

MARKER-BASED HIERARCHICAL SEGMENTATION AND CLASSIFICATION APPROACH FOR HYPERSPECTRAL IMAGERY

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ABSTRACT

The Hierarchical SEGmentation (HSEG) algorithm, which is a combination of hierarchical step-wise optimization and spectral clustering, has given good performances for hyperspectral image analysis. This technique produces at its output a hierarchical set of image segmentations. The automated selection of a single segmentation level is often necessary. We propose and investigate the use of automatically selected *markers* for this purpose. In this paper, a novel Marker-based HSEG (M-HSEG) method for spectral-spatial classification of hyperspectral images is proposed. First, pixelwise classification is performed and the most reliably classified pixels are selected as markers, with the corresponding class labels. Then, a novel constrained marker-based HSEG algorithm is applied, resulting in a spectral-spatial classification map. The experimental results show that the proposed approach yields accurate segmentation and classification maps, and thus is attractive for hyperspectral image analysis.

Index Terms— Hyperspectral images, hierarchical segmentation, classification, marker selection.

1. INTRODUCTION

Hyperspectral imaging records a detailed spectrum of light arriving in each pixel [1], which makes it possible to identify physical materials and classify regions within the image scene with much higher accuracies when compared to panchromatic or multispectral sensors. While most classification techniques process each pixel independently using its spectral values only (one of the most frequently used techniques are Support Vector Machines (SVM) [2]), recent studies have shown the advantage of including information about spatial dependencies for accurate image analysis, i.e., performing spectral-spatial classification [3, 4].

In previous works, we have distinguished spatial structures in the image by performing unsupervised segmentation. Then, each region was classified by applying a majority vote rule over the pixelwise classification results [5]. The Hierarchical SEGmentation (HSEG) method, which is a combina-

tion of hierarchical step-wise optimization and spectral clustering [6], has shown good performance for spatial analysis of hyperspectral images. Unlike most other segmentation techniques, the HSEG generates at its output a hierarchical set of image segmentations. It is often necessary to choose one or several relevant hierarchical segmentation levels. The automated selection of the hierarchical level(s) can be achieved by incorporation of some additional knowledge into a segmentation procedure. In this paper, we propose and investigate the use of automatically derived *markers*, or region seeds, for this purpose.

In [4], we have proposed to use probability estimates obtained by the pixelwise SVM classification in order to choose the most reliably classified pixels as markers of spatial regions. Furthermore, a Minimum Spanning Forest (MSF) rooted on the selected markers was constructed, resulting in a segmentation and classification map. The described approach has performed well in classification.

In this paper, we adapt the classification-based approach for marker selection proposed in [4], in order to define relevant markers for the HSEG procedure. Thus, a new Marker-based HSEG (M-HSEG) method for spectral-spatial classification of hyperspectral data is proposed. First, probabilistic pixelwise classification is applied and a map of markers is constructed by selecting the most reliably classified pixels. Then, a novel constrained M-HSEG algorithm is applied, resulting in a classification map. We propose and discuss several ways of integrating markers into the HSEG technique.

The paper is organized as follows. In the next section, a new M-HSEG approach is presented. Experimental results are discussed in Section 3. Finally, conclusions are drawn in Section 4.

2. PROPOSED CLASSIFICATION METHOD

The flow-chart of the proposed M-HSEG classification method is shown in Fig. 1. A hyperspectral image can be considered as a set of n pixel vectors $\mathbf{X} = \{\mathbf{x}_j \in \mathbb{R}^B, j = 1, 2, \dots, n\}$. Classification consists in assigning each pixel to one of K in-

formation classes. In the following, each step of the proposed procedure is described.

2.1. Classification-based marker selection

As we proposed in [4], markers of spatial regions are automatically selected using classification results. The following algorithm is applied for this purpose:

1) **Pixelwise classification:** A probabilistic pixelwise SVM classification of a hyperspectral image is performed [2, 7]. This step results in a classification map (where each pixel has a unique class label) and a probability map (containing probability estimates for each pixel to belong to the assigned class).

