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Efficient Segmentation and Classification of Remote Sensing Image Using Local Self Similarity

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ABSTRACT- Segmentation and classification are important role in remote sensing image analysis. Recent research shows with the aim of images can be described in hierarchical structure or regions. In this project, we submit application graph laplacian energy as generic measure for segmentation. We capture in geometric outline of region in an image by using apply local self similarity features. This paper finds application in remote sensing image analysis. It decreases the redundancy in the hierarchy by order of magnitude with small loss or performances. We have achieved better performance from graph laplacian energy method. I improve the efficiency using unsupervised learning.

I. INTRODUCTION

In this paper, we suggest a new hierarchical image analysis method that applies the graph Laplacian energy (LE) [9] as a generic measure for segmentation. With segmentation results available, we continue to the classification step using local self-similarity (LSS) [10] to integrate the local contextual and shape information. We exhibit the effectiveness of the proposed classification method in urban-area land-cover classification using VHR remote sensing images.

The contributions of this paper are threefold. First, we use the graph LE to explain the VHR remote sensing image in a hierarchical structure. It places of interest the high-level semantic structure of an image. Second, we introduce a method to extort local contextual and shape information in local regions using LSS. Finally, we exhibit the feasibility of a classification system for remote sensing images by combine both high-level and low-level information.

This paper is organized as follows. Section II explains the segmentation method using the graph LE. Section III describes the classification step by extracting LSS features and training support vector machines (SVMs). Finally, in Section IV, we present the experimental results, which include comparisons between the proposed method and different classification approaches in the literature. Conclusions of this paper are drawn in Section V.

II. HIERARCHICAL REPRESENTATION USING GRAPH LE

Figure. 1. Example of watershed segmentation. The left hand is the original image. The right hand shows the corresponding watershed segmentation results.

Let *G* be an (*n*,*m*) graph with *n* vertices and *m* edges and *A* be its adjacency matrix. Let d_i be the degree of the *i*th vertex of *G* and *D* be the corresponding degree matrix, where *D* (*i*, *i*) = d_i. Then, L = D − A is the Laplacian, and the graph LE is defined as

$$\mathrm{LE(G)} = \sum_{i=1}^{n} \left| \lambda_i - \frac{2m}{n} \right| \quad \text{……..(1)}$$

Where λ_i denotes eigen values of the Laplacian matrix and 2m/*n* is the average vertex degree.

Based on this definition, we propose a novel method to take out hierarchical structure from remote sensing images. First, we compute the image gradient and cut the remote sensing images into small connected regions using watershed segmentation [8]. An example of the segmentation results is shown in Figure. 1. This tread generates the bottom level of the hierarchy and transforms the input image into a region adjacency graph.

The subsequently step is to merge neighboring regions from bottom up pattern to create a hierarchical tree description. In each merging iteration, we merge the most related pairs of neighboring regions and treat the newly merged regions as parent nodes. The merging continues awaiting there is only one region left. The initial watershed segmentation consequences are set as level 1.

The merging can be handling all arbitrary shape. Each region measured as single Gaussian $\Omega = (\mathrm{N}, \mu, \mathrm{C})$, in which Ω is a region, *N* indicates the number of pixels in this region, and μ and *C* are the mean and covariance of the property vectors at every pixel, respectively. If two regions (Ω_i and Ω_j) can be merged, the modern region ($\Omega = \Omega_i + \Omega_j$) is represented as

$$\Omega = \left(\mathrm{N_i} + \mathrm{N_j}, \frac{\mathrm{N_i}\mu_i + N_j\mu_j}{N_i + N_j}, \frac{\mathrm{N_i C_i} + N_j \mathrm{C_j}}{\mathrm{N_i} + \mathrm{N_j}} + e \right) \quad \text{………(2)}$$

The "error" term *e* compensate the eigen space for the differentiation between the means of the model, which is

$$\mathrm{e(i,\ j)} = \frac{\mathrm{N_i N_j}}{\mathrm{N_i} + N_j} (\mu_i - \mu_j)^{\mathrm{T}} (\mu_i - \mu_j) \quad \text{…….(3)}$$

To estimate the graph LE of each merged region, we need to get the adjacency matrix at each merging step. The adjacency matrix is biased using the error measure. If regions Ω_i and Ω_j are linked, the weight is w (*i*, *j*) = exp(−*e*(*i*, *j*) / e_{max}), in which *e* e_{max} is the maximum value of *e*(*i*, *j*) above all connected pairs.

