Research on RCS Similarity Algorithm of Non-cooperative Target Model

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Abstract. The RCS similarity evaluation is an important content of non-cooperative target model assessment. Aiming at the problems of the existing similarity measurement methods applied to the RCS similarity evaluation of non-cooperative target model, this paper proposes an algorithm which can quantitatively reflect the RCS similarity of non-cooperative target model. In order to better adapt to different data sets and make the algorithm more flexible, the weighting operators and penalty factors are introduced to further optimize the algorithm.

1. Introduction

After the non-cooperative target entity model is built, it needs to be evaluated from multiple dimensions, including the dimensions and materials, structural strength and accuracy, electromagnetic scattering characteristics, etc. The RCS measurement and similarity evaluation are important operation contents\cite{1}, and the similarity of RCS between the solid model and theoretical model will directly affect the effect of model application.

When analyzing the RCS similarity of the non-cooperative target model, the RCS measured data set and the theoretical data set can be regarded as two sets of high-dimensional spatial data, and the similarity of the two sets of data can be evaluated by calculating the distance function or correlation coefficient. However, the two methods are difficult to accurately reflect the numerical proximity of the two sets of data, and the calculation results cannot correctly reflect the actual similarity\cite{2-3}. In view of the large amount of RCS data of the non-cooperative target model, the similarity judgment method based on hypothesis test can also be considered\cite{4}. However, this method can only qualitatively reflect the fitting of measured data set and theoretical data set, and cannot make further judgments on the similarity of the non-cooperative target model.

Aiming at the deficiencies of the above algorithms, this paper proposes an algorithm which can quantitatively reflect the RCS similarity of the non-cooperative target model, and discusses the extended application of the algorithm.

2. The improved similarity algorithm

The RCS measurement of the non-cooperative target model needs to obtain RCS values under different grazing angles and azimuth angles, and the amount of data obtained is usually large. Assuming that the RCS measured values of the model at $n$ key positions are obtained during the test, it is necessary to find out the $n$ theoretical values at the same positions from the RCS theoretical spatial distribution map. Assuming that the measured data set is $X=(x_1,x_2,\ldots,x_n)$ and the theoretical data set is $Y=(y_1,y_2,\ldots,y_n)$, the
RCS similarity evaluation of the non-cooperative target can be transformed into the similarity analysis of the data sets $X$ and $Y$.

2.1. The traditional similarity algorithms

Traditional similarity algorithms include the distance function, the correlation coefficient, the hypothesis test, etc. If the above algorithms are simply applied to the RCS similarity evaluation of the non-cooperative target model, there will be different problems. The following two sets of data are taken as examples to analyze.

Example 1: This paper generates two sets of random data as the RCS measured data set and theoretical data set (each with 1000 data), which respectively obey the normal distribution $N(0,100)$ and $N(8,105)$, and the data are arranged from small to large, denoted as $X = (x_1, x_2, \ldots, x_{1000})$ and $Y = (y_1, y_2, \ldots, y_{1000})$.

In the distance function method, taking the Euclidean distance as an example, the Euclidean distance of $X$ and $Y$ is 281.84, but it is difficult to draw a conclusion whether $X$ and $Y$ are similar by this value. The range of Euclidean distance of two sets of data is $[0, +\infty)$. If there is no reference distance for comparison and no other constraints, the result calculated by the distance function is meaningless.

In the correlation coefficient method, taking Pearson correlation coefficient as an example, the correlation coefficient of $X$ and $Y$ is calculated to be 0.9972, which can only reflect the change trend of $X$ with $Y$, and is difficult to directly reflect the similarity of the two sets of data. In fact, there are some other problems when the correlation coefficient method is applied to the RCS similarity evaluation as follows.

1. It is difficult to accurately reflect the closeness of the two sets of data.
2. There is a phenomenon that the value cannot correctly reflect the actual degree of similarity.

In the hypothesis test method, the probability density function curve and cumulative distribution function curve of $X$ and $Y$ are shown in Figure 1. Taking the K-S test as an example, when the significance level is 0.05, the analysis results show that the distribution of $X$ and $Y$ is consistent. However, it is difficult to draw a conclusion from the analysis results of the hypothesis test that how similar the two sets of data are.

2.2. The improved similarity algorithm

This paper considers that the following conditions should be met for the similarity algorithm of the RCS measured data set $X = (x_1, x_2, \ldots, x_n)$ and theoretical data set $Y = (y_1, y_2, \ldots, y_n)$ of the non-cooperative target.
model.

