Spectral Active Clustering of Remote Sensing Images

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Zifeng Wang[1], Gui-Song Xia[1], Caiming Xiong[2], Liangpei Zhang[1]

[1] Key State Laboratory LIESMARS, Wuhan University, Wuhan 430072, China
[2] Department of Computer Science, State University of New York at Buffalo, NY, USA

ABSTRACT

Mining useful information from remote sensing images is a longstanding and challenging problem in earth observation, among which images clustering is used to discover meaningful scene information, by grouping similar image pixels into clusters. The main difficulty of image clustering, however, lies in the fact that imperfect similarity measure between images usually leads to bad clustering results. Supervised classification with labeled training samples can partially solve this problem, but the collection of such labeled data is usually time-consuming and sometimes impossible in many real problems. This paper presents an *active* remote sensing image clustering algorithm by *integrating simple human queries into the clustering process*. More precisely, we propose a spectral active clustering method that can actively query the oracle (such as human) to improve the image clustering performance. We first construct a k-nearest neighbor (k-NN) graph of the remote sensing images. We then iteratively select the most informative pairwise constraints and purify the k-NN graph, by removing the edges between images from different classes. The final clustering on the purified k-NN graph leads to more accurate result. The proposed method has been evaluated on three high-resolution remote sensing image datasets. It achieves the state-of-the-art performance and demonstrates high potentials in practical remote sensing applications.

Index Terms— Information mining, remote sensing image clustering, active clustering

1. INTRODUCTION

Nowadays, remote sensing images capture in details wide surfaces and result in extremely large volumes of data with high spectral and spatial resolution. However, the large amount of remote sensing images are at present weakly exploited due to their large sizes and time-consuming visual analysis [1]. This demands to develop more efficient methods for mining information from these large scale remote sensing images.

In this paper, we are interested in remote sensing image classification. As we know, most of the classification methods require labeled training data from experts, while the annotation of which is usually expensive and sometimes impossible to acquire in many real problems. Alternatively, clustering (or unsupervised classification) approaches are more suitable when no labeled data is available [2]. Survey of different clustering methods has been presented in [3]. One main difficulty of these methods, however, lies in the fact that their performances heavily depend on the similarity matrices between images, which are usually far from perfect on real problem. One possible solution is to integrate acceptable and weak priori knowledge, that are easy to achieve without expertise, into the clustering process, and to build semi-supervised [4] or active clustering algorithms [5, 6].

This paper introduces a new active clustering algorithm for remote sensing images with weak human queries. More precisely, we propose a spectral active clustering method that can actively query the oracle (such as human) to purify the similarity matrix and finally improve the images clustering performance. In particular, given remote sensing images, we first construct a k-nearest neighbor (k-NN) graph, on which the clustering will perform. To get near-perfect similarity matrices, we propose to interactively purify the k-NN graph, by actively selecting the most informative pairwise constraints. (In our work, the pairwise image constraints are "similar" or "dissimilar" given by an oracle, which is much easier than that of collecting labeled data.) The purified similarity matrices lead to a updated k-NN graph and are finally used to achieve the clustering of images. Unlike previous active clustering method [5, 7], we use vertex uncertainty instead of pairwise uncertainty for selecting informative vertexes on the k-NN graph. To our knowledge, our work is the first time to develop an active clustering method for remote sensing images, which has high potentials in real problem of mining information from earth observation images. The proposed method demonstrates the state-of-the-art classification and annotation results on three high-resolution satellite image datasets.

The rest of this paper is organized as follows. Section 2 recalls the basics of spectral image clustering. Section 3 introduces the proposed spectral active clustering framework for remote sensing images. Section 4 presents experimental results and Section 5 gives some conclusion remarks.

2. SPECTRAL IMAGE CLUSTERING

Spectral clustering, which makes use of the spectrum of the similarity matrix of the data to perform clustering, is one of

the most popular clustering algorithms, due to its efficiency and the simplicity of implementation [8].

Constructing a k***-NN graph of images*** : Given a set of images (or regions of an image) $I = \{I_1, I_2, \cdots, I_n\}$, described by some visual features f_i, denote the similarity matrix as S, with each elements s_{ij} representing a measure of the similarity between f_i, f_j of I_i, I_j. The similarity graph is thus defined by $G = (V, E)$, where each vertex $v_i \in V$ represents an image I_i and two vertices I_i, I_j are connected if s_{ij} is larger than a certain threshold, and the edge $e_{ij} \in E$ is weighted by s_{ij}. In our case, we refer the graph G as a k-NN graph, which implies that for a vertex v_i only the vertices with the first k largest similarity measure are connected to it.

