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A Comparative Study of Fuzzy Techniques Used for High Resolution Imagery

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Abstract: Image segmentation is crucial to object-oriented remote sensing imagery analysis. A novel texture segmentation algorithm is proposed for high-resolution remote sensing imagery, in which texture clustering is first carried out as loose constraint for later segmentation. The algorithm is based on region adjacency graph models of region adjacency graph, which can achieve fast node merging, defending on the global optimum. Here the spectral, texture and shape features, is established to measure the similarity between nodes and gives the same semantic descriptions for the texture objects. During the merging process, optimal sequence merging interacts with texture clustering to refine the real edges of a texture region. This algorithm cannot only merge the homogenous texture segments with spectral variability easily but can also detect the real object boundaries well. It found that the execution time of modified Fuzzy clustering techniques decreases the number of clusters increases. But in the other techniques the execution time increases when the numbers of clusters increases and detect the boundaries not well. The Modified Fuzzy Techniques detect the hidden details with more accuracy.

Keywords: Adaptive Fuzzy C-Means, Modified Fuzzy C-Means, Texture Segmentation, region merging

I. INTRODUCTION

Digital image processing is a process in which observed image data or image entities are grouped together to form a number of segments in such a way entities within a segment are more similar to each other than to those in other segments. The segmented objects are thereby organized into an efficient representation that characterizes the population being sampled.

A. Gabor Vector:

The optimal minimizing of the joint uncertainty of localization properties in the space and frequency domains [19], the Gabor feature has been considered as one of the best texture descriptions. The Gabor energy texture feature, which has better discrimination properties for different textures [20], is used in this paper, and the texture distance *dt*, including the region-pair and cluster distances, will be described hereinafter.

A 2-D Gabor function can be written as

$$g\lambda,\theta,\phi(x,y) = \exp\left(-\frac{x^2+r^2y^2}{2\delta^2}\right)\cos\left(2\pi\frac{x'}{\lambda}+\varphi\right)$$

Where λ is the wavelength, θ specifies the orientation, r is the ellipticity, δ/λ determines the half-response spatial frequency bandwidth, and ϕ determines the symmetry. In this paper, three wavelengths and eight orientations are selected in accordance with experience. The three wavelength parameters λ are set to 4.5, 7, and 11, respectively, and the eight orientations are $i\pi/8$, ($i = 0, \ldots, 7$). The values of the other parameters are set as follows: $r = 1$, $\delta/\lambda = 0.56$, and Ψ is zero, corresponding to center-symmetric function, or $-\pi/2$, corresponding to antisymmetric function.

The Gabor energy is defined as

$$h\lambda,\theta(x,y) = \sqrt{r^2\lambda,O(x,y)+r^2\lambda,-\frac{\pi}{2}(x,y)}$$

where $r\lambda,\theta,0(x, y)$ and $r\lambda,\theta,-(\pi/2)(x, y)$ correspond to the filtered images by $g\lambda,\theta,0(x, y)$ and $g\lambda,\theta,-(\pi/2)(x, y)$, respectively. In this paper, the texture feature of each region is represented by a 24-dimension vector $f = [h0,0, h0,1, \ldots, h2,6, h2,7]$, and the texture average energy distance of a region pair is defined as

$$dtr = \sum_{b=1}^{n}\sqrt{\sum_{\lambda=1}^{s}\sum_{\theta=1}^{d}(u\lambda,\theta,b,\propto - u\lambda,\theta,b,\beta)}$$

where n is the number of spectral bands, s represents the number of wavelengths, d is the number of orientations, and $u\lambda,\theta,b,\alpha$ and $u\lambda,\theta,b,\beta$ are the average energies of pixels in regions α and β with wavelength λ and orientation θ in band b, respectively.

B. Fuzzy C-Means Clustering:

Fuzzy C-Means clustering (FCM) to cluster all the points to *k clusters. Then, apply nng to find the distance of two texture* clusters to which the region pair belongs is defined as

$$dtc = \begin{cases} d_{ij} = \sum_{b=1}^{n} \sqrt{\sum_{\lambda=1}^{s}\sum_{\theta=1}^{d} (h\lambda,\theta,b,i - h\lambda,\theta,b,b,j)^2}, & i \neq j \\ d_{ij} = \frac{\min(d_{ij})}{2} - 1, & i \neq j \end{cases}$$

where n is the number of spectral bands, s represents the number of wavelengths, d is the number of orientations, and $u\lambda,\theta,b,\alpha$ and $u\lambda,\theta,b,\beta$ are the average energies of pixels in regions α and β with wavelength λ and orientation θ in band b, respectively.

