Early Identification of Plant Stress in Hyperspectral Images

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German University in Cairo

Early Detection of Drought Stress in Barley

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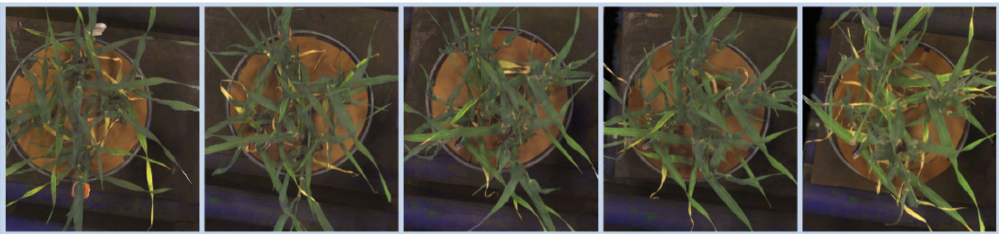
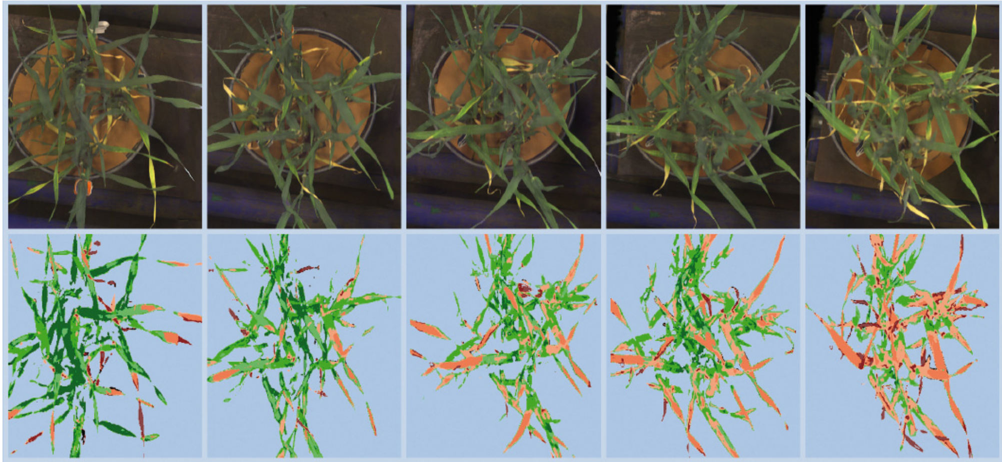
Time Series



RGB Pictures Time Series
Barley Experiment Drought Stress
Greenhouse

Early Detektion of Drought Stress in Barley

Make the Unobservable Observable



Interpreted Hyperspectral Signatures

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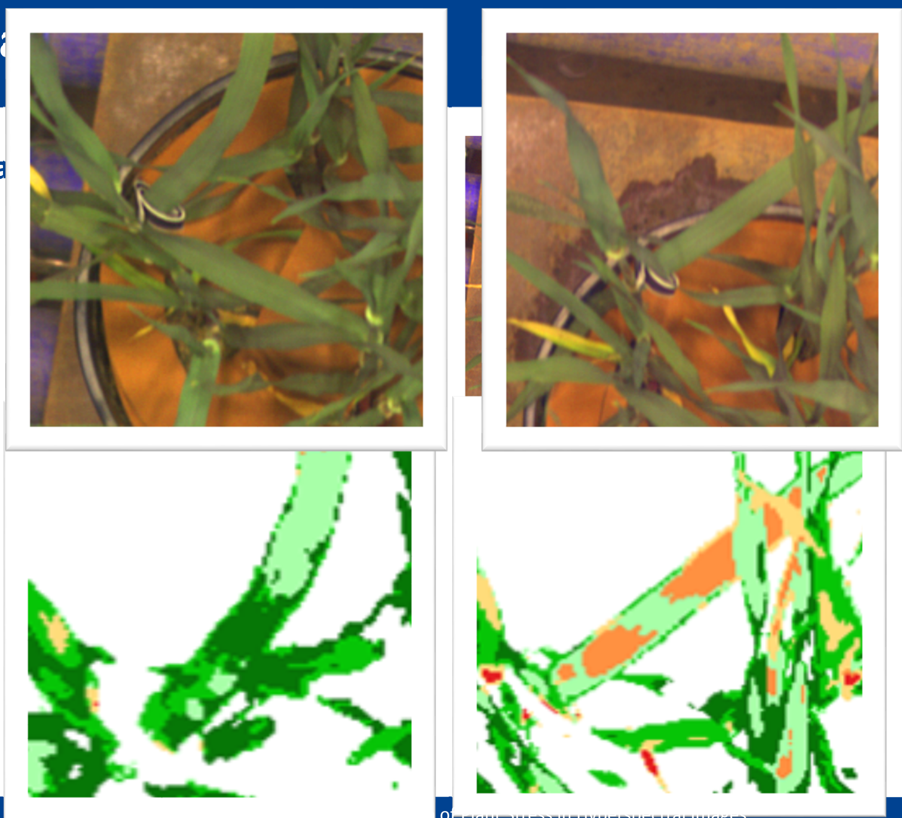