Spectral clustering algorithm : Spectral image clustering [8] then works with the eigenvectors of the normalized Laplacian matrix L of G, using k-means algorithm. The normalized Laplacian matrix L is computed as

$$L = I - D^{-1/2} S D^{-1/2},$$

where I is the identity matrix and D is the diagonal matrix as $D_{ii} = \sum_{j=1}^{n} s_{ij}$. In order to deal with large scale remote sensing images, some large scale spectral clustering algorithm can be used to compute L more efficiently.

3. SPECTRAL ACTIVE CLUSTERING OF REMOTE SENSING IMAGES

This section presents the proposed spectral active clustering approach for remote sensing images. The flowchart of the algorithm is depicted in Fig. 1.
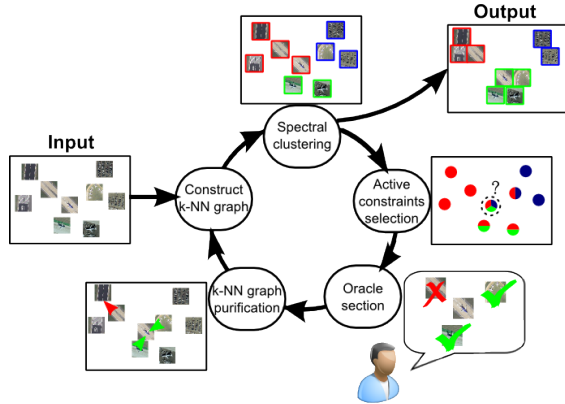

Fig. 1. Flowchart for spectral active clustering. Refer to the text for more details.

Given a set of image (or image regions) as inputs, we first construct the k-NN graph followed by a spectral clustering algorithm, as described in Section 2. We iteratively obtain new constraints by actively selecting the most informative image and querying the oracle. Active learning helps us to find out the most informative image, which is also the most uncertain one, according to the current clustering result and the k-NN graph. With new constraints, the k-NN graph is purified

and spectral clustering performs again on the updated k-NN graph. The algorithm iterates this process until the oracle is satisfied with the result or the k-NN graph is fully purified.

In what follows, we precise the criterions for active constraints selection and the k-NN graph purification.

Active Constraints Selection Ideally, in a perfect k-NN graph, each image should belong to the same class as all its neighbors do. Consequently, vertices connected in the k-NN graph will be assigned to the same cluster. In order to look for new constraints to purify the k-NN graph, we try to find out the image whose neighbors contain the "worst edge" (edge linked images belonging to different classes). For the class label c of vertices, we use cluster labels instead of the real labels which are still unavailable. In order to measure the disordered level of an image I_i on the graph G, we use an entropy criterion defined as

$$H(I_i) = -\sum_{\ell} P_{I_i}(\ell) \log P_{I_i}(\ell), \tag{1}$$

where $P_{I_i}(\ell) = \frac{\#\{c_v = \ell, v \in N_{I_i}\}}{k}$ is the probability of the neighbors that are assigned to the cluster ℓ, with N_{I_i} as the neighborhoods of I_i on G. We thus choose the most disordered image I_{i^*}, *i.e.* $I_{i^*} = \arg\max_{I_j \in G} H(I_j)$, as the vertex on the graph for querying. Consequently, the active edges are thus $\{(I_{i^*}, I_j); e_{i^*j} = 1, I_j \in G\}$, which link the image I_{i^*} and its neighbors. We query the oracle along these edges to obtain new constraints.

k-NN Graph Purification As mentioned before, there are two kind of pairwise constraints: similar and dissimilar, called "must-link" and "cannot-link" on the graph which respectively link images to the same and different classes. A simple constraint augmentation process is described in Fig. 2. It enables us to obtain more constraints from known ones. By purifying the k-NN graph, all the "cannot-link" edges in the graph will be removed, while the similarity values of "must-link" edges are set to 1.
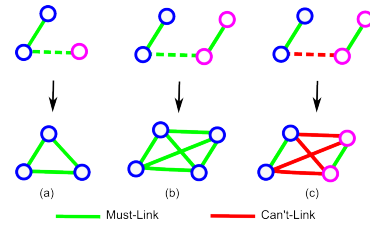

Fig. 2. Our constraint augmentation process.

4. EXPERIMENTAL RESULTS

We evaluates the proposed spectral active clustering method on remote sensing image classification and annotation.

