Reconstruction of Target Fluctuation Characteristics Based on L_M Algorithm

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Abstract. High-precision are conducive to accurate analysis of radar detection performance. Therefore, building a highly accurate target RCS undulation characteristic library plays an important role in target detection and recognition field. Traditional RCS fluctuation models are not very accurate and can not describe target fluctuation characteristics at frequency zone. To solve this problem, a new method is proposed, which is based on the L_M (Levenberg-Marquardt) optimization algorithm to compress the target fluctuation characteristics. Firstly, RCS fluctuation characteristics of radar targets are obtained by calculating the full-angle RCS of the simple model. Then the L_M optimization algorithm is used to calculate the neuron parameters and perform experimental fitting. Finally, compared with traditional modeling and theoretical data, which can validate the superiority and effectiveness of the proposed method.

1. Introduction
Swerling model is firstly used to detect radar performance by Swerling in the 1960s [1-3]. Then he developed the model into a chi-square distribution model [2-3]. In order to improve the fitting accuracy, scholars have also proposed Rice distribution and lognormal distribution [4-5]. These distributions still have use value. With the development of aircraft, the RCS (radar cross of section) undulation of targets can not be accurately expressed by traditional models [6]. Therefore, a new RCS fluctuation model is needed for high-precision fitting. In order to solve the problem that the traditional log-normal distribution can't fit the stealth aircraft which mean value ratio is less than 1, Shi Weiqiang et al proposed a complete form of log-normal distribution, which has a better fitting effect to the stealth aircraft [7]. Reference [8] combines the modeling of target RCS fluctuation model and track simulation, and proposes a modeling method of target dynamic RCS fluctuation model, which is closer to the actual application. Although the traditional model has high versatility, it is increasingly unsuitable for the needs of radar detection performance at this stage. With the development of artificial intelligence in recent years, big data processing technology has become more perfect, and radar target recognition technology based on artificial intelligence has become the current development trend in the field of detection and recognition [9]. At the same time, the development of agile frequency radar makes agile frequency tracking a new tracking method, and traditional modeling methods are difficult to fit the target fluctuations caused by frequency changes. In order to solve this problems, this paper used L_M neural network optimization algorithm to compress and reconstruct the fluctuation model.
2. L_M Neural Network Optimization Algorithm

2.1. Neural Network Algorithm
Artificial Neural Networks (ANNs) is an algorithmic mathematical model that imitates animal neural networks and performs distributed parallel information processing\cite{10}. The network relies on the number of neural network layers and the dimension of each layer's parameter matrix, and adjusts the weight threshold between nodes to achieve the purpose of information processing, and has self-learning and adaptive capabilities\cite{11-13}. The basic unit of the neural network is a neuron, and the basic model is shown in Figure 1, the input vector \( \mathbf{X} \). After neuron processing, the output vector is \( \mathbf{Y} \). The relationship of a basic neuron can be expressed as\cite{14-15}:

\[
\mathbf{A} = \mathbf{WX} + \mathbf{\theta} \tag{1}
\]

\[
\mathbf{Y} = f(\mathbf{A}) \tag{2}
\]

Where \( \mathbf{W} \) denotes weight matrix, \( \mathbf{\theta} \) is threshold matrix, \( f \) is nonlinear activation function, \( \mathbf{X} \) is input vector and \( \mathbf{Y} \) is the output vector.

2.2. L_M Algorithm
L_M optimization algorithm, which is also known as "Levenberg-Marquardt" method. This algorithm combines the advantages of the gradient descent algorithm and the Gauss-Newton method\cite{16}, it overcomes the shortcomings of the traditional BP neural network based on slow convergence and easy to fall into local optimal\cite{17}. Therefore, we can more accurately and quickly extract the important parameters of the target fluctuation characteristics by using the L_M optimization algorithm. The neural network of L_M algorithm includes input layer, hidden layer and output layer. The basic model is shown in Figure 2.

