DETERMINATION OF CEREAL TYPE AND GROWTH STAGE USING SIMULATED REFLECTANCE DATA

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ABSTRACT:

Imaging spectroscopy data can provide detailed information about vegetation type and growth stage over large areas. Our goal is to investigate the potential of hyperspectral data to assess the agricultural land use. We focus in particular on the development of a classification technique enabling the identification of selected agricultural crops and their growth stages. During the growing season different plant properties like chlorophyll content, water content and biomass are coupled with plant cover changes leading to high variabilities in their reflectance spectra. Nevertheless, every plant type of a specific growth stage features typical spectral characteristics enabling a separation. The classification is based on simulated hyperspectral reflectance data. Multitemporal three dimensional plant models of winter rye, winter wheat and winter barley are created with AmapSim and linked to field measured ASD spectra using ray racing. Based on these artificial reflectance data a classification in terms of plant type and growth stage is performed by pairwise Minimum Distance Classification (pMDC). Classes are separated by a set of predefined spectral features one against one. The classification is applied on a hyperspectral HyMAP image with masked cereal crop fields. The results yield an overall accuracy of 91.9% for the crop type and phenological determination.

1. INTRODUCTION

The agricultural system of vegetation and soil has a high temporal dynamic. This results in a different canopy reflectance signal for each growth stage of each crop type, that must be treated as an individual class in a classification task to build a transferable classifier for crop types. Therefore, it is a challenging task to get a sufficient amount of training samples for the parameterisation of a supervised classifier. One method is the collection of training data from a high amount of images covering the whole phenological development of the crop types. A second method is to collect field measurements. Here we have the problem of different spatial resolution and a changed viewing geometry compared to an airborne spectrometer leading to different fractional abundances of plants and soils.

For this reason the simulation of canopy reflectance could be a proper tool to generate input data for the parameterisation of a supervised classifier. A large number of forward models of canopy scattering have been developed for different applications to simulate canopy reflectance (e.g., Goel, 1988; Goel & Thompson, 2000). "Typically a form of radiative transfer approach to describe the (dominant) volume scattering behaviour of the canopy-soil system" (Disney et al., 2006) is used by these models to simulate relatively homogenous canopy types like crops. Enhanced methods incorporate the natural canopy struc-

ture by the use of 3D plant models and 3D soil models (Lewis, 2007). This enables the possibility to include detailed reflectance properties of plant parts and to use ray traycing for the calculation of the overall canopy reflectance.
In this manner simulated canopy reflectance data for selected crop types and growth stages are generated and used to develop and parameterise a new supervised classifier. In this study its applicability to real HyMap data is presented.

2. SIMULATION OF CROP CANOPY REFLECTANCE

2.1 Data

The simulation process requires spectral information about the phenological development of plant organs for detailed modelling and the total canopy signal for validation purpose. Furthermore, geometric data describing the plant's shape and size are needed to model the plants. To obtain a natural structure of the 3D canopy model the distribution and density of the plants within the canopy are estimated in the field.

2.1.1 Reflectance of Plants, Canopy and Soil

Reflectance spectra were measured for winter rye (Secale cereal L.), winter wheat (Triticum L.) and winter barley (Hordeum vulgare L.) canopies at two different test sites in Germany (Beelitz-Wittbrietzen and Berlin-Dahlem) with the FieldSpec Pro FR (ASD, 1999). The measurements were collected under clear sky conditions 5 cm above different plant organs using an 8° foreoptic. The measured parts of the plant are leaf, culm and ear. The data are corrected for spectral artefacts (detector jumps) and bands with low signal-to-noise-ratio (SNR) caused by atmospheric radiative absorption are removed.

2.1.2 Geometry of Plants, Canopy and Soil

Plant geometry was recorded simultaneously to the spectral acquisition. Thereby geometric information about shape, sizes, composition and arrangement (angles and distances) were measured. Additionally, several height profiles of the soil were measured for further surface modelling. These data are the input parameters for building the topology and geometry of the 3D plants as well as the structure of the 3D canopy-soil-system.

2.2 Modelling a 3D Canopy

The generation of the virtual 3D landscape is based on 3D Plant Models, soil background information including a soil DEM and plant positions and density within the canopy.

