







Spectral Imaging for Plant Phenotyping

NMBU NOVA PhD course
15 • June • 2023, Gerrit Polder





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Introduction




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Introduction

- Gerrit Polder,
 - 30 years at Wageningen University & Research.
 - Senior scientist computer vision for plant phenotyping
- Background: Electronics/Applied Physics.
 - PhD on Spectral Imaging
- Aim of this lecture:
 - To introduce spectral imaging and show its value to applications in plant phenotyping.




Contact: gerrit.polder@wur.nl




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Properties to monitor




Width

Height




Physical structure
such as height,
width, number of
leaves etc.

Chemical components
such as chlorophyll,
anthocyanin, moisture
etc.

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Why spectral imaging?




Biosystems Engineering
Volume 164, December 2017, Pages 49-67


Review

Close range hyperspectral imaging of
plants: A review

Puneet Mishra^{a,*}, F.R. de Mol, Shahrin M. Mohd Asari^a, Ana H.
Belen Dierckx^a, Paul Scheunders^a




and internal structure of p
leaves



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


Puneet Mishra^{a,*}, Gerrit Polder^a & Anastasia Vilioti^a


Current Robotics Reports 1, 43-48 (2020) | Cite this article
2206 Accesses | Citations | Y Almetric | Metrics



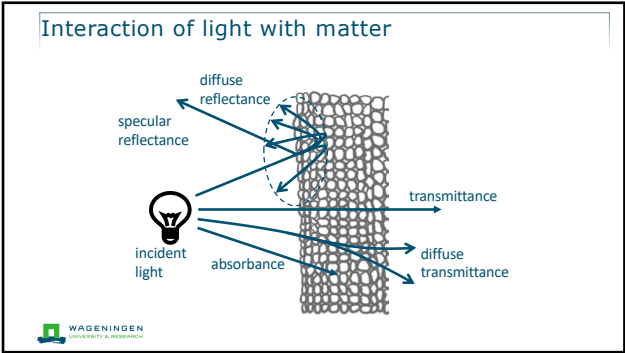
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Spectral Analysis

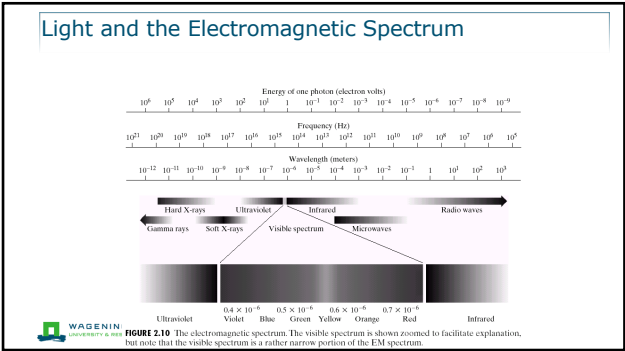




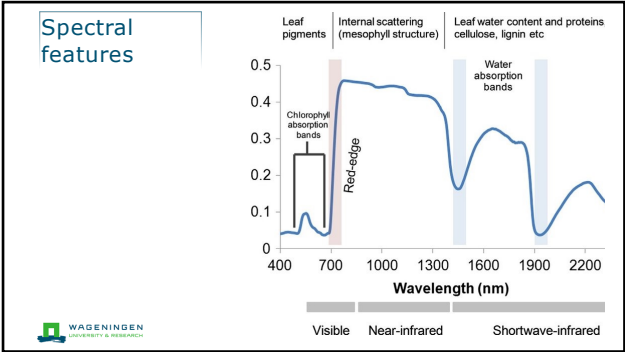
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Spectral Imaging

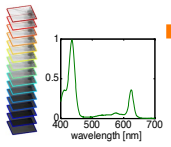




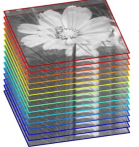
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spectral imaging – imaging spectroscopy


Spectroscopy




Imaging Spectroscopy



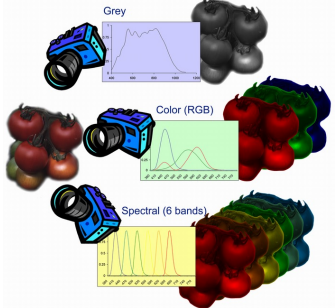
Imaging






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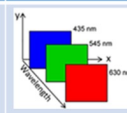
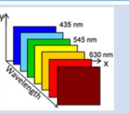
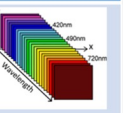