2) **Marker selection:** A connected components labeling is applied on the classification map. Then, each connected component is analyzed as follows:

- If a region is large (number of pixels in the regions $> M$), its marker is defined as the $P\%$ of pixels within this region with the highest probability estimates.
- If a region is small, its potential marker is formed by the pixels with probability estimates higher than a defined threshold S .

At the output of the marker selection step, a map of m markers is given, where each marker $\mathbf{O}_i = \{\mathbf{x}_j \in \mathbf{X}, j = 1, 2, \dots, \text{card}(\mathbf{O}_i); L_{\mathbf{O}_i}\}$ ($i = 1, \dots, m$) consists of one or several pixels (which are not necessarily spatially connected) and has a class label $L_{\mathbf{O}_i}$.

2.2. Marker-based HSEG

The following outline of the HSEG algorithm is based on the description given in [6]:

1) Initialize the segmentation by assigning a region label for each pixel. If a pre-segmentation is provided, label each pixel according to the pre-segmentation. Otherwise, label each pixel as a separate region.

2) Calculate the Dissimilarity Criterion (DC) value between all pairs of spatially adjacent regions.

3) Find the smallest DC value $dissim_val$ and set $thresh_val$ equal to it. Then merge all pairs of spatially adjacent regions with $dissim_val = thresh_val$.

4) If the parameter $S_{weight} > 0.0$, merge all pairs of spatially non-adjacent regions with $dissim_val \leq S_{weight} \cdot thresh_val$.

5) If convergence is not achieved, go to step (2).

Different measures can be used for computing DCs between regions, such as $L1$ norm, Infinity (Inf) norm, Spectral Angle Mapper (SAM) between the region mean vectors [6]. The optional parameter S_{weight} tunes the relative importance of spectral clustering *versus* region growing.

The main idea behind the marker-based HSEG algorithm consists in assigning a marker label for each region containing

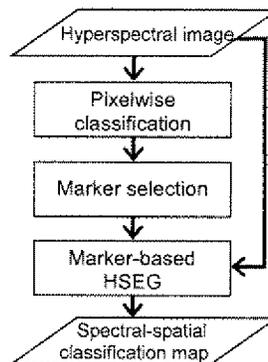


Fig. 1. Flow-chart of the proposed *M-HSEG* classification scheme.

marker pixels, and merging regions with an additional condition: two regions with different marker labels can not be merged together. The proposed **M-HSEG algorithm** can be summarized as follows:

- Initialize the segmentation by labeling either the whole marker, or a separate non-marker pixel as one region. Assign for every region the corresponding marker label (which is equal to zero for non-marked regions).
- At each iteration, perform HSEG, with an additional condition: two regions with different non-zero marker labels have the DC equal to infinity (in practice, the upper maximum value of *float*) and are never merged together. When a marked region is merged with a non-marked region, the resulting region keeps the marker label inherited from the marked region.
- Stop the iterative process when either a number of regions is equal to the number of markers (thus, no more merging is possible) or the smallest DC between any two neighboring regions is higher than the preset (or computed) threshold.

2.3. Implementations of the marker-based HSEG algorithm

We have investigated the performance of three different implementations of the proposed M-HSEG approach. One implementation, *M-HSEG¹*, is based on the description given in the previous subsection. All the pixels belonging to the same marker are initialized as one region, and then iterative region merging is performed.

A second implementation, *M-HSEG²*, first initializes each pixel as one region and assigns a marker label for every region (equal to zero for non-marked regions). During the region merging procedure, the regions with equal non-zero

