

# Multiple Spectral-Spatial Classification Approach for Hyperspectral Data

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**Abstract**—A new multiple classifier approach 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 pixelwise classification and a segmentation map. Different segmentation methods based on dissimilar principles 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 for two hyperspectral airborne images. 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

## I. INTRODUCTION

Hyperspectral imaging is a relatively recent technique in remote sensing. Acquired remotely by airborne or spaceborne sensors, hyperspectral data are comprised of hundreds of spatially co-registered images corresponding to different spectral channels [1], [2]. Figure 1 illustrates the structure of a hyperspectral image. Every pixel is presented as a  $B$ -dimensional feature vector across the wavelength dimension, called the spectrum of the material in this pixel. This rich information in every spatial location increases the capability to distinguish different physical materials. Thus, hyperspectral imagery opens new perspectives for image classification, which is an important task for a wide variety of applications (precision agriculture, monitoring and management of the environment, security issues).

However, such a large number of spectral channels, usually coupled with limited availability of reference data<sup>1</sup>, presents

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<sup>2</sup>By *reference data*, we mean manually labeled pixels which are used for training classifiers followed by assessment of classification accuracies.

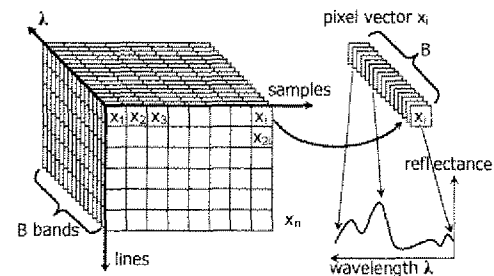


Fig. 1. Structure of a hyperspectral image.

challenges to image analysis. While pixelwise classification techniques process each pixel independently without considering information about spatial structures [3], [4], [5], [6], further improvement of classification results can be achieved by considering spatial dependencies between pixels, i.e., by performing spectral-spatial classification [7], [8], [9], [10], [11], [12].

Segmentation techniques, partitioning an image into homogeneous regions with respect to some criterion of interest (called homogeneity criterion, e.g., intensity or texture), are powerful tools for defining spatial dependencies [13]. In previous works, we have distinguished spatial structures in the hyperspectral image by performing unsupervised segmentation [12], [14], [15]. Watershed, partitional clustering and Hierarchical SEGmentation (HSEG) techniques have been used for this purpose. Segmentation and pixelwise classification were applied independently, then results were combined using a majority voting rule (see Figure 2). Thus, every region from a segmentation map was considered as an adaptive homogeneous neighborhood for all the pixels within this region. The described technique led to a significant improvement of classification accuracies and provided more homogeneous classification maps, when compared to classification techniques using local neighborhoods in order to include spatial information into a classifier.

An alternative way to get accurate segmentation results consists in performing a marker-controlled segmentation [13], [16]. The idea behind this approach is to select for every spatial object one or several pixels belonging to this object (called a *region seed*, or a *marker* of the corresponding region) and to grow regions from the selected seeds, so that every region in the resulting segmentation map is associated with one region seed. The markers of regions can be chosen either manually, or automatically. Recently we have proposed to use probability estimates obtained by the pixelwise Support Vector Machines (SVM) classification in order to select the most reliable classified pixels as markers, i.e., seeds of spatial regions [17]. Furthermore, image pixels were grouped into a Minimum Spanning Forest (MSF), where each tree was rooted on a classification-derived marker. The decision to connect a pixel, which was not yet in the forest, to one of the trees in the forest was based on its similarity to one of the adjacent pixels already belonging to the forest. By assigning the class of each marker to all the pixels within the region grown from this marker, a spectral-spatial classification map was obtained. 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 performances of the selected pixelwise classifier (e.g., the SVM classifier in our previous work [17]).

In this work, we aim to mitigate the dependence of the marker selection procedure from the choice of a pixelwise classifier. This can be achieved by using not a single classification algorithm for marker selection, but an ensemble of classifiers, i.e., *multiple classifiers*. For this purpose, several individual classifiers must be chosen and combined within one system in such a way that the complementary benefits of each classifier are used, while their weaknesses are avoided.

In this paper, a new **marker selection method** based on a **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 in the preliminary step of the marker selection procedure, each of them combining the results of a pixelwise classification and one of the unsupervised segmentation techniques (see Figure 2). By using spectral-spatial classifiers in this step, spatial context in the image is taken into account, and classification maps are more accurate when compared to pixelwise classification maps. This leads to more accurate marker selection results. The proposed marker selection method is incorporated into a new **Multiple Spectral-Spatial Classification (MSSC) scheme (MSSC-MSF)** based on the construction of an MSF from region markers.

In order to assess the importance of spectral-spatial approaches for marker selection, we have also implemented a **Multiple Classification scheme (MC-MSF)**. Here, spectral-spatial classification maps are replaced by the maps obtained using pixelwise classification techniques. Finally, a marker map is computed and an MSF from the selected markers is constructed.

Although the classification approach proposed in this paper has been designed for hyperspectral data, the method is general

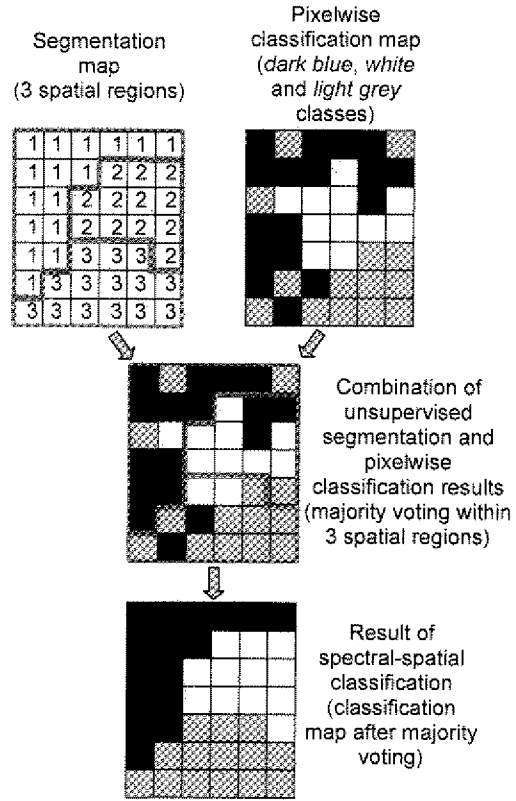


Fig. 2. Example of spectral-spatial classification using majority voting within segmentation regions.