The Gabor energy feature is not perfect, because it may fluctuate considerably even in homogeneous texture. Therefore, in this paper, texture clustering is used to obtain an original homogeneous texture. The cluster distance is proposed as a loose constraint for adjusting the distance between regions.

C. Statistical Region Merging:

Using the difference in membership values to decide the merging of neighboring regions can reduce the number of regions. The different in membership values is calculated for neighboring regions and expresses the degree of similarity between two adjacent regions. Adjacent regions are considered homogenous when they have a small difference in membership value. The final merging is achieved by merging all homogenous neighboring regions until the number no of regions is equal to number of ground truth image regions.
This is summarized as follows:

D. Merging Algorithm:

Objective: From an initial segment image an RAG is constructed and processed using set merging criterion until the no of region is equal to the number of ground truth regions.
Input: Original images and the calculate Gabor energy vector obtained by both Fuzzy C- means and Modified fuzzy C-means

Steps:
1. Initialize processing process for an image.
2. Calculate the Gabor vector and average energy.
3. Find the homogenous value for using clustering techniques.
4. Begin iterative process of adjacent regions are to be merged.

In this merging method, an iterative merging process is then used to merge homogenous neighboring regions until the merging objective is achieved.

E. Region Adjacency Graph: (RAG)

RAG is a data structure for representing the connection of partitions. The definition of RAG is described as follows: The image of K-partition can be expressed by a simple graph $G = (V,E)$, where V is a set of nodes that represent the regions and E represents all the edges between two arbitrary adjacent regions. A cost is assigned to each edge ei,j when region vi is adjacent to region vj .

F. Modified Fuzzy C means Clustering:

We have compare to adaptive fuzzy cluster, the clustering image identify and the apply Nearest Neighbor Graph (NNG) have applied and measure the distance between two regions and then applied to the region merging. But Modified fuzzy clustering find the partition image, apply the distance measure between homogenous values.
Modified Fuzzy C-means techniques, the clustering of dataset can be performed by minimizing an objective function for known number of cluster. Main objective function is:

$$J_m(U,v,X) = \sum_{i=1}^{c}\sum_{k=1}^{N}(U_{ik})^m D_{ik}$$

Where m is the real number m€[0,∞] is weighting exponent on each fuzzy membership. U is fuzzy membership function, v is geometric cluster prototype.
Distance measure is described as:

$$D_{ik} = D_{ik}\left(1 - \propto \frac{\sum_j \in neighbours\, U_{ij} * P_{kj}}{\sum_j P_{kj}}\right)$$

D_{ik} is some measure of similarity between vi and x_k. U_k is the degree of membership of x_i in the cluster k.
Where P_{kj} is the respect to the pixel||k-j||, α is Constant, that satisfies the condition $0 \leq \alpha \leq 1$. Ui_k is the degree of membership of x_i in the cluster k.

I. WATERSHED METHOD WITH MERGING:

This initial over segmentation is due to the high sensitivity of the watershed algorithm to the gradient image intensity variations, and, consequently, depends on the performance of the noise reduction algorithm. Over segmentation is further reduced by thresholding the gradient magnitude prior to the application of the watershed transform. The output of the watershed transform is the starting point of a bottom-up hierarchical merging approach, where at each step the most similar pair of adjacent regions is detected and merged. Here, the region adjacency graph (RAG) is used to represent the image partitions and is combined with a newly introduced nearest neighbor graph (NNG), in order to accelerate the region merging process.

RAG is a data structure for representing the connection of partitions. The definition of RAG is described as follows: The image of K-partition can be expressed by a simple graph
$G = (V,E)$, where V is a set of nodes that represent the regions and E represents all the edges between two arbitrary adjacent regions.

Step 1) Use the watershed method to obtain the origin regions of the image.

Step 2) Scan the partition image to initialize RAG by calculating the cost of each edge, and form NNG by searching for the minimum cost edge of each node.

Step 3) Search all the cycles in NNG, and store them in an auxiliary array.