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Phowo 2015 - Early Identification of Plant Stress in Hyperspectral Images
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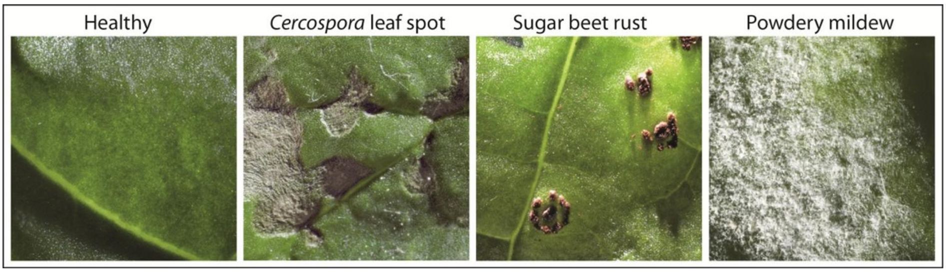
Outlook of the Talk

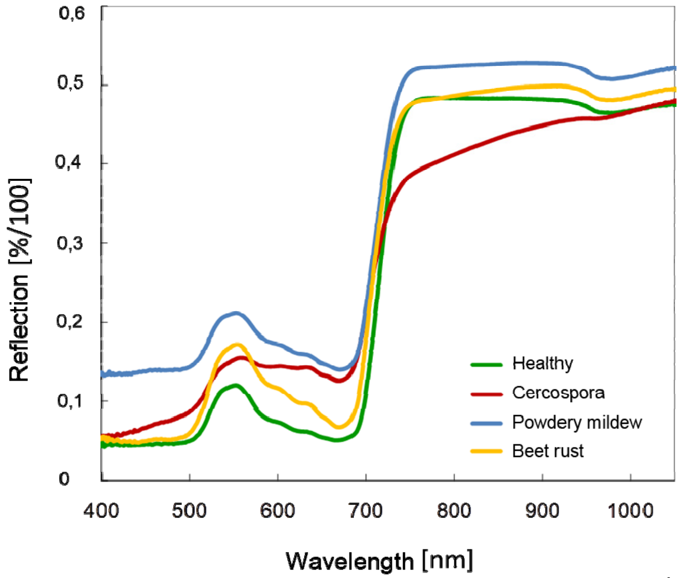
- Hyperspectral Signatures and their relation to physiological processes within the plan
- Early Detection of Plant Diseases with a Combination of Vegetation Indices
- Reconstruction of Features
- Labelling with Nonnegative Matrix Factorization and Archetypes

