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HYPERSPECTRAL IMAGING FOR EARLY DETECTION OF FOLIAR FUNGAL DISEASES ON SMALL GRAIN CEREALS: A MINIREVIEW

***Maksims Fiļipovics**[1,2]
[1]Latvia University of Life Sciences and Technologies, Latvia
[2]Lithuanian Research Centre for Agriculture and Forestry, Lithuania
*Corresponding author's e-mail: maksims.filipovics@lbtu.lv

Abstract
Globally crop pathogens and pests cause significant yield and quality losses in agriculture production systems. Foliar fungal diseases of small grain cereals are economically among the most important diseases worldwide and in the Baltics. Finding an effective, reliable, and easily accessible method for plant disease diagnosis still presents a challenge. Currently used methods include visual examination of the affected plant, morphological characterization of isolated pathogens and different molecular, and serological methods. All of these methods have important limitations, especially for large-area applications. Hyperspectral imaging is a promising technique to assess fungal diseases of plants, as it is a non-invasive, indirect detection method, where the plant's responses to the biotic stress are identified as an indicator of the disease. Hyperspectral measurements can reveal a relationship between the spectral reflectance properties of plants and their structural characteristics, pigment concentrations, water level, etc., which are considerably influenced by biotic plant stress. Despite the high accuracy of the information obtained from hyperspectral detectors, the interpretation is still problematic, as it is influenced by various circumstances: noise level, lighting conditions, abiotic stress level, a complex interaction of the genotype and the environment, etc. The application of hyperspectral imaging in everyday farming practice will potentially allow farmers to obtain timely and precise information about the development of diseases and affected areas. This review provides an introduction into issues of hyperspectral imaging and data analysis and explores the published reports of worldwide research on the use of hyperspectral analysis in the detection of foliar fungal diseases of small-grain cereals.
Key words: hyperspectral image cube, data analysis, spectral vegetation indices, computer vision, machine learning, deep learning.

Introduction

Human population relies heavily upon consistent and stable production of crops. One of the most important groups of crops in the Baltics is small grain cereals – wheat (*Triticum aestivum L.*), rye (*Secale cereale L.*), oat (*Avena sativa L.*) and barley (*Hordeum vulgare L.*), (Official statistics portal of Latvia (2023); Official statistics portal of Lithuania (2023) Statistics Estonia; (2023)).

Conventional and integrated cultivation of small grain cereals involves intensive fungicide application because these crops are susceptible to many fungal diseases. Most common fungal leaf diseases of small grain cereals in the Baltics are caused by the following pathogens: *Blumeria graminis, Parastagonospora nodorum, Puccinia recondita, Puccinia striiformis, Zymoseptoria tritici, Fusarium spp., Rhynchosporium secalis, Pyrenophora teres, Pyrenophora avenae* and *Pyrenophora tritici-repentis* (Sooväli & Koppel, 2003; Semaškiene & Ronis, 2004; Skuodienė & Nekrošienė, 2009; Bankina *et al*., 2011; Gaurilčikiene *et al*., 2011; Bankina *et al.*, 2013).

Plant health monitoring and early pathogen detection are critical to reduce the spread of disease and promote effective management practices. For pathogenic fungi detection and severity evaluation, three methods are currently used: (i) visual examination of diseased plants; (ii) pathogen identification on morphological features; (iii) molecular and serological methods (Martinelli *et al*., 2015). Visual disease examination by the agronomist or plant pathologist is mostly used in everyday farming, especially in small farms, but along with some advantages, like low costs, speed, the possibility to evaluate the status of infection, and no need for expensive infrastructure, there are some crucial limitations including high variability of conclusions due to different levels of individual knowledge and experience, human error and difficulty/impossibility to precisely monitor a large area of the crop (Bock *et al*., 2010; Martinelli *et al*., 2015). Additionally, visual examination of some fungal diseases is ineffective in the early stages, when there are no visual symptoms, such as lesions on the surface of the leaves, and only physiological/biochemical response mechanisms of plants, such as the reduction of the photosynthesis, are involved (West *et al.*, 2003). Identification of pathogens based on morphological features involves the isolation of fungal pathogens on suitable standard agar medium and analysis of culture characteristics, e. g. colony morphology, color, and asexual structures like sporangia, conidia, chlamydospores, sclerotia, etc. Light microscopes are used to study fungal structures (sporangia, conidia, and others), and the conclusions about the taxonomy and classification of a pathogen are based on the characteristics of the listed structures (Narayanasamy, 2011). This approach is more accurate than visual assessment. However, it also involves expensive infrastructure, and it is restricted to large-scale applications, and *in vitro* cultivation is time-consuming (Narayanasamy, 2011). Molecular and serological methods mostly involve PCR (Polymerase Chain Reaction), hybridization, or biochemical assays. Molecular and serological methods are accurate and very sensitive, but they are restricted to large-scale applications, because of complicity and costs. They are unsuitable for disease status monitoring as they involve collecting samples mostly from plants with already clearly visible symptoms of disease; in some cases, it may misrepresent the real status of infections. Besides, molecular and serological methods require detailed sampling procedures, as well as expensive infrastructure (Martinelli *et al.*, 2015; Kashyap & Kumar, 2021).

