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Research Article

Extracting Pole Characteristics of Complex Radar Targets for the Aircraft in Resonance Region Using RMSPSO_ARMA

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The extraction algorithm of target characteristics resonance set at the high-frequency band plays a significant role in defense applications like early warning. The paper proposes a new method to extract the characteristic resonance set of radar targets in the resonance frequency region using an autoregressive moving average model optimized by root mean square propagation particle swarm optimization. Considering that the total scattering response in the resonant region consists of early-time and late-time responses, the autoregressive moving average model approximate the total scattering responses to avoid errors caused by intercepting the late-time response. Further, the paper investigated the impact of the swarm optimization algorithm on the accuracy of moving average model parameters when obtaining the resonance set at different target aspects. The extracted characteristic resonance results within a range of azimuth directions through an aircraft target paradigm indicate that the new method is more convenient and precise than the matrix beam prediction method.

1. Introduction

Within the working frequency range of high-frequency surface wave radar (HFSWR), the scattering characteristics of aircraft targets are basically in the resonant frequency region [1]. As a fundamental basis for radar target recognition in the resonance region, the characteristics of the complex resonance, namely the pole, can reveal the internal relationship between the time-domain response of the target and its inherent physical characteristics through a series of resonant frequencies and attenuation factors. Therefore, deriving the complex pole of a radar target has theoretical and practical significance in recognizing the unknow radar target [2, 3]. Introducing the singularity expansion method (SEM) theory provided a solid foundation for the research of pole extraction methods and opened up new directions for subsequent target recognition methods [4, 5]. Ideally, it considers the radar target to be linear, and the system's poles are determined by the characteristics of the target itself, independent of factors such as the target's aspect angle and motion speed [6, 7]. Various pole extraction methods have been developed, such as the polynomial or the state-space method [8].

In the polynomial method, the poles are obtained by calculating the roots of higher-order equations, and the introduction of additional poles can further improve the accuracy of pole estimation. Although the Prony method and Kumaresan Tufts (KT) method derived from polynomial models have achieved phased results, the Prony method has always been unable to eliminate the impact of early-time and late-time aliasing [9, 10].

Furthermore, the operability of the Kumaresan-Tufts (KT) method needs to be improved [11]. The state-space method is used to describes scattering characteristics of the late response of the target, enabling each parameter in the state-space algorithm for estimating parameters to have practical physical significance [12]. The state-space method has developed matrix beam prediction methods, such as E-pulse and orthogonal vector fitting iterative methods [13]. The matrix beam prediction method is relatively stable with noise, but both the E-pulse methods and the iterative method have problems with high computational complexity and difficult parameter selection calculating [14, 15].

Since most traditional methods are based on the late response only, it is necessary to intercept the late-time onset accurately, or it can lead to aliasing between early and late-time responses and thus degrade the accuracy of the estimated poles due to truncation errors. Henceforth, we consider using the ARMA model to approximate the total scattering response to avoid truncation errors. However, this overall approximation approach has high requirements for the parameter estimation of the model, which can lead to a parameter dependency problem. From this, we explore using particle swarm optimization (PSO) to optimize the ARMA model parameters preliminary. In addition, the root mean square propagation (RMSprop) is introduced into the adaptive inertia weight strategy of the PSO algorithm to improve the convergence speed and global optimization ability of the standard PSO algorithm, ultimately achieving optimal estimation of ARMA model parameters and thus better extraction of pole parameters, i.e, resonant frequency and attenuation factor. Henceforth, the core contribution of this research is to establish a series of processes that can accurately extract the pole characteristics of complex targets of HF radar. In the proposed RMSPSO_ARMA algorithm, the aliasing of early and late responses is effectively avoided, and the problem of parameter dependence for ARMA in the actual extraction process is adequately solved. Meanwhile, this method can also be applied to cutting-edge radar detection technology and has strong foresight [2, 3].

In the remainder of the paper, Section 2 presents the method and describes the new process of the extraction algorithm, including the ARMA model approximation algorithm and RMSPSO algorithm based on the adaptive inertia weight decreasing strategy. Section 3 presents the extraction results of the new method using an aircraft target and compares it to the matrix beam prediction method. Finally, Section 4 presents the conclusions and points out future developments.

2. Methods

2.1. ARMA Model Approximation Algorithm. The response of an object excited by an electromagnetic pulse is the superposition of a series of attenuated sinusoidal oscillations. The complex natural frequency, composed of its attenuation factor and oscillation frequency, is the pole of the target.