2.2.1 3D Plant Model

The plant models are simulated using the software AmapSim (Barczi et al. 2007). that provides a tool to reconstruct plants virtually based on real measurements. It also contains a structural growth model based on botanical theory to simulate plant morphogenesis producing accurate, complex and detailed plant architectures. Shape parameters of the plant organs leaves, stems and ears were acquired at different growth stages to define the organ sizes and their growth dynamics. For further information see Barczi et al. (2007).

The following growth stages for winter rye, winter wheat and winter barley are modelled:
tillering, stem elongation, ripening and senescence. Furthermore late senescence growth stage of barley is modelled because of strong optical changes during this growth stage.
As an example three simulated growth stages of winter rye and their naturally appearance is shown in Figure 1.

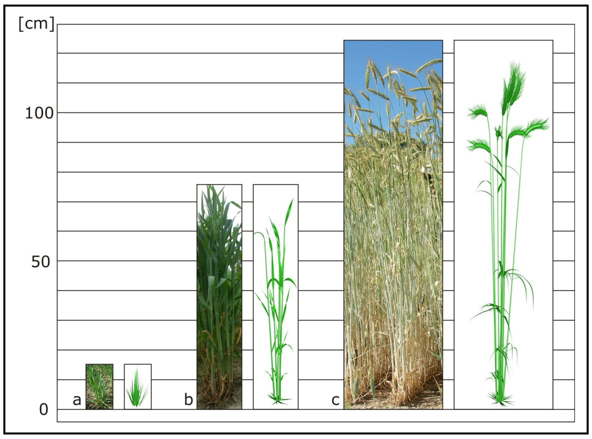

Figure 1. Real and simulated rye plants at three growth stages: a) tillering, b) stem elongation, c) development of fruits.

2.2.2 3D Soil Model and Canopy Geometry

Field-measured height profiles are used to generate a soil DEM with typical geometry and furrow distances. The furrows results of mechanical drilling of the seed. The plant models were placed to the DEM by cloning and including a random rotation around their vertical axis (Lewis 1999). The distances between the furrows and the number of plants placed within a defined section have a direct impact on the density of the canopy.

2.3 Canopy Reflectance Simulation

Canopy reflectance data is determined by the acquisition and illumination geometry as well as the geometry and spectral information of the objects on the surface. To obtain these mixed spectra an artificial 3D crop field was built up and measured virtually by ray tracing. Ray tracing is a method to generate two dimensional (2D) image data by tracing the path of light through a 3D scene onto an image plane (Glassner, 1989).
The reflectance of the virtual 3D canopy is estimated by the Advanced RAdiometric RAy Tracer (ARARAT) developed by Philip Lewis (Lewis, 1999; Lewis & Muller, 1992). ARARAT calculates the canopy reflectance based on 3D canopy descriptions with associated spectral information, camera imaging properties and illumination conditions by using reverse ray tracing. For detailed information see Lewis (1999).
Several camera models are implemented in the ARARAT software. For this study the planar camera model for central perspective measurements was used since a spectrometer is measuring in an analogous manner (ASD, 1999). Since, the infield canopy spectra were measured in nadir direction the virtual camera was adjusted in the zenith viewing position. The illumination of the 3D scene is described by azimuth (180°) and zenith angle (30°) of the sun assuming parallel rays.

3. METHODS

The basic idea of this work is to use simulated spectra for the parameterisation of a classifier that can be applied on real image data. To evaluate the potential of several standard classification methods (Tab.1) we applied them on reflectance data, PCA transformed data (9 components), Discriminant Analysis Feature Extraction (DAFE) transformed data (Kuo & Landgrebe 2001: 19ff) and an image including spectral features defined based on knowledge. The features are assumed to be invariant against spectral variations of classes and BRDF effects and thus, should enable the development of a stable and transferable classifier compared to a classification on reflectance data (Heiden, 2007). The basic set of features include ratios, depth and areas of absorption bands as well as coefficients of polynomial approximations, averages and standard deviation that are calculated within different spectral intervals.

Considering the acquisition date of the HyMap image (20.06.2007) acquired in the south west of Berlin and the weather conditions of the growing period the input training classes are reduced to the possible ones which are:

- winter rye - ripening, senescence,
- winter wheat - ripening, senescence,
- winter barley - ripening, early senescence, late senescence.

