Research Article

Parameter Estimation of Attribute Scattering Center Based on Water Wave Optimization Algorithm

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For the problem of attribute scattering center parameter estimation in synthetic aperture radar (SAR) image, a method based on the water wave optimization (WWO) algorithm is proposed. First, the segmentation and decoupling of high-energy regions in SAR image are performed in the image domain to obtain the representation of a single scattering center. Afterwards, based on the parameterized model of the attribute scattering center, an optimization problem is constructed to search for the optimal parameters of the separated single scattering center. In this phase, the WWO algorithm is introduced to optimize the parameters. The algorithm has powerfully global and local searching capabilities and avoids falling into local optimum while ensuring the optimization accuracy. Therefore, the WWO algorithm could ensure the reliability of scattering center parameter estimation. The single scattering center after solution is eliminated from the original image and the residual image is segmented into high-energy regions, so the parameters of the next scattering center are estimated sequentially. Finally, the parameter set of all scattering centers in the input SAR image can be obtained. In the experiments, firstly, the parameter estimation verification is performed based on the SAR images in the MSTAR dataset. The comparison of the parameter estimation results with the original image and the reconstruction based on the estimated parameter set reflect the effectiveness of the proposed method. In addition, the experiment is also conducted using the SAR target recognition algorithms based on the estimated attribute parameters. By comparing the recognition performance with other parameter estimation algorithms under the same conditions, the performance superiority of the proposed method in attribute scattering center parameter estimation is further demonstrated.

1. Introduction

Synthetic aperture radar (SAR) has all-day and all-weather high-resolution imaging capabilities, which is widely used in military and civilian fields [1–4]. Unlike clear and intuitive optical images, SAR images reflect the electromagnetic scattering characteristics of the target, in which the appearance of the target is not obvious, which brings obstacles to image interpretation. In order to quantitatively describe the distribution characteristics of SAR images, the researchers model the local scattering phenomenon by means of the scattering center model. The most representative one is the attribute scattering center model [5–7]. The attribute scattering center model contains attribute parameters related to the local structures of the target, such as intensity distribution, positions, and lengths. SAR target recognition methods based on the attribute scattering centers also fully verified the effectiveness of attribute parameters for distinguishing different targets [8–11]. However, the form of the attribute scattering center model is complicated, so the parameter estimation problem is a hard one. In the early stage, researchers used the “divide and conquer” strategy to realize the sequential estimation of each scattering center in the image domain. In the parameter estimation of a single scattering center, many classical optimization algorithms are usually used, such as the genetic algorithm, simulated annealing, particle swarm algorithm, and wolf swarm algorithm [12–16]. According to the theory of compressive sensing, the researchers also designed the attribute scattering center estimation algorithms based on sparse representation [17], assuming that the attribute scattering centers in a single SAR image are sparsely distributed in the entire parameter space. The sparse representation methods avoid the local decoupling in the image domain, but the consistency of the
estimated results with the original image is often difficult to guarantee. In addition, it has strong randomness. For this aspect, in order to ensure the physical meanings of the scattering center parameters, the scattering center estimation algorithm in the image domain has stronger reliability.

In this paper, based on the traditional image domain attribute scattering center estimation methods, the water wave optimization (WWO) algorithm is introduced to realize the parameter optimization of a single scattering center. For a single scattering center image area decoupled from the image domain, the best attribute parameters are obtained through the WWO algorithm. Inspired by the theory of shallow water waves, researchers proposed a new heuristic algorithm in 2015, i.e., the WWO algorithm [18]. The algorithm is inspired by the theoretical model of shallow water waves. The individual water waves use propagation, refraction, and wave breaking to effectively search in the solution space. It has the advantages of concise principle, fewer control parameters, and easy implementation. At present, the WWO algorithm has been widely used and verified in the fields of task allocation, image processing, etc., with higher accuracy and robustness [19–23]. For this reason, this paper introduces the WWO algorithm into the parameter estimation of the single attribute scattering center to obtain more reliable estimation results. In the experiment, the MSTAR dataset is used to verify the proposed method, including the contributions to the parameter estimation of SAR images and the target recognition based on attribute scattering center matching, respectively. The experimental results prove the effectiveness of the proposed method and its superiority compared with the existing methods.