According to electromagnetic field theory, most electromagnetic scattering problems can be written in the form of integral equations as follows [16]:

$$\int_l K(z,z')I(z')dz' = V(z). \tag{1}$$

Discretization of (1) in matrix equations using the method of moments yields,

$$Z(s)I(s) = V(s), \tag{2}$$

$Z(s)$ is the $N \times N$ th system matrix, $I(s)$ is the $N \times 1$ th response vector, and $V(s)$ is the $N \times 1$ th order excitation vector. The natural frequencies s_α (α stands for the order of the resonance in the signal) and corresponding natural mode vectors $[v_\alpha]$ of the system for zero excitation are obtained first, which requires

$$Z(s_\alpha) \cdot v_\alpha = 0. \tag{3}$$

The necessary and sufficient condition for (3) to yield a nonzero solution is that the determinant of the coefficient matrix is zero, that is.

It is also assumed that the response vector $I(s)$ in (2) can also be written as

$$I(s) = \sum_\alpha \frac{I_\alpha(s)}{s - s_\alpha} + W(s), \tag{4}$$

where $I_\alpha(s)$ is the unknown residue vector, $W(s)$ is the holomorphic function vector, in a certain neighborhood of s_α, $W(s)$ can be written as the analytic function vector. $I'(s)$ in the neighborhood of s_α to obtain

$$I(s) = \sum_\alpha \frac{I_\alpha(s_\alpha)}{s - s_\alpha} + I'(s). \tag{5}$$

The expansions of $Z(s)$, $I(s)$, and $V(s)$, are substituted in (2), and similar items are combined according to the power of $(s - s_\alpha)$. Comparison of terms with $(s - s_\alpha)^{-1}$ yields.

$$Z(s_\alpha) \cdot I_\alpha(s_\alpha) = 0, \tag{6}$$

and comparison of terms with $(s - s_\alpha)^0$ yields.

$$Z_1(s_\alpha) \cdot I_\alpha(s_\alpha) + Z(s_\alpha) \cdot I'(s_\alpha) = V(s_\alpha). \tag{7}$$

Comparison of (3) and (6) yields

$$I_\alpha(s) = \eta_\alpha(s)v(s_\alpha), \tag{8}$$

where $\eta_\alpha(s)$ is the complex coupling coefficient

$$\eta_{\alpha 0} = \eta_\alpha(s_\alpha). \tag{9}$$

Thus, (10) is obtained as

$$I_\alpha(s_\alpha) = \eta_{\alpha 0}(s)v(s_\alpha). \tag{10}$$

To solve $\eta_{\alpha 0}(s)$, the coupling vector μ_α is defined as

$$Z(s_\alpha)^T \cdot \mu_\alpha = 0. \tag{11}$$

If $Z(s)$ is a symmetric matrix, then μ_α is actually v_α. In this way, if (10) is substituted in (8), the coupling coefficient can be obtained by using (11).

$$\eta_{\alpha 0} = \frac{{\mu_\alpha}^T V(s_\alpha)}{{\mu_\alpha}^T Z_1(s_\alpha)v_\alpha}. \tag{12}$$

Substituting (8) in (4) yields

$$I(s) = \sum_\alpha \frac{\eta_\alpha(s)v_\alpha}{s - s_\alpha} + I'(s). \tag{13}$$

The time-domain solution of the corresponding vector can be obtained using the Laplace transform inversion formula and the residue theorem.

$$i(t) = \sum_\alpha \eta_\alpha(s)v_\alpha e^{s_\alpha t}. \tag{14}$$

From the previous derivation, it can be observed that the key to solving transient electromagnetic problems with the SEM is to obtain μ_α, ν_α, and $\eta_{\alpha 0}$.

Based on the assumption of (4), according to the Mitlag–Leffler theorem on the meromorphic function in the theory of complex variable functions, the current density on the surface of ideal conductive scatter can be written as [16],

$$J(s) = \sum_{\alpha} \eta_\alpha \nu_\alpha(s) \left\{ \frac{1}{s - s_\alpha} + P_\alpha(s) \right\} + J_e(s), \tag{15}$$

where, $P_\alpha(s)$ is the polynomial and $J_e(s)$ is the holomorphic function.

