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A NON-LOCAL FUZZY C-MEANS CLUSTERING SEGMENTATION ALGORITHM BASED ON COMENTROPY AND BETWEEN-CLUSTER SCATTER MATRIX TO OVERCOME THE INHERENT COHERENCE SPECKLES OF SAR IMAGES

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ABSTRACT

The fuzzy c-means (FCM) algorithm and many of its variations have been widely adopted for image segmentation tasks. However, these methods are unable to present satisfactory segmentation results when dealing with synthetic aperture radar (SAR) images owing to the intrinsic speckle noise. In order to achieve the effective segmentation of SAR images, a robust FCM algorithm, namely NCBS_FCM, is proposed. The nonlocal spatial information is utilized to reduce the effect of speckle noise. Furthermore, NCBS_FCM takes advantage of the comentropy based on local gray histogram to acquire the adaptive weighting parameter for nonlocal spatial information term, which can achieve a better balance between speckle suppression and edge detail preservation. In addition, this paper incorporates the between-cluster scatter term into the objective function to adjust the distance between the cluster centers accordingly. Therefore, NCBS_FCM is more robust to various images and achieves satisfactory segmentation accuracy. Experiments on simulated and real SAR images show that NCBS_FCM outperforms other proposed variations of FCM by a significant margin.

Index Terms— nonlocal spatial information, adaptive weighting parameter, between-cluster scatter term, fuzzy C-means, synthetic aperture radar (SAR) image segmentation

1. INTRODUCTION

As a critical part in image preprocessing, image segmentation directly affects the accuracy of subsequent image interpretation [1]. Nowadays, there are many image segmentation algorithms with different emphasis in the field of optical image. However, due to the special imaging mechanism of SAR images and the inherent speckle noise, the SAR image segmentation is more complicated [1].

Existing algorithms can be roughly divided into the following categories. (1) Threshold segmentation: classify pixels by delineating thresholds. However, we found that many small ”ripples” will appear in the SAR image after threshold segmentation, and even the ground objects can not be recognized. (2) Edge detection segmentation: detecting edge points and dividing the boundaries of different sub-areas. However, the contour of each region in SAR image is an intermittent and incompletely connected ”dotted line”, it is difficult to detect reliable edges due to the influence of speckle on the edges. (3) Regional segmentation: through the consistency of the internal characteristics of the region to complete the segmentation. One of the most widely used region segmentation algorithms is clustering [2]. In addition, algorithms based on deep learning have attracted great attention in recent years. However, the application of deep learning in SAR image segmentation is greatly limited because the number of SAR images is often difficult to match the scale of optical images.

In this paper, we propose a robust non-local fuzzy c-means algorithm with comentropy and between-cluster scatter matrix (NCBS_FCM) with the following properties: 1) NCBS_FCM employs adaptive similarity measure to obtain more accurate measurement of the similarity between two pixels. 2) Nonlocal spatial information, which is obtained by investigating a larger neighborhood, is utilized to reduce the effect of speckle noise. 3) NCBS_FCM takes advantage of the comentropy based on local gray histogram to acquire an adaptive weighting parameter for the nonlocal spatial information term, which leads to a better balance between speckle suppression and edge detail preservation. 4) NCBS_FCM introduces the between-cluster scatter term into the objective function to adjust the distance between the cluster centers flexibly. As a consequence, this algorithm is more adaptive to various images and achieves satisfactory segmentation accuracy.

2. METHODOLOGY

2.1. Nonlocal Spatial Information Term

The nonlocal mean (NLM) algorithm [3, 4] takes advantage of realizing noise smoothing. The formula of NLM algorithm is defined as 1-4, where $\tilde{x}_i$ denotes the nonlocal mean value of the pixel i, and S_i^S represents the search window with radius

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S centered at the pixel i.

