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Research Article

SAR Image Segmentation Based on Improved Grey Wolf Optimization Algorithm and Fuzzy C-Means

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An improved Grey Wolf Optimization (GWO) algorithm with differential evolution (DEGWO) combined with fuzzy C-means for complex synthetic aperture radar (SAR) image segmentation was proposed for the disadvantages of traditional optimization and fuzzy C-means (FCM) in image segmentation precision. In the process of image segmentation based on FCM algorithm, the number of clusters and initial centers estimation is regarded as a search procedure that searches for an appropriate value in a greyscale interval. Hence, an improved differential evolution Grey Wolf Optimization (DE-GWO) algorithm is introduced to search for the optimal initial centers; then the image segmentation approach which bases its principle on FCM algorithm will get a better result. Experimental results in this work infers that both the precision and efficiency of the proposed method are superior to those of the state of the art.

1. Introduction

Image segmentation plays a very important role in the interpretation and understanding of SAR images. It has received an increasing amount of attention and therefore hundreds of approaches have been proposed over the last few decades [1]. At present, SAR images have been widely used in hydrology, remote sensing, military, and other fields, to obtain accurate information of remote sensing image which is the key for better application. Among them, SAR image segmentation is an important step to understand the image information. The SAR image is a coherent image with a complex background. Because of the influence of speckle noise, the image quality is reduced. Some theories have been applied in image segmentation, such as the level set [2], Markov random field [3], based on textons [4], multiscale [5], threshold method [6], validity-guided (re)clustering (VGC) algorithm [7], and fuzzy C-means clustering (FCM) algorithm [8], which have achieved good segmentation results and have a good reference function. In these theories, Fuzzy C-means (FCM) algorithm is the most classical method of fuzzy clustering. It has advantages of conforming to human's cognitive characteristics, easy implementation, simple description, and good segmentation effect [9]. The FCM algorithm for improving the validity of fuzzy clustering [10] and the semisupervised c-means algorithms [11] have also achieved good segmentation results in the magnetic resonance image segmentation experiment. In recent years, many scholars have proposed lots of SAR image segmentation method combined with FCM algorithm. For instance, modified FCM SAR image segmentation method is based on GLCM feature [12], multiresolution analysis of wavelet [13], kernel theory [14], etc.

In recent decades, there is a growing significant attention for nature-inspired computation, among which the two most popular algorithms are swarm intelligence (SI) and Evolutionary Algorithms (EAs). SI, like Ant Colony (ACO) algorithm [15], Artificial Fish Swarm (AFS) [16] algorithm, Artificial Bee Colony (ABC) algorithm [17], and Particle Swarm Optimization (PSO) [18] algorithm, is enlightened by animal foraging behavior. EAs, such as Genetic Algorithm (GA) [19], Evolutionary Programming (EP) [20, 21], and Evolution Strategy (ES) [22, 23], are inspired from natural selection and survival of the fittest in the natural world. Owing to the simplicity and flexibility of EAs and SI, various methods are developed for image engineering, which almost

cover all related fields, including image enhancement, image denoising, super resolution restoration, image registration, digital watermarking, edge detection, image fusion, image compression, texture classification, image retrieval, image recognition, and image segmentation [24–37]. Similar to the existing nature-inspired algorithms, a new mimic algorithms on the basis of the behavior of grey wolves was proposed in the last few years. Grey Wolf Optimization (GWO) algorithm has been clearly proved to be better than Particle Swarm Optimization (PSO), Gravitational Search Algorithm (GSA), Differential Evolution (DE), Evolutionary Programming (EP), and Evolution Strategy (ES), which are well-known metaheuristics. [38]. As a powerful optimization tool, GWO algorithms have been utilized in complex function optimization, parameter identification, robot path planning, classical engineering design problems, etc. However, its application in image segmentation is seldom studied. Regarding the insufficient diversity of the wolves in some cases, the agents of GWO still may face the risk of stagnation in local extremum. This problem may often appear when the conventional GWO cannot perform a smooth transition from exploration to exploitation potential by more iteration [39]. This paper employs DEGWO algorithm to estimate the FCM algorithm initial centers for SAR image segmentation. An improved modified GWO algorithm combined with differential evolution algorithm is proposed for solving the global problems.

The remaining of this paper is organized as follows. Section 2 makes a brief summary of the features of grey wolves and describes the working mechanism of GWO algorithm. Section 3 gives the definition of FCM algorithm and introduces a useful method to estimate the number of clusters. Section 4 shows how to employ DE-GWO-FCM algorithm to the segmentation of SAR images. Some typical experiments on simulated image and real SAR images are carried out in Section 5, where both segmented images and segmenting precision are compared among some nature-inspired methods. Finally, Section 6 summarizes our work and the future prospects.

