of deep cameras is to obtain the phenotypes of crops under natural conditions and use them to analyze crop trait information [149]. Machine vision algorithms are combined with image processing functions to eliminate unwanted crop data or information from the image, while retaining only relevant information about the precise measurement [150]. Deep estimation, color enhancement, identification, and segmentation of regions of interest are techniques that offer reliable results for further analysis of the information obtained. This information significantly improves crop varieties and provides solutions and a theoretical basis for research in the field of precision agriculture.

4.1.2. Radar

In the non-structured farmland environment, the autonomous navigation of agricultural robots is difficult because of the inherent uncertainty in the operating environment. Many agricultural robots use computer vision and other sensors to supplement their GPS data for navigation, but the method based on machine vision is sensitive to the surrounding light conditions. When the working environment of the agricultural robot is high-stalk crops, the blades will block the GPS antenna, and the problem of positioning loss is very likely to occur. At the same time, the variable light intensity will affect the camera's image collection and other factors. The accuracy can be higher with advanced vision systems (including depth perception, LiDAR, other scanning sensors, and artificial intelligence for decision-making and classification). Therefore, radar navigation technology can be used to realize autonomous navigation between rows of agricultural robots [89].

For the autonomous navigation of agricultural robots, since it is not necessary to measure the height of the measured object and the distance from the measured object to the LiDAR, high beam, low-cost solid-state 3D LiDAR, has been widely used in the field of agricultural robots. Figure 9 lists the different types and applications of LiDAR. For example, Weiss et al. [151] used FX6 LiDAR (Nippon Signal Co., Ltd., Tokyo, Japan) and developed the RANSAC-Algorithm for machine vision, so that agricultural robots can implement detection of a single plant between cornrows and generate a crop row map of a single plant, to provide accurate location data for future plant protection, fertilization, or weeding, as well as other individual plant care work. Zhang et al. [58] designed a low-cost laser radar and gyroscope clustering technology, to extract sparse point cloud data on the trunk and to realize the autonomous navigation of a rubber-tapping robot intelligent rubber cutting platform and rubber forest information collection. In a forest environment with different row spacings and plant spacings, the robot's position was obtained using the extended Kalman filter algorithm, and the heading and lateral errors of the cutting robot were analyzed. Most existing studies have focused on detecting single plants or crop behaviors, and the planned path is a straight line. Although this is convenient for robot control, it is not conducive to avoiding obstacles such as a fruit tree canopy and pedestrians between rows.

Another area of application for radar sensor technology is precision agriculture, which aims to reduce expense and significantly increase yields. In precision agriculture, field crop phenotypic information reflects the relationship between crop growth and its growth environment. Traditional field crop phenotype information is obtained by manual measurement, which is time-consuming, labor-intensive, and may cause poor data objectivity. As such, the emergence of large-scale field crop phenotyping platforms with LiDAR as the core sensor is well suited to meet the needs of fine field crop phenotyping information collection, by accurately recording and evaluating parameters (e.g., soil conditions or yields) for optimally adapting land tillage (seeding and fertilization) to various conditions [26,153,154]. For example, installing LiDAR on ground mobile robots, for the localization and identification of trees in orchard environments, allows the precise determination of a trunk's height, volume, and mass, and thus the expected yield [155–157].

(**a**) (**b**) (**c**) (**d**)

Figure 9. Application of radar in the agricultural robots. (**a**) A heavy-duty platform for autonomous navigation in kiwifruit orchards [59]. (**b**) Robot sensing maize plants [151]. (**c**) Robot system [58]. (**d**) Robot platform for data acquisition [152].

4.2. Information Fusion

Due to the uncertainty of the working environment of agricultural robots, and the flexibility of operation in a narrow range, sometimes more sensors will be used to collect the relevant navigation information. Then, multi-sensor information fusion technology should be comprehensively used to complete the correct estimation of the position and state of the machine, to achieve reliable automatic navigation [75,158]. At the same time, different types of sensors need to be installed, to improve the intelligence of agricultural robots. The commonly used ones include anti-collision, infrared, ultrasonic, laser, visual, tactile, and so on, to complete the information fusion of multiple sensors and obtain more reliable and accurate information [159,160]. Therefore, agricultural robots must integrate different subsystems, transmit the required information, and ensure correct synchronization [161]. Moreover, such robotic systems must be cost-effective and ensure human safety, while protecting the environment, crops, and machinery.

Agricultural robots are a class of intelligent agricultural equipment, which can use technologies such as multi-sensor fusion and automatic control to realize automatic and intelligent production of agricultural equipment operating in natural environments [162]. The main research on information fusion from different sensors includes fusion structure, fusion algorithm, sensor ranging, target recognition, autonomous navigation, and path planning [163,164]. The multi-sensor information fusion method is essential for information fusion. Therefore, specific decision-making needs are required, and appropriate fusion methods are adopted. Note that a robot body is loaded with various sensors such as LiDAR, ultrasonic, and vision sensors [165,166]. Based on the environment sensing technology of multi-sensor information fusion, the object's shape, speed, and distance are simulated and computed through complex algorithms, to achieve highly stable motion and data collection and processing functions of the robot in the agricultural environment. Du et al. [167] used an industrial camera to design a high-throughput lettuce phenotype visual measurement method, for the problem of comparative analysis of the growth of different lettuce varieties, under the same cultivation environment, and established a quantitative evaluation method for variety selection and breeding, as shown in Figure 10. Wang et al. [168] combined unmanned technology with electronically controlled seeding technology to develop a large field corn seeding robot. Through integrating operation process seeding status information (seeding depth, missed seeding, and fault detection) with the positioning information (longitude and latitude signals from the Beidou system) of the unmanned tractor, and developing a set of electronically controlled seeding controllers, based on this, they created an integrated system for unmanned seeding operations, applicable to large field operations, as shown in Figure 11.

Figure 10. Lettuce Breeding Phenotyping Robot [167].

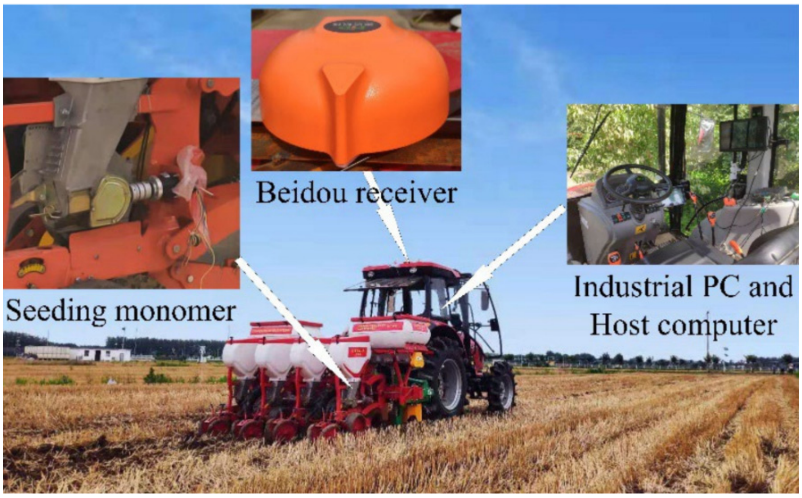


Figure 11. Field seeding robot [168].

