

Field robots for plant phenotyping

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Advances in plant phenotyping for more sustainable crop production

Edited by Professor Achim Walter, ETH Zurich, Switzerland

E-CHAPTER FROM THIS BOOK





Field robots for plant phenotyping

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- 1 Introduction
- 2 Specific challenges associated with field robots
- 3 Currently available field robots for phenotyping
- 4 Sensors and technologies for phenotyping field robots
- 5 Robotic arms for fruit phenotyping and harvesting
- 6 Conclusion and future trends
- 7 Where to look for further information
- 8 References

1 Introduction

Plant phenotypes are collections of information concerning the composition, responses, performance and growth of plants based on the monitoring of their physical appearance or characteristics (e.g. height, leaf inclination, colour, yield) (Furbank and Tester, 2011; Gjuvsland et al., 2013; Freimer and Sabatti, 2003; Houle et al., 2010). Phenotyping is an essential manifestation of the synergy between genotyping and the environment. Whereas genotyping concerns the final appearance of plant growth and development, the results of phenotyping can differ according to several environmental factors. The main factors that interfere with the process and results of plant growth are transcriptome, proteome and metabolome, as well as the induction of mutations in specific genes within the plant genome (Pieruschka and Poorter, 2012). As a result, plants of the same genotype can exhibit varying phenotypic features in different environments. The analysis of phenotypes can provide valuable information for the functional analysis of genomes and molecular breeding, thus helping to enhance yields with plants that are resistant to drought, salinization, disease and other consequences of climate change (Tester and Langridge, 2010; Yang et al., 2013; Pan, 2015; Araus et al., 2018).

The traditional estimation method for phenotyping relies primarily on human observation, manual measurement or destructive sampling tests (Pask et al., 2012; Maiti et al., 2004; Qiu et al., 2018). In addition to being time-consuming and labour-intensive, such processes produce test results with low

accuracy. As phenotyping in plant breeding has advanced, a large number of scientific research institutions and organizations have been investing in research on the acquisition of phenotypic information. Sensor technologies have been advancing at the same time. The field now has access to a variety of sensors, including ground spectrometers and colour, thermal, multispectral and hyperspectral imaging devices, in addition to light detection and ranging (LiDAR), amongst other possibilities (Zhang et al., 2019; Chéné et al., 2012; Andújar et al., 2015; Stovall et al., 2017; Sakamoto et al., 2012; Falco et al., 2015; Stoll et al., 2008). Research investments in these devices have brought about a qualitative leap in the development of phenotyping monitoring while also driving the construction of sensor-carrying platforms - within the context of this chapter, 'field robots'. Phenotyping field robots are autonomous, self-driving devices that are equipped with a range of sensors that are able to reach each spot on the field and carry higher payloads than are possible with unmanned aerial vehicles (UAVs). Testing methods that rely on manual, handheld sensors obstruct the ability to meet the demand for high-throughput information in phenomics research. New directions within this field include multi-sensor deployment, continuity, synchronicity and high throughput. Developments have also included the introduction of field robots, the Internet of Things (IoT), large vehicle platforms and remote-sensing platforms (e.g. UAVs and satellites) (Shakoor et al., 2017; Hunt et al., 2005; Thomason et al., 2011; Henry et al., 2002; Mirik et al., 2011). A conceptual depiction of the integrated system created by the Netherlands Plant Eco-phenotyping Centre (NPEC) is presented in Fig. 1.

Methods of phenotype monitoring have been enriched by the application of the IoT. This technology uses a variety of sensors with different functions to process phenotypic data and to achieve mutual communication between sensors based on the technology of wireless sensor networks (WSN). Finally, plant-phenotyping parameters are obtained by applying the inversion model between sensor data and plant phenotypes (Fan et al., 2021). The common application of open-field IoT consists largely of deploying fixed monitoring nodes. For example, Liu et al. propose intelligent sensing nodes for farmlands and the associated field-deployment method, which is capable of efficiently sensing various parameters, including the leaf area index (LAI) of rice and wheat crops (Liu et al., 2015). In addition, Bauer et al. (2019) designed low-cost sensors based on the technology of WSN and interconnected them with in situ agricultural sensor networks in order to estimate crop LAI (Bauer et al., 2019). Furthermore, Avotins et al. (2020) used IoT technology to design a camera for recording the single-image normalized difference vegetation index (SI-NDVI). The device can be used to continuously obtain NDVI data on greenhouse tomatoes and diagnose tomato quality according to diurnal variations in NDVI (Kviesis et al., 2020). Another new hotspot of agricultural research involving IoT technology has to do with the combination of fixed nodes with UAVs and

