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Close Range Spectral Imaging for Disease Detection in Plants Using Autonomous Platforms: a Review on Recent Studies

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Abstract

Purpose of Review A short introduction to the spectral imaging (SI) of plants along with a comprehensive overview of the recent research works related to disease detection in plants using autonomous phenotyping platforms is provided. Key benefits and challenges of SI for plant disease detection on robotic platforms are highlighted.

Recent Findings SI is becoming a potential tool for autonomous platforms for non-destructive plant assessment. This is because it can provide information on the plant pigments such as chlorophylls, anthocyanins and carotenoids and supports quantification of biochemical parameters such as sugars, proteins, different nutrients, water and fat content. A plant suffering from diseases will exhibit different physicochemical parameters compared with a healthy plant, allowing the SI to capture those differences as a function of reflected or absorbed light.

Summary Potential of SI to non-destructively capture physicochemical parameters in plants makes it a key technique to support disease detection on autonomous platforms. SI can be broadly used for crop disease detection by quantification of physicochemical changes in the plants.

Keywords Imaging spectroscopy · Plant phenotyping · Plant pathogen detection · NIRS · Non-destructive · Spectroscopy · Rapid · Automation · Phenotyping

Introduction

Worldwide, plant diseases lead to major yield and quality losses in agriculture production systems [1]. Diseases are mainly caused by pathogenic microorganisms such as fungi, viruses, bacteria, mycoplasmas and protozoa [2]. Typically, diseases start with the introduction of a vector or infested plant material at a location, which in time spreads to neighbouring plants leading to significant damage, even before it is visible to humans. For detection of pathogens, different molecular and serological methods, such as enzyme-linked immunosorbent assay (ELISA) and polymerase chain reaction (PCR), can be used to target specific proteins and deoxyribose nucleic acid (DNA) sequences, respectively.

These molecular and serological methods provide a highly specific detection of pathogens; however, they are destructive and limited to the laboratory and require highly skilled manpower. Despite such detection being of high interest to scientific research towards understanding the plant-pathogen interactions, these methods cannot be used in situ for real-time detection of diseases in plants before the symptoms are visible. Furthermore, these destructive methods cannot be used to follow the progress of the disease or the effect of crop protection compounds that are being used to control the disease spread. Early detection of disease or disease symptoms using non-destructive sensors is of high interest as it can directly benefit the agricultural systems by reducing associated losses [3–5].

Early non-destructive disease detection in plants is a key emerging topic [6]. To accomplish this task, autonomous platforms are increasingly being implemented [7, 8]. An autonomous agricultural platform in field conditions can be understood as a robotic vehicle with a range of sensors integrated to

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it (an example: http://www.agrointelli.com/). An autonomous platform in greenhouse conditions can be understood as an automated platform supporting plant growth and monitoring with a range of sensors (an example: https://www.psb.ugent.be/phenotyping/phenovision). With advancements in non-destructive sensing and computing power, autonomous platforms are providing results and conclusions in real time, which were previously limited to days of experiments. In recent years, promising applications of spectral imaging (SI) are emerging for detecting disease in plants in the open field as [9•, 10•] combination of two complementary sensing modalities, i.e. spectroscopy and imaging, where the imaging captures the physical shape and structure of the plants and the spectroscopy captures complementary chemical properties of plants. In all, SI provides distribution of physicochemical properties of plants brought by the disease in a spatially preserving way.

In the present review, a small introduction of SI and what it can detect in relation to plant disease is explained. Furthermore, a comprehensive overview of the recent research related to disease detection in plants by using autonomous robotic platforms is provided. Key benefits and challenges of SI for plant disease detection, either in the greenhouse or in the open field, are highlighted, and future directions are outlined.

What Is Spectral Imaging?

SI combines traditional imaging with spectroscopy. Unlike colour red, green and blue (RGB) imaging SI refers to a group of techniques which captures more than just the red, green and blue wavelength bands. SI can be explored in different parts of electromagnetic radiation (EMR) ranging from the high-energy X-rays to the very low-energy microwaves [11]. A typical SI setup is composed of three main components: a light source, a spectrograph or filter system, and a detector for image generation. Based on the spectral range to be explored, the components are selected to meet the selectivity and sensitivity. The images generated by SI are three dimensional (3D) with two spatial ($x \times y$) and one spectral dimension (z). Particularly, in the spectral range of 400–2500 nm, the data is highly collinear and requires advanced multi-variate statistical tools to extract and model patterns. A better understanding of SI and data analysis can be found in recent reviews [12••, 13].

What Does Spectral Imaging Detect in Diseased Plants?