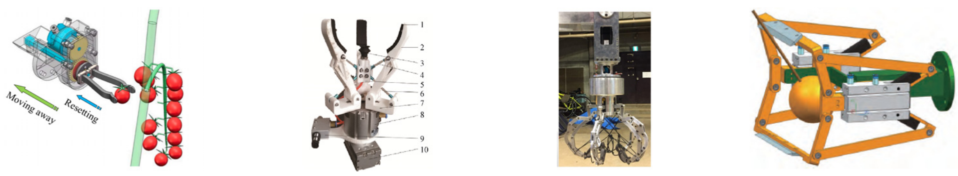
Environmental awareness, an auxiliary component of agricultural robots, is also vital. Ensuring safe interaction between robots and target objects and their surroundings through multi-sensor information fusion is the basis for agricultural robots accomplishing their operational tasks. As sensors for agricultural robots to obtain external information, future research works should mainly focus on: (1) The various agricultural robots obtaining different information of the operation scene, based on the principle of sensors, the development of new materials, and new methods of universal modular sensors. (2) Agricultural robots need muscular mobility and passability in natural scenes, and then require environmental sensing sensors to achieve dynamic recognition and rapid decision-making in complex scenes. The agricultural robots' complex operating environment and diverse operating objects eventually lead to each agricultural robot needing to be equipped with a multi-sensor information fusion system applicable to a single working condition. Therefore, it is urgent to develop a multi-sensor information fusion system applicable to agricultural robots, and develop a low-cost, highly robust general-purpose agricultural robot-specific controller.

5. Discussion

At present, agricultural robots can replace humans in simple agricultural production, but they can still not meet the requirements when facing complex operations with complex agronomic processes. With the development of robotics and the continuous improvement of image processing technology, the research of agricultural robots working in complex unstructured farmland has become a current research hotspot. Agricultural robots comprise a mobile chassis, robotic arms, end-effectors, and environmental sensing systems [169].

Agricultural robots can move in a planned manner, because of their complete motion mechanism, and the corresponding control system and drive system. Drive systems for agricultural robots are classified according to energy conversion modes, as electric, hydraulic, pneumatic, and new drive units, or integrated systems that combine them for application. Thus, when designing the drive system of agricultural robots, we need to match the appropriate control method to the working scenario, to improve the robustness during operations.

When designing the end-effectors for agricultural robots, based on a full grasp of the physical nature of the work object, we need to explore how to accomplish the operational goals, and need not imitate a human entirely using two hands to perform the work, as long as the same effect is obtained [69,170]. In addition, there are many kinds of robotic arms for agricultural robots, depending on the operating environment and the object, where the size, weight, and cultivation method of the object are the main factors affecting the construction of the robotic arm, whose primary role is to move the end-effector to the target position. In short, agricultural robot's end-effector design should respond to the individual differences of the operation object and improve the operation efficiency, without damaging the operation target. It is a difficult area for current research work. Depending on the principle of grasping and cutting fruit stems, the end-effector of harvesting robots can be divided into clamping and non-clamping. At present, the clamping end-effectors mainly utilize a multi-finger type, suction cup type, soft body bionic type, or other methods; the non-clamping types include a direct cutting type, inhalation cut off type, inhalation hook cut type, and inhalation twist off type, with a cutting or twisting action; the structures used today are also very numerous, and include scissor type, rotary blades and other physical shears, and electrical heated wire, laser cutting, and other cutting methods; according to the different principles and applications, as shown in Figure 12. In addition, the end-effector can attach certain auxiliary mechanisms such as suction cups, pushers, and various sensors to accomplish accurate picking and reduce damage. For example, end-effectors based on force perception are capable of realistically and accurately outputting the appropriate operating force, according to the working environment, and are particularly suitable for grasping fruits with a large volume and weight. For example, a force sensing end-effector can output a realistic, accurate, and appropriate operating force, according to the working environment, which is especially suitable for grasping fruits with a large volume and weight.



(**a**) (**b**) (**c**) (**d**)

Figure 12. Method of execution of end-effectors: (**a**) Clamping rotation. (**b**) Suction holding twist off. (**c**) Clamping and shearing. (**d**) Bite type cut-off.

In the background of the continuous development of robotics and the improvement of image processing technology, agricultural robot have learnt how to accomplish various tasks intelligently, efficiently, and safely, and according to their operating environment [171]. The various different operation objects remain a hot research issue [172,173]. Agricultural robots need to integrate artificial intelligence technology and be equipped with LiDAR, a depth camera, infrared camera, spectral camera, robotic arm, and other equipment, based on the fusion of multi-sensor information, to achieve a high stability of robot movement in the agricultural environment.

6. Conclusions and Outlook

6.1. Conclusions and Challenges

This review article focused on reviewing actuators and sensors for applications in agricultural robots. Since end-effectors and robotic arms are now required to achieve accurate operation, flexible operation, and crop protection, the existing techniques have also been described. However, there are still some problems remaining to be solved in the research of related fields. This is reflected in:

(1) The combination of agricultural machinery and agronomy is not common.

Field crops have achieved a high degree of mechanization, while orchards, hilly mountains, and other mechanization areas are still relatively behind, especially those with manual picking work. The current stage of agricultural equipment is far from being able to meet the needs of the development of modern agricultural production. We have found that it is necessary to increase the adaptiveness and versatility of actuators and end-effectors for the flexible operation of agricultural robots, in order to apply them to all operating environments, for cost reduction and efficiency improvements. In addition, to guarantee the best operating performance of agricultural robots with actuators, control strategies are indispensable. We have explored various practical control methodologies for both the trajectory control and operational mechanism control, such that agricultural robots can be properly controlled in complex farmland environments.

(2) The development situation is positive, but the technology is lacking.

A low level of technical maturity and a lack of core algorithms have led to the reduced versatility of the developed agricultural robots. Although various advanced agricultural sensors are used in agricultural robots, to obtain data from agricultural environmental factors (such as the soil, crops, climate, etc.) and to detect patterns and correlations between variables, we have identified the vital role of assistive systems and technologies, including environmental perception and information fusion, in ensuring the high performance of agriculture robots. Our view is that the advanced vision (including depth perception, scanning sensors such as LiDAR, and artificial intelligence for decision making and classification) applied to agricultural robots needs to be robust against environmental changes and multi-sensor information fusion should be comprehensively used to achieve reliable automatic navigation, control, and manipulation.

(3) More variety, but insufficient design and optimization.

End-effectors are an essential component of agricultural robots. There are many problems caused directly or indirectly by an inadequate design of end-effectors, mainly due to a lack of reliability of their own drive systems during operation, resulting in a poor accuracy, serious damage, and poor applicability to complex environments. In addition, because these end-effectors adopt new technologies and materials, their higher cost restricts applications. Therefore, we believe that end-effectors need to be developed based on the similarity of operating objects, and the development of a new drive system, taking into account the biomechanical characteristics of the operating object, optimizing and improving the movement principle, and ensuring the quality of the operation, while reducing the development costs is an urgent problem to be solved in the process of the practicalization of end-effectors.

6.2. Outlook

With 5G mobile internet, big data, cloud computing, artificial intelligence, and other high-end technologies, combined with modern manufacturing, and based on existing research, the development of agricultural robots for the future is proposed in the following stages:

(1) Increase scalability and versatility.

Most agricultural robots presently adopt special actuators and unique control systems to form a closed structure, according to their functional requirements, and which cannot be expanded by replacing actuators, adding sensors, and other functional modules. Although most picking robots are suitable for certain fruits and vegetables, the use of specialized mechanical structures and control programs is not conducive to expanding the functions of picking robots. For example, if a strawberry picking robot was expanded into an apple picking robot, by modularizing the functions of the picking robot, the mechanical parts or control devices with different degrees of freedom could be replaced to adapt to different types of fruit and vegetable picking. The workload is equivalent for redesigning and redeveloping in the currently closed structure. Therefore, through research and the design of open structures and control systems, agricultural robots could achieve better scalability and versatility, and the capability for flexible operation. The development cycle of agricultural robots and the production costs could be reduced, and the utilization rate and operating performance could be further improved.

(2) Coordination of overall operation

The automatic agricultural work of robots is no longer limited to the ideal farming environment, and complex non-structural farming work is also required. Since agricultural robots are composed of mobile robot chassis, actuators, robotic arms, end-effectors, and an image recognition system, the overall operational performance depends not only on each component, but also on the cooperation and coordination between each system. Therefore, the coordination and cooperation between the subsystems of agricultural robots is still a challenging research hotspot.