In every one merging iteration, we merge the most related pair of neighboring regions, i.e., the pair with the smallest value of *e*(*i*, *j*). This merging step generates a complete hierarchy tree. In the next step, we consider this tree via graph LE. Our principle is to select those tree levels that are lower in complexity than their adjacent levels.

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Note that the standard graph LE in (1) is generally defined on a single connected graph. However, in our case, we take care of the merged regions as connected graphs so that each primary watershed region is a node in a graph. At each level except the maximum one, there are added than one connected graphs. Therefore, we extend the original graph LE definition to make it proper for computing LE at each level of the tree. We establish the normalized graph LE (nGLE). For a level with K connected graphs, we define the

$$E=\frac{n}{k}\sum_{i=1}^{k}\frac{LE(G)}{|n_i|} \qquad \ldots\ldots(4)$$

Where $G_i$is the ith connected graph of $|n_i|$ nodes and n is the amount of nodes of all the associated graphs. In the case of a single connected graph, our circle of phrase reduces to the original graph energy.

We calculate the nGLE at each level in the hierarchy independently and use the nGLE as a function of level index. Figure. 2 shows a typical nGLE curve. In this curve, local minima are met when graphs at particular levels demonstrate homogeneous node degree, which way that the graphs are close to regular graphs. They are in contact to levels that are less complex compared to the adjacent levels. We desire the highest level partition that gives the local minimum, which breaks the image into the least large components.

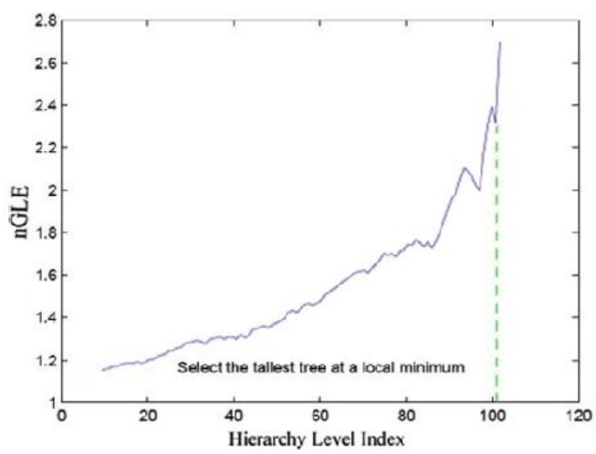

Figure.2. Graph energy as a function of level index .the plot is computed using (4) on the image in fig.1.

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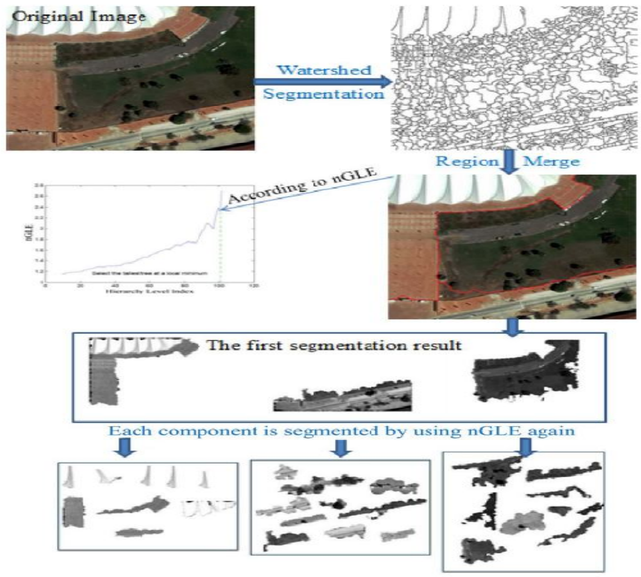

Figure.3. segmentation process.

Two levels of division, as shown in Figure. 3. The merging and segmentation processes are shown in Figure. 3. In this example, the high-resolution remote sensing image has been segmented in a hierarchical manner. From this procedure, a set of parts for each image can be created, as shown at the bottom row in Figure. 3.

III. CLASSIFICATION USING LSS

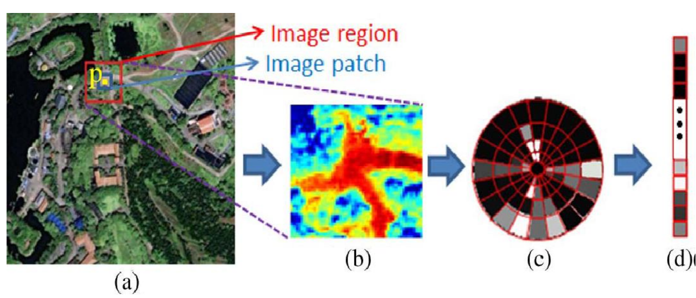

Figure.4. process of extracting the LSS descriptor of pixel p. (a) Image patch and its close neighborhood region. (b) local internal correlation surface .(c) binned log-polar representation.(d) normalized log-polar vector.