3. Simulation Experiment
In terms of angle fitting, this paper selects cylinders and flat plates as experimental objects, and conducts experimental simulation in three steps. (1) Calculating the RCS of the cylindrical target by the geometric optical method and RCS of the flat target by the physical optical method; (2) Statistically process the RCS data of the two targets to obtain the target RCS probability density curve, and then use the L_M
neural network optimization algorithm. Compress and reconstruct the data; (3) Compare and analyze the data obtained by the L_M neural network optimization algorithm with traditional statistical modeling and original data to verify the experiment. In terms of frequency fitting, this article continues to use cylinders and flat plates as experimental objects, and conducts experimental simulation in two steps: (1) fix the incident angle, change the frequency within a range, simulate the frequency conversion process of the agile radar, calculate the target RCS; (2) Processing the data to obtain the target RCS probability density curve, and then use the L_M neural network optimization algorithm to compress and reconstruct it, lastly comparing and analyzing with the original data to verify the experiment.

3.1. Cylinder
The cylinder can be used to simulate aircraft parts such as fuselage, nacelle, auxiliary fuel tank and so on. The calculation formula is as follows:

\[ \sigma = k h^2 r \sin(\theta) \frac{\sin^2(k h \cos(\theta))}{(k h \cos(\theta))^2} \]  

(3)

Where \( k \) is the wave vector, the direction is the propagation direction, the size \( k = \frac{2\pi}{\lambda} \); \( h \) is the height of the cylinder; \( r \) is the radius of the cylinder circle; \( \theta \) is the angle of incidence.

3.1.1. Angle Domain Fitting. Choose radius \( r = 0.5 \) m; height \( h = 2 \) m; incident angle \( \theta = [0, \pi] \), step length \( \pi/1000 \); wavelength \( \lambda = 1 \); \( k \) is wave vector, the direction is propagation direction, and size is \( k = \frac{2\pi}{\lambda} \). The selection of the neural network is as follows: the 20-layer learning network, the loss function is the minimum two norm, the maximum iteration step is 5000, and the iteration termination error is.

![Figure 3. Full-angle static RCS of cylinder RCS.](image_url)

![Figure 4. Fitting results of Cylinder target RCS.](image_url)
From Figure 3, the following rules can be found: (1) The RCS of the cylindrical target has symmetry, and the axis of symmetry is the direction of the incident angle of 90°, that is the axis of symmetry of the cylinder. (2) the target RCS increases with the angle increase before 90° , this is the calculation formula has an extreme value at 90 degrees.

From Figure 4, the following rules can be found: (1) The L_M optimization algorithm has the highest fitting degree to the data. it likes the restoration of the original data; (2) The lognormal distribution has the highest fitting in the traditional distribution Degree, but it can only have a good fitting effect on the long tail of the data, and cannot accurately fit the data peak. The simulation results show that the L_M optimization algorithm has higher accuracy and reliability than the traditional model in data reconstruction, and can completely simulate the original data.

3.1.2. Frequency Domain Fitting. The current development of frequency-agile radar urgently needs the corresponding fluctuation model, but the traditional modeling method can not fit the target RCS fluctuation brought by the frequency change. The L_M neural network optimization algorithm proposed in this paper can suit this demand and has a high fitting accuracy.

Choose radius $r = 0.5$ m; height $h = 2$ m; incident angle is 45°; the frequency is $[100, 200]$ MHz; the step length is 1 MHZ. The selection of the neural network is as follows: the 20-layer learning network, the loss function is the minimum two norm, the maximum iteration step is 5000, and the iteration termination error is $10^{-12}$.

The experimental result is as follows:

![Figure 5. RCS varies with frequencies of cylinder RCS.](image)

![Figure 6. Fitting results of cylinder RCS.](image)

It can be seen from Fig. 5 that the RCS of the cylindrical target increases first and then decreases with increasing frequency. In fact, the change of RCS in the Rayleigh area is irregularly oscillating, and there is no accurate model to describe it in detail. Therefore, it also increases the difficulty of fitting the target fluctuation with the parameter model. It can be seen from Figure 6 that the L_M optimization algorithm
selected in this paper still maintains a good fitting accuracy in the frequency domain, and the fitting accuracy can be achieved $10^{-12}$.

