The SAR Image Segmentation Superpixel-Based with Optimized Spatial Information

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Abstract—In this paper, we propose a method of image segmentation, which is based on superpixel and optimized spatial feature. In this paper, the superpixels are taken into account, which can reduce computational burden, and the result of over-segmentation can also be benefit for segmentation results. The main idea of this paper is based on the conventional fuzzy c-means (FCM). The conventional FCM has a better performance. However, it is sensitive to noise. In order to overcome this shortage, we incorporate spatial information of superpixels into the conventional FCM. In order to obtain the better performance, influential degree of spatial information is applied to the conventional FCM to improve segmentation performance Experimental results show that the proposed method achieves excellent performance.

I. INTRODUCTION

 $T^{\rm HE}$ purpose of image segmentation is to divide the image into disjoint regions based on the image feature. For

image segmentation, there are many studies have been made [1]. Clustering plays an important role in image segmentation. Clustering algorithms attempt to classify a voxel to a tissue class by using the notion of similarity. There are many clustering strategies, such as K-means, fuzzy c-means (FCM) and so on. The fuzzy set theory was introduced by Zadeh [2], and successfully applied in image segmentation. In 1981, Bezdek proposed the fuzzy c-means algorithm [3]. The FCM has many better characteristics, and has been widely used for image segmentation and classification [4]. However, the conventional FCM method does not take any spatial information into account, so that the result of segmentation is usually implemented by pixel intensities [5]-[7].

Many image segmentation methods were proposed based on modified FCM [8]-[11]. These methods reformulated the objective function by incorporating spatial constraint, because each of pixels can influence local neighborhood in some degree. Therefore, spatial constraint plays an important role in fuzzy clustering [12], [13]. By modifying the membership, a method of improving the robust of FCM to noise is proposed in this paper, in which optimized spatial feature of superpixel is considered.

In the field of image processing, superpixel is extensively applied [14]-[16], in which over-segmentation can obtain

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many small regions. These regions are the base of object categorization and recognition. Superpixel can represent local coherence, which are used to compute local image features and can efficiently preserve boundary information.

Extracting discriminative feature is a crucial step in the field of computer vision. These features include edge, texture, wavelet, et al, among which wavelets have multi-resolution property. The study based on wavelets has been conducted and has achieved better image segmentation [17], [18]. Furthermore, the wavelet has the other feature such as decorrelation, low entropy, flexibility and multi-direction, et al. Based on these outstanding features, we extract meaningful superpixels. In view of the mutual influence of neighboring and similar superpixles, we incorporate the relation into FCM and optimize the influential degrees to improve segmentation performance. In this paper, synthetic aperture radar (SAR) images are tested, and experimental results show that this method is more effective than other segmentation methods.

The main contributions of this paper are: 1) by using neighboring and similar superpixels to adjust membership, the better segmentation results are obtained. 2) influential degree of spatial information is optimized to improve segmentation performance.

II. RELATED WORKS

Many methods related to image segmentation based on FCM have been proposed. By using bilateral filtering, literature [19] reduces the noise and smoothes the image slightly. Then the image segmentation is conducted based on FCM algorithm. This method implements both smoothness and uniformity of the image segmentation. Using the Sigma filter principle to change the neighboring pixels of targets, a modified-FCM is proposed [20], in which the effect of noise can be reduced. For further reducing the effect of noise, several methods were proposed to improve the performance and robustness. Based on spatial and multiresolution constraints, literature [21] proposed a modified FCM algorithm, in which spatial and multiresolution information are incorporated, and the more effective segmentation performance are achieved. To improve the robustness, a spatial constraint penalty term is added in the objective function of standard FCM in [22], in which the neighboring pixels is used as spatial information. In [23], the undecimated wavelet decomposition is used to represent the texture information. This method has the characteristic of robustness to noise, and the kernel FCM incorporating spatial constraints is applied to the image segmentation.

Recently, image processing based superpixel has attracted more attention. A method of computing superpixel based on geometric-flow is described in [24]. This method can remain

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the boundary of image and a large size of image can be over-segmented in a matter of minutes. In [25], a superxiel classification based optic cup segmentation is proposed, in which each optic disc image is firstly over-segmented into superpixels, and then the mean intensities, center and the location features are extracted from each superpixel to classify it as cup or non-cup. The method reduces computational complexity and improves edge sharpness.

