# PLANT DISEASE DETECTION BY MEANS OF REMOTELY SENSED HYPERSPECTRAL LEAF REFLECTANCE DATA

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***Abstract:*** *Plant disease detection with remote sensing techniques, based on hyperspectral reflectance measurements, is a challenging area that can have a significant economic and environmental impact on agricultural yield management. Leaf spectral reflectance is a sensitive indicator of a variety of environmental factors affecting plants such as stress, diseases, drought, and senescence. This study aims to relate changes in plant physiological status caused by a biotic stress (viral infection) to leaf spectral reflectance and to identify wavebands that best discriminate this disease. Young potato plants, cultivar Armada, infected with Potato Virus Y (PVY) are investigated. Hyperspectral reflectance data were collected by a portable fiber-optics spectrometer in the visible and near-infrared spectral ranges (400–1100 nm). Wavebands with most disease sensitivity were identified by means of four empirical approaches and statistical analyses (Student's t-test, cluster analysis). The results demonstrate that hyperspectral reflectance data in red and red edge spectral ranges (680–740 nm) allow detection and quantification of plant stress due to viral infection and are most sensitive to related changes in biophysical parameters.*

# УСТАНОВЯВАНЕ НА ЗАБОЛЯВАНИЯ НА РАСТЕНИЯ ЧРЕЗ ДИСТАНЦИОННИ ХИПЕРСПЕКТРАЛНИ ДАННИ ЗА ОТРАЗЕНАТА ОТ ЛИСТАТА РАДИАЦИЯ

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***Ключови думи:*** *хилерспектрални дистанционни изследвания, спектрално отражение на листата, вирусна инфекция, позиция на червения ръб*

***Резюме:*** *Откриване на болести по растенията чрез метод за дистанционни изследвания, базиращ се на хиперспектрални измервания на отразена радиация, е предизвикателна област, която може да окаже значително икономическо и екологично въздействие върху управлението на добивите в селското стопанство. Спектралното отражение на листата е чувствителен показател за различни фактори на околната среда, влияещи върху растенията като стрес, болести, суша и стареене. Това проучване има за цел да свърже промените във физиологичното състояние на растенията, причинени от биотичен стрес (вирусна инфекция) и да идентифицира спектралните диапазони, които най-добре разграничават това заболяване. Изследвани са млади картофени растения сорт Армада, заразени с картофен вирус Y (PVY). Хиперспектралните отражателни данни са регистрирани с преносим спектрометър във видимата и близката инфрачервени области на спектъра (400–1100 nm). Вълновите диапазони с най-голяма чувствителност към болестта бяха идентифицирани с помощта на четири емпирични подхода и статистически анализи (t-тест на Стюдънт, клъстерен анализ). Резултатите показват, че хиперспектралните отражателни данни в червения спектрален диапазон и в червения ръб (680–740 nm) дават възможност за установяване и количествена оценка на растителния стрес поради вирусната инфекция и са най-чувствителни на промените във биофизичните параметри.*

## Introduction

The reliable detection and identification of plant disease and plant stress are very essential for preventing the loss in yield of the agricultural crops [1]. Monitoring of plant health and detecting pathogens early are essential to reduce disease spread and facilitate effective management practices. It is difficult to monitor the plant diseases manually at each stage, which requires more effort and time. The traditional molecular methods such as serological assays and nucleic acid-based methods (PCR variants) are the most available and effective to confirm disease diagnosis, but they are not very reliable at the asymptomatic stage [2]. Remote sensing (RS) technologies are innovative and alternative methods for effective, reliable, and early detection of pathogen infections. RS techniques coupled with spectroscopy-based methods allow high spatialization of results, these techniques may be very useful as rapid preliminary identification of primary infections [3]. The RS scientific community defines plant disease monitoring as: detection (deviation from healthy), identification (diagnosis of specific symptoms among others and differentiation of various diseases), and quantification (measurement of disease severity, e.g., percent leaf area affected) [4].

RS techniques provide opportunities for non-destructive detection of plant diseases, especially hyperspectral technologies. RS is a technique obtaining information on an object by measuring the electromagnetic energy reflected/backscattered or emitted by the surface of the Earth [5]. The increased spatial resolution of recent satellite sensors and the decrease in the cost of data acquisition are making RS really competitive for the integration with traditional techniques. RS offers the advantages of a large amount of data from the spectral response and the possibility of working at different spatial scales, with available sensor resolution from a single leaf level to an entire region [3].

