

## A SEGMENT-BASED REFERENCE SPECTRA DEFINITION FOR MULTISENSOR IMAGE DATA

*Ansgar Greiwe and Manfred Ehlers*

University of Osnabrueck, Research Centre for GIS and Remote Sensing (FZG), Germany  
email: {ansgar.greiwe, manfred.ehlers}@uos.de

### **ABSTRACT**

Many applications of remote sensing – like, for example, urban monitoring – require high resolution data for a correct determination of object geometry. These data contain often limited spectral information (e.g. three band RGB orthophotos) which may lead to classification errors between classes like water, dark pavements or dark rooftops. Additional Information about the material of an urban object's surface is needed to separate these classes.

Co-registered hyperspectral data could be used to provide this information. As a precondition for the analysis of hyperspectral data, the definition of endmembers representing the urban materials is necessary. Urban surface endmembers, however, are often a result of the mixture of manmade materials. This means that they display flat spectra. In addition, some of these endmembers have similar spectral features and are hardly separable in feature space. As a consequence, algorithms based on the analysis of spectral features alone like Pixel Purity Index (PPI) lead to a smaller number of defined urban surface endmembers. The presented approach determines instead of endmember as “pure” material pixel reference spectra in image space by a semi-automatic process.

After a segmentation of the high spatial resolution orthophotos, the resulting segments will be used to detect those pixels in the hyperspectral data set which represent candidates for the definition of reference spectra. The correlation matrix of the reference candidates' spectra is used afterwards to define a new feature space. Reference candidates with a similar spectral behavior could be grouped into a reference spectra definition by a special cluster algorithm. The resulting reference spectra are stored in a spectral library and used the classification of hyperspectral data.

### **INTRODUCTION**

Over the last years, urban applications of remote sensing have been performed by using high spatial resolution sensors to detect object shapes in a sufficient accuracy. These digital cameras or scanners usually provide less than 10 bands (sometimes only RGB) to characterize the spectral feature of recorded data. This limited spectral information may lead to classification errors between visibly similar land use classes like water, dark pavements or dark rooftops. As a result, in many cases additional information like the object's height or texture is used to improve the classification results. Previous work of the authors (i) shows, that additionally available hyperspectral data of the same area could be used in a feature based data fusion approach in order to improve the classification results.

For the standard workflow of an analysis of hyperspectral data the definition of a set of endmembers, representing “pure” material spectra is a precondition for the classification of these data. The definition of such a spectral library could be carried out by measurements of spectra in situ with a field spectrometer or by a definition of such “pure” pixels in image space of the data that have to be analyzed. A well known approach for such a definition is the Pixel Purity Index (PPI). However, in urban studies, the reference materials are often a result of a mixture of manmade materials. As a result, this mixture leads to flat spectral features, or, in addition, some of these materials have similar spectral features and are hardly separable in feature space. As a consequence, algorithms based on the analysis of spectral features like the PPI can hardly be used to separate spectral similar (urban) material spectra.

This approach is similar to the PPI on so far that it determines endmembers as reference spectra in image space. But instead of using the whole image as data source for a reference pixel estimation, only those pixel are accepted, that are part of a homogenous area. These areas are derived by segmentation of the high spatial resolution image data. After this filtering procedure, the reference candidates are grouped together according to their spectral features and stored as reference spectra in a spectral library.

## AVAILABLE DATA

### Digital Orthophoto

In June 2004, a Kodak DC14n (14 megapixel digital camera) was mounted on the Local Earth Observation (LEO) platform (ii). This platform contains a gyro stabilized platform which is capable of carrying analog middle format cameras as well as digital small format cameras. The Kodak DC14n has a 36 mm by 24 mm full format CMOS with a sensor's pixel size of 8  $\mu\text{m}$ . Two image blocks were flown during the 2004 LEO campaign. With a focal length of 50 mm, photos with a spatial resolution of 15 cm (flying height 950 m) and 25 cm (flying height 1600 m) were taken. By constructing a mosaic of 80 images, a digital orthophoto with a spatial resolution of 25 cm was produced with a accuracy of  $s_{x,y} = 0.2$  m. A subset of this orthoimage containing a part of the inner city Osnabrueck was defined as test area for this study.