The three remote sensing image sets we used are:
(1) *A GeoEye-1 image in Beijing* as in Figure 4: the image is of size 4000×4000 and is partitioned into 1600
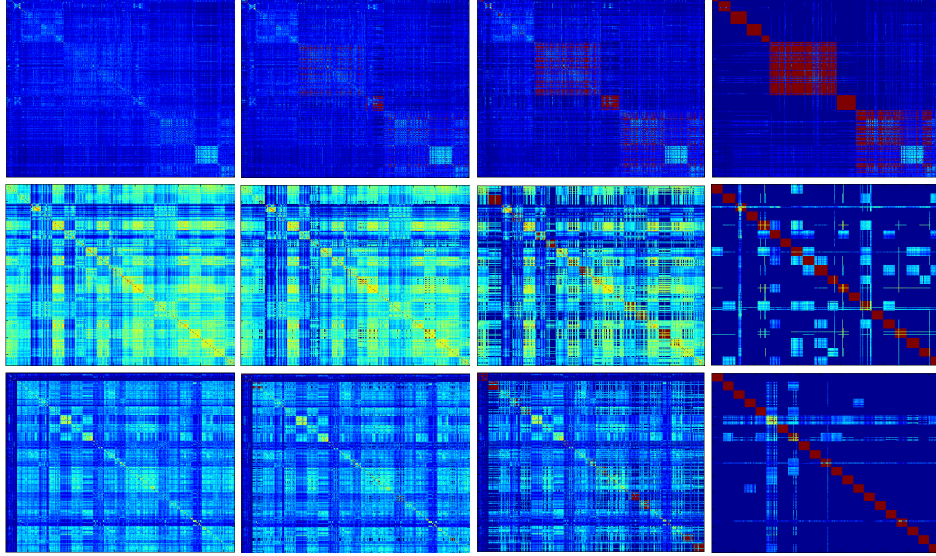
Fig. 3. The evaluation of the similarity matrix with the iterative purification of the k-NN graph. From left to right: the similarity matrices at 1, 75, 150 and 225 iterations. From top to bottom: the similarity matrices of the GeoEye-1 image in Beijing, the WhuSPL datset [9], and the UCM datset [10]. Observe that with the iterations the similarity matrices become more and more discriminative.

tiles with size of 100×100 pixels. We try to annotate the tiled images as in [11], who also provides its human-labeled groundtruth. (2) *WhuSPL dataset* [9], containing 20-class high-resolution satellite images with about 50 samples per each categories. (3) *UCM dataset* [10], which contains 21-class high-resolution satellite images with 100 samples per each categories.

In our experiments, to characterize each image or image tile, we calculate the bag of dense SIFT descriptors [12] and bag of color descriptors in each image. Thus, the image I_i is described by a histogram-like vector h_i of length M. The pairwise similarities matrix S is calculated by histogram intersection kernel as $s_{ij} = \sum_m^M \min(h_i[m], h_j[m])$.

We compare our algorithm with three currently proposed methods: spectral clustering (SC) algorithm [8], semi-supervised spectral clustering (S^{3}C) algorithm [4] and the M^{3}DA-RF algorithm [11], a recently proposed full-supervised method on our task. Remark that, instead of collecting pairwise constraints actively, S^{3}C [4] performs spectral clustering by using pairwise constraints provided before clustering. The M^{3}DA-RF [11] is full-supervised and requires labeled data from experts as training sample. In current experiments, our method exits the active clustering loop when the oracle is satisfied with the results. For a fair comparison, we use the same number of pairwise constraints for the S^{3}C [4] algorithm. In order to evaluate the performance of clustering algorithms (as that for supervised algorithms, e.g. M^{3}DA-RF), the clustering accuracy is computed by assigning the label of each cluster as its closest class in the groundtruth.

Fig. 3 illustrates the evaluation of the similarity matrices

with the iterative purification of the k-NN graph on each data set. Note that, on all the three dataset, with more active iterations (i.e. more queries from oracle) are used the similarity matrices become more and more discriminative. This verifies the efficiency and the necessariness of the active selection procedure of our proposed method.

We compare the clustering performances of SC, S^{3}C and our method on WhuSPL dataset [9] and UCM dataset [10]. The accuracies are respectively 39.2%, 58.5% and 98.8% on WhuSPL dataset and 35.7%, 47.9% and 96.3% on UCM dataset of the three algorithms.

