CLASSIFICATION OF HYPERSPECTRAL DATA USING SUPPORT VECTOR MACHINES AND ADAPTIVE NEIGHBORHOODS

Y. Tarabalka [a,b], J. A. Benediktsson [b], J. Chanussot [a]

[a] GIPSA-Lab, Grenoble Institute of Technology, Domaine Universitaire – BP 46, 38402, Saint-Martin-d'Hères, France - yuliya.tarabalka@hyperinet.eu, jocelyn.chanussot@lis.inpg.fr
[b] Faculty of Electrical and Computer Engineering, University of Iceland, Hjardarhaga 2-6, 107, Reykjavik, Iceland - benedikt@hi.is

KEY WORDS: Hyperspectral images, Spectral-spatial classification, Segmentation, Adaptive neighborhoods, Majority vote

ABSTRACT:

A new spectral-spatial classification scheme for hyperspectral images is presented. Pixel-wise Support Vector Machines classification and segmentation are performed independently, and then the results are combined, using the majority vote approach. Thus, every region from a segmentation map defines an adaptive neighborhood for all the pixels within this region. The use of several segmentation techniques is investigated: watershed, partitional clustering and hierarchical image segmentation (HSEG). The developed classification scheme substantially improves the classification accuracies and provides classification maps with more homogeneous regions, compared to pixel-wise classification. The proposed method is especially suitable for classification of images with large spatial structures, and when different classes have dissimilar spectral responses.

1. INTRODUCTION

Hyperspectral (HS) imaging is a relatively new technique in remote sensing that acquires hundreds of images corresponding to different spectral channels. The rich spectral information of HS images increases the capability to distinguish different physical materials, leading to the potential of a more accurate image classification.

An extensive literature on the classification of HS images is available, among them pixel-level processing techniques that assign each image pixel to one of the classes based on its spectral values (Chang, 2003; Landgrebe, 2003). In particular, Support Vector Machines (SVM) classification has given good accuracies when applied to HS images (Camps-Valls & Bruzzone, 2005; Fauvel, 2007). In order to further improve the classification results, spatial information should also be incorporated into the classifiers. In previous studies, morphological filters (Fauvel, 2007) and Markov random fields (Farag *et al.*, 2005) were exploited to include spatial context in the SVM classification. Though classification accuracies were improved compared to pixel-wise classification, the use of these methods raises the problem of scale selection.

In this paper, a new spectral-spatial classification scheme for HS images is presented. The proposed method combines the results of a pixel-wise SVM classification and a segmentation map, using the *majority vote* approach (Tarabalka *et al.*, 2008). Thus, the segmentation defines an *adaptive neighborhood* for each pixel.

In the next section, we discuss several techniques for segmentation of an HS image. In Section 3, the proposed scheme is described. Experimental results are discussed in Section 4 and the final conclusions are presented in Section 5.

2. SEGMENTATION OF HYPERSPECTRAL IMAGES

Segmentation can be defined as an exhaustive partitioning of the input image into regions, each of which is considered to be homogeneous with respect to some criterion of interest. Segmentation of an HS image is a challenging task. In this paper, the use of several segmentation techniques is investigated: watershed, partitional clustering, hierarchical image segmentation (HSEG).

2.1 Watershed

The watershed transformation is a powerful technique of mathematical morphology for image segmentation. The watershed is usually applied to the gradient function, and it divides an image into regions, so that each region is associated with one *minimum* of the gradient image (Beucher & Lantuejoul, 1979).

The extension of a watershed technique to the case of HS images has been investigated in (Noyel *et al.*, 2007; Tarabalka *et al.*, 2008). In this paper, we present watershed results, obtained by the scheme described in (Tarabalka *et al.*, 2008): First, a one-band Robust Color Morphological Gradient (RCMG) for the HS image is computed. By applying watershed transformation using a standard algorithm (Vincent & Soille, 1991), the image is partitioned into a set of regions, and one subset of watershed pixels, *i.e.*, pixels situated on the borders between regions. Finally, every watershed pixel is assigned to the neighboring region with the "closest" median (the distance between the vector median of this region and the watershed pixel is minimal).

2.2 Partitional clustering

The use of partitional clustering for HS image segmentation is discussed in (Tarabalka *et al.*, 2009). Clustering aims at grouping pixels, so that pixels belonging to the same cluster are spectrally similar. Here we present segmentation results based on the partitional clustering using the Expectation Maximization (EM) algorithm for the Gaussian mixture resolving (Tarabalka *et al.*, 2009). We assume that pixels belonging to the same cluster are drawn from a multivariate Gaussian probability distribution (an upper bound on the number of clusters must be chosen). The parameters of the distributions are estimated by the EM algorithm. When the algorithm converges, the partitioning of the set of image pixels into C clusters is obtained. Thus, each pixel has a numerical label of the cluster it belongs to. However, as no spatial information is used during the clustering procedure, pixels with the same cluster label can form a connected spatial region within the spatial coordinates, or can belong to disjoint regions. In order to obtain a segmentation map, a connected components labeling algorithm is applied to the output image partitioning obtained by clustering.