2. Attributed Scattering Center Model

As a parameterized model to describe the local scattering characteristics of radar targets in the high-frequency area [24], the attribute scattering center model has stronger description capabilities than the previous geometric theory of diffraction (GTD) model [25, 26] in both the physical and signal layers. In [8–11], SAR target methods were developed based on the attributed scattering center model, which verified its significant advantages in improving the robustness of target recognition. Based on the attributed scattering center model, the scattering characteristics of a single scattering center are described as follows:

\[
E_i(f, \phi; \theta_i) = A_i \cdot \left( j \frac{f}{f_c} \right)^{\alpha_i} \cdot \exp \left( -j\frac{4\pi f}{c} (x_i \cos \phi + y_i \sin \phi) \right) \\
\cdot \sin \left( \frac{2\pi f L_i \sin(\phi - \theta_i)}{c} \right) \cdot \exp \left( -2\pi f y_i \sin \phi \right).
\]

In equation (1), \( f \) represents the frequency of the incident wave and \( \phi \) is the azimuth angle. \( \theta_i = [A_i, \alpha, x_i, y_i, L_i, \theta_i, \gamma_i] \) is the attribute parameter set. Specifically, \( A_i \) represents the relative amplitude of different scattering centers; \( x_i, y_i \) record the positions of the scattering center; \( \alpha_i \) is a frequency-dependent factor whose value is directly related to the local structure; for the distributed scattering centers, \( L_i \) and \( \theta_i \) respectively represent the length and direction angle; for the localized scattering centers, \( \gamma_i \) refers to the position-dependent parameter.

For a SAR image containing an interested target, there are several scattering centers. Then, based on the attribute scattering center model, the overall scattering characteristics of the target can be described as follows:

\[
E(f, \phi; \theta) = \sum_{i=1}^{P} E_i(f, \phi; \theta_i),
\]

where \( \theta = \{ \theta_i \} (i = 1, 2, \ldots, P) \) is the attribute scattering center set of the target; \( P \) represents the number of the scattering centers.

3. Method Description

3.1. Parameter Estimation in the Image Domain

Although the description accuracy of the attribute scattering center model is high, its complex form makes the parameter estimation problem a complicated and hard one. In general, the SAR image data to be analyzed can be expressed as follows:

\[
D(f, \phi) = E(f, \phi; \theta) + N(f, \phi),
\]

where \( E(f, \phi; \theta) \) is the model component described in equation (2); the noise component \( N(f, \phi) \) in the image is generally modeled as a Gaussian distribution. Under the framework of the maximum likelihood estimation, the joint estimation process of the parameter set is described as follows:

\[
\hat{\theta}_{ML} = \arg \min_{\theta} ||D - E(\theta)||^2.
\]

Equation (4) gives the ideal form of the parameter estimation of the attribute scattering centers. However, due to the complexity of the model itself and the large number of parameters, the optimization process is nonconvex, which is easy to fall into the local optimum, resulting in unstable and inaccurate estimation results. As a remedy, the researchers proposed a "divide and conquer" strategy in the image domain, which separates the image area of a single scattering center according to the significant characteristics of the effective scattering center [8–11]. Afterwards, an optimization algorithm can be used to estimate the parameters of a single scattering center. Then, the parameters of all scattering centers can be obtained sequentially. According to
previous works, the process of the image domain parameter estimation algorithm can be generally divided into three steps: decoupling, single scattering center parameter estimation, and sequential estimation. First, the input SAR image is analyzed, and the image segmentation algorithm is used to obtain the region with the largest energy as the image domain representation of a single scattering center. Then, for the decoupled single scattering center data, the optimization is performed under the constraints of the attribute scattering center model to obtain the best attribute parameters. Here, it is necessary to introduce an appropriate optimization algorithm to ensure the precision of the parameter estimation. Finally, the estimated components are removed from the original image (the reconstruction result of the scattering center is subtracted from the original image) to update the input image, and the parameters of the next scattering center are obtained. Through sequential iterative updates, the attribute parameter set of all scattering centers of the target can be output when the termination condition is met.

