Detection system of smart sprayers: Status, challenges, and perspectives

Sun Hong[1], Li Minzan[1*], Qin Zhang[2]

(1. *Key Laboratory of Modern Precision Agriculture System Integration Research, China Agricultural University, Beijing* 100083, *China*;
2. *Center for Precision & Automated Agricultural Systems, Washington State University, Prosser,WA 99350, USA*)

Abstract: A smart sprayer comprises a detection system and a chemical spraying system. In this study, the development status and challenges of the detection systems of smart sprayers are discussed along with perspectives on these technologies. The detection system of a smart sprayer is used to collect information on target areas and make spraying decisions. The spraying system controls sprayer operation. Various sensing technologies, such as machine vision, spectral analysis, and remote sensing, are used in target detection. In image processing, morphological features are employed to segment characteristics such as shape, structure, color, and pattern. In spectral analysis, the characteristics of reflectance and multispectral images are applied in crop detection. For the remote sensing application, vegetation indices and hyperspectral images are used to provide information on crop management. Other sensors, such as thermography, ultrasonic, laser, and X-ray sensors, are also used in the detection system and mentioned in the review. On the basis of this review, challenges and perspectives are suggested. The findings of this study may aid the understanding of smart sprayer systems and provide feasible methods for improving efficiency in chemical applications.

Keywords: smart sprayer, target detection, weed control, disease detection, chemical application
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1 Introduction

Weed control, disease infection, and insect damage are significant issues in agricultural crop production. Weeds compete with crop plants for moisture, nutrients,and sunlight. If uncontrolled, disease infection and insect damage have detrimental effects on crop yield and quality. A number of studies have documented the yield loss associated with weeds, disease, and insect infestations[1]. Shrefler et al.[2] found that competition from spiny amaranth (*Amaranthus spinosus* L.) in lettuce fields reduced head weight and quality. Martelli et al.[3] reported that nearly 60% of the total losses in grape production worldwide are due to virus diseases. Yang[4] indicated that the widespread Greenburg outbreak occurs every five to seven years with considerable yield losses.

The use of chemicals has contributed to weed control and prevention of biotic stresses such as diseases and insect infestation. However, many surveys and experiments revealed that excessive use of pesticides, fungicides, and herbicides resulted in waste, chemical residues in foods and emission into the air and soil.

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Biographies: Sun Hong, PhD, Lecturer in the China Agricultural University. Her research focuses on agriculture intelligent detection using spectral technology and image processing. Tel: +86-10-62737924, Email: sunhong@cau.edu.cn.
Qin Zhang, PhD, professor in Washington State University, 24106 N Bunn Rd, Prosser, WA 99350, United States. He has been a professor in the University of Illinois's agricultural engineering department. His research areas include mechanical and electrical engineering and computer-aided farming systems. Tel: 1-309-786-9360, Email: qinzhang@wsu.edu.
***Corresponding author: Li Minzan,** PhD, professor in China Agricultural University. His research focuses on precision agriculture, especially on spectral analysis and application. The research topics include crop growth status monitor, soil nutrition detection and the sensor development. Tel: +86-10-62737924, Email: limz@cau.edu.cn.

Dependence on chemicals imposes potential adverse effects on human health and the environment[5-10], and growing concern has emerged regarding the increasing number of issues associated with inefficient chemical use[11,12].

Three general spraying patterns are currently used (Figure 1): broadcast, band, and targeted spraying. The traditional method of broadcast spraying is characterized by considerable inefficiency because an entire area is sprayed regardless of whether there are targets or non-targets presented in the area. This approach has resulted in up to 60%-70% of off-target losses[13]. To reduce waste and environmental pollution stemming from off-target losses, band and targeted spraying methods were developed. In band spraying, only selected regions are treated. Experimental results in the field showed that band application and mechanical practice can reduce chemical use and impose minimal environmental effects[14-16]. The target spraying system involves the detection of damaged or infected plots or plants in the field, and features real-time control of sprayer operation. Brown et al.[17] compared the ground deposits and runoff resulting from targeted spraying with those from conventional broadcasting spraying in dormant orchards. Their results showed that targeted spraying achieved a 41% reduction in ground deposition and reduced pesticide concentration in surface water runoff by 44%. The target spraying system is a precise method for reducing unnecessary chemical spraying that may affect environmentally sensitive areas, humans, and non-targeted crops.