2.3 Hierarchical image segmentation

The HSEG algorithm is a segmentation technique which is based on iterative hierarchical step-wise optimization (HSWO) region growing method. Furthermore, it provides a possibility of merging non-adjacent regions by spectral clustering (Tilton, 2008). Thus, the processing both in the spatial and spectral domain are combined.

The NASA Goddard's RHSEG software provides an efficient implementation of the HSEG algorithm. We have investigated the use of this technique for the segmentation of HS images.

We propose to use a Spectral Angle Mapper (SAM) as the criterion of dissimilarity between pixel vectors (this criterion is frequently used in HS image analysis). Furthermore, the optional parameter *spclust_wght* tunes the relative importance of spectral clustering *versus* region growing. Here we present the results obtained with $spclust\_wght = 0.0$ (region growing only) and $spclust\_wght = 0.1$.

RHSEG gives as output a hierarchical sequence of image partitions. In this structure, a particular object can be represented by several regions at finer levels of details, and can be assimilated with other objects in one region at coarser levels of details. This gives a flexibility to choose an appropriate level of details in the segmentation map (by using manual or automatic selection). If $spclust\_wght > 0.0$, labeling of connected components has to be performed after RHSEG, in order to obtain a segmentation map where each spatially connected component has a unique label.

3. SPECTRAL-SPATIAL CLASSIFICATION SCHEME

As depicted in Figure 1, the proposed spectral-spatial classification scheme is composed of the following steps:

1. Segment an HS image into homogeneous regions using one of the techniques described in the previous section.
2. Perform pixel-wise classification of the HS image using an SVM classifier*.
3. For every region in the segmentation map, assign all the pixels to the most frequent class within this region (*majority vote* rule).

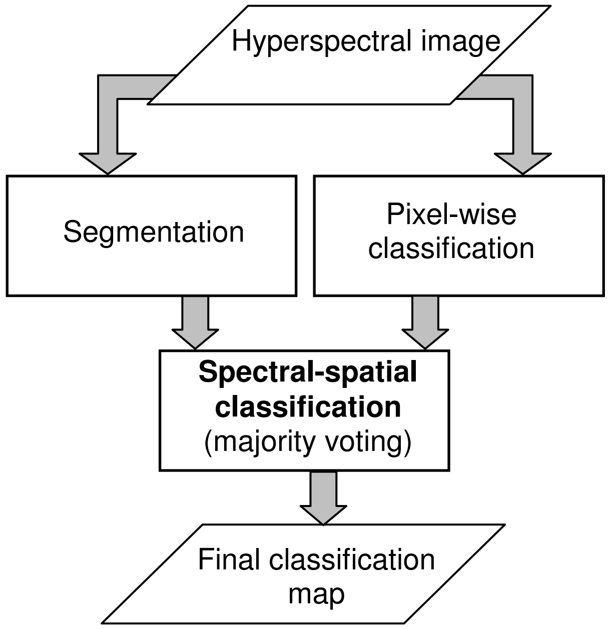

Figure 1. Flow-chart of the proposed spectral-spatial classification scheme

Thus, for each pixel, the region it belongs to as defined by the segmentation map is used as its adaptive neighborhood for the spatial regularization following a pixel-wise classification.

4. EXPERIMENTAL RESULTS

Experimental results are presented for a 103-band ROSIS-03 (Reflective Optics System Imaging Spectrometer) image of the University of Pavia, Italy (acquired by DLR). The image is 610 by 340 pixels, the spatial resolution is 1.3 m per pixel. The number of data channels of the ROSIS-03 sensor is 115, with a spectral range from 0.43 to 0.86 μm.

* Other classifiers could be used. However, an SVM is extremely well suited to classify HS data (Licciardi *et al.*, 2009).

The 12 most noisy channels were removed, and the remaining 103 bands were used for the experiments. The reference data contain nine classes of interest, which are detailed, with the number of test and training samples for each class, in Table 1.

