Imaging and Applied Optics 2018 (3D, AIO, AO, COSI, DH, IS, LACSEA, LSC, MATH, pcAOP) © OSA 2018

Supervised Classification of Hyperspectral Images using Side Information

Karen Sanchez[1], **Carlos Hinojosa**[2], **Henry Arguello**[2]

[1]*Department of Electrical Engineering, Universidad Industrial de Santander, Bucaramanga, Colombia, 680002*

[2]*Department of Computer Science, Universidad Industrial de Santander, Bucaramanga, Colombia, 680002*

karen2178740@correo.uis.edu.co, carlos.hinojosa@saber.uis.edu.co, henarfu@uis.edu.co

Abstract: This paper proposes a classification method that fuses superpixels-segmentation information from an RGB image with a hyperspectral image without estimating the high spatial-spectral resolution cube. This methodology improves the classification accuracy while boosting the performance.

OCIS codes: (100.6890) Three-dimensional image processing, (110.4234) Multispectral and hyperspectral imaging, (100.3010) Image reconstruction techniques.

1. Introduction

Hyperspectral imaging (HSI) allows the acquisition of spatial information at different electromagnetic frequencies. The acquired information is commonly regarded as a 3D image where two dimensions correspond to the spatial information and the third one represents the spectral wavelengths. Typically, these images are used for the identification and classification of features in a scene based on the available amount of spectral information. In particular, in hyperspectral image classification, the data points correspond to the spectral signatures of the scene which are associated with a specific land-cover class. HSI provides rich spectral information, however its low spatial resolution makes it difficult to attain accurate classification. On the other hand, some recent works propose to improve the hyperspectral image quality using side information from a high spatial resolution RGB sensor [1]. This work proposes a method for HSI classification with an RGB image as side information. The high-resolution RGB spatial image is segmented into a predefined number of superpixels [2], which are then fused with a low-resolution hyperspectral cube. Each superpixel is associated with the corresponding class through the spectral signatures. This methodology reduces the number of pixels to be classified, hence, the computational requirements and the classification time are also reduced.

2. Proposed HSI Supervised Classification Approach

The aim of the proposed method is to improve the spatial information of the HSI using an RGB image as side information, in order to improve the classification accuracy. The flowchart of the algorithm is depicted in Fig. 1. First, rearrange the $N_h \times N_h \times L_h$ HSI data cube into the 2D matrix $\mathbf{F}_h \in \mathbb{R}^{N_h N_h \times L_h}$ and, similarly, the $N_m \times N_m \times L_m$ RGB image into the matrix $\mathbf{F}_m \in \mathbb{R}^{N_m N_m \times L_h}$, where N_h, N_m represent the spatial dimensions and L_h, L_m the number of spectral bands of the HSI and RGB image, respectively. In general, the main goal is to obtain a rich spatial and spectral fused cube $\mathbf{F} \in \mathbb{R}^{\mathbf{N_m N_m \times L_h}}$ with superpixel information extracted from the RGB image. The fused cube will be used later for the classification process. Using the above notation, the proposed fusion method can be formulated as the following optimization problem

$$\min_{\mathbf{F}} \frac{1}{2} \|\mathbf{F}_h - \mathbf{D}_m \mathbf{F}\|_F^2 + \lambda \|\mathbf{F}\|_*, \tag{1}$$

where $\mathbf{D}_m \in \mathbb{R}^{N_h N_h \times N_m N_m}$ is a downsampling matrix operator,$\|\cdot\|_F$ stands for Frobenius norm and λ is a regularization parameter. As pixels in $\mathbf{F}$ are grouped in segments, the nuclear norm $\|\mathbf{F}\|_*$ is minimized in Eq. 1 since pixels (rows) in the same group share a common low-rank pattern [3]. In order to incorporate the segmentation information in $\mathbf{F}$, a superpixel algorithm runs first over the RGB image where the number of desired segments N_{seg} is specified. Then, an upsampling matrix operator $\mathbf{U_w}^T \in \mathbb{R}^{N_m N_m \times N_{seg}}$ is designed, such that $\mathbf{F} = \mathbf{U_w}^T \bar{\mathbf{F}}$. The matrix $\bar{\mathbf{F}} \in \mathbb{R}^{Nseg \times L_h}$ contains the spectral information from the HSI image and the superpixel segmentation information obtained from the RGB image. Then, assuming that $\text{Rank}(\bar{\mathbf{F}}) \approx \text{Rank}(\mathbf{F})$, the optimization problem in Eq. 1 can be rewritten as

$$\min_{\bar{\mathbf{F}}} \frac{1}{2} \|\mathbf{F}_h - \mathbf{D}_m \mathbf{U_w}^T \bar{\mathbf{F}}\|_F^2 + \lambda \|\bar{\mathbf{F}}\|_*. \tag{2}$$

Finally, the classification of the spectral scene is achieved using a k-nearest neighbor classifier which was trained using some samples from $\mathbf{F}$.