2. GWO Algorithm

As a kind of social animal, grey wolves live in colonies and exhibit many features. This algorithm is inspired by the social hierarchy and hunting strategies of grey wolves in the wild. It can be regarded as a robust swarm-based optimizer [40–45]. The following discusses its working mechanism.

In GWO, A complete wolf pack consists of alpha (α), beta (β), delta (δ), and omega (ω). The best wolves should be treated as α and β and δ assist other wolves (ω) in exploring more favorable regions of solution space. The alphas are leaders of the pack, and they are responsible for making decisions. The alphas decisions are dictated to the pack. The betas are subordinate wolves that can be either male or female, and they help the alpha in decision making or other activities. The best candidate to be the alpha mostly may be betas. The omega wolves are scapegoat of pack, they have to submit to all the other dominant wolves. The deltas have to submit alphas and betas, but they dominate the omega. Scouts, sentinels, elders, hunters, and caretakers belong to this category [46].

In conventional GWO, in order to mathematically model encircling behavior, (1)–(4) are used [38].

$$\vec{D} = \left|\vec{C} \cdot X_P(t) - \vec{X}(t)\right|, \tag{1}$$

$$\vec{X}(t+1) = X_P(t) - \vec{A} \cdot \vec{D}, \tag{2}$$

where t is iteration, $\vec{A}$ and $\vec{C}$ are random vectors, $\vec{X}$ indicates the position vector of a grey wolf, and $\vec{X}_P$ is location of the prey. The random $\vec{A}$ and $\vec{C}$ vectors are calculated as [38]

$$\vec{A} = 2a \cdot r_1 - \vec{a}, \tag{3}$$

$$\vec{C} = 2\vec{r}_2, \tag{4}$$

where components of $\vec{a}$ are a temporal parameter and linearly decreased from 2 to 0 over the course of iterations, and r1, r2 are random vectors in $[0, 1]$. Grey wolves are capable of identifying the position of the prey and to enclose them. Alpha is the guide in the hunting process. The beta and delta might contribute to hunting as well in some conditions. According to the difference in the rank of the wolves, in order to have better knowledge about the potential location of prey, the alpha, beta, and delta are assumed as the best, the second best, and the third best candidate solution, respectively. The first three best candidate solutions obtained can lead other hunters (including the omegas) to update their positions according to the position of the best search agents [40]. So the states of the updated solutions of wolves are determined by [38]

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}, \tag{5}$$

where t shows recent iteration and $\vec{X}_1, \vec{X}_2, \vec{X}_3$ denote the final state of the updated solutions, they are defined as in (6)–(8), respectively.

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \left(\vec{D}_\alpha\right), \tag{6}$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \left(\vec{D}_\beta\right), \tag{7}$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \left(\vec{D}_\delta\right), \tag{8}$$

where $\vec{X}_\alpha$, $\vec{X}_\beta$, and $\vec{X}_\delta$ denote the locations of alpha, beta, and delta, respectively, in the swarm at a given iteration t, $\vec{A}_1$, $\vec{A}_2$, and $\vec{A}_3$ show random vectors, and $\vec{D}_\alpha$, $\vec{D}_\beta$, and $\vec{D}_\delta$ are defined using (9)-(11), respectively.

$$\vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right|, \tag{9}$$

$$\vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right|, \tag{10}$$

$$\vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right|, \tag{11}$$

where $\vec{C}_1$, $\vec{C}_2$, and $\vec{C}_3$ are defined as representing random vectors.

Input: MaxIter Number of iterations for optimization,
n Number of grey wolves in the pack.
1: Initialize a population of n grey wolves positions randomly.
2: **While** Stopping criteria not met **do**
3: Calculate the fitness values based on α, β, δ positions
4: Update Alpha, Beta, and Delta
5: Update a; A; and C
6: Update the Position of search agents including omegas
7: **end**
Output: x_α Optimal grey wolf position, $fit(x_\alpha)$ Best fitness value.

Algorithm 1: Algorithm GWO.

The updating of parameter a controls the tradeoff between exploration and exploitation in the grey wolf optimizer (GWO). Parameter a is linearly decreased in each iteration to range from 2 to 0 according to

$$a = 2\left(1 - t\frac{1}{MaxIter}\right), \tag{12}$$

where MaxIter is the total number of iterations allowed for the optimization and t is the iteration number. Algorithm GWO outlines the Grey Wolf Optimization (GWO) algorithm in Algorithm 1.