By combining optimization algorithm with clustering, the performance of clustering can be improved. Literature [26] proposed a new extended fuzzy particle swarm optimization algorithm, and this method introduced spatial analysis. This method not only can increase the robustness with respect to the presence of noise, but also can reduce computational burden. A new classification based on FCM algorithm based on fuzzy neural network is introduced in [27], which improve the performance of classification result. Literature [20] constructs two models about feature attraction and distance attraction of neighborhood pixels. This method not only improved robustness of FCM algorithm to noise, but also increased edge sharpness of results.

III. SUPERPIXEL

A. Superpixel

Figure 1 shows superpixel segmentation, in which the image is divided into superpixels and each superpixel shows the same visual appearance, which can cause substantial speed-up of subsequent processing. Therefore, the careful choice of the superpixel method [24] and its parameters for the particular application are crucial. We use TurboPixels [24] to extract superpixels from an image, in which one superpixel is roughly uniform in texture and gray, so that the boundaries of regions are preserved.



Fig.1. The result of superpixel. (a) Original image, (b) Superpixel image.

B. Feature extraction

In order to encode gray, texture and spatial information into superpixels, we describe each superpixel j by a 7-dimensional wavelet feature vector $\mathbf{F}_j = (f_1, f_2, ..., f_7)$, in which \mathbf{F}_j is the average wavelet value of all pixels in superpixel j across 3 layers. This feature is represented as $\mathbf{F} \cdot Sp_j$ is the average location of all pixels in superpixel j.

C. Selection of neighboring and similar superpixels

In order to reduce the computational complexity, the superpixel is applied in this paper. The feature of neighboring and similar superpixles has been studied in [28]. The chosen superpixle j is represented in red in Fig. 2(a). According to

the Euclidean distance, the nearest superpixels of superpixel j are labeled in blue in Fig.2(b). The neighboring superpixels are located around the superpixel j, which is shown in blue in Fig. 2(c). Calculating the Euclidean distance of the wavelet feature between the superpixel j and the nearest superpixels p, we can select the most similar superpixles for each superpixel j, which are labeled in yellow in Fig.2(c). The most similar superpixels are out side of neighborhood of the chosen superpixel, and are close to the chosen superpixel. For a chosen superpixel, the influence of the neighboring and similar superpixles is considered, and these superpixels construct the nearest set of a chosen point.



Fig.2. (a) A chosen superpixel, (b) The nearest superpixels of the chosen superpixel, (c) Neighboring superpixels and Similar superpixels.

IV. SUPERPIXEL-BASED FCM WITH OPTIMIED INFLUENTIAL DEGREE

A. Fuzzy c-means clustering

FCM is a method to partition a set of data point into corresponding cluster by membership. Let $x = \{x_1, x_2, ..., x_N\}$ be a set of data points. FCM can let a data point belongs to one or more clusters. The conventional FCM was developed to minimize the objective function as follows:

$$J(U,V) = \sum_{i=1}^{C} \sum_{j=1}^{N} u_{ij}^{m} \|x_{j} - v_{i}\|^{2}$$
(1)
s.t. $\sum_{i=1}^{C} u_{ij} = 1, \quad j = 1, 2, ..., N$

where $u_{ij} \in [0,1]$ is membership, and $m \in [1,+\infty)$. $V = \{v_1, v_2, ..., v_c\}$ is the centroids of data. u_{ij} and v_i can be updated by the following algorithm:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{d_{ij}}{d_{kj}}\right)^{\frac{2}{m-1}}}$$
(2)

$$v_{i} = \frac{\sum_{j=1}^{N} u_{ij}^{m} x_{j}}{\sum_{j=1}^{N} u_{ij}^{m}}$$
(3)

where d_{ij} is the Euclidean distance between the i - th centroid and the j - th data, $d_{ij} = ||v_i - x_j||, i = 1, 2, ..., C$.

The conventional FCM algorithm is sensitive to noise, and thus may not obtain the ideal segmentation results. The main reason is that the method does not take the spatial contextual information in image processing. In order to improve this situation, we incorporate neighboring and similar superpixel into membership function.