Imaging and Applied Optics 2018 (3D, AIO, AO, COSI, DH, IS, LACSEA, LSC, MATH, pcAOP) © OSA 2018

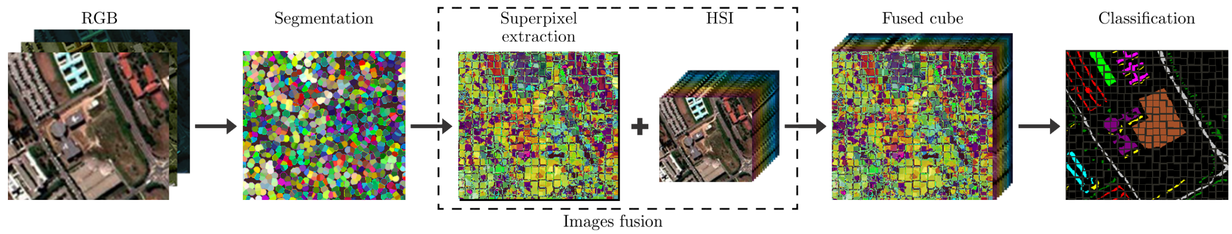
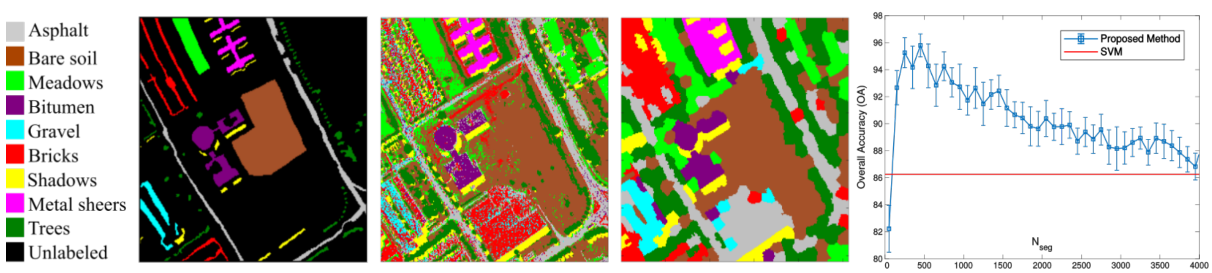


Fig. 1: Proposed methodology. An RGB image is segmented into a predefined number of superpixels. Superpixels are used to train the HSI image and a high spectral and spatial resolution image is obtained. Finally, the superpixels are classified.

3. Simulations and Results

The proposed HSI classification approach was tested on a region of the ROSIS Pavia University data set with size 64×64 pixels and 103 spectral bands. This subimage includes nine main land-cover classes: Asphalt, Bare Soil, Meadows, Bitumen, Gravel, Bricks, Shadows, Trees and Metal Sheers. The used RGB image is from the same region and has a size of 256×256 pixels of spatial resolution and 3 spectral bands. The proposed approach was compared with the support vector machine (SVM) classifier which is well known to provide high accuracy results in HSI classification. In the training step, 50 samples for each class are chosen at random. Figures 2 (b) and (c) depict the visual classification results for the two classification methods. The ground-truth image is also provided for comparison purposes in Fig 2 (a). Furthermore, Table 1 shows the numerical results for each of the nine land-cover classes (producer's accuracy), the overall accuracy (OA), the kappa coefficients and the running time of each algorithm [4]. All the numerical results, except the Kappa coefficients and the running time, are given in percentage and are the average of 25 simulations. The shown results for the proposed method were obtained using $N_{seg} = 450$. It is important to note that the provided running time of the proposed method includes the fusion step (solve Eq. 2). From the visual and quantitative results, it can be clearly observed that the proposed method provides a higher classification accuracy in comparison with the SVM classifier.



(a) (b) (c) (d)

Fig. 2: (a) University of Pavia reference image. Classification results by (b) SVM algorithm, and (c) proposed method. (d) Overall accuracy of classification for the proposed method varying the number of segments (N_{seg}) in the superpixel algorithm; the obtained overall accuracy for the SVM classifier is also provided for comparison purposes.

Table 1: Quantitative classification metrics comparison between different methods for the Pavia Image

	Asphalt	Bare Soil	Meadows	Bitumen	Gravel	Bricks	Shadows	Metal Sheers	Trees	OA	Kappa	Time (s)
Proposed Method	82.23	100	99.69	97.37	96.50	89.57	93.53	99.86	96.24	95.79	0.9497	0.6365
SVM	81.33	88.82	97.18	89.55	70.36	64.36	98.95	99.57	98.65	86.43	0.8422	3.3932

4. Conclusion

A supervised hyperspectral image classification method was proposed in this paper. Our approach uses an RGB image as side information which improves the spatial information of the HSI and, in addition, the segmentation obtained from a superpixel algorithm is incorporated in the optimization problem boosting the classification performance.

References

1. X. Yuan, T. Tsai, R Zhu, P. Llull, D. Brady, and L. Carin, "Compressive hyperspectral imaging with side information," *IEEE Journal of selected topics in Signal Processing*, vol. 9, no. 6, pp. 964–976, (2015).
2. S. Zhang, S. Li, W. Fu, and L. Fang, "Multiscale superpixel-based sparse representation for hyperspectral image classification," *Journal of Remote sensing*, vol. 9, no. 2, (2017).
3. Z. He, L. Liu, R. Deng, Y. Shen, "Low-rank group inspired dictionary learning for hyperspectral image classification" *Elsevier Signal Processing Journal*, vol. 120, pp. 209–221, (2016).
4. Humboldt State University Geospatial Online, "Introduction to Remote Sensing: Accuracy Metrics", https://goo.gl/vK2KKj.