Research advance in phenotype detection robots for agriculture and forestry

Yuanqiao Wang[1,2†], Jiangchuan Fan[1,3†], Shuan Yu[1], Shuangze Cai[1], Xinyu Guo[3*], Chunjiang Zhao[1*]

(1. *Beijing Key Laboratory of Digital Plant, Beijing Research Center for Information Technology in Agriculture, China National Engineering Research Center for Information Technology in Agriculture (NERCITA), Beijing 100097, China*;
2. *College of Information Engineering, Northwest A&F University, Yangling 712100, Shaanxi, China*;
3. *Beijing PAIDE Science and Technology Development Co., Ltd., Beijing 100097, China*)

Abstract: The continuous development of robot technology has made phenotype detection robots a key for extracting and analyzing phenotyping data in agriculture and forestry. The different applications of agricultural robots and phenotype detection robots were discussed in this article. Further, the structural characteristics and information interaction modes of the current phenotype detection robots were summarized from the viewpoint of agriculture and forestry. The publications with keywords related to clustering distribution were analyzed and the currently available phenotype robots were classified. Additionally, a conclusion on the design criteria and evaluation system of plant phenotype detection robots was summarized and obtained, and the challenges and future development direction were proposed, which can provide a reference for the design and applications of agriculture and forestry robots.

Keywords: computer vision, plant phenotype detection robot, phenotyping analysis, sensor, evaluation system, device clustering

DOI: 10.25165/j.ijabe.20231601.7945

Citation: Wang Y Q, Fan J C, Yu S, Cai S Z, Guo X Y, Zhao C J. Research advance in phenotype detection robots for agriculture and forestry. Int J Agric & Biol Eng, 2023; 16(1): 14–25.

1 Introduction

The American Society of Robotics and the United Nations Organization for Standardization define a robot as a programmable, multi-functional manipulator or a specialized system that can be changed and programmed by a computer to perform different tasks. Robots are widely used in agricultural production and other fields[1-4].

Since the 1990s, there have been related studies on the design and use of agricultural robots[5]. There is a growing trend in the functional diversity of agricultural robots in China and abroad, which are gradually being promoted for ordinary agricultural production activities. Besides, researchers have redefined traditional farm management concepts and upgraded inefficient planting methods with more efficient phenotype equipment and methods for large-scale plant phenotype evaluation. The upgrade ensures that agricultural production can effectively cope with the global burden of food insecurity. Thus, this review is examined the need to understand the relationship between genotype and phenotype and the necessity of using a robot specifically designed for plant phenotype extraction because it is a major challenge of using robots in the agricultural industry[2].

Plant phenotype profiling measures specific plant traits using particular methods and protocols[6-11]. Plant traits are related to plant structure, biochemistry, and function at the cellular, canopy, and plant levels[6,12,13]. However, the traditional labor-intensive data collection method cannot meet the increasing demand for plant phenotype data. Besides, the traditional phenotype acquisition method has human error, which is not in line with the concept of precision agriculture[1,8,14,15].

Since the 2000s, intelligent mechanical technology and sensor technology have been applied in the field of plant phenotyping[16]. Researchers have built camera control equipment to achieve the acquisition of phenotype data, for example, carrying environmental sensors on mechanical trellises to obtain real-time information on plant growth environment; carrying RGB cameras on agricultural tractors to obtain images of plant canopies; carrying camera platforms on gliders to obtain large-scale group-scale overhead images of farmland, etc.[3,4,8,17] These data can help researchers quickly understand the plant growth condition so that they can respond to unexpected situations in the cultivation process in time. The recent development of machine learning algorithms and big data technologies since the 2010s has increased the intelligence of agricultural robots (Figure 1). For instance, gantry platforms and pipeline phenotype platforms can extract data in high time sequence, while unmanned aerial vehicles (UAV) and self-propelled robot platforms have greatly improved data acquisition quality and efficiency[18-20].

Accurate measurement and rapid processing of phenotype information are key in plant phenomics. Current plant monitoring

Received date: 2022-09-30 **Accepted date:** 2023-01-03

Biographies: Yuanqiao Wang, Under Postgraduate, research interest: machine vision for agricultural applications and agricultural intelligent equipment, Email: yuanqiao_wang@163.com; **Jiangchuan Fan**, PhD candidate, research interest: plant phenotypes, Email: fanjc@nercita.org.cn; **Shuan Yu**, PhD candidate, research interest: plant phenotypes, Email: yushuan_1994@163.com; **Shuangze Cai**, Under Postgraduate, research interest: plant phenotypes, Email: 905555691@qq.com.

†These authors contributed equally to this work.

***Correspondence: Xinyu Guo**, PhD, research interest: plant phenotypes. Beijing PAIDE Science and Technology Development Co., Ltd., Beijing 100097, China. Tel: +86-10-51503422, Email: guoxy@nercita.org.cn; **Chunjiang Zhao**, Professor, research interest: smart agriculture. Beijing Research Center for Information Technology in Agriculture, China National Engineering Research Center for Information Technology in Agriculture (NERCITA), Beijing 100097, China. Tel: +86-13801308848, Email: zhaocj@nercita.org.cn.

and phenotype techniques require agricultural equipment with multiple sensors. These sensors are non-destructive, quantitative, and multi-scale, and facilitate high-throughput data generation. Phenotype detection robots, the new multi-functional real-time monitoring platform, are the choice machine for many botanists and agricultural scientists since they generate phenotype data through fully autonomous monitoring systems. And the phenotype robots have the advantages of small size, high autonomy, and the ability to process phenotype data in real time[21-24].

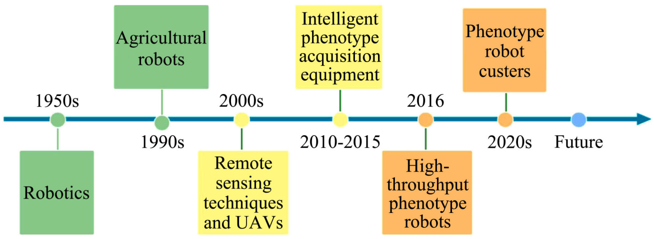


Figure 1 Development timeline of traditional agricultural and phenotype detection robots

Thus, this paper reviews the latest agricultural and forestry phenotype detection robots and their application worldwide and provides a comprehensive review of related researches. The current status of phenotype data parsing, the advantages of using robots, and the development potential of phenotype detection robots were assessed based on their design principles, work characteristics, and evaluation indicators[25]. Finally, the future development prospects of phenotype detection robots for specific traits and environments, multi-source plant phenotype detection methods, and phenotype detection robot clusters were refined.

2 Definition, characteristics, and work modes of phenotype detection robots designed for agriculture and forestry

2.1 Phenotype detection robots for agricultural and forestry applications

This section summarizes the structure and functional characteristics of the current robots for agricultural and forestry applications (Figure 2), accordingly providing new definitions for phenotype detection robots. A phenotype detection robot is an instrument that can independently run in a lane or field row, extract plant phenotype information, and analyze the data in a piece of intelligent mechanical equipment (such as an industrial computer). Phenotype detection robots are replacing traditional phenotype equipment and have attracted more attention worldwide. And this definition helps to refine the work of plant phenotype with the intersection of agriculture and computer[4,26-30].

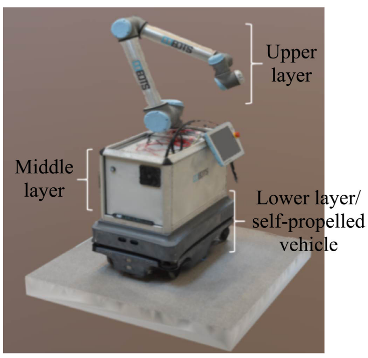


Figure 2 Basic structure concept diagram of phenotype detection robot

2.2 Characteristics of phenotype detection robots

2.2.1 Structural features

Phenotype robots are mainly divided into upper and lower ends or upper, middle, and lower structures[26,31,32]. The upper layer has a robotic arm, which interacts with sensors to extract plant phenotype data accurately. The middle structure is for human-computer interaction and includes the stabilizer equipped with sensors, server computers, and the Pan/Tilt/Zoom (PTZ). This part controls the robot and can be connected to a power backup or other equipment. The lower layer has autonomous mobile devices used to achieve functions such as tracking, navigation, and obstacle avoidance. These features and functional modules facilitate the high-throughput acquisition of plant phenotype data. Robots can improve data quality and analysis. Moreover, they combine three-dimensional plant gene maps with plant phenotype data, which is essential for regional differentiation characteristics and intergenerational evolution rules.

The upper layer of the robot has a flexible manipulator and various non-affecting sensor equipment that combines several computer algorithms and programming modules to achieve the characteristic of simple equipment operation and full automation. In most cases, the upper and middle layers of the phenotype detection robots cannot be combined because PTZ is located in the middle of the robot, but the relevant human-computer interaction equipment and sensors can be mounted without causing interference. But in some special cases, such as requiring a smaller robot, the top layer, and the middle layer can be integrated into one section. The middle part is important in coordinating and controlling the whole equipment. When the robots do not need a lot of human-machine interaction, the experimental sites are too narrow for movement; the upper and lower layers can form a whole to reduce the equipment volume. Finally, rubber tires, metal crawlers, or ground tracks can facilitate movement under different soil hardness, terrain, and topography (Figure 3).

Note: Row 1 presents the crawler and universal wheeled robot bases.

Figure 3 Three common types of movement phenotype robots

For example, using rubber tire sets with flexible steering motors can improve obstacle avoidance ability when working in an outdoor environment with hard soil. On very soft or muddy roads, the metal track can guarantee passability. In a narrow indoor environment or the greenhouse, repositioning the upper part of the robot on the ground can greatly improve efficiency.

