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SAR image segmentation based on Artificial Bee Colony algorithm

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ABSTRACT

Due to the presence of speckle noise, segmentation of Synthetic Aperture Radar (SAR) images is still a challenging problem. This paper proposes a fast SAR image segmentation method based on Artificial Bee Colony (ABC) algorithm. In this method, threshold estimation is regarded as a search procedure that searches for an appropriate value in a continuous grayscale interval. Hence, ABC algorithm is introduced to search for the optimal threshold. In order to get an efficient fitness function for ABC algorithm, after the definition of grey number in Grey theory, the original image is decomposed by discrete wavelet transform. Then, a filtered image is produced by performing a noise reduction to the approximation image reconstructed with low-frequency coefficients. At the same time, a gradient image is reconstructed with some high-frequency coefficients. A co-occurrence matrix based on the filtered image and the gradient image is therefore constructed, and an improved two-dimensional grey entropy is defined to serve as the fitness function of ABC algorithm. Finally, by the swarm intelligence of employed bees, onlookers and scouts in honey bee colony, the optimal threshold is rapidly discovered. Experimental results indicate that the proposed method is superior to Genetic Algorithm (GA) based and Artificial Fish Swarm (AFS) based segmentation methods in terms of segmentation accuracy and segmentation time.

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]. Different from optical images, SAR images are inherently contaminated by speckle noise, which inevitably deteriorates the performance of segmentation. Approaches with good performance are often involved in complex computation which may lead the whole process to be more expensive in terms of time. So it is still an urgent task to devise simple and efficient methods.

Generally, existing segmentation approaches dealing with SAR images can be divided into two categories: segmentation based on texture and segmentation based on grey levels. The former partitions an image into several homogeneous regions with respect to specific textures. However it is often difficult to determine an exact discrimination for a texture field as well as the number of segmentation areas, especially when the image contains similar texture fields. The latter divides an image into several regions by some thresholds. Hence, an issue of segmentation in this case is a threshold estimation problem [2,3]. Currently, there are five classes of widely used estimation methods, namely, image statistic methods, between class variance methods, entropy methods, moment preserving methods and quadtree methods [4]. This paper aims at the segmentation based on grey levels, and moreover proposes a new entropy method for SAR images.

Nature-inspired computation has received significant attention in recent decades, in which the two most popular algorithms are Evolutionary Algorithms (EAs) and Swarm Intelligence (SI). EAs, such as Genetic Algorithm (GA), are inspired from natural selection and survival of the fittest in the natural world. SI, like Artificial Fish Swarm (AFS) algorithm and Particle Swarm Optimization (PSO) algorithm, is enlightened by animal foraging behavior [5]. 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, superresolution restoration, image registration, digital watermarking, edge detection, image fusion, image compression, texture classification, image retrieval, image recognition, image segmentation, etc. [6–19].

Similar to the existing nature-inspired algorithms, a few of researchers proposed some mimic algorithms on the basis of the behavior of honey bees in the last few years [20–25]. This paper focuses on the most popular one, i.e. the ABC algorithm presented by Karaboga in 2005 [24], which has been clearly proved to be better than PSO algorithm, GA, Evolutionary Algorithm (EA), Differential Evolution (DE) and Particle Swarm inspired Evolutionary

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Algorithm (PS-EA) in the case of numerical function optimization [25,26]. As a powerful optimization tool, soon after its production, ABC algorithm is successfully applied to complex function optimization, robot path planning, parameter identification, job-shop scheduling, etc. However, its application in image segmentation is seldom studied. This paper employs ABC algorithm to estimate the global threshold for SAR image segmentation. In addition, to acquire a reasonable foraging guide for the bee colony, we combine discrete wavelet transform with Grey theory to obtain an improved two-dimensional grey entropy that is used as the fitness function of ABC algorithm [13].

The remaining of this paper is organized as follows. Section 2 makes a brief summary of the features of honey bees and describes the working mechanism of ABC algorithm. Section 3 gives the definition of grey number in Grey theory, and introduces an improved two-dimensional grey entropy for threshold estimation. Section 4 shows how to employ ABC algorithm to the segmentation of SAR images. Some typical experiments on noise-free images, noise images and real SAR images are carried out in Section 5, where both segmented images and segmenting time are compared among some nature-inspired methods. Finally, Section 6 summarizes our work and the future developments.

2. ABC algorithms

As a kind of social insects, honey bees live in colonies and exhibit many features. These features include bee foraging, bee dance, queen bee, task selection, collective decision making, nest site selection, mating, pheromone laying and navigation systems, which can be used as models for intelligent applications. Actually, a lot of researchers have been inspired to develop algorithms by the behaviors of bees [20–25]. A survey of the algorithms based on the intelligence in bee swarms and their applications has been presented in [20].

As mentioned in Section 1, the ABC algorithm proposed by Karaboga and Basturk is one of the most popular algorithms [24,25]. The following discusses its working mechanism.

In ABC algorithm, an artificial bee colony consists of employed bees, onlookers and scouts. A bee waiting on the dance area to obtain the information about food sources is called an onlooker, a bee going to the food source is named as an employed bee, and a bee carrying out random search is called a scout. The position of a food source denotes a possible solution to the optimization problem, and the nectar amount of a food source represents the quality of the associated solution. Initially, a randomly distributed population is generated. For every food source, there is only one employed bee. So the number of employed bees is equal to the number of food sources. Thereafter, the positions (solutions) will be updated repeatedly with the following cycles until the maximum iteration is reached or stop conditions are satisfied. Each employed bee always remembers its previous best position, and produces a new position within its neighborhood in its memory. According to the greedy criterion, the employed bee updates its food source. In other words, when the new food source is better, the old food source position is updated with the new one. After all employed bees finish their search process, they share the information about the direction and distance to food sources and the nectar amounts with onlookers via a so-called waggle dance in the dancing area. By the observation on the waggle dance, each onlooker chooses a food source depending on the probability value associated with the food source, and searches the area within its neighborhood to generate a new candidate solution. And then, the greedy criterion is applied again just as it works in the employed bees. If a position cannot be improved after a predetermined number of cycles, the position should be abandoned; meanwhile, the corresponding employed bee becomes a scout. The abandoned position will be replaced with a new randomly generated food source [24–26].