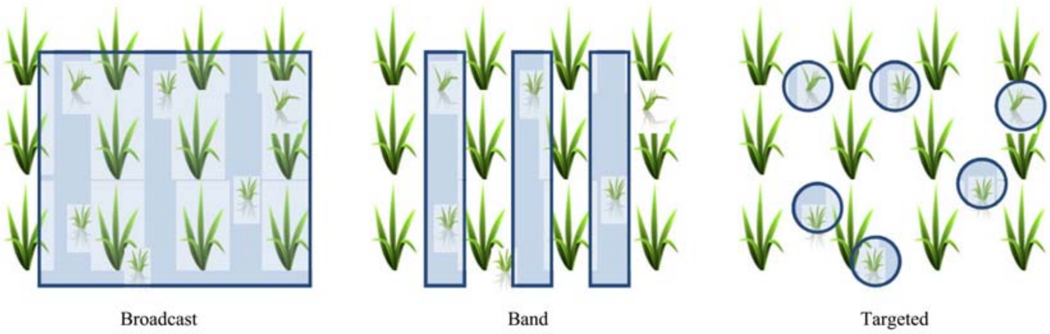

Figure 1 Three general spraying patterns: Broadcast, band and targeted spraying

Traditional target spraying is manually carried out with a hand-held pump. With the development of sensing techniques and mechanical cultivation, the “smart sprayer” was developed to satisfy the requirements for automatic spraying. The smart sprayer is an integrated system of target detection sensors, analytical methods, atomizing spray devices, and control systems. The smart sprayer contributes the following advantages to sustainable agriculture: (1) real-time detection of crop growth; (2) targeted analysis and decision making regarding chemical sprays; and (3) precise operation and reduction of manual labor through optimized tools. It is an efficient approach to solve the issues of chemical waste reduction and product quality enhancement.

In this study, the smart sprayer based on the detection technique was discussed. The target detection and spray control systems were analyzed. The results showed that in this system, various sensing techniques, such as machine vision, spectral analysis, and remote sensing, are applied. These are widely used in plant recognition and classification. The general applications and development status of the smart sprayer were also described. On the basis of the summary of related research, challenges and perspectives were suggested.

2 Smart spraying system

Slaughter et al.[18] observed that a general-purpose autonomous robotic weed control system has four core technologies: sensing technology for detection (machine vision and hyperspectral imaging), global positioning system for guidance (Real-time Kinematic Global Positioning System), variable rate application techniques, and robotics for spraying execution (micro-spray, cutting, thermal, and electrocution). A smart spraying system should consist of a detection system and a chemical spraying system (Figure 2). A detection system integrates target detection sensors, data processing, and decision making systems, while a spraying system includes a spraying control unit and sprayer (nozzle). The detection system of smart sprayers is used to detect information on target areas and make spraying decisions. The spraying system controls sprayer operation. Upon acquisition of information, the nozzles are activated to spray chemicals over the target area.

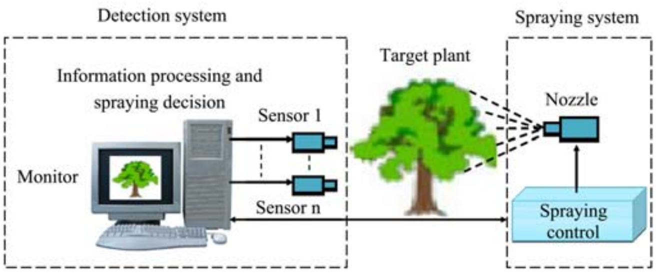

Figure 2 Smart spraying system based on sensing technology

2.1 Detection system

A detection system, benefits from sensing technologies, includes image sensors, spectrometers, remote sensing devices, thermographs, and laser sensors, among others (Figure 3). Typically, these technologies are developed on the basis of spectroscopy. The analysis of spectral characteristics reveals that green plants typically display low reflectance in the visible region because of their strong absorptance by photosynthetic and accessory plant pigments. By contrast, little absorptance is achieved by subcellular particles or pigments in the near-infrared (NIR) region. Spectral technology can be used to detect plant patches[19-21]. Three main methods are applied: image analysis with a camera/filter, spectrophotometric measurement, and remote sensing.

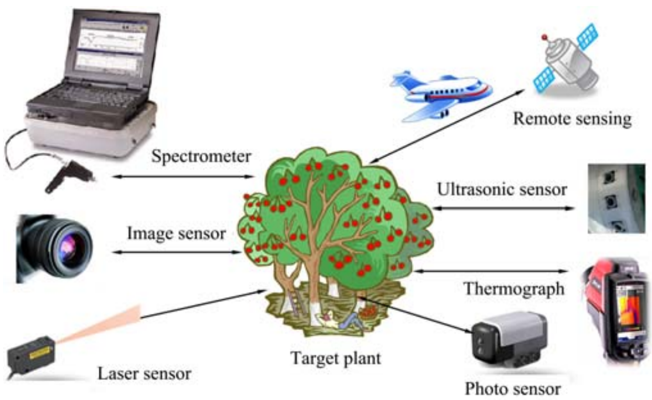

Figure 3 Target detection sensors

In weed detection, the elimination of weeds between crop rows is achieved through machine vision, which distinguishes weeds from the soil background[22-24]. Ahmed et al.[25] applied biological morphology algorithms to segment the shape and structure of weeds in the field. The shapes of weeds were classified by edge segmentation and more than 94% classification accuracy was obtained from 140 images. Burks et al.[26] analyzed the visual texture features of weed images. The color co-occurrence method used by the authors generated a classification accuracy of 93% among five weed species and soil types. Prion et al.[27] found that the combination of filters that were centered at 450 nm, 550 nm and 700 nm was sufficient for discriminating weeds from carrots at an accuracy of 72%.