Phenotype robots rely on various sensors to complete autonomous targets and navigation[33-37]. Moreover, the continuous improvement of data accuracy requirements in medicine, military, and agricultural industries has nurtured improved sensitivity and data quality of robots and sensors. For example, RGB cameras now have a shell with power interfaces and data transfer interfaces that can be stably assembled on robots. Some multispectral cameras or thermal imagers can also be assembled in special card slots and integrated into the phenotype robots or other platforms on phenotype or UAV platforms. Thus, users can finish all the necessary tasks across these interfaces using preset parameters[26,38-40].

Most of these improved features are changed from traditional agricultural robots[4,41]. These features present the basic applications for sensors and robotic equipment, but their efficiency and intelligence do not meet the increasingly complex needs of agricultural experiments. Phenotype detection robots for agriculture and forestry require higher autonomy than traditional equipment and pinpoint accuracy. A phenotype robot has higher flexibility and environmental adaptability than a rail-mounted gantry system or other fixed phenotype platforms. Similarly, phenotype detection robots have greater advantages than unmanned aerial vehicle platforms (UAPs) or other commonly used phenotype platforms in terms of operational complexity and usage conditions.

2.2.2 Functional features

Phenotype detection robots for agriculture and forestry have different functional characteristics from other phenotype platforms for several reasons. First, they have more angles to collect much more multiple data than data from a single view. Besides, these phenotype detection robots are able to get inside the plant canopy and extract the microscopic phenotype information from the front, side, top, or other specific angles. The foreground and background of the captured images can also be changed accordingly, which greatly enriches data diversity.

Secondly, these phenotype robots collect more accurate microscopic phenotype data than UAPs and other large fixed platforms. Some phenotype robots sacrifice “high throughput” with data acquisition from field ridges and cluster plants, providing more information[34,42-45]. Moreover, some images from inside the canopy can also reflect more plant characteristics, thus, achieving another breakthrough in plant phenomics. Most phenotype robots perform position tracking or self-guided navigation. These robots use the GPS positioning system to build maps through close-range LiDAR scans of precise movements and real-time obstacle avoidance. Furthermore, they can accommodate pre-lay positioning-magnetic sheets or auxiliary road signs in the test area for tracking. Additionally, Young et al.[25], showed that self-propelled robots can correct their running trajectory by calculating the deflection angle in real-time, thus, moving with higher precision[32,34,46].

Finally, these phenotype detection robots are more scalable, implying that users can quickly replace the sensors according to different structures and data extraction needs. Such characteristics can greatly reduce experimental costs and complexity. The scalability cooperates with the structural evaluation indicators, reflecting the core ideas of precision and smart agriculture and forestry[47].

2.2.3 Conditions and the phenotype detection robot workflow

The phenotype robot requires an experimental plan according to the experimental site and purpose. Robots should be adjusted, and relevant sensor parameters preset to complete the relevant task. After that, robots run at the specified time. During experimentation, the health of the device is monitored to ensure proper workflow. Afterward, the equipment should be stored properly and the data saved for future uses (Figure 4). Phenotype detection robots can interact with experimental targets and environments in real-time. The robot makes different judgments and action feedback according to different goals. The two-way communication between the robot and the external environment ensures autonomous task completion. Communication involves transmitting the signal from the experimental site to the robot and information processing in the first interaction. The information feedback includes tracking navigation and obstacle avoidance, target detection, and sensor position adjustment. After that, the second interaction occurs. Here, the robot profiles plant phenotypes and continuously transmits plant phenotype information to the terminal device until the end of the task[14,15,26,29,30,34,46,47].

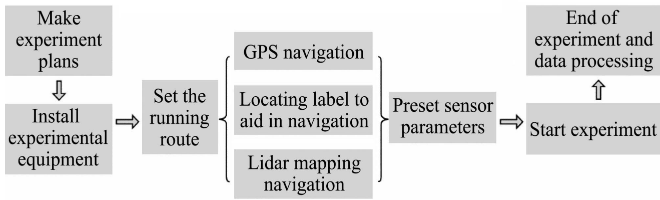


Figure 4 Phenotype detection robot workflow

The final information from the robot can be divided into spectral (image) and text (scalar) data. These data are generally collected by specific sensors, such as RGB cameras, multispectral sensors, hyper-spectrometer, obscure chlorophyll fluorescence cameras, transflectometer, environmental temperature and humidity sensors, and others (Table 1).

Table 1 Sensor types and corresponding phenotype detection robots and data types

Sensors	Phenotype detection robot	Phenotype data types
RGB camera	All kinds of robots	RGB photos/plant height/crown width
Multispectral camera	All kinds of robots	Multispectral data of leaves
Hyperspectral camera	Large indoor robots with a black box	Hyperspectral data of leaves, stems, and roots
3D LiDAR	All kinds of robots	Point cloud data of leaves, roots, and stalks
Thermal infrared camera	All kinds of robots	Leaf temperature/Plant temperature
Depth camera	All kinds of robots	RGB photos/Depth photos/Point cloud
Chlorophyll fluorescent camera	Robot with a robotic arm or PTZ	Chlorophyll fluorescence image of plant leaves
Transmissometer/ reflectometer	Robot with a robotic arm or PTZ	Leaf transmittance and reflectance
Temperature and humidity sensor	All kinds of robots	Temperature and humidity information of the plant-growth environment
Light intensity sensor	All kinds of robots	Light intensity

The spectral data acquisition conditions of RGB and depth images are similar. However, continuous shooting is necessary for agricultural and forest plants at specified angles of view and frames under sufficient lighting conditions[30,48,49]. Therefore, teams using phenotype robots design a suitable enclosure and install an external light to ensure the data quality according to plant phenotype and experimental requirements. Some users use high-precision robotic arms to stably extract microscopic phenotypes. Collecting multispectral and thermal infrared images[12,50] should be performed under natural light conditions. Thus, reasonable planning is required aiming for a shooting time between 10:00 am to 3:00 pm. Shadowing caused by the equipment itself requires consideration. However, hyperspectral images and chlorophyll fluorescence meters[42,51,52] can control interference from an external complex light environment to reduce imaging noise when acquiring pictures. Such sensors generally need to be used with a black box and a controllable light source.

However, scalar data mainly include 3D point cloud[9,36,41,53-58], ambient temperature, and humidity information. The point cloud of plants is generally obtained by scanning with a depth camera or 3D-LiDAR. The robot should maintain a stable operation to obtain scalar data continuously with reduced noise caused by the vibration of the vehicle body. Plant environmental and growth information can be tabulated Table 2 according to the recorded time and sequence for subsequent analysis and processing.

3 Development status

This paper extensively investigated the publications related to phenotype detection robots in agriculture and forestry and summarized the current classification and development status of phenotype detection robots.

3.1 Citation analysis

A search on the Web of Science core database using the keywords "robot" and "plant" from 1992 to 2022 identified 1203 articles on plant robotics. Adding the keyword "phenotype" retrieved 11 publications. Moreover, the most common keywords were "plant protection robot", "automation technology", and "computer software and computer application". These keywords reflect that the current phenotype data was obtained from traditional or improved agricultural robots. Plant protection robots were the majority (Table 2). Replacing the search terms with "phenotype" and "robot", it yielded 65 related literatures. The 65 papers were mainly published after 2016. The keywords of the 65 papers mainly included multidisciplinary sciences, computer science artificial intelligence, and computer science theory methods (Figure 5).

The VOSviewer classified the node locations and clustering results of the keywords "plant" and "robot" into three major categories (Figure 6).

Table 2 Plant environment and growth information correspond to different data, times, and sequences of data collection

Topic	Quantities	Keywords of literature
Robot & Plant	1203	1. Robotic systems 2. Sensor 3. Plant science
Robot & Plant Phenotype	11	1. Plant phenotyping 2. Computer artificial intelligence 3. High throughput
Unmanned Ground Vehicle & Phenotype	19	1. Multidisciplinary science 2. Plant phenotyping 3. Artificial intelligence
Phenotype & Robot	65	1. Multi-sensor platform 2. High-throughput 3. Plant phenotyping

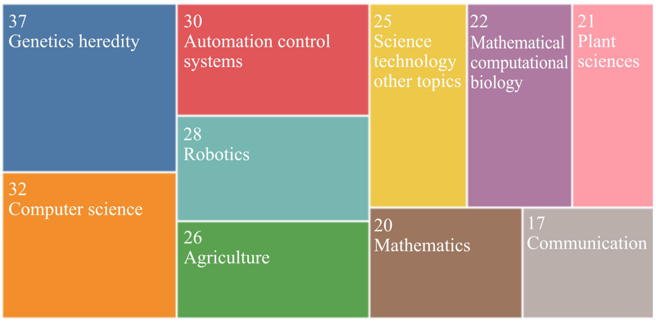


Figure 5 Keyword frequencies in retrieved papers using 'phenotype' and 'robot' as keywords