Plant Diseases

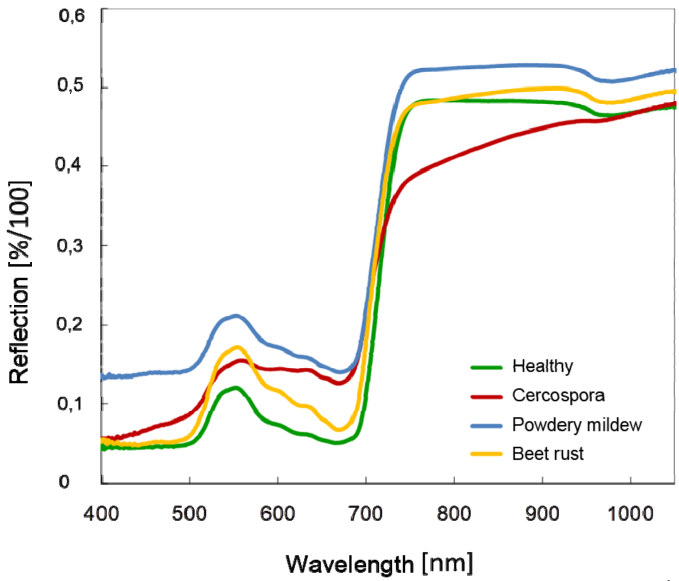


RGB-Images, Symptoms visible with the naked eye

Plant Diseases
Characteristic Hyperspectral Signatures



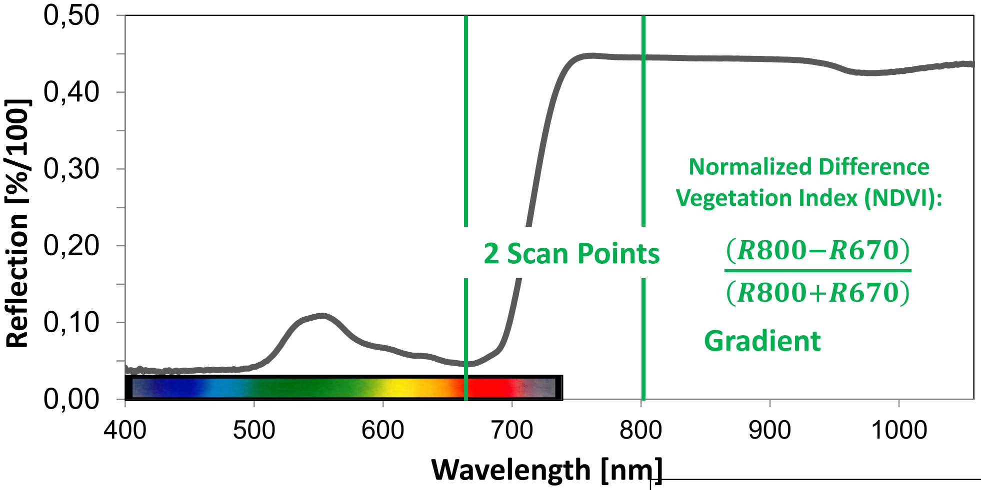
Plant Diseases
Hyperspectral Signature



Means give an overly optimistic Impression

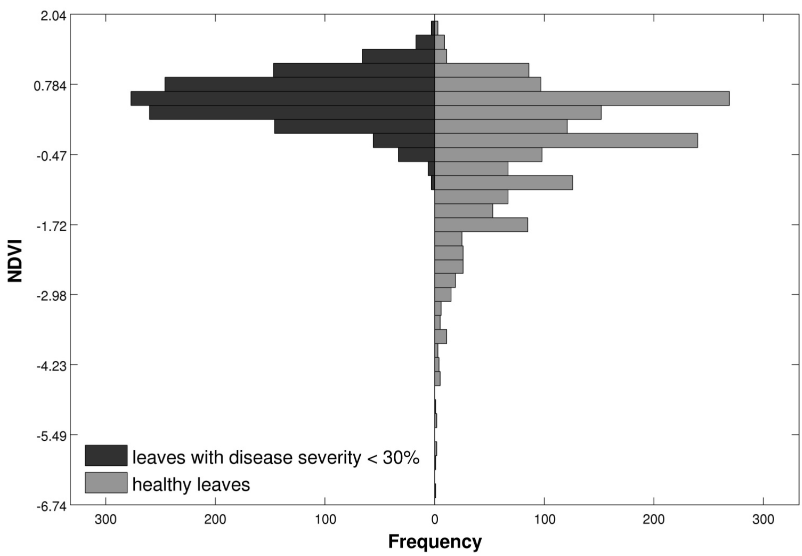
How to represent the information contained in hyperspectral signature

Vegetation Indices, using the example of NDVI



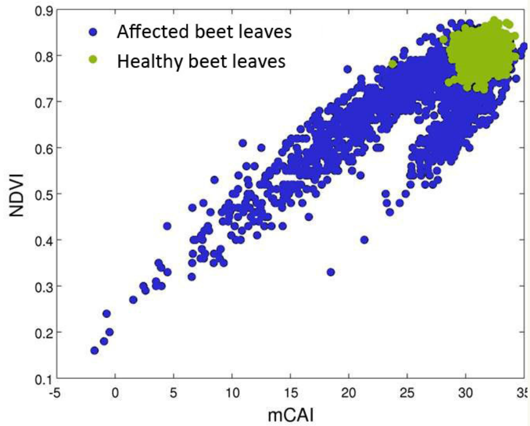
- limited information
- Bad signal noise

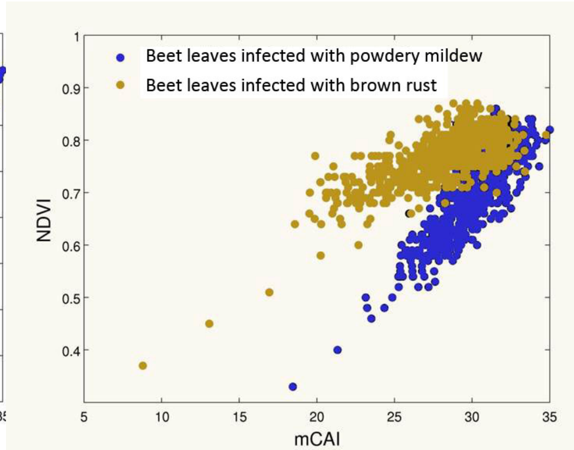
Healthy versus innoculated



Rumpf 2012: Finding spectral features for the early identification of biotic stress in plants. *Dissertation Till Rumpf 2012*