3.2. Parameter Estimation Based on WWO Algorithm. In the WWO algorithm, the problem space is analogous to the seabed, and each individual in the population is analogous to a “water wave” object [18]. Each water wave has two attributes: initial wave height and wavelength. The core of the WWO algorithm is to assign a wavelength inversely proportional to its fitness for each solution and to make each solution propagation (search) range proportional to its wavelength: the closer the point to the sea level, the better the corresponding solution. The WWO algorithm mainly conducts efficient search in the problem space by simulating the three operations of water wave propagation, refraction, and wave breaking. Without loss of generality, the following takes solving the maximum value as an example to introduce the WWO algorithm.

Step 1: the dissemination stage. In each iteration, all individual water waves need to enter the propagation stage. The expression of the propagation process in each dimension is

$$ st(d) = s(d) + N_r \lambda L(d), $$

where $N_r$ is a random number in the interval $[-1,1]$; $\lambda$ is the wavelength of the water wave; $L(d)$ is the length of the solution space in the dimension $d$; $s(d)$ is the position of the individual $s$ in the dimension $d$; $s'(d)$ is the position of the water wave in the dimension $d$ after the propagation process. If the new individual exceeds the boundary, the new individual is given a random position in the dimensional search space. After the propagation process is completed, calculate the new individual fitness value generated by the propagation; if $\text{fit}(st) > \text{fit}(s)$, then $s'$ is replaced to $s$ and the initial wave height of the wave height dimension $h_{\text{max}}$ is updated; otherwise, the wave height $h$ is reduced by 1. If the new individual is better than the original individual and better than the best individual in the group, it enters the stage of breaking waves. After each iteration is completed, all water waves update their wavelengths according to the following equation:

$$ \lambda = \lambda \theta \left[ \text{fit}(s) - F_{\text{max}} + \varepsilon \right] / \left[ \text{fit}_{\text{max}} - \text{fit}_{\text{min}} + \varepsilon \right], $$

where $\text{fit}_{\text{max}}$ and $\text{fit}_{\text{min}}$ are the maximum fitness value and the minimum fitness value of the group, respectively; $\theta$ is the wavelength attenuation factor; $\varepsilon$ is a constant greater than zero to prevent the denominator from being 0.

Step 2: refraction stage. The individual wave height $h$ of the water wave is determined whether it is 0. If the wave height of the water wave $h$ is reduced to 0, the next generation of individuals will be produced through the following refraction operation; if the wave height $h$ is not 0, the individual will enter the next round of iteration.

$$ s' (d) = N \left( \frac{s'(d) + s(d) \left| s'(d) - s(d) \right|}{2} \right), $$

where $s^*$ is the best individual in the population; $N (\mu, \sigma)$ is a Gaussian random number with the mean $\mu$ and standard deviation $\sigma$. After the refraction process is completed, the water height is updated to $h_{\text{max}}$, and the individual’s wavelength $\lambda'$ is updated. If the fitness is negative, the wavelength is updated according to the following equation to take the reciprocal:

$$ \lambda' = \lambda \frac{\text{fit}(s)}{\text{fit}(s')} \frac{1}{\text{fit}(s')} $$

Step 3: wave breaking stage. When the group finds that a new individual has a better fitness value than the best individual $s^*$ in the current group, then break the waves. The main process of breaking waves is to randomly select search $k$ individuals whose dimensions are around the individual $s^*$, and search for nearby areas $s^*$. The new wave individual is updated according to the following equation in the selected dimension to obtain the new individual:

$$ s' (d) = s(d) + \beta N (0,1) L(d), $$

where $\beta$ is the wave breaking factor, generally taken in the interval $[0.001, 0.01]$. If the individual fitness value of the generated water wave is not better than that of the individual $s^*$, then keep it; otherwise, produce the best individual replacement $s^*$.