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Gerrit Polder, Wageningen University & Research

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Spectral imaging

Point Spectroscopy	Color Cameras	Multispectral Cameras	Hyperspectral cameras
			
High spectral but zero spatial info	High Spatial but very low spectral info	High spatial and moderate spectral info	High spatial AND spectral info

Source: <http://www.spectrazone.com/spectral-imaging/>

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The 'hype' in spectral imaging

- What is the meaning of hyperspectral?
- Over spectral imaging?
- Beyond spectral imaging?
- Exceeding spectral Imaging?
- Above normal spectral imaging?

Dictionary

hyper |ˈhɪpər|

adjective (informal)

hyperactive or unusually energetic: eating sugar makes you hyper.

ORIGIN

1940s; abbreviation of hyperactive.

hyper- |ˈhɪpər|

prefix

1 over, beyond, above: hypernym.

2 exceeding, hyperbolic.

3 excessively, above normal: hyperthyroidism.

4 relating to hypernatremia: hypernatremia.

ORIGIN

from Greek *hyper* 'over, beyond'.

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The 'hype' in spectral imaging

What's next?

Difference Between Multispectral and Hyperspectral Data

	Visible	SWIR	LWIR
Broadband			
Multispectral	Band 1: 45-52	Band 2: 52-60	Band 3: 60-68
Hyperspectral	100s of Bands		
Ultraspectral	1000s of Bands		

Source: Makki, Ihab. (2017). Hyperspectral Imaging for Landmine Detection.

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What about spectral data?

Hype

relative reflection

wavelength [nm]

Pixel

Spectral image

Y (time)

λ (spectral axis)

Usually with different x, y and λ dimensions, the data matrix is not a cube at all!

.....'images' are combined to form a three-dimensional (x,y,λ) hyperspectral data cube

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Hyperspectral analysis?

- Example of publications where the term hyperspectral analysis is used for normal point spectroscopy
- Hyperspectral analysis of soil polluted with four types of hydrocarbons**
- Hyperspectral Analysis of Leaf Pigments and Nutritional Elements in Tallgrass Prairie Vegetation**

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<https://aviris.jpl.nasa.gov>

Please note that we are working to use the terms "imaging spectroscopy" and "imaging spectrometer data" rather than "hyperspectral." This allows us to communicate more clearly with our physics, chemistry, and biology science colleagues.

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For further reading

JSI

G. Polder and A. Gowen, J. Spectral Imaging 9, a4 (2020)

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Peer Reviewed Letter

openaccess

The hype in spectral imaging

Gerrit Polder^a and Aoife Gowen^b

^aWageningen University & Research, Wageningen, Netherlands, E-mail: gerrit.polder@wur.nl

^bSpectral Imaging Research Group, School of Biosystems and Food Engineering, University College Dublin, Ireland, E-mail: aoife.gowen@ucd.ie