Combination of Multiple Vegetation Indices
NDVI and mCAI





NDVI (Normalized difference vegetation index)

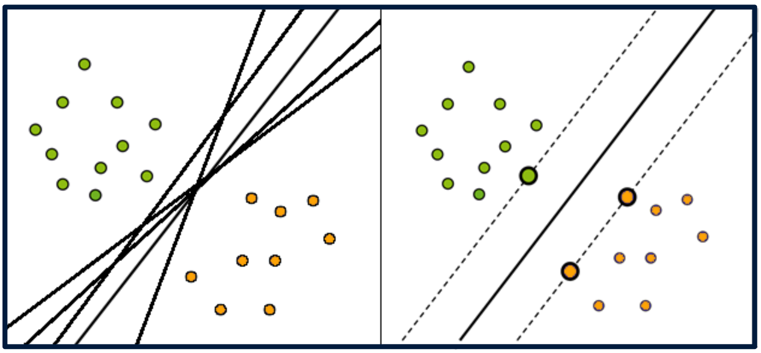
$$\frac{R_{800} - R_{670}}{R_{800} + R_{670}}$$

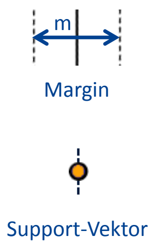
mCAI (modified Clorophyll Absorption Integral)

$$\frac{R_{545} + R_{752}}{2} * (752 - 545) - \sum_{i=545}^{752} R_i * b$$

Rumpf 2012: Finding spectral features for the early identification of biotic stress in plants. *Dissertation*

Support Vector Machines





- Discriminating hyperplane with maximal margin
- Minimizes the structural Risk (according to Vapniks Statistical Learning Theory)
- Minimizes Risk of Overfitting

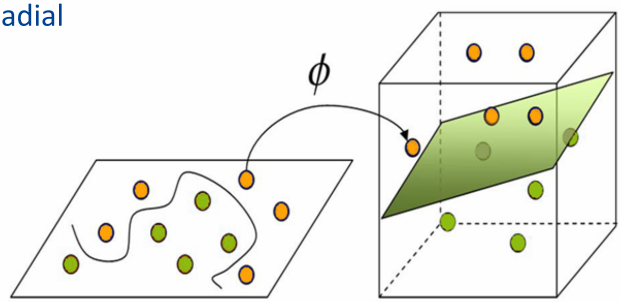
Non-Linear Support Vector Machines …

Nonlinear Kernels such as Radial Basis Functions

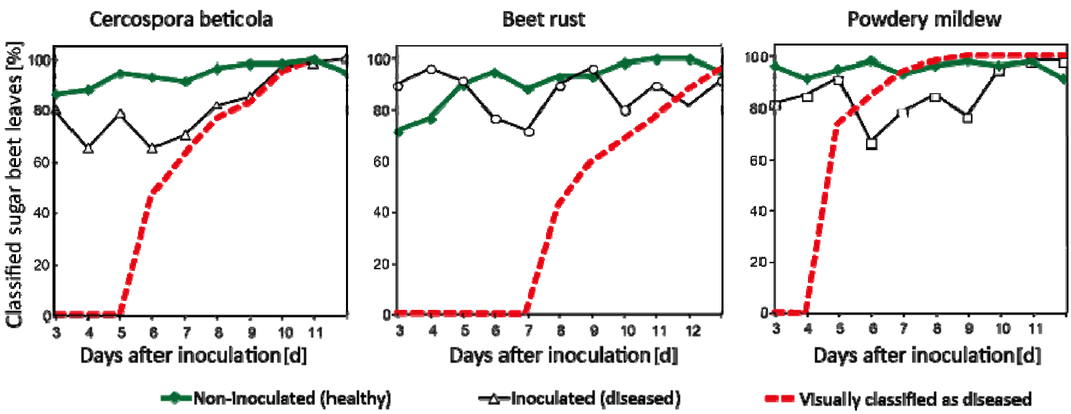
$$k(\boldsymbol{x}_i, \boldsymbol{x}_j) = e^{-\frac{\|x_i - x_j\|^2}{\sigma}}$$

provide high-dimensional nonlinear Models

by implicit transformation to a feature space where samples become linear separable



Early Prediction of Plant Diseases
using multiple Vegetation Indices and SVMs



Rumpf, Mahlein, Steiner, Oerke, Dehne, Plümer 2010: Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance In*: Computers and Electronics in Agriculture, 74(1). S. 91-99.*