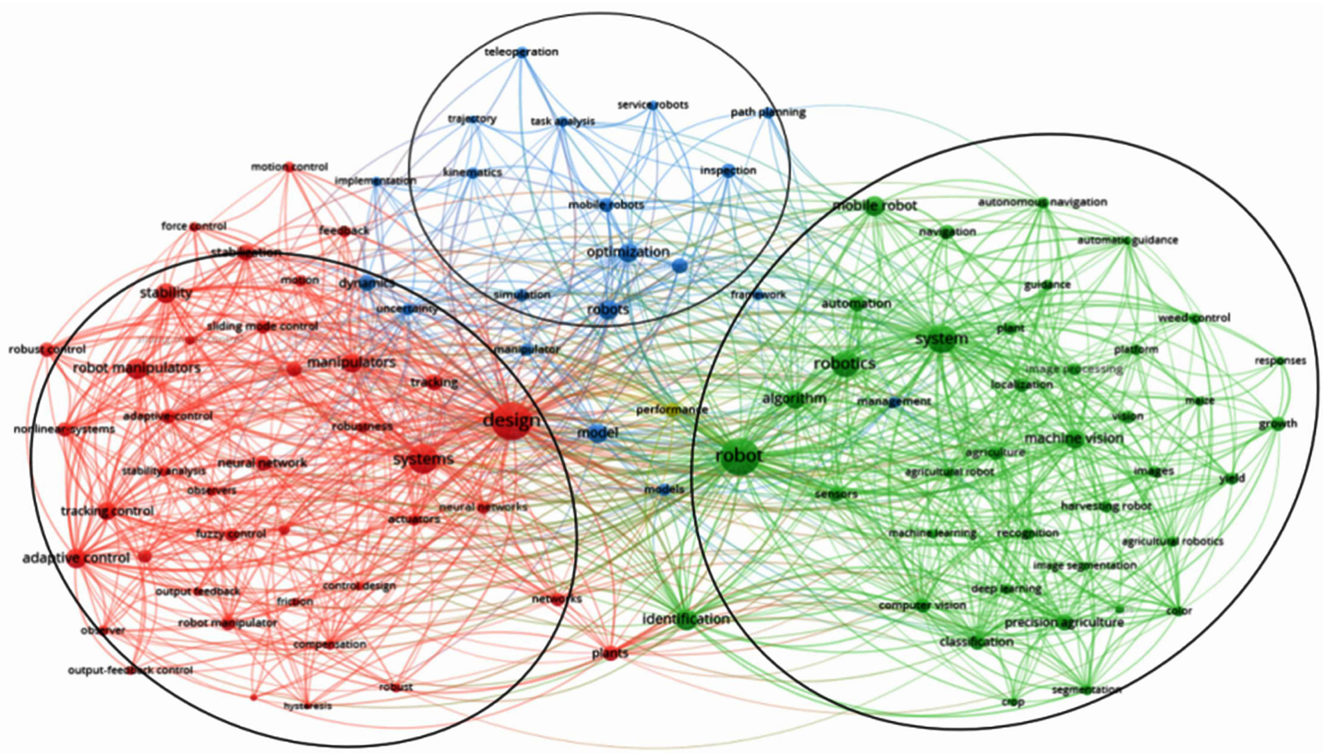


Figure 6 Phenotype robots retrieved from January 2015 to June 2022

1) The red cluster concentrates on the robot body parts combined with field automation control, mechanical design, manufacturing, path planning algorithm, and user operating system. This section analyzes the running trajectory, control method, and interaction means to provide an important theoretical and structural scientific basis for designing intelligent plant robots.

2) The blue cluster focuses on the crops and the corresponding specific phenotype extraction methods. The literature mainly includes methods and equipment for targeted data acquisition from the external plant structure and organ composition, such as stem length, plant height, leaf shape, and leaf number. It also provides application ideas for related practitioners to understand the basis of the phenomics of plants.

3) The green cluster focuses on the quantitative analysis of

plant phenotypes. This part mainly starts from different types of sensors and data, different branches of artificial intelligence and regression analysis algorithms, and different growth cycles, organs, tissues, and other plant fields. These papers also analyzed and studied the internal relationship between plant phenotypes and algorithms. The literature covered cluster analysis, the perspective of the sensors carried by the robots, and the solutions to the problems of robot information acquisition, especially plant information acquisition. Besides, this literature provided data supporting plant cultivation and breeding.

The statistics above show that the current research on data extraction and analysis for specific phenotypes is relatively separate from research on agricultural robots. However, the increasing demand for plant phenotype information and data accuracy for agricultural and forestry-based plant phenotype detection robots have gradually become research hotspots in related fields.

Depending on the equipment structure and application scenarios, phenotype detection robots can be divided into several divisions.

3.2 Classification of phenotype robots

According to different usage scenarios, phenotype detection robots can be divided into large-scale and small-scale types. Large-scale phenotype robots are used in orchards or field environments, but small plant phenotype robots operate in greenhouses with controlled conditions[9,47,59,60]. The characteristics of the orchard or field environments are large crop planting areas, changeable weather conditions, and complex soil topography. At maturity, the vegetation or crops are relatively tall, and detecting the canopy interior can be difficult. Therefore, field environment phenotype robots require good multi-terrain operation and high-throughput data acquisition capabilities. In contrast, greenhouse robots require a small experimental space, complete supporting facilities, and small environmental changes. The passability of the robot must match the different experimental sites. Thus, the robot should have good obstacle avoidance and be equipped with a mechanical arm, a pan-tilt, and other multi-angle, multi-directional smart devices[25,61,62].

Based on the different operating types, phenotype robots can be divided into three categories: cross ridge, self-propelled, and small robots with integrated robotic arms. Cross ridge and self-propelled robots can be adapted to most data collection tasks in most field environments. This is because both kinds of robots adopt the underlying platform design that is more suitable for the field environment, and both have good passability. Self-propelled robots can also be used in large greenhouses or greenhouses because of the smaller size of the robot compared to the straddle robot. Small robots with integrated robotic arms are designed for cramped greenhouse environments and can penetrate deep into the canopy for data acquisition. All these have their own adaptation scenarios, while self-propelled robots which can work between ridges are the most applicable category. In general, these robots can solve problems related to data diversity. Besides, phenotype robots can quickly disassemble and replace parts, so that different sensors can be used to accurately extract phenotype data of different plants.

Phenotype detection robots are very popular around the world because they have similar structural characteristics to traditional agricultural robots, especially vegetation monitoring and fruit, and vegetable picking robots. Both phenotype and traditional agricultural robots have underlying mobile platforms and upper modules. Thus, both robots can easily complete functional migration and development. The specific research on phenotype robots by teams from different countries will be explained in section 3.3.

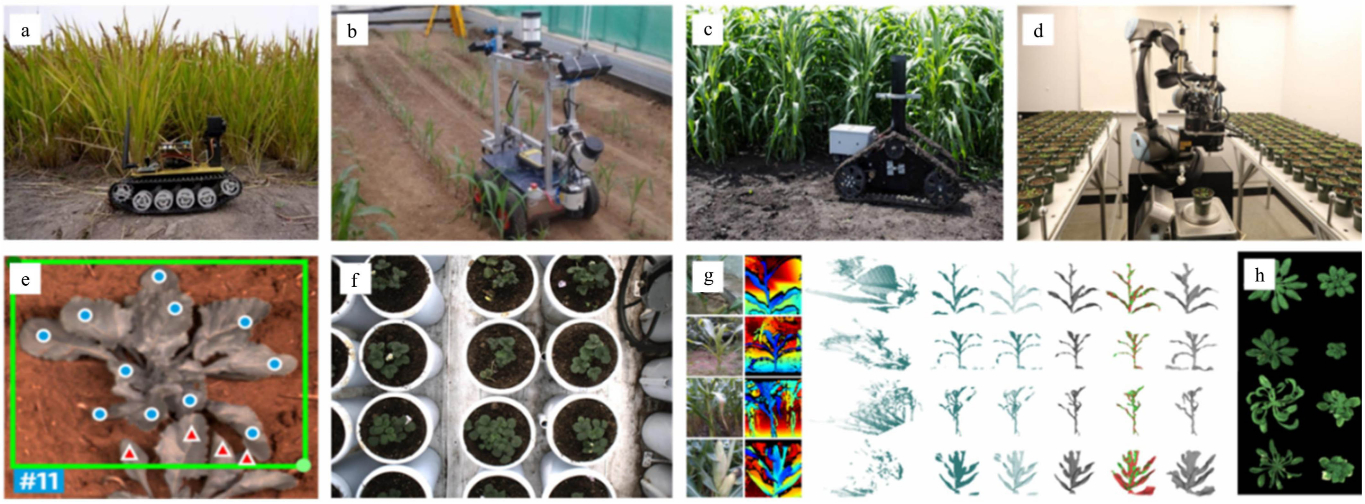
3.3 Ground-propelled phenotype detection robots

As mentioned above, phenotype detection robots are extensively applicable to the current field of plant phenomics. Global teams have designed and developed different robot platforms to meet different experimental contents (Table 3). For example, Weyler et al.[29], from the University of Bonn, Germany, used a large-scale phenotype robotic device to extract phenotype images of sugar beet plants at the seedling stage. This device that runs across ridges and moves within the same ridge is equipped with an RGB camera for photographing beet seedlings from an overhead angle. The team used these images to detect and discriminate weeds from beet plants instantly. They used a keypoint-based deep learning algorithm to implement the beet leaf count function (Figure 7e).

In 2018, the School of Agricultural Engineering at the University of Hohenheim designed a similar phenotype robot for maize plants in field and greenhouse environments[63]. The platform comprises a mobile unmanned vehicle at the bottom layer and a mechanical PTZ on the upper layer containing an industrial control computer, depth camera, and temperature and humidity-light intensity three-in-one environmental sensor. The obtained images from inside and outside the canopy are extractable from point cloud data after inverse processing, and the three-dimensional image of the leaf can be reconstructed through Poisson surface technology and image fusion and splicing technology[55,64,65]. The ability of ground phenotype robots to control error levels shows that they can generate accurate phenotype information (Figure 7b).