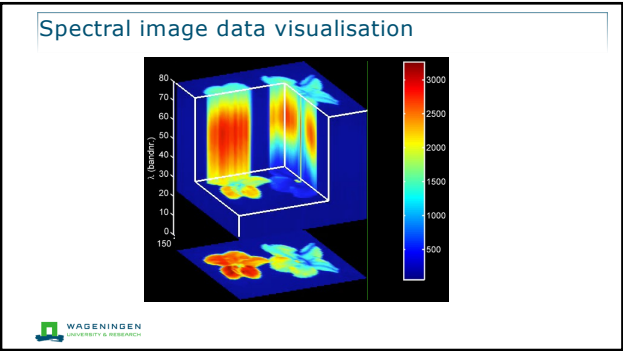
<https://doi.org/10.1255/jsi.2020.a4>



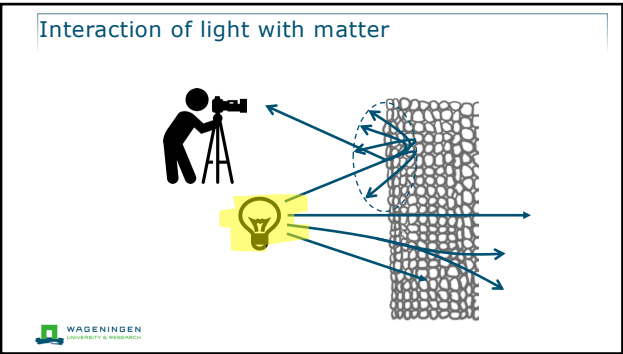


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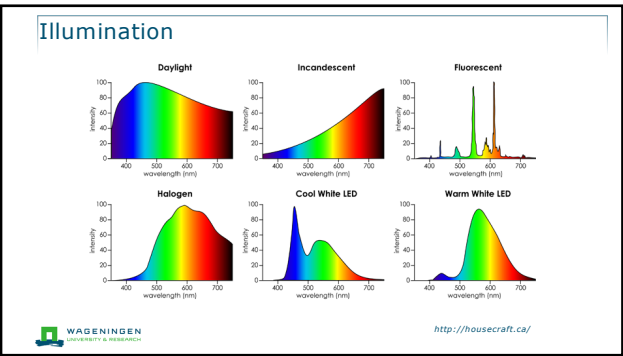
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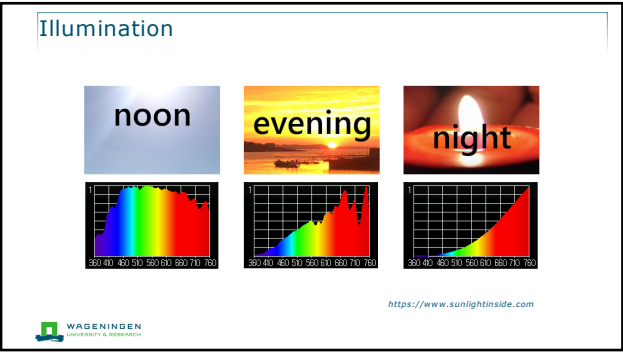
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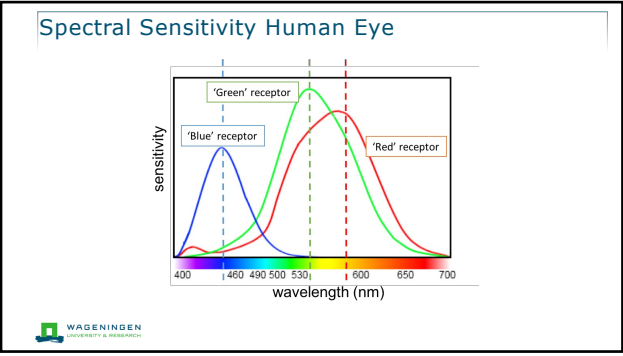
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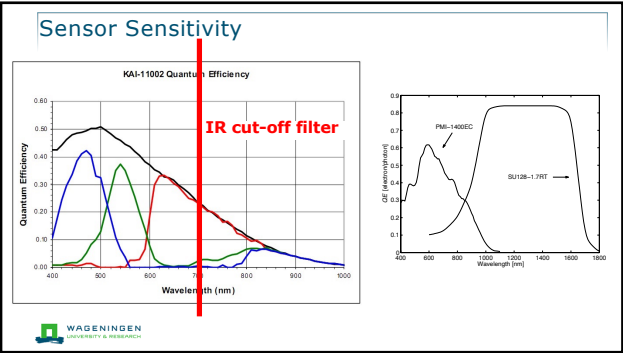
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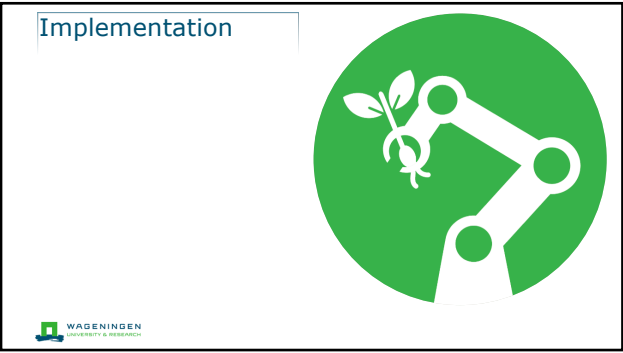
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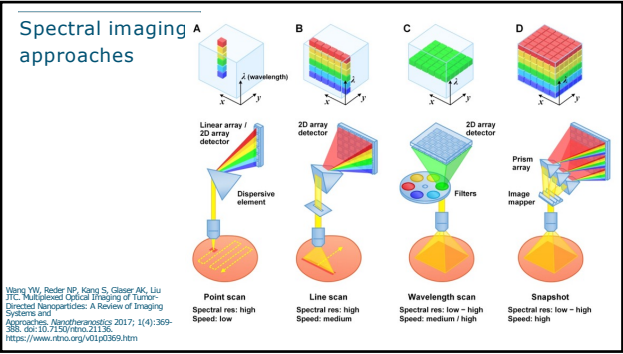
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Pushbroom spectrograph