In scientific literature the methods for RS data analyses related to detecting of plant disease can be categorized into four groups: (1) correlation and regression analysis of disease presence and severity with spectral response in specific bands and/or intervals of electromagnetic spectrum [6, 7]; (2) assessment and derivation of spectral vegetation indices (SVIs), general or specifically introduced, sensitive to disease presence [8, 9]; (3) data mining algorithms applied to spectral data processing and feature extraction/selection for data dimensionality reduction [10, 11]; and (4) machine learning and classification techniques, parametric and non-parametric, supervised and unsupervised, for producing results which are classified depending on disease presence/ absence and possibly severity levels [3, 12, 13].

The plant spectral reflectance is a sensitive indicator of a variety of environmental factors affecting plants such as stress, diseases, drought, and senescence. Measurement of leaf reflectance is a fast, non-destructive method for plant health estimation which provides valuable insight into the physiological performance of the leaves. Reflectance data indicated consistent and diagnostic differences in the red edge portion (680–740 nm) of the spectrum among the various samples and populations of leaves. The red edge of the reflectance curves, the maximum slope between the red and near-infrared (NIR) wavelengths, is strongly correlated with the foliar chlorophyll (Chl) content and is a good estimator for stress monitoring [14]. The main red edge parameter, red edge position (REP), is the inflection point of the slope of the spectrum. REP is an important index that indicates the abrupt leaf reflectance change between 680 nm and 740 nm of the vegetation spectra caused by the combined effects of strong Chl absorption and leaf internal scattering [15]. Increases in the amount of Chl result in a broadening of the major Chl absorption feature centred around 680 nm, causing a shift in the slope and REP towards longer wavelengths [16]. Various techniques have been developed for the extraction of REP parameters from different sources of spectral data with minimized estimation error and improved performance.

This study aims to relate the leaf spectral reflectance to changes in plant physiological status caused by biotic stress (viral infection) and to identify wavebands that best discriminate this disease. Young potato plants, cultivar Armada, infected with Potato Virus Y (PVY) are investigated. Several techniques have been applied and compared for accurate estimating of the REP, such as the maximum of the first derivative, the Lagrangian interpolation method, the linear extrapolation method, the first derivative main peak decomposition.

### Spectral measurements

Young potato plants, cultivar Armada, grown in controlled greenhouse conditions were investigated. Some of the plants were healthy (control) and some were infected with Potato Virus Y (PVY). Leaf spectral reflectance data were collected from fresh detached leaves by a portable fibre-optic spectrometer USB2000 (Ocean Optics, USA) in the visible and NIR spectral ranges (450–850 nm) in 1170 narrow bands at a spectral resolution of 1.5 nm. The spectral reflectance characteristics (SRC) of the investigated plants were determined as the ratio between the reflected from the leaves radiation and this one reflected from the diffuse reflectance standard.

Data analyses

The application of RS data for plant disease assessment is relying on adequate and effective data processing techniques because they are intrinsically high dimensional. Especially when dealing with hyperspectral data, in order to extract the largest amount of information data, processing and analysis techniques are a crucial asset. The data processing methods used in this study are shown in Table 1.

Table 1. Applied methods

| REP technique | Equation | Subject | Reference |
|---|---|---|---|
| Maximum of first derivative of reflectance spectrum (MFD) | $FDR_{\lambda_i} = \left(R_{\lambda_{i+1}} - R_{\lambda_i}\right)/\left(\lambda_{i+1} - \lambda_i\right)$ <br> $REP = \lambda_{\max}\left(FDR_{(\lambda)}\right)$ | First derivative of the SRC in interval 680 nm – 760 nm | [16] |
| Lagrangian interpolation method | $A = \frac{FDR_{(\lambda_{i-1})}}{(\lambda_{i-1} - \lambda_i)(\lambda_{i-1} - \lambda_{i+1})}$ <br> $B = \frac{FDR_{(\lambda_i)}}{(\lambda_i - \lambda_{i-1})(\lambda_i - \lambda_{i+1})}$ <br> $C = \frac{FDR_{(\lambda_{i+1})}}{(\lambda_{i+1} - \lambda_i)(\lambda_{i+1} - \lambda_{i-1})}$ <br> $REP = \frac{A(\lambda_i + \lambda_{i+1}) + B(\lambda_{i+1} + \lambda_{i-1}) + C(\lambda_{i-1} + \lambda_i)}{2(A + B + C)}$ | First derivative of the SRC in interval 680 nm –760 nm | [16] |
| Linear extrapolation | Red line: $FDR = m_1\lambda + c_1$ <br> NIR line: $FDR = m_2\lambda + c_2$ <br> $REP = \frac{c_2 - c_1}{m_1 - m_2}$ | First derivative of the SRC (680 nm–694 nm and 724nm–760 nm) | [17] |
| First derivative main peak decomposition | | First derivative of the SRC | Used in this study |

1. Maximum of the first derivative (MFD)

First derivatives of the leaf reflectance spectra of healthy and infected potato plants were calculated using the equation in row 1 (Table 1). REP is determined as a maximum of the peak in the spectral range 680–760 nm. Extraction of REP, which is based on derivative analysis, minimizes interpolation and computation errors; it is one of the simpler curve fitting techniques [18].