and can be applied for other types of data as well. Two hyperspectral airborne images are used to demonstrate experimental results: an image recorded by the Reflective Optics System Imaging Spectrometer (ROSIS) over the University of Pavia, Italy, and an Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) image acquired over Northwestern Indiana's Indian Pines site [18].

The paper is organized as follows. In the next section, the multiple classifier approach is briefly discussed. Section III describes the proposed classification scheme. Experimental results are discussed in Section IV. Finally, conclusions are drawn in Section V.

## II. MULTIPLE CLASSIFIER APPROACH

The traditional approach for a pattern recognition problem is to search for the individual algorithm giving the best possible classification performances. However, in many cases, the classification accuracy can be improved by using an ensemble of classifiers, or multiple classifiers. This is due to the fact that although one of the classification algorithms would yield the best performances, the sets of pixels (patterns in general) misclassified by the different algorithms would not necessarily overlap. Thus, 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 [19], [20], [21].

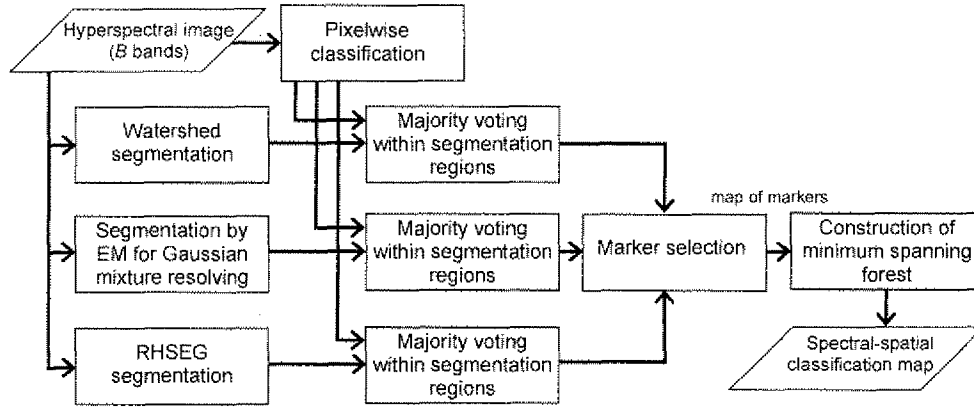


Fig. 3. Flow-chart of the proposed *MSSC-MSF* classification scheme.

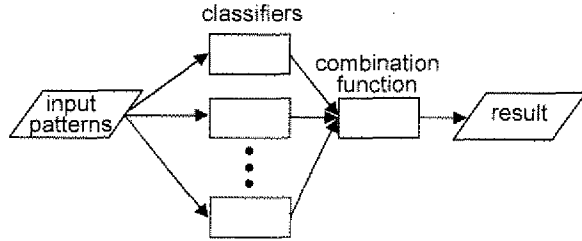


Fig. 4. Schematic diagram of a multiple classifier system.

A schematic representation of an MC system is given in Figure 4. An important issue for an efficient MC system is that the individual classifiers should be independent. More precisely, the classifiers should not agree with each other when they misclassify a pixel [20]. The complementary properties of the different classifiers selected for the MC system should ensure to a certain extent this requirement.

Another important issue is the rule for combining the individual classifiers (i.e., combination function). The individual classifier outputs, such as class labels and possibly posterior probabilities, are typically combined by voting rules, belief functions, statistical techniques, the Dempster-Shafer evidence theory, and other schemes [19]. For a given pixel, if all the classifiers agree on the same class  $k$ , the evident combination rule consists in assigning this pixel to the class  $k$  in the final classification map. On the other side, when individual classifiers disagree in assigning the given pixel, the procedure of final decision making is not that straightforward, and different combination functions may yield different results. A typical result of the MC system is a final classification map, where each pixel has a unique class label. This type of MC systems has been previously used for remote sensing image classification [21], [22], [23].

In this paper, we propose to address the combination rule issue in the following way: According to the exclusionary rule,

only the pixels where all the classifiers agree, i.e., the most reliable pixels, are kept in the classification map. The rest of the pixels are further classified by constructing an MSF rooted on the “reliable” pixels, i.e., by incorporating the spatial information into classification.

Coming back to the first issue for designing an MC system, different individual classifiers must be chosen. For instance, standard pixelwise classification algorithms can be used for this purpose, such as SVM, Maximum Likelihood (*ML*), *k*-Nearest Neighborhood (*k-NN*) methods (parametric and non-parametric techniques, based on different principles). We have used these individual techniques in the *MC-MSF* classification scheme. Furthermore, we propose to use spectral-spatial classifiers as individual classifiers for the MC system (*MSSC-MSF* classification scheme), each of them combining the results of a pixelwise classification and one of the unsupervised segmentation techniques. Different segmentation methods based on dissimilar principles lead to different classification results. The use of spectral-spatial classifiers yields more accurate classification maps, when compared to those obtained by performing pixelwise classification.

### III. PROPOSED CLASSIFICATION SCHEME

The flow-chart of the proposed *MSSC-MSF* classification method is depicted in Figure 3. At the input a *B*-band hyperspectral image is given, which 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 the  $K$  classes of interest. In the following, each step of the proposed procedure is described.