3. The Adaptive FCM Algorithm

Fuzzy c-mean, proposed by Bezdek [47], is one of the main techniques of unsupervised machine learning algorithm which is widely applied to the image segmentation [48]. Fuzzy clustering has been proved to be very well suited to deal with the imprecise nature of geographical information including remote sensing data [49]. It has been effectively used in large-scale data analysis, data mining, vector quantization, image segmentation, and pattern recognition and has important theoretical and practical value. According to the fuzzy clustering framework, each cluster is a fuzzy set and each pixel in the image has a membership value associated with each cluster, ranging between 0 and 1, measuring how much the pixel belongs to that particular cluster [50]. In the last decade, many different new optimization methods of fuzzy clustering algorithms have been proposed, such as using random projection and independent component analysis to improve fuzzy c-means clustering [51, 52] and the metaheuristic algorithms combined with FCM algorithm to improve the effect of clustering [53, 54], etc.

Suppose $X = \{X_1, X_2, \cdots X_n,\}$, which refers to a set of n data points (n pixels in an image), and the objective function of FCM algorithm is as follows:

$$J_m(U,V) = \sum_{i=1}^{c}\sum_{k=1}^{n}(u_{ik})^m d_{ik}^2(x_k, v_i), \tag{13}$$

$$d_{ik} = \|x_k - v_i\| = (x_k - v_i)^T(x_k - v_i), \tag{14}$$

where c is number of clusters, u_{ik} denotes the membership degree of x_k in the ith cluster. Meanwhile the value of u_{ik} is inside $[0,1]$, m is the weighting exponent on each fuzzy membership and is generally a value of 2, v_i is the ith cluster center, d_{ik} is the Euclidean distance between cluster center v_i and object x_k, and $\|\cdot\|$ denotes the Euclidean norm. The membership function represents the probability that a pixel belongs to a specific cluster when pixels far from the cluster centers possess low membership values and pixels in the local neighborhood of cluster centers possess high membership value, and a minimization criterion is accomplished [49]. While the FCM algorithm is based on the initial parameter set, determine the minimum objective function $J_m(U,V)$ by iterative process. U and V are defined as in

$$u_{ik} = \begin{cases} \dfrac{1}{\sum_{j=1}^{c}\left(d_{ik}/d_{jk}\right)^{2/(m-1)}}, & d_{jk} \\ 1, & d_{jk} = 0,\ j = k \\ 0, & d_{jk} = 0,\ j \neq k, \end{cases} \tag{15}$$

$$v_i = \frac{\sum_{k=1}^{n}(u_{ik})^m x_k}{\sum_{k=1}^{n}(u_{ik})^m}, \tag{16}$$

where u_{ik}, v_i denote the membership function and cluster centers, respectively.

FCM algorithm can effectively cluster analysis, but the number of clusters needs to be given first. The purpose of clustering is to classify data and try to make the distance between classes as large as possible, and the distance between data points in the class is as small as possible [55]. In order to get the adaptive number of clusters c, adaptive function of c is summarized below.

$$\overline{x} = \frac{\sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^m x_j}{n}, \tag{17}$$

$$L(c) = \frac{\sum_{i=1}^{c}\left(\sum_{j=1}^{n}u_{ij}^m\right)\|v_i - \overline{x}\|^2/(c-1)}{\sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^m\|\overline{x} - v_i\|^2/(n-c)}, \tag{18}$$

where $\overline{x}$ is central vector of the total sample and $L(c)$ is adaptive function of the number of clusters c. The molecule of $L(c)$ denotes the distance between classes, and the denominator represents the distance between data points in the class and the center. An appropriate classification usually obtains a high

Input: Image data,
Initialization Parameter: c=2, ε >0, $L(1)$=0, k=0, $V^{(0)}$.
While Stopping criteria not met **do**
  Calculate $u_{ij}^{(k)}$,
  Calculate $V^{(k+1)}$,
  If $\|V^{(k+1)} - V^{(k)}\| \leq \varepsilon$
    Break
  else
    $k = k + 1$
  end if
  Calculate $L(c)$,
  If $L(c-1) > L(c-2)$ **&&** $L(c-1) > L(c)$
    Break
  else
    $c = c + 1$
  end if
end while
Output: U Partition matrix, v Center matrix, c Number of clusters, L Adaptive function of c.

Algorithm 2: Algorithm improved FCM.

value of function $L(c)$. The pseudocode of the algorithm is presented in Algorithm 2.

4. The Modified FCM with DE-GWO-FCM Algorithm

Differential Evolution (DE) algorithm is a heuristic random search algorithm based on group differences. Compared with the evolutionary algorithm, DE preserves the global search strategy based on population and reduces the complexity of genetic operation. At the same time, the unique memory ability of DE enables it to dynamically track the current search situation, to adjust its search strategy. It has strong global convergence and robustness, does not need the aid of the feature information of the problem, and is suitable for solving some optimization problems in the complex environment which cannot be solved by conventional mathematical programming methods.

The conventional GWO algorithm updates its hunters towards the prey based on the condition of the alpha, beta, and delta (leader wolves) [39]. However, regarding the insufficient diversity of the wolves in some cases, the population of GWO is still inclined to stagnate in local extremum, and the problems of immature convergence still exist. To avoid the above-mentioned concerns, DE can assist GWO to obtain the global optimal solution. Using this concept, it can be ensured that GWO can perform global search more effectively.

