TOWARDS AN OPTIMIZED USE OF THE SPECTRAL ANGLE SPACE

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ABSTRACT

The concept of spectral angle mapping (SAM) is extended in this work by the use of self-learning decision trees (DT) to evaluate rule images. We test whether the performance of the SAM can be improved to achieve the quality of more recent machine learning classifiers in spectrally heterogeneous environments. Results show that the integration of the DT significantly increases the accuracy of the SAM of urban hyperspectral data. However, the accuracy of support vector machines is not achieved. Despite this lower accuracy, the spectral angle space as constituted by the SAM rule images appears to be a useful class-specific transformation of the data, which might be used similar to common transformations in future works.

INTRODUCTION

Spectral angle mapping (SAM) has found widespread acceptance in hyperspectral image analysis to determine spectral similarity (i,ii). This simple, yet effective method compares unknown spectra to known endmember spectra by calculating the angle between the corresponding vectors in the spectral feature space (iii). The similarity measure relates only to the spectra's shape, not to their absolute reflectance. SAM is sensitive to absorption features and achieves good results with few training samples. However, SAM performance is often less accurate than more recent developments from the field of machine learning, e.g. support vector machines (iv). Especially for environments with complex spectral properties, i.e. heterogeneous classes with multiple spectral clusters, SAM is not well suited. This study investigates, whether SAM can be improved to reach the quality of advanced classification algorithms.

In most SAM classifications of hyperspectral images, one representative endmember spectrum (EM) is selected for each class, e.g. a resampled laboratory spectrum or the mean spectrum of interactively selected areas in the image (Fig. 1, left). A rule image is generated for each EM that contains the spectral angles between the EM and the image pixels. A pixel is labelled based on its minimum value in the set of rule images. This procedure might be refined by interactively setting a maximum threshold for the angular values of individual classes to account for varying class heterogeneity (Fig. 1, centre). However, single mean spectra are not representative for spectrally complex thematic classes with high intra-class variability and possibly multi-modal distribution in spectral feature space. In these cases, it is necessary to use more than one EM per thematic class and to generate rule images with more layers than thematic classes (Fig. 1, right). The selection of representative EMs for sub-classes is complicated and an iterative definition of thresholds by the user is usually not feasible.

The present work integrates a self-learning decision tree classifier (DT) to interpet rule images during the classification of hyperspectral data from a heterogeneous urban environment. This way, the definition of thresholds for all rule images is performed automatically during the DT's training. Moreover, decisions are not based on single minimum values, but on rule sets that comprise rule images from various EMs. The automatic thresholding of the DT allows integrating a high number of EMs. Resulting rule images, i.e. EMs that do not contribute to the classification results are automatically discarded.