The main steps can be described as follows:

(1) Initialize the bee colony $X = \{x_i | i = 1, 2, \ldots, n\}$, where n denotes the population size, x_i is the ith bee.
(2) According to the fitness function, calculate the fitness f_i of each employed bee x_i, and record the maximum nectar amount as well as the corresponding food source.
(3) Each employed bee produces a new solution v_i in the neighborhood of the solution in its memory by $v_i = x_i + (x_i - x_k) \times \phi$, where k is an integer near to i, $k \neq i$, and ϕ is a random real number in $[-1, 1]$.
(4) Use the greedy criterion to update x_i. Compute the fitness of v_i. If v_i is superior to x_i, x_i is replaced with v_i; otherwise x_i is remained.
(5) According to the fitness f_i of x_i, get the probability value P_i via formulas (1) and (2).

$$P_i = \frac{fit_i}{\sum_{i=1}^{n} fit_i} \tag{1}$$

$$fit_i = \begin{cases} \dfrac{1}{1+f_i}, & \text{if } f_i \geq 0 \\ 1 + abs(f_i), & \text{if } f_i < 0 \end{cases} \tag{2}$$

(6) Depending on the probability P_i, onlookers choose food sources, search the neighborhood to generate candidate solutions, and calculate their fitness.
(7) Use the greedy criteria to update the food sources.
(8) Memorize the best food source and nectar amount achieved.
(9) Check whether there are some abandoned solutions or not. If true, replace them with some new randomly-generated solutions by $x_i = min + (max - min) \times \phi$, where ϕ is a random real number in [0, 1], min and max stand for lower and upper bounds of possible solutions respectively.
(10) Repeat steps (3)–(9), until the maximum number of iterations ($kmax$) is reached or stop conditions are satisfied.

As mentioned above, the fitness function is a key component of ABC algorithm, which evaluates the foraging quality of the colony, i.e. the accuracy of possible solutions. Besides, some control parameters, such as the number of employ bees or onlooker bees, the limit times for abandonment, the maximum number of iterations or stop conditions, need to be assigned. They would have a direct influence on the speed and stability of convergence.

3. Improved two-dimensional grey entropy

3.1. Grey number in Grey theory

Grey theory, developed by Deng in 1982, is an effective mathematical means of resolving problems containing uncertainty and indetermination [27]. This multidisciplinary and generic theory deals with systems containing poor information. Now, fields covered by Grey theory include society, economics, finance, agriculture, industry, mechanics, meteorology, ecology, hydrology, geology, medicine, etc.

In Grey theory, a random variable is regarded as a grey number, and a random process is treated as a grey process within a certain range. A grey system is defined as a system containing information presented as grey numbers. Here, we only give some simple conceptions used in our segmentation method.

Definition 1. Let x denote a closed and bounded set of real numbers. A grey number $\otimes x$ is defined as an unknown value in an interval with known lower and upper bounds for x:

$\otimes x \in [\underline{\otimes} x, \bar{\otimes} x]$

where $\underline{\otimes}x$ and $\bar{\otimes}x$ are the lower and upper bounds of $\otimes x$, respectively [27].

Definition 2. The whitening of a grey number means to specify a deterministic value for it in its defined interval. The whitened value $\tilde{\otimes}x$ of a grey number $\otimes x$, is defined as a deterministic value between the lower and upper bounds of $\otimes x$. It can be expressed as [27]

$$\tilde{\otimes}x = x', \quad x' \in [\underline{\otimes}x, \bar{\otimes}x]$$

3.2. Improved two-dimensional grey entropy

According to the definitions in Section 3.1, segmentation threshold is a grey number $\otimes x$ whose exact value is unknown, but the range of the value is known. As far as 256 grey-level images are concerned, the lower and upper bounds are 0 and 255, respectively. So the grey number standing for the segmentation threshold can be expressed as

$$\otimes x = [0, 255] = [x' | 0 \le x' \le 255]$$

In [13], we regard the segmentation threshold as a "grey number", the segmentation process as a "grey process". After the original image was transformed into the wavelet domain using an orthogonal periodic wavelet transform based on Nearly Symmetric wavelets, we acquire an approximation image reconstructed with low-frequency coefficients containing approximation information, and a gradient image reconstructed with high-frequency coefficients at the highest level containing edge and texture information. Consequently, the two images are used to constitute a co-occurrence matrix based on which a two-dimensional grey entropy is established. Unlike traditional entropies [28], the grey entropy is able to reduce noise disturbance to some extent, with the fact that most of the noise coefficients in wavelet domain are suppressed near to zero either in low-frequency or high-frequency at the highest level.

To further avoid the influence of speckle noise on SAR image segmentation, this paper replaces the approximation image with a filtered image to get a new version of grey entropy. The improved entropy can be obtained by the following steps:

(1) Decompose the original image into several subbands by a three-level Discrete Wavelet Transform (DWT). Then, reconstruct an approximation image with the low-frequency coefficients at the third level and a gradient image with the high-frequency coefficients at the third level, reflecting the approximation information and edge and texture information, respectively. According to the distribution character of noise in wavelet domain, most noise is greatly suppressed in the two reconstructed images.

(2) Deal with the approximation image by a low-pass filter, and obtain a filtered image. Obviously, this step further reduces the noise in the filtered image.

(3) Normalize the filtered image I and the gradient image G to [0, 255] by

$$I(m,n) = \text{round}\left(abs \left(\frac{I(m,n)}{\max\limits_{\forall m,n}(I(m,n))} \times (L-1) \right) \right) \tag{3}$$

$$G(m,n) = \text{round}\left(abs \left(\frac{G(m,n)}{\max\limits_{\forall m,n}(G(m,n))} \times (L'-1) \right) \right) \tag{4}$$

where round( ) is an operator to get an integer format, abs( ) is an operator to get an absolute value, $\max\limits_{\forall m,n}(I(m,n))$ and $\max\limits_{\forall m,n}(G(m,n))$ correspond to the maximum value in I and G, respectively. Besides, $L = L' = 256$ stands for the number of the grayscales in the two normalized images.

(4) Construct a $L \times L'$ filtered-gradient co-occurrence matrix $C = [c_{ij}]_{L\times L'}$, where c_{ij} stands for the number of pixel pairs satisfying $I(m, n) = i$ and $G(m, n) = j$. So, p_{ij} that denotes the probability of c_{ij} in the matrix can be computed by [28]

$$p_{ij} = \frac{c_{ij}}{\sum_{i=0}^{L-1}\sum_{j=0}^{L'-1} c_{ij}} \tag{5}$$

(5) Let (s, t) be a pair of thresholds, where s is a threshold of I and t is a threshold of G, then (s, t) will divide the matrix C into four quadrants, i.e. Q_1, Q_2, Q_3 and Q_4, as shown in Fig. 1.