In order to achieve the best clustering effect, the objective function of fuzzy c-means should be minimum [56], but the random initial clustering center has a great influence on the algorithm in this process. To solve this problem, DE-GWO can be used to search a set of global optimal centers. The accuracy of FCM clustering can be significantly improved in this way, so as to achieve better clustering results.

4.1. Fitness Function Setting. Fitness function is a benchmark set by objective function, which is used to calculate the fitness of individual wolves. The smaller it means, the better the individual is, and the bigger it means, the worse the individual is. Combining DE-GWO and FCM algorithm, the fitness function of DE-GWO is defined as in

$$fitness = J_{FCM}, \tag{19}$$

The better the effect of clustering, the smaller the value of $fitness$ of DE-GWO. By iterating the α, β, and δ positions in the algorithm, the best fitness function α can be obtained and set α as the initial centers of FCM.

4.2. Population Initialization. According to common methods of swarm intelligence algorithm initialization, in order that the population in the algorithm has diversity and randomness, the initialization formula is set as follows:

$$\left\{X_i(0) \mid x_{i,j}^L \leq x_{i,j}(0) \leq x_{i,j}^U;\ i = 1, 2, \cdots, NP;\ j = 1, 2 \cdots, D\right\}, \tag{20}$$

$$x_{i,j}(0) = x_{i,j}^L + \text{rand}(0,1)\left(x_{i,j}^U - x_{i,j}^L\right), \tag{21}$$

where NP represents the size of the grey wolf population, D denotes the dimension of the grey wolf population, rand(0, 1) is a random value inside [0, 1], and $x_{i,j}^L$ and $x_{i,j}^U$ are the lower and upper bounds of the j dimension, respectively.

4.3. Mutate. The DE algorithm uses the difference strategy to realize the individual variation. The common difference strategy is to randomly select two different individuals in the population, and after the vector difference is scaled,

the vectors are combined with the individuals which to be changed.

$$V_i(g+1) = X_{r1}(g) + F(X_{r2}(g) - X_{r3}(g)), \quad (22)$$

where r1, r2, and r3 are random values in [1, NP], F is called the scaling factor, which is a constant, and g denotes g-th generation.

4.4. Crossover. The purpose of cross operation is to select individuals randomly, because differential evolution is also a stochastic algorithm. The way of crossover operation is defined as follows:

$$U_{i,j}(g+1) = \begin{cases} V_{i,j}(g+1) & if \ \text{rand}(0,1) \le CR \\ x_{i,j}(g) & otherwise, \end{cases} \quad (23)$$

where CR is cross probability, and a new individual is randomly generated by a probability.

4.5. Choice. In DE, greedy selection strategy is adopted, that is, to choose better individuals as new individuals.

$$X_i(g+1) = \begin{cases} U_i(g+1) & if \ f(U_i(g+1)) \le f(X_i(g)) \\ X_i(g) & otherwise, \end{cases} \quad (24)$$

4.6. Update. According to the search method of GWO, we update the location of wolf by encircling, hunting, and attacking. Mutation, crossover, and selection take place in the position update process of wolves. During the iteration process, we get the best grey wolf position x_α. By summarizing the above process, the update process of DE-GWO-FCM algorithm flow is as follows.

Step 1. Determine the number of clusters c, the initial swarm size NP, number of iterations T, lower and upper bound of scaling factor, and crossover probability.

Step 2. Randomly generate the initial parent population, the mutant population, and the offspring population of wolves, respectively, and initialize the parameters a, A, and C.

Step 3. Compute the fitness of each wolf, determine the alpha, beta, and delta wolves in the parent population.

Step 4. Update a; A; and C by (12) and (3)-(4).

Step 5. According to (5), update the position of current wolves and compute the fitness of each wolf in the parent population.

Step 6. Generate mutated population.

Step 7. Generate offspring population and crossover, and compute the fitness of each wolf in the offspring population.

Step 8. If the offspring are superior to the parent, the parent population is updated.

Step 9. Reconfirm the alpha, beta, and delta wolves in the parent population, T+T+1.

Step 10. If one gets the best x_α, end the search process; otherwise, continue executing Step 3~Step 9 until the end.

After obtaining the best number and center of clusters, SAR image can be segmented by FCM algorithm. Algorithm DE-GWO-FCM outlines the differential evolution Grey Wolf Optimization algorithm. To have a better description of the DE-GWO-FCM, the pseudocode of the algorithm is presented in Algorithm 3.