- Slit-spectrometer collects a "wall" of data: pushbroom allows acquisition of a complete data cube.

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Some examples of cameras

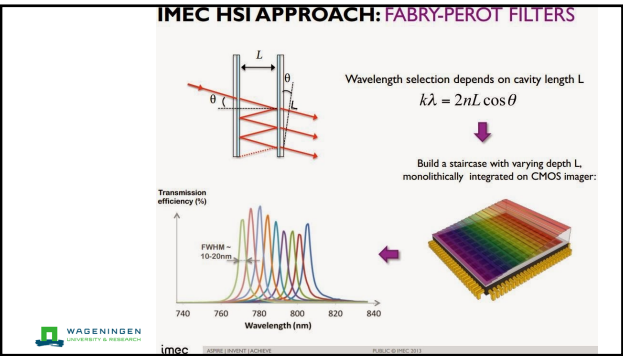
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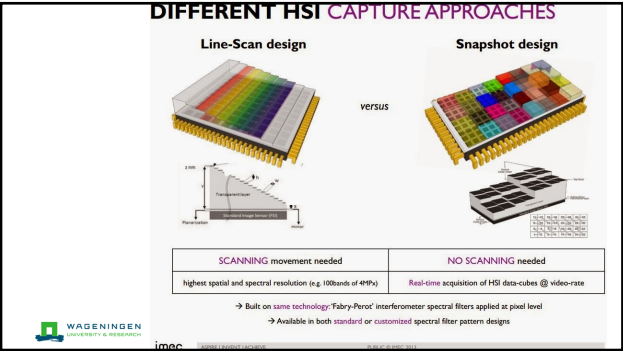
Latest developments 'snapshot cameras'

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Exercise 1
Google Colab





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Calibration /
normalisation





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Calculation spectral reflectance



$$R_{\lambda} = \frac{I_{\lambda} - B}{W_{\lambda} - B}$$

- R_{λ} - real reflection at wavelength λ
- I_{λ} - original measured reflection
- W_{λ} - spectral radiation of the illuminant
- B is the black reference
- This calculation/measurement of W_{λ} and B , needs to be done at a regular interval, at least as fast as the drift in the disturbing factors.

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Challenge with imaging spectroscopy

$Reflectance = \frac{I_{Plant}}{I_{White}}$

- Plants can be of varying sizes and white reference is flat can be at varying heights causing multiplicative effects in the Reflectance

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More effects from leaves

- Apart from global intensity differences, there can be differences due to local inclinations

I_{White}

Incident radiation
Reflected radiation
 R_s (Surface normal)

- Altogether, a mix of additive and multiplicative effects

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Challenge with imaging spectroscopy

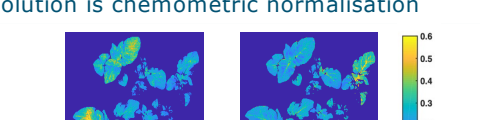
R_{Plants}

Sample Plant

Segmented Image


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A solution is chemometric normalisation



Before *After*

- Mishra, Puneet, et al. "Close-range hyperspectral imaging of whole plants for digital phenotyping: Recent applications and illumination correction approaches." *Computers and Electronics in Agriculture* 178 (2020): 105780.
- Mishra, Puneet, et al. "Utilising **variable sorting for normalisation** to correct illumination effects in close-range spectral images of potato plants." *Biosystems engineering* 187 (2020): 310-325.