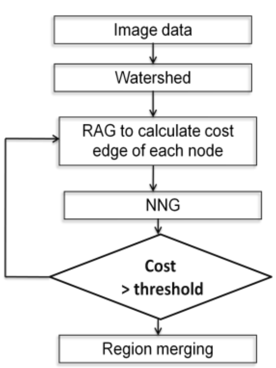
Step 4) Sort the array according to cost from low to high. Then, the first cycle in the array is the global optimal region pair.

Step 5) Merge the corresponding region pair of the first cycle in the array.

Step 6) Update RAG and NNG, and search for the changes of cycles in NNG. Then, delete the cancellation cycles from the array, and insert the newly created cycles into the appropriate position of the array in order to maintain the array's increasing order.

Step 7) Go back to Step 5) until the number of regions meets the user's requirements or the cost of the global optimal region pair is greater than the preset threshold.

A. Flowchart :



B. Example:

Figure 2: original image

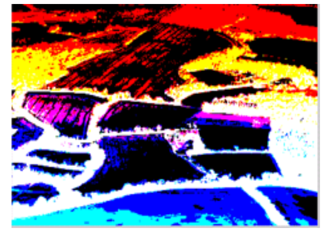


Figure 3: Gaussian Filter with watershed

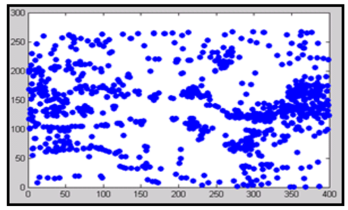


Figure 4: Region point

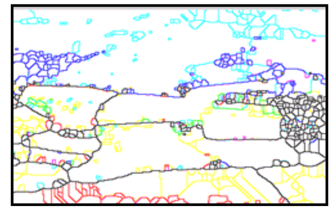


Figure 5: Extract Boundariesaries

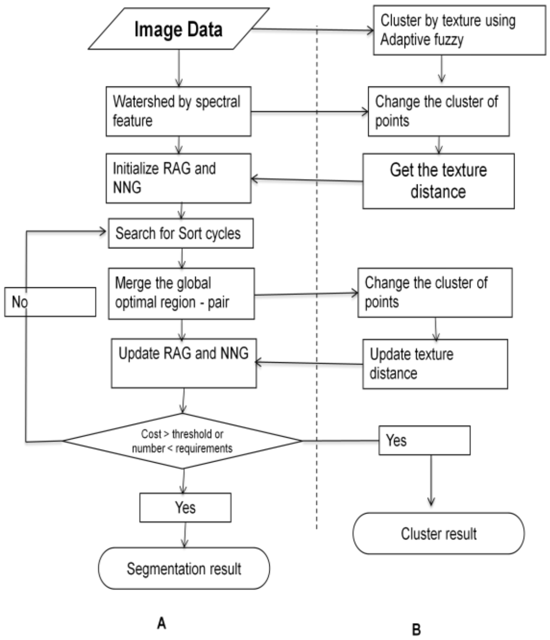
II. ADAPTIVE FUZZY C- MEANS

Adaptive Fuzzy C-means techniques (AFCM) that produces a soft segmentation while simultaneously adapting to intensity in homogeneities in the image. Adaptive Fuzzy C-means techniques were derived by incorporating a gain field term into the objective function of the standard fuzzy c-means techniques. Constraints on the gain field were used to ensure that the estimated field was smooth and slowly varying. AFCM has been shown to be effective in correcting for homogenous. Adaptive Fuzzy C-means techniques based mixtures of experts for classifying unsupervised data automatically. The watershed with merging algorithm has been improved by considering texture clustering, which cannot only distinguish objects with different texture but can also detect the edges of texture regions accurately.

For an image, the segmentation procedures are described as follows.

- **step 1.** Calculate the Gabor energy feature of the image. Use an additional layer to record the clustering is obtained
- **step 2.** Obtain the original region by using watershed method
- **step 3.** Calculate mean Gabor energy of pixels in each region . The mean Gabor vector is the texture feature of this region

A. Flowchart :



step 4. Use (3) to calculate the texture distance between one region and each adaptive cluster center. The region belongs to the cluster where the distance is smallest

step 5. Calculate the distances between two arbitrary adjacent regions based on (8), and initialize RAG and NNG

step 6. Search and sort all the cycles in NNG

step 7. Merge the global optimum region pair. Use step (3) and (4) to calculate texture feature

step 8. Update RAG and NNG, and search the changes of cycles in NNG.