The detection system is also used in disease and insect detection. To detect the yellow rust disease of winter wheat, Moshou et al.[28] measured canopy spectral reflectance. Neural networks were used to classify infected and healthy leaves, and classification accuracy reached 99%. The combined measurement of hyperspectral (450-900 nm) and fluorescence images worked effectively in discriminating a disease from a healthy plant[29]. Yang et al.[4] applied remote sensing techniques to detect stress in wheat caused by aphid infestation. Ratio-based vegetation indices (based on 800/450 nm and 950/450 nm) were found useful in differentiating stresses in wheat caused by two aphid species. Sankaran et al.[30] focused on the application of mid-infrared spectroscopy to detect Huanglongbing in citrus leaves. The spectral peak in the 9 000-10 500 nm region was found distinctly different in healthy and huanglongbing-infected leaf samples. All the results from the aforementioned studies can aid decision making for chemical spraying in the field.

2.2 Spraying system

To efficiently execute chemical spraying, the spray system was improved by using spraying techniques and variable control as bases. Air-blast and electrostatic techniques are currently applied in the sprayer[31,32]. Because the air-blast sprayer carries chemicals to the target via a large fan, it causes substantial pollution with pesticide-laden drift and mist. The electrostatic technique was developed on the basis of the principle that like charges repel and unlike charges attract. An electrostatic sprayer rectifies the problem of pesticide deposition and consequently reduces waste discharged into the ecosystem[33,34]. Furthermore, a tunnel sprayer combines the electrostatic technique with the recycle hood to spray in rows. Most of the drift and mist are recycled by deposition along the wall of the hood. The electrostatic method provides an efficient way to reduce pesticide use[35,36].

With the creation of the automatic control system and variable-rate herbicide application systems that are based on direct injection equipment, were developed to enable real-time spraying with fewer chemicals[37,38]. Smith and Thomson[39] developed a direct injection system to control pesticide concentration. Pulse width modulation technology was also applied in variable-rate field sprayers and proved to be an effective method for weed control spraying[40,41]. Bui[42] presented a VariTarget nozzle with controllable flow rate and droplet size. The nozzle combines a variable-area pre-orifice and a variable-area spray orifice, and is used with pressure regulators or an automatic rate controller.

3 Key techniques applied in the detection system of a smart sprayer

As previous studies described, target detection is fundamental to the smart spraying system for precise agricultural production. In the development of smart spraying systems, sensing technology has been emphasized as an effective method for collecting information in the field and facilitating decision making regarding precise field operations[43-45]. The applied techniques in target detection are focused on machine vision, spectral analysis, and remote image processing, among others. Single or multiple sensors are applied in smart spraying systems for special requirements: (1) target detection and measurement; (2) species recognition and classification; and (3) detection and evaluation of plant disease or level of pest damage.

3.1 Machine vision

Ground-based machine vision has been applied in target detection. In image processing, morphological features are used to segment external appearance such as shape, structure, color and pattern, as well as the form and structure of internal components[46]. The shape features of leaves have been successfully used in plant recognition and classification[47-52].

3.1.1 Application in weed control

Pérez et al.[22] proposed color and shape analysis for weed detection in cereal fields. The green and red channels of color images were used to build the image index (normalized difference index, NDI) to discriminate between vegetation and background. The shape segmentation was analyzed to distinguish between crops and weeds. The performance of the weed detection algorithms were assessed by comparing the results from visual surveying. The results showed that the correlation improved from 75% to 85% when shape analysis was used. Ghazali et al.[53] developed an intelligent real-time system for automatic weeding strategy in oil palm plantations. Three image processing algorithms were used to identify and discriminate the weed types. These are grey level co-occurrence matrix, fast Fourier transform, and scale-invariant feature transform. The results for tested offline images showed that scale-invariant feature transform achieved 99.5% and 99.8% accurate classification rates for narrow and broad weed recognition, respectively. The classification rates recorded for grey level co-occurrence matrix were 81% and 81.5%, and those for fast Fourier transform were 89.2% and 91%.