Table 3 Ground-propelled phenotype detection robots, their specialized functions, and respective research teams using them in various

Phenotypic detection robots	Operating types	Advantages	Place and usage
Auto plant detection system[61]	Cross Ridge Robot	Strong environmental adaptability, data collection can be performed under different scenes and light sources (Fields/Greenhouse)	Used by the Japanese team around 2020
Vinobot[46]	Self-propelled Robot	Combining unmanned vehicle and observation tower, monitoring crop phenotype in combination with point and surface (Fields)	Used by Mackenzie Presbyterian University team since 2017
TERRA-MEPP[25]	Self-propelled Robot	The crawler helps the device achieve high-throughput acquisition in different soil conditions (Fields)	Used by teams of University of Illinois since 2016
LQ-CropLiDAR	Self-propelled Robot between the Lines	Height, angle, and collection route can be adjusted to achieve high-throughput collection of phenotypic data (Fields/Greenhouse)	Used by teams of Beijing Academy of Agriculture and Forestry since 2020
RoAD (Robotic assay for drought)[39]	Small robots with integrated robotic arms	High degree of automation, enabling automatic monitoring, auxin regulation, and phenotype extraction (Greenhouse)	Used by the Iowa State University team since 2020
Robotanist[71]	Small robots with integrated robotic arms	Equipped with a high-resolution stereo imager to achieve accurate acquisition of 3D phenotype (Fields/Greenhouse)	Used by teams at Carnegie Mellon University in 2018
PhenoWatch	Small robots with integrated robotic arms	High-throughput, equipped with a variety of optical sensors to achieve accurate extraction of plant phenotype data (Fields/Greenhouse)	Used by teams from Nanjing Agricultural University since 2019
Robot and UAV embedded platform[58]	Cooperative system of UAP and phenotype robot	Using the collaborative measurement of two devices to help achieve 3D reconstruction of corn leaves (Fields)	Used by teams of the University of Hohenheim since 2017



a and c: The phenotype robots called Rovers designed by MIT b. A robot with PTZ designed by the University of Hohenheim d. An indoor phenotype robot called RoAD e. An example of using robot to count leaves of beet f. An example of overhead image acquisition using a phenotype robot g and h: Processing of plant phenotype data

Figure 7 Phenotype detection robot and data extraction examples

For instance, a 2019 study by the MIT Sensitive City Laboratory, Computer Science, and Artificial Intelligence Laboratory presented high-throughput phenotype robots developed for sorghum[26]. The robots, named "Rovers", use biofuel, are highly adaptable, and have unique triangular crawlers designed for different experimental environments, including the greenhouse and field. The device is also equipped with RGB and depth cameras and uses stereo imaging technology to obtain high-throughput plant surface information. Rovers have a GPS situated on top of the mast-type gimbal containing other sensors and an industrial computer fixed on the vehicle platform. At the same time, the sensor shutter settings matched other factors such as driving speed, terrain, and test path length to reduce data noise (Figure 7c).

A July 2021 publication by Iowa State University described the Robotic Drought Detection (RoAD) system, a ground robotic device designed and developed for BR and drought stress experiments of Arabidopsis in a small greenhouse environment. The device has a robotic arm, rover, bench scale, precisely-controlled watering system, RGB camera, and laser profiler; thus, it accurately identifies plant locations and moves autonomously to collect relevant information. The RoAD performs routine weighing, watering, and imaging tasks and can administer BR response assays by watering plants with Propiconazole (PCZ), a BR biosynthesis inhibitor. Furthermore, RoAD contains an automated and non-invasive robotic imaging system that accurately determines the morphological and growth-related traits of Arabidopsis and maize plants, providing insights into BR-influenced plant growth and stress responses (Figure 7).

3.4 Strengths and limitations of the currently available robots and possible solutions

Plant phenotyping essentially refers to assessments of plant phenotype traits[6,10,66,67] and characterization to guide breeding efforts. However, most phenotype equipment cannot accurately obtain different qualitative or quantitative phenotype traits of the same plant at one time. Simultaneously, it is more difficult for the equipment to achieve adaptive parameter adjustments for different plants and traits[46,68]. This challenge is also a strength as it promotes the development of targeted phenotype robots with diversified applications.

For example, a robotic arm system installed on a fixed track can complete high-throughput phenotyping through specific programs and preset parameters[12,15,43,69]. Such robots are mostly used in small-scale greenhouses or controlled environments, reducing wear and tear, thus, cutting down operation and maintenance costs and extending the service life. Additionally, these robots have more stable mechanical structures and a reasonable optical-sensor layout. They can be attached to external light sources or metal black boxes to improve imaging quality (Figure 7h).

Currently, these robots and the ground self-propelled phenotype robots (discussed under 'Ground-propelled phenotype detection robots') can function in automatic data collection and quantitative application of water and fertilizer; thus, combining the functions of traditional agricultural and modern phenotyping robots. Various features of the robot. And these devices achieve complete remote control through an encrypted connection between the server and the machine while ensuring data and experimental security and contributing to precision agriculture and breeding.

Therefore, phenotype detection robots complete some traditional agriculture besides phenotyping; thus, the efficiency and accuracy of agricultural experiments. Compared with other phenotyping devices (taking the UAPs as an example), phenotype detection robots have the following advantages:

1) High degree of autonomy and high carrying capacity to generate accurate phenotype data from a stable platform that accommodates other related equipment and sensors. The separated bottom-operating and upper-acquisition modules reduce the interference between the various sensors during operation[9,70].

2) Ability to complete indoor and outdoor environments with smooth, continuous data acquisition. Moreover, their design and modification are easy and flexible for different experimental environments and conditions[30,71].

3) Preset network coverage to comply with the higher requirements for real-time transmission of plant phenotype data since normal operation often involves real-time cultivation and breeding plan adjustments. Real-time adjustments are the core of smart agriculture and are key for present-day phenotype data collection[12,72].

4 Evaluating phenotype detection robots

This evaluation system considers several factors, including plant phenomics, mechanical design principles, manufacturing requirements, artificial intelligence, and application requirements. The evaluation aims at ensuring the high-throughput and nondestructive acquisition of phenotype data (Figure 8)[46].

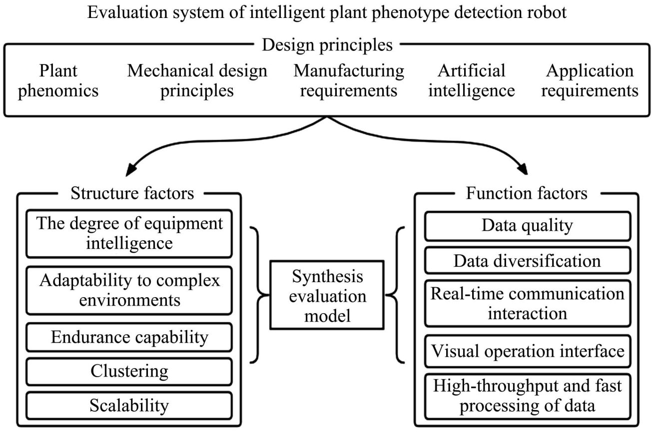


Figure 8 Main evaluation indexes of phenotype detection robot

4.1 Structural evaluation indicators

4.1.1 Degree of equipment intelligence

Phenotype detection robots reduce the influence of human factors on the experiment and realize high-throughput data collection than the traditional labor-intensive methods[1,73]. Autonomous robots can reduce human participation, costs, and manual errors, the core of smart agriculture. Therefore, structural intelligence and autonomy are considered when designing and evaluating a phenotype detection robot.

4.1.2 Adaptability to complex environments

It was argued that a phenotype detection robot should be able to work continuously in various experimental environments without major changes, such as replacing accessories or adding auxiliary equipment. Outdoor phenotype detection robots are constrained by the environment and experimental area, limiting their application during strong winds, thunderstorms, or dark weather conditions[42,74]. Crop density, soil moisture, and texture were also considered to test the robot's passability. Therefore, the environmental adaptability of the new phenotype detection robots under unfavorable conditions and high-quality data acquisition are important structural considerations.

4.1.3 Endurance capability

Battery life is a "pain point" for autonomous mechanical equipment, especially some robots. Many phenotype robots cannot continuously collect data for a long time, thus, decreasing the experimental efficiency and prolonging the experimental period. Therefore, the phenotype detection robots should have reasonable power control, autonomous return to the charging pile, and use solar energy or other environmentally friendly biomass energy to extend the service life of the device.

Phenotype robots should continuously work for 6-8 h to complete the data collection task within the plant growth cycle. Therefore, robots with these and other valuable characteristics have excellent endurance, while those below this standard supposedly have poor endurance.

4.1.4 Clustering

Multi-equipment clustering, the ability to work alongside multiple phenotype devices to phenotype plants. At present, no single robot can extract all kinds of data. For example, some optical sensors require natural light environment, while hyperspectral cameras require a black box to avoid ambient light noise. Some phenotype information requires destructive data acquisition, and some experiments are non-destructive. Therefore, the higher the degree of clustering of a phenotype robot, the more it can shorten the experimental period and improve the multi-source data acquisition, accuracy, and subsequent data processing.

4.1.5 Scalability

Traditional phenotyping equipment requires a longer time to disassemble and replace parts. Once some large phenotyping platforms and large agricultural robots are installed, replacing the equipment parts and sensors, and operating the experimental environment becomes difficult. The scalability of phenotype detection robots has become a concern of relevant researchers due to the continuously improving intelligence of phenotyping equipment. A robot that can be quickly modified and assembled becomes the first choice of experimenters. Based on scalability, phenotype detection robots can be divided into three categories: those that can realize rapid disassembly and assembly of equipment parts, those that allow local sensor replacement, and those with fixed, irreplaceable functional accessories.

4.2 Functional evaluation indicators

4.2.1 Data quality

Precision agriculture requires precise control of various plant growth indicators, and subtlety analysis quality of phenotype data is directly related to the ease and accuracy of subsequent algorithm processing[11,72,75]. Therefore, a robot that can overcome operating environment and equipment interference during the high-throughput collection of high-quality data is key to the phenotype equipment function evaluation system.

Data quality assessment varies with data types. For instance, images need to be dynamically captured according to preset camera parameters, to avoid overexposure (caused by high noise), shakes (caused by image blur), and angle or viewing distance errors. However, the chlorophyll content (SPAD), transmittance and reflectance of plant leaves, environmental temperature, and humidity need one-to-one correspondence between the measured and verification data to improve the result value and significance.