(3) Standardization of agricultural production

The environmental and geographical conditions in which crops are grown vary widely around the world. Different regions have different agricultural production environments, which bring great challenges for developing agricultural robots, because of the different technological requirements. Therefore, the standardization of agricultural production could effectively promote the development and application of agricultural robots.

Author Contributions: D.X.: investigation, writing original draft. L.C. (Liang Chen): formal analysis, data curation. L.L.: investigation, supervision. L.C. (Liqing Chen): supervision, funding acquisition. H.W.: investigation, writing-review, and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This study was funded by the National Natural Science Foundation of China (Grant No. 52175212) and the Universities Natural Science Research Project of Anhui Province (Grant No. KJ2020A0105).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Zhang, Z.B.; Li, P.; Zhao, S.L.; Lv, Z.M.; Du, F.; An, Y.J. An Adaptive Vision Navigation Algorithm in Agricultural IoT System for Smart Agricultural Robots. *CMC Comput. Mater. Continua* **2021**, *66*, 1043–1056. [CrossRef]
2. Kumar, K.N.; Pillai, A.V.; Narayanan, M.K.B. Smart agriculture using IoT. *Mater. Today Proc.* **2021**. [CrossRef]
3. Yi, X.W.; Yingkuan, W.; Yang, Z.Q. Review of smart robots for fruit and vegetable picking in agriculture. *Int. J. Agric. Biol. Eng.* **2021**, *14*, 33–54.
4. Chebrolu, N.; Lottes, P.; Schaefer, A.; Winterhalter, W.; Burgard, W.; Stachniss, C. Agricultural robot dataset for plant classification, localization and mapping on sugar beet fields. *Int. J. Robot. Res.* **2017**, *36*, 1045–1052. [CrossRef]
5. Bechar, A.; Vigneault, C. Agricultural robots for field operations: Concepts and components. *Biosyst. Eng.* **2016**, *149*, 94–111. [CrossRef]
6. Bechar, A.; Vigneault, C. Agricultural robots for field operations. Part 2: Operations and systems. *Biosyst. Eng.* **2017**, *153*, 110–128. [CrossRef]

7. Azmi, H.N.; Hajjaj, S.S.H.; Gsangaya, K.R.; Sultan, M.T.H.; Mail, M.F.; Hua, L.S. Design and fabrication of an agricultural robot for crop seeding. *Mater. Today Proc.* **2021**. [CrossRef]
8. Xiang, Y.; Noguchi, N. Development and evaluation of a general-purpose electric off-road robot based on agricultural navigation. *Int. J. Agric. Biol. Eng.* **2014**, *7*, 14–21.
9. Moysiadis, V.; Tsolakis, N.; Katikaridis, D.; Sørensen, C.G.; Pearson, S.; Bochtis, D. Mobile Robotics in Agricultural Operations: A Narrative Review on Planning Aspects. *Appl. Sci.* **2020**, *10*, 3453. [CrossRef]
10. Zhang, Z.Z.; Kayacan, E.; Thompson, B.; Chowdhary, G. High precision control and deep learning-based corn stand counting algorithms for agricultural robot. *Auton. Robot.* **2020**, *44*, 1289–1302. [CrossRef]
11. Choi, K.H.; Han, S.K.; Han, S.H.; Park, K.-H.; Kim, K.-S.; Kim, S. Morphology-based guidance line extraction for an autonomous weeding robot in paddy fields. *Comput. Electron. Agric.* **2015**, *113*, 266–274. [CrossRef]
12. Feng, L.; Chen, S.; Zhang, C.; Zhang, Y.; He, Y. A comprehensive review on recent applications of unmanned aerial vehicle remote sensing with various sensors for high-throughput plant phenotyping. *Comput. Electron. Agric.* **2021**, *182*, 106033. [CrossRef]
13. Chen, Y.; Zhang, B.; Zhou, J.; Wang, K. Real-time 3D unstructured environment reconstruction utilizing VR and Kinect-based immersive teleoperation for agricultural field robots. *Comput. Electron. Agric.* **2020**, *175*, 105579. [CrossRef]
14. Fernandez, B.; Herrera, P.J.; Cerrada, J.A. A Simplified Optimal Path Following Controller for an Agricultural Skid-Steering Robot. *IEEE Access* **2019**, *7*, 95932–95940. [CrossRef]
15. Roshanianfard, A.; Noguchi, N.; Okamoto, H.; Ishii, K. A review of autonomous agricultural vehicles (The experience of Hokkaido University). *J. Terramechanics* **2020**, *91*, 155–183. [CrossRef]
16. Tabile, R.A.; Godoy, E.P.; Pereira, R.R.D.; Tangerino, G.T.; Porto, A.J.V.; Inamasu, R.Y. Design and Development of the Architecture of an Agricultural Mobile Robot. *Eng. Agric.* **2011**, *31*, 130–142. [CrossRef]
17. Adamides, G.; Katsanos, C.; Constantinou, I.; Christou, G.; Xenos, M.; Hadzilacos, T.; Edan, Y. Design and development of a semi-autonomous agricultural vineyard sprayer: Human-robot interaction aspects. *J. Field Robot.* **2017**, *34*, 1407–1426. [CrossRef]
18. Birrell, S.; Hughes, J.; Cai, J.Y.; Iida, F. A field-tested robotic harvesting system for iceberg lettuce. *J. Field Robot.* **2020**, *37*, 225–245. [CrossRef] [PubMed]
19. Libran-Embid, F.; Klaus, F.; Tscharntke, T.; Grass, I. Unmanned aerial vehicles for biodiversity-friendly agricultural landscapes—A systematic review. *Sci. Total Environ.* **2020**, *732*, 139204. [CrossRef] [PubMed]
20. Ghafar, A.S.A.; Hajjaj, S.S.H.; Gsangaya, K.R.; Sultan, M.T.H.; Mail, M.F.; Hua, L.S. Design and development of a robot for spraying fertilizers and pesticides for agriculture. *Mater. Today Proc.* **2021**. [CrossRef]
21. Kumar, P.; Ashok, G. Design and fabrication of smart seed sowing robot. *Mater. Today Proc.* **2021**, *39*, 354–358. [CrossRef]
22. Kim, W.-S.; Lee, D.-H.; Kim, Y.-J.; Kim, T.; Lee, W.-S.; Choi, C.-H. Stereo-vision-based crop height estimation for agricultural robots. *Comput. Electron. Agric.* **2021**, *181*, 105937. [CrossRef]
23. Arbo, M.H.; Utstumo, T.; Brekke, E.; Gravdahl, J.T. Unscented Multi-point Smoother for Fusion of Delayed Displacement Measurements: Application to Agricultural Robots. *Model. Identif. Control.* **2017**, *38*, 1–9. [CrossRef]
24. Huang, C.-H.; Chen, P.-J.; Lin, Y.-J.; Chen, B.-W.; Zheng, J.-X. A robot-based intelligent management design for agricultural cyber-physical systems. *Comput. Electron. Agric.* **2021**, *181*, 105967. [CrossRef]
25. Aravind, K.R.; Raja, P.; Perez-Ruiz, M. Task-based agricultural mobile robots in arable farming: A review. *Span. J. Agric. Res.* **2017**, *15*, e02R01. [CrossRef]
26. Pierzchala, M.; Giguere, P.; Astrup, R. Mapping forests using an unmanned ground vehicle with 3D LiDAR and graph-SLAM. *Comput. Electron. Agric.* **2018**, *145*, 217–225. [CrossRef]
27. Li, S.; Hao, G. Current Trends and Prospects in Compliant Continuum Robots: A Survey. *Actuators* **2021**, *10*, 145. [CrossRef]
28. Rahok, S.A.; Ozaki, K. Application of Localization Based on the DC Magnetic Field that Occurs in the Environment on Wheel-Type Mobile Agricultural Robots. *Adv. Robot.* **2011**, *25*, 923–939. [CrossRef]
29. Sebastian, B.; Ben-Tzvi, P. Physics Based Path Planning for Autonomous Tracked Vehicle in Challenging Terrain. *J. Intell. Robot. Syst.* **2018**, *95*, 511–526. [CrossRef]
30. Gai, J.; Xiang, L.; Tang, L. Using a depth camera for crop row detection and mapping for under-canopy navigation of agricultural robotic vehicle. *Comput. Electron. Agric.* **2021**, *188*, 106301. [CrossRef]
31. Eizicovits, D.; van Tuijl, B.; Berman, S.; Edan, Y. Integration of perception capabilities in gripper design using graspability maps. *Biosyst. Eng.* **2016**, *146*, 98–113. [CrossRef]
32. Furukawa, S.; Wakimoto, S.; Kanda, T.; Hagihara, H. A Soft Master-Slave Robot Mimicking Octopus Arm Structure Using Thin Artificial Muscles and Wire Encoders. *Actuators* **2019**, *8*, 40. [CrossRef]
33. Tsolakis, N.; Bechtsis, D.; Bochtis, D. AgROS: A Robot Operating System Based Emulation Tool for Agricultural Robotics. *Agronomy* **2019**, *9*, 403. [CrossRef]
34. Xiong, Y.; Ge, Y.; Grimstad, L.; From, P.J. An autonomous strawberry-harvesting robot: Design, development, integration, and field evaluation. *J. Field Robot.* **2019**, *37*, 202–224. [CrossRef]
35. Gorjian, S.; Ebadi, H.; Trommsdorff, M.; Sharon, H.; Demant, M.; Schindele, S. The advent of modern solar-powered electric agricultural machinery: A solution for sustainable farm operations. *J. Clean. Prod.* **2021**, *292*, 126030. [CrossRef]
36. Hou, Z.; Li, Z.; Fadiji, T.; Fu, J. Soft grasping mechanism of human fingers for tomato-picking bionic robots. *Comput. Electron. Agric.* **2021**, *182*, 106010. [CrossRef]

