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HYPERSPECTRAL IMAGES AS A TOOL FOR SOIL FIELD RECOGNITION

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Abstract

Hyper-spectral imaging provides an opportunity for high-precision and detailed spectral measurements of the object of study with a wide range of applicability - from laboratory imaging of samples through field to remote satellite measurements. The paper presents a study in which the average spectral characteristics for each sample were obtained from the hyperspectral images of soil samples from three different pre-treatment fields. Spectral data were processed in the Pirouette software environment and principal component analysis was applied. Using the first three principal components, the soil fields are clearly separable. Interclass distances were also calculated. From the resulting discriminating power, wavelengths can be derived that are informative about the content of the soil fields. The sections that were determined from the modelling power from 1200 to 1250 nm; 1300 to 1350 and 1400 to 1450 nm, the wavelengths can be defined that would be used as inputs to the classifiers. The future work is developing of models for predicting micro- and macro-elements in soil using hyperspectral images.

Keywords: Hyper-spectral images; Soil field; Principal component analysis; Pirouette software

1. Introduction

Soil type is essential for farmers to determine its fertility status [1],[2]. Soil evaluation encompasses various chemical processes that determine the amount of nutrients available in the soil. Based on the results of the evaluation, recommendations are made for treating the soil fields with appropriate means - machines or using appropriate fertilizers to improve soil fertility for the respective crop.

In the recent years computer vision systems, ultrasound and infrared signals and tomographic imaging are used for quality assessment of different parameters in agriculture [3]. The computer vision-based quality inspection comprises of four main steps, namely, acquisition, segmentation, feature extraction and classification. The artificial intelligence techniques such as fuzzy logic are also widely used for the automatic analysis and detection of objects [4].

Our previous research works is related to quality assessment of soil using different sensor for measurement of the main quality soil parameters [5] and research of the influence of external factors on the measurement of a basic soil quality parameter [6]. These methods are time – consuming and are not suitable for express assessment of the whole field.

Hyper-spectral analysis is not so popular method in agriculture.

The purpose of the research is to assess the possibility for soil field recognition using hyper-spectral imaging technique.

2. Soil samples and obtaining of the hyper-spectral images

Soil samples were obtained from the three typical fields form Ruse region in Bulgaria. The 110 samples are collected and analysed.

Hyper-spectral imaging (HSI) provides the possibility of highly accurate and detailed spectral measurements of an object of view with a wide range of applicability - from laboratory imaging of samples through field to remote satellite measurements. In the case of HSI, it represents a three-dimensional hyper cube, which is a carrier of spatial and spectral information, where each pixel of the spatial part is represented by spectral information from each spectral band of the sensor.

A SPECIM model N17E sensor with 320 hyper-spectral pixels with 256 spectral bands ranging from 850nm to 1700nm was used in this study. The experiment was conducted in laboratory conditions, and 110 soil samples were taken from the three fields. The experimental setup shown in Figure 1 consists of:

1. movable base driven in one direction by precision servo motor;
2. four broad spectrum light sources;
3. hyper-spectral sensor SPECIM N17E;
4. soil sample.