4.2.2 Data diversification

The importance of data diversification was mentioned above in the cluster development of phenotype robots. The effective information contained in a single phenotype data is not enough in the context of today's agricultural needs. Many complex agronomic experiments and crop monitoring tasks require multiple types of data support, and more information can be mined in the complementarity of data to maximize benefits[30,60]. Therefore, a well-designed phenotype detection robot should collect 3-5 data types concurrently and use each other as a reference to achieve multi-scale phenotype analysis tasks. Of course, it does not mean that the more types of data collected simultaneously, the better robots it is because there is inevitably a mutual influence between sensors and differences in shooting conditions. The phenotype robot should comprehensively consider data quality and data throughput and seek to maximize experimental benefits.

4.2.3 Real-time communication interaction

With the rise and development of the concept of smart farms and blockchain technology, the proportion of data decentralization has gradually increased. Future phenotyping experiments in agriculture and forestry will not be limited to the same area. Even if the experimental sites are very close, the data obtained by the robots also needs to be transmitted to the relevant personnel as soon as possible for processing and quantitative analysis. Therefore, whether it can interact remotely and whether this interaction can be transmitted in real-time in combination with the latest communication methods and technologies is also one of the important functional designs of robots[39,76].

4.2.4 Visual operation interface

According to this review, the phenotyping platforms used by teams from various countries in recent years include self-designed and developed systems. However, the corresponding user interfaces are very small[15,30,39,42,49,77], implying high usage of these intelligent "barrier" systems. As the most promising phenotype detection robot in modern agricultural equipment, it should have a matching "one-button" control software and a convenient visual user interface to improve the usability and flexibility of the entire system[49].

4.2.5 High-throughput and fast processing of data

To a certain extent, phenotype detection robots trade high throughput for data collection accuracy and specificity. However, an excellent phenotype robot should consider both efficiency and quality to meet the current needs of high-throughput phenotype data. The total amount of phenotype data Q is expressed as,

$$Q=M\times R \tag{1}$$

where, M is the type of data that the robot can obtain in one experiment and R is the amount of data obtained by one sensor.

The data collected by the sensor must have minimal or no redundancy to facilitate accurate subsequent algorithm processing, especially when performing regression analysis. Extensively redundant data affects the entire prediction[3,30,75,78,79], a great inconvenience throughout the experimentation since some basic indicators, such as the number of plant leaves, plant disease images, and insect pest identification, are directly given. Therefore, the ability of the phenotype detection robot to perform rapid data preprocessing is an important functional evaluation index[26,46,52].

The efficiency of data processing factors in the data volume per unit time $\overline{e}$ is captured in the following equation:

$$\overline{e}=\frac{Q}{\Delta t} \tag{2}$$

where, Q is the total amount of phenotype data, and Δt is the experimental period.

Besides, the long-term processing efficiency E can be determined with the overall experimental period using the following equation:

$$E=\frac{\sum_{i=1}^{K}Q_i}{T},\ K\in N \tag{3}$$

where, K is the total number of data collection tasks across the experiment period; T is the time required to complete the whole experiment; N is a natural number.

5 Challenges and development prospects of phenotype detection robots

Currently, there are several outstanding challenges in designing and using phenotype robots. On the one hand, optical sensors dominate the detection system, but their function contradicts the complex and variable plant phenotype measurement task. On the other hand, the precise measurement and collaborative extraction of multi-source data from phenotype robots are still insufficient. In the future, plant phenotype detection robots for agriculture and forestry will inevitably improve and update iterations according to the existing problems to achieve multi-robot, multi-platform cluster development, and high-precision data collection. This improvement projection also aligns with the requirements of the relevant structural and functional evaluation indicators proposed in this paper.

5.1 High-throughput, intelligent robots

Current phenotype robots partly sacrifice high-throughput data extraction for improved flexibility and accuracy. Simultaneously, current phenotype robots have not completely replaced human resources because of limited load capacity, endurance, and data collection refinement. Thus, device operation still requires manual parameter setting and some deployment operations. Phenotype robots also face irreversible wear and tear due to prolonged operation. Solving these problems requires a lot of material and effort against the concept of sustainable development and smart agriculture. Therefore, a mature intelligent phenotype detection robot needs to be able to reduce self-wear and reduce the failure rate.

However, future phenotype detection robots developed for agriculture and forestry plants will probably have higher autonomy before experimentation, be pre-deployable, and be modeled to different places and plants. The robot can be adjusted in detail to complete the collection work as long as the data is needed. And after experimentation, the robot can transmit and save the data, check its operational status (for any faults), and give feedback in time. Moreover, experimenters can monitor and manage the robot operation in real-time through a remote control terminal, thus, realizing an "unmanned" operation (Figure 9).

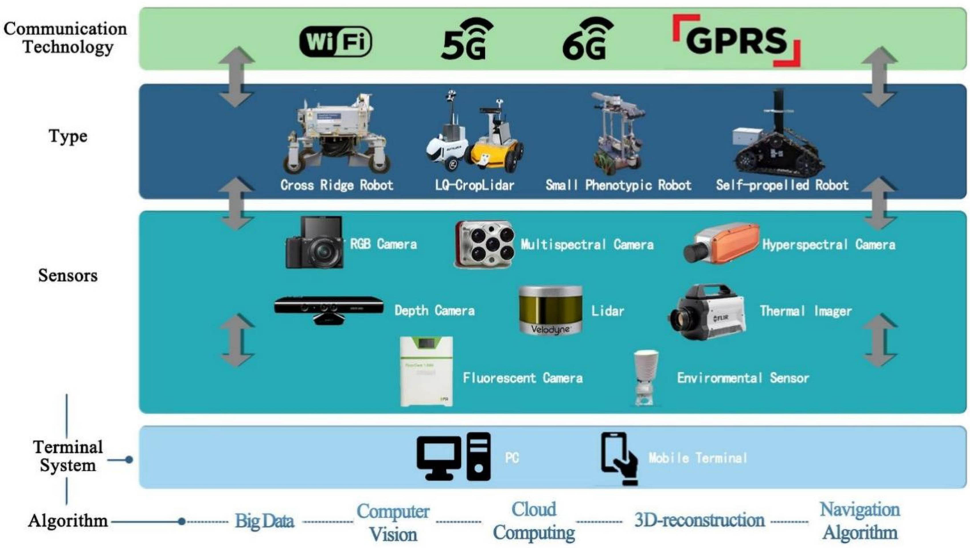


Figure 9 Components of plant phenotype detection robots for agriculture and forestry

5.2 Non-destructive extraction and precision requirements of data

Agricultural experiments based on phenotype robots should perform non-destructive data extraction, but currently, the robots are destructive[42,68,69,80]. In some cases, the robots irreversibly damage plant stems and leaves as they move and collect data. The damage can adversely affect other experiments hinged on the same batch of plants, ultimately failing the entire experiment. Therefore, reasonable robots should also reserve space for equipment use before application in agriculture and forestry experiments, achieving the coordinated development of agriculture machinery and agronomy.

In addition, due to the diversity of plant phenotypes and the great differences in the expression of the same phenotype on different plants, whether it is the spectral image data mentioned above or text data such as point clouds, it is necessary to improve Data quality to meet the needs of increasingly in-depth phenotyping tasks.

For example, some phenotype detection robots meet occlusion problems when taking images, especially on the stem part (horizontal direction) and the canopy (vertical direction). Three-dimensional information about leaves and stems is also crucial for phenotype analysis, yet 3D digital plant data collection by robots is still largely exploratory. 3D digital plant data collection still involves specific situations per plant and requires precise positioning of robotic arms and other equipment; thus, a critical development direction for future agriculture and forestry phenotype detection robots[44,52,81].

Additionally, processing phenotype data is inseparable from mathematical-statistical models and computer algorithms. The former is mostly used for scalar (text) type data parsing and the latter for spectral image processing[54,63,82,83]. Efficient software analysis developed for agriculture/forestry research will improve smart agriculture. For example, regression algorithms based on the least form algorithm can predict plant growth, while similar linear or non-linear analytical functions can also correlate plant biomass data[60,84,85,86]. Semantic segmentation and object detection algorithms can refine the anatomy of plant images, including RGB, multispectral, or thermal infrared images. Deep learning models of computer vision can perform feature analysis[63,80,87-93]. Some 3D point cloud-based processing and digitization algorithms can also reconstruct 3D plant models[53,54,64,94,95], a convenience for relevant practitioners performing global analysis of plant growth status. Moreover, continuous optimization of artificial intelligence algorithms is the basis for developing intelligent agriculture robots[6,15,20,26,29,96] (Figure 9). Hence, future phenotype robots should ensure high data quality and higher-throughput, multi-scale information extraction, especially when collecting different types of complementing data. In this way, comprehensive and accurate data analysis will be realized. Thus, the advanced robots better guide breeding work and trigger breakthroughs in phenotype detection robot technology.

5.3 Data mining challenges and intelligent human-computer interaction

The purpose of obtaining phenotype information is to classify and filter large sample data. The laws of plant growth can be analyzed using the laws and characteristics of relevant models and algorithms to better guide agricultural breeding. Therefore, the ability to analyze phenotype data is an important indicator in measuring the phenotype detection robot system[14,15,31,47]. Real-time data transmission and rapid processing are also important for intelligent phenotyping now and in the future. However, there are still many performance challenges, such as traffic stability and wireless networks monitoring edge-connected devices. Nonetheless, there is still much room for improving data processing, preservation, and in-depth information mining[76].

Our research team showed that most of the current phenotype detection robots quickly acquire and transfer phenotype data to databases in an integrated way. The preset tasks of these systems often end in data communication and interaction; that is, the data is not further processed or analyzed. After experimentation, the data must be manually downloaded and copied, which is undoubtedly inefficient. Therefore, future phenotype robots should focus on rational designing and optimizing this part of the experiment.