As long as $J(s)$ is a meromorphic function with only first-order poles, (15) is a series with only uniform convergence, which ARMA model can be approximated. In [14], L. Marin proved that the surface current density on the ideal conductive surface of finite size in a lossless medium is a meromorphic function, there is only pole singularity, not natural singularity and fulcrum [14]. Because the electromagnetic wave emitted in practical application is not an ideal impulse signal, it will be accompanied by early then late responses aliasing. In order to solve the negative effect of this error on pole extraction, the ARMA model is used to approximate the whole echo scattering. The incident bandwidth is limited, and the generated scattering echo can only have a limited number of characteristic poles. It can be seen that the order of the model is limited [4]. When the model is finite, the incident wave can be regarded as an input and combined with the target as a linear time-invariant system for rational approximation. Then the echo scattering characteristics of the target can be expressed as [17]

$$E(t) = E_e(t) + \sum_{j=-\infty}^{\infty} E_l(t) e^{s_i t}, \tag{16}$$

where $E_e(t)$ is the early response, $\sum_{j=-\infty}^{\infty} E_l e^{s_i t}$ is the late response. According to the above analysis, (16) can be described as finite order ARMA difference equation,

$$\overline{E}^s(k) = \sum_{i=1}^{n} \varphi_i \overline{E}^s(k-i) + \sum_{j=0}^{m} \theta_j \overline{E}^i(k-j), \tag{17}$$

where n and m are the order of AR and MA in ARMA model, $n < N/8$, $m < 2N/3$, and N is the number of sampling points. $\overline{E}^s(k)$ is the sampling value of target scattering field echo, $\overline{E}^i(k)$ is the sampling value of the incident field, φ_i is the autoregressive model parameter of ARMA, and θ_j is the moving average model parameter. Then the transfer function of (17) can be expressed as

$$H = \frac{\sum_{j=0}^{m} \theta_j z^{-j}}{1 - \sum_{i=1}^{n} \varphi_i z^{-i}}. \tag{18}$$

In this way, the poles of the target $s_i, i = 1, 2, \cdots, n$ can be obtained directly from the zeros of the denominator polynomial in (18). Before that, the relevant parameters of ARMA model about autoregressive order, moving average order, autoregressive coefficient and moving average coefficient need to be estimated.

2.2. The RMSPSO_ARMA Algorithm. The RMSPSO algorithm is selected to optimize and estimate the ARMA model parameters by reducing this parameter dependence, improving the estimation accuracy of the ARMA model, and overcoming the shortcomings of the cumbersome calculation process. The best parameters of the model are obtained through a global search. Based on this, the data model of echo scattering is established, and finally, the pole extraction of complex targets is completed.

The PSO algorithm is a parallel and efficient swarm intelligence optimization algorithm [18]. It has the advantages of high precision, simple process, and fast convergence in parameter optimization. It is very suitable for model optimization. PSO algorithm updates the positions and speeds of group members through adaptive learning. Each particle i has a position vector $x_i = \{x_{i1}, x_{i2}, \cdots, x_{iD}\}$ and a velocity vector $v_i = \{v_{i1}, v_{i2}, \cdots, v_{iD}\}$. The particle will move along the historical optimal position vector of the individual $p\text{best}_i$ and the global optimal position vector of the population $g\text{best}_i$, where $pbest_i = \{p\text{best}_{i1}, p\text{best}_{i2}, \cdots, p\text{best}_{iD}\}$, $g\text{best}_i = \{g\text{best}_{i1}, g\text{best}_{i2}, \cdots, g\text{best}_{iD}\}$. The position and velocity of the particle are initialized randomly within the set interval, and the D-dimension of the next iteration of the particle is updated as follows:

$$\begin{aligned} v_{id}^{k+1} &= w \cdot v_{id}^{k} + c_1 \cdot r_1 \cdot \left(p\text{best}_{\text{id}}^{k} - x_{\text{id}}^{k} \right) \\ &\quad + c_2 \cdot r_2 \cdot \left(g\text{best}_{\text{id}}^{k} - x_{\text{id}}^{k} \right), \end{aligned} \tag{19}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1}, \tag{20}$$

where $d = 1, 2, \cdots, D$; $i = 1, 2, \cdots, n$; k is the current number of iterations; v_{id} is the velocity of the current particle in the d-dimensional space; x_{id} is the position of the current particle in the d-dimensional space; c_1 is the weight coefficient of the optimal value found by the particle in its historical search; c_2 is the weight coefficient of the optimal value found by the particle in the swarm search, c_1 and c_2 are collectively referred to as learning factors, and are usually set to 2; r_1 and r_2 are uniform random numbers in the interval [0,1]; w is the inertia weight coefficient, which determines the influence of the particle's historical flight speed on the current flight speed.

As shown in (19), the inertia weight w can retain the motion inertia of particles so that particles can expand the search and improve the global search ability of particles. In order to give full play to the characteristics of a single particle, the concept of the adaptive learning rate of RMSprop is introduced into the inertia weight of the PSO [19]. Adaptive inertia weight can provide appropriate values according to the search information of different particles in different dimensions for faster convergence speed and higher solution accuracy.

