SPECTRAL PARTITIONING FOR HYPERSPECTRAL REMOTE SENSING IMAGE CLASSIFICATION

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ABSTRACT

In this paper, we present a new approach for spectral partitioning which is intended to deal with ill-posed problems in hyperspectral image classification. First, we use adaptive affinity propagation (AAP) to intelligently group the original spectral bands. Such grouping strategy not only allows us to reduce the number of spectral bands, but also to provide a different perspective on the original hyperspectral data. Then, a multiple classifier system (MCS) based on multinomial logistic regression (MLR) is applied. The system is trained using different band subsets resulting from the previously conducted intelligent grouping, and the results are combined to produce a final classification result. Our experimental results, conducted using the well-known hyperspectral scenes collected by the Airborne Visible Infra-Red Imaging Spectrometer (AVIRIS) over the Indian Pines region in NW Indiana, indicate that the proposed method can provide important advantages in terms of classification, in particular, when the number of training samples available *a priori* is very low.

***Index Terms*—** Hyperspectral classification, spectral partitioning, adaptive affinity propagation (AAP), multiple classifier system (MCS), multinomial logistic regression (MLR).

1. INTRODUCTION

Hyperspectral remote sensing is a fast growing area that now plays a significant role in landcover/land-use extraction, environmental target mapping and monitoring, ground physical quantity retrieval, etc. [1]. Hyperspectral image classification is an important technique for hyperspectral data exploitation [2]. However, it is well-known that the limited availability of training samples may condition the success of hyperspectral image classification techniques [3, 4]. On the other hand, ground or manual collection of labeled training samples is too expensive and time consuming, particularly considering the large quantity of available hyperspectral image products [5]. Moreover, the curse of dimensionality is an important problem affecting classification, i.e., the high number of available spectral bands and the existing correlation between them imposes problems when conducting successful classification with limited training samples [6]. These situations have led to important developments in the field of semi-supervised learning [7], active learning (AL) [8], transductive learning [9], multiple learning systems (MLS) [10], and other new learning methods developed to exploit information from unlabeled samples [11, 5].

To cope with these relevant issues, another strategy has been to develop new distance/similarity measurement strategies for hyperspectral band reduction/selection and dimensionality reduction [12, 13, 14, 15]. Specifically, the high existing correlation between bands has been exploited to design new methods for reducing data dimensionality, including methods that have found great popularity such as principal component analysis (PCA) [16], linear discriminant analysis (LDA) [17] or the minimum noise fraction (MNF) [18]. In fact, it has been reported in previous works that classification after dimensionality reduction or band selection generally outperforms classification based on the original hyper-

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spectral data (in addition to reducing computational complexity) [19] [20].

However, the use of band selection may discard some useful information depending on the considered application. With the aforementioned issues in mind, in this work we propose a new concept of spectral partitioning for feature analysis which aims at intelligently finding suitable spectral partitions in the original hyperspectral data, while remaining faithful to the original physical spectral characteristics. The presented approach provides a different perspective on the selection of different band combinations from the original image for classification purposes. Specifically, we develop an adaptive affinity propagation (AAP) strategy for hyperspectral band partitioning, which provides a partitioning strategy in which unsupervised clustering is used to automatically select a number of clusters and centering parameters. We use correlation to measure the similarity/distance between the spectral bands of the selected training samples as input to AAP. In order to evaluate the proposed AAP method, we use a multiple classifier system (MCS) based on the multinomial logistic regression (MLR) [21, 22]. Our experimental results are conducted using the well-known AVIRIS Indian Pines data set, indicating that the presented approach can successfully mitigate issues of high dimensionality in hyperspectral image classification.

2. PROPOSED METHOD

2.1. Adaptive Affinity Propagation (AAP) and Reassignment

AAP was originally presented in order to automatically search for the optimal number of clusters [22]. Compared with the traditional affinity propagation approach reported in [23], AAP can get rid of instabilities. In this work, we exploit this concept to automatically determine the number of bands to be retained from the original hyperspectral data. As a result, the number of spectral bands retained after partitioning may vary and include non-continuous bands representing most of the information in the original data. In this process, noise and water-absorption bands are discarded, since bands belonging to the same partition share high correlation and similarity. Based on these two main aspects, we reassign the partitions into new band groups by taking into account high frequency/significance group subsets.