37. Zhang, B.; Xie, Y.; Zhou, J.; Wang, K.; Zhang, Z. State-of-the-art robotic grippers, grasping and control strategies, as well as their applications in agricultural robots: A review. *Comput. Electron. Agric.* **2020**, *177*, 105694. [CrossRef]
38. Luo, K.; Wu, Z.; Cao, C.; Qin, K.; Zhang, X.; An, M. Biomechanical Characterization of Bionic Mechanical Harvesting of Tea Buds. *Agriculture* **2022**, *12*, 1361. [CrossRef]
39. Valente, D.S.M.; Momin, A.; Grift, T.; Hansen, A. Accuracy and precision evaluation of two low-cost RTK global navigation satellite systems. *Comput. Electron. Agric.* **2020**, *168*, 105142. [CrossRef]
40. Xue, J.; Zhang, L.; Grift, T.E. Variable field-of-view machine vision based row guidance of an agricultural robot. *Comput. Electron. Agric.* **2012**, *84*, 85–91. [CrossRef]
41. Hiremath, S.A.; van der Heijden, G.W.A.M.; van Evert, F.K.; Stein, A.; ter Braak, C.J.F. Laser range finder model for autonomous navigation of a robot in a maize field using a particle filter. *Comput. Electron. Agric.* **2014**, *100*, 41–50. [CrossRef]
42. Lammie, C.; Olsen, A.; Carrick, T.; Azghadi, M.R. Low-Power and High-Speed Deep FPGA Inference Engines for Weed Classification at the Edge. *IEEE Access* **2019**, *7*, 51171–51184. [CrossRef]
43. Guzman, L.E.S.; Acevedo, M.L.R.; Guevara, A.R. Weed-removal system based on artificial vision and movement planning by A* and RRT techniques. *Acta Sci.-Agron.* **2019**, *41*, e42687. [CrossRef]
44. Esposito, M.; Crimaldi, M.; Cirillo, V.; Sarghini, F.; Maggio, A. Drone and sensor technology for sustainable weed management: A review. *Chem. Biol. Technol. Agric.* **2021**, *8*, 18. [CrossRef]
45. Hossain, M.Z.; Komatsuzaki, M. Weed Management and Economic Analysis of a Robotic Lawnmower: A Case Study in a Japanese Pear Orchard. *Agriculture* **2021**, *11*, 113. [CrossRef]
46. Wu, X.; Aravecchia, S.; Lottes, P.; Stachniss, C.; Pradalier, C. Robotic weed control using automated weed and crop classification. *J. Field Robot.* **2020**, *37*, 322–340. [CrossRef]
47. Mirbod, O.; Choi, D.; Thomas, R.; He, L. Overcurrent-driven LEDs for consistent image colour and brightness in agricultural machine vision applications. *Comput. Electron. Agric.* **2021**, *187*, 106266. [CrossRef]
48. Nehme, H.; Aubry, C.; Solatges, T.; Savatier, X.; Rossi, R.; Boutteau, R. LiDAR-based Structure Tracking for Agricultural Robots: Application to Autonomous Navigation in Vineyards. *J. Intell. Robot. Syst.* **2021**, *103*, 61. [CrossRef]
49. Navas, E.; Fernandez, R.; Sepulveda, D.; Armada, M.; Gonzalez-de-Santos, P. Soft Grippers for Automatic Crop Harvesting: A Review. *Sensors* **2021**, *21*, 2689. [CrossRef]
50. Chen, J.; Qiang, H.; Wu, J.; Xu, G.; Wang, Z. Navigation path extraction for greenhouse cucumber-picking robots using the prediction-point Hough transform. *Comput. Electron. Agric.* **2021**, *180*, 105911. [CrossRef]
51. Koivumäki, J.; Zhu, W.-H.; Mattila, J. Energy-efficient and high-precision control of hydraulic robots. *Control. Eng. Pract.* **2019**, *85*, 176–193. [CrossRef]
52. Zhang, Z.; Igathinathane, C.; Li, J.; Cen, H.; Lu, Y.; Flores, P. Technology progress in mechanical harvest of fresh market apples. *Comput. Electron. Agric.* **2020**, *175*, 105606. [CrossRef]
53. Xiong, Y.; Peng, C.; Grimstad, L.; From, P.J.; Isler, V. Development and field evaluation of a strawberry harvesting robot with a cable-driven gripper. *Comput. Electron. Agric.* **2019**, *157*, 392–402. [CrossRef]
54. Tu, X.; Gai, J.; Tang, L. Robust navigation control of a 4WD/4WS agricultural robotic vehicle. *Comput. Electron. Agric.* **2019**, *164*, 104892. [CrossRef]
55. Zhou, X.; Zhou, J. Data-Driven Driving State Control for Unmanned Agricultural Logistics Vehicle. *IEEE Access* **2020**, *8*, 65530–65543. [CrossRef]
56. Li, Z.; Chen, L.; Zheng, Q.; Dou, X.; Yang, L. Control of a path following caterpillar robot based on a sliding mode variable structure algorithm. *Biosyst. Eng.* **2019**, *186*, 293–306. [CrossRef]
57. Chen, L.; Wang, P.; Zhang, P.; Zheng, Q.; He, J.; Wang, Q. Performance analysis and test of a maize inter-row self-propelled thermal fogger chassis. *Int. J. Agric. Biol. Eng.* **2018**, *11*, 100–107. [CrossRef]
58. Zhang, C.; Yong, L.; Chen, Y.; Zhang, S.; Ge, L.; Wang, S.; Li, W. A Rubber-Tapping Robot Forest Navigation and Information Collection System Based on 2D LiDAR and a Gyroscope. *Sensors* **2019**, *19*, 2136. [CrossRef]
59. Jones, M.H.; Bell, J.; Dredge, D.; Seabright, M.; Scarfe, A.; Duke, M.; MacDonald, B. Design and testing of a heavy-duty platform for autonomous navigation in kiwifruit orchards. *Biosyst. Eng.* **2019**, *187*, 129–146. [CrossRef]
60. Guevara, J.; Gene-Mola, J.; Gregorio, E.; Torres-Torriti, M.; Reina, G.; Cheein, F.A.A. Comparison of 3D scan matching techniques for autonomous robot navigation in urban and agricultural environments. *J. Appl. Remote Sens.* **2021**, *15*, 024508. [CrossRef]
61. Shao, Y.; Han, X.; Xuan, G.; Liu, Y.; Gao, C.; Wang, G.; Hu, Z. Development of a multi-adaptive feeding device for automated plug seedling transplanter. *Int. J. Agric. Biol. Eng.* **2021**, *14*, 91–96. [CrossRef]
62. Wang, L.; Wang, Y.; Dai, D.; Wang, X.; Wang, S. Review of electro-hydraulic hitch system control method of automated tractors. *Int. J. Agric. Biol. Eng.* **2021**, *14*, 1–11. [CrossRef]
63. Li, J.; Li, S.; Zhang, Y.; Liu, M.; Gao, Z. Development and test of hydraulic driven remote transporter. *Int. J. Agric. Biol. Eng.* **2021**, *14*, 72–80. [CrossRef]
64. Roshanianfard, A.; Noguchi, N.; Kamata, T. Design and performance of a robotic arm for farm use. *Int. J. Agric. Biol. Eng.* **2019**, *12*, 146–158. [CrossRef]
65. Yang, Y.; Zhang, G.; Chen, Z.; Wen, X.; Cheng, S.; Ma, Q.; Qi, J.; Zhou, Y.; Chen, L. An independent steering driving system to realize headland turning of unmanned tractors. *Comput. Electron. Agric.* **2022**, *201*, 107278. [CrossRef]

