Hierarchical Classification of Land-cover Types using RAG-based Merging

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***Abstract*—A multistage hierarchical clustering technique, which is an unsupervised technique, was suggested in this paper for classifying large remotely-sensed imagery. The multistage algorithm consists of two stages. The "local" segmentor of the first stage performs region-growing segmentation by employing a RAG-based merging with the restriction that pixels in a cluster must be spatially contiguous. The "global" segmentor of the second stage, which has not spatial constraints for merging, clusters the segments resulting from the previous stage. The second stage is an agglomerative hierarchical clustering procedure which merges the best MCN defined in spectral space, and then generates a dendrogram which represents a hierarchy of consecutive merging processes. The experimental results show that the new approach proposed in this study is quite efficient to analyze very large images. The technique was then applied to classify the land-cover types using the remotely-sensed data acquired from the Korean peninsula.**

Keywords-*segmentation, classification, unsupervised analysis, region growing, multiwindow operation, hierarchical clustering, RAG, dendrogram*.

I. Introduction

Most approaches to the image classification require *a priori* class-dependent knowledge of parameterized models for the data. In many instances, however, the parameter values of the models are not known *a priori*, and the process of gathering training samples to estimate parameters is often infeasible or very expensive. In addition, the classification results much depend on the number of classes selected in the specific analyzed area, but it is very complicate to determine the class number, as known as "cluster validation," particularly for remotely sensed data. Therefore, it is necessary that classification procedures perform the unsupervised learning of the parameters including the number of classes and the image classification simultaneously. For the unsupervised analysis, agglomerative hierarchical clustering technique [1] is one of the most appropriate approaches.

Due to advances in sensor technology, it is now possible to acquire high-resolution or hyper-spectral data over large geographical area. These image data possess much detailed spatial or spectral information, but one of challenging problems in processing this extensive dimensional data is the computational complexity resulting from processing the vast amount of data volume. Especially, the unsupervised classification that makes use of hierarchical clustering may require enormous processing time for large images. Lee [2][3] used a multistage classification approach based on regional growing, which is computationally efficient for the unsupervised classification. The multistage algorithm includes two stages of segmentation. The first stage performs region-growing segmentation that confines merging to spatially adjacent clusters and then generates an image partition such that no union of any neighboring segments is uniform The "local" segmentor employs a merging procedure based on regional adjacency graph (RAG). To alleviate the memory problem and improve the computational performance of the algorithm, this approach uses a multi-window strategy of boundary blocking operation for the local segmentor. In the second stage, the image partition resulting from the regional segmentation is classified into a small number of distinct states by a sequential merging operation. The "global" segmentor uses the conventional agglomerative hierarchical clustering scheme that merges step-by-step small two regions into a large one.

In Lee [2], the clustering procedure in the regional segmentation performs the search for the best pair to be merged among the mutual closest neighbor (MCN) pairs and update the set of MCN pairs at every iteration. It results in computational inefficiency for the segmentation. To improve computation for the analysis of extensive imagery, Lee [3] proposed a region growing segmentation which links two adjacent regions that are an MCN pair, using "closest neighbor chain (CN-chain)." It does not require the search of the best pair and the update of the set of MCN pairs. This study has been suggested an alternative approach which merges all the MCN pairs simultaneously and then generates the new set of MCN pairs. An agglomerative hierarchical clustering for the global segmentor has proposed for an unsupervised image classification through the dendrogram of consecutive merging. The proposed algorithm includes searching a set of MCN Pairs using the data structures of spectral adjacency graph (SAG) and Min-Heap. It also employs a multi-window system in spectral space to define the spectral adjacency.

II. CN-BASED CLUSTERING

The computational efficiency of hierarchical clustering segmentation is mainly dependent on how to find the best pair to be merged. Let $I_n = \{1,2,\cdots,n\}$ be an index set of pixels of a sample image, $J_M = \{1,2,\cdots,M\}$ be an index set of regions associated with $\mathbf{G}_J = \{G_j \subseteq I_n \mid j \in J_M\}$ that is a partition of I_n, $\mathbf{R}_J = \{R_j \subseteq I_n \mid j \in J_M\}$ be a region neighborhood system such that R_j is the index set of neighborhood regions of region *j*. The closest neighbor of region *j* is defined as

$$\mathrm{CN}(j) = \arg\min_{k \in R_j} d(j,k)$$

where *d*(*j*,*k*) is the dissimilarity measure between regions *j* and *k*, and R_j is the index set of regions considered to be merged with region *j*. The pair of regions is then defined as MCN iff *k* = CN(*j*) and *j* = CN(*k*). If a cutting rule that

$$\mathrm{CR}(j,k) < \mathrm{CR}_{\max}.$$

In the RAG for the local segmentor, the neighborhood set R_j is defined with the regions which are spatially adjacent. The set of SAG for the global segmentor is defined

$$R_j = \{k : |\mu_j - \mu_k| \le \vartheta v_d\}$$

where μ_j is a mean intensity vector, v_d is an unit vector of spectral boundary and θ is a constant related to the size of spectral boundary window. Figs 1 and 2 show the examples of RAG and SAG for the segmentors.