Combining recent discoveries in microelectronics, optics, and data analysis an innovative and technology-based optical method, hyperspectral imaging has been developed, which can be also applied to a plant disease detection. Hyperspectral imaging is easy to use, non-destructive, and can be implemented in automated systems (e.g. unmanned aerial vehicles), considerably lowering workload (Mahlein, 2016). The main idea of using hyperspectral imaging is to measure the relationship between the spectral reflectance properties of plants and their structural features, pigment concentrations, water levels, etc., which are affected by plant biotic stress (Mahlein, 2016).

Materials and Methods

In the present study, the monographic method was used. The results of worldwide research on the use of hyperspectral analysis in the detection of foliar fungal diseases of small grain cereals (wheat, rye, oat, and barley) were studied as well as overall issues of hyperspectral imaging and data analysis were analysed and summarized.

Results and Discussion

Basic principles of hyperspectral imaging

Contrary to widely used consumer digital cameras which capture only three bands of the electromagnetic spectrum (red, green, and blue light), a hyperspectral sensor measures up to several hundred bands of the electromagnetic spectrum in the wavelength range of visible (400–700 nm), near-infrared (700–1000 nm) and short-wave infrared (1000–2500 nm) part of the electromagnetic spectrum (Lowe, Harrison, & French, 2017; Thomas *et al.*, 2018). Each pixel in a hyperspectral image acquires a different set of information about the reflectance (or transmittance) in each spectral band, and the sum of this information is called the spectral signature or spectral profile (Delalieux *et al.*, 2007; Mahlein *et al.*, 2013; Rumpf *et al.*, 2010).

Interactions between plant biophysical (e.g. leaf surface, tissue structure) and biochemical properties (e.g. pigment and water content) determine the patterns of leaf reflectance spectra (Blackburn & Ferwerda, 2008). Generally for green leaves, the visible light (VIS) region of electromagnetic radiation (400–700 nm) is responsible for light absorption by photosynthetic and other pigments; the near-infrared (NIR) region (700–1100 nm) is dominated by dry matter absorption; and in the shortwave infrared (SWIR) region (1100–2500 nm) water absorption occurs (Mishra *et al.*, 2017). Significant changes in leaf reflectance induced at specific wavelengths in the visible (380–750 nm) and far-red (690–720 nm) ranges are more important than changes in reflectance in other regions of the electromagnetic spectrum to diagnose biotic stress (Carter, 1994 cited by Marín-Ortiz *et al.*, 2020; Carter & Knapp, 2001).

Non-imaging hyperspectral sensors measure the average spectral reflectance in the field of view without spatial information. The area with a full spectral profile is obtained, the size of the area covered depends on the focal length, the angle of view, and the distance from the target. Because symptoms of early plant diseases often appear at sizes smaller than 1 mm, the use of non-imaging sensors for disease detection in some situations is limited (Thomas *et al.,* 2018). This is why hyperspectral imaging offers much higher capabilities in disease detection.