Tian et al.[54,55] developed a precision chemical application system guided by machine vision. As shown in Figure 4, multiple cameras are used to collect images in the field. Each image is first segmented with an environmentally adaptive segmentation algorithm, which specifies the boundaries of a region in the hue, saturation, and intensity (HSI) color space. The crop rows are identified and the inter-row area is used for the measurement of weed infestation conditions. The inter-row weeds are separated from crop plants. Weed numbers in each unit area and average weed size are used as basis for making spraying decisions. The test results for the system showed that it can save herbicide by 48% with 0.5% weed coverage as the control zone threshold.

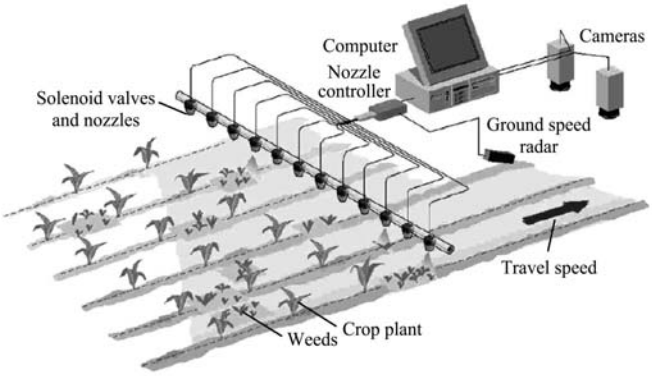

Figure 4 Sprayer system based on machine vision

3.1.2 Application in disease detection

Camargo and Smith[56] studied a machine vision system for the identification of the visual symptoms of plant disease. The diseased regions shown in the digital images of cotton crops were enhanced and segmented. A set of shape and appearance features were extracted: (1) Eight parameters were used to describe the shape features, including solidity, extent, major and minor axis lengths, eccentricity, centroid, diameter, and area of the diseased region. (2) The co-occurrence matrix was applied to calculate image texture. (3) The dimensions were measured using the fractal dimension method. (4) The lacunarity was calculated using the gliding box algorithm, and associated with patterns of spatial dispersion. In addition, grey levels, grey histogram discrimination and a Fourier descriptor were considered. A machine learning method based on a support vector machine algorithm (SVM) was used to build the classification model. Groups of candidate features were used as input for the classifier. The classification results indicated that the highest classification rate (83%) was achieved for group texture, while the lowest was achieved for the features making up the group shape (55%). When all the features were used, however, a classification accuracy of 90% was reached.

To verify the need for fungicide application in the early stage of rust infection, Cui et al.[57] detected soybean rust by image processing. A manual threshold-setting method based on the hue, saturation, and intensity color model was originally developed for segmenting infected areas from plant leaves. Two disease diagnostic parameters, ratio of infected area and rust color index, were extracted. They were used as symptom indicators for quantifying rust severity. To automatically segment the infected region, the centroid of leaf color distribution in the polar coordinate system was investigated. Leaf images with various levels of rust severity were collected and analyzed. Validation results showed that the threshold-setting method was capable of detecting soybean rust severity under laboratory conditions, whereas the centroid-locating method presented potential for field application.

3.2 Spectral analysis

The spectral characteristics of vegetation are powerful parameters used to estimate biomass or vegetation vigor. The general applied wavelength of green vegetation is referred from the visible (400-700 nm) to the NIR spectrum (700-2 500 nm). The analyses of spectral characteristics are a rapid, nondestructive technique for crop feature selection and classification.

3.2.1 Analysis of spectral characteristics

Spectral characteristics can describe the pigments and biochemical components in plants. Studying these features is an effective method of identifying plant species and health status. A number of studies have documented plant detection using spectral techniques[58,59].

To guide fungicide application in grapevines, Naidu et al.[60] discussed the spectral characteristics of grape with grapevine leafroll disease (GLD). The differences in spectral characteristics between healthy and infected leaves were found at the green (near 550 nm), short-wave NIR (near 900 nm), and NIR (near 1 600 and 2 200 nm) peaks. Stepwise discriminant analysis was applied to evaluate the wavelengths and vegetation indices for GLD detection. Wavelengths (531, 570, 752 nm, etc.) and vegetation indices (normalized difference vegetation index, NDVI), red-edge vegetation stress index (RVSI), photochemical reflectance index (PRI), etc., were selected to measure the reflectance changes of GLD-infected leaves. The classification results showed that the multiple variables produced higher accuracy than the single variable did. The classification, in which RVSI was used for all infected leaves, resulted in an accuracy of 0.72. When RVSI was combined with the reflectance in the blue band (470-490 nm) and 526 nm wavelength, the accuracy increased to 0.78. Similarly, the highest classification accuracy for non-symptomatic leaves (752 nm) was 0.71 when a single variable was used. The same variable, combined with the NIR band (765-830 nm), 970 and 684 nm wavelengths, and PRI, generated a classification accuracy of 0.75. The spectral reflectance technique presents promising potential for GLD detection.