### Hyperspectral Image Data

During the HyEurope2003 campaign, coordinated by the German Space Centre (DLR) in Oberpfaffenhofen, the hyperspectral image data were obtained by a north-south transect over the City of Osnabrueck. The used HyMap Sensor records 128 reflective bands covering the visible and near infrared range (VNIR) and the short wave infrared domain (SWIR) between 0.4  $\mu\text{m}$  and 2.5  $\mu\text{m}$ . With an operating altitude of 1500 m and a scan frequency of 16 Hz data could be recorded with a ground projected instantaneous field of view (GIFOV) of 3 m across and 4 m along flight track. The recorded radiances were corrected to absolute reflectances using the FLAASH software package (FLAASH = Fast Line-of sight Atmospheric Analysis of Hyperspectral Cubes). A subset of 118 bands of the 126 band original sensor data was taken for further processing. The scanned lines were interpolated to a regular raster by the parametric geocoding approach implemented in the software package PARGE (iii). Best results for the geometric accuracy were achieved with a normalized digital surface model derived from High Resolution Stereo Camera (HRSC-A) data. The geometric accuracy of the image data was estimated to be 1.5 m (one sigma).



Figure 1: Geometric accuracy of geocoded hyperspectral image data. Left: normalized digital surface model (nDSM), centre: geocoded hyperspectral data without nDSM, right: geocoded image data with use of nDSM,

## SEGMENT BASED REFERENCE SPECTRA DEFINITION

### Image Segments

In a first step, image segments could be derived from the high spatial resolution image data by using a region growing segmentation technique like the Fractal Net Evaluation Approach (FNEA). This approach belongs to the group of region growing strategies and is implemented in the software eCognition (iv). The size and shape of the image segments is highly dependent on the so called "scale-parameter". The value of this parameter has to be chosen with respect to the scale of the image objects and the data being processed. We chose a scale parameter which allows a differentiation even between dark objects like trees and their shadows. The disadvantage of this parameter selection, however, is that it leads to small fuzzy segments even for relatively homogenous surfaces like rooftops (Fig. 2).

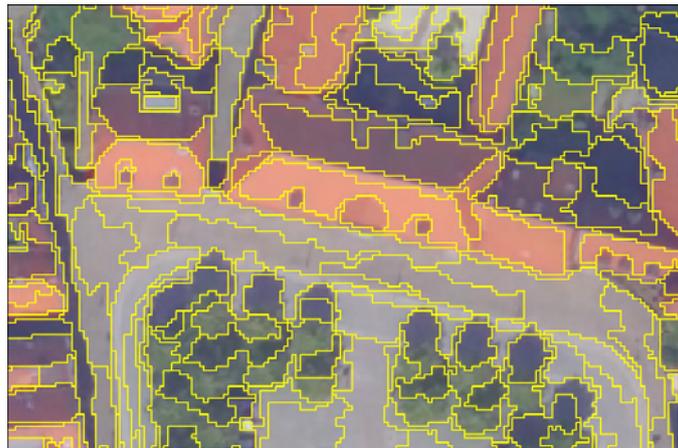


Figure 2: Image segments of high spatial resolution orthophoto.

### Reference Pixel Candidates

As already explained, an image segment can be viewed as a group of pixel (of the high spatial resolution orthophoto) that represents a homogenous area because of their similarity in the RGB feature space. If the high resolution and the hyperspectral data are accurately geocoded, the image segments from the orthophoto could be used like a cookie cutter on the hyperspectral data for the definition of "reference candidate" pixel for material spectra definition. If an image segment is large enough to include the N8 neighbours of hyperspectral data pixel (1,5 m pixel size) this hyperspectral pixel must also be in a homogenous area. For example, this homogenous image area could be a place paved with red concrete (Fig. 3 left). One possible way of selecting reference spectra could be a manual selection of all pixel that are inside segments of the same material (Fig. 3, red). This approach determines the reference spectrum in a automated algorithm from all pixel that are inside a segment (Fig. 3, yellow)