4.7. Adaptive Fuzzy c-Means Clustering Algorithm Based on DE-GWO Optimization. Through the analysis of (17)-(18), an adaptive image segmentation method is proposed. The algorithm adaptively searches the optimal number of clusters and initial centers, and it is not easy to fall into local extreme points, thus obtaining the optimal classification results. In summary, the process of ADE-GWO-FCM algorithm flow is as follows:

(1) Initialization, determine the fuzzy exponent m, lower and upper bound of scaling factor, crossover probability, initial swarm size NP, and the number of initial clusters c=2 (default classification number>=2)

(2) Image clustering analysis by DE-GWO-FCM method

(3) Calculate the cost function L based on (17)-(18). If the value of a begins to become smaller, turn to fourth step; otherwise, set $c+1 \longrightarrow c$, and turn to third step

(4) Set $c-1 \longrightarrow c$, calculate initial center by DE-GWO-FCM, and get the final segmentation image

5. Experimental Results and Performance Analysis

5.1. Segmentation Results on Simulated Image. All the images and data utilized in this work are available [57]. In order to compare the efficiency of our method with others, segmentation methods based on FCM, GA-FCM, and ABC-FCM algorithm are used to segment some typical images. Experimental results are given in Figure 1, covering a noise-free optical image, an optical image polluted by synthetic noise (composed of salt and pepper noise with density 0.02, speckle noise with variance 0.005, and Gaussian noise with mean 0 and variance 0.01), and a real SAR image. In this experiment, for GA algorithm, the population size is 20, the maximum number of iterations is 100, binary digits of variable are 16, the crossover probability is 0.7, and the mutation probability is 0.01. In ABC algorithm, the population size is 20, the maximum number of iterations is 100, and the number of restrictions to give up the search is 20, and the lower and upper bounds are 0 and 255, respectively. In DE-GWO algorithm, the lower bound of scaling factor is 0.1, the upper bound of scaling factor is 0.9, the crossover probability is 0.1, the population size is 20, and the maximum iteration is 100. Because when the number of optimal clusters is not reached, the more the number of clusters is, the longer

Input: X Image data
1: Determine the initial swarm size NP, the number of initial clusters c, iterations T, lower and upper bound of scaling factor and crossover probability.
2: Randomly generate the initial the parent population, mutant population and offspring population of wolves respectively, and initialize the parameter a; A; and C.
3: Compute the fitness of each wolf in the parent population
4: **Set** X_α to be the best wolf, **Set** X_β to be the second best wolf, **Set** X_δ to be the third best wolf
5: **While** (Stopping criteria not met) or (t<T) **do**
6: **for** each wolf in the parent population
7: Update a; A; and C
8: Update the position of current wolves by Eq. (5)
9: Compute the fitness of each wolf
10: **end for**
11: Generate Mutated population
12: Generate offspring population and crossover
13: **for** each wolf in the offspring population
14: Crossover
15: Compute the fitness of each wolf
16: **end for**
17: **If** the offspring are superior to the parent
18: Update the parent population
19: **end if**
20: Update X_α, X_β and X_δ
21: t=t+1
22: **end while**
23: **Return** X_α, X_β and X_δ
24: $X_\alpha \longrightarrow$ **FCM**
Output: U Partition matrix, target image

Algorithm 3: Algorithm DE-GWO-FCM.

the algorithm runs, the clearer the segmented image is. In order to facilitate the analysis and comparison of algorithm performance, we set the same number of clusters in several algorithms.

In Figure 1, it is clear to see that, under the same number of clusters, the FCM algorithm has the fastest convergence rate because of its simple structure; however, because the initial center is randomly generated, the accuracy is relatively low. The accuracy of the GA-FCM and ABC-FCM algorithms is better than FCM, but effects of their convergence are not stable. The proposed algorithm is relatively complex; it is a hybrid algorithm combining differential evolution and GWO, but the speed of the proposed algorithm is similar to that of ABC-FCM, the algorithm has been steadily converging, and the variant machine can avoid the algorithm falling into the local minimum.

In Figure 2, this is the convergent graph of the four algorithms. Because these four algorithms use the value function of FCM algorithm as the search basis, under the same clustering number, the smaller the value of FCM value function, the better the search performance of the algorithm. It is clear to see that, under the same number of clusters, compared with the contrast algorithm, the value of the FCM function obtained by the proposed method is the smallest.

In the field of image segmentation, there are many evaluation criteria. Precision, recall, and F-measure are widely used and approved. Precision rate represents the proportion of pixels detected by the segmentation algorithm in the whole region. Recall rate indicates the degree of agreement between the number of pixels detected by the segmentation algorithm and the area in the artificial annotation true value (GT). The F-measure value is the harmonic mean synthesized by precision and recall, which can reflect the comprehensive quality of image segmentation. The area of the given annotation is represented by G. The pixel area detected by the algorithm is represented by S. The formula is defined as follows:

$$Precision = \frac{G \cap S}{S}, \tag{25}$$

$$Recall = \frac{G \cap S}{G}. \tag{26}$$

Most of the time, not only the high accuracy rate but also the high recall rate is needed, so F-measure is used as the evaluation mechanism of the overall performance.

$$F_\beta = \frac{\left(1 + \beta^2\right) \bullet Precision \bullet Recall}{\beta^2 \bullet Precision + Recall}. \tag{27}$$

Parameter F_β is the most common F1-measure standard when a equals 1.

