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A MULTIPLE CLASSIFIER APPROACH FOR SPECTRAL-SPATIAL CLASSIFICATION OF HYPERSPECTRAL DATA

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ABSTRACT

A new multiple classifier method for spectral-spatial classification of hyperspectral images is proposed. Several classifiers are used independently to classify an image. For every pixel, if all the classifiers have assigned this pixel to the same class, the pixel is kept as a marker, i.e., a seed of the spatial region, with the corresponding class label. We propose to use spectral-spatial classifiers at the preliminary step of the marker selection procedure, each of them combining the results of a pixel-wise classification and a segmentation map. Different segmentation approaches lead to different classification results. Furthermore, a minimum spanning forest is built, where each tree is rooted on a classification-driven marker and forms a region in the spectral-spatial classification map. Experimental results are presented on a 103-band ROSIS image of the University of Pavia, Italy. The proposed method significantly improves classification accuracies, when compared to previously proposed classification techniques.

Index Terms— Hyperspectral images, classification, segmentation, multiple classifiers, minimum spanning forest

1. INTRODUCTION

The accurate classification of remote sensing images is an important task for many applications, such as monitoring and management of the environment, precision agriculture, security issues. Hyperspectral (HS) imagery, which records a detailed spectrum of light arriving at each pixel [1], opens new perspectives in image analysis and classification. While pixel-wise classification techniques process each pixel independently from the pixels in its neighborhood [1, 2], further improvement of classification accuracies can be achieved by considering spatial dependencies between pixels [3, 4].

Segmentation techniques, partitioning an image into homogeneous regions, are a powerful tool for defining spatial dependencies. In previous works, we have performed unsupervised segmentation of HS images in order to distinguish spatial structures [4, 5]. Segmentation and pixel-wise classification were applied independently, then results were combined using a majority voting rule. Thus, every region from a segmentation map has been considered as an adaptive homogeneous neighborhood for all the pixels within this region.

However, unsupervised image segmentation is a challenging task, since the measure of region homogeneity must be chosen. An alternative way to get accurate segmentation results consists in performing a marker-controlled segmentation. Recently we have proposed to use probability estimates obtained by the pixel-wise Support Vector Machines (SVM) classification in order to choose the most reliable classified pixels as markers, i.e., seeds of spatial regions [6]. Furthermore, image pixels were grouped into a Minimum Spanning Forest (MSF), where each tree was rooted on a classification-derived marker and formed a region in the spectral-spatial classification map. The described technique led to a significant improvement of classification accuracies when compared to previously proposed methods. The drawback of this method is that the choice of markers strongly depends on the performance of the selected pixel-wise classifier.

In this work, we aim to mitigate the dependence of the marker selection procedure from the choice of a pixel-wise classifier. For this purpose, a new ***marker selection method*** based on the ***multiple classifier (MC)*** system is proposed. Several classifiers are used independently to classify an image. Furthermore, a marker map is constructed by selecting the pixels assigned by all the classifiers to the same class. We propose to use spectral-spatial classifiers at the preliminary step of the marker selection procedure, each of them combining the results of a pixel-wise classification and one of the unsupervised segmentation techniques. The proposed marker selection method is incorporated into a new ***Multiple Spectral-Spatial Classification scheme (MSSC-MSF)*** based on the construction of an MSF from region markers.

The paper is organized as follows. First, the MC approach is discussed. Section 3 describes the proposed classification scheme. Experimental results are discussed in Section 4. Finally, conclusions are drawn in Section 5.

This research is supported in part by the Marie Curie Research Training Network “HYPER-I-NET”.

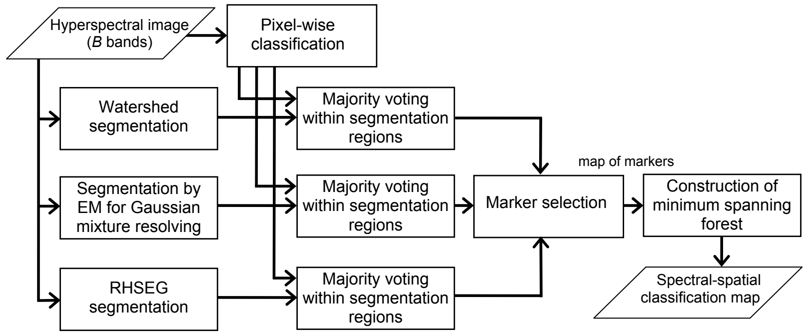

Fig. 1. Flow-chart of the proposed *MSSC-MSF* classification scheme.

2. MULTIPLE CLASSIFIER APPROACH

The traditional approach for a pattern recognition problem is to search for the best individual classification algorithm. However, in many cases, the classification accuracy can be improved by using an ensemble of classifiers. The aim of an ***MC*** system is to determine an efficient combination method that makes use of the complementary benefits of each classifier, while tackling the individual drawbacks [7].