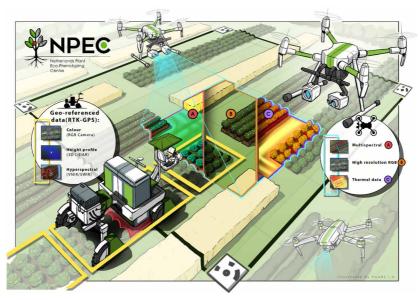


Figure 1 Artist's impression of a field robot and several drones collecting phenotypic information in a field. Courtesy: Netherlands Plant Eco- phenotyping Centre (NPEC) (2021).

unmanned ground vehicles (UGVs). In this regard, Gao et al. (2020) designed a cooperation scheme between UAV and fixed IoT sensor nodes in the field, in which the IoT nodes are used to obtain meteorological parameters. The UAV serves as an image-acquisition node in order to obtain hyperspectral crop images for the diagnosis of pests (Gao et al., 2020). With regard to the methods of data collection, Uddin et al. (2018) propose a UAV dynamic method that can efficiently and intelligently select fixed IoT field nodes for collecting data through mobile UAV nodes. The method could potentially reduce the energy consumption of fixed IoT nodes and extend their service life (Uddin et al., 2018). As demonstrated by these studies, the application of agricultural IoT technology can facilitate the acquisition of phenotypic information on plants. In the open-field environment, however, sensors and mechanical devices are exposed to harsh weather conditions, thereby decreasing the lifetime of any IoT instrument and requiring frequent maintenance. Although fixed nodes can be used to cover a large area at the same time, their use in full-range testing is severely limited, as fixed nodes cannot move by themselves.

A research team at the American University of Rome in Italy started investigating variable-rate fertilizer applicators and their supporting technologies based on optical-sensing information in 1993. This research led to the 2002 development of the real-time variable fertilizer applicator known as 'GreenSeeker', which uses spectral reflectance to monitor crop-growth

information and calculate nutritional status in crops (Lukina et al., 2001). This system was followed by the vehicle-mounted crop growth sensor Yara N-Sensor, which was first tested in 1998 and mounted on agricultural tractors in 2002 (Link et al., 2003). Since then, digital sensors have increasingly been used for open-field vehicle platforms. This study traces the early development of the tractor as a vehicle platform in the process of acquiring high-throughput data. In the actual testing process, however, it is easy to cause irreversible damage to fields and field crops due to the large weight, low chassis and lack of a field-control robot model. It is thus not conducive to sustainable development.

Aerial remote-sensing platforms allow the rapid, real-time acquisition of large-area crop-phenotypic information. One common type, the UAV, offers the advantages of high efficiency, flexibility, convenient operation and strong terrain applicability. Combined with its lower cost and greater accessibility, the recent increase in the popularity of UAVs has led to the widespread use of this technology for plant phenotyping (Sagan et al., 2019). A large body of research results has been accumulated with regard to the use of UAVs to acquire information on the phenotypic characteristics of plants (Xie and Yang, 2020). The characteristic phenotypic parameters that can be obtained using UAVs include LAI, nutritional parameter status, biotic and abiotic threats (Su et al., 2019; Buchaillot et al., 2019; Chivasa et al., 2020). As the demand for agricultural monitoring has increased, a variety of satellite sensors have been introduced to the market. New monitoring methods have emerged (e.g. fluorescence, multispectral and hyperspectral measurements). The classification of plants and the measurement of their phenotypic information can be achieved effectively through the analysis of medium-resolution or high-resolution satellite images. Commonly used satellite series include the Sentinel-1/2 satellites, the WorldView satellite and the Landsat satellite. More specific applications of satellite images are referenced in an overview published by Zhang et al. (2020). Although high-altitude satellite images cover the most comprehensive range, they are subject to three important disadvantages: some of these images are expensive; some have only low resolution and, in many cases, the image quality is diminished by clouds, thereby requiring extensive optical correction.

Lightweight field robots offer a number of advantages over large tractors or UAVs: flexible operation, minimal impact on soil and crops, durability and the ability to accommodate larger payloads (Michaels et al., 2015a,b). It is more difficult for field robots to obtain phenotypic data on large-scale plant groups simultaneously than it is for drones and satellites. They are nevertheless capable of providing all-around, multi-angle and automatic monitoring of the mounted sensors, which makes them highly suitable for integrating state-of-the-art AI technologies (Grigorescu et al., 2020; Zhou et al., 2018). Based on the advantages of field robots in phenotyping monitoring, more mature platforms have been introduced on the market, and several have performed well in

field experiments. It is important to note, however, that different countries and regions have different plant species and varieties. Most existing field robots focus only on specific plant species with similar growth characteristics, and none of the existing phenotypic robots is capable of the comprehensive general monitoring of multiple plant species.

