Semi-supervised Remote Sensing Image Segmentation Using Dynamic Region Merging

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Abstract. This paper introduces a remote sensing image segmentation approach by using semi-supervised and dynamic region merging. In remote sensing images, the spatial relationship among pixels has been shown to be sparsely represented by a linear combination of a few training samples from a structured dictionary. The sparse vector is recovered by solving a sparsity-constrained optimization problem, and it can directly determine the class label of the test sample. Through a graph-based technique, unlabeled samples are actively selected based on the entropy of the corresponding class label. With an initially segmented image based semi-supervised, in which the many regions to be merged for a meaningful segmentation. By taking the region merging as a labeling problem, image segmentation is performed by iteratively merging the regions according to a statistical test. Experiments on two datasets are used to evaluate the performance of the proposed method. Comparisons with the state-of-the-art methods demonstrate that the proposed method can effectively investigate the spatial relationship among pixels and achieve better remote sensing image segmentation results.

Keywords: Semi-supervised, Remote Sensing Image, Image segmentation, Dynamic region merging.

1 Introduction

Existing works on remote sensing image segmentation mainly focus on either feature dimension reduction or semi-supervised classification. Traditional feature dimension reduction methods, such as Independent Component Analysis and Principal Component Analysis. The discriminative approach to classification circumvents the difficulties in learning the class distributions in high dimensional spaces by inferring the boundaries between classes in the feature space[1,2]. Support vector machines (SVMs) [3] and multinomial logistic regression [4], are among the state-of-the-art discriminative techniques to classification. Due to their ability to deal with large input

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spaces efficiently and to produce sparse solutions, SVMs have been successfully used for hyperspectral supervised classification [5-7]. The multinomial logistic regression has the advantage of learning the class distributions themselves. Effective sparse multinomial logistic regression methods are available [8]. These ideas have been applied to hyperspectral image classification [9]. In order to improve the classification accuracy, some methods have integrated spatial information[10,11,12].

In region-based methods, a lot of literature has investigated the use of primitive regions as preprocessing step for image segmentation [13]. The advantages are regions carry on more information in describing the nature of objects, and the number of primitive regions is much fewer than that of pixels in an image. Starting from a set of primitive regions, the segmentation is conducted by progressively merging the similar neighboring regions according to a certain predicate, such that a certain homogeneity criterion is satisfied. In previous works, there are region merging algorithms based on statistical properties [14], graph properties [15]. Most region merging algorithms do not have some desirable global properties, even though some recent works in region merging address the optimization of some global energy terms, such as the number of labels [16] and the area of regions.

In this paper, we introduce a new semi-supervised clustering algorithm which exploits the spatial contextual information. The algorithm implements two main steps: (a) the semi-supervised clustering algorithm [17] to infer the class distributions; and (b) segmentation, by inferring the labels from a posterior distribution built on the learned class distributions and on a multi-level logistic (MLL) prior. The class distributions are modeled with a multinomial logistic regression, where the regressors are learned using both labeled and, through a graph-based technique, unlabeled samples. The spatial contextual information is used both in building the graph accounting for the feature "closeness"and in the MLL prior. The region merging segmentation is computed via a min-cut based integer optimization algorithm. Fig.1 illustrates the flowchart of the proposed method.

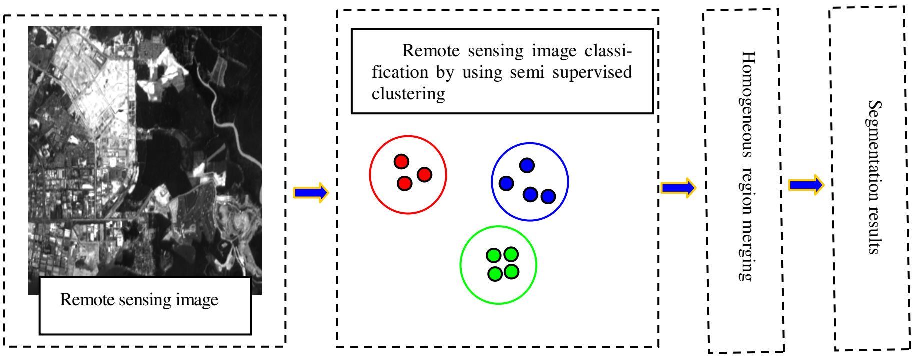


Fig. 1. The flowchart of the proposed remote sensing image classification method by using semi-supervised and region merging

The rest of the paper is organized as follows. Section 2 introduces the proposed remote sensing image classification method by using the spatial information. Experimental results and comparison with the state-of-the-art methods on two datasets are provided in Section 3. Finally, we conclude the paper in Section 4.