3.2. Tablet
The flat panel can simulate certain planes of the aircraft such as vertical tail, engine inlet, tail nozzle, radome, etc. The calculation formula is as follows [6]:

$$\sigma = \frac{4\pi A^2}{\lambda^2} \cos^2 \theta \sin^2 \frac{f_1}{f_2}$$

(4)

Where $A = ab$ represents the product of the length and width of the tablet, $\theta$ is the coordinate azimuth, $\phi$ is the coordinate pitch angle, $f_1 = k a \sin \theta \cos \phi$, $f_2 = k b \sin \theta \sin \phi$, $k$ is the wave vector, the direction is the propagation direction, and the size is $k = \frac{2\pi}{\lambda}$.

3.2.1. Angle Domain Fitting. Choose $a = 1$ m, $b = 1$ m, $\lambda = 1$ m; incident angle $\theta = [0, \pi]$, step length $\pi / 1000$; $\phi = [0, \frac{\pi}{2}]$; the frequency is [100, 200] MHz, step length is 1 MHz; The selection of the neural network is as follows: the 20-layer learning network, the loss function is the minimum two norm, the maximum iteration step is 5000, and the iteration termination error is $10^{-12}$.

![Figure 7. Full angle static RCS of flat target](image1)

![Figure 8. RCS undulation fitting results of flat target](image2)

Comparing the flat target of Fig. 7 with the cylindrical target, it can be found that the RCS of the flat target changes more complicatedly on azimuth angle and the pitch angle, and the target has a low peak in the azimuth angle of 90°.
It can be found from Figure 8: (1) both the Swerling model and the log-normal distribution model can fit the trend of detection probability well, but the fluctuation of the change cannot be fully described; (2) The L_M optimization algorithm has the best fitting results are in good agreement with the original data.

In terms of tablet fitting, the traditional model can fit the RCS change trend of the tablet target, but it is difficult to show the fluctuation. The L_M optimization algorithm can meet the needs of both. The algorithm has accuracy and reliability that the traditional model does not.

3.2.2. Frequency Domain Fitting. Calculate the target RCS value of the tablet by the calculation formula, and then perform the fitting to verify the feasibility of the algorithm.

Choose $a = 1\text{ m}, b = 1\text{ m}$; incident angle $\theta = \frac{\pi}{4}$; $\varphi = \frac{\pi}{4}$; The selection of the neural network is as follows: the 20-layer learning network, the loss function is the minimum two norm, the maximum iteration step is 5000, and the iteration termination error is $10^{-12}$.

![RCS change with frequency](image)

**Figure 9.** RCS changes with frequencies of flat target.

![Comparison of simulation results](image)

**Figure 10.** RCS undulation fitting results of flat target.

It can be seen from the simulation of Figure 9 that the target RCS oscillates randomly with frequency, but the whole can be viewed as a sinusoidal oscillation and the period is not fixed. In terms of data fitting, it can be derived from Figure 10 that the target RCS fluctuation model has two peaks, and there is no long tailing phenomenon of traditional angle domain fitting, so it is impossible to perform traditional fitting using traditional models. And the mean square error of the fluctuation simulation results and the original data is on the order of $10^{-10}$ by Using the algorithm in this paper, and the fitting accuracy meets the needs of detection performance analysis, which can be applied to the detection performance analysis of agile frequency radar.
4. Conclusion
Aiming at the problem that the accuracy of the traditional target fluctuation model is not high and the frequency fluctuation cannot fit the target fluctuation, this paper proposes a new method of compressing and reconstructing the target RCS fluctuation model using the L_M neural network optimization algorithm. The article verifies the reliability and accuracy of the proposed method from the angle domain and frequency domain. The angle domain simulation of the ellipse and the plate verifies the advantages of the method over the traditional model in fitting accuracy and the storage space over the original data. The simulation results are in line with theoretical expectations. In the frequency domain, this aspect still has good fitting accuracy, which solves the problem that the traditional undulation model cannot be applied to the agile radar. The research results can be applied to radar detection performance evaluation, which is of great significance for improving the radar's target detection capability.

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