Xu et al.[61] measured the spectral characteristics of tomato leaves damaged by leaf miners. Tomato leaf damage was classified into five scales using the severity levels observed on the surfaces of the plant leaves as bases. The analysis showed clear differences in spectral reflectance at various levels of infestation. Spectral reflectance significantly decreased with increasing severity level at the short NIR wavelengths (800-1 100 nm), but increased with rising severity level in the individual bands of 1 450 and 1 900 nm. A high correlation coefficient was observed between the severity level and sensitive bands of 1 450 and 1 900 nm. Jones et al.[62] diagnosed bacterial spot on tomato using the spectral technique. A laboratory spectrophotometer was used to collect the diffused reflectance of infected leaf samples. The correlation coefficient spectrum, PLS regression, and an SMLR procedure were used to identify important wavelengths. The selected wavelengths (395, 630, 633-635, 750-760 nm, etc.) were used to construct predictive models by PLS and SMLR. The results showed that the PLS model predicted disease in the validation dataset with an R^2 of 0.77, and the SMLR model yielded the best prediction with an R^2 of 0.82.

Rumpf et al.[63] applied hyperspectral data to detect leaf spot disease, sugarbeet rust, and powdery mildew on sugarbeet leaves. Nine spectral vegetation indices [NDVI, ratio vegetation index (RVI), etc.], related to physiological parameters, were used as features for automatic classification. A support vector machine algorithm was used to classify early differentiation between healthy and infected plants. The discrimination results showed a classification accuracy of up to 97%. The multiple classifications of healthy leaves and diseased leaves, showing symptoms characteristic of the three diseases, achieved a classification accuracy higher than 86%. Moshou et al.[28] investigated the differences in spectral reflectance between healthy and diseased wheat plants [infected by early-stage *Puccinia striiformis* (yellow rust)]. The authors built classification models based separately on quadratic discrimination and self-organizing maps (SOMs). As a result, classification performance increased from 95% to higher than 99%. These results were encouraging for the development of a cost-effective optical device for recognizing yellow rust at an early stage.

In weed management, Vrindts et al.[64] measured the canopy reflectance of maize, sugarbeet, and seven weed species at 400-2 000 nm. The spectral characteristics were also analyzed. Six wavelengths (555, 675, 815, 1 265, 1 455, and 1 665 nm) at characteristic points in the spectrum were selected to derive the RVI. The STEPDISC and DISCRIM procedures in SAS were applied in the discrimination of crops (maize and sugarbeet) from weeds. The classification result showed that crop and weeds could be recognized at an accuracy of higher than 97%. More than 90% of sugarbeet and weeds could be identified correctly using a line spectrograph (480-820 nm) in classifying the plants. With the application of the spectral technique, the WeedSeeker sensor module was developed to detect the presence of weeds by measuring the reflectance of weeds and bare ground. The module serves as a useful tool for locating weeds[65]. Using the same theory, Wang et al.[66] designed an optical weed sensor to classify wheat, bare soil, and weeds, for which classification rates of 100%, 100%, and 71.6%, respectively, were obtained.

3.2.2 Multi-spectral image processing

Aside from imaging objects in the visible region (400-700 nm), some multispectral images, discussed in terms of the visible and NIR bands, are widely applied in plant detection[67]. Moushou et al.[29] detected yellow rust disease in winter wheat by the fusion of hyperspectral and multispectral image data. Hyperspectral reflection images of healthy and infected plants were taken with an imaging spectrograph under field and ambient lighting conditions. Multispectral fluorescence images of the same plants were taken simultaneously using UV-blue excitation. The fraction of pixels in one image, recognized as diseased, was set as the final fluorescence disease variable called the lesion index. A spectral reflection method, based on only three wavebands (680 nm, 725 nm, and 750 nm), was developed to discriminate diseased from healthy plants, with an overall error of 11.3%. The fluorescence-based method was less accurate, with an overall discrimination error of 16.5%. However, a 94.5% discrimination rate was obtained using the fused images. Data fusion was also performed using an SOM neural network, which decreased the overall classification error to 1%. The experimental results clearly demonstrated that the data fusion from different optical sensors exhibited tremendous potential for the development of tractor-mounted disease detection systems.

Cui et al.[68] detected soybean rust infection and severity. Both a portable spectrometer and a multispectral CCD camera were used to collect spectral information of different rust severity from the leaves. Vegetation indices were used to investigate the possibility of detecting rust infection; these include the NDVI, green NDVI, RVI, difference vegetation index (DVI), and so on. The results indicated that DVI showed positive correlation with rust severity. The infected region in the leaf was segmented by manual threshold. Three image parameters were defined as the ratio of infected area, lesion color index, and rust severity index. The severity of infection was evaluated. The results showed that the rust severity index positively correlated with the severity of rust infection. The research also demonstrated that the multispectral imaging method enabled laboratory-scale quantitative detection of soybean rust.