2 Remote Sensing Image Segmentation by Using Semi-supervised Classification and Region Merge

In this section, we introduce the proposed remote sensing image segmentation method by using semi-supervised clustering method as shown in Fig.1. First, we introduce the remote sensing image constraint process by semi-supervised clustering. Next, we describe the region merging process on the classified remote sensing image.

2.1 Semi-supervised Image Segmentation

Semi supervised clustering [18] means Grouping of objects such that the objects in a group will be similar to one another and different from the objects in other groups with related to certain constraints or prior information.

The Fig.2 represents the semi supervised clustering model. The three clusters are formed using certain constraints or prior information. Besides the similarity information which is used as color knowledge, the other kind of knowledge is also available by either pair wise (must-link or cannot-link) constraints between data items or class labels for some items. Instead of simply using this knowledge for the external validation of the results of clustering, one can imagine letting it "guide" or "adjust" the clustering process, i.e. provide a limited form of supervision. There are two ways to provide information for semi supervised clustering: search based or similar based.

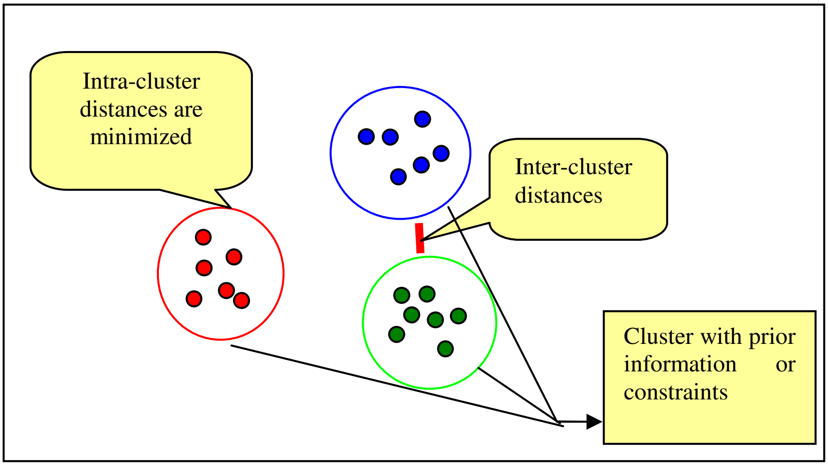


Fig. 2. Semi supervised clustering model

Recently, spectral methods have become increasingly popular for clustering. These algorithms cluster data given in the form of a graph. One spectral approach to semi-supervised clustering is the pixel spatial correlation. In the proposed method, the relationship among pixels in the remote sensing image is formulated in a remote sensing image structure. In this part, we introduce the remote sensing image construction procedure by using pixel spatial correlation. In the constructed remote sensing image $G = \{V, E, W\}$, each vertex denotes one pixel in the remote sensing image $X = \{x_1, x_2, ..., x_n\}$. Therefore, there are n vertices totally in G.

In a remote sensing image structure, each hyperedge connects multiple vertices. To construct the hyperedge, the spatial correlation of pixels are taken into consideration. In this process, each pixel is selected as the centroid and connected to its spatial neighbors, which generates one hyperedge. This hyperedge construction method is under the assumption that spatial connected pixels should have large possibility to have the same labels. As each pixel generates one hyperedge, there is a total of n hyperedges.

Let the selected number of spatial neighbors be K, and there are totally $K+1$, vertices in one hyperedge. Each hyperedge $e \in E$ is given a weight $w(e) = 1$, which reveals that all hyperedges are with equal influence on the constructed hypergraph structure. Though each hyperedge plays an equal role in the whole hypergraph structure, the pixels connected by one hyperedge may be not close enough in the feature space. Therefore, these pixels may have different weights in the corresponding hyperedge. For a hyperedge $e \in E$, the entry of the incidence matrix H of the hypergraph G is generated by:

$$H(v,e) = \begin{cases} 1 & \text{if } v = v_c \\ \exp(-d^2(v, v_c)/2\sigma^2 & \text{otherwise} \end{cases} \tag{1}$$

where v_c is the centroid pixel, $d(v, v_c)$ is the distance between one v in E and v_c, and σ is the mean distance among all pixels. Under this definition, the pixels in one hyperedge which are similar to the centroid pixel in the feature space can be strongly connected by the hyperedge, and other pixels are with weak connection by the hyperedge.

By using the generated incidence matrix H, the vertex degree of a vertex $v \in V$ and the edge degree of a hyperedge $e \in E$ are generated by:

$$d(v) = \sum_{e \in E} H(v,e) \tag{2}$$

and

$$d(e) = \sum_{v \in V} H(v,e) \tag{3}$$

In the above formulation, D_v and D_e denote the diagonal matrices of the vertex degrees and the hyperedge degrees respectively, and W denotes the diagonal matrix of the hyperedge weights, which is an identity matrix.