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. We have investigated the use of three techniques for hyperspectral image segmentation, as described hereafter.

### A. 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 [24].

The extension of a watershed technique to the case of hyperspectral images has been investigated in [15], [25]. In this paper, we present watershed results, obtained by the scheme we proposed and described in [15]: First, a one-band Robust Color Morphological Gradient (RCMG) [26] for the hyperspectral image is computed.

For each pixel vector  $\mathbf{x}_p$ , let  $\chi = [\mathbf{x}_p^1, \mathbf{x}_p^2, \dots, \mathbf{x}_p^e]$  be a set of  $e$  vectors contained within a structuring element  $E$  (i.e., the pixel  $\mathbf{x}_p$  itself and  $e - 1$  neighboring pixels). A  $3 \times 3$  square structuring element with the origin in its center is typically used. The *Color Morphological Gradient (CMG)*, using the Euclidean distance, is computed as:

$$CMG_E(\mathbf{x}_p) = \max_{i,j \in \chi} \{\|\mathbf{x}_p^i - \mathbf{x}_p^j\|_2\}, \quad (1)$$

i.e., the maximum of the distances between all pairs of vectors in the set  $\chi$ . One of the drawbacks of the CMG is that it is very sensitive to noise. To overcome the problem of outliers, the RCMG has been proposed [26]. The scheme to make a CMG robust consists of removing the two pixels that are furthest apart and then finding the CMG of the remaining pixels. This process can be repeated several times until a good estimate of the gradient is obtained.

Thus, the RCMG, using the Euclidean distance, can be defined as:

$$RCMG_E(\mathbf{x}_p) = \max_{i,j \in [\chi - REM_r]} \{\|\mathbf{x}_p^i - \mathbf{x}_p^j\|_2\}, \quad (2)$$

where  $REM_r$  is a set of  $r$  vector pairs removed. If  $E$  is a  $3 \times 3$  square structuring element,  $r = 1$  is recommended [26].

Furthermore, watershed transformation is applied on the gradient image, using a standard algorithm [27]. As a result, 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<sup>2</sup> (the distance between the vector median of this region and the watershed pixel is minimal).

### B. Segmentation by expectation maximization

The Expectation Maximization (EM) algorithm for the Gaussian mixture resolving belongs to the group of partitional clustering techniques [14], [29]. The use of partitional clustering for hyperspectral image segmentation has been discussed in [14]. 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.

<sup>2</sup>A standard vector median [28] for the region  $S = \{\mathbf{s}_j \in \mathbb{R}^B, j = 1, 2, \dots, t\}$  is defined as  $\mathbf{s}_{VM} = \arg \min_{\mathbf{s} \in S} \{\sum_{j=1}^t \|\mathbf{s} - \mathbf{s}_j\|_1\}$

Each image pixel can be statistically modelled by the following probability density function:

$$p(\mathbf{x}) = \sum_{c=1}^C \omega_c \phi_c(\mathbf{x}; \boldsymbol{\mu}_c, \boldsymbol{\Sigma}_c) \quad (3)$$

where  $C$  is the number of clusters,  $\omega_c \in [0, 1]$  is the mixing proportion (weight) of cluster  $c$  with  $\sum_{c=1}^C \omega_c = 1$ , and  $\phi(\boldsymbol{\mu}, \boldsymbol{\Sigma})$  is the multivariate Gaussian density with mean  $\boldsymbol{\mu}$  and covariance matrix  $\boldsymbol{\Sigma}$ :

$$\phi_c(\mathbf{x}; \boldsymbol{\mu}_c, \boldsymbol{\Sigma}_c) = \frac{1}{(2\pi)^{B/2} |\boldsymbol{\Sigma}_c|^{1/2}} \exp\left\{-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu}_c)^T \boldsymbol{\Sigma}_c^{-1} (\mathbf{x} - \boldsymbol{\mu}_c)\right\}. \quad (4)$$

The parameters of the distributions  $\psi = \{C, \omega_c, \boldsymbol{\mu}_c, \boldsymbol{\Sigma}_c; c = 1, 2, \dots, C\}$  are estimated by the EM algorithm, as described in [14]. An upper bound on the number of clusters, which is a required input parameter, is recommended to be chosen slightly superior to the number of classes.

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 [30] is applied to the output image partitioning obtained by clustering.

The total number of parameters to be estimated by the EM algorithm is  $P = (B(B+1)/2 + B+1)C + 1$ , where  $B$  is a dimensionality of feature vectors. If the value of  $B$  is large,  $P$  may be quite a large number. This may cause the problem of the covariance matrix singularity or inaccurate parameter estimation results. In order to avoid these problems, we propose to previously apply a feature reduction, using the method of piecewise constant function approximations (PCFA) [31], which has shown good performances for hyperspectral data feature extraction.

### C. 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 [32].

The following outline of the HSEG algorithm is based on the description given in [33], [32]:

- 1) Initialize the segmentation by assigning for each pixel a region label. 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 value between all pairs of spatially adjacent regions.
- 3) Find the smallest dissimilarity criterion 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 a parameter  $S_{wght} > 0.0$ , merge all pairs of spatially non-adjacent regions with  $dissim\_val \leq S_{wght} \cdot thresh\_val$ .
- 5) If convergence is not achieved, go to step (2).

In order to reduce computational demands, a Recursive divide-and-conquer approximation of HSEG (RHSEG) has been developed. The NASA-Goddard RHSEG software provides an efficient implementation of the RHSEG algorithm.