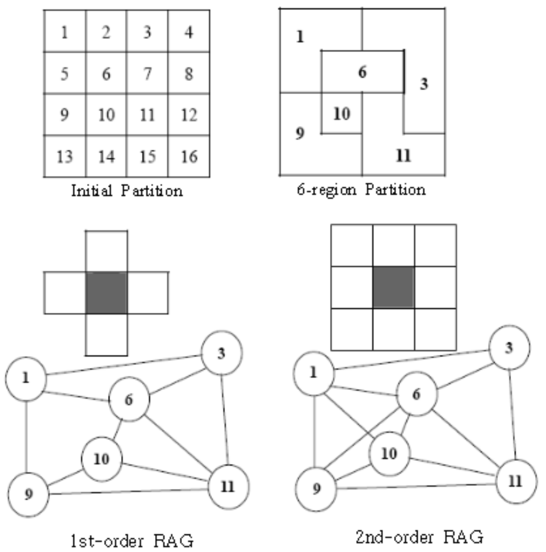


Figure 1. Examples of RAG for local segmentor.

Cluster	Intensity
1	100
2	108
3	115
4	97
5	91
6	112

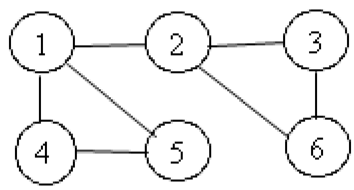


Figure 2. Example of SAG with $\theta v_d = 10$ for global segmentor.

III. EXPERIMENTS

In this study, a Mahalanobis distance measure was used as *d*(*j*,*k*). The experiments were processed by a PC system of Windows XP Professional64 with two Dual-core Intel Xeon 3.0GHz Processors and 8GB RAM:

The proposed method was first evaluated using single/multiband 8-bit simulation images generated using three different patterns by adding white Gaussian noise. The methodology was then applied to QuickBird multispectral data acquired from two regions on the Korean peninsula.

Table 1 shows the CPU times of local segmentor for different image sizes. The computation time linearly increases when increasing the image size. Tables 2 and 3 show the classification errors of global segmentor for the images with different signal-to-noise ratios (SNRs) and different number of bands. The global segmentor performed quite well for less noisy data and more spectral information. Next, the 4 band data of QuickBird acquired over Korean Peninsula was applied for land-cover classification. Fig. 3 shows the observed data and the results of local segmentation of sub-area and Fig. 4

TABLE 1. CPUTIMES OF RAG LOCAL SEGMENTATION FOR 3 BAND IMAGES OF DIFFERENT SIZES (SIZE = S×1024×1024).

S	CPUT	CPUT/S
4	20.05	5.01
16	88.44	5.53
36	205.78	5.72
64	372.59	5.82
100	588.79	5.89
144	850.71	5.91
196	1165.09	5.94
256	1534.48	5.99

TABLE 2. AVERAGE CLASSIFICATION ERRORS IN PERCENTAGE OF SAG GLOBALSEGMENTATION FORDIFFERENT NUMBER OF BANDS OF 4096×4096 SIZE.

Number of Bands	Pattern		
	A	B	C
1	17.17	39.53	40.12
3	0.35	0.52	3.06
5	0.11	0.21	1.42
10	0.04	0.08	0.52
20	0.01	0.03	0.15

TABLE 3. AVERAGE CLASSIFICATION ERRORS IN PERCENTAGE OF SAG GLOBAL SEGMENTATION FOR 3 BAND IMAGES OF 4096×4096 WITH VARIOUS SNRS.

SNR	Pattern		
	A	B	C
0.5	4.68	4.53	16.03
1.0	0.35	0.52	3.06
2.0	0.03	0.05	0.32
3.0	0.00	0.01	0.04
6.0	0.00	0.00	0.00