An important issue for an efficient MC system is that the individual classifiers should not agree with each other when they misclassify a pixel. The complementary properties of the different classifiers should ensure this requirement. Another important issue is the rule for combining the individual classifiers. In the proposed method, these two issues are addressed in the following way: 1) Different segmentation methods based on dissimilar principles lead to different classification results. 2) According to the exclusionary rule, only the most reliable pixels, i.e., the pixels where all the classifiers agree, are kept in the initial classification map. The rest of the pixels are further classified by constructing an MSF rooted on the "reliable" pixels.

3. PROPOSED CLASSIFICATION SCHEME

The flow-chart of the proposed *MSSC-MSF* classification method is depicted in Figure 1. At the input a B-band HS image is given, which can be considered as a set of n pixel vectors. Classification consists in assigning each pixel to one of the K classes of interest. In the following, each step of the proposed procedure is described.

1) Watershed segmentation: Watershed transformation is a powerful morphological approach to image segmentation which combines region growing and edge detection. 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 [5]. We have extended a watershed method to the case of HS images in [5]: First, a one-band Robust Color Morphological Gradient (RCMG) for the HS image is computed. By applying watershed transformation using a classical algorithm [8], the image is partitioned into a set of regions.

2) Segmentation by expectation maximization: The Expectation Maximization (EM) algorithm for the Gaussian mixture resolving belongs to the group of partitional clustering techniques [4]. Clustering aims at finding groups of spectrally similar pixels. We assume that pixels belonging to the same cluster are drawn from a multivariate Gaussian probability distribution. The parameters of the distributions are estimated by the EM algorithm. When the algorithm converges, the partitioning of the set of image pixels into clusters is obtained. However, as no spatial information is used during the clustering procedure, pixels with the same cluster label can form a connected spatial region, 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.

3) RHSEG segmentation: The Hierarchical image SEGmentation (HSEG) algorithm is a segmentation technique based on iterative hierarchical step-wise optimization region growing method. Furthermore, it provides a possibility of merging non-adjacent regions by spectral clustering [9]. NASA's RHSEG software provides an efficient implementation of the HSEG algorithm. We have investigated the use of the RHSEG technique for segmentation of HS images, choosing the standard Spectral Angle Mapper (SAM) between the region mean vectors as the dissimilarity criterion [9], and the parameter $spclust\_wght = 0.1$ (merging of spatially adjacent regions is favored). RHSEG gives as output a hierarchical sequence of image partitions. A segmentation map at the relevant level of hierarchy is chosen interactively. Finally, labeling of connected components is performed, in order to obtain a segmentation map where each spatially connected component has a unique label.

4) Pixel-wise classification: Independently of the previous steps, a pixel-wise classification of the HS image is performed. We propose to use an SVM classifier for this purpose which is well suited for classifying HS data [2]. This step results in a classification map (each pixel has a unique class label).

5) Majority voting within segmentation regions: Each of the obtained segmentation maps is combined with the pixel-wise classification map using the majority voting principle: For every region in the segmentation map, all the pixels are assigned to the most frequent class within this region. Thus, three segmentation maps combined with the pixel-wise classification map result in three spectral-spatial classification maps.

6) Marker selection: This step consists in computing a map of markers, using spectral-spatial classification maps from the previous step and exclusionary rule: For every pixel, if all the classifiers agree, the pixel is kept as a marker, with the corresponding class label. The resulting map of markers contains the most reliable classified pixels.

7) Construction of an MSF: In the final step, image pixels are grouped into an MSF rooted on the selected markers [6]. Each pixel is considered as a vertex $v \in V$ of an undirected graph $G = (V, E, W)$. Each edge of this graph connects a couple of vertices corresponding to the neighboring pixels (in the following, we simply call vertices as pixels). Furthermore, a weight is assigned to each edge, which indicates the degree of dissimilarity between two pixels connected by this edge. We use an 8-neighborhood and the SAM measure for computing weights of edges, as described in [6].

Given a graph $G = (V, E, W)$, the *MSF* rooted on a set of m distinct vertices $\{t_1, ..., t_m\}$ consists in finding a spanning forest $F^* = (V, E_{F^*})$ of G, such that each distinct tree of F^* is grown from one root t_i, and the sum of the edges weights of F^* is minimal. Prim's algorithm can be used for building the MSF [6]. A classification map is obtained by assigning the class of each marker to all the pixels grown from this marker.

4. EXPERIMENTAL RESULTS AND DISCUSSION

Experimental results are presented for a ROSIS (Reflective Optics System Imaging Spectrometer) image of the University of Pavia, Italy. The image is 610 × 340 pixels, with a spatial resolution of 1.3 m per pixel and 103 spectral channels. The reference data contain nine classes of interest. More information about the image, with the number of training and test samples for each class can be found in [4].

The segmentation of the considered image is performed, using the three different techniques discussed in the previous section. For the EM algorithm, the maximum number of clusters is chosen equal to 10 (typically slightly superior to the number of classes), and a feature reduction has been previously applied, using the method of piecewise constant function approximations [10] to get a 10-band image.