The speed of the next generation iteration of particles v_{id} is determined by the accumulation of momentum, the distances from the individual optimal position and the group optimal position to the current particle position, as shown in (19). The optimal position of the group is more instructive for particle motion. Therefore, the gradient g_{ij} of the particle

i in j-dimension can be considered as the distance from the globally optimal $gbest_j$ to x_{ij} of the particle in the current dimension, as shown in

$$g_{ij} = gbest^i - x_{\mathrm{ij}}, \tag{21}$$

with the increase in the number of iterations, each particle i tends to the optimal position of the group, and the gradient of the particle g_{ij} of the particle will decrease gradually. Therefore, we use an exponentially weighted average. Equation (8) is used to update the gradient and accumulation $\sum_t [g^2]$ of the current dimension as follows

$$\sum_{ij} g^2 = \rho \cdot \sum_{i(j-1)} g^2 + (1-\rho) \cdot g_{ij}^2. \tag{22}$$

The parameter ρ is the weighting coefficient, where $\rho \in (0,1)$

Finally, the inertia weight w_{ij} of the particle i in the j-dimension is updated according to (23), α and β the adjustment coefficients are, $\alpha \in (90,100)$, $\beta \in (0.4, 0.5)$.

$$w_{ij} = \frac{\sqrt{\sum_{ij} g^2}}{\alpha} + \beta. \tag{23}$$

In the initial stage of the RMSPSO, the distance from the global optimal $gbest_j$ in the current dimension to the x_{ij} is large, and the calculated inertia weight w_{ij} is significant, which is conducive to global search. In the final stage, g_{ij} is small, and the calculated w_{ij} is small, which is conducive to local optimization and finding the optimal solution. Thus, through this strategy, the diversity and convergence of the RMSPSO can be well guaranteed.

The main steps of the RMSPSO_ARMA method are as follows:

Step 1: Setting the maximum number of iterations, the number of particles, and the particle dimension D. In the defined search space, the velocities and positions of particles in all dimensions are randomly generated.

Step 2: Calculate the initial fitness value of the particles and update the historical optimal position of a single particle *pbest* and the global optimal position of particle groups *gbest*.

Step 3: Calculate the inertia weight w of each dimension of all particles according to (21)–(23).

Step 4: Update the speed and position of each particle according to (19) and (20).

Step 5: After the position update is completed, the current fitness values of all particles are calculated, and the new *pbest* and *gbest* are obtained by comparing the current fitness values with the fitness values calculated by the historical optimal position *pbest* of the particles and the fitness values calculated by the global optimal position *gbest*.

Step 6: Perform the iterative operation by continuously circulating from Step 3 to Step 5. When the number of iterations reaches the preset maximum, the search is stopped to obtain the optimal autoregressive p and moving average order q.

The autoregressive parameters $\varphi_i\,(i = 1, 2, \cdots, n)$, moving average parameters $\theta_j\,(j = 1, 2, \cdots, m)$ and residual variance σ_a^2 of ARMA model will be estimated.

The autoregressive parameter vector φ_i can be obtained by moment estimation, according to the Yule-Walker estimation method as follows.

$$\begin{pmatrix} \hat{\varphi}_1 \\ \hat{\varphi}_2 \\ \vdots \\ \hat{\varphi}_n \end{pmatrix} = \begin{pmatrix} \hat{\rho}_m & \hat{\rho}_{m-1} & \cdots & \hat{\rho}_{m-n+1} \\ \hat{\rho}_{m+1} & \hat{\rho}_m & \cdots & \hat{\rho}_{m-n+2} \\ \vdots & \vdots & & \vdots \\ \hat{\rho}_{m+n-1} & \hat{\rho}_{m+n-2} & \cdots & \hat{\rho}_m \end{pmatrix}^{-1} \begin{pmatrix} \hat{\rho}_{m+1} \\ \hat{\rho}_{m+2} \\ \vdots \\ \hat{\rho}_{m+n} \end{pmatrix}, \tag{24}$$

where, $\hat{\varphi}_i$ is the estimation vector of φ_i, $\hat{\rho}_i$ is the estimated value of the autocorrelation function of the sample, which can be calculated from the observed datas.