By far, the best results are obtained applying Minimum Distance Classification (MDC) and Support Vector Machines (SVM) with the one-against-one (OAO) approach on the feature image. Thus, the robustness of spectral features is confirmed.

The bad performance of maximum likelihood classification is due to the small variance of training samples that does not allow a reasonable estimation of the covariance matrix for each spectral class (Richards 1999: 189) compared to real image data acquired with the HyMap sensor (see Fig. 2).

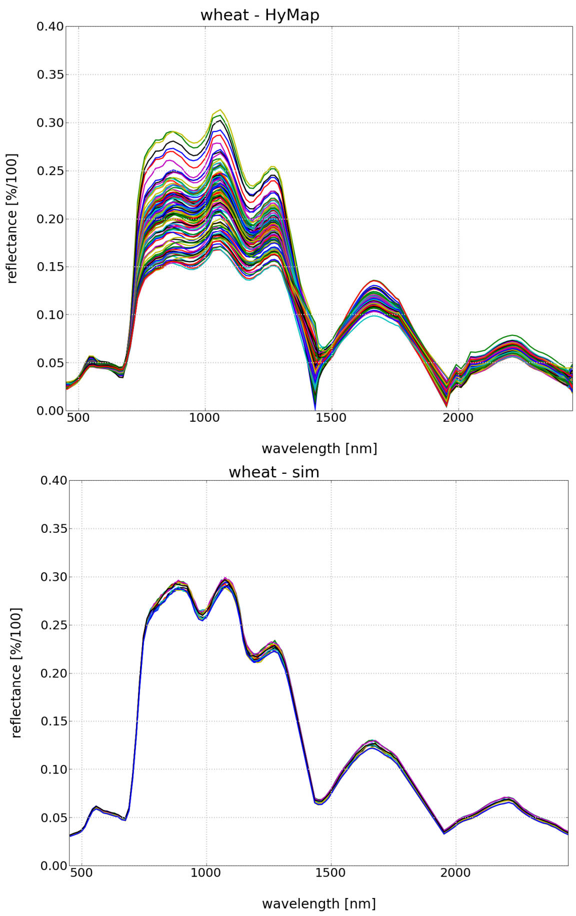

Figure 2. Difference of the class variances between simulated and HyMap reflectance data (HyMap from 20.06.2007 at Wittbrietzen test site)

In this study the only changing parameter is the composition of the used plants. To increase the variance many parameters for each class can be changed like viewing geometry, illumination geometry, soil, different plant parameters and many more. Considering the processing time of an individual spectrum, of 1h up to 24h, depending on the growth stage, a strong limitation for the number of simulated spectra is set. These conditions lead to very low variance within the training data of a class.

For that reason it is necessary to develop a classifier that is able to handle this situation. We therefore combine the most promising concepts of the individual classifications into a new classifier which is described in the next section. These concepts are:

- Robustness of spectral features,
- Reduction of the dimensionality of the feature space by knowledge based feature selection,
- Reduction of the dimensionality of the feature space by OAO approach.

The developed pairwise minimum distance classifier (pMDC) consist of numerous individual MD-classifiers, one for each class decision. This necessitates an additional step to determine the final class of a pixel but has a great advantage against the simultaneous classification of all classes: Each pairwise class decision is taking place in an optimised feature space which consists of only the few relevant spectral features defined for each pair of classes. The OAO approach is especially suitable for the case of a high number of classes as planned to be implemented in the future and for a small amount of training data.

The combination of the individual classification results of the pMDC is schematically illustrated in Figure 3 for an image with 4 pixels. In the first run the class decisions of the pairwise MD-classifiers are counted for each pixel. The class with the highest score gets accounted for each pixel. In case of an ambiguous class decision caused by a draw the decision of the pairwise MD-classifier of the relevant classes is counted twice.