B. Superpixel-based FCM with optimized spatial information

In order to make the above formulas feasible to superpixel, we replace data set $x = \{x_1, x_2, ..., x_N\}$ with superpixel set $\{Sp_j\}_{j=1}^{N_i}$. The above formula shows that the result of segmentation is mainly determined by membership and the fuzzy centroids. The modified V is defined by

$$\mathbf{v}_{i} = \frac{\sum_{j=1}^{N_{s}} (u_{ij}^{'})^{m} \mathbf{F}_{j}}{\sum_{j=1}^{N_{s}} (u_{ij}^{'})^{m}}$$
(4)

where v_i represents the *i*-*th* element of matrix V, N represents the number of superpixel.

The proposed approach uses neighboring and similar information to establish the spatial model. The model is described as follows:

$$u_{(D)ij} = \sum_{k=1}^{S} u_{ik} d_{jk} / \sum_{k=1}^{S} d_{jk}$$
(5)

$$u_{(T)ij} = \sum_{k=1}^{S} u_{ik} X_{jk} / \sum_{k=1}^{S} X_{jk}$$
(6)

where $d_{jk} = \exp(-\|Sp_j - Sp_k\|)$ is the relative distance between superpixel *j* and superpixel *k*, and the wavelet feature distance between superpixel *j* and superpixle *k* is $X_{jk} = \exp(-\|\mathbf{F}_j - \mathbf{F}_k\|)$. The total number of neighboring superpixels and similar superpixels corresponding to superpixel *j* is *S*. The modified membership is as follow:

$$\begin{cases} h_{ij} = \alpha_1 u_{(T)ij} + \alpha_2 u_{(D)ij} \\ \alpha_1 + \alpha_2 \le 1 \end{cases}$$
(7)

$$u'_{ij} = u_{ij}h_{ij} / \sum_{c=1}^{C} u_{cj}h_{cj}$$
(8)

where α_1 and α_2 are influential degrees. The objective function is described as follows:

$$J_m(U,V) = \sum_{i=1}^{C} \sum_{j=1}^{N_s} (u_{ij}^{*})^m \left\| \mathbf{F}_j - \mathbf{v}_i \right\|^2$$
(9)

C. Optimizing influential degrees

Particle swarm optimization (PSO) is a stochastic optimization algorithm inspired by the social behavior of bird flock, and proposed for the first time by Kennedy and Eberhart [29]. As a relatively new evolutionary algorithm,

which has developed in the past few years and many research achievements related to it have been published. The PSO algorithm is easy to understand and can be implemented in a few lines of code.

In PSO, each particle is a potential solution, and the swarm is composed of particles. The problem solution space is formulated as a searching space. Each position in the searching space corresponds to a candidate solution of the problem. Each particle is to find the best position in the searching space. The best position coincides with the best fitness value called "pbest". For all the particles, a best value is a global best position and is called "gbest", which is tracked by particle swarm optimizer. During flight each particle adjusts its position in accordance with its own experience and the experience of neighboring particles.

In this algorithm, $\alpha_{id} = (\alpha_{i1}, \alpha_{i2})$ represent the i-th particle, and it presents influential degrees (α_1, α_2) , we know that (α_1, α_2) is the position of the i-th particle. $V_{id} = (v_{i1}, v_{i2})$ represents the velocity of the i-th particle. $pbest_{id} = (p_{i1}, p_{i2})$ is the best position of the particles, and $gbest_{id} = (g_{i1}, g_{i2})$ is the best position of the swarm.

$$\begin{cases} V_{id}^{(k+1)} = wV_{id}^{(k)} + c_1 \times Rand(.) \times (pbest_{id}^{(k)} - \alpha_{id}^{(k)}) \\ + c_2 \times rand(.) \times (gbest_{id}^{(k)} - \alpha_{id}^{(k)}) \\ \alpha_{id}^{(k+1)} = \alpha_{id}^{(k)} + V_{id}^{(k+1)} \end{cases}$$
(10)

where *w* is the inertia weight, c_1 and c_2 are acceleration factors; *Rand*(.) and *rand*(.) generate random values, which distribute in the interval from 0 to 1; *k* represents the iteration number.

In our experiments, the number of particle is 30, the largest evolution number is 30, and c_1 and c_2 are equal to 2.

V. IMPLEMENTATION OF THE PROPOSED METHOD

Initialization: The number of clustering categories is *C*, the m = 2 represents the degree of fuzziness, the thresholds are $\delta = 0.001\%$ and $\varepsilon = 0.1\%$, the centroid *V* is randomly set, and initially α_1, α_2 .