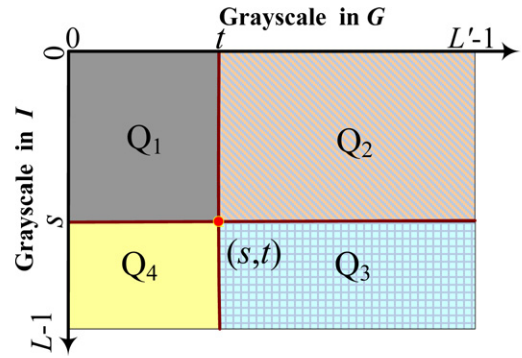

Fig. 1. The position of (s, t) in the filtered-gradient co-occurrence matrix.

Suppose that Q_1 and Q_4 denote objects and backgrounds respectively, that is, there are some dark objects in bright surroundings. Then, either in Q_1 or Q_4, the grayscale values of most pixels are similar or even the same, while their gradient values are very small. On the other hand, Q_2 stands for edge and texture in object regions, and Q_3 stands for edge and texture in background regions. Their Shannon conditional entropies can be computed by

$$H(E|O) = -\sum_{i=0}^{s}\sum_{j=t+1}^{L'-1} p_{ij}^{Q_2} \log_2 p_{ij}^{Q_2}$$

$$H(E|B) = -\sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L'-1} p_{ij}^{Q_3} \log_2 p_{ij}^{Q_3}$$

According to the two-dimensional conditional entropy, when the difference between objects and backgrounds reaches to the biggest value, (s, t) is the best position to segment I and G. Based on the definition of grey number, both s and t are grey numbers since their values are unknown and their bounds are specified as [0, 255]. Therefore, the improved two-dimensional grey entropy can be given as [13]

$$H_{grey}(s,t) = \frac{1}{2}(H(E|O) + H(E|B)) = \frac{1}{2}\left[\left(-\sum_{i=0}^{s}\sum_{j=t+1}^{L'-1} p_{ij}^{Q_2} \log_2 p_{ij}^{Q_2} \right) + \left(-\sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L'-1} p_{ij}^{Q_3} \log_2 p_{ij}^{Q_3} \right) \right] \tag{6}$$

where

$$p_{ij}^{Q_2} = \frac{c_{ij}}{\sum_{i=0}^{s}\sum_{j=t+1}^{L'-1} c_{ij}}, \quad p_{ij}^{Q_3} = \frac{c_{ij}}{\sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L'-1} c_{ij}}, \quad L = L' = 256.$$

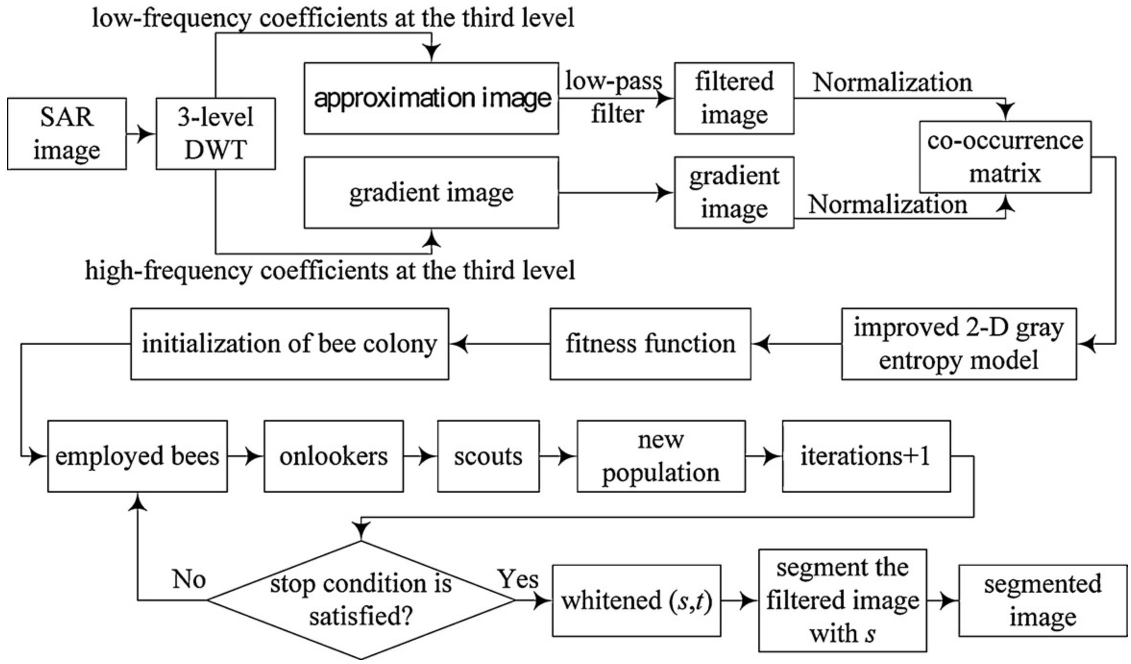

Fig. 2. Flow chart of SAR image segmentation method based on ABC algorithm.

Obviously, once the value of formula (6) is the maximum one, the corresponding (s, t) must be the best pair of thresholds. Hence, image threshold segmentation would be implemented with the whitening process of grey numbers (s, t). As for the searching for the position of (s, t), the traditional brute-force method is quite time consuming. In order to speed up the whitening process, we adopt the swarm intelligence optimization algorithm, namely, ABC algorithm.

4. SAR image segmentation based on ABC algorithm

As far as SAR image segmentation is concerned, the global threshold estimation can be regarded as a search procedure which searches for a proper integer in a continuous integer interval [0, 255]. Hence, it is feasible to apply ABC algorithm to find the optimal threshold. Due to the special imaging mechanism, SAR image contains serious speckle noise, so it is required that the segmentation algorithm is robust to noise pollution.

As described in Section 3.2, the improved two-dimensional grey entropy may suppress the influence of speckle noise on segmentation results. Thus, formula (6) is selected to serve as the fitness function of ABC algorithm. Here, each bee in ABC algorithm is two-dimensional, standing for a pair of grey numbers (s, t). The population size, i.e. the numbers of bees, is the number of possible thresholds searched in parallel. The position of a food source represents a possible threshold, and the nectar amount of a food source corresponds to the quality of a segmented image evaluated by formula (6).

The basic procedure of SAR image segmentation based on ABC algorithm is shown in Fig. 2.

