

SEGMENTATION AND CLASSIFICATION OF HYPERSPECTRAL DATA USING WATERSHED

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ABSTRACT

The paper presents a new segmentation and classification scheme to analyze hyperspectral (HS) data. The Robust Color Morphological Gradient of the HS image is computed, and the watershed transformation is applied to the obtained gradient. After the pixel-wise Support Vector Machines classification, the majority voting within the watershed regions is performed. Experimental results are presented on a 103-band airborne ROSIS image, of the University of Pavia, Italy. The integration of the spatial information from the watershed segmentation into the HS image classification improves the classification accuracies, when compared to the pixel-wise classification.

Index Terms— hyperspectral images, mathematical morphology, segmentation, classification, watershed

1. INTRODUCTION

Over the past few years, the growing availability of hyperspectral (HS) images has opened the door to numerous new applications. The fine spectral resolution of the data provides an invaluable source of information regarding the physical nature of the different materials composing the remotely sensed scene. The accurate analysis of these materials and their spatial organization or distribution are crucial in many applications (precision agriculture, monitoring and management of the environment, security and defense issues, etc.).

However, taking full advantage of the offered potential requires new algorithmic developments. Most of the methods designed for standard multispectral images actually fail when confronted to HS data: The well known curse of dimensionality prevents robust statistical estimations, usual vector norms become meaningless and so on. All these issues gathered a lot of attention over the past few years.

First attempts to classify HS data were designed to assign each pixel to one of the classes based on its spectra [1] (usu-

ally feature selection process precedes classification, to reduce dimensionality of data). In particular, a Support Vector Machines (SVM) and other kernel-based methods were applied for this purpose, giving good classification results [2, 3].

Another modification to improve classification results consists in integration of spatial and spectral information during the image analysis. It means that the decision to assign pixel to the specific class is based on the feature vector of this pixel and on the information from pixels of its neighborhood. The previous studies, where neighborhoods were defined using morphological filters [3] and morphological leveling [4], show promising results in incorporating the spatial and spectral information. In this study, these neighborhoods are replaced by the segmentation result obtained by the watershed algorithm.

In the paper, a new segmentation and classification scheme to analyze HS data is discussed. In the next section, we give a short overview of the watershed technique. In Section 3, the proposed scheme is described. In Section 4, the experimentation results are given. Finally, conclusions are drawn in Section 5.

2. WATERSHED SEGMENTATION

The watershed transformation is a powerful technique of mathematical morphology for image segmentation [5, 6]. It considers a two-dimensional one-band image as a topographic relief, the value of a pixel h standing for its elevation. The watershed lines divide image into catchment basins, so that each basin is associated with each minimum in the image.

The transformation is usually applied to the gradient function that defines transitions between regions. Typically, result of watershed on the gradient image without any additional processing is extremely over-segmented. This drawback can be reduced using some pre-processing (e.g., area filtering) or post-processing (e.g., merging of similar neighboring regions).

Several aspects should be considered while segmenting the HS image by watershed [7]. The input (gradient) im-

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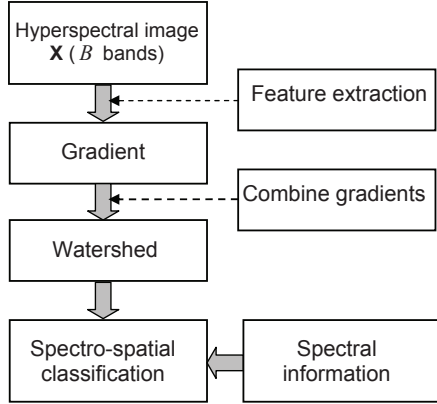


Fig. 1. Flow-chart of the proposed segmentation and classification scheme.

age/images to perform watershed should be defined. Gradient on a multivariate function can be obtained in different ways, which will be discussed in the next section.

The other question to be exploited is how to use the information from pixels in the regions to improve the image classification, what will be also discussed further.

3. SEGMENTATION AND CLASSIFICATION SCHEME

The general flow-chart of the proposed segmentation and classification scheme is given in Figure 1.

On the input we have a B -band HS image. Let us consider this image as a set of n pixel vectors $\mathbf{X} = \{\mathbf{x}_j \in \mathbf{R}^B, j = 1, 2, \dots, n\}$. For the input of the *watershed* step a one-band gradient image must be calculated. Different strategies are possible here.

Before computing the gradient, *feature extraction* can be performed, applying one of the transformations, such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), Maximum Noise Fraction (MNF), etc. The aim of this step is to obtain either one- or multi-band image which would contain the maximum information to distinguish between the spatial structures in the image.