2 Specific challenges associated with field robots

Based on their operating environments, phenotyping field robots can be roughly classified suitable for use indoors (controlled environment) or in the field (uncontrolled environment) (Kirchgessner et al., 2016; Pieruschka and Schurr, 2019). Research on indoor robots pre-dates that on field robots. In 2003, Belgian CropDesign pioneered the development of a high-throughput phenotyping monitoring platform known as TraitMill (Reuzeau et al., 2006), which uses a plant-to-sensor working mode and which can automatically obtain phenotypic information on potted plants in a greenhouse. Since that time, scientific research institutions in Germany, Australia, the Czech Republic and other countries have also successfully launched numerous platforms for acquiring phenotypic information indoors (Deery et al., 2014; Yang et al., 2013). Several of these platforms are displayed in Fig. 2.

Most of the indoor high-throughput phenotyping platforms and automated robot facilities mentioned above focus on monitoring changes in above-ground plant characteristics. To observe below-ground characteristics, researchers have explored innovative monitoring solutions for soil and plant roots involving rhizotrons and Ecotrons. Rhizotrons are amongst the earliest non-destructive below-ground sensing platforms. Due to limitations in sensor technology, early rhizotron facilities relied on human inspection through cellars or underground corridors with transparent glass windows. By entering such facilities, researchers



Figure 2 Indoor phenotyping platforms. (a) WIWAM xy is a robot for the high-throughput and reproducible phenotyping of seedlings and small plants (e.g. Arabidopsis). (b) Conveyor Scanalyzer is an automated high-throughput platform for indoor environments (e.g. glasshouses, growth rooms, climate chambers). (c) TraitFinder is a powerful tool that automates plant phenotyping and screening applications.

could directly observe root phenotyping and soil condition (Klepper and Kaspar, 1994). Despite their advantages, massive underground observation facilities are expensive, are troublesome to maintain and have major destructive effects on the soil structure. The rapid advancement of sensor technology and the continuous improvement of automated robotics technology have allowed the continuing development of small, highly accurate observation devices. The research and development of Ecotrons have at least partially facilitated the study of the relationship between above-ground phenotyping, belowground phenotyping and environmental characteristics. The device's more intelligent control is able to monitor soil status, plant-root phenotyping and the above-ground phenotypic characteristics of plants, while simulating different natural environmental conditions in order to control changes in ecological environmental factors to induce different stress conditions in plants (Granjou and Walker, 2016; Roy et al., 2021). Indoor platforms for plant phenotyping monitoring offer high accuracy and reliable repeatability, and they are not easily disturbed by the external environment. These approaches to monitoring below-ground aspects have nevertheless been criticized as deviating from the actual growth environment, such that the phenotypic information extracted with these systems is negatively affected by the artificial growth conditions to which plants are exposed (Jiang et al., 2018).

Phenotyping open-field robots are subject to even more challenges than is the case for other robots. First, farmland environments are challenging and complex, often with relatively harsh terrain characterized by stones and uneven surfaces. In addition, the spacing of plants is often too narrow for robots to move between rows. Because of these conditions, robots must be able to respond guickly to differences in terrain and ensure highly accurate autonavigation. Second, the growth of plants is directly affected by the environment and growth period, and plant morphology changes accordingly. Moreover, due to the diversity of sensing principles applied in phenotyping, the sensors used for phenotyping require a variety of monitoring heights and angles. The acquisition of phenotypic information by field robots should be able to adapt to sensor-monitoring requirements and changes in plant morphology. Finally, field-planting areas are larger than those of greenhouses. Mobile robots are often expected to work in teams or to work in conjunction with other tools (e.g. IoT devices and drones), in order to achieve high-efficiency monitoring. Fieldwork also places higher demands with regard to safety and the communication between various devices.

3 Currently available field robots for phenotyping

The development of field-phenotyping robots begins with the transformation of agricultural machinery. Phenotypic information is obtained by mounting

sensors on tractors or sprinklers, as is the case with applications of the GreenSeeker airborne sensor developed by the NT Company (Wójtowicz et al., 2016) and the Yara N-sensor from the Agri Con GmbH Company (Link et al., 2003). Although the load capacity of these agricultural machinery platforms is sufficient to meet the needs of high-throughput testing, they are highly likely to cause damage to plants and soil during operation, and it is difficult to perform all-around and multi-view testing for different sensors. With the development of automation technology and robot technology, agricultural machinery platforms have been gradually replaced by more field-specific robots.

3.1 The design of the current field robots

After a period of development, the design of field robots has become more diverse. Depending on chassis and operating modes, they can be roughly divided into the categories of track, crawler, foot and wheeled robots, as shown in Fig. 3.