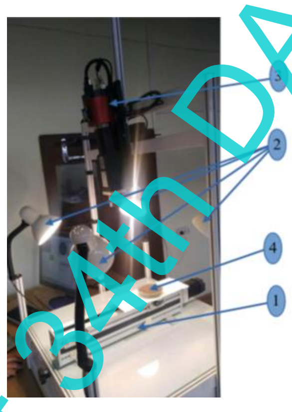
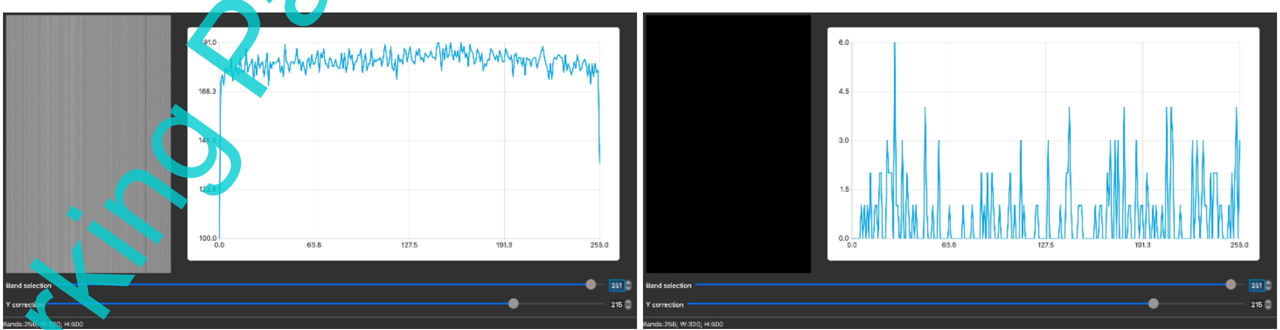


Fig. 1. Experimental setup with soil sample

Equal weight amounts were taken from all soil samples, each placed in a Petri cuvette and one hyper-spectral image is obtained.

Since HSIs received from the sensor are in raw form, this requires additional processing. Due to the influence of the environment (temperature, humidity, etc.) and specific features of the sensor, there is minimal static noise in the data, expressed in a non-uniform static offset with respect to the wavelength for each spectral band. To remove static sensor spectral noise from each HSI of the samples, a black HSI captured with the lens fully closed with the same sensor and under the same conditions during the experiment was used.



(a) (b)

Fig. 2. Spectral characteristics of one pixel
(a) – with static noise; (b) – with removed noise

3. Spectral data processing

The correct selection of an area of the photographed soil sample is essential for the quality of the research result. It should include only the subject of study without the background or side objects present in the frame of the original image. There are various ROI determination methods based on mathematical analysis and transformation, aiming to form a mask to remove unwanted pixels. Techniques based on Principal Component Analysis (PCA), Cluster Analysis, K-means algorithm, Fuzzy C-means algorithm, similarity between spectral characteristics (similarity) based on correlation coefficients, etc. are widely used. [7].

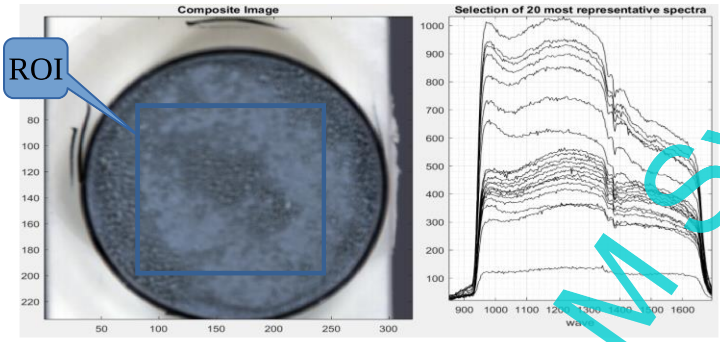
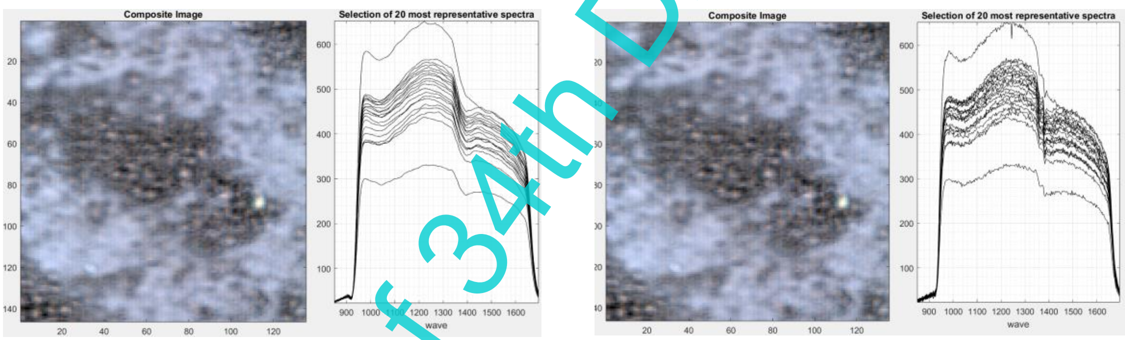