Main steps of our method are briefly explained as below:

(1) Decompose the original image with a three-level DWT. Then low-frequency coefficients at the third level reflecting the approximation information are reconstructed as an approximation image, while high-frequency parts at the third level possessing information on edge and texture are reconstructed as a gradient image.
(2) Employ a low-pass filter (a circular averaging filter) to deal with the approximation image and obtain a filtered image.
(3) Normalize the gradient image I and the filtered image G to [0, 255] by the formulas (3) and (4). After that, construct a 256×256 filtered-gradient co-occurrence matrix C to get the improved two-dimensional grey entropy.
(4) Treat the two-dimensional grey entropy as the fitness function of ABC algorithm, and set the control parameters in ABC algorithm, including the population size, the limit times for abandonment, the maximum number of iterations, etc.
(5) By the cooperation and information-sharing of multiple cycles of employed bees, onlookers and scouts, the best bee gradually approaches to the optimal threshold, and at the same time the grey numbers (s, t) are whitened.
(6) Segment the filtered image I with the optimal threshold s and get the final segmented image.

5. Experimental results and performance analysis

5.1. Comparisons of segmentation performance

In our study, all images are 256×256 with 256 grayscale. To compare the efficiency of our method with others, segmentation methods based on GA and AFS algorithm are used to segment some typical images. Experimental results are given in Fig. 3, covering a noise-free optical image, an optical image polluted by synthetic noise (composed of Gaussian noise with mean 0 and variance 0.01, speckle noise with variance 0.005, and salt and pepper noise with density 0.02), and a real SAR image.

In this experiment, for ABC algorithm, the population size is 10, the maximum number of iterations is 30, and the limit times for abandonment is 10, the lower and upper bounds are 0 and 255 respectively. In GA, the population size is 50, the maximum number of iterations is 70, binary digits of variable are 16, the crossover probability is 0.7, and the mutation probability is 0.01. In AFS algorithm, the visual distance of artificial fish is 50, the crowding index is 0.5, the maximal moving step is 3, the try times is 5, the population size is 30, and the maximum iteration is 100.

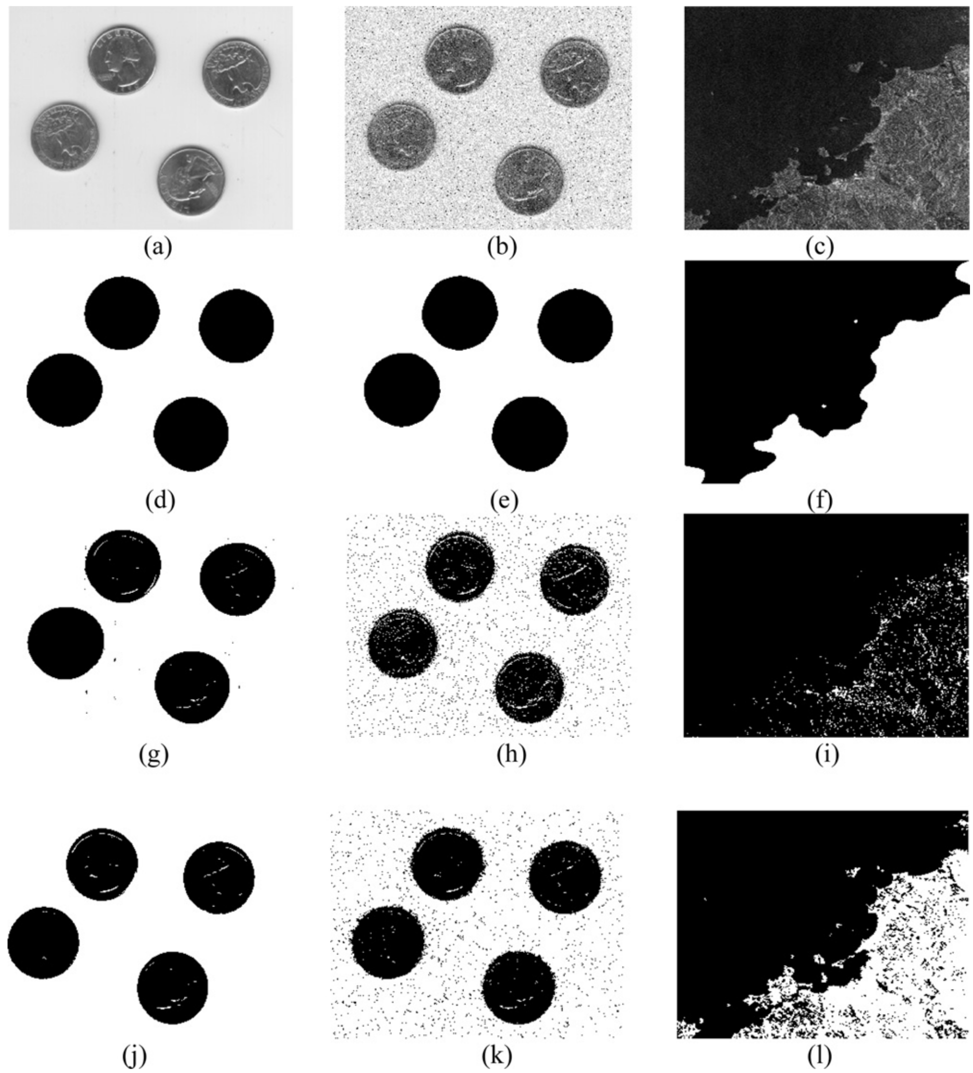

Fig. 3. Comparative experiments on image segmentation. (a) Noise-free optical image; (b) optical image polluted by synthetic noise; (c) real SAR image; (d) segmented image of (a) by our method; (e) segmented image of (b) by our method; (f) segmented image of (c) by our method; (g) segmented image of (a) by [12]; (h) segmented image of (b) by [12]; (i) segmented image of (c) by [12]; (j) segmented image of (a) by [19]; (k) segmented image of (b) by [19]; (l) the segmented image of (c) by [19].

Table 1
Comparison on segmentation time in case of Fig. 3(a).

Method	SI scheme	Fitness function	Threshold	Time(s)
Our method	ABC	Improved two-dimensional grey entropy	205	**5.821**
The method in [12]	GA	Two-dimensional entropy	207	14.391
The method in [13]	GA	Two-dimensional grey entropy	206	17.640
The method in [19]	AFS	Two-dimensional Otsu	187	12.015

Table 2
Comparison on segmentation time in case of Fig. 3(b).

Method	SI scheme	Fitness function	Threshold	Time(s)
Our method	ABC	Improved two-dimensional grey entropy	204	**6.669**
The method in [12]	GA	Two-dimensional entropy	163	15.358
The method in [13]	GA	Two-dimensional grey entropy	207	19.152
The method in [19]	AFS	Two-dimensional Otsu	162	12.546

Table 3
Comparison on segmentation time in case of Fig. 3(c).