If a one-band image with good distinguishing capability between structures can be obtained, the algorithm for computing a gradient and watershed is straightforward. For instance, a morphological Beucher gradient [8] can be applied.

If, however, as the input of the *gradient* step we still have a multi-band image, we can proceed in different ways, which can be grouped into the following two categories [9]:

1. Multidimensional gradient methods: The gradients of every spectral band are computed and consequently

combined into one gradient image. To combine gradients, the supremum or sum operator can be used [7].

2. Vector methods: Vectorial gradients are computed, based on the defined distance between pixel vectors.

Here we present experimental results based on the vectorial gradient of the original HS image (the *feature extraction* step is omitted). The *Robust Color Morphological Gradient (RCMG)* proposed by Evans and Liu [9] is used.

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 .

A *Color Morphological Gradient (CMG)* is computed as:

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

i.e., the maximum of the distances between all pairs of vectors in the set χ . If $o = 2$, the L_2 norm is used.

One of the drawbacks of the CMG is that it is very sensitive to outliers, because its magnitude is derived from the two vectors in the structuring element that are furthest apart. To overcome the problem of outliers, the authors of [9] have proposed to use the RCMG.

The scheme to make the 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 (that defines real edges in the image) is obtained.

Thus, the *RCMG* can be defined as:

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

where REM_r is a set of r vector pairs removed.

In our experiments, we used (2) to compute the RCMG, with a 3×3 square structuring element E (center of E is in the center of the square), $o = 2$ and $r = 1$. Furthermore, the algorithm of Vincent and Soille [6] was used to compute the watershed transformation (based on 8-neighbor connectivity). The output of the *watershed* step is the image partitioning into a set of regions, so that each region contains the subset of m pixel vectors $\mathbf{S} = \{\mathbf{s}_j \in \mathbf{R}^B, j = 1, 2, \dots, m\}$, $\mathbf{S} \subseteq \mathbf{X}$, and one subset contains pixels that are situated on the borders between regions (watershed pixels).

It is often desirable to produce a segmented image where each pixel belongs to some region. In this case, each watershed pixel can be assigned to one of the regions in its neighborhood. For this purpose, we compute for every region \mathbf{S} the standard vector median [10]:

$$\mathbf{s}_{VM} = \operatorname{argmin}_{\mathbf{s} \in \mathbf{S}} \left\{ \sum_{j=1}^B \|\mathbf{s} - \mathbf{s}_j\|_1 \right\} \quad (3)$$

Every watershed pixel is assigned to the neighboring region with the "closest" median (the distance between vector

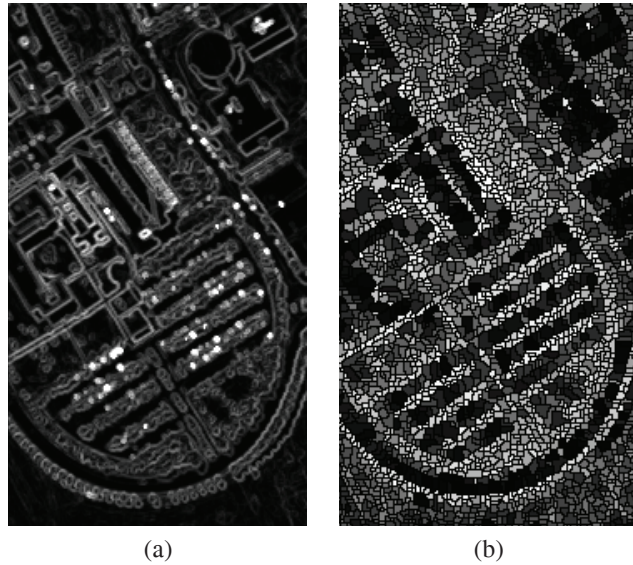


Fig. 2. University of Pavia image: a) RCMG with $r = 1$, $o = 2$; (b) watershed regions.

median of this region and the watershed pixel vector is minimal; L_1 norm is used).

After the image is segmented into regions, this spatial information should be used to improve the classification results.

One of the approaches to integrate spectral and spatial information can consist in classifying every region using its vector median as a feature. The results of the other approach which is more accurate are shown in this paper. First, a SVM classification on the original HS image is performed. Then within each region we assign all the pixels to the most frequent class inside this region (*majority vote* approach).

