Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics
San Antonio, TX, USA - October 2009

UNSUPERVISED CLASSIFICATION OF LARGE DIMENSIONAL IMAGERY USING RAG/SAG-BASED MERGING

Sang-Hoon Lee
Dept. of Industrial Engineering
Kyungwon University, Seongnam, Korea
shl@kyungwon.ac.kr

ABSTRACT

A multistage region merging technique, which is an unsupervised technique, has been 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 region must be spatially contiguous. The “global” segmentor of the second stage, which has not spatial constraints for merging, merges 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 high-resolution mutispectral satellite data acquired from the Korean peninsula.

***Index Terms*—** Segmentation, classification, region growing, agglomerative hierarchical clustering, RAG, SAG, dendrogram, remote sensing.

1. INTRODUCTION

Most approaches to image classification require *a priori* class-dependent knowledge of parameterized models for the data. In many instances of remote sensing, 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 an unsupervised learning of the parameters including the number of classes and image classification simultaneously. For the unsupervised analysis, agglomerative hierarchical clustering technique [1] is the most plausible approach.

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] 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) [3]. 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 segmention. In the second stage, the image partition resulting from the local segmentation is classified into a small number of distinct states by a sequential merging operation. This “global” segmentor uses an agglomerative hierarchical clustering scheme that merges step-by-step small two regions into a large one.

In Lee [2], the merging 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, this study has proposed an alternative approach which merges all the MCN pairs simultaneously and then generates the new set of MCN pairs. It does not require the search of the best pair and the update of the set of MCN pairs. An agglomerative hierarchical clustering for the global segmentor has been 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 [4]. It also employs a multi-window system in spectral space to define the spectral adjacency.

2. RAG/SAG-BASED MCN MERGING

The computational efficiency of region merging 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 $k = \mathrm{CN}(j)$ and $j = \mathrm{CN}(k)$.

In the adjacency graph, each region is represented by a graph node and there exists the edge between two nodes if the corresponding regions are neighboring. A merging cost is assigned to each edge as dissimilarity measure between two neighboring regions. The RAG/SAG-based algorithm merges the regions connected by the edge with the minimum cost, which must be a MCN. In the RAG for the local segmentor, the neighborhood set R_j is defined with the regions which are spatially adjacent. In the SAG for the global segmentor, the neighborhood set is defined as

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

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.

3. 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 Kangwon areas on the Korean peninsula.

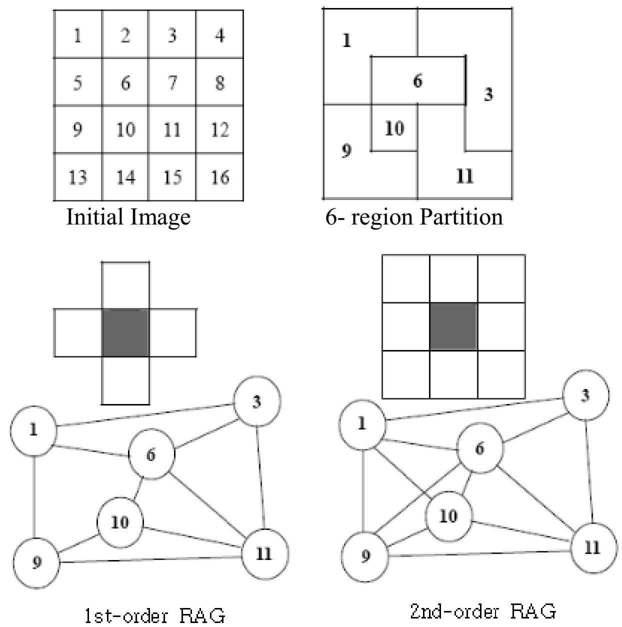


Figure 1. Examples of RAG for local segmentor.

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

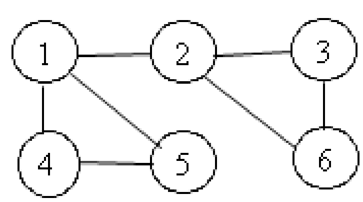


Figure 2. Example of SAG with $\theta v_d = 10$ for global segmentor.

TABLE 1. CPU TIMES OF RAG-BASED 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

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 various numbers of bands and signal-to-noise ratios (SNRs). The global segmentor performed quite well for more spectral information and less noisy data. Next, the RAG/SAG-based MCN merging was applied for land-cover classification using 4 band data of QuickBird of 9256×12363. Fig. 3 shows the observed data and enlarged image of 50×50 sub-area. Fig. 4 contains the results of local segmentation and classification (global segmentation) of sub-area. Fig. 5 contains the table output of hierarchical linking in the last 10 iterations of global segmentation and the corresponding dendrogram