Plants, unlike animals, lack an adaptive immune system limiting their ability to adapt to diseases based on the memories from past infections [14]. However, due to a highly evolved genome, plants possess a wide range of resistance activities which can counteract the disease-causing pathogens. The resistance activities are activated as soon as the plant receives a signal about coming in contact with a potential vector. Plant defence includes morphological and structural changes at the cell wall, with a massive and directed reorganisation within the host cells; changes in gene expression and general metabolism [15, 16].

At first, the symptoms can be identified locally, where the vector interacted with the host tissue: early physiological and structural changes reflect a deviation in photosynthetic activity. Local symptoms might include changes in concentrations of photosynthetic pigments such as chlorophylls, changes in water content and an increase in plant defence-response metabolites. Changes in cell structure at the site of infection can also be noted utilising microscopic techniques. SI in the spectral range of 400–2500 nm is of high interest, as it can provide access to plant biochemical parameters. Specifically, the visible (VIS) part (400–700 nm) provides information on the plant pigments, such as chlorophylls, anthocyanins and carotenoids, and the near-infrared (NIR) (700–2500 nm) supports quantification of biochemical parameters, such as sugars, proteins, water and fat contents, and cell structure of plant tissues [12••, 17, 18]. SI captures this information by measuring the percent of light being reflected/absorbed at specific wavelengths. For example, chlorophyll absorption peaks at 465 and 665 nm, while water absorbs at approximately 1400 and 1900 nm. With a change in plant physiological status, the presence of these specific compounds will change, influencing the absorption in relevant spectral bands. Diseased tissue exhibits clear differences in physicochemical properties compared with a healthy tissue, which allows the SI to capture those differences in the function of reflected or absorbed light (400–2500 nm). Therefore, the information captured by SI can be extracted to develop models for disease detection and severity quantification.

Recent Applications

A large number of applications can be found that utilise SI for disease detection (Lowe et al., 2017) [19]. However, there exist a limited number of applications, where SI has been integrated with automated agricultural platforms. A summary of recent applications of SI for disease detection (past 5 years) is provided in Table 1. A separate column is presented to highlight if the study utilised an autonomous platform. A study excluding an autonomous platform can be understood as a future direction for the implementation of the disease-detection technique in autonomous platforms.

Table 1 Summary of recent works on disease detection on plants with spectral imaging

Disease	Autonomous	Material	Platform description	Spectral range	Data processing	References
Powdery mildew	Yes (green house)	Barley	Spectral imaging with automated sensor positioning system inside the greenhouse	VNIR (400–1000 nm)	Simplex volume maximisation (SiVM) and support vector machine (SVM)	[21••]
	No (laboratory conditions)	Barley	Imaging setup with translation stage for sample presentation	VNIR (400–1000 nm)	Linear discriminant analysis (LDA) and feature selection with ReliefF	[25]
Grey mould leaf infection (*Botrytis cinerea*, fungi)	Semi (indoor)	Tomato	Plant growth chamber with additional lightening to ensure uniform illumination	5 bands: red, green, blue, near-infrared and red-edge	Self-organising classifier to classify healthy and infected tissue	[3]
Potato Y virus (*Potyviridae*, virus)	Semi (field condition)	Potato	A tractor-mountable measurement box carrying spectral imager, protection from external lighting and embedded PC	VNIR (400–1000 nm)	Deep learning (fully convolutional neural network)	[10•]
Tulip break virus	Semi (field condition)	Tulip	Field rail system with hand driven trolley platform	RGB combined with NIR	Deep learning (Faster R-convolutional neural network)	[9•]
Sclerotinia sclerotiorum (fungi)	No (laboratory conditions)	Oilseed rape	Indoor setup with translation stage used for imaging the plants	VNIR (384–1034 nm)	Partial least square discriminant analysis, SVM, radial basis function neural network, emerging learning neural network to detect disease	[23]
Apple scab (*Venturia inaequalis*, fungus)	No (laboratory conditions)	Apple	Indoor spectral imaging setup with translation stage for samples presentation	SWIR (1000–2500 nm)	Partial least square discriminant analysis (PLS-DA)	[22]
Anthracnose (*Colletotrichum*, fungi)	Yes (field)	Strawberry	A mobile (4 wheels) platform with mounted spectral sensor (non-imaging)	VNIR and SWIR (350–2500 nm)	Vegetation indexes, step wise discriminant analysis (SDA), Fisher discriminant analysis (FDA), k-nearest neighbours (kNN)	[20••]
	No (laboratory conditions)	Strawberry	Imaging setup with translation stage for sample presentation	VNIR (400–1000 nm)	Spectral angle mapper (SAM), SDA, correlation measure (CM), partial least square regression (PLSR)	[26]
Downy mildew (*Peronosporaceae*, fungi)	Semi (green house)	Grapevine	Sensors and the light source arranged on a motorise line stage moving above the plants	Two systems: non-imaging: (350–2500 nm) and spectral imaging: (400–2500 nm) and (940–2550 nm)	SAM + 3 downy mildew indices	[27]
Early blight (*Alternaria solani*, fungi)	No (laboratory conditions)	Tomato	Imaging setup with translation stage for sample presentation	VNIR (380–1023 nm)	Extreme learning machine (ELM) classifier model, successive projections algorithm (SPA)	[24]
Fire blight (*Erwinia amylovora*, bacteria)	Semi (field condition)	Apple	Cameras mounted to an agricultural utility vehicle; an unmanned octocopter + multispectral camera	RGB combined with infrared + non-imaging VNIR and SWIR (350–2500 nm)	Vegetation indexes, PLSR and quadratic kernel support vector machine (QSVM)	[28]
Late blight (*Phytophthora infestans*, fungi)	No (laboratory conditions)	Tomato	Imaging setup with translation stage for sample presentation	VNIR (380–1023 nm)	Extreme learning machine (ELM) classifier model, successive projections algorithm (SPA)	[24]
		Cucumber		946 nm to 2016 nm	PLS-DA, least square S-SVM	[29]