Track robots often use the gantry structure constructed with two supports and a connecting beam in the middle. The sensors are fixed on the beam with the vision field perpendicular to the crop canopy. Rails or tracks on both sides of the field plots enable the gantry to move repeatedly along a fixed trajectory. Sensors can move along the beam to obtain phenotypic data. Another type of track robot is the rope camera, which often uses hanging ropes and electric hinges to drive sensors along the plant canopy (Kirchgessner et al., 2016; Bai et al., 2019). The PhenoField gantry robot (co-designed by Robepec and Meca3d and located in France) can test the abiotic stress of wheat (Beauchêne

Robot types	Robots	Advantages	Disadvantages
Track robots		Strong load capacity High repeatability Extremely convenient control	Requires long-term maintenance Low moving flexibility High investment Relatively small monitoring area Complex structure
Crawler robots		Strong ability to cross obstacles Powerful terrain adaptability High moving stability	Slow speed and low efficiency Loud/noisy Majordamage to crops
Legged robots		Good manoeuvrability Small ground-touch area Low damage to crops	Complex control method Poor moving stability Slow speed and low efficiency
Wheeled robots	To the	Easy to control High mobility High working efficiency Conducive to sensor deployment	Poor ability to cross obstacles Easy to slip on muddy ground

Figure 3 Field robots with different structural designs (Beauchêne et al., 2019; Virlet et al., 2016; Susko et al., 2018; Basu et al., 2020; Young et al., 2019; Zhang et al., 2013; Dorhout, 2021; Shafiekhani et al., 2017; De Solan et al., 2015).

et al., 2019). In 2016, the University of Arizona's Maricopa Agricultural Center built the world's largest gantry robot, the Field Scanalyzer, which has 200-metre steel rails and can acquire phenotypic information on energy sorghum across an areas of more than 1.5 acres (Virlet et al., 2016). The structure of the FieldScan robot (manufactured by Phenospex) is similar to that of other track robots (Vadez et al., 2015). In general, the width and height of track robots depends on the size of the plots on which they are used. One important advantage of these devices is that they are able to carry large numbers of sensors for continuously monitoring a specific area, with reliable repeatability. Given that the platform is exposed to the natural environment for a long time, however, it requires frequent maintenance. Moreover, the track structure does not provide sufficient flexibility, and the monitoring area is relatively small.

Crawler robots offer the advantages of strong obstacle-crossing ability and stable operation. They are often used in agriculture for purposes of automatic land preparation prior to sowing and mechanical harvesting (as reported by Zhang et al., 2013; Noguchi and Barawid Jr., 2011; and Takai et al., 2013). Given the shortcomings of the crawler structure's large contact area, low ground clearance and inability to perform cross-row operations, it causes considerable damage to the plants and soil during movement. Several applications have been developed for the acquisition of phenotypic information. For example, Young et al. (Young et al., 2019; Baharav et al., 2017) developed a small-tracked field robot-the Transportation Energy Resource from Renewable Agriculture Mobile Energy-crop Phenotyping Platform (TERRA-MEPP)-for the purpose of monitoring energy sorghum. This platform is able to run between planting rows, with the sensor perspective extended through sensor support in order to obtain phenotypic information on sorghum. Another small crawler robot was developed by Ibex Automation Ltd. for the purpose of weed identification and precision weeding (Basu et al., 2020). This robot nevertheless causes damage to plants, due to the low ground clearance of its chassis. This problem is difficult to resolve.

Research on legged robots has only recently started, and the related technologies are still under active investigation with regard to sophisticated control, unstable movement and other matters. Dorhout (2021) designed a legged robot—the 'metal crab'—that can explore field conditions using a camera and other sensors mounted and assisted by agricultural equipment in such operations as sowing, fertilizing, planting, dispersing herbicides or picking fruit. Although a report has been published on agricultural auxiliary equipment (Toyama and Yamamoto, 2009), we have not found any successful application for obtaining phenotypic information. In addition to the field of agriculture, research on legged robots has been conducted in industrial settings. The Legged Squad Support System (LS3) introduced by Boston Dynamics in recent years has been used to perform various functions, including moving motion

control, obstacle crossing and navigation. For example, the Spot robot was used in a sheep-herding demonstration in 2020.¹ Due to the combination of more intelligent AI systems, the robot can also cope with various sudden situations, and it performs outstanding teamwork (Raibert et al., 2008). This technology will soon have excellent applications within the context of agriculture and plant phenotyping.