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

DC	Number of samples	M-HSEG ^r		M-HSEG ^p		M-HSEG ^{op}				SVM	SVMMSF	
		L1	SAM	L1	SAM	L1	SAM	SAM	SAM		L1	SAM
		0.0									0.2	0.5
OA		90.44	91.32	92.44	92.86	95.96	96.20	96.35	95.50	94.96	96.74	91.31
AA		85.69	88.03	89.59	90.43	95.00	95.26	95.49	94.18	92.56	95.66	92.64
κ		87.90	89.02	90.43	90.96	94.88	95.18	95.37	94.30	93.61	95.86	89.11
Water	12734	97.41	97.80	97.41	97.80	97.41	97.74	97.74	97.69	98.12	98.63	87.99
Trees	2405	83.75	71.03	88.63	78.44	94.40	90.32	90.36	89.77	90.48	92.51	89.14
Meadows	1788	93.34	91.70	94.08	89.31	94.20	95.45	95.62	93.69	94.08	95.51	93.52
Bricks	2140	70.38	70.95	79.67	75.36	84.27	85.97	87.77	86.02	79.86	85.59	87.87
Bare soil	4677	87.39	92.47	86.66	92.45	99.29	99.31	99.33	99.01	97.12	99.29	98.00
Asphalt	4844	88.55	89.26	92.33	92.85	93.77	94.91	95.01	92.48	93.52	95.10	93.04
Bitumen	972	78.98	86.62	84.82	88.96	93.63	94.80	94.80	92.46	82.48	94.37	92.57
Tile	1112	71.44	93.81	82.72	98.89	98.06	98.80	98.80	96.49	97.41	99.91	100
Shadows	2020	100	98.64	100	99.80	100	100	100	100	99.95	100	91.61

marker labels have a zero DC value, while the regions with different non-zero marker labels have the DC equal to infinity.

A third implementation, M-HSEG^{op}, first initializes each pixel as one region. If the given pixel is marked, the corresponding region obtains a new non-zero marker label, with the corresponding information class. Thus, at the initialization step all the markers are split into one-pixel markers. Then, iterative region merging is performed, providing that regions with different markers cannot be merged together. At the final step, the regions containing pixels of the same initial marker are merged together.

The implementations M-HSEG^p and M-HSEG^{op} can be useful when images contain large regions with high intra-region spectral variation. In this case, it may be advantageous to compute region feature vectors over parts of these regions.

3. EXPERIMENTAL RESULTS AND DISCUSSION

We applied the proposed M-HSEG approach to two hyperspectral airborne images described in the following:

1) The *Center of Pavia* image was acquired by the ROSIS sensor over the urban area of Pavia, Italy. The image is of 785 by 300 pixels, with a spatial resolution of 1.3 m/pixel and 102 spectral channels. A three-band false color image is shown in Fig. 2. Nine classes of interest are considered, which are detailed in Table 1, with the number of labeled samples for each class. Thirty samples for each class were randomly chosen from the reference data as training samples. The remaining samples composed the test set.

2) The *Indian Pines* image is of vegetation area that was recorded by the AVIRIS sensor. It is of 145 by 145 pixels, with a spatial resolution of 20 m/pixel, 200 spectral channels and sixteen information classes. More information about the image, with the used training-test set can be found in [4].

For both images, the probabilistic one-versus-one SVM

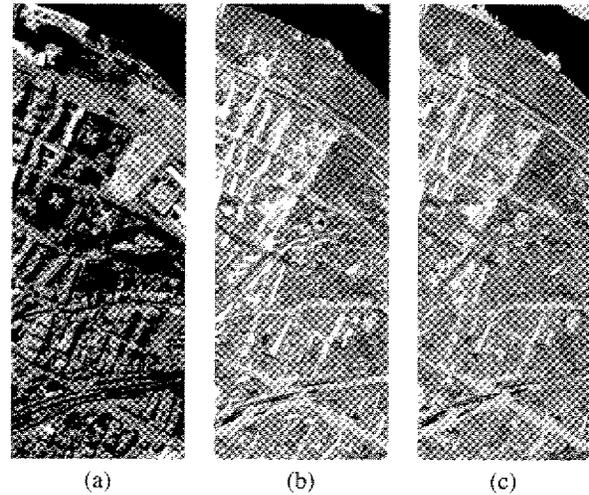


Fig. 2. *Center of Pavia* image. (a) Three-band color composite. (b) M-HSEG^{op} classification map (SAM DC, $S_{wght} = 0.2$). (c) SVMMSF classification map (SAM DC).