Slaughter et al.[69] used multispectral images (384-810 nm) to distinguish lettuce plants from weeds. The images were collected using a temperature-controlled camera equipped with a transmission grating lens and blue filter. The RVI and NDVI were evaluated to distinguish between weeds and crops. The RVI, obtained at 644 and 810 nm, resulted in a 57% classification rate, while the NDVI, obtained at 640 and 810 nm, showed a classification rate of 60%. Then a set of different wavebands were used in related indices. The multiple indices (12 for RVI and 65 for NDVI) indicated an average classification accuracy of 90.3% in 150 plants. The same system was applied in a tomato field[70], and correctly recognized 95% of tomato foliage and more than 84% of four weed species (black nightshade, lamb squarter, red root pigweed, and purslane).

Piron et al.[71] applied the multispectral stereoscopic vision system to detect in-row weeds. The multispectral images were measured with the filters centered at 450 nm, 550 nm, and 700 nm. The manual segmentation between crops and weeds was carried out in three steps: (1) ground-plant segmentation resulting in a clean plant mask for each multispectral image; (2) segmentation between crops and weeds by manual creation of crude masks over the multispectral images; and (3) the creation of clean plant masks for each class (crops and weeds) by a logical AND operation on the corresponding masks from the first two steps. The plant height (h) and number of days after sowing were calculated on the basis of stereoscopic information. The multispectral and stereoscopic data were combined to distinguish the in-row weeds from carrots. The results showed a classification accuracy of 86%.

3.3 Remote sensing

Remote sensors can acquire large-scale object information by aerial photography, satellite imaging, and ground-based data collection. The analysis of spectral characteristics and vegetation indices are generally applied in the data processing. Such analyses have been used effectively in monitoring the incidence of a number of plant disease infections[72-74].

Grisham et al.[75] applied hyperspectral remote sensing to detect sugarcane yellow leaf virus (SCYLV) infection in asymptomatic leaves. The SCYLV was predicted with an accuracy of 73% using resubstitution and cross-validation. The spectral analysis revealed that the discrimination wavelengths were in the ultraviolet (220-320 nm), blue (400-500 nm), green (500-590 nm), red (590-650 nm), and NIR (740-850 nm) ranges. The SCYLV infection influenced the concentration of several leaf pigments, including violaxanthin, β-carotene, neoxanthin, and chlorophyll *a*. Pigment data and the discriminant function derived with resubstitution were also used to predict SCYLV infection, with an accuracy of 80% and cross-validation yielded 71% accuracy.

Qin and Zhang[76] examined the applicability of the broadband high spatial resolution Airborne Data Acquisition and Registration (ADAR) system in remote sensing data to detect rice sheath blight. On the basis of the field symptom measurements, a comprehensive field disease index (DI) was constructed to measure infection severity. The direct digital number, band ratio indices, and standard difference indices were used to examine possible correlations between field and image data. The correlation coefficient (above 0.62) indicated that broadband remote sensing imagery has the capability to identify rice disease. However, the lightly diseased plants were difficult to separate from the healthy plants. For the same purpose, Huang et al.[77] evaluated the applicability and accuracy of hyperspectral imagery in quantifying the DI of yellow rust (biotrophic *Puccinia striiformis*) in wheat (*Triticum aestivum* L.). The airborne hyperspectral images of the site were acquired over two successive seasons. According to the data analysis, the PRI exhibited a significantly negative linear relationship with DI ($R^2 = 0.91$). Figure 5 shows the potential of PRI for quantifying yellow rust infection levels in winter wheat.

To avoid insects damage and manage citrus pests, Du et al.[78] combined multispectral remote sensing and variable rate technology with environmental modeling. An airborne multispectral technique was developed to identify tree health problems in a citrus grove. An unsupervised linear unmixing method was applied to classify grove images and quantify symptom severity for appropriate infection control. The environmental model (PRZM-3) was applied to estimate environmental effects. The results indicated that the developed system reduced nonpoint source pollution by 92%. Luedeling et al.[79] evaluated the feasibility of detecting spider mite damage in orchards. The visible and NIR reflectance of peach canopy were measured. Normalized difference indices were evaluated for correlation with mite damage. The results showed that index values were linearly correlated with mite damage (R^2 = 0.47), allowing for the identification of mite hotspots. These studies demonstrated the potential of remote sensing application in detecting plant growth status and precision spraying control.