2.2 Region Merging

The previous stage only removes redundant regions that do not annoy object semantics. The main purpose of this paper is to represent homogenous objects with few regions. Such homogeneous objects may be extractable more easily than other complex objects, since their components have very similar statistical properties to each other. However, low contrast boundaries between objects may result in merging objects of different semantics. To avoid non-semantic merging, we perform a ternary classification for segmented regions. We determine the class of a region R_i , $C(R_i)$, as follows.

$$C(R_i) = \begin{cases} H, \text{if } \sigma_i^2 \leq VHR\_TH \\ IAH, \text{if } C(R_j) = H, \exists R_j \in \xi(R_i) \\ IH, \text{otherwise} \end{cases} \tag{3}$$

where VAR_TH is the variance of the largest region. Here, H, IAH and IH are abbreviations of a homogeneous region, inhomogeneous region adjoining a homogeneous region, and inhomogeneous region adjoining only inhomogeneous regions, respectively.

After classification, we examine only regions of class H for merging, and regard regions of class H or IAH as valid merging candidates. That is, we examine R_i and R_j for merging such that $C(R_i) = H$ and $R_j \in \xi(R_i), C(R_j) \neq IH$. This restriction is to prevent two regions of different semantic contents from being merged. Here $\xi_M(R_i)$ is selected by using gradient-based criterion.

Pixel p is defined as a boundary pixel between R_i and R_j, if there are two pixels, p_i and p_j such that $p_i \in R_i$, $p_j \in R_j$, and $p_j \in N_4(p_j)$, where $N_4(p)$ is a set of pixels neighboring p by 4-connectivity. Then, merging candidates $\xi_M(R_i)$ for a given R_i can be determined by considering the weakness of boundary pixels. If R_j satisfies both conditions, $C(R_i) \neq IH$ and at least half of the boundary pixels between two regions have gradient values less than $2\sqrt{VAR\_TH}$, R_j is an element of $\xi_M(R_i)$. Using these merging candidates, we perform the following algorithm until it terminates automatically.

Step 1: Find R_i such that $C(R_i) = H$ and $\xi_M(R_i) \neq \phi$.

Step 2: If there is no such region, the merging procedure is terminated. Otherwise, find merging pair (R_i, R_j) that provides the smallest value of variance after merging, and then merge them.

Step 3: Classify the merged region to H in order to expand this region continuously by merging.

Step 4: Go to step 1.

3 Experiments

In this section, we first describe the testing datasets and then discuss the experimental results and the comparison with the state-of-the-art methods.

3.1 The Testing Datasets

In our experiments, two datasets are employed to evaluate the performance of the proposed method. The first dataset is the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) image taken over NW Indiana's Indian Pine test site, which has been widely employed. The Indian Pine dataset is with the resolution of 145 ×145 pixels and has 220 spectral bands. 20 bands are removed due to the water absorption bands. There are originally 16 classes in total, ranging in size from 20 to 2455 pixels. Some small classes have been removed and only 9 classes are selected for evaluation. The details information about the selected classes is shown in Table 1.

Table 1. Details of the Indian Pine Dataset

Class	#Pixels	Class	#of pixels	Class	#of Pixels
Soybeans-no till	972	Corn-no till	1428	Grass/pasture	483
Soybeans-min	2455	Corn-min	830	Grass/trees	730
Soybeans-clean till	593	Woods	1265	Hay-windrowed	478
Total	9134				

3.2 Compared Methods

To evaluate the effectiveness of the proposed remote sensing image segmentation approach, the following methods are employed for comparison.

1. Semi-Supervised Graph Based Method [8]. In semi-supervised graph based method, the hyperspectral image classification is formulated as a graph based semisupervised learning procedure. All pixels are denoted by the vertices in the graph

structure, which is able to exploit the wealth of unlabeled samples by the graph learning procedure.

2. Graph-based methods [16], in which each sample spreads its label information to its neighbors until a global stable state is achieved on the whole dataset.
3. Supervised Bayesian approach with active learning [19], which by using supervised Bayesian approach to hyperspectral image segmentation with active learning.

3.3 Experimental Results

In our experiments, the number of labeled training samples for each class varies from 10 to 100, i.e., {10, 20, 30, 50, 100}. To evaluate the hyperspectral image classification performance, the widely used overall accuracy (OA) and the Kappa statistic are employed [9] as the evaluation metrics. In the following experiments, K is set as 12, and $VAR_{\max} = 40$.

Experimental comparisons on the testing datasets are shown in Fig. 4 and Fig. 6. In comparison with the state-of-the-art methods, the proposed method outperforms all compared methods in the testing databases. Here we take the experimental results when 10 samples per class are selected as the training data as an example. In the Indian Pine dataset, the proposed method achieves a gain of 1.23%, 3.50%, 0.03%, and 34.38% in terms of the OA measure and a gain of 3.92%, 27.60%, 0.44%, and 30.52% in terms of the Kappa measure compared with semi-supervised, graph-based method, supervised bayesian methods. Experimental results show that the proposed method achieves the best image segmentation performance in most of cases in the testing dataset, which indicates the effectiveness of the proposed method, as shown in Fig. 3.