4. EXPERIMENTAL RESULTS AND DISCUSSION

The image used for experiments is recorded from the ROSIS-03 (Reflective Optics System Imaging Spectrometer) optical sensor. The image scene is the area surrounding the University of Pavia, Italy (provided by DLR). The image is 610 by 340 pixels, the spatial resolution is 1.3 m per pixel. The number of bands of the ROSIS-03 sensor is 115 with a spectral coverage ranging from 0.43 to 0.86 μ m. The 12 most noisy channels have been removed, and the experiments are conducted on the 103-band image. Nine classes of interest are considered, namely: Asphalt, meadows, gravel, trees, metal sheets, bare soil, bitumen, bricks and shadows. More information about the used image, with the number of test and training samples for each class can be found in [3].

First, the RCMG was computed for the HS image. Then, the watershed transformation is applied to the gradient, leading to an image partitioning of 11802 regions (see Fig. 2).

It can be seen from the gradient image that the principal borders are defined. However, as the remote sensing image of an urban area contains some complex and small structures, that may be of interest or not, a lot of "noisy" edges are seen in the image. In our experiments, we do not want to classify cars to a special class. But as the spectral response of cars is quite different from that of the surrounding objects and the size of cars is small, it leads to the appearance of undesirable strong borders in the gradient. A solution to reduce the number of these "noisy border pixels" may consist in filtering the original HS image. For this purpose, for instance, a morphological alternate sequential filter can be used [8]. But in this case the information about the small objects we are interested in classifying to a separate class can be lost.

The obtained watershed result was severely oversegmented, as expected. The colors of each region in Figure 2.(b) correspond to the label of this region, scaled in order to obtain a grey-scale 8-bit image. However, in our case, a remaining oversegmentation is not a crucial problem, since we are more interested in classification than segmentation.

To perform the SVM classification of the HS image, the LIBSVM library was used [11]. The multi-class pairwise (one versus one) SVM classification, with Gaussian RBF kernel was performed (with parameters $C = 128$, $\gamma = 0.125$).

After the pixel-wise SVM classification, the *majority vote* within the watershed regions was performed. The watershed pixels have been either left not processed during the majority voting (*No WHEDs* approach), or assigned to the regions with the "closest median" before the majority voting was performed considering all the pixels (*With WHEDs* approach).

The overall and average accuracies (OA and AA) and kappa coefficient (κ) [3] for the pixel-wise SVM and combined spectro-spatial classification are presented in Table 1. Figure 3 depicts the classification map for the *With WHEDs* approach, with the class-specific accuracies given in Table 2.

Table 1. Classification Accuracies in Percentage for the Pixel-Wise SVM and Combined Spectro-Spatial Classification.

Accuracy	Pixel-wise SVM	SVM + Majority vote	
		<i>No WHEDs</i>	<i>With WHEDs</i>
OA	82.08	84.41	86.64
AA	89.11	90.70	92.13
κ	77.49	80.32	83.05

As can be seen from Table 1, combining of the spatial information obtained by watershed segmentation with the spectral classification results improves substantially the classification accuracies. The *With WHEDs* approach gives the best accuracies, improving the overall accuracy by 4.56% comparing to the pixel-wise classification and by 2.23% comparing to the *No WHEDs* approach.

The spectro-spatial classification reduces significantly the noise in the classification map. But on the image (see Fig. 3)



Fig. 3. Classification map for the combined spectro-spatial classification (With WHEDs approach).

we see some rough borders, and more accurate segmentation is needed to refine them.

Classification accuracies were improved by the spectro-spatial classification for almost all the classes, except for the classes *gravel* and *shadows*, but those accuracies were non-significantly reduced. For some classes like *asphalt*, *bitumen*, *bricks* accuracies were much improved, i.e., in range of 5.5% to 9%, due mostly to the noise reduction.

5. CONCLUSIONS

This paper presents one of the first reported studies on the design of a watershed based segmentation algorithm for HS data. A further step forward towards the integration of spatial and spectral information for the classification of HS data was proposed in the paper.

Results of the combined spectro-spatial classification, using the majority voting within the regions obtained by the segmentation algorithm, are promising. In the future, we plan to improve the segmentation results using additional filtering and merging of regions.

6. REFERENCES

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Table 2. Class-specific accuracies for the Combined Spectro-Spatial Classification (With WHEDs approach).

Classes	Class-spec. acc. (%)
1-asphalt	94.28
2-meadows	76.41
3-gravel	69.89
4-trees	98.30
5-metal sheets	99.78
6-bare soil	97.51
7-bitumen	97.14
8-bricks	98.29
9-shadows	97.57

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