Table 1 (continued)

Disease	Autonomous	Material	Platform description	Spectral range	Data processing	References
Mosaic virus (various genera, virus)	No (laboratory condition)		Imaging setup with translation stage for sample presentation			
Target and bacteria spots	No (laboratory condition)	Tomato	Non-imaging spectrometer	350–2500 nm	Vegetation indexes	[30]
Cercospora leaf spot (*Cercospora beticola*)	No (laboratory condition)	Sugar beet	Imaging setup with translation stage for sample presentation	460–850 nm	Vegetation indexes and spherical k-means	[31]

Recent studies show that automated SI for plant disease detection is used either in a field or in a greenhouse setting. In the field, there are three main automation approaches being implemented: first is a fixed rail-guided system, where the mobile platform travels over the plant lines and continuously captures the images. Such a system was successfully used by Gerrit Polder et al. (2019) for the tulip break virus (TBV) detection in the standing plants. The second type of field system includes a platform mounted on autonomous tractors. A tractor-mountable system was successfully implemented by [10•] for potato Y virus detection utilising a measurement box mounted in front of the tractor, carrying a spectral imager, protection from ambient lighting and an embedded PC. The third type of field systems is autonomous vehicles with integrated sensors, scouting the fields. Such a 4-wheel system with mountable spectral sensors was utilised by [20••] to detect anthracnose in strawberry plants. However, the application utilised a point spectrometer rather than SI. In the greenhouse scenario, the automation involves either automated movements of plants to the sensor compartments (via tracks or rails) or the movement of sensors to the plants for data acquisition. In recent work, [21••] utilised an automated greenhouse for detecting powdery mildew in Barley, where an automated sensor positioning system travelled amongst the plant pots for imaging.

The major data processing approaches for utilising SI for disease detection included the use of vegetation indexes [20••], chemometric methods such as partial least square regression (PLS) [22], machine learning methods such as support vector machines (SVMs) [23], self-organising classifiers (SOC), extreme learning machines (ELM) [24] and deep learning (DL) approaches such as convolutional neural networks (CNN) [10•].

Discussion and Outlook

A range of applications related to the use of SI in the autonomous platform can be found; however, it can be understood from Table 1 that for the imaging applications, the spectral range used was mainly in the VNIR range (~400–1000 nm). There are two reasons for this. First, spectral cameras in the complete spectral range (400–2500 nm) are not available in the market. Sensing in the VNIR (400–1000 nm) and the SWIR (1000–2500 nm) range requires different electronic detectors, meaning multiple cameras need to be purchased and applied. Second, the cost of SWIR is almost 5 times compared with the VNIR sensors, making the VNIR the preferred choice for integration with the autonomous setups. Furthermore, VNIR range has the benefit that it captures the signal of photosynthetic pigments, which is present only in the spectral range of about 400–700 nm, as well as the 3rd overtones of proteins, fats and moisture present in the range of 700–1000 nm.