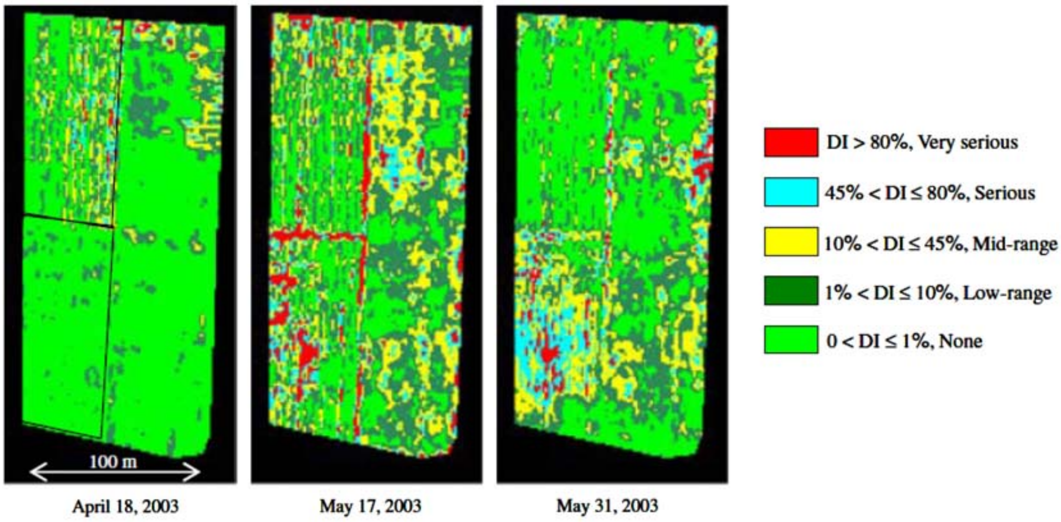

Figure 5 Classified disease index images derived from airborne images

3.4 Others

3.4.1 Thermography

Thermal imaging, or infrared thermography imaging, is a type of infrared imaging technology. The thermographic camera detects radiation in the infrared range of the electromagnetic spectrum (9 000–14 000 nm) and produces radiation images. The surface temperature of leaves is a short-term phenomenon influenced by a variety of plant species, growth status, site-specific conditions, climatic factors, and the interactions among these variables. Thermal imaging can monitor plant temperature distribution and plant energy[80]. Thus, it is expected to enable effective observation of plant disease symptoms and provide guidance for pesticide spraying control.

In wheat fields, Lenthe et al.[81] used an infrared thermographic system to monitor the incidence and severity of disease induced by microclimatic conditions. Experiments were conducted on the detection and differentiation of leaf wetness at single-leaf and crop canopy scales under controlled conditions. Although the results demonstrated the excellent potential of thermography for detecting plant health in terms of water status, its combination with other detectors was suggested to make up a precision detection system.

Nicolas[82] developed a sensing system for optimizing data on fungicide application to the pathogen *Septoria tritici* in winter wheat. The data were obtained in the optical (visible and NIR) and thermal infrared spectral range. The sensors were suspended above plots that differed in terms of data on the candidate fungicide application to the wheat canopy, and constituted a range of different infestation levels. The analysis of the relationship among the severity of the infestation, yield, and sensing data showed that the severity of *S. tritici* infestation was associated with a decrease in the NDVI and an increase in the canopy surface temperature. In both optical and thermal ranges, the NDVI was more relevant to fungicide determination than to the thermal information. However, the thermal infrared information increased the precision of the measurements. Menesatti et al.[83] analyzed the potential of detecting the distribution of pesticide quality using infrared thermal images as bases. The pesticide distribution quality was compared to the temperature differences observed in the thermal images in pre-treatment and post-treatment stages. According to the analysis, evaluating the quality of pesticide distribution from orchard sprayers is possible.

Studies indicated that the application of thermal imaging was influenced by the interaction among plant water stress, nutritional content, and environmental conditions. More comprehensive researches should be devoted to this issue in the future.

3.4.2 Ultrasonic, laser, and X-ray sensors

Automatically measuring canopy characteristics or stem position is an essential step in orchard spraying management. A variety of different sensors, such as ultrasonic, laser, and X-ray sensors, can be applied. Ultrasonic sensors generate high-frequency sound waves and evaluate the echo received by the sensor. The calculated time interval between signal transmission and echo receipt can determine the distance of the sensor to an object. These sensors are used to measure tree size and density, as well as control the spray system in orchards[84]. A 10-transducer ultrasonic system was used to measure the canopy volume of trees in an orchard[85,86]. The ultrasonic system measured volumes with an average prediction accuracy higher than 90% and a high correlation with manual measurements (R^2 = 0.95-0.99). Schumann and Zaman[87] developed software for real-time ultrasonic mapping of tree canopy size. The results indicated that the ultrasonic system is a reliable method for target site-specific management in orchards.