When determining most similar pair of regions, we propose to choose the standard Spectral Angle Mapper (SAM) between the region mean vectors and as the dissimilarity criterion [32]. The SAM measure between  $\mathbf{u}_i$  and  $\mathbf{u}_j$  ( $\mathbf{u}_i, \mathbf{u}_j \in \mathbb{R}^B$ ) determines the spectral similarity between two vectors by computing the angle between them. It is defined as

$$SAM(\mathbf{u}_i, \mathbf{u}_j) = \arccos \left( \frac{\sum_{b=1}^B u_{ib} u_{jb}}{[\sum_{b=1}^B u_{ib}^2]^{1/2} [\sum_{b=1}^B u_{jb}^2]^{1/2}} \right). \quad (5)$$

The optional parameter  $S_{wght}$  tunes the relative importance of spectral clustering *versus* region growing. If  $S_{wght} = 0.0$ , only merging of spatially adjacent regions is performed. If  $0.0 < S_{wght} \leq 1.0$ , merging between spatially adjacent regions is favored compared to merging of spatially non-adjacent regions by a factor of  $1.0/S_{wght}$ . As discussed in [34], the optimal parameter  $S_{wght}$  can be chosen based on *a priori* knowledge about information classes contained in the image. If some classes have very similar spectral responses, we recommended to choose  $S_{wght} = 0.0$  or close to this value<sup>3</sup>. Otherwise, we recommend increasing the possibility of merging spatially non-adjacent regions. If  $S_{wght} > 0.0$ , labeling of connected components has to be applied after RHSEG in order to obtain a segmentation map where each spatially connected component has a unique label.

RHSEG provides as output a hierarchical sequence of image partitions. In this sequence, 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 hierarchical sequence allows flexibility in choosing the appropriate level of detail for the segmentation map. When training data is available, it is a simple process to quantitatively evaluate the segmentation results at each hierarchical level versus the training data to select the appropriate level of detail. Otherwise an appropriate level of segmentation detail can be chosen interactively with the program HSEGViewer [32], or an automated method, tailored to the application, can be developed such as explored in [35].

#### D. Pixelwise classification

Independent of the previous steps, a pixelwise classification of the hyperspectral image is performed. We propose to use an SVM classifier for this purpose. Other pixelwise classifiers could be used. However, SVM perform extremely well in

classifying high-dimensional data when a limited number of training samples are available [5], [36]. We refer the reader to [5], [37] for details on SVM technique. This step results in a classification map, where each pixel has a unique class label.

#### E. Majority voting within segmentation regions

Each of the obtained unsupervised segmentation maps is combined with the pixelwise 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 (see an illustrative example in Figure 2). Thus,  $q$  segmentation maps combined with the pixelwise classification map result in  $q$  spectral-spatial classification maps (since we propose to use three different segmentation techniques, in this particular case  $q = 3$ ).

#### F. Marker selection

This step consists of 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  $m$  markers contains the most reliably classified pixels.

#### G. Construction of a Minimum Spanning Forest

In the final step, image pixels are grouped into an MSF rooted on the selected markers [17]. Each pixel is considered as a vertex  $v \in V$  of an undirected graph  $G = (V, E, W)$ , where  $V$  and  $E$  are the sets of vertices and edges, respectively, and  $W$  is a mapping of the set of the edges  $E$  into  $\mathbb{R}^+$ . Each edge  $e_{i,j} \in E$  of this graph connects a couple of vertices  $i$  and  $j$  corresponding to the neighboring pixels. Furthermore, a weight  $w_{i,j}$  is assigned to each edge  $e_{i,j}$ , which indicates the degree of dissimilarity between two vertices (i.e., two corresponding pixels) connected by this edge. We propose to use an 8-neighborhood and the SAM measure for computing weights of edges, as described in [17].

Given a graph  $G = (V, E, W)$ , the MSF rooted on a set of  $m$  distinct vertices  $\{t_1, \dots, t_m\}$  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 [38]

$$F^* \in \arg \min_{F \in SF} \left\{ \sum_{e_{i,j} \in E_F} w_{i,j} \right\}, \quad (6)$$

where  $SF$  is a set of all spanning forests of  $G$  rooted on  $\{t_1, \dots, t_m\}$ .

In order to obtain the MSF rooted on  $m$  markers corresponding to the vertices  $t_i, i = 1, \dots, m$ , an additional root vertex  $r$  is added and is connected by the null-weight edges to the vertices  $t_i$ . The minimum spanning tree of the constructed graph induces an MSF in  $G$ , where each tree is grown on a vertex  $t_i$ ; the MSF is obtained after removing the vertex  $r$ . Prim's algorithm can be used for building the MSF (see Algorithm 1) [39]. The efficient implementation of

<sup>3</sup>The analysis reported in this paper was performed with version 1.40 of the RHSEG software. The recently released version 1.50 of RHSEG produces similar segmentation results, except that it can exhibit improved results for larger values of  $S_{wght}$  especially for data sets containing classes with mostly dissimilar spectral responses.

**Algorithm 1** Prim's Algorithm**Require:** Connected graph  $G = (V, E, W)$ **Ensure:** Tree  $T^* = (V^*, E^*, W^*)$  $V^* = \{v\}$ ,  $v$  is an arbitrary vertex from  $V$ **while**  $V^* \neq V$  **do**Choose edge  $e_{i,j} \in E$  with minimal weight such that  
 $i \in V^*$  and  $j \notin V^*$  $V^* = V^* \cup \{j\}$  $E^* = E^* \cup \{e_{i,j}\}$ **end while**

the algorithm using a binary min-heap is possible [40], the resulting time complexity of the algorithm is  $O(|E|\log|V|)$ . Finally, a spectral-spatial classification map is obtained by assigning the class of each marker to all the pixels grown from this marker.

## IV. EXPERIMENTAL RESULTS AND DISCUSSION

Two different hyperspectral images were used for the experiments, with different contexts (one urban area and one agricultural area) and recorded by different sensors (ROSIS and AVIRIS airborne imaging spectrometers). These data sets and the corresponding results are discussed in the next two sections.