Agricultural big data also requires diversified data storage and backup to improve data security and facilitate asynchronous parallel processing of multi-source data; thus, the intersection of agriculture and computer technology should not only consider the robot technology and phenotype detection algorithm, but also the real-time sharing and the security of data[52,53,82].

Future phenotype detection equipment also needs relevant software control, big data, and cloud computing analysis platforms. These platforms need to have the following capabilities (Figure 9)[15,26,64]:

1) Integrate the software and newsletter interfaces using reasonable software architecture and network channel divisions to operate multiple devices remotely.

2) The robot system can remotely enter different types of data into the database, and realize data sharing among multiple devices. This can not only improve the efficiency of agricultural and forestry experiments, and facilitate subsequent data processing, but also improve the security and reliability of data storage, enabling data sharing.

3) Quickly resolve phenotype traits by fully using cloud computing and other methods in future phenotype detection robot systems to help non-computer practitioners and lay people use cutting-edge algorithms to quickly analyze plant phenotype data.

In conclusion, accelerating the integration of plant phenomics and computer science can facilitate agriculture and promote the development of artificial intelligence. Finally, a virtuous circle will be formed between academia-academia, academia-industry, and industry-industry.

5.4 Multi-device collaborative measurement and robot clustering

Inaccurate technologies limit current phenotype robots for tracking and balancing the passage between different places; thus, they meet the requirements of micro-level data collection. While other robots also face difficult design and assembly problems in different environments, these unfavorable factors directly affect the agronomic experiment cycle and cost[46]. The same quality is also necessary for developing coordinated and different equipment clusters.

Currently, the phenotyping platform based on UAV technology is the most common system for obtaining high throughput phenotype data in field experiments[43,97]. The UAPs can monitor plant phenotypes and synergistically analyze other traits by taking pictures of plant canopies. Therefore, UAV equipment is widely used in research in related fields. Unfortunately, the UAV technology is not applicable in a conventional greenhouse environment[15,98] because of height incompatibilities with the greenhouse roof (3-10 m), which is unsuitable for drones. In addition, the natural environment easily affects data collection in the air. Bad weather and high-altitude occlusion also hamper normal drone flight[42,74,99]. Therefore, combining the respective advantages of drones and phenotype robots can be a breakthrough in multi-scale data acquisition (Figure 10).

Figure 10 Phenotype detection robot cluster of agriculture and forestry plants

The concept of "machine cluster" in plant phenotyping will become mainstream in the future (as shown in Figure 10) because of the developments in communication and phenotype equipment technologies. The fifth-generation communication technology (5G) is now mature, and research on the sixth-generation communication technology (6G) is on the agenda of the relevant practitioners at home and abroad[97,100]. In other words, real-time information transmission, and sharing will become the mainstream of various industries in the future. As an important part of the communication, the concept of "decentralization" will also be applied to future phenotype detection equipment. "Decentralization" means that each node in a multi-node system has a high degree of autonomy and can be freely connected to other nodes to form a new connection unit for distributed processing and centralized management and control of tasks. These network conditions can be used on multiple ground robots of the same kind or deploy different phenotype robots for coordinated control. These network conditions can form a cluster array and collect various data types, large samples, high-throughput, and improve data accuracy[39,101,102].

In the future, the application of cluster robots will become the main means of obtaining plant phenotype data[9,26]. Different phenotype traits of the same plant or trait detection tasks on different varieties can be completed by intelligent robots. The technology can also be rolled out to a larger area. Besides, robots with different structural characteristics can also make up for the shortcomings of other robots in their respective application scenarios. For example, the same agronomy experiment can account for field and greenhouse environments, different climatic conditions, and altitudes. These robot clusters also improve the more robust, complete, and accurate three-dimensional data.

6 Conclusions

The phenotype detection robot of agriculture and forestry plants is an intelligent device formed by the combination of a cutting-edge high-throughput plant phenotyping platform and traditional agricultural robots, which has broad application prospects. There are many disciplines involved in such equipment, such as artificial intelligence and data science, mechanical design and manufacturing automation, plant breeding, inertial navigation, communication, etc. The development of phenotype robots also provides more efficient and robust sensing and control systems. Therefore, a highly functional plant phenotype robot with high use value should start from the above disciplines, comprehensively analyze its limitations, and improve its speed, accuracy, safety, and reliability. This paper aims to redefine the agricultural and forestry plant phenotype detection robot, separate this concept from the general agricultural robot, realize the targeted deployment of agricultural experimental equipment, and lay a theoretical foundation for future research.

Acknowledgements

This work was funded by the Construction of Collaborative Innovation Center of Beijing Academy of Agricultural and Forestry Sciences (KJCX201917), Beijing Nova Program (Z211100002121065), Science and Technology Innovation Special Construction Funded Program of Beijing Academy of Agriculture and Forestry Sciences (KJCX20210413).

[References]

[1] Wang Z, Xun Y, Wang Y K, Yang Q H. Review of smart robots for fruit and vegetable picking in agriculture. Int J Agric & Biol Eng, 2022; 15(1): 33–54.

[2] Bechar A, Vigneault C. Agricultural robots for field operations: Concepts and components. Biosystems Engineering, 2016; 149: 94–111.

[3] Itzhaky Y, Farjon G, Khoroshevsky F, Shpigler A, Bar-Hillel A. Leaf counting: Multiple scale regression and detection using deep CNNs. BMVC, Newcastle, 2018; 328p.

[4] Dong M, Yu H, Zhang L, Wu M, Sun Z P, Zeng D, et al. Measurement method of plant phenotypic parameters based on image deep learning. In: Lakshmanna K, ed. Wireless Communications and Mobile Computing, 2022; 2022: 1–9.

[5] He W, Beck M, Martin W. Vision intelligence and software control for the automation of plant micropropagation. Measurement Science and Technology, 1992; 3(1): 38. doi: 10.1088/0957-0233/3/1/005.

[6] Zhang Y, Tian Z Z, Ma W Q, Zhang M, Yang L L. Hyperspectral detection of walnut protein contents based on improved whale optimized algorithm. Int J Agric & Biol Eng, 2022; 15(6): 235–241.

[7] Chehab E W, Eich E, Braam J. Thigmomorphogenesis: A complex plant response to mechano-stimulation. Journal of Experimental Botany, 2009; 60: 43–56.

[8] Guo C L, Tang Y N, Lu J S, Zhu Y, Cao W X, Cheng T, et al. Predicting wheat productivity: Integrating time series of vegetation indices into crop modeling via sequential assimilation. Agricultural and Forest Meteorology, 2019; 272–273: 69-80.

[9] Zhou M K, Xia J F, Yang F, Zheng K, Hu M J, Li D, et al. Design and experiment of visual navigated UGV for orchard based on Hough matrix and RANSAC. Int J Agric & Biol Eng, 2021; 14(6): 176–184.

[10] Taghavi Namin S, Esmaeilzadeh M, Najafi M, Brown T B, Borevitz J O. Deep phenotyping: Deep learning for temporal phenotype/genotype classification. Plant Methods, 2018; 14(1): 66. doi: 10.1186/s13007-018-0333-4.

[11] Yang C. Plant leaf recognition by integrating shape and texture features. Pattern Recognition, 2021; 112: 107809. doi: 10.1016/j.patcog.2020.107809.

[12] Liu W, Zou S S, Xu X L, Gu Q Y, He W Z, Huang J, et al. Development of UAV-based shot seeding device for rice planting. Int J Agric & Biol Eng, 2022; 15(6): 1–7.

[13] Forrest K L, Bhave M. Major intrinsic proteins (MIPs) in plants: a complex gene family with major impacts on plant phenotype. Funct Integr Genomics, 2007; 7(4): 263–289.

[14] Wang Y J, Mao Q Y, Zhu H Q, Zhang Y, Ji J M, Zhang Y Y. Multi-modal 3D object detection in autonomous driving: a survey. arXiv, 2021; 2106: 12735. doi: 10.48550/arXiv.2106.12735.

[15] Jin X L, Li Z H, Atzberger C. Estimation of crop phenotyping traits using unmanned ground vehicle and unmanned aerial vehicle imagery. Remote Sensing, 2020; 12(6): 940. doi: 10.3390/rs12060940.

[16] Schauer N, Semel Y, Roessner U, Gur A, Balbo I, Carrari F, et al. Comprehensive metabolic profiling and phenotyping of interspecific introgression lines for tomato improvement. Nature biotechnology, 2006; 24: 447–454.

[17] Lu Y, Chen X Y, Wu Z X, Yu J Z, Wen L. A novel robotic visual perception framework for underwater operation. Frontiers of Information Technology & Electronic Engineering, 2022; 23: 1602–1619.

[18] Puliti S, Dash J P, Watt M S, Breidenbach J, Pearse G D. A comparison of UAV laser scanning, photogrammetry and airborne laser scanning for

precision inventory of small-forest properties. Forestry: An International Journal of Forest Research, 2020; 93(1): 150-162.

[19] Yuan H L, Liu Y M, Song M H, Zhu Y, Cao W X, Jiang X P, et al. Design of the mechanical structure of a field-based crop phenotyping platform and tests of the platform. Agronomy, 2022; 12(9): 2162. doi: 10.3390/agronomy12092162.

[20] Roldán J, Garcia-Aunon P, Garzón M, de León J, del Cerro J, Barrientos A. Heterogeneous multi-robot system for mapping environmental variables of greenhouses. Sensors, 2016; 16(7): 1018. doi: 10.3390/s16071018.

[21] Huang M F, Xu G Q, Li J Y, Huang J P. A method for segmenting disease lesions of maize leaves in real time using attention YOLACT++. Agriculture, 2021; 11(12): 1216. doi: 10.3390/agriculture11121216.