When the sequence MA(0, m) is constructed and the moment estimates of the θ_j and σ_a^2 can be set that

$$\overline{\omega}_t = x_t - \hat{\varphi}_1 x_{t-1} - \cdots - \hat{\varphi}_n x_{t-n}, \tag{25}$$

$\overline{\omega}_t$ is approximately regarded as sequence MA(0, m), that is,

$$\overline{\omega}_t \cong a_t - \theta_1 a_{t-1} - \cdots - \theta_m a_{t-m}, \tag{26}$$

where, $\{a_t\}$ is called a residual sequence. Then, the estimation equation of the autocorrelation function of the $\{\overline{\omega}_t\}$ can be derived as follows

$$\hat{r}_0(\overline{\omega}) = \hat{\sigma}_a^2\left(1 + \hat{\theta}_1^2 + \cdots + \hat{\theta}_q^2\right), \tag{27}$$

$$\overline{r}_k(\overline{\omega}) = \hat{\sigma}_a^2\left(-\hat{\theta}_k + \hat{\theta}_1\hat{\theta}_{k+1} + \cdots + \hat{\theta}_{q-k}\hat{\theta}_q\right), \tag{28}$$

where, $k = 1, 2, \cdots, q$. $\{r(\overline{\omega})\}$ is the estimated value of the autocorrelation function of sequence MA(0, m). Then the direct method is used to obtain the solutions, which are the estimated values of moving average parameters θ_j and residual variance σ_a^2 of the ARMA model.

In practical application, to reduce the calculation dimension, whether the residual variance is significantly stable is taken as the criterion to judge whether the model has established, $\min(\sigma_a^2)$ and can be selected as the fitness function of the RMSPSO_ARMA model. Then the residual is calculated as follows:

$$a_i = x_i - \sum_{k=1}^{n} \varphi_k x_{i-k} + \sum_{j=1}^{m} \theta_j a_{i-j}, \tag{29}$$

where, $i = 1, 2, \cdots, m+1$, when $i-k \le 0$, $x_{i-k} = 0$; when $i-j \le 0$, $a_{i-j} = 0$.

The main steps of the whole extraction process are shown in Figure 1.

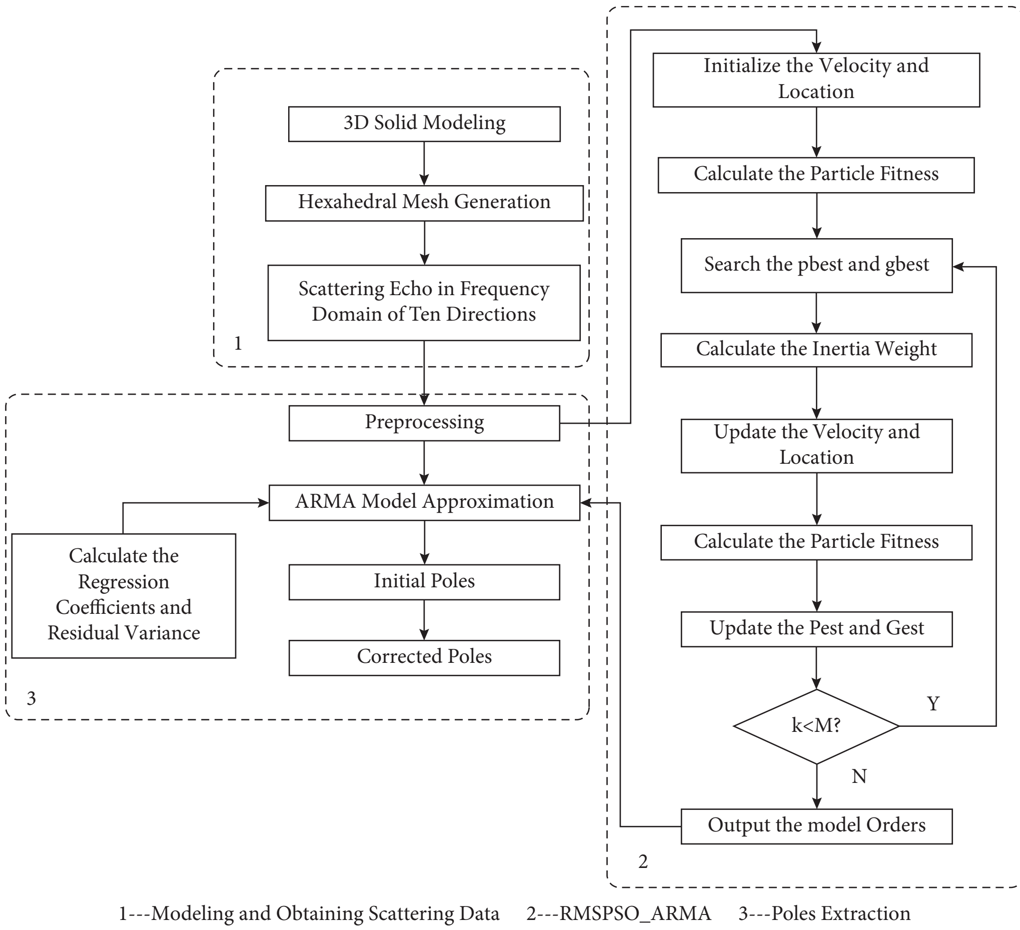

Figure 1: The primary processes of pole extraction.