## A. Classification of the University of Pavia Image

The *University of Pavia* image was recorded by the ROSIS optical sensor over the urban area of the University of Pavia, Italy. The image is  $610 \times 340$  pixels, with a spatial resolution of 1.3 m/pixel. The number of data channels in the acquired image is 115 (with a spectral range from 0.43 to  $0.86 \mu\text{m}$ ). The 12 most noisy channels have been removed, and the remaining 103 bands were used for the experiments. Nine classes of interest are considered, which are detailed in Table I. Figure 5 shows a three-band false color image and the reference data. The training and test sets are composed of 3921 and 40002 pixels, respectively. More information about the image, with the number of training and test samples for each class can be found in [14].

The segmentation of the considered image was performed, using the three different techniques discussed in the previous section. For the EM algorithm, the maximum number of clusters was chosen equal to 10 (typically slightly superior to the number of classes). Before applying the EM technique, a feature extraction on the original 103-band image was applied, using the method of PCFA [31] to get a 10-band image  $\mathbf{Y}_{UP}$ . Pixels from the training set were used for selecting features. The method produced an averaging of the following groups of adjacent spectral channels: 1-4, 5-10, 11-24, 25-35, 36-43, 44-68, 69-72, 73-75, 76-79, 80-103.

For the RHSEG algorithm we chose  $S_{weight} = 0.1$  since the image of this urban area contains classes with mostly dissimilar spectral responses. A segmentation map at an appropriate level of segmentation detail was chosen interactively with the program HSEGViewer. The obtained watershed, EM

and RHSEG segmentation maps contained 11802, 22549 and 7575 regions, respectively.

The multiclass pairwise SVM classification, with the Gaussian Radial Basis Function (RBF) kernel, of the original image was performed, with the parameters chosen by fivefold cross validation:  $C = 128$ ,  $\gamma = 0.125$ . The results of the pixelwise classification were combined with the segmentation results, using the majority voting approach. Finally, the marker selection (see Figure 5(g); 132521, i.e., 64% of pixels were selected as markers) and the construction of an MSF were performed, resulting in the *MSSC-MSF* spectral-spatial classification map depicted in Figure 5(h).

Table I summarizes the global and class-specific accuracies of the pixelwise SVM, segmentation plus majority voting (*WH+MV*, *EM+MV*, *RHSEG+MV* for three segmentation techniques, respectively) and the proposed *MSSC-MSF* classification methods. The following measures of accuracy were used: Overall Accuracy (OA is the percentage of correctly classified pixels), Average Accuracy (AA is the mean of class-specific accuracies, i.e., the percentage of correctly classified pixels for each class) and kappa coefficient ( $\kappa$  is the percentage of agreement, i.e., correctly classified pixels, corrected by the number of agreements that would be expected purely by chance [41]). 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 [7], 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*) [17].

In addition, we assessed the importance of spectral-spatial approaches for marker selection. For this purpose we replaced the *WH+MV*, *EM+MV*, *RHSEG+MV* classification maps by three maps obtained using standard pixelwise classification techniques (we call this modified scheme an *MC-MSF* classification method). SVM, Maximum Likelihood (ML) and 3-Nearest Neighborhood (3-NN, using the SAM distance) methods were used for this purpose. The ML and the 3-NN techniques were applied on the 10-band image  $\mathbf{Y}_{UP}$  feature vectors. The accuracies of the modified *MC-MSF* classification, as well as pixelwise classification results are given in Table I.

As can be seen from Table I, the SVM method gives the highest accuracies among all the pixelwise classification techniques. All the spectral-spatial approaches yield higher classification accuracies when compared to pixelwise methods. The proposed MC approach for marker selection improves accuracies, when compared to those obtained by classification techniques used in the preliminary step of the marker selection procedure, both for the *MC-MSF* and *MSSC-MSF* methods. The best global and the best class-specific accuracies for most classes are achieved by applying the proposed *MSSC-MSF* method. According to the results of the McNemar's test [42], the *MSSC-MSF* classification map is significantly more accurate when compared to those obtained by other classification approaches, using 5% level of significance. In this case, the overall accuracy is improved by 16.9 percentage points and the average accuracy is improved by 10.3 percentage points, when