Owing to the characteristics and advantages of the WWO algorithm, this paper introduces it into the parameter estimation of the attribute scattering centers. For the single scattering center data obtained by decoupling the image domain, the WWO algorithm is used to solve the best attribute parameters. According to the strategy of order inertial estimation, the parameter set of all attribute scattering centers in the SAR image is obtained.
4. Experiments

4.1. Preparation. This paper tests the proposed method based on the SAR image samples in the MSTAR dataset. This dataset contains SAR images of 10 types of vehicle targets shown in Figure 1. The resolution of these images reaches 0.3 m, and the local scattering phenomenon of the target is obvious. In this experiment, the proposed method is used to estimate the scattering center parameters of MSTAR SAR images. Since the true value of the scattering center parameters of these SAR images is unknown, the validity of the estimation results can only be preliminary determined by comparing the correspondence between the estimated parameters and the strong local scattering of the target (mainly the position parameters) and the consistency between the reconstructed image and the original image. In addition, since the attribute scattering center has been widely used in the SAR target recognition, this paper further evaluates the effectiveness of the proposed method by comparing the parameter estimation results with other ones in the sense of contributions to the recognition performance.

4.2. Parameter Estimation Performance. The proposed method is used to verify a typical SAR image from the MSTAR dataset, and the upper limit of the number of scattering centers is chosen to be 15. Figure 2 shows the projection result of the position parameters on the original SAR image. It can be seen that there is a strong agreement with the local strong scattering center of the target, indicating that the accuracy of the position parameter in the estimation result has a higher accuracy. Figure 3(a) shows the target image reconstructed based on the estimated scattering centers. The classical image correlation is used as the measurement degree, and the similarity between it and the original SAR image is calculated to be 0.932, indicating that the reconstructed result is very similar to the original image.
image. The high correlation indicates the validity of the estimation results of various attribute parameters of the scattering center. Figure 3(b) shows the residual component after the subtraction between the original image and the reconstructed image. Intuitively, the reconstruction residual is mainly from the background component, which is redundant due to clutters or noises. Through the estimation of the target scattering center in the original SAR image and reconstruction, the background factors existing in the original image are effectively eliminated, which has strong support for the analysis of target characteristics. The above results all show the effectiveness of the proposed method for estimating the parameters of the scattering centers in SAR images.

4.3. Target Recognition Performance. In [8–11], SAR target recognition methods are designed based on the attribute scattering centers. One of the typical scenarios is to classify the 10 types of targets shown in Figure 1 under the standard operating condition, under which the training and test sets are shown as Table 1. In order to further verify the effectiveness of the proposed scattering center parameter estimation method, the results of different estimation algorithms can be used for the same SAR target recognition method based on the attribute scattering centers. Then, the recognition performance can be compared. Accordingly, this paper employs different attribute scattering center estimation algorithms, i.e., the simulated annealing, the particle swarm, and sparse representation, to extract the attribute scattering centers. Then, the estimated scattering centers are matched using the method in [9] to classify the 10-class test samples in Table 1. Under different algorithms, the average recognition rates obtained by the recognition method are listed in Table 2. The comparison shows that the attribute scattering center estimated based on the proposed method can achieve the highest average recognition rate, indicating that it has a greater contribution to the recognition performance, reflecting its relatively higher estimation accuracy. Therefore, the contribution of different scattering center extraction algorithms to target recognition can indirectly reflect the stronger effectiveness of the proposed method.

5. Conclusion

To handle the problem of attributed scattering center parameter estimation in SAR images, this paper proposes a method based on the WWO algorithm. On the basis of the traditional image domain “divide and conquer” strategy, the WWO algorithm is introduced to estimate the parameters of each attribute scattering center in a sequential way. In the experiments, the performance of the proposed method is tested based on the MSTAR dataset. First, a typical demonstration of parameter estimation is carried out based on MSTAR SAR images. The effectiveness of the proposed method is verified by comparing the estimated position
parameters with the position of strong scattering points in
the image and the similarity between the reconstructed
image and the original one. Afterwards, the contribution of
different parameter estimation algorithms to SAR target
recognition is compared, which further reflects the superior
performance of the proposed method.

Data Availability

The MSTAR dataset is publicly available.

Conflicts of Interest

The authors declare no conflicts of interest.

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