- Step 1. By over-segmentation using TurboPixels to obtain the superpixels of the input image.
- Step 2.Obtain the wavelet feature **F** of each superpixel by performing wavelet transform on the input image.
- Step 3. Find neighboring superpixels and similar superpixels for each superpixel. The number of similar superpixels is S_N , where $S_N = \log(X \times Y)$, X and Y represent the width and height of image, respectively.
- Step 4. Accoring to (5)-(8), obtain the membership of each superpixel and the updated membership.
- Step 5. According to (4), get the cluster centroids.
- Step 6. Repeat Step 4 and Step 5 until $\max(|U^{(k)} U^{(k+1)}| / U^{(k)}) \le \varepsilon \text{ is met.}$
- Step 7. Using the method of PSO to optimize the influential degrees, i.e. α_1 and α_2 . If

$$|J_m(U,V)^{(t)} - J_m(U,V)^{(t+1)}| / J_m(U,V)^{(t)} \le \delta$$
 is

satisfied, or the maximum of the evolutionary generation reaches, the iteration is terminated; otherwise, return to Step 4. Fig.3 presents the steps of the proposed method. When the proposed method is

conducted in MATLAB on a Pentium (R) Dual-Core E5300 2.6GHz PC with 2GB memory and the Windows 7 operating system, the average CPU time required for extracting feature of superpixels and segmenting an image of size 256×256 is about 340s.



Fig.3. The implementation of the proposed method

VI. EXPERIMENTAL AND ANALYSIS

In this paper, real SAR images have been carried out to test our proposed method. In this experiment, we use wavelet feature F to perform SAR image segmentation. SAR1 is the size of 550×400, Theodore Roosevelt Memorial Bridge, Washington, D.C. Ku-Band Radar, 1-m resolution. SAR2 is the size of 470×450, China Lake Airport, California, Ku-Band Radar, 3-m resolution. SAR3 is of 512×304 pixels in size. In comparison, FCM method, Nyström method and K-means clustering method are used for segmentation. These methods use wavelet feature F. In experiments, because the optimal α_1 and α_2 of several images of the same class are relatively similar values, we initially set the both values with the optimal value respectively, which will be benefit for the rapid convergence of the objective function and the outstanding segmentation performance. The initial value of α_1 and α_2 is 0.16 and 0.20 respectively. All segmentation results are shown in Fig.4, Fig.5 and Fig.6; Fig. 4(a), 5(a) and 6(a) are the original image; Fig. 4(b), 5(b) and 6(b) are FCM segmentation results; Fig. 4(c), 5(c) and 6(c) show Nyström segmentation results; Fig. 4(d), 5(d) and 6(d) present K-means segmentation results. As Figures (b), (c) and (d) show that there are many incorrectly segmented regions, and these compared methods can not effectively segment the different regions. It is obvious that the Figures

(b), (c) and (d) can not get ideal results. The main reason is that spatial constrains are not considered. Fig. 4(e), 5(e) and 6(e) are the segmentation results of the proposed method, and the results show that proposed method can accurately divide an image into different regions. The result of Fig. 4(e) shows that the bridge, lawn and river are divided correctly. In Fig. 5(e), the living area, the runway and other area are accurately segmented. In Fig. 6(e), the airplane, the runway and lawn are accurately segmented. The neighboring and similar superpixels promote this outstanding performance, and the optimizing process also contributes to this performance. Fig. 7 shows the relationship between segmentation results and evolutionary generation. With the increase of evolutionary generation, the segmentation results become more desirable.

VII. CONCLUSIONS

In this paper, a superpixel-based FCM clustering with optimized spatial information is explored. A set of wavelet feature is introduced into the SAR image segmentation. In the clustering process, we take the influence of neighboring and similar superpixles into consideration. The outstanding segmentation results are benefit from optimized influential degrees of spatial information. The experimental results show that the validity and feasibility of the proposed method.



(d) (e) Fig. 4. Real SAR1 image segmentation. (a) Original image, (b) FCM result, (c) Nyström result, (d) K-means result and (e) our result.



(a) SAR2







Generation

Fig. 7.The objective function value of our method for segmenting four real SAR images.

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