Method	SI scheme	Fitness function	Threshold	Time(s)
Our method	ABC	Improved two-dimensional grey entropy	95	**4.832**
The method in [12]	GA	Two-dimensional entropy	131	13.460
The method in [13]	GA	Two-dimensional grey entropy	94	17.740
The method in [19]	AFS	Two-dimensional Otsu	62	6.441

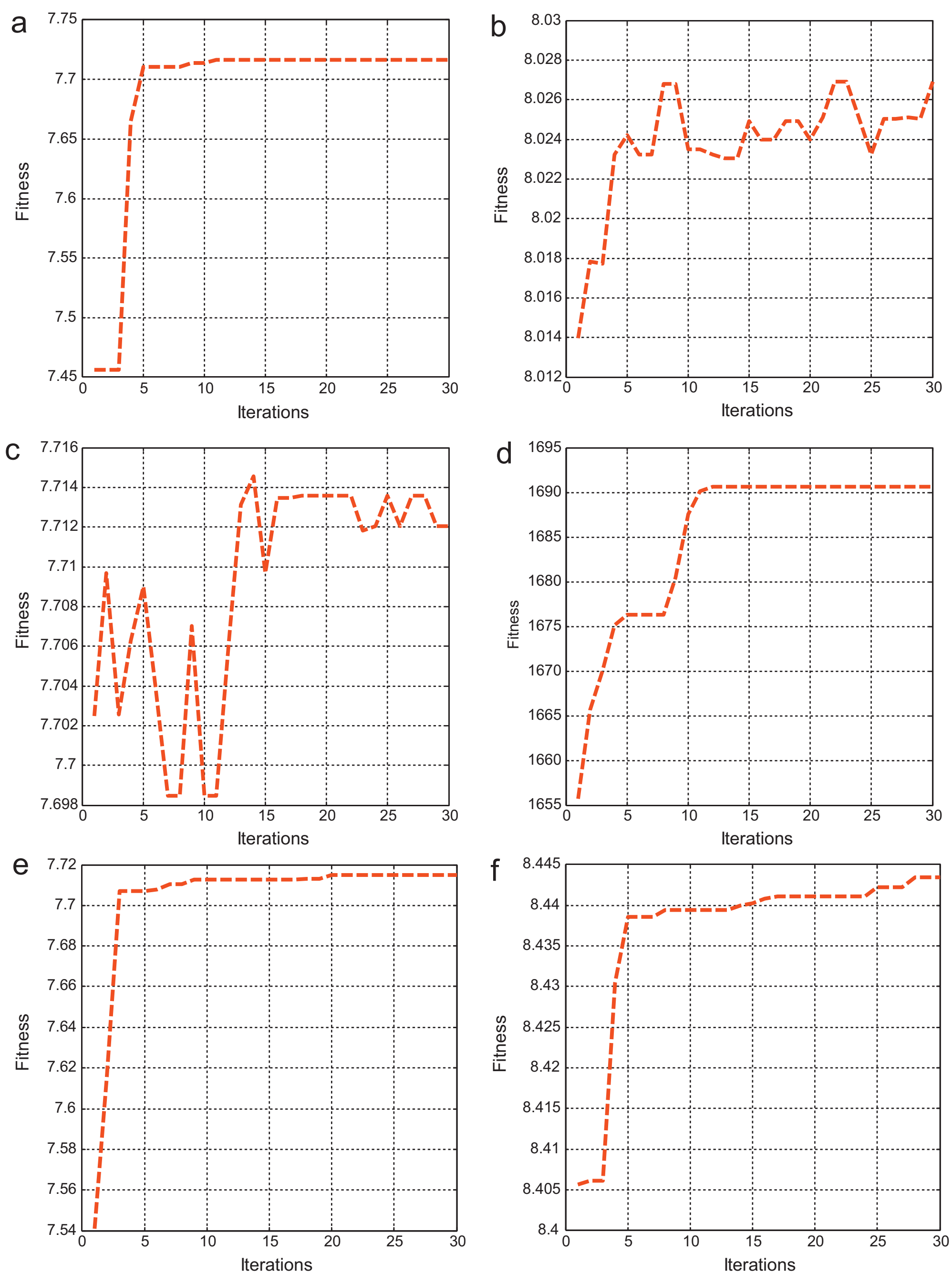

Fig. 4. Comparisons on convergence speed. (a) Fitness trace of ABC algorithm; (b) fitness trace of GA [12]; (c) fitness trace of GA [13]; (d) fitness trace of AFS algorithm [19]; (e) fitness trace of improved GA [12]; (f) fitness trace of improved GA [13].

In Fig. 3, it is clear to see that, there are texture targets, a lot of noise and over-segmentation phenomenon in the segmented images obtained by [12]. [19] provides with a medium effect in case of the noise-free optical image, but its performance deteriorates once noise is involved, especially resulting in an alveolate seashore when the real SAR image is segmented. Compared to the two methods in [12,19], no matter whether the segmenting image is polluted by noise or not, our method always obtains satisfying binary images with clear contours and continuous edges. That is because there are two kinds of operations to suppress noise in the improved two-dimensional grey entropy, as described in steps (1) and (2) of Section 3.2. The first kind of operation is implemented in wavelet domain, since both the approximation image and the gradient image are reconstructed with wavelet coefficients at the highest level. The second kind of operation happens in spatial domain, when a low-pass filter is employed to deal with the approximation image. Note that the final image is the segmented result of the filtered image using the whitened grey numbers *s*, which almost makes the noise disappear completely.

5.2. Comparisons of segmentation time

To compare the segmenting time spent in Fig. 3, some experimental results are listed in Tables 1–3, in which the best results are in bold.