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[illegible]

Projects



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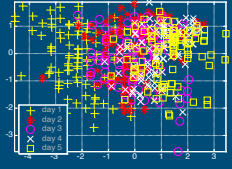
[illegible]

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[illegible]

Ripening of tomatoes

- Scatter plot of feature analysis of the RGB and spectral images.
- Classes 1-5 represent the



SPECTRAL IMAGE ANALYSIS FOR MEASURING RIPENESS OF TOMATOES

Published by the American Society of Agricultural and Biological Engineers, St. Joseph, Michigan www.asabe.org

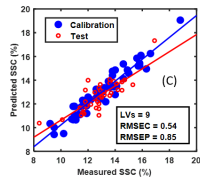
Citation: Transactions of the ASAE, Vol. 45(4): 1155-1161, (doi: 10.13031/2013.9924) @2002

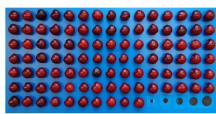
Authors: G. Polder, G. W. A. M. van der Heijden, I. T. Young

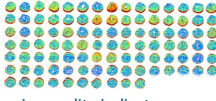
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Example cases - Cherry sweetness



(A) 

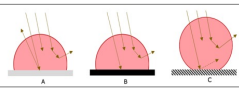
(B) 

- Cherry sweetness is a major quality indicator
- Here we try to predict sweetness in cherry non-destructively

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Light penetration in tomatoes



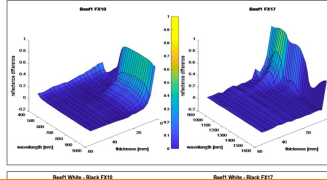
$\frac{I}{I_0} = e^{-\mu x}$

engineering
proceedings

Proceeding Paper
Light Penetration Properties of Visible and NIR Radiation in Tomatoes Applied to Non-Destructive Quality Assessment [†]

Merel Arink ¹, Haris Ahmad Khan ¹ and Gerrit Polder ^{2,*}

MDPI



Sweet White - Black F135


Sweet White - Black F137


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Salinity stress in tobacco leaves


- Salinity stress severely affects plant growth and causes significant yield reductions
- It commonly occurs in arid and semi-arid zones naturally or because of anthropogenic influences such as irrigation with reclaimed water

جامعة الملك عبد الله
للعلوم والتقنية
King Abdullah University of
Science and Technology






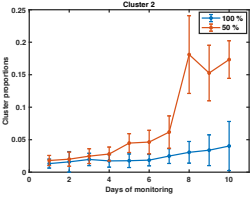
Puneet Mishra, et al. "Close range hyperspectral imaging for mapping salinity stress induced by Red Sea water irrigation in Tobacco leaves." HSI 2015 conference, Coventry, UK.




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Drought stress in Arabidopsis plants with portable imaging spectroscopy



Mishra, Puneet, et al. "Early detection of drought stress in Arabidopsis thaliana utilizing a portable hyperspectral imaging setup." 2019 10th Workshop on Hyperspectral Imaging and Signal Processing: Evolution in Remote Sensing (WHISPERS). IEEE, 2019.




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Drought stress detection in arabidopsis in digital phenotyping framework



06/July 09/July 13/July 15/July 20/July 23/July 26/July 28/July 30/July 02/Aug 04/Aug

W2




D2





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Monitoring crop status - goal

- Crop growers need information on status of the leaves before they are removed during crop cultivation.
- Currently this can only be done using leaf samples sent to an external laboratory.
- Can spectral imaging be used for measuring leaf and fruit compounds non-destructively?



Anja Dieleman
Esther Meinen
Jeroen van Arkel
Kees Weerheim

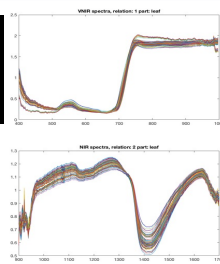


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Monitoring crop status - experiment

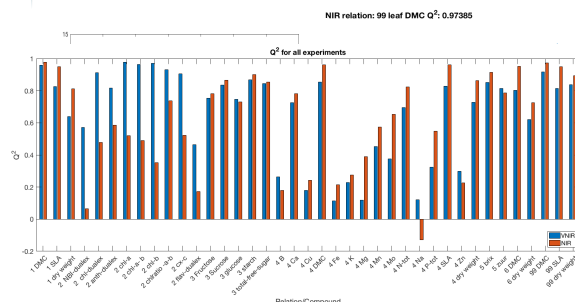
- VNIR HSI, Specim V10e, 400-1000nm
- NIR HSI, Specim N17, 900-1700nm
- 412 leaf samples
- 200 fruits
- Supervised foreground/background segmentation
- Average spectrum per sample
- Reference measures
- Partial Least Square (PLS) regression, using leave one out cross validation.