$$\tilde{x}_i = \sum_{j \in S_i^S} W_{ij} X_J \tag{1}$$

$$S_{ij} = ||(v(N_i) - v(N_j))||_{2,\sigma}^2 \tag{2}$$

$$w_{ij} = \frac{1}{Z_j} e^{-S_{ij}/h_2} \tag{3}$$

$$Z_j = \sum_{j \in S_i^S} e^{-S_{ij}/h_2}. \tag{4}$$

2.2. Improved Similarity Measure

Although the NLM algorithm has a good performance in noise smoothing in general, it's flawed in detail preservation. Ji, J. et al. [5] argued that for a pixel at the boundary, most pixels in its search window have dissimilar neighborhood configuration with it. Hence, points that are excessively different from the center pixel should be excluded to get accurate results. An adaptive binary weight function can be defined as follows:

$$t_{ij} = \begin{cases} 1 & |x_i - x_j| \leq ts \\ 0 & |x_i - x_j| > ts \end{cases} \tag{5}$$

where $j \in N_i$, ts denotes the threshold of the grayscale difference between the center pixel and its neighborhood. It is noteworthy that the value of ts hinges on the noise level and grayscale of the image. Accordingly, the improved similarity metric between two patches defined as

$$S_{ij}^{'} = ||T_i \cdot (v(N_i) - v(N_j))||_{2,\sigma}^2 \tag{6}$$

where $T_i = t_{ij}, j \in N_i$ is the adaptive binary weight matrix. Combining these proposed improved similarity measure S_{ij} and filter parameter h, the weight and the normalizing factor can be computed as follows:

$$w_{ij} = \frac{1}{Z_j} e^{-S_{ij}^{'}/h_i^2}, \tag{7}$$

$$Z_j = \sum_{j \in S_i^s} e^{-S_{ij}^{'}/h_i^2}. \tag{8}$$

2.3. Adaptive Weighting Parameter for nonlocal term

As the weight of nonlocal spatial information, α controls the anti-noise ability and regional consistency of the algorithm. Thus, it is unreasonable to use a fixed α for all the pixels.

For a pixel i, its adaptive weighting parameter for nonlocal term λ_i which is based on information entropy of local gray histogram is set as:

$$\lambda_i = (1 - \frac{W_i}{max\{W_i, i \in \Omega\}}), \tag{9}$$

$$W_i = e^{EN_i} - 1, \tag{10}$$

$$\sigma = median\{var_i, i \in \Omega\}, \tag{11}$$

where $EN_i = -\sum_{l=1}^{n} p_l log P_l$ is the comentropy based on gray histogram of the square neighborhood centered on the pixel i, n denotes the quantized number of grayscale and p_l is the frequency corresponding to quantized gray level l. Further, var_i is the neighborhood variance of pixel i and ω signifies complete set of image pixels.

2.4. Fuzzy Within-Cluster and Between-Cluster Scattering Term

The within-cluster, between-cluster and total scattering matrixes of FCM [6] can be defined as formulae 12-14. Let $tr(\cdot)$ denote the trace of the matrix, then $tr(M_W)$ and $tr(M_B)$ can be applied to measure the compactness in the cluster and the separation between clusters respectively [7]. Consequently, we introduce the within-cluster scattering term and the between-cluster scattering term as formula 16.

The standard FCM algorithm only considers the within-cluster scattering term while there is no reciprocal relationship between $tr(M_W)$ and $tr(M_B)$ in fuzzy clustering. Therefore, it is necessary to add the between-cluster scattering term to the objective function for the purpose of minimizing the compactness in the cluster and maximizing the separation between clusters, simultaneously.

$$M_W = \sum_{k=1}^{c} \sum_{i=1}^{n} u_{ki}^m (x_i - v_k)(x_i - vk)^T \tag{12}$$

$$M_B = \sum_{k=1}^{c} \sum_{i=1}^{n} u_{ki}^m (\bar{x} - v_k)(\bar{x} - vk)^T \tag{13}$$

$$M_W = \sum_{k=1}^{c} \sum_{i=1}^{n} u_{ki}^m (x_i - \bar{x})(x_i - \bar{x})^T \tag{14}$$

$$T_W = tr(M_W) = \sum_{k=1}^{c} \sum_{i=1}^{n} u_{ki}^m ||x_i - v_k||^2 \tag{15}$$

$$T_B = tr(M_B) = \sum_{k=1}^{c} \sum_{i=1}^{n} u_{ki}^m ||\bar{(x)} - v_k||^2 \tag{16}$$