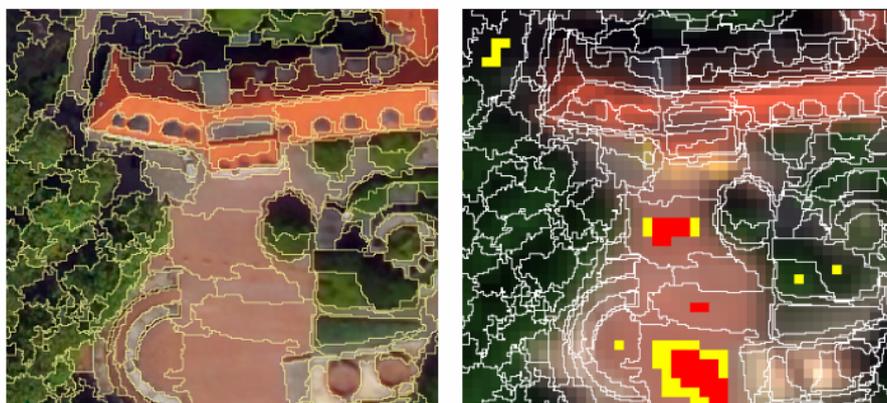


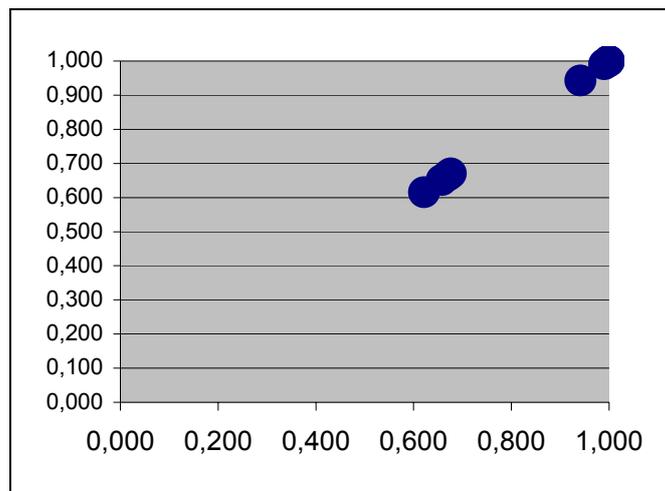
Figure 3: Left: Image Segments, Right: Hyperspectral data with overlay of segments

## Merging candidates to form a reference spectrum

After defining the candidates using a GIS-overlay function, pixels with similar spectral features have to be grouped together as a material reference spectrum. As a measure for the spectral similarity between the candidates, the correlation of the spectra of all candidate pixels is estimated. With  $n$  given candidate pixels, a  $n \times n$  correlation matrix is the result and the data inside this correlation matrix can be viewed as a new feature space (Tab. 1). This transformed feature space is  $n$ -dimensional for  $n$  given candidate pixels (the rows of the matrix defines the candidates, the columns are the observations). Candidates with spectral similarity are “spatially” grouped in this new feature space due to their similar correlation coefficients (Fig. 4).

*Table 1: Correlation matrix introduced as new feature space for reference spectra candidates. Candidate 1 to 6 build one group, Candidates 7 to 10 another.*

	1	2	3	4	5	6	7	8	9	10
1	1,000	1,000	0,999	0,997	0,990	0,942	0,621	0,676	0,670	0,657
2	1,000	1,000	1,000	0,997	0,991	0,943	0,616	0,671	0,664	0,651
3	0,999	1,000	1,000	0,997	0,991	0,944	0,611	0,666	0,659	0,644
4	0,999	0,997	0,997	1,000	0,994	0,949	0,632	0,681	0,671	0,655
5	0,997	0,991	0,991	0,994	1,000	0,977	0,656	0,695	0,685	0,668
6	0,990	0,943	0,944	0,949	0,977	1,000	0,684	0,700	0,691	0,672



*Figure 4: Candidates of table 1 displayed in a two-dimensional scatterplot (observation 1 vs. observation 2).*

Due to the high correlation of the pixels’ spectra, the feature space introduced above is also highly correlated (see Fig. 4). After a Principal Component Analysis of the data, a decorrelated feature space remains for further analysis.

## Cluster Strategy

Clustering is a well known common approach to group objects with similar feature values in an  $n$ -dimensional feature space. Due to the high correlation of the feature space, the point clusters are formed as long chains, if the first three principal components of the correlation matrix are used as feature space. Therefore we decided to implement a single link cluster algorithm. The threshold for this algorithm – the maximum distance between two candidates – is derived from the average nearest distance of the proximity matrix of all candidates.

## RESULTS AND CONCLUSIONS

For a defined test site, image segments for several materials like water, cobblestone pavement and different rooftop material like copper, red clay and zinc were selected to test the approach. The candidates were defined using selected segments and an N8 filtering routine. The correlation matrix of these candidates spectra was calculated and the first three principal components of this matrix were clustered by the single link algorithm (Fig. 5).