Class		Samples	
No	Name	Train	Test
1	Asphalt	548	6304
2	Meadows	540	18146
3	Gravel	392	1815
4	Trees	524	2912
5	Metal Sheets	265	1113
6	Bare Soil	532	4572
7	Bitumen	375	981
8	Bricks	514	3364
9	Shadows	231	795
Total		3921	40002

Table 1. Information classes and training-test samples

All the segmentation techniques described in Section 2 were used in the experiments, and the best found results for each technique are shown in this paper:

1. Watershed segmentation (**WH**) was applied, using the RCMG, as described in Section 2.1.
2. Segmentation by partitional clustering using the EM algorithm for the Gaussian mixture resolving (**EM**) was performed, with the maximum number of clusters equal to 10. To avoid the problem of the covariance matrix singularity or inaccurate parameter estimation results, feature reduction has been previously applied, by averaging over every 10 neighboring bands[*].
3. The HSEG segmentation (**HS**) was applied with $spclust\_wght = 0.0$ and $spclust\_wght = 0.1$. Segmentation maps for several levels of hierarchy were chosen interactively in both cases, in order to be used for spectral-spatial classification. Here, the results leading to the best classification accuracies are shown (that correspond to the hierarchical levels 400 and 500, respectively).

Table 2 gives the number of regions for the resulting segmentation maps. The analysis of undersegmentation/oversegmentation level was conducted. It is concluded that: a) there is almost no undersegmentation in the obtained results; b) all the segmentation results are oversegmented. However, as was explained in (Tarabalka *et al.*, 2008), oversegmentation is not a crucial problem for this research, as the final goal is not to obtain the segmentation result, but to classify the image. Thus, by performing segmentation we are searching for spatial regions of pixels that belong to the same physical object. It is evident that undersegmentation is not desired. Therefore, the obtained oversegmented maps can be further used for spectral-spatial classification.

The multi-class pairwise (one *versus* one) SVM classification, with the Gaussian Radial Basis Function kernel, of the original image was performed (with parameters $C = 128$, $\gamma = 0.125$), using the LIBSVM library (http://www.csie.ntu.edu.tw/~cjlin/libsvm).
The results of pixel-wise classification were combined with the segmentation results, using a majority vote approach.

Table 2 gives global and class-specific classification accuracies for the pixel-wise SVM and proposed spectral-spatial classification. The following measures of accuracy were used: Overall Accuracy (OA), Average Accuracy (AA) and kappa coefficient κ. Figure 2 shows the classification map for the spectral-spatial classification using the HSEG segmentation map with $spclust\_wght = 0.1$ (that

[*] The first three bands of the 103-band image were omitted when performing the averaging over bands.

corresponds to the best classification accuracies).

	SVM	+WH	+EM	+HS	+HS
scw				0.0	0.1
OA	81.01	85.42	93.59	90.00	**93.85**
AA	88.25	91.31	94.39	94.15	**97.07**
κ	75.86	81.30	91.48	86.86	**91.89**
1	84.93	93.64	90.72	73.33	**94.77**
2	70.79	75.09	**92.73**	88.73	89.32
3	67.16	66.12	82.09	**97.47**	96.14
4	97.77	98.56	**99.21**	98.45	98.08
5	99.46	99.91	**100**	99.10	99.82
6	92.83	97.35	96.78	98.43	**99.76**
7	90.42	96.23	92.46	95.92	**100**
8	92.78	97.92	97.80	98.81	**99.29**
9	**98.11**	96.98	97.74	97.11	96.48
NOR		11802	21450	7231	7575

Table 2. Global and class-specific classification accuracies in percentage (scw – *spclust_wght*; NOR – Number of Regions in the segmentation map)

The developed classification scheme substantially improves the classification accuracies and provides classification maps with more homogeneous regions, compared to pixel-wise classification. All segmentation maps lead to higher classification accuracies. The best global accuracies are achieved when performing spectral-spatial classification using the HSEG algorithm for image segmentation with $spclust\_wght = 0.1$ (i.e. performing segmentation both in the spatial and spectral domain). In this case, the overall accuracy is improved by 12.8% and the average accuracy improved by 8.8% compared to the pixel-wise SVM classification. Classification using the EM segmentation map also gives very high accuracies, though slightly lower than when using the HSEG technique. Watershed segmentation performs worse than other segmentation techniques for the given data set. From here, the conclusion can be made that the considered image contains classes with mostly dissimilar spectral responses. Therefore, segmentation using cluster-based methods gives accurate results.