3. Results and Analysis

An aircraft with a length of 18.9 m, a wingspan of 13.56 m, and a main height of 5.08 m was selected. The simulation setup was divided into three steps: First, according to the physical structure of the aircraft, the aircraft model was accurately established and meshed based on Computer Simulation Technology Microwave Studio. Figure 2 shows the hexahedral meshing model of the aircraft. The second was to obtain the scattering of the target. The frequency range of the incident wave was from 0.15 MHz to 30 MHz, with one sampling point every 0.15 MHz. The radar scattering echoes were calculated within the azimuth plane which ranged from 0° to 90° at 10° intervals. This was determined by considering the calculation amount, convergence effect and calculation accuracy of many simulation tests. Figure 3 shows the echo scattering values of the aircraft in different directions. Third, the RMSPSO_ARMA method was applied to extract the pole characteristics of the aircraft, and the extracted characteristic values are all normalized by $\pi c/L$ (L is the length of the aircraft).

Figures 4 and 5, respectively, show the pole distributions of the aircraft within ten different azimuth directions extracted by the matrix beam prediction method [20] and the method presented herein. We focused on the analysis and comparison aspects. First, from the comparison of the clustering of the poles, it is evident that the pole positions in different directions in Figure 5 are more concentrated (less spread), while the poles estimated in Figure 4 are more spread. These findings show that the poles in Figure 5 are closer to the real poles. This is because some target information is lost compared with the late response intercepted by the matrix beam prediction method. The method in this study directly approximates the entire scattered echo, which contains more complete target information. Therefore, the estimated pole set is more accurate. Second, the pole integrity is analyzed, as shown for pole 1 in Figure 5. Note that there is one more pole in Figure 5 than in Figure 4, and the aggregation of this pole is relatively high, which means

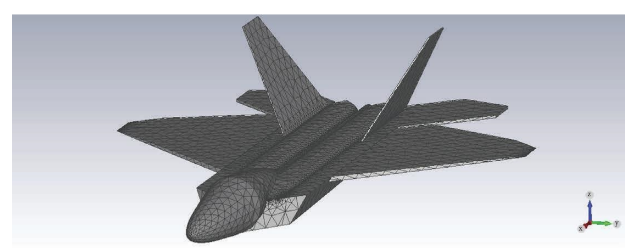

Figure 2: Hexahedron meshing model of the aircraft.

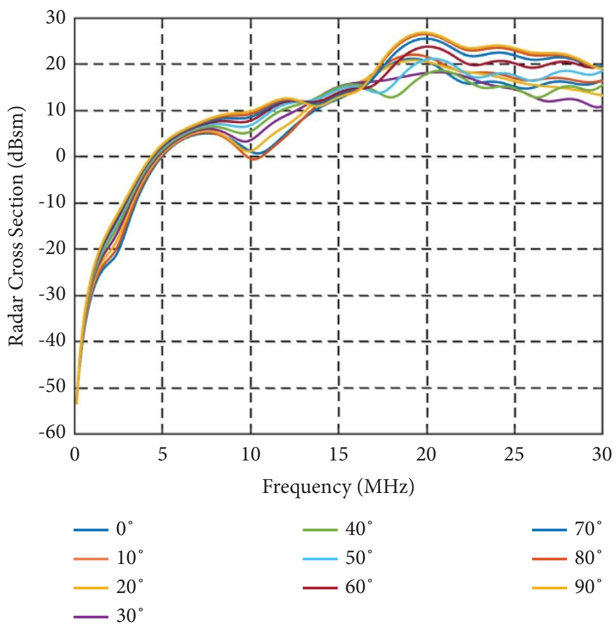

Figure 3: The target RCS profile at HF band per ten azimuth direction.