2.2. Multiple Classifier System (MCS)

In order to perform the classification after band selection, we use the MLR classifier in MCS fashion. Specifically, a standard MCS is constructed in this paper by training different MLR classifiers using each band group reassigned separately. This enhances the capability of the MLR to deal with ill-posed problems. Then, decision fusion is exploited to generate a final classification result. The adopted strategy presents several advantages. On one hand, we promote diversity among classifiers. On the other hand, different band combinations from the original set of bands provide different perspectives on the original hyperspectral data which can be fully exploited in the classification process. In the following section we provide an experimental evaluation of the presented approach based on AAP and MCS concepts.

3. EXPERIMENTS

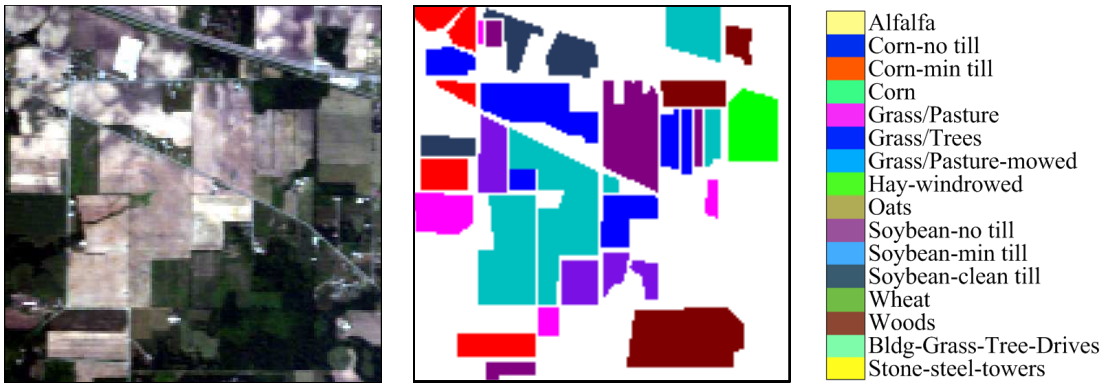
3.1. Hyperspectral Data

The hyperspectral scene used in experiments was collected by the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) over the Indian Pines region in NW Tippecanoe County, Indiana in June of 1992. This scene, acquired over a mixed area of two-thirds agriculture, and one-third forest or other natural perennial vegetation, early in the growing season, consists of 145×145 pixels and 220 spectral channels in the wavelength range from 0.4 to 2.5μm, with nominal spectral resolution of 10nm, moderate spatial resolution of 20m by pixel, and 16-bit radiometric resolution. The number of bands has been reduced to 200 by discarding water absorption and noisy bands, while the number of classes actually employed is nine after removing the small classes with small number of pixels. For illustrative purposes, Fig. 1(a) shows a false-color composition of the AVIRIS Indian Pines scene, while Fig. 1(b) shows the reference map available for the scene, displayed in the form of a class assignment for each labeled pixel, with several mutually exclusive reference classes shown in Fig. 1(c), *i.e.*, for a total of 9345 samples.

3.2. Experiments and Discussion

Several aspects of the presented method have been studied in our experiments, including: the number of clusters (N_C) extracted after AAP partitioning, the number of reassigned band subsets (N_R), and the number of reassigned bands (N_{SUB}). We also evaluate their impact in the final classification accuracy of the presented approach. Our experiments can be summarized as follows:

- First, we perform classification using the proposed approach using all the original spectral bands.
- Then, we evaluate the effectiveness of AAP partitioning by comparing the results provided by our method with the classification results obtained using different numbers of clusters, ranging from 2 to N_B-1 (where N_B denotes the total number of spectral bands).
- Finally, in order to analyze the impact of N_{SUB}, we perform classification experiments using the proposed approach by considering values of this parameters ranging between 2 and its maximum value. The relationship between N_R and N_{SUB} is also explored.