(1) The similarity results should have a unified range. This paper takes (0,1], and the larger the value is, the more similar the two sets of data are. The value close to 0 indicates that the two sets of data are very different, and the value of 1 indicates that the two sets of data are exactly the same.

(2) On the premise of the same attention to each data, the contribution of each dimensional data should be equivalent and independent. Equivalence means that the influence of each dimension data on the overall similarity is consistent and limited, and independence means that the similarity of single-dimensional data in a certain dimension should not have an impact on the similarity of single-dimensional data in other dimensions. This paper defines the similarity of single-dimensional data as S_i and the overall similarity as S.

(3) In the case of the same difference, the RCS similarity should be different relative to different theoretical reference values.

In order to meet the above conditions, this paper uses the absolute value of the ratio of the difference between x_i and y_i to the theoretical value y_i, i.e. \(|(x_i - y_i) / y_i|\) (hereinafter referred to as the difference ratio), as the calculation parameter of the RCS similarity, and defines the calculation formula of the similarity of single-dimensional data of x_i and y_i as follows.

\[
S_i = e^{-|x_i - y_i| / y_i}, \quad (y_i \neq 0)
\]

The simulation results show that the value in the RCS theoretical data set is equal to 0 on a large scale is extremely low. For the case of y_i=0, two solutions are considered as follows.

(1) You can eliminate the dimension with a value of 0 in the theoretical data set Y and the corresponding dimension in the measured data set X, and then analyze the similarity of X and Y with 0 values removed.

(2) For all dimensions with a value of 0 in the theoretical data set Y, you can find out the corresponding data in the measured data set X, and assign the corresponding value of S_i through data analysis and manual decision.

The calculation formula of the overall similarity is as follows.

\[
S = \frac{1}{n} \sum_{i=1}^{n} S_i
\]

The overall similarity S has the following properties.

(1) The value range of S is (0,1]. The larger the value is, the more similar the measured data set X and the theoretical data set Y are.

(2) The minimum value of S tends to 0 infinitely, which means that the difference ratio between the measured data set X and the theoretical data set Y in each dimension is close to infinity, and the similarity of X and Y is the smallest.

(3) The maximum value of S is 1, which means that the values of the measured data set X and the theoretical data set Y are equal in each dimension. In this case, X and Y are completely consistent, and the similarity is the largest.

3. The improved similarity algorithm for further optimization

The improved similarity algorithm takes into account the equivalent contribution of each dimension, and unifies the similarity results into the range of (0,1], which initially has the ability to quantitatively and intuitively reflect the similarity of two RCS data sets. In order to better adapt to different RCS data sets and make the similarity algorithm more flexible and reasonable, the weighting operators and penalty factors are introduced to further optimize the algorithm.

3.1. The weighting operators

In the actual application of the non-cooperative target model, the degree of attention to the RCS values of different viewing directions is different in some cases. Therefore, the weighting operator w_i is introduced to represent the importance of RCS values in different viewing directions. The value range of w_i is (0,1]. The larger the value of w_i is, the higher the degree of attention to the RCS value in this
direction is, which means the greater contribution and influence on the overall similarity. The weighted similarity algorithm is as follows.

$$S' = \frac{1}{n} \sum_{i=1}^{n} w_i S_i$$  \hspace{1cm} (3)

3.2. The penalty factors

For the calculation formula of the similarity of single-dimensional data (Formula (1)), there is a phenomenon that the difference ratio and similarity do not meet the expectation in some ranges, as shown in Figure 2.

It can be seen from Figure 2 that when the difference ratio reaches 0.6, the similarity calculated by Formula (1) is still as high as 0.698, which is not in line with the conventional decision logic. Therefore, the penalty factors $\alpha$ and $\beta$ are introduced to make the optimized algorithm meet the following conditions.

1. When the difference ratio is less than $a$, the similarity of single-dimensional data is greater than $S_u$.
2. When the difference ratio is greater than $b$, the similarity of single-dimensional data is reduced to below $S_l$.