Imaging hyperspectral sensors or hyperspectral cameras obtain image data with spatial and high spectral resolution (Terentev *et al.*, 2022). Mostly the cameras are divided by spectral range: (i) visible and near-infrared (VNIR) cameras have a spectral range of 400–1000 nm and (ii) short-wave infrared (SWIR) cameras provide a spectral range of 900–2500 nm (Moghadam *et al.*, 2017; Bohnenkamp *et al.*, 2021) and by the spectral scanning type: push-broom, point scan, and snapshot (Kim & Cho, 2019; Mishra *et al.*, 2020). In recent years, a wide range of mini and medium-sized hyperspectral cameras for reasonable prices have been developed, and they can be used to capture small-size features of vegetation (at leaf and canopy level) including investigation of crop growth status, detection of early signs of crop stress caused by disease, weeds, nutrition deficiency, etc. (Lu *et al.*, 2020).

A hyperspectral imaging system consists of four main elements: (i) a camera, (ii) a light source, (iii) a sample stage (no obligate), and (iv) corresponding control software (Morais *et al.*, 2019). The main elements of the imaging unit are the lenses, an imaging spectrograph, and an area detector. The light from the object passes through the objective lenses and enters a spectrograph. A spectrograph is a device used to disperse light into specific wavelengths. The scattered light is projected onto a detector that converts the photons into electrical signals that can be measured as the strength of different wavelengths into intensity values. Mostly there are two types of detectors – charge-coupled-device (CCD) camera or complementary metal-oxide-semiconductor (CMOS) camera (Mishra *et al*., 2017; Morais *et al*., 2019).

Different environmental conditions affect the results of hyperspectral imaging, of which lighting is the most important. The lighting system should provide adequate light intensity and composition without critical prevalence in a specific wavelength range, including sunlight other light sources such as tungsten halogen lamps (with different modifications), mercury or metal halide lamps, and light-emitted diodes (LED), can be used, each of the light sources has its advantages and limitations (Mahlein *et al.*, 2015). For the lighting calibration the measurement of reference material, with known reflection is another obligatory element to normalize the images (Lowe, Harrison, & French, 2017).

Data analysis

Hyperspectral imaging involves the integration of two acquisition modes: spectroscopy and imaging (Amigo, Babamoradi, & Elcoroaristizabal, 2015). A camera detects spectral signatures and spatial information from the surface of an object within the sensor field of view. A hyperspectral image consists of a series of narrow-band sub-images arranged across the reflectance spectrum, forming a 3-D cube or spectral hypercube (Amigo, Babamoradi, & Elcoroaristizabal, 2015; Mishra *et al.*, 2017). The hyperspectral curve obtained by measuring plant leaves contains noise and variations of structural features, so there is a need to do some curve transformations that should be performed before spectral analysis to describe the spectral curve more accurately and according to the most important structural features (Song *et al*., 2011). Generally, information gathering from hyperspectral images requires the following steps (methods): (i) preprocessing treatment, (ii) feature extraction, (iii) analysis, and (iv) acquisition of desired information (Bravo *et al*., 2003; Morais *et al.*, 2019).

From a plant disease detection perspective, different data analysis methods are used to answer three main questions: (i) Is the disease present? (ii) What specific disease is affecting the plant? and (iii) How severe is the disease (quantifying the degree of severity)? There are two main approaches to answering those questions: (i) the use of spectral vegetation indices or (ii) the use of computer vision, machine learning, and deep learning methods.

Besides detecting the presence of disease, an important task for image analysis is to distinguish between different diseases and identify a specific pathogen. A possible solution is spectral information divergence classification, which compares the deviation between the observer spectra and reference spectra (spectral library or averaged spectra of interest from the data), where similarity is based on the smaller deviation value. If the divergence value between the observed spectrum and a reference spectrum is larger than a set threshold, the observed spectrum is not classified as matching the reference spectrum (Du *et al*., 2004).