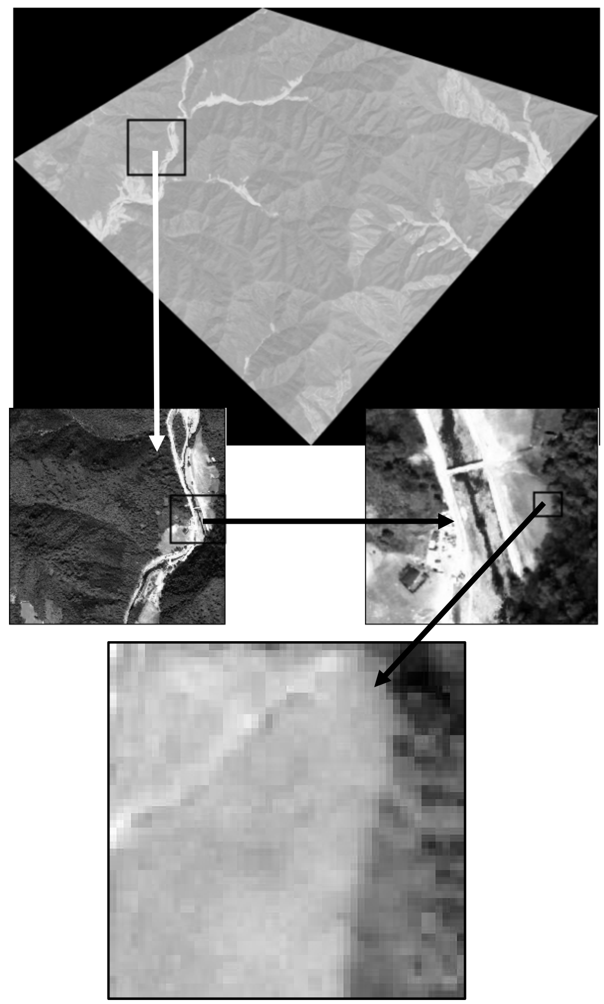
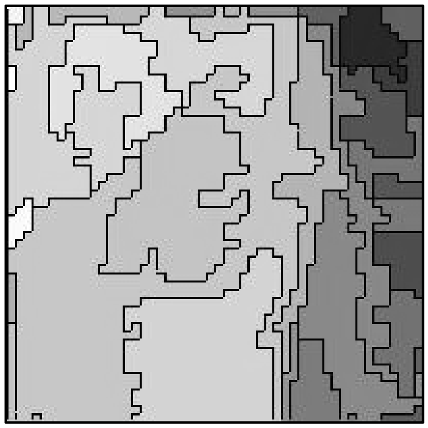
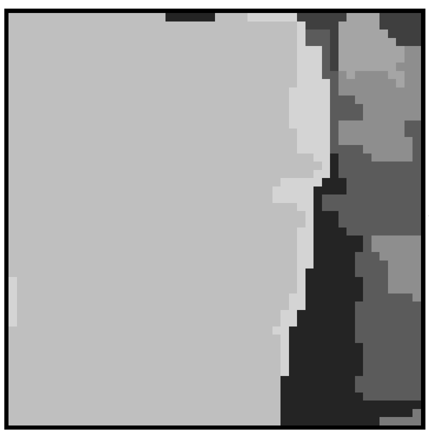


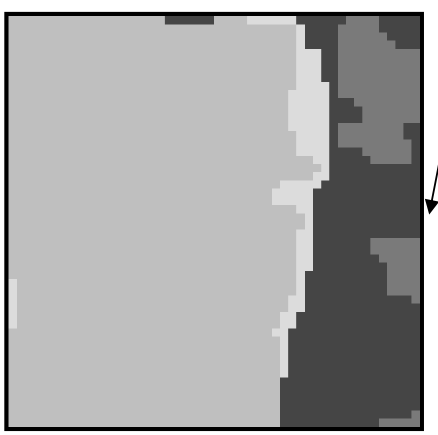
Figure 3. 4-band QuickBird image of 9256×12363 and 50×50 image of sub-area.



(33-region segmentation)



(10 Classes)



(5 Classes)

Figure 5. Results of local segmentation and classification for 50×50 image of sub-area.

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

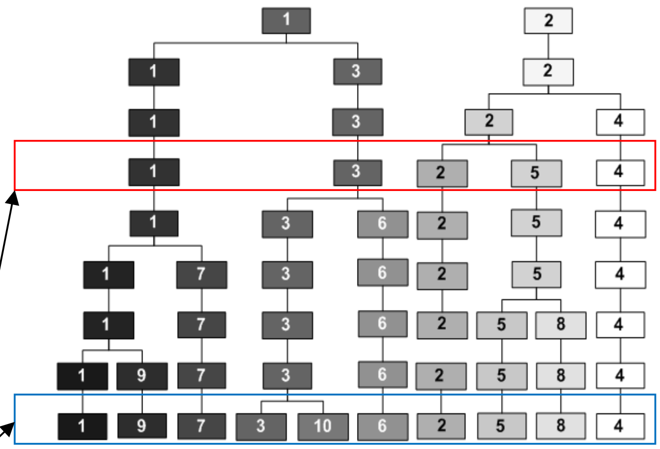


Figure 4. Table output of hierarchical linking and dendrogram

4. CONCLUSION

The local segmentation of RAG-based MCN merging is a very efficient region-growing algorithm using a data structure for representing image partitions. Since its computation time is linearly dependent on image sizes, the algorithm is practical for the application of very large dimensional data.

The conventional agglomerative hierarchical clustering merges two small clusters into large one at each iteration by selecting the best pair of all possible candidates, and thus its computation time and memory become prohibitive when the image is oversegmented in the local segmentation. The global segmentor of SAG-based MCN merging is not dependent on the initial number of regions generated from the local segmentor. In remote sensing, ground scenes are usually covered with complicate land-cover types. The dendrogram which displays the relation of hierarchical linking can be used for a robust cluster validation of remotely sensed images observed from a complex scene.

REFERENCES

[1] M. R Anderberg, M. R. *Cluster Analysis for Application*, Academic Press, NY, 1973

[2] S-H.Lee, "Unsupervised image classification using spatial region growing segmentation and hierarchical clustering," *Korean J. Remote Sensing*, vol. 7, pp.57-70 (in Korean) , 2001

[3] T. Pavlidis, *Structural Pattern Recognition*, New York: Springer, 1980.

[4] C. vanWyk, *Data Structures and C Programs*. Reading, MA: Addison-Wesley, 1988.