The comparative results in Tables 1–3 indicate that our method is significantly faster than the other three methods in [12,13,19]. The segmenting time of the methods tested here is ordered as our

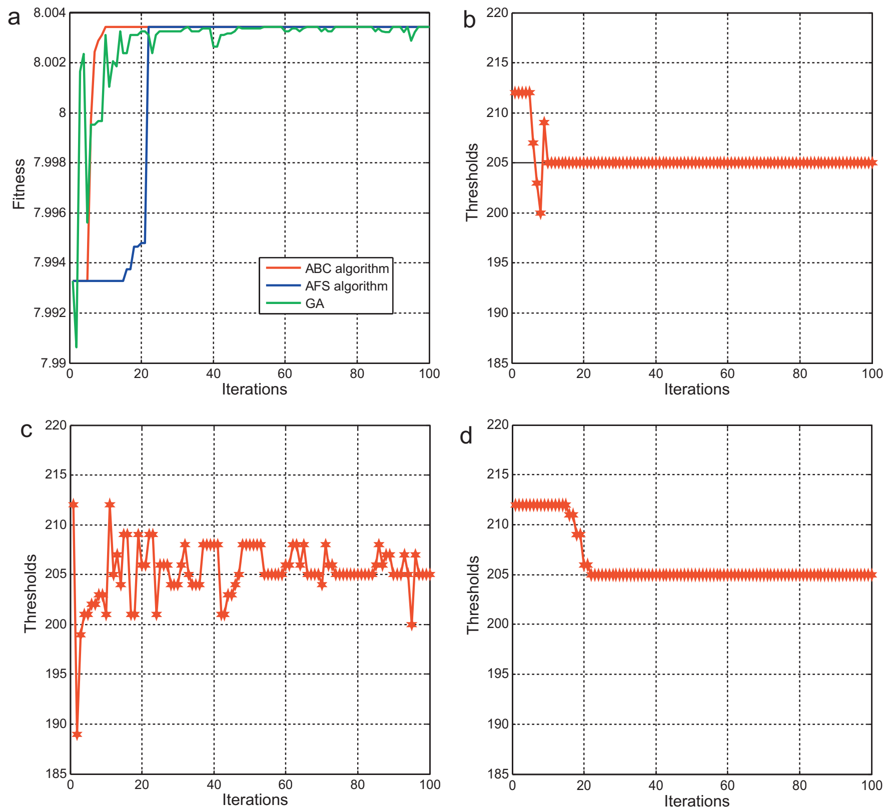

Fig. 5. Traces of fitness and thresholds in case of Fig. 3(a). (a) Fitness traces of the three algorithms; (b) threshold trace of ABC algorithm; (c) threshold trace of GA; (d) threshold trace of AFS algorithm.

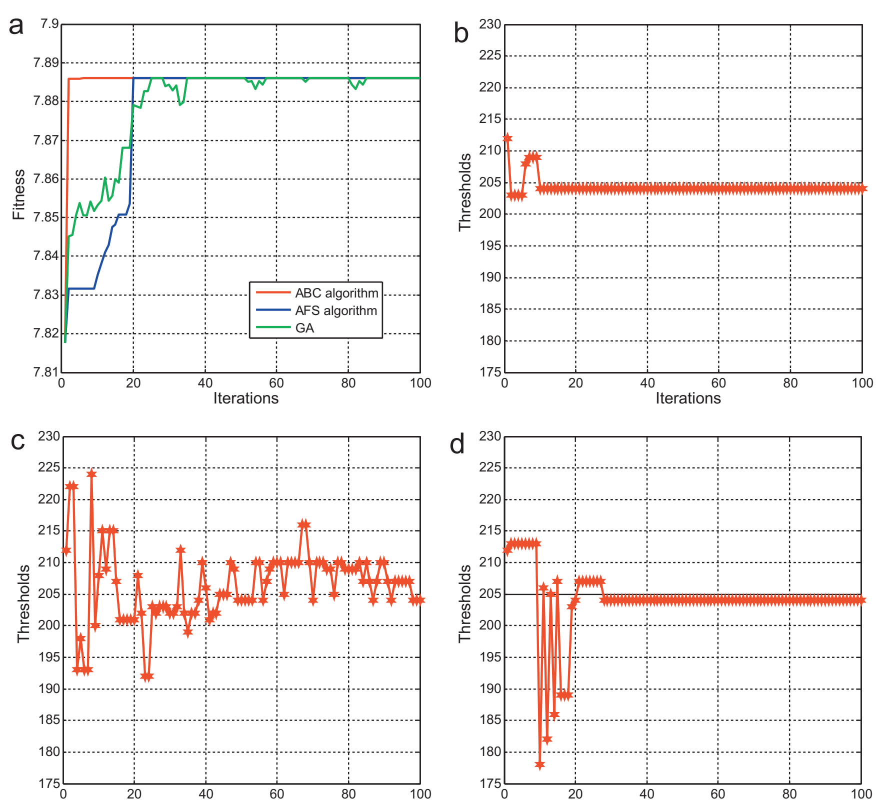

Fig. 6. Traces of fitness and thresholds in case of Fig. 3(b). (a) Fitness traces of the three algorithms; (b) threshold trace of ABC algorithm; (c) threshold trace of GA; (d) threshold trace of AFS algorithm.