[22] Chen G, Muriki H, Pradalier C, Chen Y S, Dellaert F. A hybrid cabledriven robot for non-destructive leafy plant monitoring and mass estimation using structure from motion. arXiv, 2022; 2209: 08690. doi: 10.48550/arXiv.2209.08690.

[23] Jiang Z, Guo Y, Jiang K, Hu M, Zhu Z. Optimization of intelligent plant cultivation robot system in object detection. IEEE Sensors Journal, 2021; 21: 19279–19288.

[24] Xie Z J, Gu S, Chu Q, Li B, Fan K J, Yang Y L, et al. Development of a high-productivity grafting robot for *Solanaceae*. Int J Agric & Biol Eng, 2020; 13(1): 82–90.

[25] Young S N, Kayacan E, Peschel J M. Design and field evaluation of a ground robot for high-throughput phenotyping of energy sorghum. Precision Agric, 2019; 20(4): 697–722.

[26] Atefi A, Ge Y, Pitla S, Schnable J. Robotic technologies for high-throughput plant phenotyping: Contemporary reviews and future perspectives. Front Plant Sci, 2021; 12: 611940. doi: 10.3389/FPLS.2021.611940.

[27] Paraforos D S, Reutemann M, Sharipov G, Werner R, Griepentrog H W. Total station data assessment using an industrial robotic arm for dynamic 3D in-field positioning with sub-centimetre accuracy. Computers and Electronics in Agriculture, 2017; 136: 166–175.

[28] Potena C, Nardi D, Pretto A. Fast and accurate crop and weed identification with summarized train sets for precision agriculture. Intelligent Autonomous Systems, 2017; 531(14): 105–121.

[29] Virlet N, Sabermanesh K, Sadeghi-Tehran P, Hawkesford M J. Field Scanalyzer: An automated robotic field phenotyping platform for detailed crop monitoring. Functional Plant Biol, 2017; 44(1): 143. doi: 10.1071/FP16163.

[30] Weyler J, Milioto A, Falck T, Behley J, Stachniss C. Joint plant instance detection and leaf count estimation for in-field plant phenotyping. IEEE Robot Autom Lett, 2021; 6(2): 3599–3606.

[31] Andrade-Sanchez P, Gore M A, Heun J T, Thorp K R, Carmo-Silva A E, French A N, et al. Development and evaluation of a field-based high-throughput phenotyping platform. Functional Plant Biol, 2014; 41(1): 68. doi: 10.1071/FP13126.

[32] Sivakumar A, Modi S, Gasparino M, Ellis C, Baquero Velasquez A, Chowdhary G, et al. Learned visual navigation for under-canopy agricultural robots. Robotics: Science and Systems XVII, 2021. doi: 10.15607/RSS.2021.XVII.019.

[33] Derby S J, McFadden J. Treadbot multi-head robot for high throughput applications. ASME International Mechanical Engineering Congress and Exposition, 2009; 43(772): 157–164.

[34] Xiao D Y, Gong L, Liu C L, Huang Y X. Phenotypebased robotic screening platform for leafy plant breeding. IFACPapersOnLine, 2016; 49(16): 237–241.

[35] Sabzi S, Abbaspour-Gilandeh Y, García-Mateos G, RuizCanales A, Molina-Martínez A M, Arribas J I. An automatic nondestructive method for the classification of the ripeness stage of red delicious apples in orchards using aerial video. Agronomy, 2019; 9(2): 84. doi: 10.3390/agronomy9020084.

[36] Bao Y, Tang L, Srinivasan S, Schnable P S. Field-based architectural traits characterisation of maize plant using time-of-flight 3D imaging. Biosystems Engineering, 2019; 178: 86–101.

[37] Wang Y T, Li M Z, Ji R H, Wang M J, Zhang Y, Zheng L H. Novel encoder for ambient data compression applied to microcontrollers in agricultural robots. Int J Agric & Biol Eng, 2022; 15(4): 197–204.

[38] Ma Z, Wang Y, Zhang T S, Wang H G, Jia Y J, Gao R, et al. Maize leaf disease identification using deep transfer convolutional neural networks. Int J Agric & Biol Eng, 2022; 15(5): 187–195.

[39] Fan J C, Zhang Y, Wen W L, Gu S H, Lu X J, Guo X Y. The future of Internet of Things in agriculture: Plant high-throughput phenotypic platform. Journal of Cleaner Production, 2021; 280: 123651. doi: 10.1016/j.jclepro.2020.123651.

[40] Magistri F, Marks E, Nagulavancha S, Vizzo I, Läebe T, Behley J, et al. Contrastive 3D shape completion and reconstruction for agricultural robots using RGB-D frames. IEEE Robotics and Automation Letters, 2022; 7: 10120–10127.

[41] Kahraman S, Bacher R. A comprehensive review of hyperspectral data fusion with lidar and sar data. Annual Reviews in Control, 2021; 51: 236–253.

[42] Shu M Y, Shen M Y, Zuo J Y, Yin P F, Wang M, Xie Z W, et al. The application of UAV-based hyperspectral imaging to estimate crop traits in maize inbred lines. Plant Phenomics, 2021; 2021: 9890745. doi: 10.34133/2021/9890745.

[43] Zaman-Allah M, Vergara O, Araus J L, Tarekegne A, Magorokosho C, Zarco-Tejada P J, et al. Unmanned aerial platform-based multi-spectral imaging for field phenotyping of maize. Plant Methods, 2015; 11: 35. doi: 10.1186/s13007-015-0078-2.

[44] Christiansen M, Laursen M, Jørgensen R, Skovsen S, Gislum R. Designing and Testing a UAV Mapping System for Agricultural Field Surveying. Sensors, 2017; 17(12): 2703. doi: 10.1186/s13007-015-0078-2.

[45] Zermas D, Morellas D, Mulla D, Papanikolopoulos N. 3D model processing for high throughput phenotype extraction–the case of corn. Computers and Electronics in Agriculture, 2020; 172: 105047. doi:10.1016/j.compag.2019.105047.

[46] Xiang L, Nolan T M, Bao Y, Elmore M, Tuel T, Gai J, et al. Robotic Assay for Drought (RoAD): An automated phenotyping system for brassinosteroid and drought responses. Plant J, 2021; 107(6): 1837–1853.

[47] Yao L, van de Zedde R, Kowalchuk G. Recent developments and potential of robotics in plant eco-phenotyping. Jez JM, Topp CN, eds. Emerging Topics in Life Sciences, 2021; 5(2): 289–300.

[48] Vit A, Shani G. Comparing RGB-D sensors for close range outdoor agricultural phenotyping. Sensors, 2018; 18(12): 4413. doi: 10.3390/s18124413.

[49] Buzzy M, Thesma V, Davoodi M, Mohammadpour Velni J. Real-time plant leaf counting using deep object detection networks. Sensors, 2020; 20(23): 6896. doi: 10.3390/s20236896.

[50] Rincón M G, Mendez D, Colorado J D. Four-dimensional plant phenotyping model integrating low-density LiDAR data and multispectral images. Remote Sensing, 2022; 14(2): 356. doi: 10.3390/rs14020356.

[51] Tian Y, Xie L, Wu M, Yang B, Ishimwe C, Ye D, et al. Multicolor fluorescence imaging for the early detection of salt stress in arabidopsis. Agronomy, 2021; 11(12): 2577. doi: 10.3390/agronomy11122577.

[52] Zhang L, Maki H, Ma D, Sánchez-Gallego J A, Mickelbart M V, Wang L, et al. Optimized angles of the swing hyperspectral imaging system for single corn plant. Computers and Electronics in Agriculture, 2019; 156: 349–359.

[53] Sampaio G S, Silva LA, Marengoni M. 3D reconstruction of non-rigid plants and sensor data fusion for agriculture phenotyping. Sensors, 2021; 21(12): 4115. doi: 10.3390/s21124115.

[54] Zhang C, Gao H, Zhou J, Cousins A, Pumphrey M O, Sankaran S. 3D robotic system development for high-throughput crop phenotyping. IFAC-PapersOnLine, 2016; 49(16): 242–247.

[55] Wang J S, Tao B, Gong Z Y, Yu W F, Yin Z P. A mobile robotic 3-D measurement method based on point clouds alignment for large-scale complex surfaces. IEEE Transactions on Instrumentation and Measurement, 2021; 70: 1–11.

[56] Ninomiya S. High-throughput field crop phenotyping: current status and challenges. Breed Sci, 2022; 72(1): 3–18.

[57] Luo B H, Yang J, Song S L, Shi S, Gong W, Wang A, et al. Target classification of similar spatial characteristics in complex urban areas by using multispectral LiDAR. Remote Sensing, 2022; 14(1): 238. doi: 10.3390/rs14010238.

[58] Jiang Y, Li C Y, Paterson A H, Sun S P, Xu R, Robertson J. Quantitative analysis of cotton canopy size in field conditions using a consumer-grade RGB-D camera. Front Plant Sci, 2018; 8: 2233. doi: 1.3389/fpls.2017.02233.

[59] Gonzalez F, Castro M P G, Narayan P, Walker R, Zeller L. Development of an autonomous unmanned aerial system to collect time-stamped samples from the atmosphere and localize potential pathogen sources. J Field Robotics, 2011; 28(6): 961–976.

[60] Bailey B N, Stoll R, Pardyjak E R, Miller N E. A new three-dimensional energy balance model for complex plant canopy geometries: Model

development and improved validation strategies. Agricultural and Forest Meteorology, 2016; 218–219: 146-160.

[61] Araus J L, Cairns J E. Field high-throughput phenotyping: The new crop breeding frontier. Trends in Plant Science, 2014; 19(1): 52–61.

[62] Chapman S C, Merz T, Chan A, Jackway P, Hrabar S, Dreccer M F, et al. Phenocopter: A low-altitude, autonomous remote-sensing robotic helicopter for high-throughput field-based phenotyping. Agronomy, 2014; 4: 279–301.