Spectral Vegetation Indices (SVI) is a widely used approach for analyzing and detecting changes in plant physiology and chemical composition (Mahlein *et al.*, 2013). The indices are based on the reflectance (or absorption) of certain wavelengths and are designed to evaluate various plant parameters, such as pigment content (Blackburn, 1998), leaf area (Rouse *et al.*, 1974 cited by Bravo *et al.*, 2003) or water content (Peñuelas *et al*., 1993 cited by Mahlein *et al.*, 2013). Usually, a particular spectral vegetation index has a quantitative relationship to a specific trait of interest, i.e. the pigment or water content of the products (Mahlein *et al.*, 2013). Spectral vegetation indices are evaluated using a specified formula, which usually combines the reflectance of a few bands into a single index. One of the most commonly used spectral vegetation indices is the Normalized Difference Vegetation Index (NDVI) (Rouse *et al.*, 1974 cited by Bravo *et al.*, 2003) it is used to estimate biomass, plant vitality, and 'greenness'. The popularity of NDVI is linked to its potential for application at the field scale, its ability to separate vegetation and soil, or evaluate the vitality of the crop (Bravo *et al.*, 2003). There are also other common SVIs: Red edge normalized ratio ($NR_{red\ edge}$); Photochemical reflectance index (PRI); Green chlorophyll index (Cl_{green}); Carotenoid reflectance index (CRI); Simple ratio index (SRI); Water index (WI); Moisture stress index (MSI), etc. (Lowe, Harrison, & French, 2017; Zhang & Zhou, 2019).

Several successful efforts have been also made to apply spectral vegetation indices for the detection of plant diseases (Hatfield *et al.*, 2008), but wide-scale usage for specific disease detection has not been attempted, because these indices lack disease specificity and do not assess other factors, such as abiotic stress, coupled biotic stress factors, etc. (Mahlein *et al.*, 2013). A possible solution could be the combination of different wavelengths with spectral disease indices which allows the detection of the disease with spectral sensors, considering that each disease has a specific spectral signature (Mahlein *et al.*, 2013).

As an example, the health index is based on the normalized reflectance difference at 534 to 698 nm and the absolute reflectance at 704 nm. The health index can be combined with the powdery mildew index, which is calculated on the normalized reflectance difference of 520 and 584 nm and the absolute reflectance at 724 nm (Mahlein *et al.,* 2013). Generally, disease detection based on spectral vegetation indices or spectral disease indices is characterized as a simpler method, which doesn't include complicated data analysis, data library collection, and machine learning, but the main disadvantage is low specificity and a narrow possibility to use it for early disease detection.

A direction with higher practical application potential is data analysis using machine learning, deep learning, and computer vision methods. The deep learning approach is based on different neural networks (convolutional, artificial, radial basis function neural networks, etc.), and the difference is related to the used vision system (Arens *et al.*, 2016; Lowe, Harrison, & French, 2017; Ramya *et al.*, 2020). Artificial neural networks are interconnected collections of nodes called 'neurons' where every 'neuron' analyses one element of input data or one pixel of the image (Ramya *et al.*, 2020).

The machine learning approach is based on an algorithm to model knowledge of data, in other words, it is a data analysis technique that teaches computers (artificial intelligence) to do what humans and animals naturally learn from experience. There are four types of machine learning: unsupervised learning, semi-supervised learning, supervised learning, and reinforcement learning (Ramya *et al.,* 2020).

Generally, deep learning is more complex than disease detection based on vegetation indices, but with the added efforts very impressive rates of classification and recognition are achievable.

Hyperspectral imaging application for foliar fungal disease detection on small grain cereals

In the last couple of decades, a lot of research has been done involving the use of hyperspectral imaging for the detection of disease or severity evaluation of fungal disease of small grain cereals, but most often in wheat. Some examples are analysed below.

Zhao *et al*. (2014) studied the severity of yellow rust (caused by *Puccinia striiformis*) on individual plant leaves of wheat using a field portable hyperspectral spectrometer. The results indicated that changes in the content of foliar water and chlorophyll were induced by yellow rust, but the reflectance values varied depending on the adaxial or abaxial surfaces of the leaf. Authors conclude that hyperspectral measurements of wheat leaves to evaluate severity are more appropriate at later stages of disease development (Zhao *et al*., 2014). Guo *et al.* (2020) examined the possibility of yellow rust identification on wheat leaves based on spectral and textural features of hyperspectral images. A support vector machine and different features (optimum wavebands, vegetation indices, and textural features) were used with the best results reached when the models included a combination of both spectral and textural features (Guo *et al.,* 2020).