A stem detection system, which uses a portable X-ray source, was developed for smart weed control in transplanted tomato fields. The system projects an X-ray beam perpendicular to the crop row and parallel to the soil surface[88]. The main stem of a plant absorbs X-ray energy, decrease the intensity of the detected signal and enabling stem detection even under heavy leaf cover. The signal is used to control the operation of a pair of weed knives. The detector consists of a linear array of photodiodes aligned perpendicular to the soil. This configuration helps differentiate branches (which only some of the photodiodes are angled and blocked) and stems (which have the same vertical alignment) as arrays, thereby blocking all the photodiodes. A field trial was conducted in a 15 m section of rows containing 39 tomato seedlings. At a speed of 1.6 km/h, the detection system correctly identified all the 39 stems of upright plants.

In addition, a laser scanning system was proven applicable to measure tree canopy height, width, and volume[89]. An increasing number of studies have reported that the combined system of lasers and other sensors can be applied in target detection and smart spraying control[90]. Nevertheless, such an integrated system is a non-selective sprayer with an ultrasonic, laser, or X-ray sensor control system. It effectively functions only when tree canopy or stems are detected in the associated zone without any selection and precision evaluation. Thus, building a target smart sprayer necessitates the combination of the integrated system with other target sensors.

3.5 Summary of the detection techniques for the smart sprayer

A smart spraying system is a targeted spraying system that features efficient chemical application and imposes minimal effects on the environment. It is an effective technology that satisfies the requirements of precision agriculture. The target detection and spraying control systems in smart sprayers have been discussed in the literature review section. The detection system is used to determine information on target areas, and facilitates decision making regarding spraying. The spraying system is used to control sprayer operation. Various sensing techniques including machine vision, spectral analysis, remote sensing, and so on, are applied. These are widely used in plant recognition and classification. Table 1 showed the summary of the detection techniques adopted for the smart spraying system.

Table 1 Detection techniques for the smart sprayer

No.	Sensor	Application	
1	Machine vision	Application	Weed detection, species classification, target recognition
		Evaluation	It can be applied to satisfy various requirements. The images are affected by environmental factors, such as light, target cover, and so on
2	Spectral analysis	Application	Weed detection and classification, disease incidence, and insect damage evaluation
		Evaluation	The spectral characteristics are different and change for different targets at different stages or conditions; the sensitive wavelength and vegetation index are complex issues

3	Remote sensing	Application	Target area detection, disease incidence, and insect damage detection
		Evaluation	A good way to guide a helicopter sprayer. It presents good detection accuracy, but limited by the costs. In addition, it is inapplicable in small areas
4	Thermal image	Application	Disease symptom and severity detection
		Evaluation	Thermal images are influenced by the interaction among plant water stress, nutritional content, and environmental conditions
5	Ultrasonic/laser/x-ray	Application	Object measurement and detection
		Evaluation	Non-selective sprayer with a sensor control system functions effectively only when tree canopy or stems are detected in the associated zone.

4 Conclusions

Although considerable researches have been conducted on detection, most of these studies were carried out under ideal conditions. Three major technical challenges, due to uncontrolled environmental conditions, are confronting sensor application in agricultural production:

(1) Lighting conditions. Lighting conditions are some of the most challenging issues in the field application of machine vision and spectral analysis. Plant reflectance can increase under intense sunlight, thereby pose difficulties in plant detection because of decreased differentiation among plant characteristics. Increased plant reflectance also distorts image colors. Thus, the data cannot be used for species classification under changing environments.

(2) Leaf coverage. Leaf coverage is an important aspect of crop recognition and discrimination, especially for machine vision. Weeds that grow near crops or between rows of crops are difficult to measure and classify. The information on canopy spectral reflectance may also lead to misclassification.

(3) Growth status. As indicated in numerous studies, plant disease or growth status can be detected by the color changes in plant images, spectral reflectance changes, or vegetation index characteristics of remote data. Different situations may affect the target; thus, the symptoms may also manifest differently.

Despite these challenges, future developments are foreseeable to continue exhibiting trends of using detection techniques to improve spraying efficiency and reduce the environmental effects of agrochemical input. The findings of this study may aid the understanding of smart sprayer technology, and provide feasible methods for improving efficiency in chemical applications.

(1) According to documented reports, multiple target features can be segmented from data derived by a single sensor. For example, machine vision can be used to classify weeds and crops as plant infection or crop damage symptoms are segmented in the images. To segment more information from a single sensor, real-time processing algorithms should be developed.

(2) With regard to the limitations of a single sensor, multi-sensing information can serve as a supplement to improve detection accuracy. With the development of sensing techniques, an integrated system with more than one or two detection sensors will be widely used. As a result, data fusion for such devices should be developed.

(3) Meanwhile, smart sprayers will be designed to satisfy unique specifications. With the development of intensive agricultural methods, specialized mechanical or chemical sprayers will be created for different applications.

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