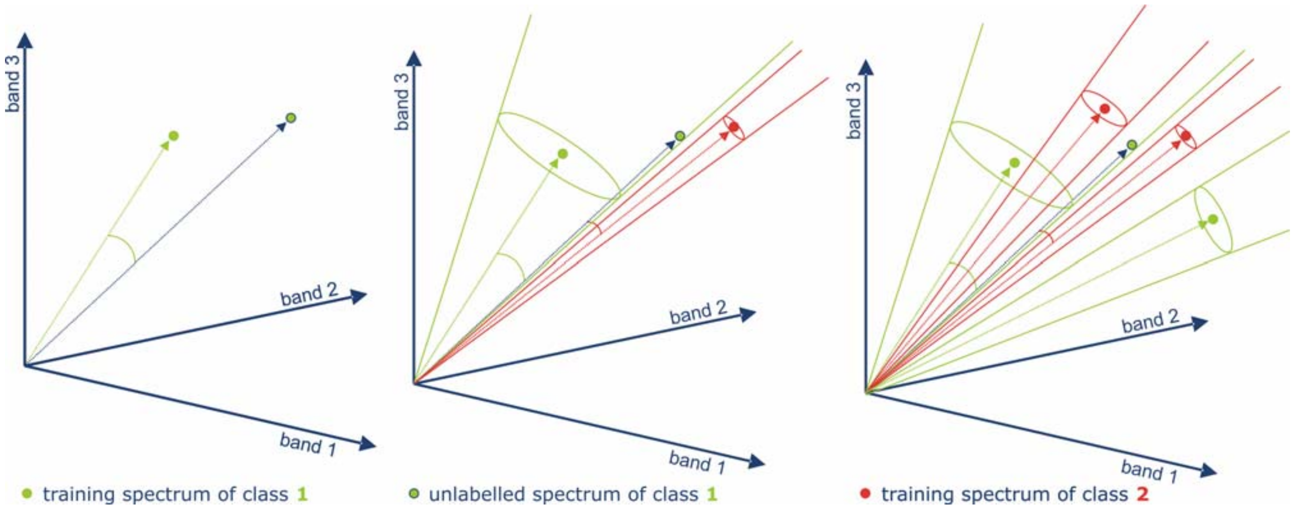

Figure 1: Concept of SAM in 3-D feature space. Similarity of unknown spectrum and EM is evaluated based on the spectral angle between the vectors representing the spectra (left). By introducing thresholds, differences in class heterogeneity are considered during classification (centre). For complex class distributions with spectral sub-classes, more than one EM per class and individual thresholds for each EM are required (right).

METHODS

SAM was performed on image data from the Hyperspectral Mapper (HyMap). The 7277 x 512 pixel image was acquired over Berlin, Germany on 20 June 2005 and covers a heterogeneous urban environment at a ground instantaneous field of view of 4 m. The data was corrected for atmospheric effects and transformed to reflectance values following (v). It was then reduced to 114 bands based on the signal-to-noise ratio. From previous studies, extensive training data for supervised classification of 5 land cover classes and reference data for the accuracy assessment of the results existed. The pixels of the training and reference data were randomly selected from the image and labelled based on high resolution aerial photographs (Tab. 1).

Table 1: Number of training and reference pixels of five land cover classes.

	Vegetation	Buildings	Roads	Soil	Water
Training	626	558	553	257	110
Reference	565	224	309	72	83

Altogether, six different setups were explored to assess the advanced SAM classification (Fig. 2). At first, three different sets of rule images were generated: (1) a set of 5 rule images based on 1 mean spectrum per class, (2) a set of 125 rule images based on 25 spectra per class, which were randomly selected from all training pixels, and (3) a set of 50 rule images based on interactively selected spectra. This selection aimed at representing the spectral heterogeneity of the 5 classes and hence comprised different numbers of EMs per class. These three sets were then evaluated in two ways: (1) by labelling each pixel based on its minimum value in all rule images and (2) by applying a self learning DT on the set of rule images. The See5 algorithm was used to generate the DT (vi). The training was performed using all 2052 training pixels.