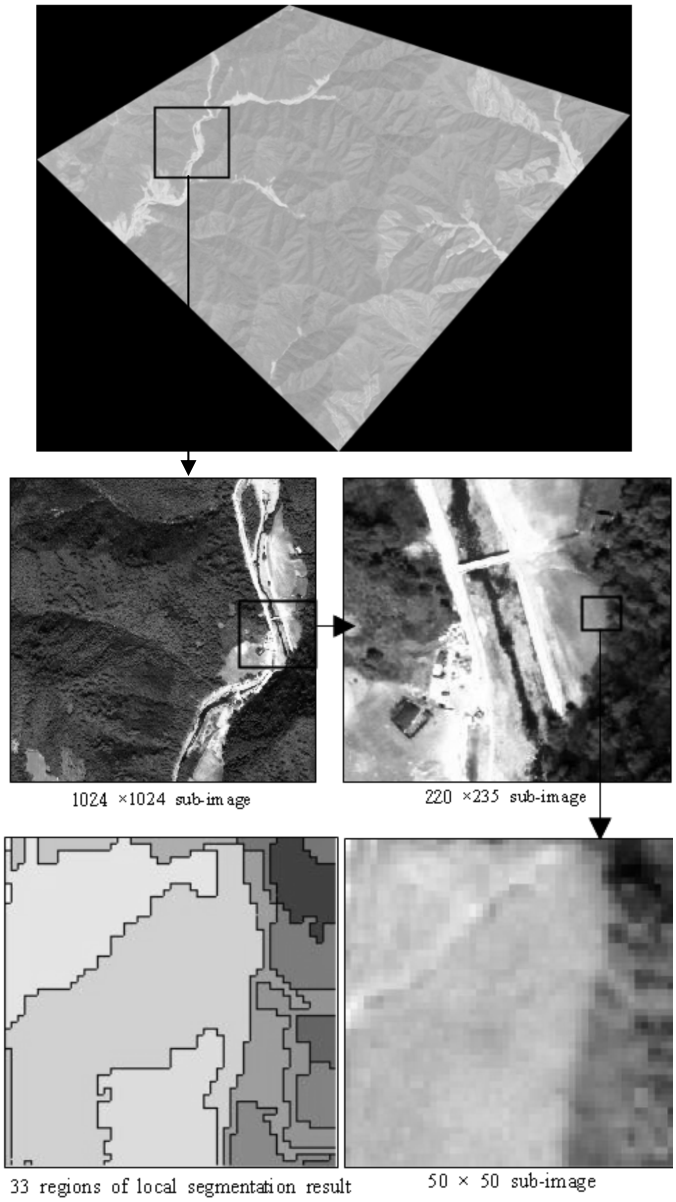
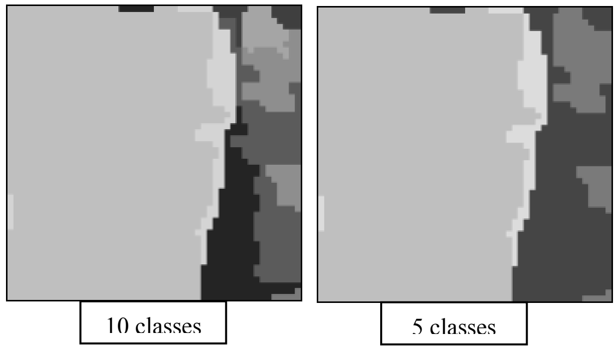


Figure 3. 4-band QuickBird image of 9256×12363 acquired over Kangwon area in Korean Peninsula, sub-images and partitioned sub-image of 50×50 of RAG local segmentation.



Iteration	1	2	3	4	5	6	7	8	9	10
Linking		**1**	**1**	**2**	**2**	**3**	**1**	**5**	**1**	**3**

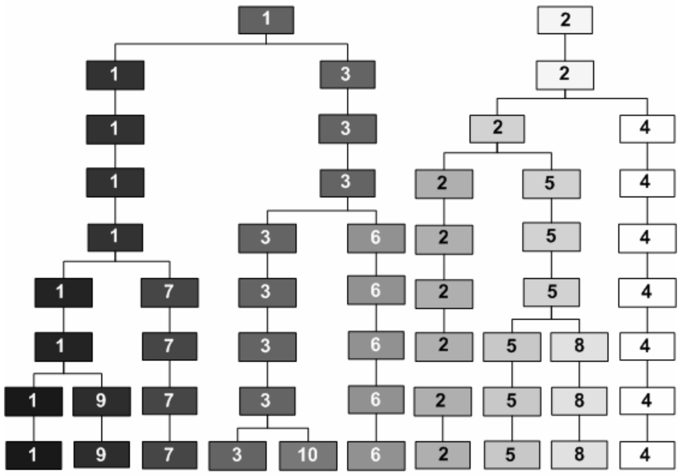


Figure 4. Classified images with 5 and 10 classes of SAG global segmentation, table output of hierarchical linking and corresponding dendrogram

IV. CONCLUSION

The local segmentation using the RAG data structure is a very efficient region-growing algorithm based on a hierarchy which exists in the scene information. Its computation time is linearly dependent on image sizes. The conventional agglomerative hierarchical clustering merges two small clusters into large one at each iteration by selecting the best pair of all possible candidates. For a very large number of initial regions generated from the local segmentor, its requirement of memory for the dissimilarity coefficients makes it unable to classify them. The SAG global segmentor is not dependent on the initial number of regions.

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