(a) (b) (c)

Fig. 1. (a) False color composition of the AVIRIS Indian Pines data. (b) Ground-truth map used for evaluation purposes. (c) Class labels in the ground-truth map.

In our experiments we randomly select at least 100 pixels per class, which comprises only 9.6% of the total number of available labeled samples samples (9345). With this configuration, AAP finds a value of N_C = 3. We also set N_R = 6 empirically and analyze the values of overall accuracy (OA) obtained as a function of the number of clusters. In this context, it is worth mentioning that the number of reassigned bands N_{SUB} fluctuated between 30 and 34 as the number of clusters change. The results obtained under this configuration are reported in Fig. 2, which shows the obtained OAs as a function of the number of clusters for the proposed band selection approach in comparison with the results obtained using all the original spectral bands. As indicated in Fig. 2, the presented AAP method can effectively increase classification accuracies by means of intelligent dimensionality reduction, increasing the OA from 68.50% to more than 80% (depending on the number of clusters). It is also worth mentioning that the optimal number of clusters selected by AAP (N_C = 3) performs better than any other tested number. This indicates that AAP provides an effective strategy to automatically select the number of clusters for maximizing classification accuracy.

For illustrative purposes, Fig. 3 shows the obtained classification accuracies by using the proposed configuration with the original original hyperspectral image and with the presented method using N_C = 3 as estimated by the AAP procedure. Significant advantages can be observed in the classification map reported for the proposed strategy.

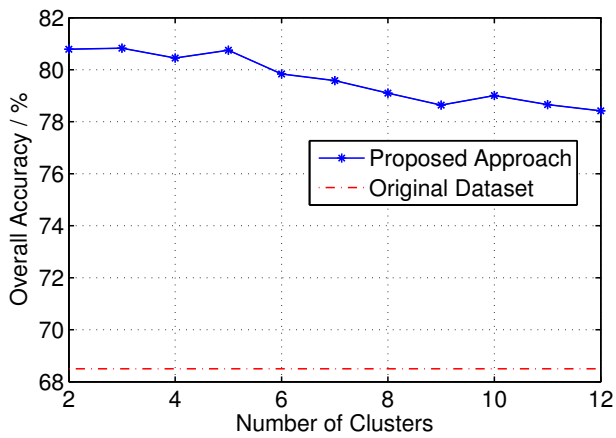


Fig. 2. OA as a function of the number of clusters for the proposed approach.

4. CONCLUSIONS AND FUTURE LINES

In this paper, we have presented a new spectral partitioning method based on adaptive affinity propagation (AAP) for hyperspectral image classification. The proposed method, which uses a multinomial logistic regression (MLR) method embedded in a multiple classification framework (MCS), has been shown to be useful in a scenario dominated by the limited availability of trainign samples. Our experimental results with the well-known AVIRIS Indian pines data set indicate superior classification results than those reported for the original hyperspectral scene. Our future work will focus on developing additional comparisons with other spectral partitioning approaches in order to fully substantiate the advantages that the proposed method can provide from the viewpoint of dimensionality reduction and classification accuracy. Additional strategies for band reassignment in the proposed method will be also explored.

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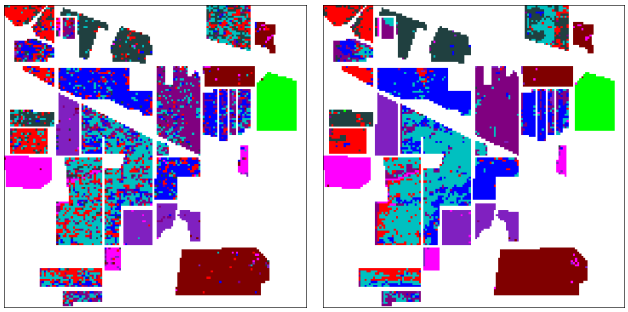

Original data set (OA=68.50%) | Proposed approach (OA=80.83%)

Fig. 3. Classification maps obtained by the proposed approach using the original hyperspectral data set and the proposed approach, with the number of band clusters automatically estimated by AAP as $N_C = 3$.

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