Wheeled robots are the most common amongst the field robots that are currently used for plant phenotyping, due to their simple control and stable operation. Research on wheeled robots is also attracting considerable attention from scientific research institutions and enterprises around the world. Related research has been conducted by Shafiekhani et al. (Shafiekhani et al., 2017), Weiss and Biber (Weiss and Biber, 2011) and Reina (Reina et al., 2018) on wheeled robots with low ground clearance, including the Husky A200 and the Volksbot RT3. These robots have exhibited good performance in the phenotyping of plants with large row spacing (e.g. sorghum, apple, peach). Wheeled robots with ground clearance higher than 0.5 m-such as the Ladybird developed by the University of Sydney (Underwood et al., 2017), the Bonirob co-developed by Bosch (Pretto et al., 2020), and the Robotti by Agrointelli-can operate effectively with dwarf-row plants (e.g. soybeans, lettuce, potatoes). The Proximal sensing cart, a wheeled robot developed by White et al. (Bai et al., 2016; Yuan et al., 2018; White and Conley, 2013), has a high ground clearance, but movement must be assisted by human thrust. This simple robot is actually a modified bicycle, which requires human power to move over fields. It has been used successfully in wheat fields. The structure of the PhenoMobile® Lite designed by the Australian Plant Phenomics Facility is similar to that of the proximal sensing cart. It is also equipped with sensors-including a global positioning system (GPS) and an inertial measurement unit (IMU)-which allow it to perform automatic phenotyping monitoring (De Solan et al., 2015). Wheeled robots with higher ground clearance (>1.2m), including the Phenomobile developed by the Australian Plant Phenomics Facility (Deery et al., 2014) and the Gecko developed by the University of Queensland, can be used for the phenotyping of taller plants. These robots are equipped with height-adjustable supports, with a broad adjustment range that is able to accommodate the different test heights of sensors.

4 Sensors and technologies for phenotyping field robots

Physiological and biochemical changes in plants cause differences in their phenotypic traits, which subsequently result in changes in their absorption, reflection and refraction of certain spectral features (Feng et al., 2008a;

¹ https://blog.rocos.io/rocos-partners-with-boston-dynamics

Thenkabail et al., 2000). Such changes in data on spectral features offer an efficient, non-destructive and accurate means of retrieving phenotypic information. Many scientific research institutions have carried out related research on spectrum-sensing technology and published results with reference significance. For example, information on red-light reflection provides good inversion results for the LAI and chlorophyll (Thenkabail et al., 2000); the near-infrared band (740-1100 nm) provides an effective means of monitoring biomass (Shibayama and Akiyama, 1989, 1991); and the combination of the near-infrared band and the red-edge band can be used to detect nitrogen change (Yao et al., 2019; Zhu et al., 2008).

Based on the aforementioned principles, various non-imaging and imaging sensors have been applied to research on the use of field robots in phenotyping monitoring, as shown in Table 1. These instruments can acquire information that cannot be seen by the naked eye. The most prevalent non-imaging sensors are portable ground spectrometers. Examples include ASD Fieldspec (Feng et al., 2008b; Wang et al., 2012), GreenSeeker (Osborne, 2007), RapidScan (Miller et al., 2018) and SPAD (Uddling et al., 2007). Applications of imaging sensors on plant-phenotyping platforms include visible-light cameras, multispectral cameras, hyperspectral imagers, time-of-flight cameras, fluorescence cameras, thermal-infrared cameras and ground-based LiDAR.

Portable ground spectrometers adopt photoelectric sensing technology and use photosensitive components to convert photoelectric information. For example, electrical signals can be processed in order to calculate the characteristic band spectral vegetation index and then to invert specific phenotyping information. Commonly used vegetation indices include the normalized difference vegetation index (NDVI) (Tucker, 1979), the ratio vegetation index (RVI) (Ni et al., 2017), the soil-adjusted vegetation index (SAVI) (Huete, 1988) and the enhanced vegetation index (EVI) (Liu and Huete, 1995). The retrievable phenotypic parameters include nitrogen nutrition, biomass, chlorophyll content and water content.

Compared to non-imaging instruments, imaging sensors can obtain information on plant image, spectrum or three-dimensional structure with a high volume of visualization information. With regard to the acquisition of phenotypic information, in addition to relying on the vegetation index for inversion, the image sensors can intuitively extract leaf colour, flowering period, plant height, crown coverage, crop water status and other parameters according to the differences between the imaging-sensor perception method and the data-processing methods. The extracted phenotypic information can be combined with AI technologies to perform the rapid identification of plant diseases, biological stress and abiotic stress (Valente et al., 2019). For example, Sakurai et al. (2018) propose a fully convolutional network (FCN) (Long et al., 2015) for semantic plant-image segmentation. Shi et al. (2019) combine deep