According to the commonly used image segmentation evaluation criteria, the proposed algorithm and existing

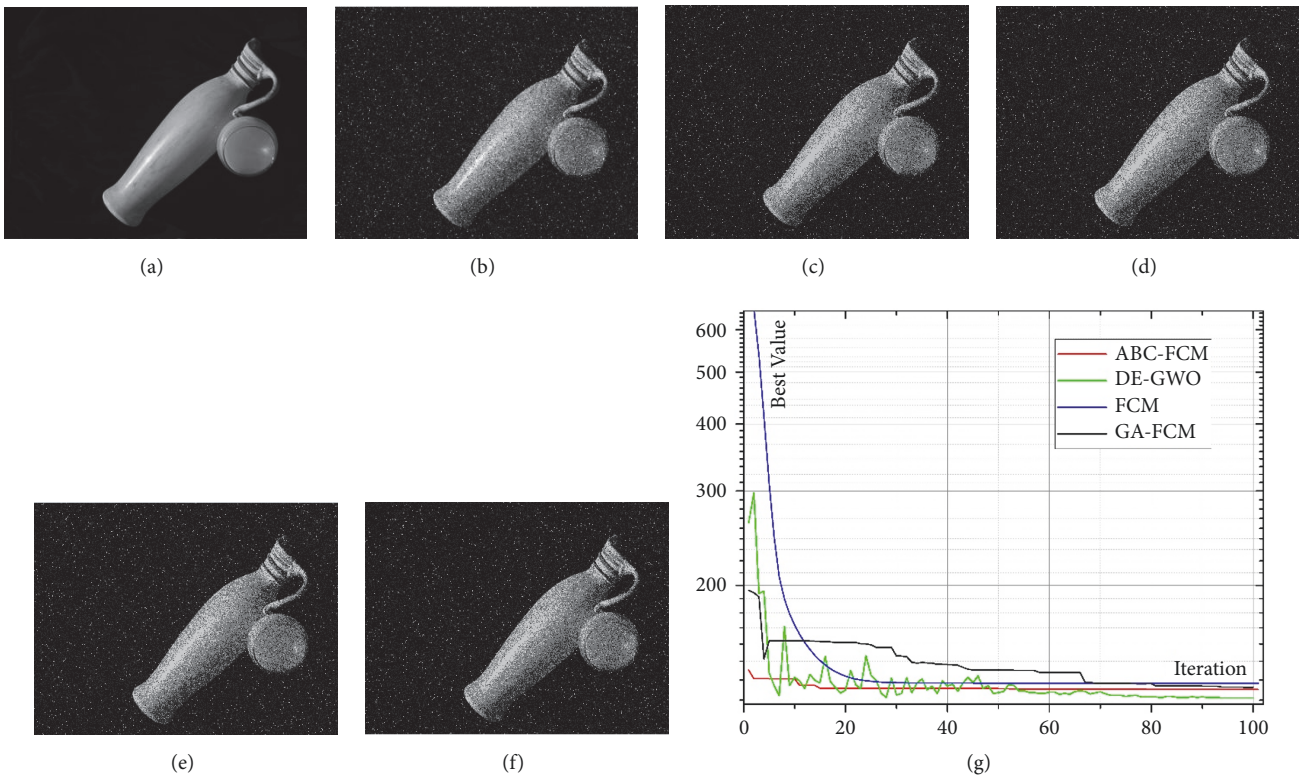

Figure 1: Comparative experiments on image segmentation. (a) Noise-free optical image; (b) optical image polluted by synthetic noise; (c) segmented image by DE-GWO; (d) segmented image by ABC-FCM; (e) segmented image by GA-FCM; (f) segmented image by FCM; (g) best value of the four approaches.

Table 1

category	Precision	Recall	F1-measure
DE-GWO-FCM	0.9382	0.7770	0.8500
ABC-FCM	0.9253	0.7654	0.8378
GA-FCM	0.9296	0.7385	0.8231
FCM	0.8998	0.7414	0.8130

segmentation algorithms are evaluated from the aspects of segmentation accuracy, recall rate, and overall accuracy index. The results of the several experiments are shown in Table 1.

Combined with the experimental results, when the image contains synthetic noise, the overall accuracy of the algorithm is better than other comparison algorithms.

5.2. Segmentation Results on Real SAR Images. This section describes the application of our method to real SAR images. Figure 3 shows the segmentation results of the proposed algorithm and the contrast algorithms for real SAR images.