The multi-class pairwise SVM classification, with the Gaussian Radial Basis Function kernel, of the original image is performed, with the parameters chosen by fivefold cross validation: $C = 128$, $\gamma = 0.125$. The results of the pixel-wise classification are combined with the segmentation results, using the majority voting approach. Finally, the marker selection and the construction of an MSF are performed, resulting in the *MSSC-MSF* classification map depicted in Figure 2.

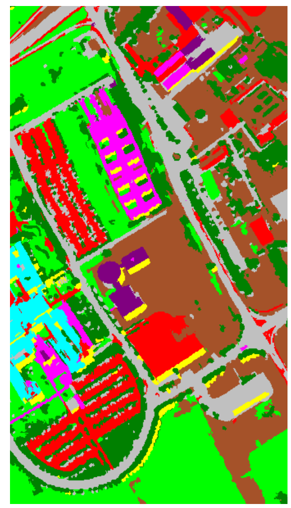

Fig. 2. Classification map obtained by the *MSSC-MSF* method for the University of Pavia image.

Table 1 summarizes the accuracies of the pixel-wise SVM, segmentation + majority voting (*WH+MV*, *EM+MV*, *RHSEG+MV* for three segmentation techniques, respectively) and the proposed classification method. In order to compare performances of the proposed technique with the previously proposed methods, we have also included results of the well-known ECHO spatial classifier [3], as well as the results obtained using the construction of an MSF from the probabilistic SVM-derived markers followed by majority voting within connected regions (*SVMMSF+MV*) [6]. Furthermore, we assess the importance of spectral-spatial approaches for marker selection. For this purpose, we have replaced the *WH+MV*, *EM+MV*, *RHSEG+MV* classification maps by three maps obtained using standard pixel-wise classification techniques. Maximum Likelihood (*ML*), SVM and 3-Nearest Neighborhood (*3-NN*, using the SAM distance) methods have been used for this purpose. The accuracies of the modified *MC-MSF* classification, as well as pixel-wise classification results are given in Table 1.

As can be seen from the table, both the global and most of the class-specific accuracies are substantially improved by the proposed *MSSC-MSF* method, when compared to previous spectral-spatial classification techniques. The overall accuracy is improved by 16.9 percentage points, when compared

Table 1. Classification Accuracies in Percentage for the *University of Pavia* Image: Overall Accuracy (OA), Average Accuracy (AA), Kappa Coefficient (κ) and Class-Specific Accuracies.

	3-NN	ML	SVM	ECHO	WH+MV	EM+MV	RHSEG +MV	SVMMSF +MV	MC-MSF	MSSC-MSF
OA	68.38	79.06	81.01	87.58	85.42	94.00	93.85	91.08	87.98	**97.90**
AA	77.21	84.85	88.25	92.16	91.31	93.13	97.07	94.76	92.05	**98.59**
κ	59.85	72.90	75.86	83.90	81.30	91.93	91.89	88.30	84.32	**97.18**
Asphalt	64.96	76.43	84.93	87.98	93.64	90.10	94.77	93.16	87.01	**98.00**
Meadows	63.18	75.99	70.79	81.64	75.09	95.99	89.32	85.65	83.24	**96.67**
Gravel	62.31	64.57	67.16	76.91	66.12	82.26	96.14	89.15	75.37	**97.80**
Trees	95.95	97.08	97.77	**99.31**	98.56	85.54	98.08	91.24	98.97	98.83
Metal sheets	99.73	99.91	99.46	99.91	99.91	**100**	99.82	99.91	99.91	99.91
Bare soil	57.42	70.03	92.83	93.96	97.35	96.72	99.76	99.91	93.24	**100**
Bitumen	82.67	90.62	90.42	92.97	96.23	91.85	**100**	98.57	95.11	99.90
Bricks	77.08	90.10	92.78	97.35	97.92	98.34	99.29	99.05	97.00	**99.76**
Shadows	91.57	98.87	98.11	**99.37**	96.98	97.36	96.48	96.23	98.62	96.48

to the SVM classification. The *MSSC-MSF* classification accuracies are much higher than the *MC-MSF* accuracies. These results prove the importance of the use of MC systems and spatial information throughout the classification procedure.

5. CONCLUSIONS

In this paper, a new MC method for spectral-spatial classification of HS images is proposed. First, a marker map is constructed by selecting the pixels assigned by several spectral-spatial classifiers to the same class. This ensures a robust and reliable selection. Then, an MSF rooted on the selected markers is built. Experimental results did show that the proposed method improves classification accuracies, when compared to previously proposed classification schemes, and provides classification maps with homogeneous regions. The presented classification accuracies are higher than all previous results we have found in the literature for the same data. Similar results are obtained for other datasets acquired by the ROSIS and the AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) sensors.

In conclusion, the proposed methodology succeeded in taking advantage of multiple classifiers and the spatial and the spectral information simultaneously for accurate HS image classification.

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