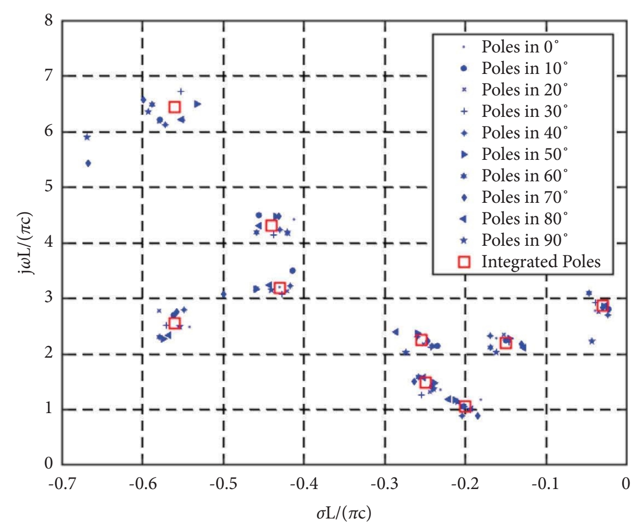

Figure 4: The extracted pole distribution of the matrix beam prediction method. The blue marks are the original poles extracted along ten directions, and the red marks are obtained after correction.

that pole 1 is also an actual pole. This is explained by the fact that the poles extracted by this method are more complete than those extracted by the matrix beam prediction method because the matrix beam prediction method does not correctly select the parameters of poles in the calculation process.

Hence, the pole parameters are optimally estimated with the help of the RMSPSO_ARMA algorithm. Thus, more complete pole characteristics can be extracted. Based on the above analysis, it can be observed that the test on the aircraft achieved the expected results, and the pole features extracted

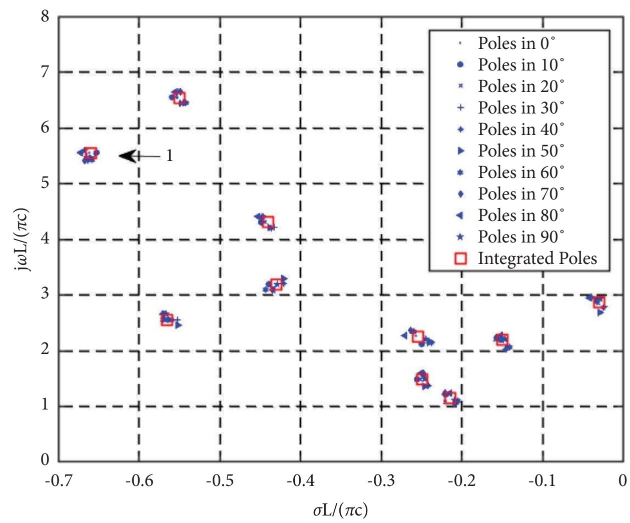

Figure 5: Extracted pole distribution in ten directions using the developed method. The blue marks denote the original poles extracted per azimuth directions, and the red marks represent the corrected poles set.

from their scattering echoes have higher accuracy and integrity. These results demonstrate that this method is feasible, effective, and more accurate than the matrix beam prediction method.

4. Conclusions

In this research, a series of processes that can accurately extract the pole characteristics of complex targets of high-frequency radar is developed, and the core contribution is the root mean square propagation particle swarm optimization at autoregressive moving average model optimized algorithm. In this method, the autoregressive moving average model is used to approximate the whole scattering echo of complex radar targets reasonably, and the root mean square propagation particle swarm optimization algorithm is applied to optimize the parameters in the model accurately. In this way, the negative influence of early and late responses aliasing in the scattering signal and the problem of parameter dependence caused by the model method are avoided, and the potential informations of pole characteristics is effectively extracted. The method is tested on the complex aircraft. The results indicate that the pole feature extracted from the scattering echo of the target has higher accuracy and integrity than the matrix beam prediction method. The successful performance of this characteristic extraction technology provides a theoretical basis for the complex radar target recognition method in engineering practice, which will be conducive to developing the modern radar system.

In future research, more noncooperative radar targets will be studied quantitatively for feature extraction and target recognition based on the method proposed in this study. This work will be divided into three main parts. The first step will involve the construction of a large number of solid models for ships and aircraft. The second step will use the improved pole extraction method to obtain the pole characteristics of the targets and establish a systematic database. The third step will identify the targets according to the pole database. The target recognition rate can, in turn, further confirm the performance of pole feature extraction. In addition, the method will be adapted to new developments in pole feature extraction and target recognition technology. It is expected that this future research can continue to solve the problems of large pole characteristic errors and the low recognition rates of complex radar target poles.