Due to the possibility of SI to capture a wide range of the physicochemical parameter, SI can be used for untargeted plants disease detection, thus not looking for specific pathogens but rather capturing the overall symptoms or changes. This has a major benefit over destructive chemical methods which are focussed on identifying specific pathogens responsible for the damage. The main benefit of SI is its ability to non-destructively capture the spatially distributed spectral properties of plants which can be used to localise the spots of diseases in initial stages which might be missed by destructive analysis. The other major benefit of SI is the ability to perform a real-time detection during acquisition. Real-time detection can be performed by pre-training a model on a small calibration set and then deploying the model onboard an autonomous platform.

A major difficulty with the implementation of SI is the illumination effects caused by the interaction of light with the complex geometry of plants and their surroundings [12••]. Such an interaction of light causes scattering effects which may mask the real spectral responses. These effects should be corrected for before further data processing. Another challenge is the integration of white reference with the autonomous setup. White reference is required to calculate plant reflectance. Proper positioning of white reference with respect to the plants can reduce major differences in the illumination. However, there is no single solution and the positioning needs to be adapted for different types of plants and their growth stages.

Until now, most of the SI utilised line-scan cameras; however, new snapshot SI systems are emerging in the market which opens possibilities for easy implementation of SI to autonomous setups. In a technical perspective, the future direction should be towards an integration of multiple sensors with autonomous setups, such as the two spectral cameras (VNIR and SWIR) and the 3D-shaped sensors. Another step is their information fusion to deal with the illumination effects. Another major trend is the application of advance concepts from the deep learning domain, such as reinforcement learning and recurrent neural networks (RNNs). As one of the major benefits of integrating SI with autonomous platforms, we foresee the early identification of diseases via precision agriculture, which could lead to early application of plant protection products for sustainable farming practices. As presented in the work, currently, there is little literature on disease detection using spectral imaging on autonomous platforms. Given the fast developments in both affordable SI sensors and autonomous platforms, a huge increase in application can be foreseen.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

References

Papers of particular interest, published recently, have been highlighted as:
• Of importance
•• Of major importance

1. Savary S, Willocquet L, Pethybridge SJ, Esker P, McRoberts N, Nelson A. The global burden of pathogens and pests on major food crops. Nat Ecol Evol. 2019;3:430.
2. Lucas GB, Campbell L. Introduction to plant diseases: identification and management. Berlin: Springer Science & Business Media; 2012.
3. Fahrentrapp J, Ria F, Geilhausen M, Panassiti B. Detection of gray mold leaf infections prior to visual symptom appearance using a five-band multispectral sensor. Front Plant Sci. 2019;10. https://doi.org/10.3389/fpls.2019.00628.
4. Sankaran S, Mishra A, Ehsani R, Davis C. A review of advanced techniques for detecting plant diseases. Comput Electron Agric. 2010;72:1–13.
5. Martinelli F, Scalenghe R, Davino S, Panno S, Scuderi G, Ruisi P, et al. Advanced methods of plant disease detection. A review. Agron Sustain Dev. 2015;35:1–25.
6. Ali MM, Bachik NA, Muhadi NA, Yusof TNT, Gomes C. Non-destructive techniques of detecting plant diseases: a review. Physiol Mol Plant Pathol. 2019;108. https://doi.org/10.1016/j.pmpp.2019.101426.
7. Virlet N, Sabermanesh K, Sadeghi-Tehran P, Hawkesford MJ. Field scanalyzer: an automated robotic field phenotyping platform for detailed crop monitoring. Funct Plant Biol. 2017;44:143–53.
8. Shakoor N, Lee S, Mockler TC. High throughput phenotyping to accelerate crop breeding and monitoring of diseases in the field. Curr Opin Plant Biol. 2017;38:184–92.
9.• Polder G, Westeringh Nvd, Kool J, Khan HA, Kootstra G, Nieuwenhuizen A. Nieuwenhuizen, Automatic detection of tulip breaking virus (TBV) using a deep convolutional neural network. IFAC-PapersOnLine. 2019;52:12–7. **Use of novel deep learning in spectral imaging for detecting plant disease**.