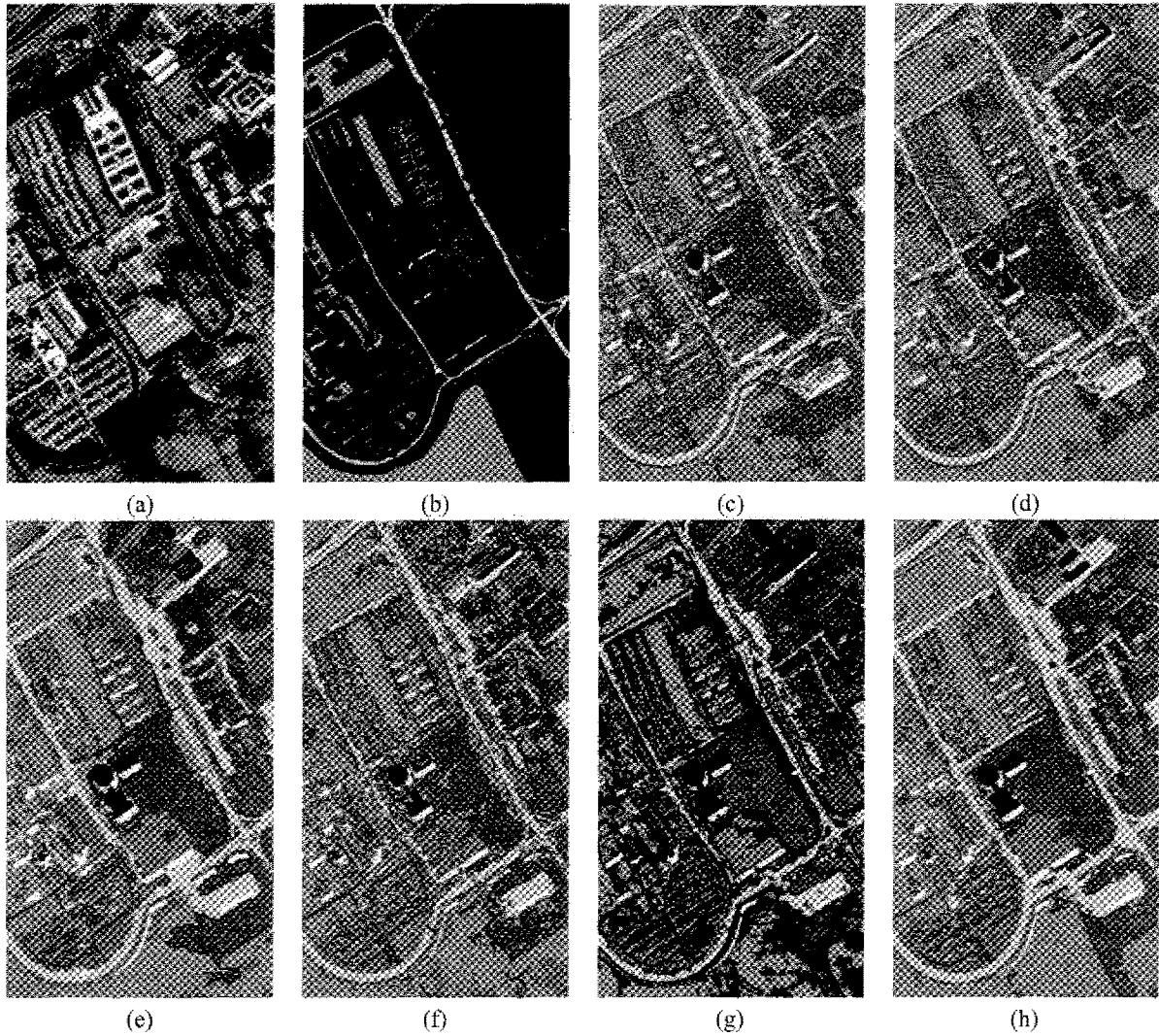


Fig. 5. University of Pavia image. (a) Three-band color composite. (b) Reference data: Asphalt, meadows, gravel, trees, metal sheets, bare soil, bitumen, bricks and shadows. (c) SVM pixelwise classification map. (d) ECHO classification map. (e) SVMMSF+MV classification map. (f) MC-MSF classification map. (g) MSSC-MSF marker map. (h) MSSC-MSF classification map.

TABLE I  
CLASSIFICATION ACCURACIES IN PERCENTAGE FOR THE University of Pavia IMAGE: OVERALL ACCURACY (OA), AVERAGE ACCURACY (AA), KAPPA COEFFICIENT ( $\kappa$ ) 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	<b>97.90</b>
AA	77.21	84.85	88.25	92.16	91.31	93.13	97.07	94.76	92.05	<b>98.59</b>
$\kappa$	59.85	72.90	75.86	83.90	81.30	91.93	91.89	88.30	84.32	<b>97.18</b>
Asphalt	64.96	76.43	84.93	87.98	93.64	90.10	94.77	93.16	87.01	<b>98.00</b>
Meadows	63.18	75.99	70.79	81.64	75.09	95.99	89.32	85.65	83.24	<b>96.67</b>
Gravel	62.31	64.57	67.16	76.91	66.12	82.26	96.14	89.15	75.37	<b>97.80</b>
Trees	95.95	97.08	97.77	<b>99.31</b>	98.56	85.54	98.08	91.24	98.97	98.83
Metal sheets	99.73	99.91	99.46	99.91	99.91	<b>100</b>	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	<b>100</b>
Bitumen	82.67	90.62	90.42	92.97	96.23	91.85	<b>100</b>	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	<b>99.76</b>
Shadows	91.57	98.87	98.11	<b>99.37</b>	96.98	97.36	96.48	96.23	98.62	96.48

compared to the SVM classification. All the class-specific accuracies are higher than 96%. Only the accuracy for the class *shadows*, representing small spatial structures, is slightly reduced when compared to the SVM results (the drawback of applying spectral-spatial classification to small structures was discussed for instance in [14]). The *MSSC-MSF* classification accuracies are much higher than the *MC-MSF* accuracies. Furthermore, the presented classification accuracies are higher than all previous results we have found in the literature for the same data.

Figure 5 depicts the *MC-MSF* and *MSSC-MSF* classification maps, as well as the SVM, *ECHO* and *SVMMSF+MV* classification maps given for comparison. In Figure 5(g) [*MSSC-MSF* marker map], it can be seen that the marker pixels, i.e., the most reliable classified pixels, are typically located at the center of spatial structures, while borders of structures are under a high risk of being misclassified. The *MSSC-MSF* classification map [see Figure 5(h)] contains much more homogeneous regions when compared to the maps obtained by other pixelwise and spectral-spatial approaches. These results prove the importance of the use of MC systems and spatial information throughout the classification procedure.

### B. Classification of the Indian Pines Image

The proposed scheme was also tested on the *Indian Pines* image of a vegetation area, acquired by the AVIRIS sensor over the Indian Pines site in Northwestern Indiana. The image has spatial dimensions of 145 by 145 pixels, with a spatial resolution of 20 m/pixel. Twenty water absorption bands (104-108, 150-163, 220) have been removed [18], and a 200-band image was used for the experiments. The reference data contain sixteen classes of interest, which represent mostly different types of crops and are detailed in Table II. A three-band false color image and the reference data are presented in Figure 6. We have randomly chosen 50 samples for each class from the reference data as training samples, except for classes “*alfalfa*”, “*grass/pasture-mowed*” and “*oats*”. These classes contain a small number of samples in the reference data. Therefore, only 15 samples for each of these classes were chosen randomly to be used as training samples. The remaining samples composed the test set.