[63] Vázquez-Arellano M, Reiser D, Paraforos D, Garrido-Izard M, Griepentrog H. Leaf area estimation of reconstructed maize plants using a time-of-flight camera based on different scan directions. Robotics, 2018; 7(4): 63. doi: 10.3390/robotics7040063.

[64] Guan H O, Liu M, Ma X D, Yu S. Three-dimensional reconstruction of soybean canopies using multisource imaging for phenotyping analysis. Remote Sensing, 2018; 10(8): 1206. doi: 10.3390/rs10081206.

[65] Shi W N, van de Zedde R, Jiang H Y, Kootstra G. Plant-part segmentation using deep learning and multi-view vision. Biosystems Engineering, 2019; 187: 81–95.

[66] Erdle K, Mistele B, Schmidhalter U. Comparison of active and passive spectral sensors in discriminating biomass parameters and nitrogen status in wheat cultivars. Field Crops Research, 2011; 124(1): 74–84.

[67] Boogaard F P, Rongen K S A H, Kootstra G W. Robust node detection and tracking in fruit-vegetable crops using deep learning and multi-view imaging. Biosystems Engineering, 2020; 192: 117–132.

[68] Colaço A F, Molin J P, Rosell-Polo J R, Escolà A. Application of light detection and ranging and ultrasonic sensors to high-throughput phenotyping and precision horticulture: current status and challenges. Hortic Res, 2018; 5(1): 480–490.

[69] Duckett T, Pearson S, Blackmore S, Grieve B, Chen W H, Cielniak G, et al. Agricultural robotics: the future of robotic agriculture. ArXiv, 2018; 1806: 06762. doi: 10.48550/arXiv.1806.06762.

[70] Wang B, Gao Y, Sun C, Blumenstein M, La Salle J. Can walking and measuring along chord bunches better describe leaf shapes? 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017; pp.2047–2056.

[71] Oishi Y, Habaragamuwa H, Zhang Y, Sugiura R, Asano K, Akai K, et al. Automated abnormal potato plant detection system using deep learning models and portable video cameras. International Journal of Applied Earth Observation and Geoinformation, 2021; 104: 102509. doi: 10.1016/j.jag.2021.102509.

[72] Kutnjak D, Tamisier L, Adams I, Boonham N, Candresse T, Chiumenti M, et al. A primer on the analysis of high-throughput sequencing data for detection of plant. Microorganisms, 2021; 9(4): 841. doi: 10.3390/microorganisms9040841.

[73] Barnett J, Duke M, Au C K, Lim S H. Work distribution of multiple Cartesian robot arms for kiwifruit harvesting. Computers and Electronics in Agriculture, 2020; 169: 105202. doi: 10.1016/j.compag.2019.105202.

[74] Huang J X, Gómez-Dans J L, Huang H, Ma H Y, Wu Q L, Lewis P E, et al. Assimilation of remote sensing into crop growth models: Current status and perspectives. Agricultural and Forest Meteorology, 2019; 276–277: 107609. doi: 10.1016/j.agrformet.2019.06.008.

[75] Sun G X, Li Y B, Wang X C, Hu G Y, Wang X, Zhang Y. Image segmentation algorithm for greenhouse cucumber canopy under various natural lighting conditions. Int J Agric & Biol Eng, 2016; 9(3): 130–138.

[76] Xiang L R, Bao Y, Tang L, Ortiz D, Salas-Fernandez M G. Automated morphological traits extraction for sorghum plants via 3D point cloud data analysis. Computers and Electronics in Agriculture, 2019; 162: 951–961.

[77] Atefi A, Ge Y F, Pitla S, Schnable J. In vivo human-like robotic phenotyping of leaf traits in maize and sorghum in greenhouse. Computers and Electronics in Agriculture, 2019; 163: 104854. doi: 10.1016/j.compag.2019.104854.

[78] He K M, Zhang X Y, Ren S Q, Sun J. Deep residual learning for image recognition. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas: IEEE, 2016; pp.770–778. doi: 10.1109/CVPR.2016.90.

[79] Dyrmann M, Christiansen P, Midtiby H S. Estimation of plant species by classifying plants and leaves in combination J Field Robotics, 2018; 35(2): 202–212.

[80] Jing Z W, Guan H Y, Zhao P R, Li D L, Yu Y T, Zang Y F, et al. Multispectral LiDAR point cloud classification using SE-PointNet++. Remote Sensing, 2021; 13(13): 2516. doi: 10.3390/rs13132516.

[81] Das S, Christopher J, Apan A, Roy Choudhury M, Chapman S, Menzies N W, et al. UAV-thermal imaging and agglomerative hierarchical clustering techniques to evaluate and rank physiological performance of wheat genotypes on sodic soil ISPRS Journal of Photogrammetry and Remote Sensing, 2021; 173: 221–237.

[82] Elnashef B, Filin S, Lati R N. Tensor-based classification and segmentation of three-dimensional point clouds for organ-level plant phenotyping and growth analysis Computers and Electronics in Agriculture, 2019; 156: 51–61.

[83] Cao X F, Yu K Q, Zhao Y R, Zhao H H. Current status of high-throughput plant phenotyping for abiotic stress by imaging spectroscopy: A review. Spectroscopy and Spectral Analysis, 2020; 40(11): 3365–3372. (in Chinese)

[84] Jin Y C, Liu J Z, Xu Z J, Yuan S Q, Li P P, Wang J Z. Development status and trend of agricultural robot technology. Int J Agric & Biol Eng, 2021; 14(4): 1–19.

[85] Peña J M, Torres-Sánchez J, de Castro A I, Kelly M, López-Granados F. Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (UAV) images. Suarez O D, ed. PLoS One, 2013; 8(10): e77151. doi: 10.1371/journal.pone.0077151.

[86] McCool C, Perez T, Upcroft B. Mixtures of Lightweight Deep Convolutional Neural Networks: Applied to agricultural robotics. IEEE Robot Autom Lett, 2017; 2(3): 1344–1351.

[87] Aich S, Josuttes A, Ovsyannikov I, Strueby K, Ahmed I, Duddu H S, et al. DeepWheat: Estimating phenotypic traits from crop images with deep learning. In: 2018 IEEE Winter Conference on Applications of Computer Vision (WACV), Lake Tohoe: IEEE, 2018; pp.323–332. doi: 10.1109/WACV.2018.00042.

[88] Yin X, Li W H, Li Z, Yi L L. Recognition of grape leaf diseases using MobileNetV3 and deep transfer learning. Int J Agric & Biol Eng, 2022; 15(3): 184–194.

[89] Ho Tong Minh D, Ienco D, Gaetano R, Lalande N, Ndikumana E, Osman F, et al. Deep recurrent neural networks for winter vegetation quality mapping via multitemporal SAR Sentinel-1. IEEE Geosci Remote Sensing Lett, 2018; 15(3): 464–468.

[90] Li K, Wang S, Zhang X, Xu Y, Xu W, Tu Z. Pose recognition with cascade transformers. arXiv: 2021; 2104: 06976. doi: 2021. 10.48550/arXiv.2104.06976

[91] Hairmansis A, Berger B, Tester M, Roy S J. Image-based phenotyping for non-destructive screening of different salinity tolerance traits in rice. Rice, 2014; 7(1): 16. doi: 10.1186/s12284-014-0016-3.

[92] Li Y T, He L Y, Jia J M, Chen J N, Lyu J, Wu C Y. High-efficiency tea shoot detection method via a compressed deep learning model. Int J Agric & Biol Eng, 2022; 15(3): 159–166.

[93] Simon M, Frédéric B, Benoit de S, Scott T, Dan D, Stéphane J, et al. High-throughput phenotyping of plant height: comparing unmanned aerial vehicles and ground LiDAR estimates. Frontiers in Plant Science, 2017; 8: 02002. doi: 10.3389/fpls.2017.02002.

[94] Hosoi F, Nakabayashi K, Omasa K. 3-D modeling of tomato canopies using a high-resolution portable scanning Lidar for extracting structural information. Sensors, 2011; 11(2): 2166–2174.

[95] Zhou S Z, Kang F, Li W B, Kan J M, Zheng Y J. Point cloud registration for agriculture and forestry crops based on calibration balls using Kinect V2. Int J Agric & Biol Eng, 2020; 13(1): 198–205.

[96] Mueller-Sim T, Jenkins M, Abel J, Kantor G. The Robotanist: A ground-based agricultural robot for high-throughput crop phenotyping 2017 IEEE International Conference on Robotics and Automation (ICRA), 2017; pp.3634–3639.

[97] Ma L, Li M, Tong L, Wang Y, Cheng L. Using unmanned aerial vehicle for remote sensing application. In: 21st International Conference on Geoinformatics, 2013; pp.1–5.

[98] Zhang C H, Kovacs J M. The application of small unmanned aerial systems for precision agriculture: A review. Precision Agric, 2012; 13(6): 693–712.

[99] Prashar A, Jones H. Infra-red thermography as a high-throughput tool for field phenotyping. Agronomy, 2014; 4(3): 397-417.

[100] Vidal V, Honório L, Pinto M, Dantas M, Aguiar M, Capretz M. An edge-fog architecture for distributed 3D reconstruction and remote monitoring of a power plant site in the context of 5G. Sensors, 2022; 22(12): 4494. doi: 10.3390/s22124494.

[101] Shamshiri R R, Weltzien C, Hameed I A, Yule I J, Grift T E, Balasundram S K, et al. Research and development in agricultural robotics: A perspective of digital farming. Int J Agric & Biol Eng, 2018; 11(4): 1–14.

[102] Lu W, Zeng M J, Qin H H. Intelligent navigation algorithm of plant phenotype detection robot based on dynamic credibility evaluation. Int J Agric & Biol Eng, 2021; 14(6): 195–206.