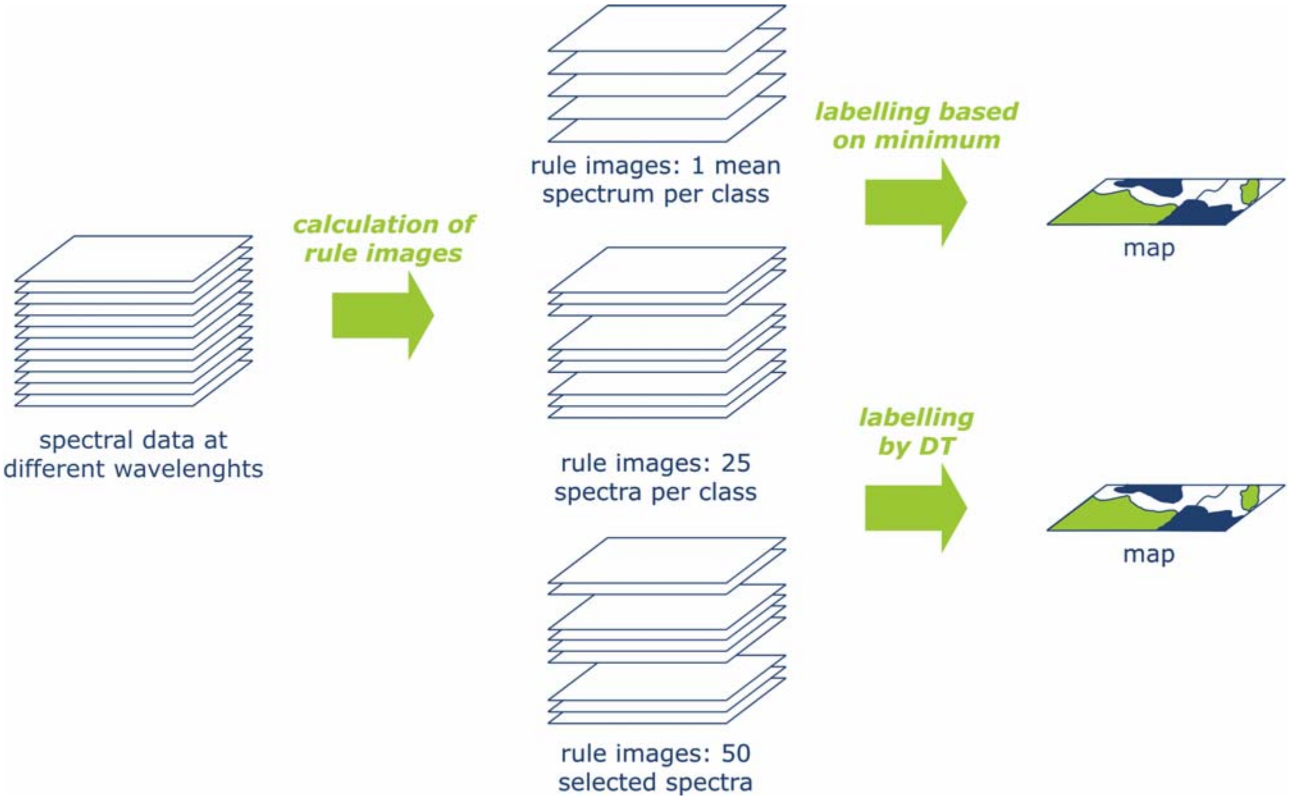

Figure 2: Workflow of SAM. Six different approaches were performed. Details see text.

RESULTS & DISCUSSION

The results of the SAM classification with decisions based on minimum values were significantly improved by introducing more than one EM per class (Tab. 2). The accuracy of vegetation remains equally high for individual classes, while values for buildings and roads are improved and pixels falsely assigned to soil or water (e.g. shadow pixels) decrease (Fig. 3). This is confirmed by the individual class statistics (not shown) and can be explained by the heterogeneous spectral distribution of the classes. The fact that 50 interactively selected EMs lead to a better performance than 125 EMs, i.e. 25 per class, underlines the importance to represent spectrally extreme EMs in the training data set for SAM.

Table 2: Overall accuracies for the five land cover classes as achieved by the six different approaches for spectral angle mapping.

	Minimum value	DT
1 mean per class	70.4%	77.0%
25 random per class	72.7%	77.0%
50 interactively selected	74.7%	78.9%

The use of the self-learning DT for the evaluation of the rule images had even greater influence on the overall accuracy. For all three sets of rule images, significantly higher accuracies were achieved. Actually, equal accuracies were achieved on the 5 rule images generated from mean spectra and on the set of 25 per class. This shows that the DT defines very useful thresholds. Moreover, the DT uses the rule images for all 5 classes to define rules for each individual class, i.e. a class label relies on the similarity to its corresponding rule image, but also to the dissimilarity to the rule images of the other classes. The highest accuracy of 78.9% was achieved for the DT-based mapping using the set of 50 interactively selected rule images.