2.5. Proposed Algorithm

Combining the nonlocal spatial information, adaptive weighting parameter and the between-cluster scattering term, we construct a novel fuzzy clustering algorithm, nonlocal fuzzy c-means algorithm with comentropy and between-cluster scatter matrix (NCBS_FCM). The objective function is

$$J_m = \sum_{k=1}^{c} \sum_{i=1}^{n} u_{ki}^m ||x_i - v_k||^2 + \lambda_i \sum_{k=1}^{c} \sum_{i=1}^{n} u_{ki}^m ||\bar{x}_i^{'} - v_k||^2 - \sum_{k=1}^{c} \sum_{i=1}^{n} \mu_k u_{ki}^m ||\bar{x} - v_k||^2, \tag{17}$$

where λ_i is the adaptive weighting parameter for nonlocal term calculated by formula 12 and μ_k controls the effect of the between-cluster scattering term which is updated as

$$\mu_k = \frac{(\eta/4)min_{k' \neq k}||v_k - v_{k'}||^2}{max_j||\bar{x} - v_j||^2} \quad 0 \leq \eta \leq 1. \tag{18}$$

The objective function is minimized by the Lagrange multiplier method, thus we can obtain the update formulas of the membership u_{ki} and the cluster center v_k as follows:

$$u_{ki} = \frac{(||x_i - v_k||^2 + \lambda_i||\tilde{x}_i^{\cdot} - v_k||^2 - \mu_k||\bar{x} - v_k||^2||)^{-\frac{1}{m-1}}}{\sum_{j=1}^{c}(||x_i - v_j||^2 + \lambda_i||\tilde{x}_i^{\cdot} - v_j||^2 - \mu_j||\bar{x} - v_j||^2||)^{-\frac{1}{m-1}}}, \tag{19}$$

$$v_k = \frac{\sum_{i=1}^{n}(x_i + \lambda_i \tilde{x}_i^{\cdot} - \mu_k \bar{x})u_{ki}^m)}{\sum_{i=1}^{n}(1 + \lambda_i - \mu_k)u_{ki}^m}. \tag{20}$$

3. EXPERIMENTAL RESULTS AND ANALYSIS

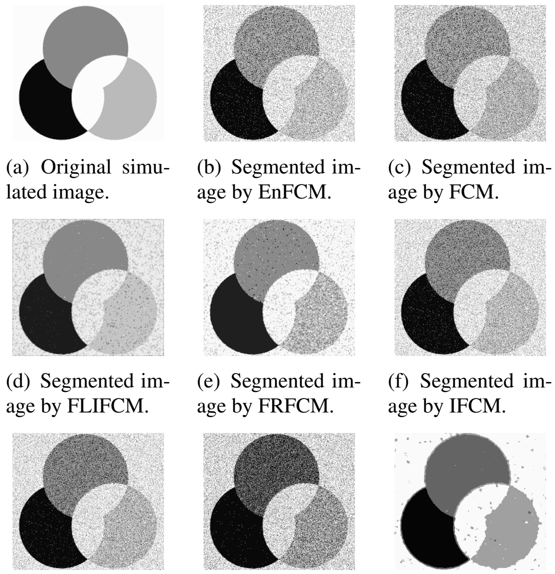
3.1. Experimental Results and Analysis of Simulated SAR Image Segmentation

Due to the lack of true geomorphology as the reference for SAR images, it's difficult to evaluate the segmentation results quantitatively. Thus, we utilize simulated SAR images evaluate the performance of segmentation algorithms objectively. In order to make the simulated SAR images as similar as possible to the real SAR images, three kinds of noise-salt and pepper noise, gaussian noise and speckle noise should be added to the simulated SAR images. After successfully simulating the SAR images, the variants of FCM algorithm, EnFCM , FCM, FLIFCM, FRFCM, IFCM, IFFCM and MFCM are introduced and carried out to compare the robustness and precision with NCBS_FCM.

Figure 1(b)-1(i) show the segmentation results of eight different algorithms in sequence. It can be seen that Figure 1(b)-1(i) have poor regional uniformity, and there are a mass of misclassified pixels, especially EnFCM, FCM, IFCM, IFFCM and MFCM algorithms. Relatively speaking, from the visual effect, among all the algorithms, NCBS_FCM has the least misclassification pixels and its segmentation results are closest to the original simulated SAR image. In addition to the visual aspect, segmentation accuracy (SA) and adjusted rand index (ARI) are also used to quantitatively evaluate the segmentation effect of various algorithms. As can be seen from the table 1NCBS_FCM algorithm has the best segmentation quality. In summary, among all the listed algorithms, NCBS_FCM has the most optimal SA and ARI, which is consistent with the visual results.