2. Lagrangian interpolation method

The Lagrangian technique uses three points interpolation for estimating REP. It is applied to the first-derivative transformation of the reflectance spectrum. The technique fits a second-order polynomial curve to three bands, which need not be equally spaced, centered around the maximum slope position. A second derivative is then performed on the Lagrangian equation to determine the maximum slope position (equations at row 2 in Table 1) [16].

3. Linear extrapolation

The linear extrapolation technique is designed to mitigate the destabilizing effect of the double peak feature on the correlation between Chl and REP and track changes in slope near 700 nm and 725 nm, where derivative peaks (Fig. 1) occur [17]. The REP is calculated as the wavelength at the intersection of two straight lines (Eqs. at row 3 in Table 1) extrapolated through two points on the far-red flank and two points on the NIR flank of the red edge (680–740 nm) first derivative reflectance spectrum.

4. First derivative main peak decomposition

This method is applied when a double-peak feature is observed in the first derivative of the reflectance spectrum. The position and amplitude of the peak around 700 nm can be used as an estimator of the Chl content. The change in the amplitude of the second peak indicates the change of the biomass or/and the internal structure of the cellular tissue. The first peak is greater when the Chl effects dominate, which occurred during the initial and final stages of the plant cycle [19].

Results and discussion

The averaged SRC over all measurements (up to 30 areas) of healthy (control) and infected with PVY potato leaves are shown in Fig. 1a). The spectral reflectance of infected leaves increased in

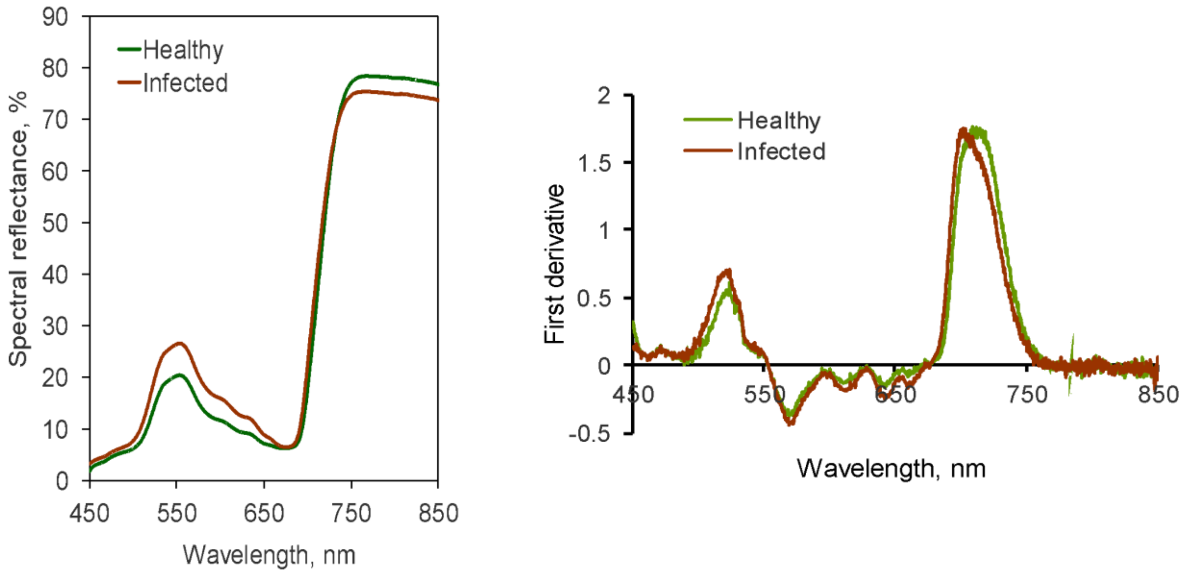


Fig.1 a) Averaged spectral reflectance characteristics (SRC) of healthy and infected potato leaves; b) first derivative curves of the averaged SRC of healthy and infected leaves

the green peak (500-670 nm) and decreased in the NIR range due to a reduction of the Chl content and changes in leaf tissue. The first derivative curves in the range of red edge wavelengths (Fig.1b) are shifted towards the shorter wavelengths because of the narrowing of the Chl absorption peak, centered around 680 nm. This shift is an indicator of the reduction of the Chl content in leaves and for changes in the physiological status of plants, respectively, for the presence of a disease. The spectral distribution of REPs of the reflectance spectra of all measured areas of healthy and infected leaves, obtained by the first derivative method, is shown in Fig. 2. Two separate clusters are being formed, testifying to significant changes of data in the red edge spectral range. The location of the REPs and the results of statistical analysis are given in Table 2.