66. Zhang, Z.; Jia, X.; Yang, T.; Gu, Y.; Wang, W.; Chen, L. Multi-objective optimization of lubricant volume in an ELSD considering thermal effects. *Int. J. Therm. Sci.* **2021**, *164*, 106884. [CrossRef]
67. Chen, Z.; Yang, M.; Li, Y.; Yang, L. Design and experiment of tomato picking end-effector based on non-destructive pneumatic clamping control. *Trans. CSAE* **2021**, *37*, 27–35.
68. Amritanandamayi, D.M.; Udupa, G.; Sreedharan, P. A novel underactuated multi-fingered soft robotic hand for prosthetic application. *Robot. Auton. Syst.* **2018**, *100*, 267–277. [CrossRef]
69. Jiang, Z.; Hu, Y.; Jiang, H.; Tong, J. Design and force analysis of end-effector for plug seedling transplanter. *PLoS ONE* **2017**, *12*, e0180229. [CrossRef] [PubMed]
70. Gao, J.; Zhang, F.; Zhang, J.; Yuan, T.; Yin, J.; Guo, H.; Yang, C. Development and evaluation of a pneumatic finger-like end-effector for cherry tomato harvesting robot in greenhouse. *Comput. Electron. Agric.* **2022**, *197*, 106879. [CrossRef]
71. Liu, Y.; Zhong, Y.; Wang, C. Recent advances in self-actuation and self-sensing materials: State of the art and future perspectives. *Talanta* **2020**, *212*, 120808. [CrossRef]
72. Naoshi, K.; Mitsuji, K.; Noboru, N. *Agricultural Robotics (I) Fundamentals and Theory*; Qiao, J.; Chen, B., Translators; China Agricultural University Press: Beijing, China, 2009.
73. Tawk, C.; Gillett, A.; in het Panhuis, M.; Spinks, G.M.; Alici, G. A 3D-Printed Omni-Purpose Soft Gripper. *IEEE Trans. Robot.* **2019**, *35*, 1268–1275. [CrossRef]
74. Elmoughni, H.M.; Yilmaz, A.F.; Ozlem, K.; Khalilbayli, F.; Cappello, L.; Atalay, A.T.; Ince, G.; Atalay, O. Machine-Knitted Seamless Pneumatic Actuators for Soft Robotics: Design, Fabrication, and Characterization. *Actuators* **2021**, *10*, 94. [CrossRef]
75. Rovira-Mas, F.; Saiz-Rubio, V.; Cuenca-Cuenca, A. Augmented Perception for Agricultural Robots Navigation. *IEEE Sens. J.* **2021**, *21*, 11712–11727. [CrossRef]
76. Martin, P. A Future-Focused View of the Regulation of Rural Technology. *Agronomy* **2021**, *11*, 1153. [CrossRef]
77. Sun, Y.N.; Pan, Z.Q. RBF network based motion trajectory optimization for robot used in agricultural activities. *Emir. J. Food Agric.* **2018**, *30*, 883–892. [CrossRef]
78. Zhang, T.; Huang, Z.; You, W.; Lin, J.; Tang, X.; Huang, H. An Autonomous Fruit and Vegetable Harvester with a Low-Cost Gripper Using a 3D Sensor. *Sensors* **2019**, *20*, 93. [CrossRef] [PubMed]
79. Zhang, L.; Ahamed, T.; Zhang, Y.; Gao, P.; Takigawa, T. Vision-Based Leader Vehicle Trajectory Tracking for Multiple Agricultural Vehicles. *Sensors* **2016**, *16*, 578. [CrossRef]
80. Bengochea-Guevara, J.M.; Conesa-Munoz, J.; Andujar, D.; Ribeiro, A. Merge Fuzzy Visual Servoing and GPS-Based Planning to Obtain a Proper Navigation Behavior for a Small Crop-Inspection Robot. *Sensors* **2016**, *16*, 276. [CrossRef]
81. Wang, H.; Liu, L.; He, P.; Yu, M.; Do, M.T.; Kong, H.; Man, Z. Robust adaptive position control of automotive electronic throttle valve using PID-type sliding mode technique. *Nonlinear Dyn.* **2016**, *85*, 1331–1344. [CrossRef]
82. Hu, Y.; Wang, H.; He, S.; Zheng, J.; Ping, Z.; Shao, K.; Cao, Z.; Man, Z. Adaptive Tracking Control of an Electronic Throttle Valve Based on Recursive Terminal Sliding Mode. *IEEE Trans. Veh. Technol.* **2021**, *70*, 251–262. [CrossRef]
83. Jia, W.K.; Tian, Y.Y.; Duan, H.C.; Luo, R.; Lian, J.; Ruan, C.Z.; Zhao, D.A.; Li, C.J. Autonomous navigation control based on improved adaptive filtering for agricultural robot. *Int. J. Adv. Robot. Syst.* **2020**, *17*. [CrossRef]
84. Mousakazemi, S.; Ayoobian, N.; Ansarifar, G.R. Control of the reactor core power in PWR using optimized PID controller with the real-coded GA. *Ann. Nucl. Energy* **2018**, *118*, 107–121. [CrossRef]
85. Wang, H.; Noguchi, N. Adaptive turning control for an agricultural robot tractor. *Int. J. Agric. Biol. Eng.* **2018**, *11*, 113–119. [CrossRef]
86. Wang, L.; Zhang, H. An adaptive fuzzy hierarchical control for maintaining solar greenhouse temperature. *Comput. Electron. Agric.* **2018**, *155*, 251–256. [CrossRef]
87. Zavlangas, P.G.; Tzafestas, S.G. Motion control for mobile robot obstacle avoidance and navigation: A fuzzy logic-based approach. *Syst. Anal. Model. Simul.* **2003**, *43*, 1625–1637. [CrossRef]
88. Pradhan, S.K.; Parhi, D.R.; Panda, A.K. Motion control and navigation of multiple mobile robots for obstacle avoidance and target seeking: A rule-based neuro-fuzzy technique. *J. Syst. Control. Eng.* **2009**, *223*, 275–288. [CrossRef]
89. Malavazi, F.B.P.; Guyonneau, R.; Fasquel, J.B.; Lagrange, S.; Mercier, F. LiDAR-only based navigation algorithm for an autonomous agricultural robot. *Comput. Electron. Agric.* **2018**, *154*, 71–79. [CrossRef]
90. Essen, H.A.V.; Nijmeijer, H. Non-linear model predictive control for constrained mobile robots. In Proceedings of the 2001 European Control Conference (ECC), Porto, Portugal, 4–7 September 2001.
91. Kraus, T.; Ferreau, H.J.; Kayacan, E.; Ramon, H.; De Baerdemaeker, J.; Diehl, M.; Saeys, W. Moving horizon estimation and nonlinear model predictive control for autonomous agricultural vehicles. *Comput. Electron. Agric.* **2013**, *98*, 25–33. [CrossRef]
92. Tian, Z.; Gao, X.; Guo, P. Network Teleoperation Robot System Control Based on Fuzzy Sliding Mode. *J. Adv. Comput. Intell. Intell. Inform.* **2016**, *20*, 828–835. [CrossRef]
93. Chowdhary, G.; Gazzola, M.; Krishnan, G.; Soman, C.; Lovell, S. Soft Robotics as an Enabling Technology for Agroforestry Practice and Research. *Sustainability* **2019**, *11*, 6751. [CrossRef]
94. Birglen, L.; Schlicht, T. A statistical review of industrial robotic grippers. *Robot. Comput. Integr. Manuf.* **2018**, *49*, 88–97. [CrossRef]
95. Williams, H.A.M.; Jones, M.H.; Nejati, M.; Seabright, M.J.; Bell, J.; Penhall, N.D.; Barnett, J.J.; Duke, M.D.; Scarfe, A.J.; Ahn, H.S.; et al. Robotic kiwifruit harvesting using machine vision, convolutional neural networks, and robotic arms. *Biosyst. Eng.* **2019**, *181*, 140–156. [CrossRef]