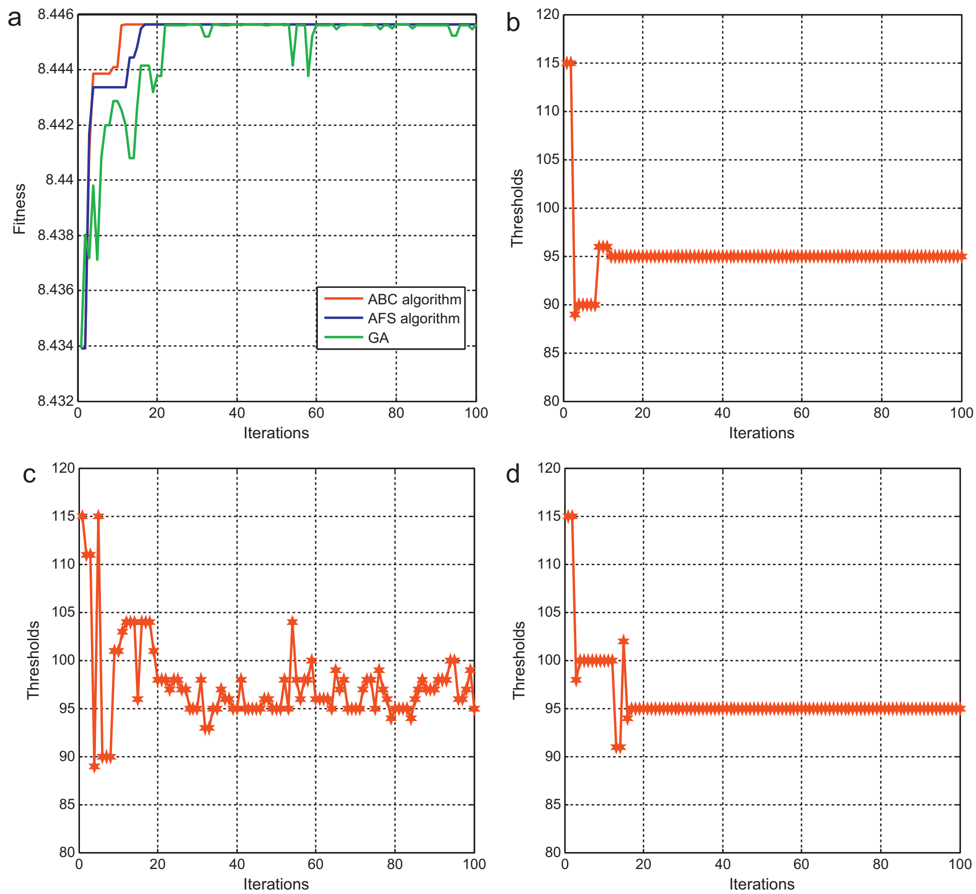

Fig. 7. Traces of fitness and thresholds in case of Fig. 3(c). (a) Fitness traces of the three algorithms; (b) threshold trace of ABC algorithm; (c) threshold trace of GA; (d) threshold trace of AFS algorithm.

method < the method in [19] < the method in [12] < the method in [13].

On the other hand, we can see obviously that the thresholds of our method and the method in [13], are almost the same because their fitness functions are similar, significantly better than the thresholds of GA and AFS based methods. Particularly, Tables 1 and 2 show that our method is robust to noise pollution for the fact that the segmentation threshold (204) of the optical image polluted by synthetic noise is so close to the segmentation threshold (205) of the noise-free optical image.

5.3. Comparison of convergence speed

In order to compare the convergence speed among our method, GA based methods in [12,13], AFS based method in [19], and improved-GA based methods in [12,13], we compare their performance when all the population sizes are 20, all the maximum iterations are 30, and other parameters are the same as those in Section 5.1. Note that compared with GA, elitism scheme is adopted in the improved GA. Then their respective fitness traces are displayed in Fig. 4.

Fig. 4(a) illustrates that ABC algorithm converges at the 11th iteration and finds the optimal threshold stably. Fig. 4(b) and (c) shows the GA in [12,13] do not converge yet at the 30th iteration, so they certainly cannot find the optimal threshold, partially because the previous best chromosome is not kept. Fig. 4(d) shows AFS algorithm converges at the 12th iteration, comparable to ABC algorithm. Fig. 4(e)–(f) indicates the improved GA in [12] converges at the 23rd iteration, while the improved GA in [13] seems not to converge when the maximum number of iterations is reached. More experimental results show that AFS algorithm and the two improved GA methods are not stable if the population size = 20 and the maximum iteration = 30. On the contrary, ABC algorithm is not only fast but also stable and convergent in the same conditions. From the viewpoint of sociology, the labor division in a colony may be helpful to increases the production efficiency, so a partial reason for the improvement of convergence speed in ABC algorithm may be the emergence of employed bees, onlookers and scouts.

5.4. Comparison of nature-inspired algorithms

The above experimental results indicate that our method outperforms the methods in [12,13,19]. To compare the convergence performance of ABC algorithm, GA, and AFS algorithm, this group of experiments run with the same settings, comprising the fitness functions (improved two-dimensional grey entropy), the maximal iterations (100), the population size (50) with the same initial population distribution, over the 10 runs. The traces of fitness and thresholds are given in Figs. 5–7.

Figs. 5–7 show the convergent performance of the algorithms can be ordered as ABC > AFS > GA. ABC algorithm keeps the best performance for all these test images, though these images involve noise-free images, images polluted by noise and real SAR images, and may have many local optimization. Moreover, ABC algorithm converges very quickly, especially at initial part. Sometimes the threshold does not change for several iterations, but dramatically changes at some iterations, which is due to the probability in proportion to the profitability of the food source.

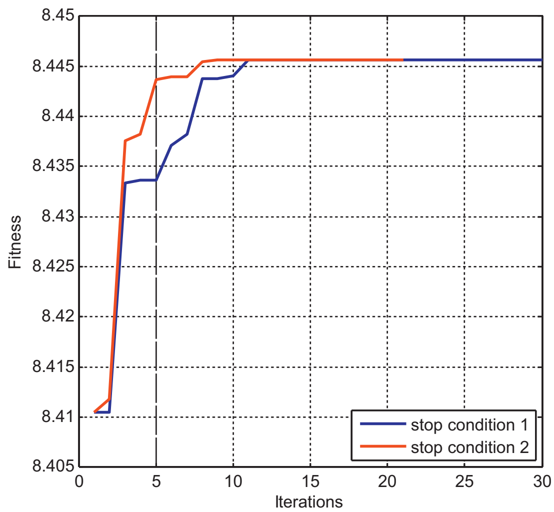

Fig. 8. Fitness traces in different stop conditions.

5.5. Comparison on different stop conditions in ABC algorithm

To compare the influence of different stop conditions on ABC algorithm, a typical group of experimental results in Fig. 3(c) are illustrated in Fig. 8, where the stop condition 1 means the maximum iterations = 30 and the stop condition 2 is specified that the optimal bee is not updated for continuous 10 iterations and the maximum iterations $\leq$ 30. Other parameters of ABC algorithm are selected as the same as the values in Section 5.1. Note that the following results are over the 10 runs with the same initial population distributions.

In Fig. 8, it is clear to see that under condition 2, the search is finished when the iteration = 21, while the search is finished when the iteration = 30 under condition 1. So, an appropriate stop condition is advantage to rapidly gain the optimal solution in applications. In addition, it is found that under the two conditions, both of the traces have converged before the 11th iteration, which again confirms the outstanding performance of ABC algorithm.

5.6. Analyses on the time-complexity of our method

The total consuming time of our method is composed of two parts. The first part is spent on steps (1)–(3) in Section 4, which includes the time to wavelet decompose, wavelet reconstruct, do the low-pass filtering, and construct the filtered-gradient co-occurrence matrix. So the spent time is in proportion to the image size. The second part is spent after the co-occurrence matrix is created. So the consuming time is independent of the image size, since the searching space of ABC algorithm is always [0, 255] and the computation amount of the fitness function is invariable. In this part, the consuming time is in proportion to the population size and the maximum iteration of ABC algorithm. At the same time, it is also relevant to other parameters of ABC algorithm, such as stop conditions, the limit times for abandonment, and initial distribution of population.