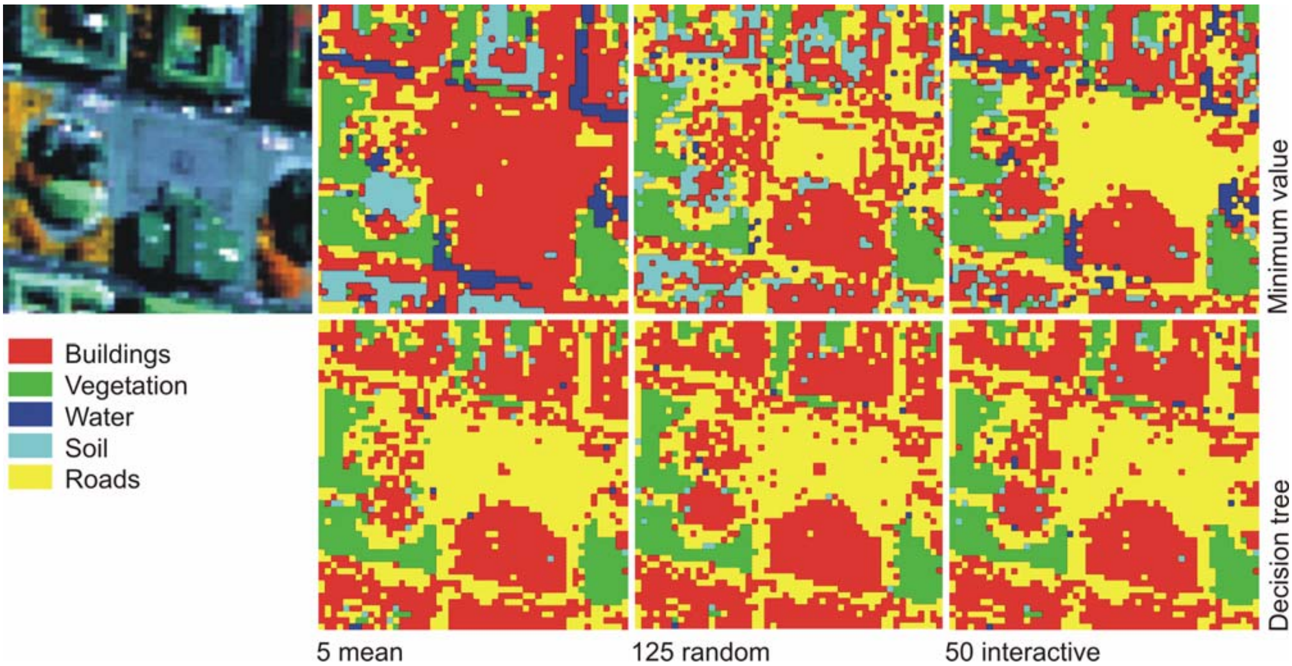

Figure 3: Results from the SAM classification using six different approaches described in this work. The original HyMap data (R: 829 nm; G: 1648 nm; B: 662 nm) is shown for orientation

For matters of comparison the DT was applied directly to the 114 original spectral bands and it achieved an accuracy of 77.6%. The slight difference between this value and the 78.9% achieved with the DT on the set of 50 rule images rather underlines the performance of the DT. However, the accuracy achieved by the DT on the 50 rule images is higher than that achieved on the 114 original spectral bands and 77% overall accuracy are already achieved on the 5 rule images that base on the classes' mean spectra. Therefore, the spectral angle space, as described by the rule images, appears to be a useful representation of the 5 land cover classes. The generation of SAM rule images can thus be seen as a class-specific transformation of the data into a lower dimensional space. This transformation is not bound to any statistical measures and it differs from other transformations in the reduction of illumination differences.

By using support vector machines with the same training data, an accuracy of over 86% was achieved (vii). The performance of all SAM approaches presented is hence significantly lower, even with advanced strategies and the use of the DT. Thus, SAM appears not optimal for the classification of heterogeneous urban environments.

CONCLUSIONS & OUTLOOK

It was shown that the integration of a self-learning DT into the SAM classification is generally possible and significantly improves results for a heterogeneous environment. Results are still below those from machine learning classifiers and the individual application of the DT on the original data achieves only slightly inferior results. The suggested approach should be tested in a different environment, e.g. in the context of geological applications with surfaces that show distinct mineralogical absorption features.

To further improve the integration of a self-learning DT into the evaluation of the SAM rule images a method to automatically search for the ideal EMs and for the training of the DT should be included.

Results show that the spectral angle space, i.e. the space described by the rule images with the spectral angles, is a low-dimensional, class-specific representation of original features. By generating rule images, a class-oriented transformation or feature extraction is performed that might be used in other advanced classification problems.

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