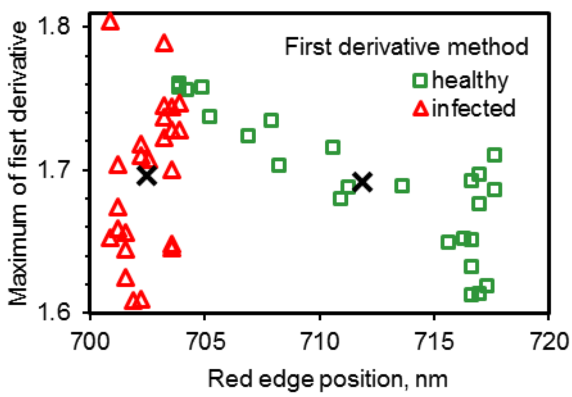


Fig. 2. REPs of the reflectance spectra of healthy and infected potato plants, cultivar Armada. The averaged REP values are shown by a black X.

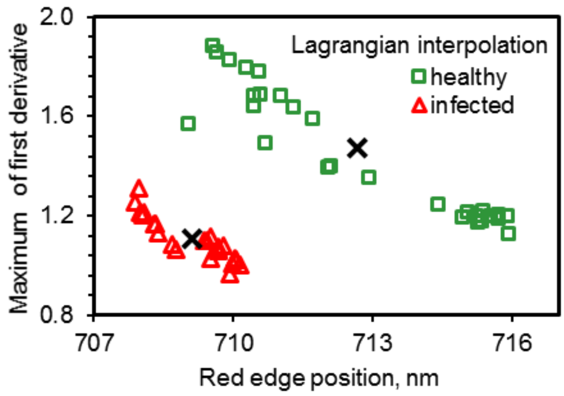


Fig. 3. REPs of the reflectance spectra of healthy and infected potato plants, cultivar Armada. The averaged REP values are shown by a black X

The three point Lagrangian interpolation technique was applied to the first derivatives of the reflectance spectra following the algorithm:

1. Wavelength $\lambda_{max}$ and the value of the maximum of the first derivative (MDF) at $\lambda_{max}$ were determined;

2. Values of the first derivative of the reflectance spectra at wavelengths 10 nm before and 10 nm after $\lambda_{max}$ were determined;

3. REPs were calculated by the equations in row 2 of Table 1.

The distribution of the REPs, calculated by the Lagrangian interpolation method, is shown in Fig. 3. Similar to the results from the first method two clusters are separated. The calculated REPs and the results from statistical analysis are given in Table 2.

Algorithm of the linear extrapolation method:

1. The slope on the far-red flank of the first derivative reflectance spectrum in red edge was extrapolated with a straight line through two points (680–694 nm);

2. The slope on the NIR flank of the first derivative reflectance spectrum in red edge was extrapolated with a straight line through two points (732–760 nm);

3. The REP was calculated as the wavelength at the intersection of two straight lines (equations at row 3 in Table 1).

The REPs are shown in Fig. 4 and the results from the statistical analysis are given in Fig. 4.

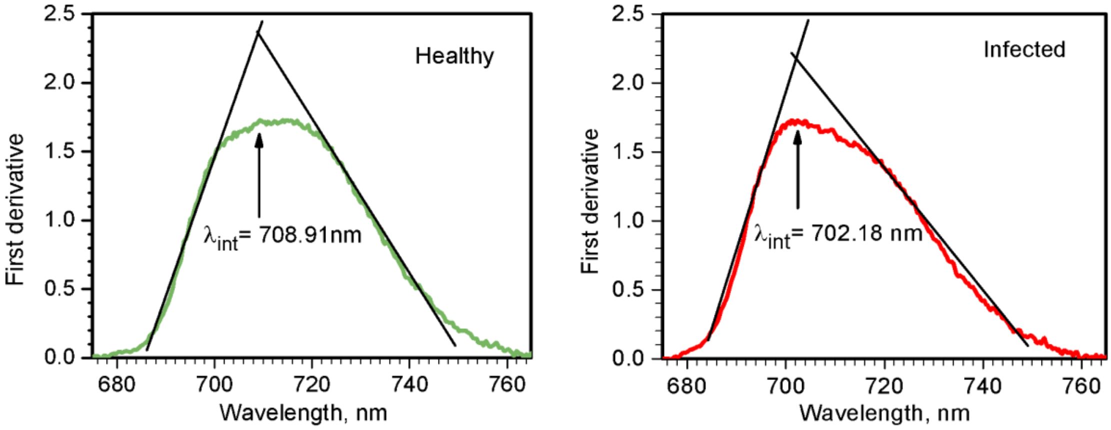


Fig. 4. Red edge position of the averaged SRC of healthy and infected potato leaves, cultivar Armada, obtained by the linear extrapolation method