Infection of plants by wheat powdery mildew (caused by *Blumeria graminis* f. sp. *tritici*) was studied by Zhang *et al.* (2016) using hyperspectral imaging analysis to detect the effect of differentiating background (shadows) on the effectiveness of identification of infected and healthy plant leaves. Five different vegetation indices and classification and regression trees were used to analyze the data. Healthy leaves were identified with the highest accuracy of 99.2%, while infected leaves were determined with an accuracy of 88.2% and 87.8%, respectively (Zhang *et al.*, 2016). In another study of powdery mildew, a hyperspectral imaging dataset and machine learning algorithms were used (Zhao *et al.,* 2020). Three methods were compared – random forest, principal component analysis, and the successive projections algorithm. The highest accuracy of 93.33% by a cross-validation method was reached by applying a support vector machine model based on principal component analysis (Zhao *et al.,* 2020).

For Septoria tritici spot disease detection and severity assessment, a hyperspectral data library of the canopy from 335 wheat cultivars was collected using a spectroradiometer by Yu *et al.* (2018). The authors obtained the following results: (i) canopy reflectance and selected indices could be used to quantify Septoria tritici patches, and (ii) the best efficiency was achieved, using normalized difference water index with an accuracy of 93% (Yu *et al.*, 2018). On 18 different wheat genotypes and disease-free plots, Anderegg *et al*. (2019) collected time-resolved hyperspectral reflectance data from the canopy. The lack of specificity and disease assessments were confirmed by gained results although used data analysis methods based on reflectance spectra at individual time points were indicative of the presence and severity of Septoria tritici blotch infections.

A microscope with a hyperspectral camera was used to study the interaction between powdery mildew and barley genotypes with high susceptibility by Kuska *et al.* (2017). Qualitative and quantitative assessments of pathogens were used to explain changes in hyperspectral signatures. Analysis of hyperspectral images which reflects the development of the disease revealed spectral characteristics of hyperspectral response against the pathogen. Hypersensitive response spot localization was based on an advanced data mining approach before the spots became visible on the RGB images. Gained results show that sensor-based phenotyping is suitable to facilitate expensive and time-consuming visual assessment of plant disease resistance (Kuska *et al.*, 2017). In another research barley plants inoculated with powdery mildew, brown rust (caused by *Puccinia hordei*), and net blotch (caused by *Pyrenophora teres*) were studied using data mining techniques of hyperspectral time-series image datasets (Wahabzada *et al.*, 2015). The authors were able to identify differences between the symptoms of three pathogens and illustrate the crucial trends of spectra during disease development on barley plants (Wahabzada *et al.,* 2015).

Most of the studies were conducted in controlled conditions and inoculation was done by known pathogens; however, in field conditions plants are exposed to abiotic stresses, such as salinity, extreme temperature, nutrient stress, or drought, resulting in decreased plant defence capacity and increased susceptibility to biotic stresses that cause additional changes into disease detection models (Mittler & Blumwald, 2010; Szittya *et al*., 2003; Zhu *et al.,* 2010). Additionally, some studies have revealed that plants prioritize their responses to attain one of the individual stresses which involved in combination of biotic and abiotic stress combinations (Atkinson *et al.,* 2012; Schenke, Bottcher, & Scheel, 2011). Therefore, analysing hyperspectral data gained in field conditions abiotic stress factors should be considered (Suzuki *et al.*, 2014).

Conclusions

1. There has been a significant increase in the scientific literature over the recent couple of decades, focusing on detecting biotic and abiotic stress in plants using hyperspectral image analysis.
2. Early detection of crop diseases would allow controlling the spread of the disease more effectively, thus reducing yield and quality losses and minimizing the negative impact of agriculture on the environment.
3. One of the main reasons for the increase in usage of hyperspectral imaging is the reduction of the costs of a camera and the improvement of technical parameters.
4. The number of vegetation and disease indices is increasing, the combination of different indices and significant wavelengths can improve the effectiveness of disease status indication; however, the accuracy is affected by other abiotic/biotic factors.
5. Computer vision, machine learning, and deep learning methods have a great potential for practical application in the future although currently there are not many successful examples of usage for the detection of fungal diseases of small grain cereals.

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