 Table 1
 Phenotyping sensors for field robots

Phenotyping sensors (sensing principle)	Sensor type	Data type	Extractable parameters	Phenotyping information
Image sensors (photoelectric imaging sensing)	RGB cameras	RGB images	Vegetation index based on RGB band; Plant height, flowering number, spike classification and target extraction number, nitrogen status, biomass, based on RGB features diseases and stress with RGB colour characteristics	Plant height, flowering number, spike number, nitrogen status, biomass, diseases and stress with RGB colour characteristics
	Multi-spectral cameras	Spectral images of several specific bands	Vegetation index based on specific bands; targeted diseases, biological and abiotic stress features	Emergence rate, flowering rate, nitrogen status, diseases and stress with specific spectral-band features
	Hyperspectral cameras	Spectral images of continuous bands	Spectral data on each pixel of the image; multiple vegetation indices; multiple diseases, biological and abiotic stress features	Chlorophyll content, water content, protein content, nitrogen status, biomass, multiple diseases and stress
	Time of flight cameras	Depth images and RGB images	The distance from each pixel to the camera	Plant height, stem thickness, leaf inclination
	Thermal cameras	Thermal images	The temperature value of each pixel in Crop water status, stomatal the image canopy and I temperature	Crop water status, stomatal conductance, canopy and leaf temperature
	Fluorescence cameras	Fluorescence images	Visible fluorescence images in different spectral bands	Photosynthetic productivity, nitrogen status, biomass, diseases and stress with fluorescence features
	Lidar	3D point clouds images	High-resolution distance information from every point to the device	Plant height, stem thickness, flowering number, spike number, leaf inclination
Non-image sensors (photoelectric conversion sensing)	Ground hyperspectral spectrometers	Spectral data of continuous specific bands	Multiple vegetation indices based on continuous spectral bands	Chlorophyll content, water content, protein content, nitrogen status, biomass
	Ground multi-spectral spectrometers	Spectral data of Vegeta several specific bands bands	Vegetation indices based on specific bands	Nitrogen status, biomass

Source: Li et al. (2014); Perez-Sanz et al. (2017); Fiorani and Schurr (2013).

learning with multi-view images to generate a 3D point-cloud representation of a plant. Mohanty et al. (2016) have trained a deep convolutional neural network (CNN) to identify 14 crop species and 26 diseases. Fuentes et al. (2017) present a deep-learning-based approach for detecting diseases and pests in tomato plants using images captured in place by a camera with various resolutions. Li et al. (2014) report on the acquisition of current images with Al technologies, equipment and applications, and Perez-Sanz et al. (2017) summarize various image-processing methods. New imaging sensors—including X-ray computed tomography (CT), positron emission tomography (PET) and magnetic resonance imaging (MRI) (Jahnke et al., 2009)—that have been applied in other fields are gradually being used in plant phenotyping monitoring. Due to their investment costs and physical limitations, however, these instruments have thus far been used in only a limited number of institutes and only in indoor environments.

In addition to phenotypic information sensors, phenotyping robots need a variety of auxiliary functional sensors to support automatic field operations. They include GPS/real-time kinematic (RTK), IMU, LiDAR, cameras, Hall-effect sensors, ultrasonic sensors and ranging infrared sensors. For row crops, phenotyping robots require high-precision automatic navigation and path planning in order to improve their operational efficiency and avoid damage to the plants during movement. Unlike navigation in an open environment, automatic navigation in a plant-field environment requires the coordination of multiple sensors, including those listed above. While GPS/RTK can provide robots with error position information at the centimetre level, IMU can obtain a robot's three-axis attitude angle and acceleration. In addition, LiDAR and cameras can sense environmental details in real time and then cooperate with GPS/RTK and IMU to achieve simultaneous localization and mapping (SLAM). Derived from autonomous driving technology, SLAM has recently been used in the automatic navigation of agricultural robots. When a field robot starts operating from any location in the field, SLAM can use information from the sensors listed above to observe and locate its position, posture and trajectory during its movement. A SLAM system thus builds an incremental map based on its position to achieve simultaneous positioning, field map construction and automatic navigation (Durrant-Whyte and Bailey, 2006; Montemerlo et al., 2002). Two components that are essential to SLAM are LiDAR and vision technology. Despite its high accuracy, LiDAR (the core method applied during early research on SLAM) is also subject to a number of shortcomings, including high price, large volume and lack of intuitive vision information. As the popularity of consumer-level RGB-D cameras has increased, visionbased SLAM has also been applied successfully in several research fields (e.g. autonomous driving, AR and intelligent robots), with the camera being used as the primary sensor and the video stream serving as the input for achieving simultaneous positioning and construction (Jiang et al., 2017; Miro et al., 2006).

The advantages of this system include the fact that it is inexpensive and able to capture images with high resolution in order to classify objects. Its data depth is nevertheless not as good as that of LiDAR.