96. Mu, L.; Cui, G.; Liu, Y.; Cui, Y.; Fu, L.; Gejima, Y. Design and simulation of an integrated end-effector for picking kiwifruit by robot. *Inf. Process. Agric.* **2020**, *7*, 58–71. [CrossRef]
97. Davidson, J.R.; Hohimer, C.J.; Mo, C.; Karkee, M. Dual Robot Coordination for Apple Harvesting. In Proceedings of the 2017 ASABE Annual International Meeting, Spokane, WA, USA, 16–19 July 2017. [CrossRef]
98. Ling, X.; Zhao, Y.; Gong, L.; Liu, C.; Wang, T. Dual-arm cooperation and implementing for robotic harvesting tomato using binocular vision. *Robot. Auton. Syst.* **2019**, *114*, 134–143. [CrossRef]
99. Sepulveda, D.; Fernandez, R.; Navas, E.; Armada, M.; Gonzalez-De-Santos, P. Robotic Aubergine Harvesting Using Dual-Arm Manipulation. *IEEE Access* **2020**, *8*, 121889–121904. [CrossRef]
100. Zhang, B.; Zhou, J.; Meng, Y.; Zhang, N.; Gu, B.; Yan, Z.; Idris, S.I. Comparative study of mechanical damage caused by a two-finger tomato gripper with different robotic grasping patterns for harvesting robots. *Biosyst. Eng.* **2018**, *171*, 245–257. [CrossRef]
101. Russo, M.; Ceccarelli, M.; Corves, B.; Hüsing, M.; Lorenz, M.; Cafolla, D.; Carbone, G. Design and test of a gripper prototype for horticulture products. *Robot. Comput. Integr. Manuf.* **2017**, *44*, 266–275. [CrossRef]
102. Zhang, K.; Lammers, K.; Chu, P.; Li, Z.; Lu, R. System design and control of an apple harvesting robot. *Mechatronics* **2021**, *79*, 102644. [CrossRef]
103. Quan, L.; Jiang, W.; Li, H.; Li, H.; Wang, Q.; Chen, L. Intelligent intra-row robotic weeding system combining deep learning technology with a targeted weeding mode. *Biosyst. Eng.* **2022**, *216*, 13–31. [CrossRef]
104. Li, B.; Gu, S.; Chu, Q.; Yang, Y.; Xie, Z.; Fan, K.; Liu, X. Development of transplanting manipulator for hydroponic leafy vegetables. *Int. J. Agric. Biol. Eng.* **2019**, *12*, 38–44. [CrossRef]
105. Tian, G.; Zhou, J.; Gu, B. Slipping detection and control in gripping fruits and vegetables for agricultural robot. *Int. J. Agric. Biol. Eng.* **2018**, *11*, 29–34. [CrossRef]
106. Roshanianfard, A.; Noguchi, N. Pumpkin harvesting robotic end-effector. *Comput. Electron. Agric.* **2020**, *174*, 105503. [CrossRef]
107. Kurpaska, S.; Sobol, Z.; Pedryc, N.; Hebda, T.; Nawara, P. Analysis of the Pneumatic System Parameters of the Suction Cup Integrated with the Head for Harvesting Strawberry Fruit. *Sensors* **2020**, *20*, 4389. [CrossRef]
108. Lehnert, C.; McCool, C.; Sa, I.; Perez, T. Performance improvements of a sweet pepper harvesting robot in protected cropping environments. *J. Field Robot.* **2020**, *37*, 1197–1223. [CrossRef]
109. Kurpaska, S.; Bielecki, A.; Sobol, Z.; Bielecka, M.; Habrat, M.; Smigielski, P. The Concept of the Constructional Solution of the Working Section of a Robot for Harvesting Strawberries. *Sensors* **2021**, *21*, 3933. [CrossRef]
110. Yang, Y.; Zhou, Y.; Yue, X.; Zhang, G.; Wen, X.; Ma, B.; Xu, L.; Chen, L. Real-time detection of crop rows in maize fields based on autonomous extraction of ROI. *Expert Syst. Appl.* **2022**, *213*, 118826. [CrossRef]
111. Bao, X.; Niu, Y.; Li, Y.; Mao, J.; Li, S.; Ma, X.; Yin, Q.; Chen, B. Design and Kinematic Analysis of Cable-Driven Target Spray Robot for Citrus Orchards. *Appl. Sci.* **2022**, *12*, 9379. [CrossRef]
112. Pérez-Ruíz, M.; Slaughter, D.C.; Fathallah, F.A.; Gliever, C.J.; Miller, B.J. Co-robotic intra-row weed control system. *Biosyst. Eng.* **2014**, *126*, 45–55. [CrossRef]
113. Langsenkamp, F.; Sellmann, F.; Kohlbrecher, M.; Kielhorn, A.; Trautz, D. Tube Stamp for mechanical intra-row individual Plant Weed Control. In Proceedings of the 18 th World Congress of CIGR, Beijing, China, 16–19 September 2014.
114. Yang, C.; Wu, Z.; Guo, Y. Structural design of a milking robot. *Agric. Mech. Res.* **2018**, *40*, 6.
115. Liu, X.; Li, B.; Chang, J.; Zhang, G.; Wang, C. Design and analysis of double manipulator structure of medlar picking robot. *High Tech Commun.* **2019**, *29*, 175–182.
116. van Marrewijk, B.M.; Vroegindeweij, B.A.; Gené-Mola, J.; Mencarelli, A.; Hemming, J.; Mayer, N.; Wenger, M.; Kootstra, G. Evaluation of a boxwood topiary trimming robot. *Biosyst. Eng.* **2022**, *214*, 11–27. [CrossRef]
117. Mohamed, A.; Shaw-Sutton, J.; Green, B.M.; Andrews, W.; Stoelen, M.F. Soft manipulator robot for selective tomato harvesting. In Proceedings of the 12th European Conference on Precision Agriculture, Montpellier, France, 8–11 July 2019.
118. Wang, C.; Zou, X.; Tang, Y.; Luo, L.; Feng, W. Localisation of litchi in an unstructured environment using binocular stereo vision. *Biosyst. Eng.* **2016**, *145*, 39–51. [CrossRef]
119. Oberti, R.; Marchi, M.; Tirelli, P.; Calcante, A.; Iriti, M.; Tona, E.; Hočevar, M.; Baur, J.; Pfaff, J.; Schütz, C.; et al. Selective spraying of grapevines for disease control using a modular agricultural robot. *Biosyst. Eng.* **2016**, *146*, 203–215. [CrossRef]
120. You, A.; Grimm, C.; Silwal, A.; Davidson, J.R. Semantics-guided skeletonization of upright fruiting offshoot trees for robotic pruning. *Comput. Electron. Agric.* **2022**, *192*, 106622. [CrossRef]
121. Gonzalez-de-Santos, P.; Fernandez, R.; Sepulveda, D.; Navas, E.; Emmi, L.; Armada, M. Field Robots for Intelligent Farms-Inhering Features from Industry. *Agronomy* **2020**, *10*, 1638. [CrossRef]
122. Zhao, Y.; Liang, G.; Liu, C.; Huang, Y. Dual-arm Robot Design and Testing for Harvesting Tomato in Greenhouse. *IFAC PapersOnLine* **2016**, *49*, 161–165. [CrossRef]
123. Trinidad, J.B. Machine for Automatically Harvesting Fruits Cultivated in Rows. U.S. Patent Application No. 15/366,091, 7 June 2018.
124. Jin, Y.; Liu, J.; Xu, Z.; Yuan, S.; Li, P.; Wang, J. Development status and trend of agricultural robot technology. *Int. J. Agric. Biol. Eng.* **2021**, *14*, 1–19. [CrossRef]
125. Zion, B.; Mann, M.; Levin, D.; Shilo, A.; Rubinstein, D.; Shmulevich, I. Harvest-order planning for a multiarm robotic harvester. *Comput. Electron. Agric.* **2014**, *103*, 75–81. [CrossRef]