According to Figure 3, all the four algorithms can segment the edge accurately, but the proposed algorithm is better because of the better global search ability.

6. Conclusion

In this paper, a robust FCM algorithm based on improved adaptive differential evolution Grey Wolf Optimization is proposed. In essence, the segmentation effect of our method owes to GWO algorithm, which has an outstanding convergence performance. First, in order to get the best clustering number, we classify the data and maximize the distance between the classes as far as possible, and the distance between the data points within the class is as small as possible. In the GWO algorithm, the differential evolution theory is introduced, and the population variation is used to avoid the local optimal solution of the GWO algorithm. Through the adaptive differential evolution GWO algorithm, we get the initial centers and the number of clusters and put them into the FCM algorithm to complete

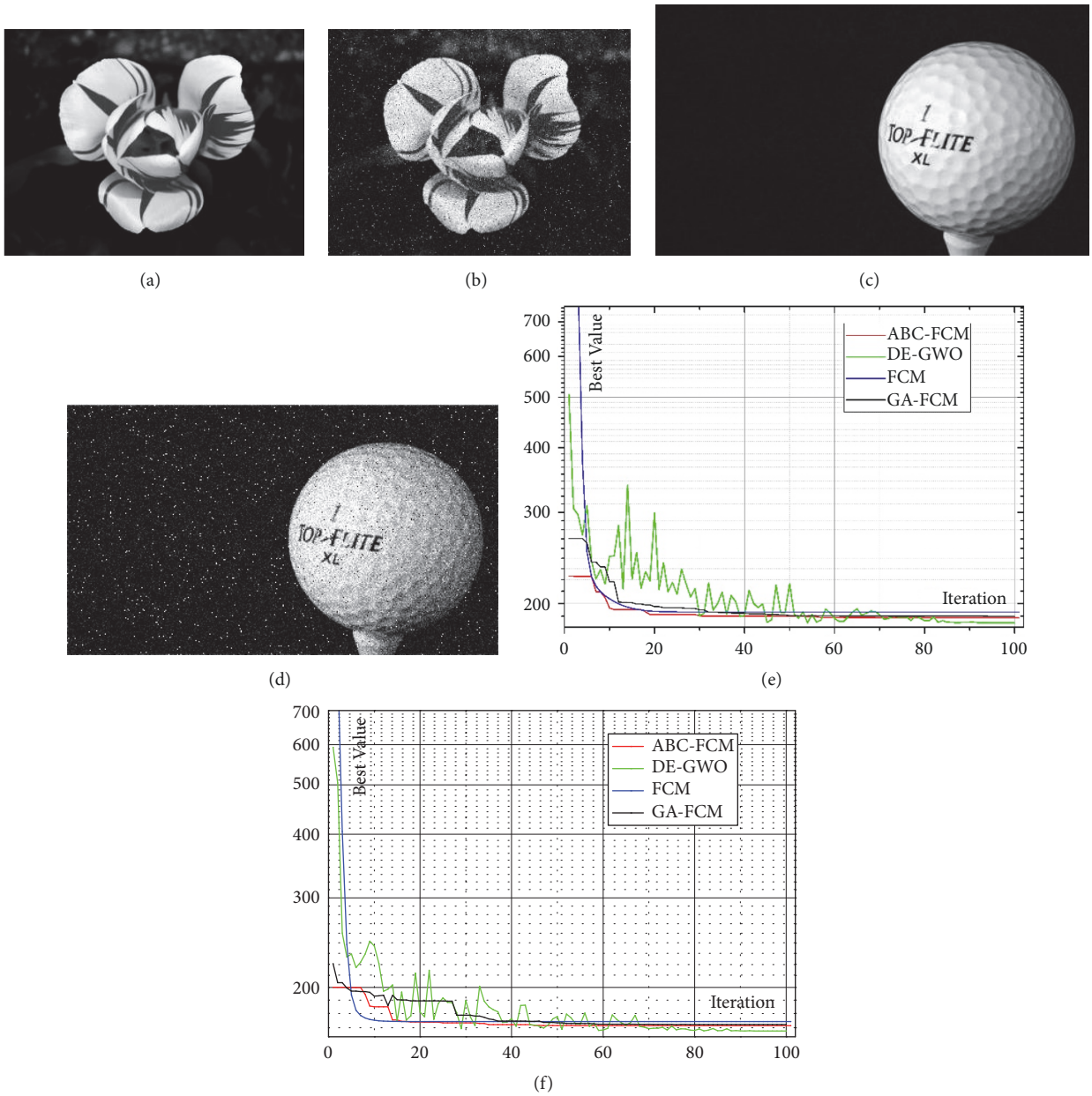

Figure 2: Comparative experiments on two images. (a) The first noise-free optical image; (b) the first optical image which is polluted by synthetic noise; (c) the second noise-free optical image; (d) the second optical image which is polluted by synthetic noise; (e) the best value of the four approaches with the first image; (f) the best value of the four approaches with the second image.

the image segmentation. Experimental results indicate that the efficiency of the proposed algorithm is higher, the misclassification rate is smaller, and the segmentation accuracy and the overall accuracy are higher, which proves the validity and correctness of the algorithm.