Figure 4 demonstrates the classification map of the proposed method in the testing dataset with different number of selected training samples per class.

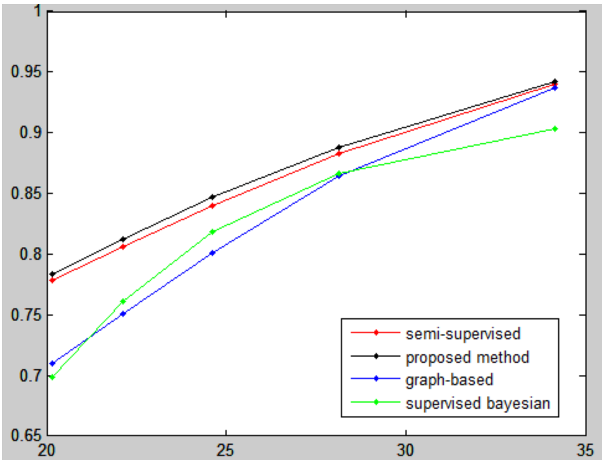
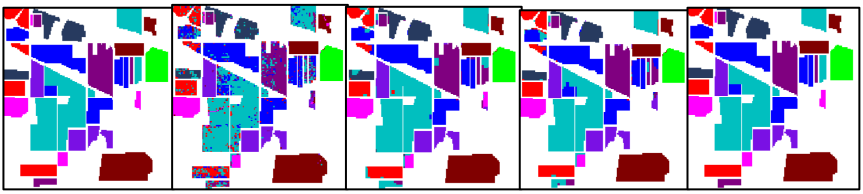
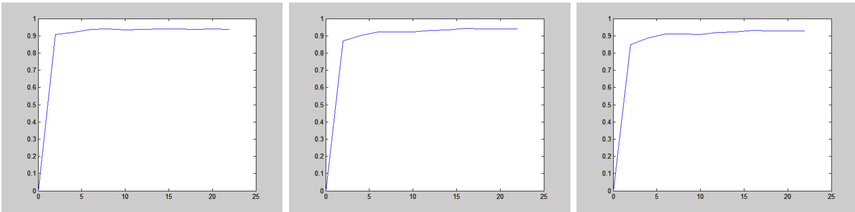


Fig. 3. The segmentation accuracy results of compared methods in the Indian Pine dataset



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

Fig. 4. Segmentation maps of the Indian Pine Sub dataset. (a) Ground truth map with 9 classes (b)-(e) Segmentation maps with 10,20,30 and 50 labeled training samples for each class.



(a) OA in Indian Pine (b) Kappa in Indian (c)AA in Indian Pine

Fig. 5. Segmentation performance comparison with different K values by using 10 training sample per class in the Indian Pine dataset

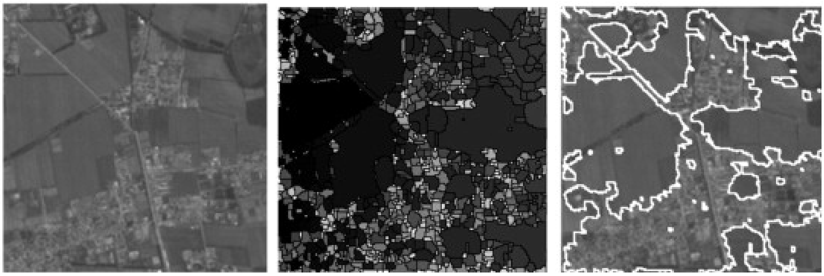


Fig. 6. Segmentation of the proposed method. (a) Ground truth map with 9 classes (b) Semi-supervised classification result (c) Region merging segmentation result.

4 Conclusion

In this paper, we propose a remote sensing image segmentation method by using the semi-supervised classification comprised with region merging. In the proposed method, the relationship among pixels in the remote sensing image is formulated in a semi-supervised clustering. In the constructed remote sensing , each vertex denotes a pixel in the image, and the remote sensing is generated by using the spatial correlation among pixels. Semi-supervised learning on the remote sensing is conducted for remote sensing image classification, and then using the region merging method to segment the classified image. This method employs the spatial information to explore the relationship among pixels, and the high dimensional feature is only used to further enhance the spatial-based correlation in the constructed remote sensing , which is able to avoid the curse of dimensionality.

Experiments on the Indian Pine datasets is performed, and comparisons with the state-of-the-art methods are provided to evaluate the effectiveness of the proposed method. Experimental results indicate that the proposed method can achieve better results in comparison with the state-of-the-art methods for remote sensing image segmentation.

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