Separation between Different Diseases

	Ground Truth				
Prediction	Healthy	Cercospora	Sugar beet rust	Powdery Mildew	*Precision*
Healthy	942	32	47	69	86,42%
Cercospora	12	748	61	13	89,69%
Sugar beet	20	88	622	14	83,60%
Powdery Mildew	46	12	10	834	92,46%
Class Recall	92,35%	85,00%	84,05%	89,68%	**88,12%**

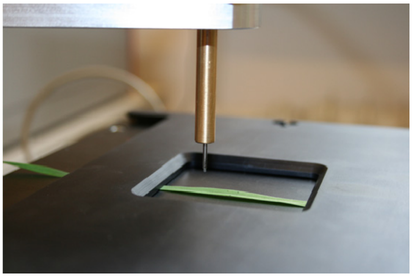
Class Recall: true positive rate, Sensitivity

Precision: true negative rate, Specifity

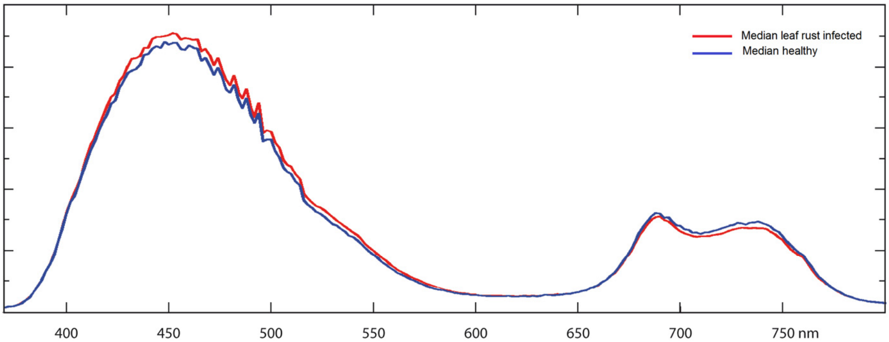
Hyperspectral Fluorescence Signatures

Feature Reconstruction

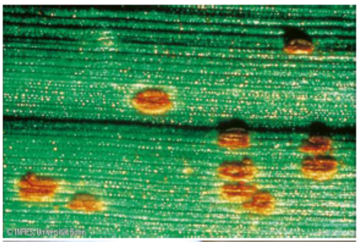
Flourescence Spectra
Presymptomatic Wheat Leaf Rust Detection

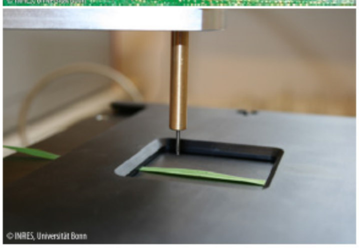


Experimental Design

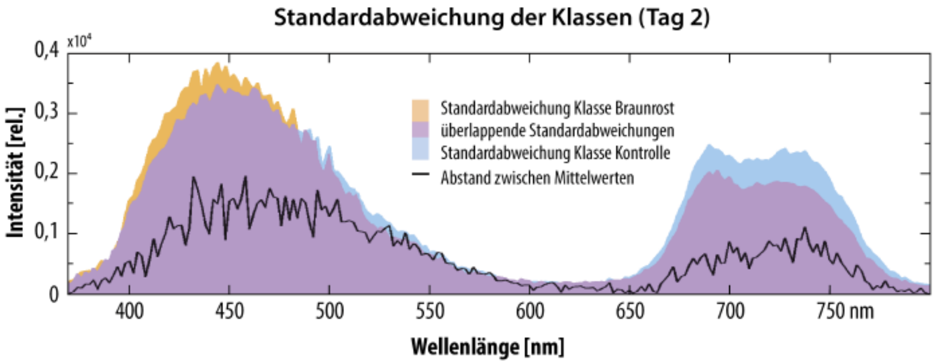


Flourescence Spectra
Presymptomatic Wheat Leaf Rust Detection



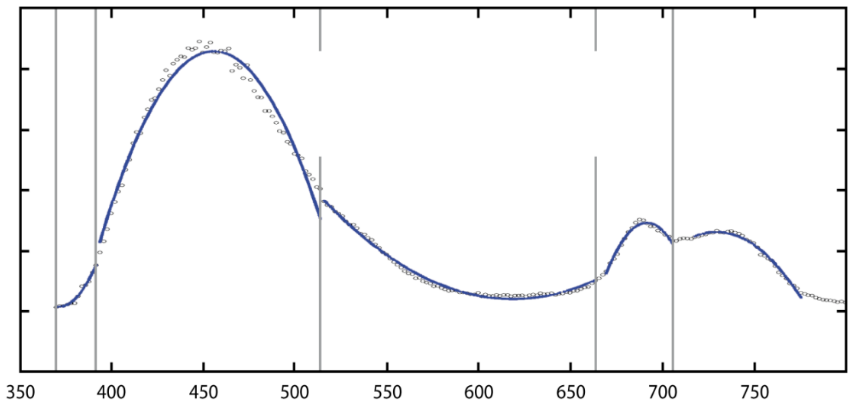


- Leaf Rust – one of the most relevant plant diseases
- caused significant crop losses in wheat
- Early Prediction is essential
- Hyperspectral Fluorescence Signatures