Table 2. Global Classification Accuracies in Percentage for the *Indian Pines* Image: Overall Accuracy (OA), Average Accuracy (AA), and Kappa Coefficient (κ).

Method	DC	S_{wght}	OA	AA	κ
M-HSEG ^r	SAM	0.0	77.53	84.54	74.48
	Inf		76.63	83.40	73.40
M-HSEG ^p	SAM		81.59	87.09	79.10
	Inf		81.16	87.54	78.62
M-HSEG ^{op}	SAM		89.23	93.44	87.72
	Inf		89.00	92.20	87.47
SVM	SAM	0.2	88.72	93.40	87.15
	Inf	0.5	89.01	93.23	87.49
SVMMSF	SAM		78.17	85.97	75.33
SVMMSF	SAM		89.65	93.48	88.19

classification with the Gaussian radial basis function kernel was applied. The optimal parameters C (penalty during the SVM optimization) and γ (spread of the RBF kernel) were chosen by fivefold cross-validation. Then, marker selection was performed with parameters $M = 20, P = 40\%$. The threshold S was chosen to be equal to the lowest probability within the highest 2% of the probability estimates for the whole image [4].

Finally, the M-HSEG segmentation of the images was performed, using the three proposed implementations. The $L1$ norm, the Inf norm and the SAM between the region mean vectors were applied as DCs. In all experiments, the M-HSEG algorithm has been run until no more merging was possible. By assigning the class of each marker to the region containing this marker, the classification maps were obtained.

Table 1 summarizes global (overall, average accuracies and kappa coefficient [5]) and class-specific accuracies of the pixelwise SVM classification and the proposed method for the *Center of Pavia* image, using the $L1$ norm and the SAM between the region mean vectors as DCs and $S_{weight} = [0.0, 0.2, 0.5]$. In order to compare the results of the proposed method with other advanced classification techniques, we have included results obtained using the construction of an MSF from the same set of markers (SVMMSF method) [4]. Table 2 reports global accuracies of the SVM and SVMMSF classification and the proposed method for the *Indian Pines* image, using the SAM and the Inf norm between the region mean vectors as DCs and $S_{weight} = [0.0, 0.2]$. The following conclusions can be drawn:

- The proposed marker-based M-HSEG method yields accurate segmentation and classification results. The average accuracy is improved by 3.1 and 7.3 percentage points when compared to the SVM classification, for the *Center of Pavia* and the *Indian Pines* images, respectively. Therefore, it is useful to include markers in the HSEG algorithm, in order to automatically select the relevant segmentation level.
- The M-HSEG^{op} implementation significantly outperforms M-HSEG^r and M-HSEG^p implementations in terms of accuracies. Thus, a region mean vector seems to be a “poor” representative feature of image regions.
- The M-HSEG^{op} method with $S_{weight} = 0.2$ performs in most cases better than when $S_{weight} = 0.0$ is used. However, classifications accuracies decrease with further increase of the S_{weight} value.
- The M-HSEG^{op} classification results are in most cases non-significantly lower when compared to the SVMMSF results. The reason may lie in the fact that region mean vectors do not well represent enough image regions. However, all the DCs give similar results when applying the M-HSEG approach. The SVMMSF method gives significantly lower accuracies when the SAM DC is applied for classification of the *Center of Pavia* image. It assigns large portions of the water to

the spatially adjacent asphalt regions, and assimilates shadows with neighboring regions (see Fig. 2). Thus, the M-HSEG technique appears to be more robust when using different DCs.

4. CONCLUSIONS

A new marker-based HSEG method for spectral-spatial classification of hyperspectral images was presented in this paper. In this method, a marker map is first constructed using probabilistic classification results. Then, the novel M-HSEG algorithm is applied, resulting in a spectral-spatial classification map. Several ways of integrating markers into the HSEG technique are proposed and investigated. Experimental results demonstrate that the proposed method yields accurate classification maps and is sufficiently robust for classifying different kinds of images. In the future, we plan to explore the choice of optimal representative features for segmentation regions, in order to further improve segmentation and classification results.

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