The feasibility of GWO-based image segmentation is demonstrated in the paper, and it offers a new option to the conventional methods with the merit of simplicity and efficiency. However, as a new heuristic model in swarm intelligence, GWO algorithm is not perfect, some control parameters of the mixed Grey Wolf Optimization algorithm (DE-GWO) have to be specified by experiences, and FCM algorithm is sensitive to noise. It is necessary for us to pay more attention to noise reduction and other new fitness functions in the future work.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

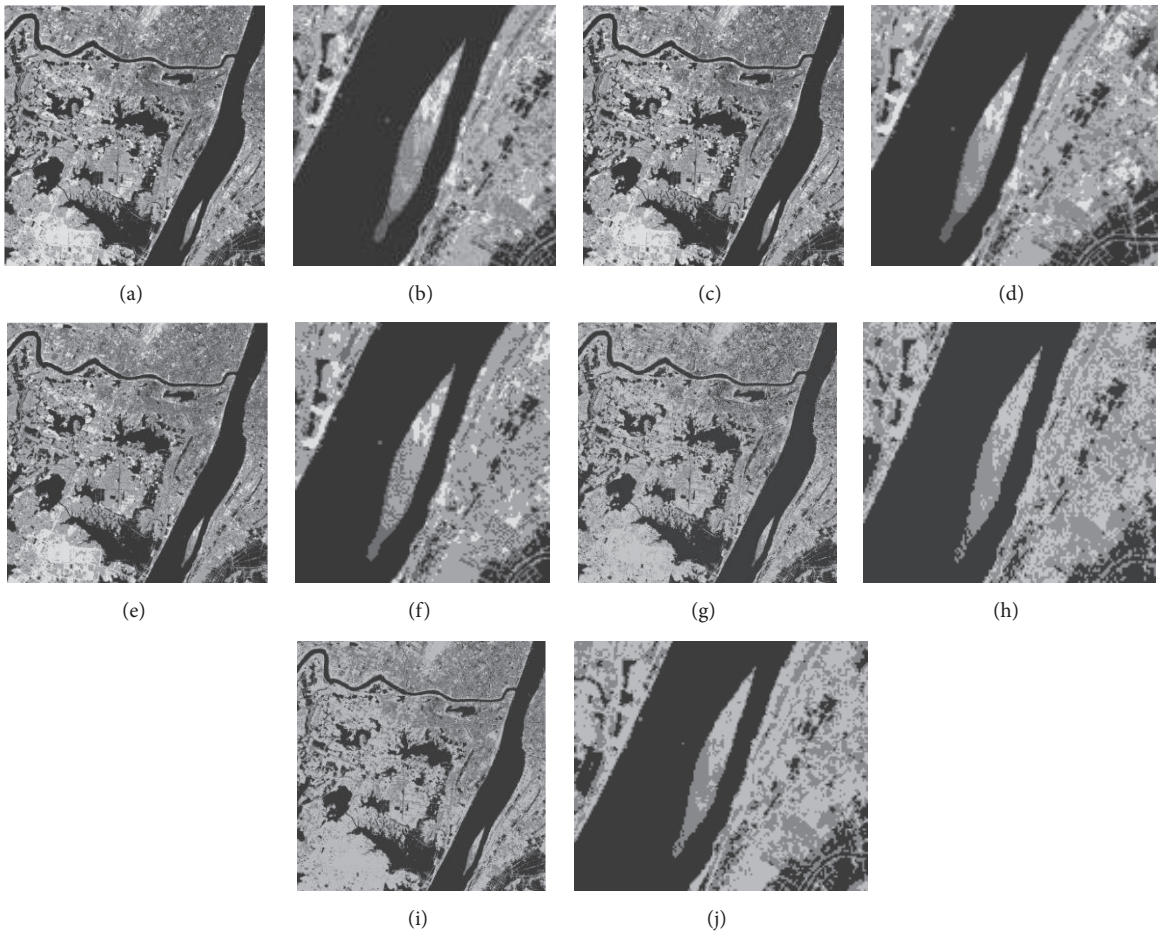

Figure 3: Comparative experiments on real SAR image segmentation. (a) A real SAR image; (b) local magnified image of (a); (c) segmented image of (a) by our method; (d) local magnified image of (c); (e) segmented image of (a) by ABC-FCM; (f) local magnified image of (e); (g) segmented image of (a) by GA-FCM; (h) local magnified image of (g); (i) segmented image of (a) by FCM; (j) local magnified image of (i).

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