- Class variabilities larger than class distances
- Distances large where variabilities high – and vice versa
- Number of features (wavelengths) larger than number of samples
- Need for discriminating features

Robust Features
Coefficients of Piecewise Polynomials of Low Degree



- Estimate coefficients $f(x) = a_3x^3 + a_2x^2 + a_1x^1 + a_0$ with least square
- take the coefficients a_3, a_2, a_1, a_0 as ***features***

Early Detection of Wheat Leaf Rust
Best Polynomial Degree

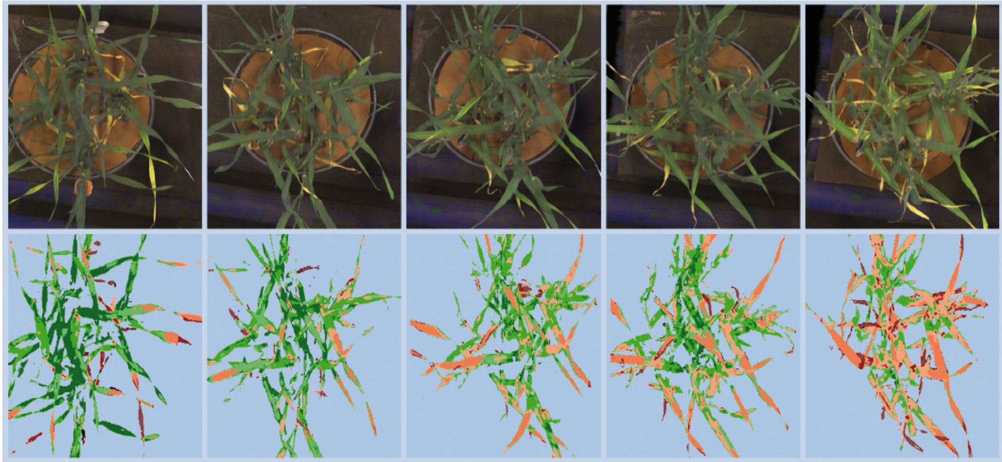
Day after Inocculation	3rd order (%)	4th order (%)	5th order (%)	6th order (%)
2	84,22	**93,05**	88,89	91,67
3	87,50	88,89	84,72	**90,28**
4	**91,67**	90,28	87,50	79,17

Römer, Bürling, Hunsche, Rumpf, Noga, Plümer 2011: Robust fitting of flourescence spectra for presymp-tomatic wheat leaf rust detection with Support Vector Machines In: *Computers and Electronics in Agriculture, 79. S. 180-188.*

Unsupervised Learning

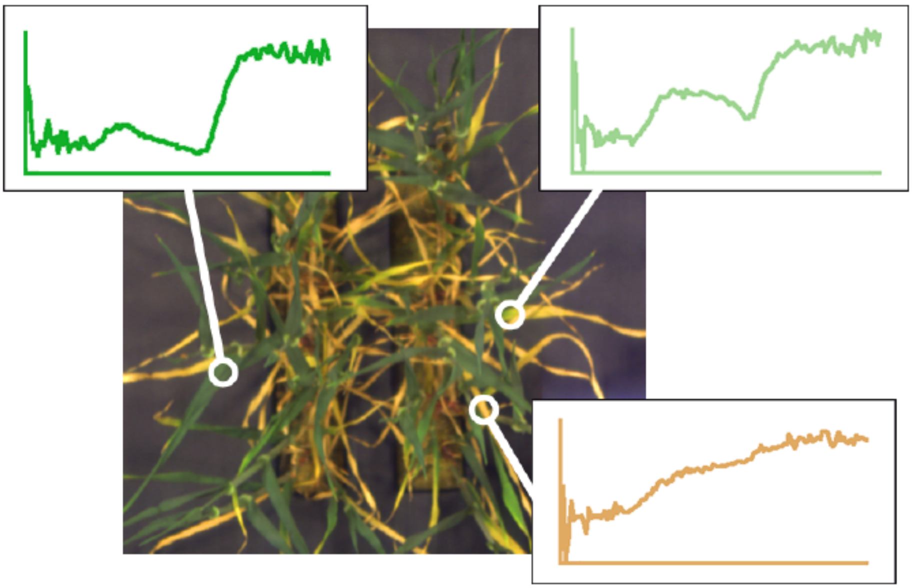
Early Detection of **Drought Stress** in Barley