It is also possible to use GPS/RTK to add geo-referencing to phenotypic information on plants in order to generate more conducive results in analysis, data classification and mapping (Xiu et al., 2010; Tamaki et al., 2013). The pitch angle and roll angle provided by the IMU can also be used to calibrate the attitude of phenotyping monitoring sensors. Hall-effect sensors can perform the robot's speed test and improve control over the robot, thereby providing precise speed change and steering.

5 Robotic arms for fruit phenotyping and harvesting

Fruit harvesting is the final link between plant cultivation and the most relevant process for yielding economic benefits. Traditional fruit harvesting depends on the manual assessment of the maturity and quality of fruit. Differences in experience with such assessment lead to wide variations in picking results across operators, with a direct impact on fruit sales. The recognition of fruit phenotypic features is an important part of plant phenotyping research. Fruit picking based on the recognition of such features can be combined with eyehand coordination to achieve the full automation of fruit harvesting, thereby improving the accuracy and work efficiency of fruit picking (Hashimoto, 2003). Results of studies on the method of acquiring fruit phenotypic information on plants are consistent with those on the method of recognition for other parts of the plant. Spectral reflectance monitoring, thermal infrared imaging monitoring and the extraction of colour features and textures have also demonstrated good recognition effects for fruit phenotypic features (Bulanon et al., 2002; Arivazhagan et al., 2010; Jiménez et al., 1999). In addition to the basic phenotyping monitoring method, AI techniques can be used to detect the position and shape of the fruit under occlusion. For example, Blok et al. (2021) use Mask R-CNN to detect the position and shape of broccoli heads for autonomous harvesting. Zhao et al. (2016) provide a systematic review of control technology based on visual sensors, as used in harvesting robots, including recognition technology for fruits and control technology for manipulators.

With regard to fruit picking, the earliest mechanized picking method relies primarily on mechanical or pneumatic methods to shake plants. However, because this non-selective picking method does not involve the identification of fruit phenotyping characteristics, it is more harmful to plants and has low work efficiency. As precision and automated fruit-picking methods have become more popular, most fruit-picking robotic arm mechanisms have come to be designed as two parts: a moving mechanism and an end effector. The mobile mechanism is used to adjust the position of the end effector, and the

end effector completes the final picking task. In current industrial production, the design of manipulators has become more mature, with structures including the cylindrical-coordinate type, the rectangular-coordinate type, the sphericalcoordinate type and the joint type (Almurib et al., 2011). When used for openfield robots, manipulators are subject to a number of complex problems, including the random growth of fruit position and occlusion of fruit. For this reason, most of the manipulators that are used for fruit picking are based on the joint type of design. Motion angle is a key factor in the design of a joint manipulator. Although joints with a low degree of freedom (DOF) lack flexibility, an increase in degrees greatly increases the difficulty of control. Kondo et al. (1996a,b) designed a 7-DOF articulated manipulator that can be used for tomato harvesting. The end effector of the manipulator is designed with Type B suction cups. After locating the fruit by binocular vision, the suction cup is used to grasp and harvest the tomato. Van Henten et al. (2003) designed a 7-DOF cucumber-harvesting manipulator. The end effector is designed with scissors that can cut the stem of cucumber while clamping it with a suction cup/gripper. De-An et al. (2011) designed a 5-DOF apple-harvesting manipulator with a spoon-shaped end effector, which can firmly fix apples and cut stems with an electric cutting device. Many studies have been conducted on various fruits to be harvested, including strawberries (Xiong et al., 2020), grapes (Badeka et al., 2020) and pumpkins (Roshanianfard and Noguchi, 2018). The design of the mobile mechanisms of these manipulators is relatively similar. Most differences have to do with size and degrees of freedom. The design of the end effector is based primarily on the comprehensive consideration of the morphological structure and texture of the target fruit.

6 Conclusion and future trends

Current studies have indicated that the use of field robots for phenotyping can improve the efficiency, quality, stability and accuracy of acquiring phenotypic information (Tsukor et al., 2012; Zhou et al., 2017). Existing phenotyping robots nevertheless continue to be designed for monitoring specific plant-growth periods or plant species. The development of different platforms for different plants is costly and time-consuming. The construction of a universal phenotyping robot platform is therefore needed. The Thorvald II robot provides several ideas for developments in this direction (Grimstad and From, 2017). The platform for this robot is designed with various drive chassis and sensor-support modules. It can adjust the height, width and drive mode of the chassis to adapt to differing field-cultivation environments and plant objects. When developing the design of phenotyping robots, however, greater attention should be paid to intelligent operations. With the support of image sensors and Al technologies, robots should be capable of recognizing the row distance and

height of plants. They should then have the ability to automatically calculate and adjust the mechanical structure in real time, thereby achieving adaptive object monitoring and autonomous operations.