Fig. 3. Selection of ROI from soil sample image

Since the captured soil samples in this study are relatively similar, a manual ROI determination method was chosen, by which regions of the soil samples with approximately equal areas were isolated from the frame. In Matlab, by means of the HyperTools 3 tool [8], a region of interest (ROI) covering only a homogeneous area with a soil sample is separated from each HSI.



(b) (b)

Fig. 4. Image ROI and spectral characteristics
(a) - no filtration applied, (b) – with applied filtration

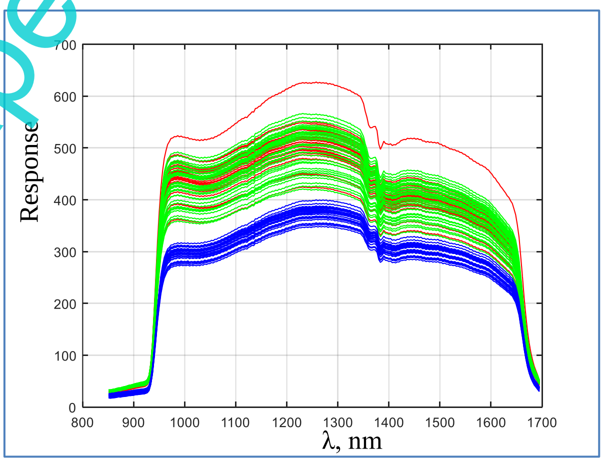


Fig. 5. Averaged spectral characteristics for each sample from the three soil fields

In order to reduce the spectral noise, while preserving the spectral shape to the maximum extent, a minimal additional spectral filtering was applied through a combination of smoothing/derivatives (Savitszki-Golay) and Standard Normal Variance (SVN) algorithms.

For the needs of the subsequent analyses for each soil sample an average spectral characteristic of the ROI was calculated. In fig. 5 presents the averaged spectral characteristics for each sample, for the three soil fields.

As a classification procedure we used SIMCA classifier which is integrated in Pirouette software and principal component analysis as a data pre-processing procedure. The result from principal component analysis with the first three components is shown on Fig. 6. It is clearly visualised separability between the classes.