Early Detection of Drought Stress in Barley

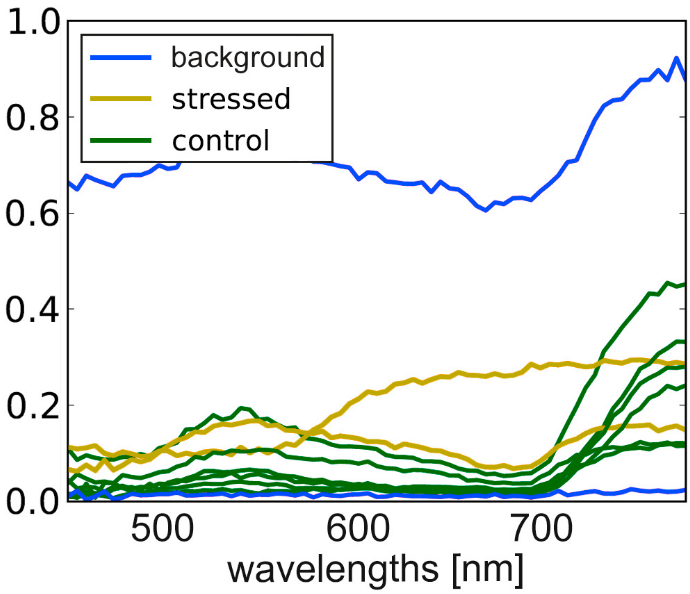


- Different **Degrees of Senescence** are represented by „**Archetypes**“
- Different Archetypes are derived by **Cluster Analysis**
- Clusters are Derived by „**Simplex Volume Maximisation**“

Archetypes (I)

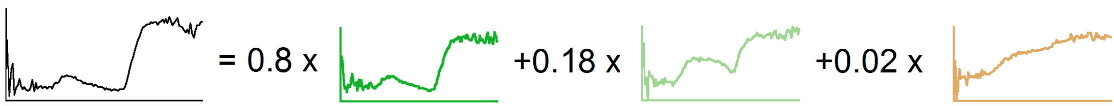


Archetypes (II)



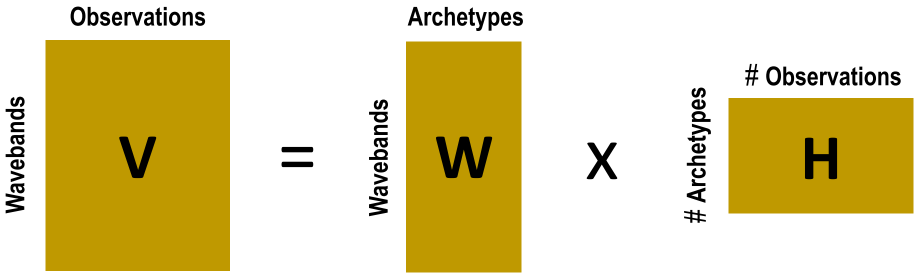
Hyperspectral Signatures
Archetypical Analysis

- Archetypes represent Degrees of Senescence
- Transform hyperspectral Signatures to a representation where
  - each Signature is represented as a nonnegative linear combination of Archetypes (Basis Vectors)



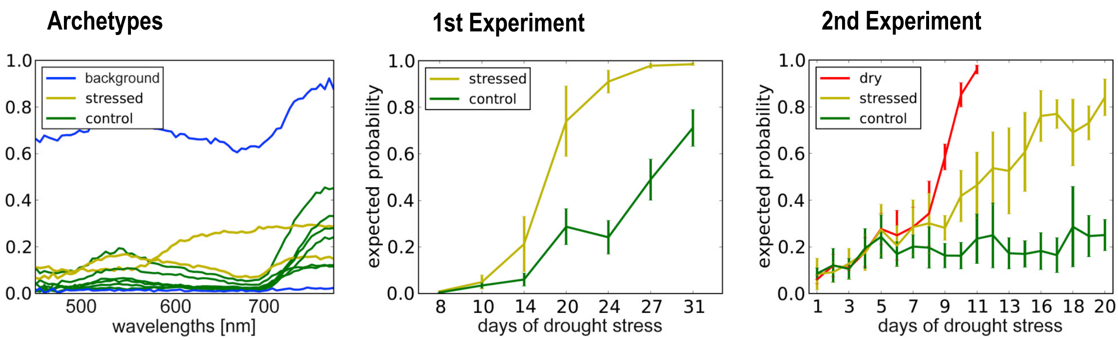
  - easy, **intuitive interpretation** of Items …
    similarity to a certain degree of senescence
  - **discrete sampling** of a **continuous process**