Segmentation of the *Indian Pines* image was performed, using the three discussed techniques. For the EM technique, the upper bound on the number of classes was chosen equal to 17, and a feature reduction has been previously applied, using the method of PCFA [31] to get a 10-band image  $\mathbf{Y}_{IN}$ . The following groups of bands were averaged: 1-18, 19-36, 37-53, 54-57, 58-61, 62-75, 76-81, 82-99, 100-140, 141-200.

Since some classes have very similar spectral responses in the *Indian Pines* image (for instance, three classes of corn and three classes of soybeans), we set  $S_{weight} = 0.0$  for the RHSEG method. A segmentation map at the relevant level of hierarchy was chosen with the program HSEGViewer. The resulting watershed, EM and RHSEG segmentation maps contained 1277, 3832 and 823 regions, respectively.

A pixelwise classification on the 200-band image was performed, using the multiclass one *versus* one SVM classifier

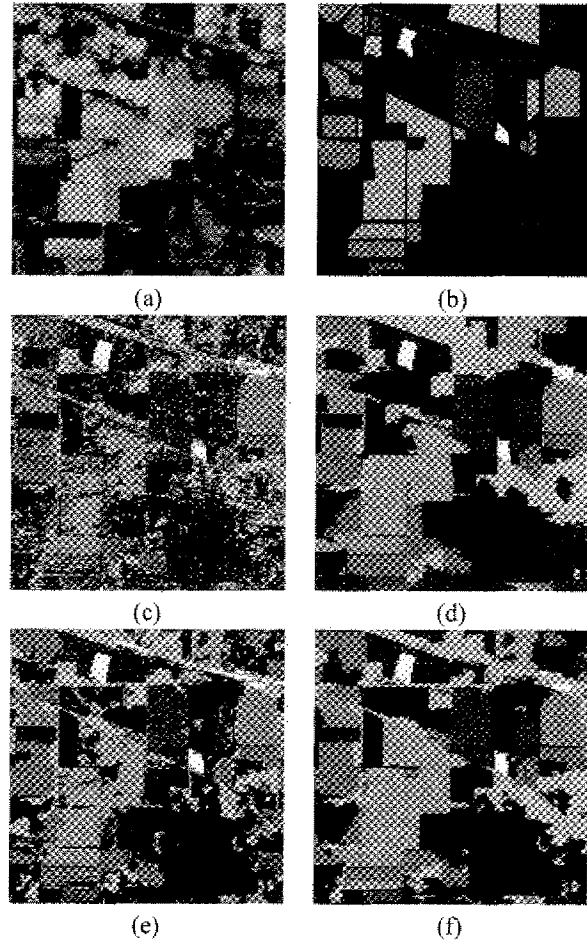


Fig. 6. *Indian Pines* image. (a) Three-band color composite. (b) Reference data: Corn-no till, Corn-min till, Corn, Soybeans-no till, Soybeans-min till, Soybeans-clean till, Grass/pasture, Grass/trees, Grass/pasture-mowed, Hay-windrowed, Oats, Wheat, Woods, Blg-Grass-Tree-Drives. (c) SVM pixelwise classification map. (d) *SVMMSF+MV* classification map. (e) *MC-MSF* classification map. (f) *MSSC-MSF* classification map.

with the Gaussian RBF kernel. The optimal parameters  $C$  and  $\gamma$  were chosen by fivefold cross validation:  $C = 128$ ,  $\gamma = 2^{-6}$ . After the segmentation results were combined with the pixelwise classification map, the marker selection (14409, i.e., 68% of pixels were selected as markers) and the MSF construction were applied, as described in the previous section.

Table II gives the global and class-specific accuracies of the pixelwise SVM, segmentation followed by majority voting and the proposed *MSSC-MSF* classification techniques. The performances of the proposed approach are compared with those obtained by the *ECHO* and *SVMMSF+MV* methods, as described in the previous section. Finally, the *MC-MSF* classification was applied in the same way as for the previous data set.

From the table, the similar conclusions as for the previous data set can be derived. The SVM classification yields the best accuracies among all the applied pixelwise methods. Spectral-spatial classification accuracies are always higher when compared to pixelwise accuracies. The proposed MC method succeeds in combining several classification results



TABLE II  
CLASSIFICATION ACCURACIES IN PERCENTAGE FOR THE *Indian Pines* IMAGE: OVERALL ACCURACY (OA), AVERAGE ACCURACY (AA), KAPPA COEFFICIENT ( $\kappa$ ) AND CLASS-SPECIFIC ACCURACIES.