Data Availability

The 3D model and MATLAB codes used to support the findings of this study are available from the first author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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References

[1] A. Karine, A. Toumi, A. Khenchaf, and M. Hassouni, “Radar target recognition using salient keypoint descriptors and multitask sparse representation,” *Remote Sensing*, vol. 10, no. 6, p. 843, 2018.

[2] A. Coluccia, A. Fascista, and G. Ricci, “Design of customized adaptive radar detectors in the CFAR feature plane,” *IEEE Transactions on Signal Processing*, vol. 70, pp. 5133–5147, 2022.

[3] A. P. Sligar, “Machine learning-based radar perception for autonomous vehicles using full physics simulation,” *IEEE Access*, vol. 8, pp. 51470–51476, 2020.

[4] F. F. H. Aldhubaib, “Enhancing the SEM signature via the optimum onset with a bistatic and cross-polarization radar configuration,” *IEEE Access*, vol. 8, pp. 86238–86245, 2020.

[5] F. Aldhubaib, “Enhancing SEM signature via bistatic radar configuration of small bisectors,” *IET Radar, Sonar & Navigation*, vol. 16, no. 6, pp. 1053–1064, 2022.

[6] J. Yang and T. K. Sarkar, “Interpolation/extrapolation of radar cross-section (RCS) data in the frequency domain using the Cauchy method,” *IEEE Transactions on Antennas and Propagation*, vol. 55, no. 10, pp. 2844–2851, 2007.

[7] W. U. Bajwa, K. Gedalyahu, and Y. C. Eldar, “Identification of parametric underspread linear systems and super-resolution radar,” *IEEE Transactions on Signal Processing*, vol. 59, no. 6, pp. 2548–2561, 2011.

[8] C. L. Bennett and J. P. Toomey, “Target classification with multiple frequency illumination,” *IEEE Transactions on Antennas and Propagation*, vol. 29, no. 2, pp. 352–358, 1981.

[9] Z. L. Wang, C. M. Tong, T. Wang, Y. J. Wang, and Q. K. Wang, “A new radar echo generation model for ultra-low altitude targets in far-field conditions,” *International Journal of Antennas and Propagation*, vol. 2022, pp. 1–11, 2022.

[10] M. L. Bencheikh, Y. Wang, and H. He, “Polynomial root finding technique for joint DOA DOD estimation in bistatic MIMO radar,” *Signal Processing*, vol. 90, no. 9, pp. 2723–2730, 2010.

[11] K. Kim, I. Choi, and H. Kim, “Efficient radar target classification using adaptive joint time-frequency processing,” *IEEE Transactions on Antennas and Propagation*, vol. 48, no. 12, pp. 1789–1801, 2000.

[12] K. Naishadham and J. E. Piou, “A robust state space model for the characterization of extended returns in radar target signatures,” *IEEE Transactions on Antennas and Propagation*, vol. 56, no. 6, pp. 1742–1751, 2008.

[13] E. Rothwell, D. Nyquist, Kun-Mu Chen, and B. Drachman, “Radar target discrimination using the extinction-pulse technique,” *IEEE Transactions on Antennas and Propagation*, vol. 33, no. 9, pp. 929–937, 1985.

[14] K. Tan, W. Li, Y. Huang, and J. Yang, “Angular resolution enhancement of real-beam scanning radar base on accelerated iterative shinkage/thresholding algorithm,” *2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, pp. 929–932, 2016.

[15] M. A. Rahman and K. B. Yu, “Total least squares approach for frequency estimation using linear prediction,” *IEEE Transactions on Acoustics, Speech, & Signal Processing*, vol. 35, no. 10, pp. 1440–1454, 1987.

[16] L. Marin, “Natural-mode representation of transient scattered fields,” *1973 Antennas and Propagation Society International Symposium*, vol. 21, no. 6, pp. 809–818, 1973.

[17] M. A. Morgan, “Singularity expansion representations of fields and currents in transient scattering,” *IEEE Transactions on Antennas and Propagation*, vol. 32, no. 5, pp. 466–473, 1984.

[18] X. Dong, H. Li, J. Tan, J. Hu, and Y. Jiang, “A PSO-cvx algorithm of sum and difference beam patterns for time-modulated antenna array,” *International Journal of Antennas and Propagation*, vol. 2021, pp. 1–9, 2021.

[19] Y. Hu, X. Sun, X. Nie, Y. Li, and L. Liu, “An enhanced LSTM for trend following of time series,” *IEEE Access*, vol. 7, pp. 34020–34030, 2019.

[20] S. Yang et al., “The complex target pole feature extraction method,” *Journal of Computational Information Systems*, vol. 9, no. 12, pp. 4885–4892, 2013.