Simplex Volume Maximization
How to Derive Archetypes

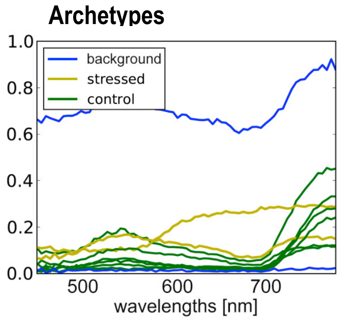


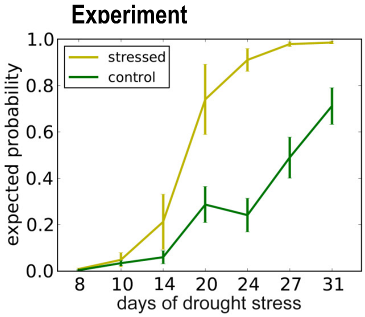
- the original high dimensional data matrix V is factorized into a sparse representation of
  - The archetypes in W
  - Nonnegative coefficients describing the linear dependencies between observed signatures and archetypes
- Efficient (~ linear time) Calculation of the Archetypes – the Matrix W – is done with *Simplex Volume Maximization*

Early Detection of Drought Stress
based on Similarities with Archetypes



- **Differences** of probability density function between observations **characteristic** for drought stressed or control plants
- Archetypes 4 days faster than combination of VIs





- On plant level drought stress prediction is based on histograms of archetypes
- Soil moisture significantly decreases since **day 8**
- Archetypes detect drought strass sinde **day 9**
- Naked eye detects drought stress on **day 14**

Römer et al., Early drought stress detection in cereals: simplex volume maximization for hyperspectral image analysis*In: Functional Plant Biology, 2012, Heft 39 (11), S. 878-890*

On-Going Work

- **Signal Noise Ratio by Incorporating 3D Geometry**
  - Inclination explains relevant Portion of Variation
  - Affords geometric calibration of short range hyperspectral cameras
- **Labelling**
  - Always lack of labelled data
  - Active Learning in combination with Archetypes
- **Model Transformation**
  - By Domain Adaptation

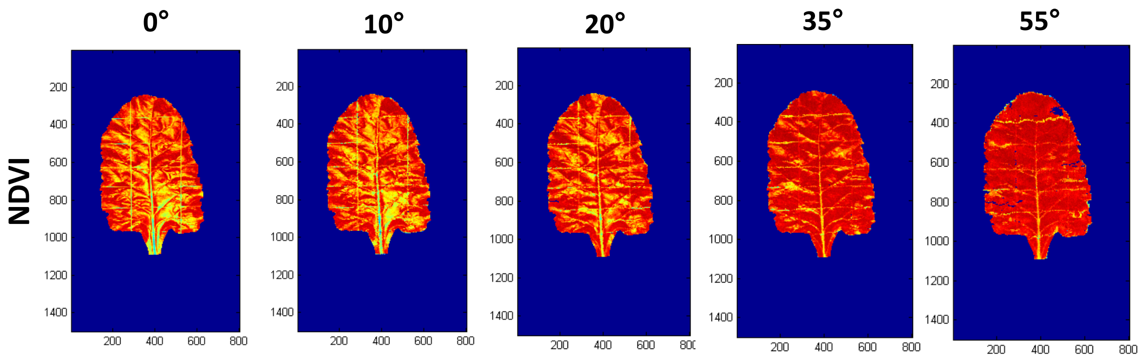
Thanks for your Attention!

Thanks to Dieter Fritsch!

Signal-Noise-Ratio: The Role of Geometry

Influence of Global leaf inclination on NDVI

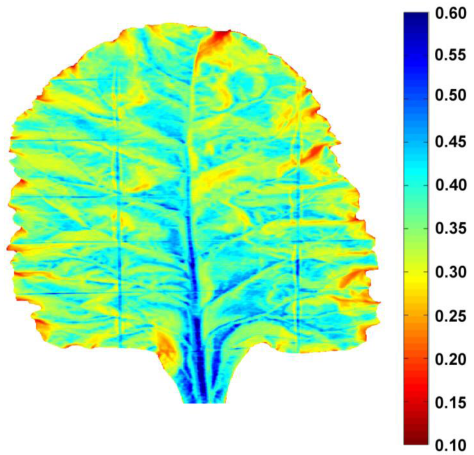
Global Inclination



Sugar Beet Leaves – different Inclinations

Role of Geometry

Influence of Local Inclination on Sum-Green-Index



Sum_Green Vegetation Index

Role of Geometry (Sugar Beet Leaf)

Influence of Local Inclination on Sum-Green-Index