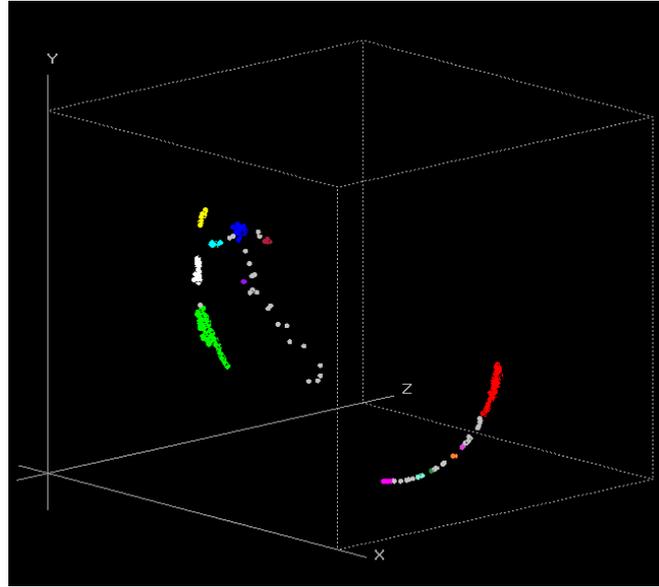


Figure 5: Cluster found by single link algorithm

Each cluster contains a group of pixel that can be viewed as – sometimes - disconnected regions of pixel in the hyperspectral image space. The mean spectra of this region and the region itself are displayed in figure 6.

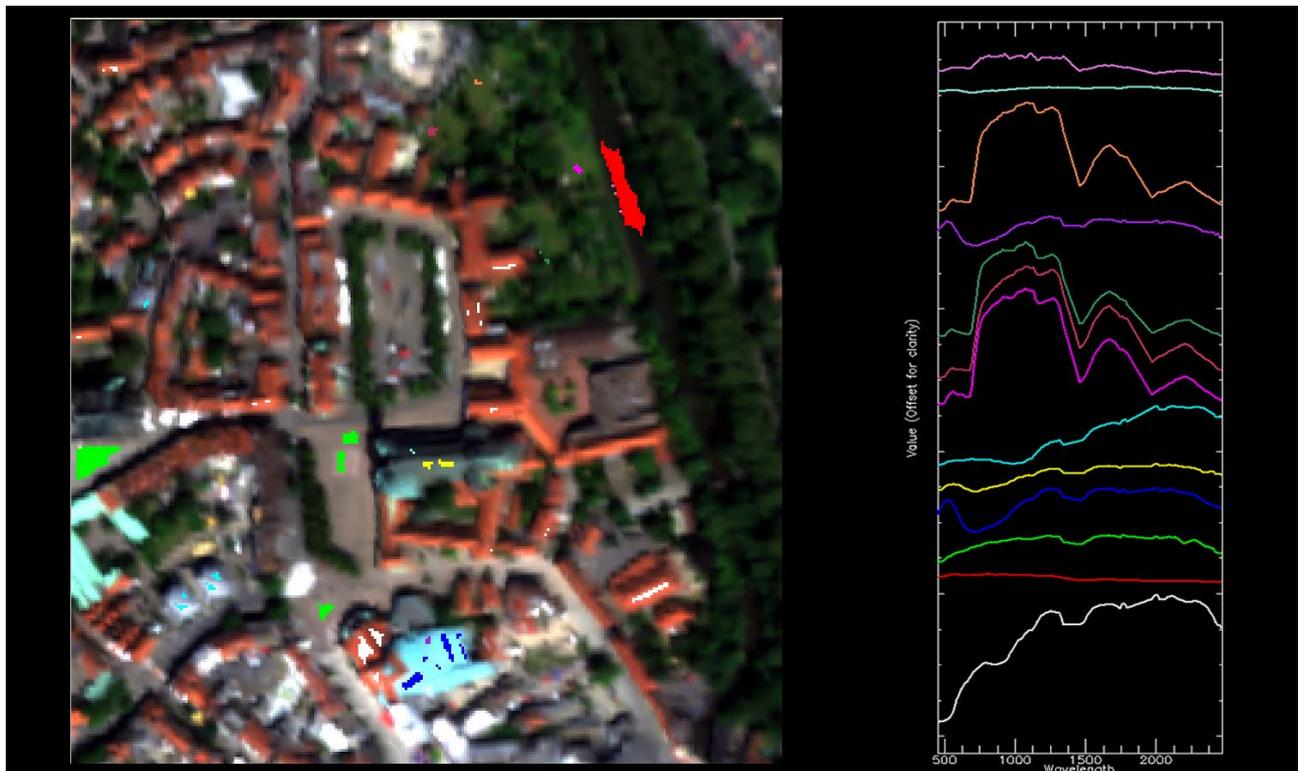


Figure 6: Left: cluster as regions, right: corresponding spectra.

The results of our approach show that at the current state of development, several similar spectra are not correctly grouped together. Nevertheless, the differentiation of rooftop material show promising results. For further development, a more customized cluster algorithm will be developed to differentiate also materials like red pavements and red clay tiles, which display a high spectral correlation.

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