step 9. Go back still (6) until the no of regions is greater than the preset threshold

B. Example:

Figure: 6 original image

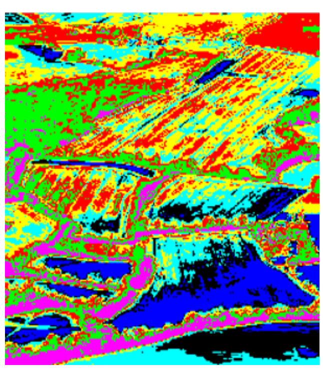


Figure: 7 Adaptive FCM

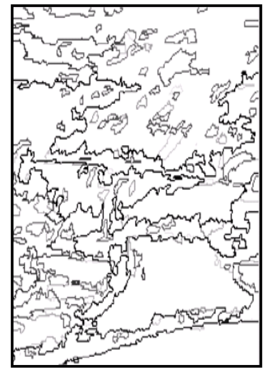


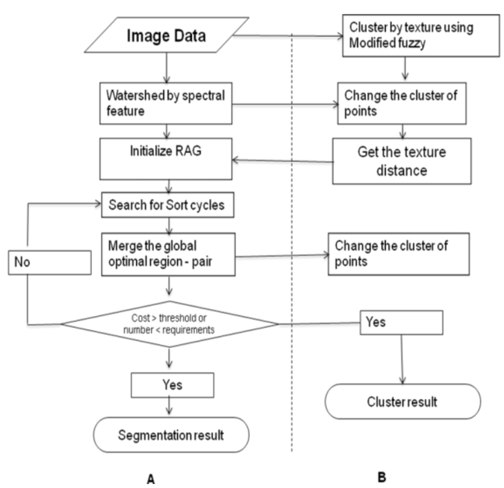
Figure:9 Extract Boundarie s

Figure :8 Cluster result   Figure 9: Ex

III. Modified Fuzzy C Means

A Conventional FCM method only uses pixel intensity information and results in crisp segmentation for noisy images. The spatial information with different modified Fuzzy C-means (Modified FCM) methods are proposed to allow the neighbors as factors and thus to attract pixels into their cluster. A modified Fuzzy C-means method classification techniques is used to provide a fuzzy partition. The implementation of a modified Fuzzy C-means method in the Satellite image segmentation. Modified Fuzzy C-means techniques, the clustering of a dataset can be performed by minimizing an objective for known as no of regions or cluster. The merging algorithm has been improved by considering texture clustering, which cannot only distinguish objects with different texture but can also detect the edges of texture regions accurately.

A. Flowchart :



For an image, the segmentation procedures are described as follows.

step 1. Calculate the Gabor energy feature of the image. Use an additional layer to record the clustering is obtained

step 2. Obtain the original region by using watershed method

step 3. Calculate mean Gabor energy of pixels in each region . The mean Gabor vector is the texture feature of this region

step 4. Use (3) to calculate the texture distance between one region and each MFCM cluster center. The region belongs to the cluster where the distance is smallest.

The region pair belongs is defined as

$$J_m(U,v,X) = \sum_{i=1}^{c}\sum_{k=1}^{N}(U_{ik})^m D_{ik}$$

Where m is the real number m € [0,∞] is weighting exponent on each fuzzy membership. U is fuzzy membership function, v is geometric cluster prototype.
Distance measure is described as:

$$D_{ik} = D_{ik}\left(1-\propto \frac{\sum_{j} \in neighbours\, U_{ij} * P_{kj}}{\sum_j P_{kj}}\right)$$

D_{ik} is some measure of similarity between vi and x_k. U_k is the degree of membership of x_i in the cluster k.
Where P_{kj} is the respect to the pixel||k-j||, α is Constant, that satisfies the condition $0\leq\alpha\leq 1$. Ui_k is the degree of membership of x_i in the cluster k.

step 5. Merge the global optimum region pair. Use step (3) and (4) to calculate texture feature

step 6. Update RAG

step 7. Go back still (5) until the no of regions is greater than the preset threshold