126. Longo, D.; Muscato, G. Design and Simulation of Two Robotic Systems for Automatic Artichoke Harvesting. *Robotics* **2013**, *2*, 217–230. [CrossRef]
127. Ye, H.; Huang, W.; Huang, S.; Cui, B.; Dong, Y.; Guo, A.; Ren, Y.; Jin, Y. Recognition of Banana Fusarium Wilt Based on UAV Remote Sensing. *Remote Sens.* **2020**, *12*, 938. [CrossRef]
128. Zhang, X.; Han, L.; Dong, Y.; Shi, Y.; Huang, W.; Han, L.; Gonzalez-Moreno, P.; Ma, H.; Ye, H.; Sobeih, T. A Deep Learning-Based Approach for Automated Yellow Rust Disease Detection from High-Resolution Hyperspectral UAV Images. *Remote Sens.* **2019**, *11*, 1554. [CrossRef]
129. Anagnostis, A.; Benos, L.; Tsaopoulos, D.; Tagarakis, A.; Tsolakis, N.; Bochtis, D. Human Activity Recognition through Recurrent Neural Networks for Human-Robot Interaction in Agriculture. *Appl. Sci.* **2021**, *11*, 2188. [CrossRef]
130. Wang, W.; Song, J.; Zhou, G.; Quan, L.; Zhang, C.; Chen, L. Development and Numerical Simulation of a Precision Strip-Hole Layered Fertilization Subsoiler While Sowing Maize. *Agriculture* **2022**, *12*, 938. [CrossRef]
131. Huynh, T.; Tran, M.-T.; Lee, D.-H.; Chakir, S.; Kim, Y.-B. A Study on Vision-Based Backstepping Control for a Target Tracking System. *Actuators* **2021**, *10*, 105. [CrossRef]
132. Kragh, M.; Underwood, J. Multimodal obstacle detection in unstructured environments with conditional random fields. *J. Field Robot.* **2020**, *37*, 53–72. [CrossRef]
133. Lee, B.; Kam, D.; Min, B.; Hwa, J.; Oh, S. A Vision Servo System for Automated Harvest of Sweet Pepper in Korean Greenhouse Environment. *Appl. Sci.* **2019**, *9*, 2395. [CrossRef]
134. Li, Y.; Huang, D.; Qi, J.; Chen, S.; Sun, H.; Liu, H.; Jia, H. Feature Point Registration Model of Farmland Surface and Its Application Based on a Monocular Camera. *Sensors* **2020**, *20*, 3799. [CrossRef]
135. Chen, Y.; Hou, C.; Tang, Y.; Zhuang, J.; Lin, J.; He, Y.; Guo, Q.; Zhong, Z.; Lei, H.; Luo, S. Citrus Tree Segmentation from UAV Images Based on Monocular Machine Vision in a Natural Orchard Environment. *Sensors* **2019**, *19*, 5558. [CrossRef]
136. Zhou, C.; Ye, H.; Hu, J.; Shi, X.; Hua, S.; Yue, J.; Xu, Z.; Yang, G. Automated Counting of Rice Panicle by Applying Deep Learning Model to Images from Unmanned Aerial Vehicle Platform. *Sensors* **2019**, *19*, 3106. [CrossRef]
137. Zhou, Y.; Yang, Y.; Zhang, B.; Wen, X.; Yue, X.; Chen, L. Autonomous detection of crop rows based on adaptive multi-ROI in maize fields. *Int. J. Agric. Biol. Eng.* **2021**, *14*, 217–225. [CrossRef]
138. Lyu, H.-K.; Yun, S.; Choi, B. Machine Learning Feature Extraction Based on Binary Pixel Quantification Using Low-Resolution Images for Application of Unmanned Ground Vehicles in Apple Orchards. *Agronomy* **2020**, *10*, 1926. [CrossRef]
139. Cubero, S.; Marco-Noales, E.; Aleixos, N.; Barbe, S.; Blasco, J. RobHortic: A Field Robot to Detect Pests and Diseases in Horticultural Crops by Proximal Sensing. *Agriculture* **2020**, *10*, 276. [CrossRef]
140. Lei, X.; Ouyang, H.; Xu, L. Mature pomegranate recognition methods in natural environments using machine vision. *Cienc. Rural* **2019**, *49*, e20190298. [CrossRef]
141. Zhou, K.; Meng, Z.; He, M.; Hou, J.; Li, T. Design and Test of a Sorting Device Based on Machine Vision. *IEEE Access* **2020**, *8*, 27178–27187. [CrossRef]
142. Adhikari, S.P.; Kim, G.; Kim, H. Deep Neural Network-Based System for Autonomous Navigation in Paddy Field. *IEEE Access* **2020**, *8*, 71272–71278. [CrossRef]
143. Zhang, S.; Wang, Y.; Zhu, Z.; Li, Z.; Du, Y.; Mao, E. Tractor path tracking control based on binocular vision. *Inf. Process. Agric.* **2018**, *5*, 422–432. [CrossRef]
144. Yin, W.; Wen, H.; Ning, Z.; Ye, J.; Dong, Z.; Luo, L. Fruit Detection and Pose Estimation for Grape Cluster-Harvesting Robot Using Binocular Imagery Based on Deep Neural Networks. *Front. Robot. AI* **2021**, *8*, 626989. [CrossRef]
145. Xiang, R.; Jiang, H.; Ying, Y. Recognition of clustered tomatoes based on binocular stereo vision. *Comput. Electron. Agric.* **2014**, *106*, 75–90. [CrossRef]
146. Nguyen, T.T.; Vandevoorde, K.; Wouters, N.; Kayacan, E.; De Baerdemaeker, J.G.; Saeys, W. Detection of red and bicoloured apples on tree with an RGB-D camera. *Biosyst. Eng.* **2016**, *146*, 33–44. [CrossRef]
147. Gu, Y.; Li, Z.; Zhang, Z.; Li, J.; Chen, L. Path Tracking Control of Field Information-Collecting Robot Based on Improved Convolutional Neural Network Algorithm. *Sensors* **2020**, *20*, 797. [CrossRef]
148. Quan, L.; Li, H.; Li, H.; Jiang, W.; Lou, Z.; Chen, L. Two-Stream Dense Feature Fusion Network Based on RGB-D Data for the Real-Time Prediction of Weed Aboveground Fresh Weight in a Field Environment. *Remote Sens.* **2021**, *13*, 2288. [CrossRef]
149. Wang, T.; Chen, B.; Zhang, Z.; Li, H.; Zhang, M. Applications of machine vision in agricultural robot navigation: A review. *Comput. Electron. Agric.* **2022**, *198*, 107085. [CrossRef]
150. Lin, G.; Tang, Y.; Zou, X.; Xiong, J.; Li, J. Guava Detection and Pose Estimation Using a Low-Cost RGB-D Sensor in the Field. *Sensors* **2019**, *19*, 428. [CrossRef] [PubMed]
151. Weiss, U.; Biber, P. Plant detection and mapping for agricultural robots using a 3D LIDAR sensor. *Robot. Auton. Syst.* **2011**, *59*, 265–273. [CrossRef]
152. Reiser, D.; Vazquez-Arellano, M.; Paraforos, D.S.; Garrido-Izard, M.; Griepentrog, H.W. Iterative individual plant clustering in maize with assembled 2D LiDAR data. *Comput. Ind.* **2018**, *99*, 42–52. [CrossRef]
153. Bietresato, M.; Carabin, G.; Vidoni, R.; Gasparetto, A.; Mazzetto, F. Evaluation of a LiDAR-based 3D-stereoscopic vision system for crop-monitoring applications. *Comput. Electron. Agric.* **2016**, *124*, 1–13. [CrossRef]