The hierarchical description of the image forms the beginning to the classification step. To extract features from every one segmented parts, the LSS method [10] is used. The LSS describes the comparison between a patch and its neighboring region in an image. It offers a single unified way to describe the inside relations in an image. The method of extracting the LSS descriptor is shown in Figure.4. It is computed as follows.

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1) Determine an $N \times N$ correlation surface ζp of an $\omega \times \omega$ patch tp with the immediate $N \times N$ region Rp using sum of squared differences (SSD) method. In this letter, $N = 30$ and $\omega = 5$. Both Rp and tp are centered at p. $\zeta p(x)$ is the correlation of tp with an $\omega \times \omega$ patch tx centered at x : $\zeta p(x) = \exp(-(SSD(tp, tx)/\delta))$, where δ represents the maximal variance of the variation between every part of patches within a very tiny neighborhood of p and the patch centered at p.

2) Discretize the correlation surface ζp on a log-polar grid, and accumulate the maximal value of ζp within each grid bin $dp\,(p, d) = \max x \in BIN\,(p,d)\{\zeta p(x)\}$.

3) Destabilize the binned log-polar vector by linearly stretching its ideals to the range [0, 1]. From each one image part generated in Section II, a set of LSS descriptors can be generated. In order to explain each part using a single vector, the bag-of-visual-words model [6] is adopted. We had it k-means clustering method for visual word encoding ($k = 300$ in our experiments), which groups the LSS descriptors into k clusters. The cluster centers are clear as the visual words, and a visual vocabulary is constructed to illustrate the content of objects. After handing over each descriptor to the closest visual word, all image parts can be represented as a histogram by plus the occurrence numbers of the visual words.

In the classification step, the SVM is worn as the classifier. The selection is for the most part based on the truth that it is one of the state of- the-art classifiers on bag-of-visual-words image representation. We implement the C-SVC in LIBSVM [3] with an *RBF* kernel. The parameters for the SVM are obtained with cross validation on a subset of physically labeled training parts.

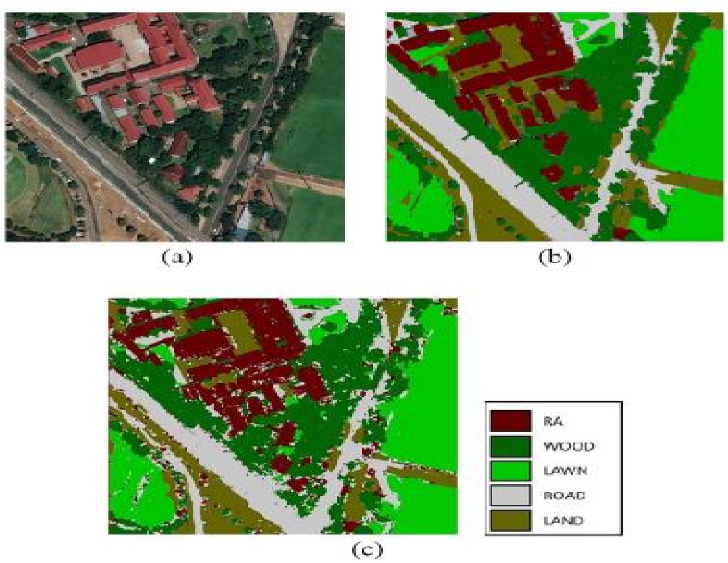

Figure.5. Example on classification result (a) experiment area. (b) Reference map. (c) Classification result.

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IV. CONCLUSION

In this paper, we have introduced graph LE as a difficulty calculate for remote sensing image analysis. With the chosen hierarchies using this power, we can get a levelheaded semantic explanation in terms of objects and object parts which help to achieve more robust classification. We also introduced the LSS for urban-area land-cover classification in remote sensing images. The planned method has achieved performance on satellite image analysis that is better than those from substitute methods. In the future, we plan to further explore the semi supervised knowledge methods in satellite image analysis. This allows the one after the other in unlabeled data to be extracted and used. Furthermore, traditional spectral features will be incorporated into our system. I improve the efficiency using unsupervised learning.

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