Fig. 4 displays the comparison of our method with the three approaches mentioned above, SC [8], S^{3}C [4] and M^{3}DA-RF [11], on the annotation of a big high-resolution satellite image, a GeoEye-1 image in Beijing. The M^{3}DA-RF [11] takes half of the labeled data as training samples and uses multi-level max-margin discriminative random field [11] for annotation. Notice that M^{3}DA-RF uses actually spatial constraints via conditional random field to improve its performance. From Fig. 4, one can see that S^{3}C gives much better result (61.8%) than that of SC (35.8%), which implies that pairwise constraints is very helpful for this task. The M^{3}DA-RF produces better result (91.6%) than S^{3}C does. This is mainly because it uses fully labeled training samples, the prior information of which is much stronger that that of weak pairwise constraints. Our method outperforms all the three methods and shows near-perfect annotation result (99.2%). This finally verifies our intuition on the proposed method, that the weak prior knowledge from the actively selected pairwise constraints can help the clustering algorithm a lot.
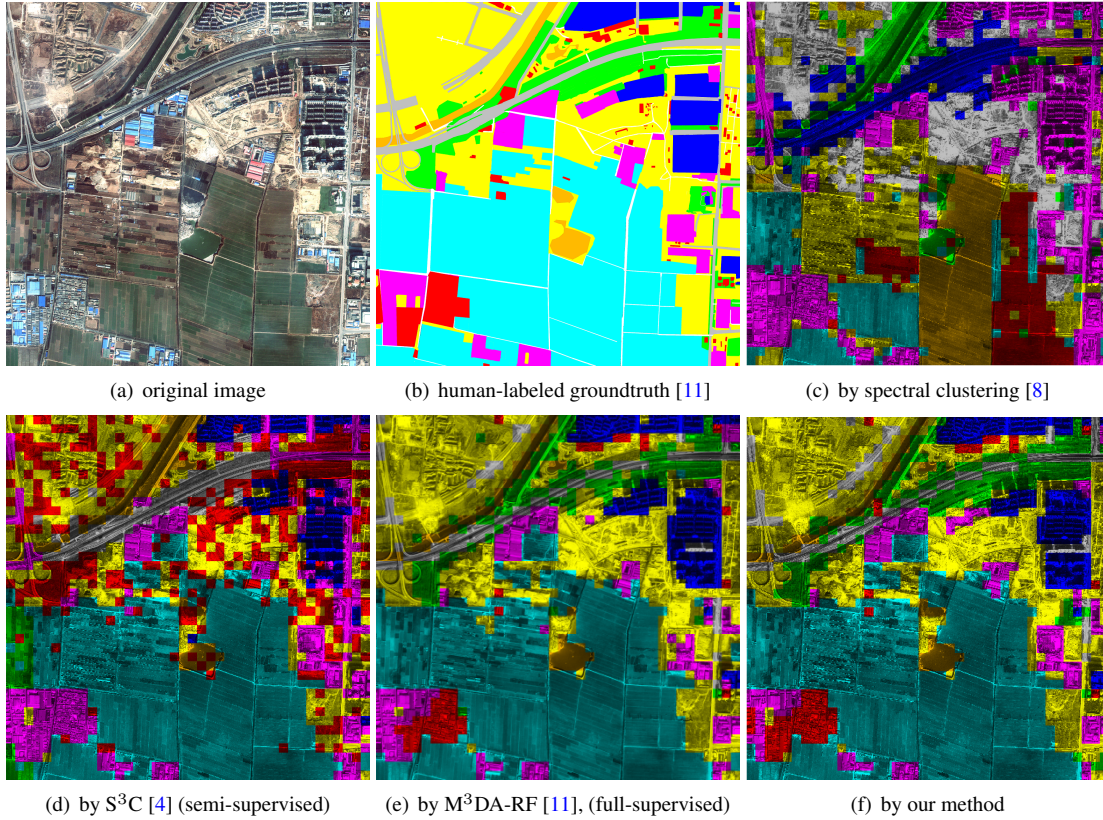
(a) original image   (b) human-labeled groundtruth [11]   (c) by spectral clustering [8]

(d) by S^{3}C [4] (semi-supervised)   (e) by M^{3}DA-RF [11], (full-supervised)   (f) by our method

Fig. 4. Comparison of different methods on the annotation of a GeoEye-1 image in Beijing. Refer to the text for more details.

5. CONCLUSION

This paper addresses the problem of remote sensing image clustering with weak priors. Our method actively queries the oracle to get weak pairwise constraints. Instead of pair uncertainty, the proposed method uses node uncertainty as active select criterion, which can more accurately select useful queries. With these acceptable a few pairwise constraints, the clustering result shows notable improvements. It is very powerful to classify remote sensing images, when there is no available labeled training data or it is hard to acquire such training data. From experiment results, we can see that the proposed method outperforms three state-of-the-art methods and shows high potentials in mining meaningful information from remote sensing images.

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