SPATIAL HYPERSPECTRAL IMAGE CLASSIFICATION BY PRIOR SEGMENTATION

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Many hyperspectral image classification algorithms are pure spectral techniques. Each pixel is classified individually, thus entirely independent from all the other pixels present in the image. However, many if not all images exhibit a high correlation between neighboring pixels, due to the presence of texture or other spatial features. The classification can be enhanced by taking advantage of the spatial features. Typical approaches post-process the classification map by means of majority analysis techniques [1], or incorporate the dependencies between neighboring pixels as prior knowledge in a Bayesian classification framework and model them by Markov Random Fields [2]. An alternative approach is based on prior segmentation of the dataset [3]. In this work we present such an approach and validate it on a hyperspectral image classification task.

1. SEGMENTATION AND CLASSIFICATION METHOD

Segmentation algorithms attempt to divide an image into a number of homogeneous and spatially connected regions. Many segmentation algorithms and many criteria to define the homogeneity of a region are available in the literature. Examples of such criteria are spectral information, texture features, edges or statistical properties. Some well known examples of segmentation techniques are watershed segmentation, region growing, contour based methods, etc.

We developed a segmentation algorithm for the segmentation of multispectral images. The basis of the algorithm consists of a model-based region-merging technique, applying a multinormal model for the pixels in each region, and estimating the model parameters using Maximum Likelihood principles. From the resulting probability density function (pdf) a generalized likelihood ratio test (GLRT) is obtained, which is used to test whether two regions belong to the same statistic and thus must be merged, or do not belong to the same statistic and thus must remain separated. Now, starting from an initial segmentation result, the GLRT is evaluated for each pair of adjacent regions. Pairs for which the value of the equation is larger than a certain threshold T, are marked. In the next step, all marked pairs are sorted and then merged. This process of marking, sorting and merging continues, until no more regions satisfy the merging criteria. A multiscale version of the framework is established by applying a wavelet transform on the multispectral image and repeating the same procedure at different resolution levels of the original image (for more information, we refer to [4]).

In this work, we propose to incorporate spatial information into a hyperspectral image classification task by segmenting the image first. Instead of classifying each individual pixel of the image, the segmented regions are classified as a whole. For each region, the average spectrum is calculated and classified with a standard classification algorithm. In this work, a Linear Discriminant Analysis (LDA) algorithm was used to illustrate the technique.

2. EXPERIMENTS AND RESULTS

The proposed technique is validated on a hyperspectral dataset of a heathland area in Belgium. This airborne hyperspectral data was obtained in June 2007 with an AHS sensor with a ground resolution of approximately 2.5m. The range of 450nm-2550nm is covered by 63 spectral bands. Ground reference data were collected in homogeneous plots of 10 meters diameter. The vegetation data of the sampled plots, approximately 1200 in total, were analyzed and plots were grouped in 6 classes: heathland, grassland, forest, sand, dunes, water bodies and arable fields.

In addition to the ground reference data, a Biological Valuation Map (BVM) is available that covers a large part of the studied area. While the ground data only contains vegetation information at a sparse set of 'point' locations, the BVM contains vegetation information for much larger areas. This makes it very well suitable for the validation of the proposed spatial technique. With the usage of the traditional ground reference data, only the spectral part of the result can be validated.

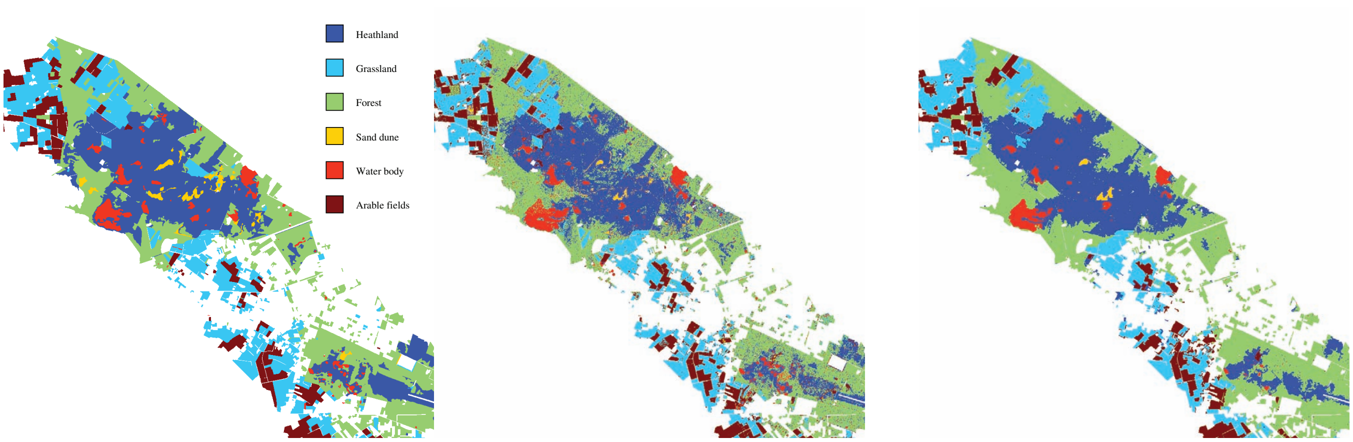
The LDA classification algorithm is trained on a subset of the ground reference data. The training set is chosen from the locations of the ground reference, so both the ground reference data and the BVM can be used for comparison. Next, the dataset

	LDA	LDA with segmentation
Heathland	82.63	81.52
Grassland	80.86	78.36
Forest	79.04	74.50
Sand dune	59.92	75.18
Water body	51.19	83.47
Arable fields	65.69	70.09
Total	77.57	77.53

Table 1. Classification accuracy (pixel percentage).

is segmented using the proposed segmentation algorithm. Due to memory and computational limitations, the segmentation is performed on a random selection of only 4 spectral bands. Then, for each region in the segmentation map, the average spectrum (with all 63 bands) is calculated and classified. The obtained classification results are compared to the pure spectral classification results with the same classification algorithms. The results are validated against the BVM rather than the ground reference data, to be able to validate not only with respect to the spectral information, but also to the spatial information that is present in the vegetation map.

From the results in figure 1, it is clear that the spectral classification produces very pixelated results, which are not desired for vegetation monitoring. After segmentation, the classification produces a vegetation map with larger, smoothed regions, while the overall classification success rate is comparable to the pure spectral classification results.



(a) Biological Valuation Map (b) LDA without prior segmentation (c) LDA with prior segmentation

Fig. 1. Classification results.

3. REFERENCES

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