The calculation formula of the similarity of single-dimensional data with penalty factors is as follows.

$$S'_i = \frac{1}{2} \left( e^{-\alpha |x_i-y_i|^2} + e^{-\beta |x_i-y_i|^2} \right), \text{ (} y_i \neq 0 \text{) } (4)$$

Example 2: This paper supposes that when the difference ratio is less than 0.3, the similarity of single-dimensional data should be greater than 0.6, and when the difference ratio is greater than 0.6, the similarity of single-dimensional data should be reduced to less than 0.2. $\alpha$ and $\beta$ are equal to 2.76 and 9.64 respectively through calculation, and the similarity of single-dimensional data is $S'_i = \frac{1}{2} \left( e^{-2.76 |x_i-y_i|^2} + e^{-9.64 |x_i-y_i|^2} \right)$. The relationship curve between difference ratio and the similarity of single-dimensional data is shown in Figure 3.
Figure 3. The curve of new algorithm.

It can be seen from Figure 3 that when the difference ratio is 0.3, the similarity of single-dimensional data is approximately equal to 0.6, and when the difference ratio is 0.6, the similarity of single-dimensional data is reduced to less than 0.2, which is in a reasonable range. The penalty factors can be adjusted flexibly according to different application needs to achieve the desired effect.

The overall similarity algorithm with weighting operators and penalty factors is as follows.

\[
S' = \frac{1}{n} \sum_{i=1}^{n} \left[ \frac{1}{2} \cdot w_i \cdot \left( e^{-\alpha \|x_i - y_i\|^2} + e^{-\beta \|x_i - y_i\|^2} \right) \right], \quad (y_i \neq 0)
\]

(5)

3.3. Algorithm comparison

The similarity algorithm proposed in this paper unifies the similarity range to (0,1], which can avoid the problem of meaningless values generated by simply applying the distance function, and can also solve the problem that the correlation coefficient method and hypothesis test method cannot quantitatively and intuitively reflect the similarity degree of two RCS data sets. Taking the difference ratio as the calculation parameter can avoid the problem of applying the algorithm proposed in reference [5] to RCS similarity evaluation of the non-cooperative target model, and the weighting operators and penalty factors are introduced to make the algorithm more flexible and adaptable.

For \( X_1 \) and \( Y_1 \) in Example 1, all weighting operators are set to 1, and the penalty factor \( \alpha \) and \( \beta \) are equal to 2.76 and 9.64 respectively. The overall similarity of \( X_1 \) and \( Y_1 \) calculated by Formula (5) is 0.745, which represents that the similarity of most dimensions of \( X_1 \) and \( Y_1 \) is greater than 74.5%, and the difference ratio is less than 0.22.

3.4. Expanded application analysis

In order to further evaluate the non-cooperative target model, the full-space RCS similarity analysis and SAR image similarity analysis can be carried out when the test conditions permit. The full-space RCS varies with the grazing angle and azimuth angle, which can be considered as a two-dimensional image, as shown in Figure 4(a). The SAR image is shown in Figure 4(b). Each pixel of the full-space RCS image and SAR image represents a numerical value.

The full-space RCS similarity analysis and SAR image similarity analysis of the non-cooperative target model can be regarded as the pixel-to-pixel similarity analysis between the theoretical image and the measured image. Due to a certain angle error in the test process, the target area of interest in the theoretical image and the measured image may be offset, and the offset direction and offset value are unknown. Therefore, this paper adopts the traversal translation method to align the target areas of the theoretical image and the measured image as much as possible, and then calculates the maximum similarity as the final judgment result.
Figure 4. The full-space RCS image (a) and SAR image (b).

Assuming that the pixels of the measured image and the theoretical image are $M \times N$, and converted into the corresponding $M \times N$-order numerical matrix $X$ and $Y$, the similarity calculation formula is as follows.

$$
S'_{k,l} = \sum_{j=1}^{N} \sum_{i=1}^{M} \left[ \frac{1}{2} \cdot w_{i,j} \cdot \left( e^{-\alpha |x_{i,j} - y_{i,j}|} + e^{-\beta |x_{i,j} - y_{i,j}|} \right) \right] \\
\frac{1}{MN}, \quad (y_{i,j} \neq 0)
$$

4. Conclusion
Aiming at the problems existing in the application of traditional algorithms to similarity analysis of the non-cooperative target model, this paper proposes a new algorithm, which has strong flexibility, can meet different analysis needs, and can make up for the shortcomings of traditional similarity algorithms. The calculation results can quantitatively and intuitively reflect the RCS similarity of the non-cooperative target model. This algorithm can also be applied to the similarity analysis of the non-cooperative target full-space RCS and SAR image.

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