Algorithm of the first derivative main peak decomposition (FDMPD):

1. FDMPD in the spectral range 670–770 nm was approximated by Origin software into two peaks. The best approximation was accepted this one with a maximum coefficient of determination $R^2$.

The wavelengths of the peak maximums are shown in Fig.5. The big peak position at 715 nm

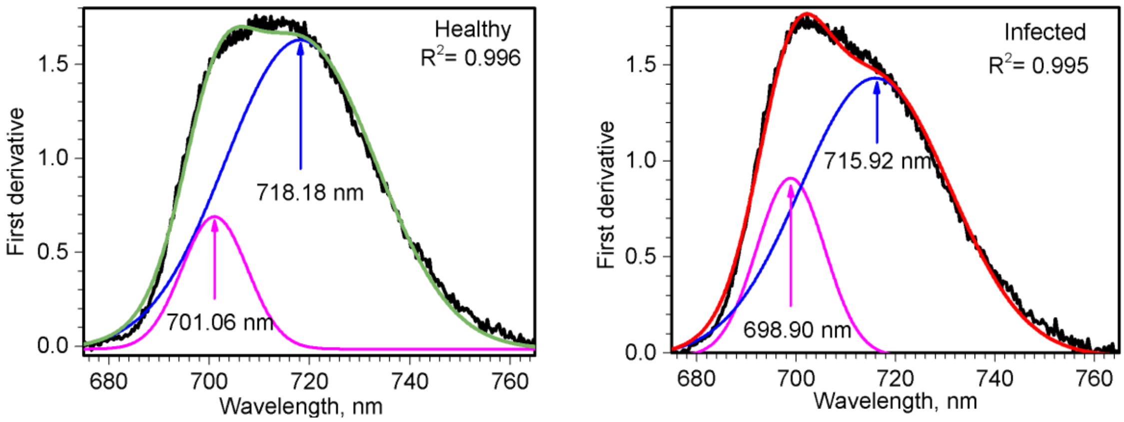


Fig. 5. Red edge position of healthy and infected potato leaves, cultivar Armada, obtained by the first derivative main peak decomposition method

to 720 nm is an estimator of the Chl content and it is shifted to the shorter wavelengths for infected leaves with 2.28 nm. The change in the amplitude of the second peak indicates the change in cell

Table 2. Results from statistical analysis (Student's t- test)

| Method | REP of SRC of healthy plants, nm | REP of SRC of infected plants, nm | t stat | p | Difference, nm | $\sigma_1$ | $\sigma_2$ |
|---|---|---|---|---|---|---|---|
| MFD | 711.89 | 702.48 | 9.12 | *** | -9.40 | 4.95 | 1.05 |
| Lagrangian interpolation | 712.67 | 709.14 | 6,74 | *** | -3.53 | 2.45 | 0.82 |
| Linear extrapolation | 694.30 | 689.35 | 19.64 | *** | -4.95 | 1.05 | 0.71 |

structure. The decrease of the amplitude and area of the first peak is related to the degradation of the leaf pigments, more strongly to the Chl. The results from statistical analysis (Student's t- test) of the REP datasets of the SRCs of healthy and infected leaves are given in Table 2, where $\sigma_1$ and $\sigma_2$ are the dispersions of the REPs distribution.

**Conclusions**

The red edge position of the reflectance spectra (680–740 nm) strongly correlated with the foliar Chl content and was extracted and evaluated from hyperspectral data as a good estimator for plant health. Four techniques for REP detection were applied and compared (maximum of the first derivative, Lagrangian interpolation method, linear extrapolation method, first derivative main peak decomposition). The best results were given by the Lagrangian interpolation method (the difference between REPs of SRC of healthy and infected potato plants is 3.53 nm). The maximum of the first derivative because of the destabilizing effect of the double-peak feature proved most inaccurate (difference - 9.4 nm). The results demonstrate that hyperspectral reflectance data in the red and red edge spectral ranges can be used to quantify the plant stress due to viral infection and related changes in biophysical parameters.

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