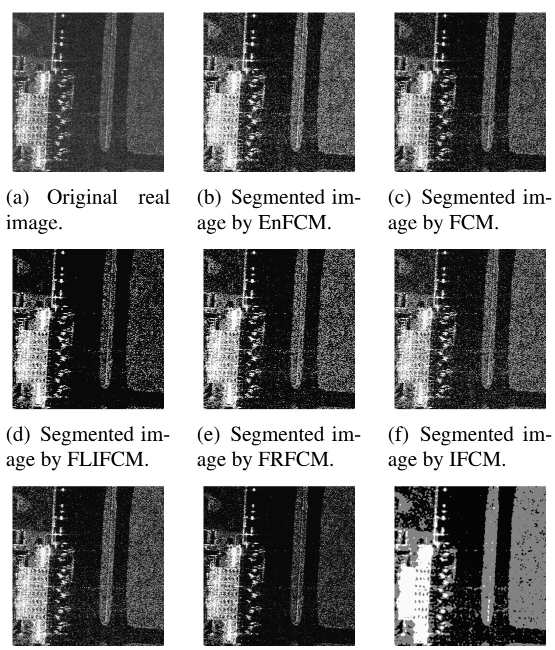
3.2. Experimental Results and Analysis of Real SAR Images

The real RadarSat-2 SAR image, shown in Figure 2, is also utilized to test the performance of segmentation algo-



(a) Original simulated image. (b) Segmented image by EnFCM. (c) Segmented image by FCM.
(d) Segmented image by FLIFCM. (e) Segmented image by FRFCM. (f) Segmented image by IFCM.
(g) Segmented image by IFFCM. (h) Segmented image by MFCM. (i) Segmented image by NCBS_FCM.

Fig. 1. The set of simulated SAR images with speckle 0.05 used to evaluate the quality of the segmentation algorithm.



(a) Original real image. (b) Segmented image by EnFCM. (c) Segmented image by FCM.
(d) Segmented image by FLIFCM. (e) Segmented image by FRFCM. (f) Segmented image by IFCM.
(g) Segmented image by IFFCM. (h) Segmented image by MFCM. (i) Segmented image by NCBS_FCM.

Fig. 2. Sementation result on real SAR image.

Table 1. Quantitative evaluation results of each algorithm on simulated images

	speckle noise:0.05)	
algorithm	SA	ARI
EnFCM	0.735928	0.516215
FCM	0.716451	0.470172
FLIFCM	0.955057	0.883494
FRFCM	0.906862	0.799625
IFCM	0.719558	0.474565
IFFCM	0.713570	0.466773
MFCM	0.534714	0.360277
NCBS_FCM	0.965504	0.908906

rithms. We can roughly divide the ground objects into three categories- buildings, grasslands and runway. And in Figure 2(a), the buildings are the most bright, followed by the grass and the runway.

Figure 2(b)-2(i) show the segmentation results of different algorithms successively. Although for real SAR images, it is impossible to use quantitative metrics to evaluate the segmentation quality of various algorithms, but it can still be distinguished from the perspective of image vision.

First, we can find that almost all algorithms can extract the road well. Secondly, almost all algorithms can accurately segment the grasslands boundary. However, for other algorithms, a large number of pixels in the inner region of the grasslands are mistakenly classified into other categories. The NCBS_FCM algorithm, although it also has some misfractions, performs better than other algorithms. Finally, it is not difficult to observe from Figure 2(a) that due to the influence of speckle, the pixels of the building are mixed with many features of other ground objects, resulting in their boundaries are not as clear as other ground objects, and its internal texture is interlaced and crisscrossed. Carefully observing the building segmentation results, we can find that other algorithms are not satisfactory in dealing with the speckle inside buildings. By contrast, the segmentation of NCBS_FCM shown in Figure 2(i) has accurate regional boundaries and great regional uniformity. Furthermore, scattered small targets and details in the image are also preserved well.

4. CONCLUSIONS

In this paper, an improved and robust FCM algorithm with comentropy and between-cluster scatter matrix (NCBS_FCM) is proposed. NCBS_FCM utilizes the comentropy based on gray histogram of square neighborhood centered on the corresponding pixel to obtain weighting parameter for nonlocal term adaptively. Additionally, NCBS_FCM effectively integrates nonlocal spatial information and between-cluster scatter term to improve the robustness and segmentation accuracy. Experiments on simulated and real SAR images shows that NCBS_FCM obtains more satisfactory segmentation results both in terms of regional uniformity and boundary precision than other fuzzy clustering methods.

5. FUNDING

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