With regard to the acquisition of phenotypic information, field robots and UAVs offer different advantages. For example, UAVs are more suitable for obtaining canopy-level phenotypic information, and they can efficiently monitor dynamic changes in plant populations (Holman et al., 2016). In contrast, given their limited test height, field robots are more suitable for obtaining phenotypic information on individual plants. Given that both group and individual characteristics are clearly of great significance to breeding, studies that combine the use of UAVs and field robots are highly valuable. Future developments in this direction could focus on drones that are capable of obtaining macro-scale information on the canopy traits of plant populations (e.g. plant emergence rate, ground coverage, LAI and nitrogen content (Burud et al., 2017; Schirrmann et al., 2016; Liu et al., 2017; Pretto et al., 2020)). The macro-scale data are used to command the phenotyping robots to go to specific areas to obtain individual phenotypic information on individual representative plants (e.g. plant height, protein content, stomatal conductance and nitrogen assimilation rate). Given the large monitoring coverage and high efficiency of drones, phenotyping robots can be operated in teams, although this obviously increases the requirements for collaboration between different software systems. The combination of information at different scales can be used to establish the relationship between phenotypic information on individual plants and group characteristics. This could improve the prediction of dynamic changes in the growth processes of individual plants and groups of plants, in addition to providing effective guidance for breeding and cultivation, thus ultimately generating maximum-yield production benefits.

When implementing phenotyping sensors, it is important to note that some sensors are still difficult to use in open-field environments, due to volume, costs, scalability and measurement requirements (e.g. PET, CT and MRI). These problems are likely to be resolved as the costs and size of sensor chips decrease and further improvements in sensor integration are achieved. In addition, the phenotyping monitoring sensors that are currently carried by field robots are used primarily to monitor the phenotypic characteristics of the above-ground parts of plants. The current technology for below-ground plant phenotyping and the evaluation of the soil environment relies on static measurement. There are no specialized methods for combining below-ground phenotyping monitoring sensors and soil-environment information sensors with moving robots. The related sensing technology and intelligent equipment have yet to be developed. Data interaction between different sensors is also important with regard to the integration of sensor data. Suppose that it is possible to assemble results from 2D data tests, 3D data tests, spectral tests and temperature tests quickly and then

systematically display them through the human-computer interaction interface. This could usher in a new era for research on plant phenotyping monitoring. At present, however, major differences exist in the control software, test methods and data-aggregation methods of different sensor platforms. There are also differences in the analytic methods, programming languages and software platforms that are used for the analysis of sensing results. To a certain extent, these differences pose obstacles to data interaction between sensor devices.

With the advent of 5G (or even 6G), the combination of AI technology and phenotyping robots based on 5G communication offers excellent potential. Limited by the speed of data transmission, most current phenotyping robots rely on a self-mounted host-computer platform to realize the calculation and storage of high-throughput data. This method increases the load of the robot, and it does not help researchers to track plant phenotyping information in real time. Researchers often need to extract data stored by the host computer for post-processing after the robots have obtained all of the results. As a result, the results lag behind the real-time growth state of the plant. Wageningen University & Research has conducted preliminary research on the use of 5G technology and achieved real-time control of weeds in sugar-beet fields (Visser, 2020). The high bandwidth and low latency characteristics of 5G technology make it possible to receive newly obtained phenotyping information on cloud platforms and remote computers. After the obtained data has been calculated through the aforementioned platforms, the results can be fed back to the field robots in real time, cooperating with the actuator to achieve totally unmanned farm management.

7 Where to look for further information

The following article provides a good overview of the subject:

• Atefi, A., Ge, Y., Pitla, S. and Schnable, J. 2021. Robotic technologies for high-throughput plant phenotyping: Contemporary reviews and future perspectives. *Frontiers in Plant Science* 12:611940.

Key research in this area can be found in the following organizations:

- Netherlands Plant Eco-phenotyping Centre (NPEC) at Wageningen University & Research (www.npec.nl).
- Australian Centre for Field Robotics University of Sydney (https://www.sydney.edu.au/engineering/our-research/robotics-and-intelligent-systems/australian-centre-for-field-robotics.html).
- UMT CAPTE, a scientific research unit based in Avignon (France), a collaboration between INRAE, ARVALIS and HIPHEN (https://umt-capte.fr/).

- Jülich Plant Phenotyping Centre (JPPC) https://www.fz-juelich.de/ibg/ibg-2/EN/_organisation/JPPC/JPPC_node.html.
- EMPHASIS, an organization that enables researchers to use facilities, resources and services for plant phenotyping across Europe (https://emphasis.plant-phenotyping.eu/).

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