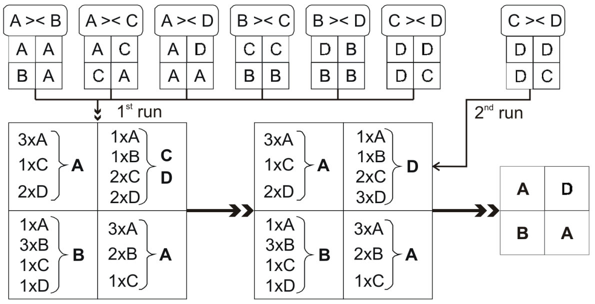

Figure 3. Classification scheme for an image with 4 pixels

4. RESULTS

The pMDC is applied on HyMap data acquired at the 20.06.2007 with masked crop fields. Compared to the results of standard classification methods (Table 1) we get a very high overall accuracy of 91.9%. The accuracies for the individual crop fields are:

- winter wheat – 95.62%,
- winter rye – 89.70%,
- winter barley – 92.90%.

The incorrect class results in the lower part of the barley field can be explained are mostly due to a strong occurrence of weed in this part of the field causing a change of the reflectance signal.

Table 1. Overall accuracy of different classifiers parameterised with simulated training samples and applied on real HyMap data

	Reflectance	PCA (9 components)	DAFE	feature image (z-score)
Maximum Likelihood	14.6	14.8	21.2	17.6
Mahalanobis Distance	1.0	0.8	1.1	2.9
Minimum Distance	4.9	4.9	8.7	63.7
SAM	13.2	14.5	11.5	27.9
SVM (OAA)	14.0	9.3	6.2	13.5
SVM (OAO)	3.8	5.7	8.4	61.1
pMDC	-	-	-	**91.9**

Using the spatial borders of the crop fields as addition information, 100% accuracy can be achieved by assigning the majority class to the fields.

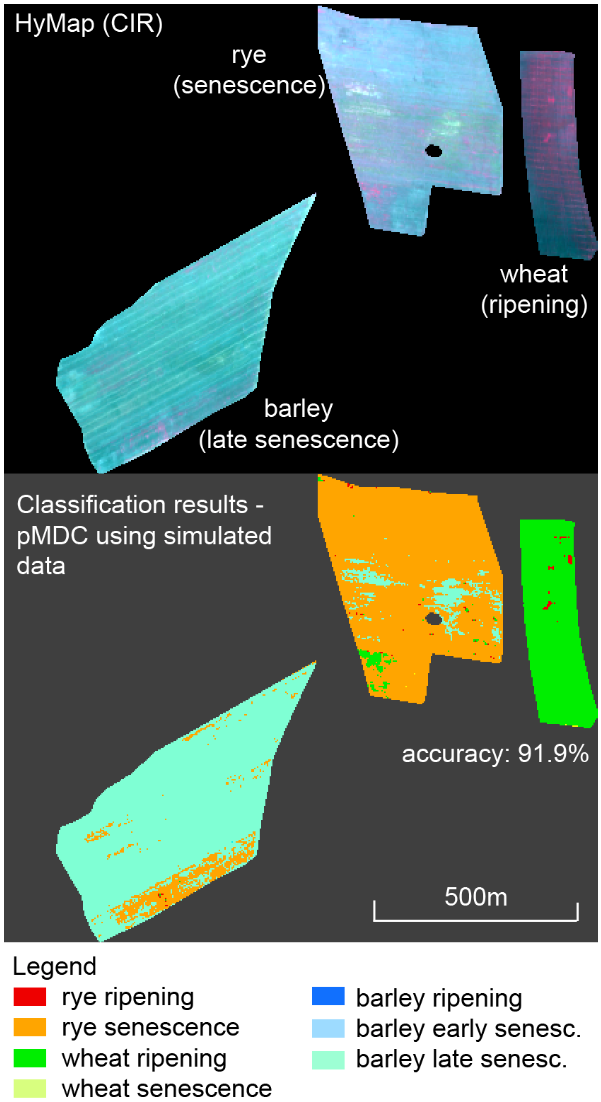

Figure 4. Classification results of the pairwise MD-classifier

5. CONCLUSION AND OUTLOOK

In this study we showed the high potential of the pMDC method to identify crop types and growth stage by using simulated reflectance data as input data. Compared to standard methods it is a significant improvement of the results.

To evaluate the robustness of this method it will be tested on more fields and different sensors in the future. Furthermore, it is planned to increase the number of growth stages that can be distinguished and to further automatise the process of classifier build-up and application to obtain a fast and accurate landuse classification of crops on demand.

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