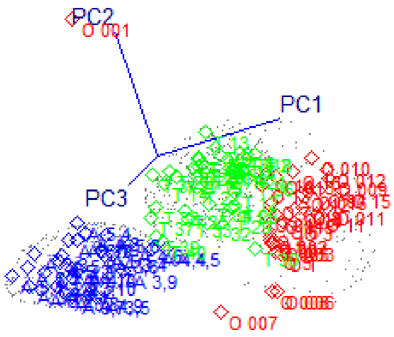


Fig. 6. Result from principal component analysis with the first three components

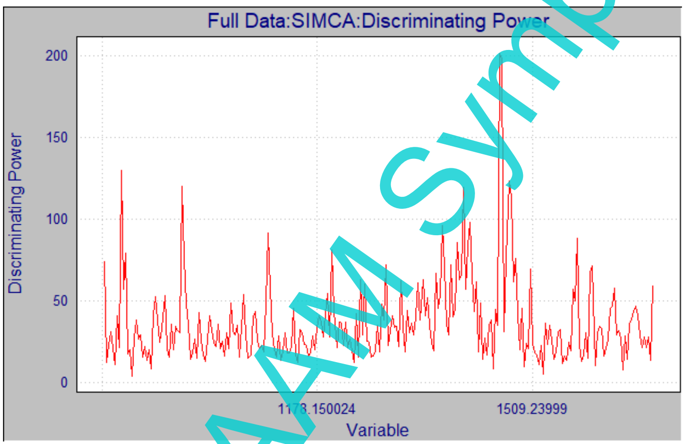


Fig. 7. Discriminating power for the three soil fields

It is also important to know which variables are best at discriminating between classes. For each wavelength, the average residual variance for each of the classes fit to all other classes and the residual variance of all classes fit to themselves are compared. This shows how important a given wavelength is to the difference between "correct" and "incorrect" classification. This is possible using Discrimination Power (DP). A value close to 0 indicates low discrimination ability in a wavelength, while a value much larger than 1 implies high discrimination power. The discriminating power is shown on Fig. 7. In the Fig. 7, the wavelengths between 860 and 1000 nm; 1200 and 1550 nm provide the most discriminating power for the classes.

Total Modeling Power determined which wavelenghts have importance for each class in the set. The ranges are from 0 to 1.

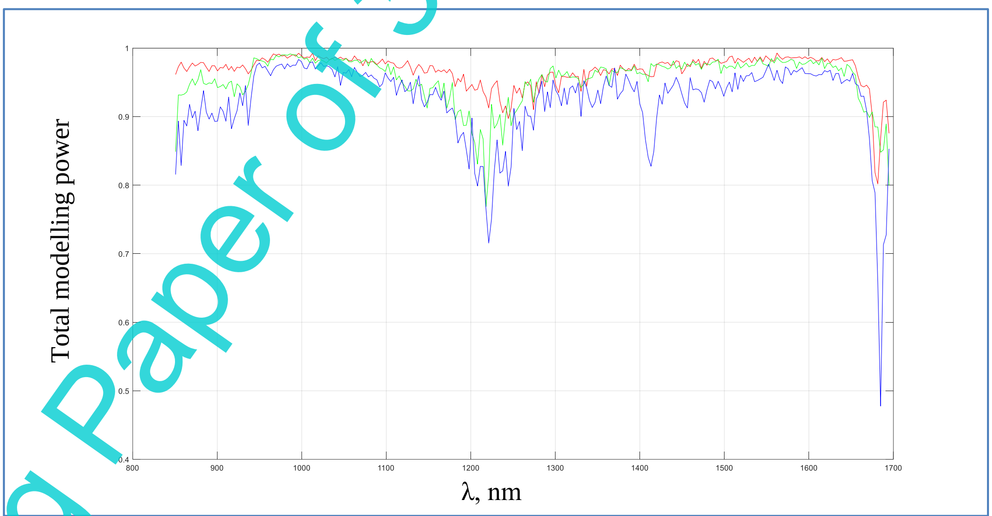


Fig. 8. Total modelling power for the three classes.

The sections of the total modelling power that were determined from 1200 to 1250 nm; 1300 to 1350 and 1400 to 1450 nm, the wavelengths can be defined that are informative and would be used as inputs to the classifiers.

The interclass distances presented in the table 1 indicate sufficiently separable classes.

	CS1@8	CS2@9	CS3@8
CS1	0.000000	3.565116	5.395718
CS2	3.565116	0.000000	5.654512
CS3	5.395718	5.654512	0.000000

Table 1. Interclass distances

4. Conclusion

The hyper-spectral images of the soil could be used as a method for express soil field recognition and assessment. The analysis of the obtained results shows that SIMCA classifier and principal component analysis as a pre-processing procedure can be used for successfully separate the soil fields.

This is of significant importance for the subsequent treatment of soil fields with a view to obtaining high yields and low production losses. From the experimental results and value of the modelling power are defined informative wavelengths for the three soil fields - 1200 to 1250 nm; 1300 to 1350 and 1400 to 1450 nm. In the future research work wavelengths will be determined for each class of data for which classification and recognition accuracy of soil fields will be evaluated. It would be a precondition for development of farmers information systems.

5. Acknowledgments

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