10.• Polder G, Blok PM, de Villiers HAC, van der Wolf JM, Kamp J. Potato virus Y detection in seed potatoes using deep learning on hyperspectral images. Front Plant Sci. 2019;10. https://doi.org/10.3389/fpls.2019.00209. **Use of novel deep learning in spectral imaging for detecting plant disease.**
11. Li L, Zhang Q, Huang DF. A review of imaging techniques for plant phenotyping. Sensors-Basel. 2014;14:20078–111.
12.•• Mishra P, Asaari MSM, Herrero-Langreo A, Lohumi S, Diezma B, Scheunders P. Close range hyperspectral imaging of plants: a review. Biosyst Eng. 2017;164:49–67. **Key review paper describing the general application of spectral imaging in plant analysis**.
13. Lowe A, Harrison N, French AP. Hyperspectral image analysis techniques for the detection and classification of the early onset of plant disease and stress. Plant Methods. 2017;13. https://doi.org/10.1186/s13007-017-0233-z.
14. Singla J, Krattinger SG. Biotic stress resistance genes in wheat, in: reference module in food science. Amsterdam: Elsevier; 2016.
15. Madani B, Mirshekari A, Imahori Y. Chapter 19 - physiological responses to stress. In: Yahia EM, editor. Postharvest Physiology and Biochemistry of Fruits and Vegetables. Sawton: Woodhead Publishing; 2019. p. 405–23.
16. Jones JD, Dangl JL. The plant immune system. Nature. 2006;444: 323–9.
17. Jacquemoud S, Verhoef W, Baret F, Bacour C, Zarco-Tejada PJ, Asner GP, et al. PROSPECT plus SAIL models: a review of use for vegetation characterization. Remote Sens Environ. 2009;113: S56–66.
18. Wahabzada M, Mahlein AK, Bauckhage C, Steiner U, Oerke EC, Kersting K. Metro maps of plant disease dynamics-automated mining of differences using hyperspectral images. PLoS One. 2015;10: 1–20.
19. Mahlein AK. Plant disease detection by imaging sensors-parallels and specific demands for precision agriculture and plant phenotyping. Plant Dis. 2016;100:241–51.
20.•• Lu J, Ehsani R, Shi Y, Abdulridha J, de Castro AI, Xu Y. Field detection of anthracnose crown rot in strawberry using spectroscopy technology. Comput Electron Agric. 2017;135:289–99. **The study utilizes autonomous platform**.
21.•• Thomas S, Behmann J, Steier A, Kraska T, Muller O, Rascher U, et al. Quantitative assessment of disease severity and rating of barley cultivars based on hyperspectral imaging in a non-invasive, automated phenotyping platform. Plant Methods. 2018;14:1–12. **The study utilizes autonomous platform**.
22. Gorretta N, Nouri M, Herrero A, Gowen A, Roger J. Early detection of the fungal disease "apple scab" using SWIR hyperspectral imaging, In: 2019 10th Workshop on Hyperspectral Imaging and Signal Processing: Evolution in Remote Sensing (WHISPERS), 2019, pp. 1–4.
23. Kong WW, Zhang C, Huang WH, Liu F, He Y. Application of hyperspectral imaging to detect Sclerotinia sclerotiorum on oilseed rape stems. Sensors (Basel). 2018;18(1). https://doi.org/10.3390/s18010123.
24. Xie C, Shao Y, Li X, He Y. Detection of early blight and late blight diseases on tomato leaves using hyperspectral imaging. Sci Rep. 2015;5:16564.
25. Kuska MT, Behmann J, Namini M, Oerke EC, Steiner U, Mahlein AK. Discovering coherency of specific gene expression and optical reflectance properties of barley genotypes differing for resistance reactions against powdery mildew. PLoS One. 2019;14. https://doi.org/10.1371/journal.pone.0213291.
26. Yeh YH, Chung WC, Liao JY, Chung CL, Kuo YF, Lin TT. Strawberry foliar anthracnose assessment by hyperspectral imaging. Comput Electron Agric. 2016;122:1–9.
27. Oerke E-C, Herzog K, Toepfer R. Hyperspectral phenotyping of the reaction of grapevine genotypes to Plasmopara viticola. J Exp Bot. 2016;67:5529–43.
28. Jarolmasjed S, Sankaran S, Marzougui A, Kostick S, Si Y, Quirós Vargas JJ, et al. High-throughput phenotyping of fire blight disease symptoms using sensing techniques in apple. Front Plant Sci. 2019;10. https://doi.org/10.3389/fpls.2019.00576.
29. Lee H, Kim MS, Lim H-S, Park E, Lee W-H, Cho B-K. Detection of cucumber green mottle mosaic virus-infected watermelon seeds using a near-infrared (NIR) hyperspectral imaging system: application to seeds of the “Sambok honey” cultivar. Biosyst Eng. 2016;148:138–47.
30. Lu JZ, Ehsani R, Shi YY, de Castro AI, Wang S. Detection of multi-tomato leaf diseases (late blight, target and bacterial spots) in different stages by using a spectral-based sensor. Sci Rep. 2018;8. https://doi.org/10.1038/s41598-018-21191-6.
31. Leucker M, Wahabzada M, Kersting K, Peter M, Beyer W, Steiner U, et al. Hyperspectral imaging reveals the effect of sugar beet quantitative trait loci on Cercospora leaf spot resistance. Funct Plant Biol. 2017;44:1–9.

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