	3-NN	ML	SVM	ECHO	WH+MV	EM+MV	RHSEG +MV	SVMMSF +MV	MC- MSF	MSSC- MSF
OA	66.27	75.41	78.17	82.64	86.63	83.60	90.86	91.80	86.66	<b>92.32</b>
AA	76.77	79.61	85.97	83.75	91.61	85.34	93.96	<b>94.28</b>	92.58	94.22
$\kappa$	62.04	72.25	75.33	80.38	84.83	81.43	89.56	90.64	84.82	<b>91.19</b>
Corn-no till	41.84	71.39	78.18	83.45	<b>94.22</b>	89.09	90.46	93.21	83.82	89.74
Corn-min till	62.24	63.01	69.64	75.13	78.06	75.64	83.04	<b>96.56</b>	74.62	86.99
Corn	73.37	85.87	91.85	92.39	88.59	65.22	95.65	95.65	<b>96.74</b>	95.11
Soybeans-no till	67.43	79.43	82.03	90.10	<b>96.30</b>	88.14	92.06	93.91	93.36	91.84
Soybeans-min till	53.91	52.65	58.95	64.14	68.82	65.67	84.04	81.97	72.91	<b>89.16</b>
Soybeans-clean till	64.72	85.99	87.94	89.89	90.78	95.04	95.39	97.16	95.92	<b>97.34</b>
Alfalfa	84.62	48.72	74.36	48.72	<b>94.87</b>	<b>94.87</b>	92.31	<b>94.87</b>	<b>94.87</b>	<b>94.87</b>
Grass/pasture	86.35	93.51	92.17	94.18	95.08	93.96	94.41	94.63	<b>98.21</b>	94.63
Grass/trees	91.97	94.69	91.68	96.27	<b>97.99</b>	96.41	97.56	97.27	97.70	97.85
Grass/pasture-mowed	<b>100</b>	36.36	<b>100</b>	36.36	<b>100</b>	<b>100</b>	<b>100</b>	<b>100</b>	<b>100</b>	<b>100</b>
Hay-windrowed	95.67	97.72	97.72	97.72	99.54	99.32	99.54	<b>99.77</b>	99.54	<b>99.77</b>
Oats	80.00	<b>100</b>	<b>100</b>	<b>100</b>	<b>100</b>	40.00	<b>100</b>	<b>100</b>	<b>100</b>	<b>100</b>
Wheat	<b>99.38</b>	98.15	98.77	98.15	<b>99.38</b>	98.77	98.15	<b>99.38</b>	<b>99.38</b>	<b>99.38</b>
Woods	86.17	95.42	93.01	94.21	97.11	96.70	98.63	<b>99.68</b>	98.47	99.44
Bldg-Grass-Trec-Drives	45.15	73.03	61.52	81.52	69.39	66.67	<b>82.12</b>	68.79	77.88	73.64
Stone-steel towers	95.56	97.78	97.78	97.78	95.56	<b>100</b>	<b>100</b>	95.56	97.78	97.78

for further improvement of accuracies. The *MSSC-MSF* yields the best OA, kappa coefficient and most of the class-specific accuracies. The AA is only slightly (non-significantly) lower when compared to that obtained by the recently proposed *SVMMSF+MV* method. Following the results of the McNemar's test, the *MSSC-MSF* and *SVMMSF+MV* accuracies are not significantly different, using 5% level of significance. These two techniques significantly outperform other classification approaches.

Figure 6 shows the SVM, *MC-MSF*, *MSSC-MSF* and *SVMMSF+MV* classification maps. As can be seen, the *MSSC-MSF* map contains much more homogeneous spatial structures, when compared to the SVM and *MC-MSF* maps, and is comparable with the *SVMMSF+MV* map. Again, spectral-spatial marker-based techniques yielded the most accurate classification maps.

Although for the *Indian Pines* image, the *MSSC-MSF* and *SVMMSF+MV* methods yield similar results, here we stress the advantages of the proposed *MSSC-MSF* approach *versus* the previous one for spectral-spatial classification:

- **Robustness:** While for the *SVMMSF+MV* method the marker selection strongly depends on the performances of the selected pixelwise classifier, the MC approach mitigates this dependence. Since in the *MSSC-MSF* scheme, different segmentation maps are combined with one pixelwise classification map, the choice of the classifier is also important. However, if in the *SVMMSF+MV* method a pixel was wrongly classified with a high probability, it will yield a wrong marker. In the new approach, the majority voting within segmentation regions can correct the misclassification result for a particular pixel, before the marker map is built.
- **Computational Complexity:** In the *SVMMSF+MV* method, the probabilistic pixelwise SVM classification part is the most time-consuming [43]. In the *MSSC-MSF*

approach, SVM classification is performed without the computation of probability estimates; this reduces the pixelwise classification part execution time. The unsupervised segmentation techniques are much less time-consuming when compared to the SVM classification. Furthermore, their efficient implementations are available, and they can be executed in parallel at the same time with the SVM classification. As a conclusion, the efficient implementation of the proposed *MSSC-MSF* approach is possible, which would run faster than the previously proposed *MSSC-MSF* method.

## V. CONCLUSIONS

Hyperspectral sensors capture images in hundreds of narrow spectral channels. The detailed spectral signatures for each spatial location provide rich information about an image scene, leading to better discrimination between physical materials and objects. However, interpretation of these high-dimensional signatures is a challenging task. Although pixelwise classification techniques have given high classification accuracies when dealing with hyperspectral data, the incorporation of the spatial context into classification procedures yields further improvement of the accuracies.

In this paper, a new method for spectral-spatial classification of hyperspectral images based on multiple classifiers 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 demonstrated that the proposed method improves classification accuracies, when compared to previously proposed classification schemes, and provides classification maps with homogeneous regions.

In conclusion, the proposed methodology succeeded in taking advantage of multiple classifiers and the spatial and the

spectral information simultaneously for accurate hyperspectral image classification. The method yields accurate results for different data sets, i.e., data containing large spatial structures and/or small and complex structures, with spectrally dissimilar and/or spectrally confusing classes. Furthermore, its efficient implementation is possible.

While performing especially well for classification of homogeneous regions, the proposed approach has a drawback common to most of spectral-spatial techniques: It produces a smoother classification map when compared to pixelwise ones, and therefore it risks impairing results near the borders between regions (where mixed pixels<sup>4</sup> are often encountered) or in textured areas. Spectral unmixing techniques [44] can be used for accurate analysis of region borders, while segmentation in the sense of texture [45] can be applied for textured regions.

In the future, we will further explore the integration of spectral-spatial approaches in MC systems for accurate and robust classification of hyperspectral images. Since the incorporation of the spatial information in classification significantly improves accuracies, it is of interest to further investigate performances of the proposed spectral-spatial approaches when a very limited number of training samples is available.

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<sup>4</sup>A mixed pixel is defined as a pixel whose value represents the average energy emitted or reflected from several different surfaces occurring within the spatial area represented by the pixel.

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