154. Siebers, M.H.; Edwards, E.J.; Jimenez-Berni, J.A.; Thomas, M.R.; Salim, M.; Walker, R.R. Fast Phenomics in Vineyards: Development of GRover, the Grapevine Rover, and LiDAR for Assessing Grapevine Traits in the Field. *Sensors* **2018**, *18*, 2924. [CrossRef] [PubMed]
155. Iqbal, J.; Xu, R.; Halloran, H.; Li, C. Development of a Multi-Purpose Autonomous Differential Drive Mobile Robot for Plant Phenotyping and Soil Sensing. *Electronics* **2020**, *9*, 1550. [CrossRef]
156. Underwood, J.P.; Jagbrant, G.; Nieto, J.I.; Sukkarieh, S. Lidar-Based Tree Recognition and Platform Localization in Orchards. *J. Field Robot.* **2015**, *32*, 1056–1074. [CrossRef]
157. Liu, L.; Mei, T.; Niu, R.; Wang, J.; Liu, Y.; Chu, S. RBF-Based Monocular Vision Navigation for Small Vehicles in Narrow Space below Maize Canopy. *Appl. Sci.* **2016**, *6*, 182. [CrossRef]
158. Martelloni, L.; Fontanelli, M.; Pieri, S.; Frasconi, C.; Caturegli, L.; Gaetani, M.; Grossi, N.; Magni, S.; Pirchio, M.; Raffaelli, M.; et al. Assessment of the Cutting Performance of a Robot Mower Using Custom Built Software. *Agronomy* **2019**, *9*, 230. [CrossRef]
159. Lou, Z.; Quan, L.; Sun, D.; Li, H.; Xia, F. Hyperspectral remote sensing to assess weed competitiveness in maize farmland ecosystems. *Sci. Total Environ.* **2022**, *844*, 157071. [CrossRef] [PubMed]
160. Wei, C.; Li, H.; Shi, J.; Zhao, G.; Feng, H.; Quan, L. Row anchor selection classification method for early-stage crop row-following. *Comput. Electron. Agric.* **2022**, *192*, 106577. [CrossRef]
161. Mao, W.J.; Liu, Z.J.; Liu, H.; Yang, F.Z.; Wang, M.R. Research Progress on Synergistic Technologies of Agricultural Multi-Robots. *Appl. Sci.* **2021**, *11*, 1448. [CrossRef]
162. Ge, Y.; Xiong, Y.; Tenorio, G.L.; From, P.J. Fruit Localization and Environment Perception for Strawberry Harvesting Robots. *IEEE Access* **2019**, *7*, 147642–147652. [CrossRef]
163. Guillet, A.; Lenain, R.; Thuilot, B.; Rousseau, V. Formation Control of Agricultural Mobile Robots: A Bidirectional Weighted Constraints Approach. *J. Field Robot.* **2017**, *34*, 1260–1274. [CrossRef]
164. Fromm, M.; Schubert, M.; Castilla, G.; Linke, J.; McDermid, G. Automated Detection of Conifer Seedlings in Drone Imagery Using Convolutional Neural Networks. *Remote Sens.* **2019**, *11*, 2585. [CrossRef]
165. Luo, Y.; Li, J.; Yu, C.; Xu, B.; Li, Y.; Hsu, L.-T.; El-Sheimy, N. Research on Time-Correlated Errors Using Allan Variance in a Kalman Filter Applicable to Vector-Tracking-Based GNSS Software-Defined Receiver for Autonomous Ground Vehicle Navigation. *Remote Sens.* **2019**, *11*, 1026. [CrossRef]
166. Li, J.; Tang, Y.; Zou, X.; Lin, G.; Wang, H. Detection of Fruit-Bearing Branches and Localization of Litchi Clusters for Vision-Based Harvesting Robots. *IEEE Access* **2020**, *8*, 117746–117758. [CrossRef]
167. Du, J.; Lu, X.; Fan, J.; Qin, Y.; Yang, X.; Guo, X. Image-Based High-Throughput Detection and Phenotype Evaluation Method for Multiple Lettuce Varieties. *Front. Plant Sci.* **2020**, *11*, 563386. [CrossRef] [PubMed]
168. Wang, W.; Wu, K.; Zhang, Y.; Wang, M.; Zhang, C.; Chen, L. The Development of an Electric-Driven Control System for a High-Speed Precision Planter Based on the Double Closed-Loop Fuzzy PID Algorithm. *Agronomy* **2022**, *12*, 945. [CrossRef]
169. Jun, J.; Kim, J.; Seol, J.; Kim, J.; Son, H.I. Towards an Efficient Tomato Harvesting Robot: 3D Perception, Manipulation, and End-Effector. *IEEE Access* **2021**, *9*, 17631–17640. [CrossRef]
170. Yuan, J. Research Progress Analysis of Robotics Selective Harvesting Technologies. *Trans. Chin. Soc. Agric. Mach.* **2020**, *51*, 1–17.
171. Wu, D.; Zhao, E.; Fang, D.; Jiang, S.; Wu, C.; Wang, W.; Wang, R. Determination of Vibration Picking Parameters of Camellia oleifera Fruit Based on Acceleration and Strain Response of Branches. *Agriculture* **2022**, *12*, 1222. [CrossRef]
172. Liu, L.; Bi, Q.; Zhang, Q.; Tang, J.; Bi, D.; Chen, L. Evaluation Method of Soil Surface Roughness after Ditching Operation Based on Wavelet Transform. *Actuators* **2022**, *11*, 87. [CrossRef]
173. Aghi, D.; Mazzia, V.; Chiaberge, M. Local Motion Planner for Autonomous Navigation in Vineyards with a RGB-D Camera-Based Algorithm and Deep Learning Synergy. *Machines* **2020**, *8*, 27. [CrossRef]