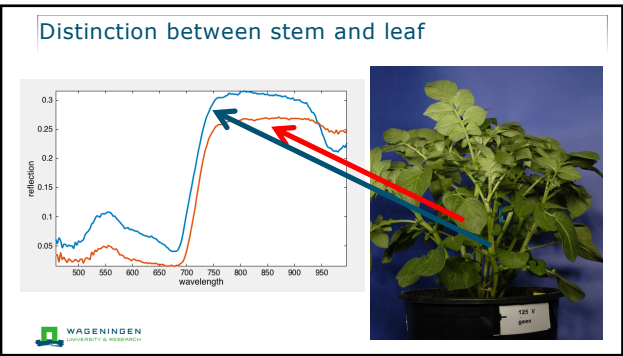
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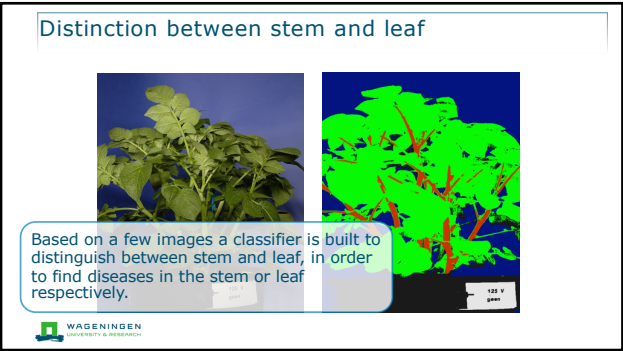
Monitoring crop status - results



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Virus Y detection in seed potatoes

- Deep learning on spectral line images
- Network adapted to $x \times \lambda$ (2D) images

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Disease detection in seed potatoes

Test image at start and end of training

Ground Truth
Network Prediction

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Disease detection in seed potatoes

Results: Row 7 (Vermont) 3/7/2019

ORIGINAL RESEARCH ARTICLE
front. Plant Sci. 01 March 2019 | <https://doi.org/10.3389/fpls.2019.00209>

Potato Virus Y Detection in Seed Potatoes Using Deep Learning on Hyperspectral Images

Gerrit Polder*, Pieter M. Blok, Hendrik A. C. de Villiers, Jan M. van der Wolf and Jan Kamp†

*Agro Food Robotics, Wageningen University & Research, Wageningen, Netherlands
†Interactions & Plant Health, Wageningen University & Research, Wageningen, Netherlands
‡Seed Crops, Wageningen University & Research, Lelystad, Netherlands

frontiers in Plant Science

Deep learning
Hyperspectral images, AI
Polarization in imaging
Detect disease!


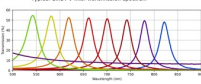

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Early disease detection using multispectral imaging


- SILOS CMS-V 4
- 8 wavelength
- Resolution
 - 2048 x 2048 (raw)
 - 682 x 682 (spectral)



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Exercise 2
Google Colab






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Take home message

- Close range imaging spectroscopy is widely deployed for physicochemical analysis of plants
- Key benefits are non-destructive and non-contact uses, which allow same plant to be monitored during complete time-frame of experiments
- Illumination correction is still a challenge, the spectral normalisation techniques seems to be the easiest and the most effective option




<https://www.wur.nl/en/Research-Results/Projects-and-programmes/Agro-Food-Robotics.htm>

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Take home message

- From my wide range of experience and application I can recommend that imaging spectroscopy is a very useful tool for plant analysis and particularly for plant phenotyping
- Future trend will be related to combining imaging spectroscopy, chemometric knowledge and artificial intelligence to mine the enormous data generated by imaging spectroscopy.



<https://www.wur.nl/en/Research-Results/Projects-and-programmes/Agro-Food-Robotics.htm>

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