6. Conclusion

In this paper, we propose a fast segmentation method for SAR images. The method regards threshold estimation as a search process and employs ABC algorithm to optimize it. In order to provide ABC algorithm with an efficient fitness function, we integrate the concept of grey number in Grey theory, multilevel DWT, low-pass filtering and maximum conditional entropy to get an improved two-dimensional grey entropy. In essence, the fast segmentation speed of our method owes to ABC algorithm, which has an outstanding convergence performance. On the other hand, the segmentation quality of our method is benefit from the improved two-dimensional grey entropy, for the fact that noise almost completely disappears, and most useful information about edge and texture is preserved. Experimental results indicate that our method is superior to GA based or AFS based methods in terms of segmentation accuracy, segmentation time, and convergence speed.

However, as a new heuristic model in swarm intelligence, sophisticated relationships of bees and various foraging possibilities make ABC algorithm go a long way before it becomes mature. For example, ABC algorithm is still weak in mathematics. As for image segmentation discussed in this study, little evidence in theory may be referred to and some control parameters have to be specified by experiences. We would like to point out that, like all global thresholding techniques, the proposed method using a single threshold merely partitions the entire image into two kinds of regions, objects and backgrounds, which is suitable for simple SAR images. However, the content of most real SAR images is complex and diverse. It is necessary for us to pay more attention to multiple thresholds and other new fitness functions in the future work.

The contribution of this paper is to demonstrate and confirm the feasibility of ABC-based image segmentation, and offers a new option to the conventional methods with the merit of simplicity and efficiency. With the efforts of researchers at home and abroad, it is hoped that ABC algorithm will be widely used like GA and PSO in the future.

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References

[1] A. El Zaart, D. Ziou, S. Wang, Q. Jiang, Segmentation of SAR images, Pattern Recognition 35 (3) (2002) 713–724.
[2] S.Q. Han, L. Wang, A survey of threshold methods for image segmentation, Systems Engineering and Electronics 24 (6) (2002) 91–94, 102.
[3] P.K. Sahoo, S. Soltani, A.K.C. Wong, A survey of thresholding technique, Computer Vision Graphics Image Process 41 (2) (1988) 233–260.
[4] S.U. Lee, S.Y. Chung, R.H. Park, A comparative performance study of several global thresholding techniques for segmentation, Computer Vision Graphics Image Process 52 (2) (1990) 171–190.
[5] P. Marrow, Nature-inspired computing technology and applications, BT Technology Journal 18 (4) (2000) 13–23.
[6] Y.Q. Wang, W.Y. Liu, Application of swarm intelligence in image processing, Computer Applications 27 (7) (2007) 1647–1650.
[7] Y. Tian, W.Q. Yuan, Application of the genetic algorithm in image processing, Journal of Image and Graphics 12 (3) (2007) 389–396.
[8] C.C. Lai, D.C. Tseng, A hybrid approach using Gaussian smoothing and genetic algorithm for multilevel thresholding, International Journal of Hybrid Intelligent Systems 1 (3) (2004) 143–152.
[9] A. Mishraa, P.K. Dutta, M.K. Ghoshc, A GA based approach for boundary detection of left ventricle with echocardio graphic image sequences, Image and Vision Computing 21 (11) (2003) 967–976.
[10] W.B. Tao, J.W. Tian, J.J. Liu, Image segmentation by three-level thresholding based on maximum fuzzy entropy and genetic algorithm, Pattern Recognition Letters 24 (16) (2003) 3069–3078.
[11] P.Y. Yin, A fast scheme for optimal thresholding using genetic algorithms, Signal Processing 72 (2) (1999) 85–95.
[12] G. Chen, H.F. Zuo, 2-D maximum entropy method of image segmentation based on genetic algorithm, Journal of Computer-Aided Design &Computer Graphics 14 (6) (2002) 530–534.
[13] M. Ma, Y.J. Lu, Y.N. Zhang, X.L. He, Fast SAR image segmentation method based on the two-dimensional grey entropy model, Journal of Xidian University 36 (6) (2009) 1114–1119.

[14] O. Salima, B. Mohamed, Ant colony system with local search for markov random field image segmentation, IEEE Transactions on Pattern Analysis and Machine Intelligence 1 (2003) 133–136.
[15] C.M. Li, L.Z. Wang, S.J. Wu, Ant colony fuzzy clustering algorithm applied to SAR image segmentation, in: CIE International Conference of Radar Proceedings, 2007, pp. 1–4.
[16] X.N. Wang, Y.J. Feng, Z.R. Feng, Ant colony optimization with active contour models for image segmentation, Control Theory and Applications 23 (4) (2006) 515–522.
[17] R.B. Zhang, J. Liu, Underwater image segmentation with maximum entropy based on particle swarm optimization, First International Multi-Symposiums on Computer and Computational Sciences 2 (2006) 360–362.
[18] F. Du, W.K. Shi, L.Z. Chen, Y. Deng, Z.F. Zhu, Infrared image segmentation with 2-D maximum entropy method based on particle swarm optimization, Pattern Recognition Letters 26 (5) (2005) 597–603.
[19] Z. Pan, Y.Q. Wu, The two-dimensional Otsu thresholding based on fish-swarm algorithm, Acta Optica Sinica 29 (8) (2009) 2115–2121.
[20] D. Karaboga, B. Akay, A survey: algorithms simulating bee swarm intelligence, Artificial Intelligence Review 31 (2009) 61–85.
[21] M. Marinaki, Y. Marinakis, C. Zopounidis, Honey Bees Mating Optimization algorithm for financial classification problems, Applied Soft Computing 10 (3) (2010) 806–812.
[22] O.B. Haddad, A. Afshar, M.A. Marino, Honey-bees mating optimization (HBMO) algorithm: a new heuristic approach for water resources optimization, Water Resources Management 20 (2006) 661–680.
[23] A. Afshar, O.B. Haddad, M.A. Marino, B.J. Adams, Honey-bee mating optimization (HBMO) algorithm for optimal reservoir operation, Journal of the Franklin Institute 344 (2007) 452–462.
[24] D. Karaboga, An Idea Based on Bee Swarm for Numerical Optimization, Technical Report-TR06, October 2005.
[25] D. Karaboga, B. Basturk, A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm, Journal of Global Optimization 39 (3) (2007) 459–471.
[26] D. Karaboga, B. Basturk, On the performance of artificial bee colony (ABC) algorithm, Applied Soft Computing 8 (1) (2008) 687–697.
[27] S.F. Liu, Y.G. Dang, Z.G. Fang, The Theory and Application of Grey System, Science Press, Beijing, 2004.
[28] J.G. Hong, Gray level-gradient cooccurrence matrix texture analysis method, Acta Automatica Sinica 10 (1) (1984) 22–25.