B. Example :

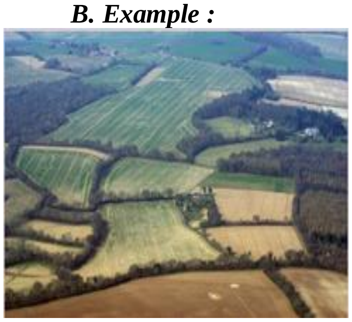


Figure 10: original image

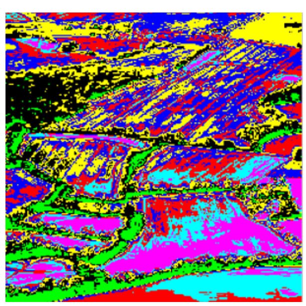


Figure 11: Modified FCM

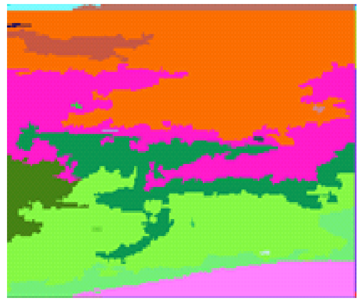


Figure 12: Cluster result

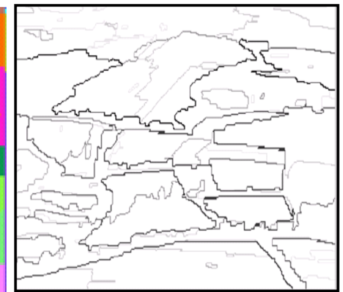


Figure 13: Extract Boundaries

IV. Quantitative Evaluation

Quantitative evaluation is based on the maximum classification accuracy which can be achieved by the segmentation result.Three kinds of object are defined in this paper: correct, acceptable and wrong objects. The ratio of regions that are correct or are acceptable objects is calculated for evaluation.

The correct object is defined as

$$P = \frac{2S}{S_{seg} + S_{ref}} > 85\%$$

Where Sseg is the area of the segment, Sref is the area of the corresponding correct object, and S is the intersection between these two areas.
An acceptable object is defined as the region with partially correct edges. For acceptable objects, the corresponding correct region can be obtained by merging (oversegmentation) or dividing (undersegmentation) once or twice. The definition of oversegmentation is

$$P = \frac{2S}{S_{segA} + S_{segB} + S_{ref}} > 85\%$$

where Sseg*A* and Sseg*B* are the areas of segments A and B, respectively. *S* is the intersection area between the reference object and the two segments. Note that segment A or B cannot contain the same rank objects. To evaluate the segmentation results, we compare our results with those of Definiens and give the qantitative evaluation in Table I.

V. Conclusion

The model is applied to RAG and NNG for high-resolution image segmentation. During the segmentation, the iterative interaction between texture clustering and optimal sequence merging steers us to detect better and more exact boundaries between regions. The experiments on an aerial image and a SPOT5 image demonstrate that our algorithm improves the segmentation accuracy between 10% and 20% compared with that by Definiens only using purely spectral features. Accurate edges are extracting Modified fuzzy c-means techniques correct the noisy image without affecting the edges. Merging process based on statistical region for the partition image. It showed sensitivity to noise. Considering the partial volume around it can compensate for region loss. The Result Analysis shows that the Modified Fuzzy C-means techniques decreases when the number of segmentation. Also we found that region value decreases in the Modified Techniques, it shows this techniques extracts the hidden details with more accuracy.

Table 1 Comparison of Segmentation Accuracy

	Objects	*No of regions*	*Correct (%)*	*Acceptable (%)*	*Total (%)*
Watershed with merging	**Main**	13	6 (46.15)	4 (30.76)	**10 (76.92)**
	Small	20	4 (20.0)	2 (10.0)	**6 (30.0)**
	Lineal	60	1 (1.66)	2 (3.3)	**3 (5.0)**
	Total	**93**	**11 (11.82)**	**8 (8.60)**	**19 (20.43)**
Adaptive fuzzy C means	**Main**	17	4 (23.53)	3 (17.64)	**7 (41.17)**
	Small	16	8 (50)	5 (31.25)	**12 (75)**
	Lineal	25	5 (20.0)	2 (8)	**7 (28.0)**
	Total	**58**	**17 (29.13)**	**9 (15.52)**	**26 (44.82)**
Modified Fuzzy C means	**Main**	14	6 (42.85)	5 (35.71)	**11 (78.57)**
	Small	15	8 (53.3)	6 (40.0)	**14 (93.33)**
	Lineal	7	3 (42.85)	2 (25.57)	**5 (71.42)**
	Total	**36**	**17 (47.22)**	**13 (36.11)**	**30 (83.35)**

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