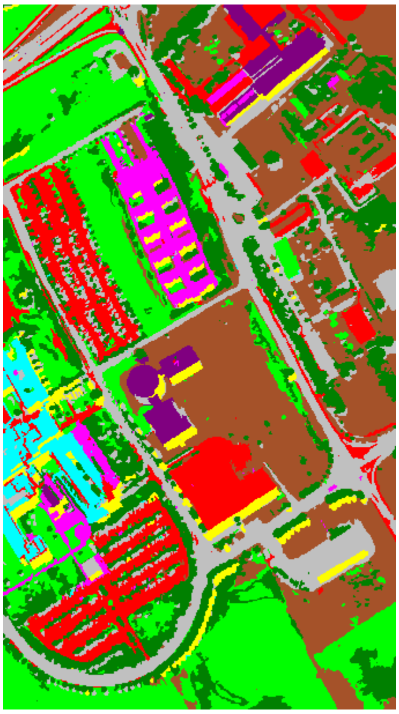

Figure 2. Classification map for the spectral-spatial classification using the HSEG segmentation map with $spclust\_wght = 0.1$

Spectral-spatial classification improves accuracies for almost all the classes, except for the class “shadows”. This class presents small spatial structures that are in danger to be assimilated with the larger structures in their neighborhood and disappear in the final classification map. Based on the shown results and our research beyond the scope of this paper, it can be concluded that the segmentation methods working in the spectral domain lead to lower risk of removing small spatial structures than those working in the spatial domain. Furthermore, as the HSEG gives a hierarchy of segmentation maps at different level of details, it is interesting to investigate how multiscale analysis can help to preserve small structures in the image.

5. CONCLUSIONS

A new spectral-spatial classification scheme for HS images is presented in this paper. Here it is proposed to perform segmentation in order to use every spatial region as an adaptive neighborhood for all the pixels within that region. Several segmentation techniques are investigated for this purpose. Furthermore, the results of a pixel-wise SVM classification and a segmentation map are combined, using the majority vote rule.

The presented experimental results did show that the proposed method significantly improves the classification accuracies and provides classification maps with more homogeneous regions, when compared to pixel-wise classification. In the future, we will investigate other approaches to fuse spectral and spatial information, in order to increase classification accuracies and robustness of the classifier.

ACKNOWLEDGEMENTS

This research is supported in part by the Marie Curie Research Training Network "HYPER-I-NET". The authors would like to thank DLR and Paolo Gamba, from the University of Pavia, Italy for providing the HS data.

REFERENCES

Beucher, S., Lantuejoul, C., 1979. Use of watersheds in contour detection. *In Int. Workshop Image Processing, Real-Time Edge and Motion Detection/Estimation.* Rennes, France: CCETT/IRISA.

Camps-Valls, G., Bruzzone, L., 2005. Kernel-based methods for hyperspectral image classification. *IEEE Trans. Geos. and Remote Sens.*, 43(6), pp. 1351–1362.

Chang, C.-I., 2003. *Hyperspectral Imaging: Techniques for Spectral Detection and Classification*. Kluwer Academic Publishers, Dordrecht.

Farag, A., Mohamed, R., El-Baz, A., 2005. A unified framework for map estimation in remote sensing image segmentation. *IEEE Trans. Geos. and Remote Sens.*, 43(7), pp. 1617–1634.

Fauvel, M., 2007. Spectral and spatial methods for the classification of urban remote sensing data. Ph.D. dissertation, Grenoble Institute of Technology.

Landgrebe, D. A., 2003. *Signal Theory Methods in Multispectral Remote Sensing*. John Wiley & Sons, Inc.

Licciardi, G., Pacifici, F., Tuia, D., Prasad, S., West, T., Giacco, F., Inglada, J., Christophe, E., Chanussot, J., Gamba, P., 2009. Decision fusion for the classification of hyperspectral data: Outcome of the 2008 GRS-S Data Fusion Contest. *IEEE Trans. Geos. and Remote Sens*., under review.

Noyel, G., Angulo, J., Jeulin, D., 2007. Morphological segmentation of hyperspectral images. *Image Analysis & Stereology*, 26, pp. 101–109.

Tarabalka, Y., Chanussot, J., Benediktsson, J. A., Angulo, J., Fauvel, M., 2008. Segmentation and classification of hyperspectral data using watershed. *In Proc. of IGARSS '08*, Boston, USA.

Tarabalka, Y., Benediktsson, J. A., Chanussot, J., 2009. Spectral-spatial classification of hyperspectral imagery based on partitional clustering techniques. *IEEE Trans. Geos. and Remote Sens*., under review.

Tilton, J. C., 2008. HSEG/RHSEG, HSEGViewer and HSEGReader user's manual (Version 1.40), Provided with the evaluation version of RHSEG available from: http://ipp.gsfc.nasa.gov/RHSEG.

Vincent, L., Soille, P., 1991. Watersheds in digital spaces: an efficient algorithm based on immersion simulations. *IEEE Trans. Pattern Analysis and Machine Intel.*, 13(6), pp. 583–598.