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Aircraft Target Classification Method Based on EEMD and Multifractal

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Abstract—Due to the limitation of low-resolution radar system and the influence of background clutter in the detection process, it is hard for low-resolution radars to classify and identify aircraft targets. To solve the above problems, a classification method for aircraft based on Ensemble Empirical Mode Decomposition (EEMD) and multifractal is proposed, in which the intrinsic modes are obtained by EEMD, and the waveform entropy in the Doppler domain is used to screen and reconstruct the intrinsic modes. The multifractal feature of the target echo data is extracted from the reconstructed signal, and then the aircraft target classification and recognition experiment is carried out with support vector machine. The experimental results show that the feature data extracted by ensemble empirical mode decomposition and multifractal analysis can be used for the classification and identification of civil aircraft and fighter aircraft, and the accuracy rate is about 98.5%, which is higher than that of time-domain multifractal method.

1. INTRODUCTION

Along with the development of modern military technology, radar plays a more and more crucial role in modern war, and the identification of targets has been the focus of research in related fields. In the current research status, high-resolution radars are more favored by most scholars [1–4]. In the radar target recognition achievements, most of them are obtained with high-resolution radar as the experimental object. However, there are still a large number of low-resolution radars in service in China that cannot determine accurate range and azimuth [5]. There is practical significance to improve the identification ability of low-resolution radars for detecting targets through signal processing. The aircraft is an important target for such radar surveillance, and the non-rigid vibration and rotating parts of the fuselage will introduce different nonlinear modulations on the echo. In general, the micro-Doppler modulation effect of aircraft target echo is primarily generated by the motion of the rotating parts on board. The Doppler spectral width of the micro-component of echo is mainly determined by the valid length and number of blades of the rotating parts, and the spectral line interval depends on the number and speed of the blades [6]. In [7], it is pointed out that the effective paddles of jet aircraft are short, and the number of paddles is large, which often requires the observation radar to have high working frequency band and pulse heavy frequency. Therefore, the aircraft target classification method based on JEM modulation feature is not applicable to jet aircraft identification for low-resolution radar echo data. Due to the intrinsic differences in the physical structure and material composition of different types of aircraft targets, the micro-components of their echoes still have distinct distribution characteristics. It will be helpful for the classification of aircraft targets if modulation, which can reflect the characteristics of aircraft targets, can be extracted effectively. In the past studies, Shao [8] et al. realized the identification of aircraft targets based on waveform features after analyzing the characteristics of low-resolution radar. Up to now, many methods [9–11] have been proposed to extract radar echoes from aircraft targets,

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such as singular value decomposition, periodic diagram, and empirical mode decomposition. However, they are not good at recognizing aircraft targets under short irradiation time and low pulse repetition frequency. Therefore, the above methods are difficult to achieve accurate classification of targets for low-resolution radar echo data.

The results show that the fractal theory performs well [12–15] in the modeling of various radar clutters. Aircraft and other human-made objects do not have fractal characteristics. Still, their existence will change the fractal behavior of clutter, and different types of aircraft targets have different effects on clutter. Li and Xie [16] came to the conclusion that defining multiple effective characteristic parameters by multifractal spectrum is helpful to realize aircraft target classification. Fan [17] proposed local multifractal spectrum to improve the performance of weak target detection.

In recent years, fractal and other nonlinear analysis methods have been introduced into the time-domain or frequency-domain analysis of conventional low-resolution radar echoes, and good results have been obtained under specific experimental conditions. However, in the background of strong clutter, the fractal and other nonlinear characteristics of radar echo will be more like the characteristics of clutter. Also, the fuselage component in the echo has little effect on the classification and identification of targets. If the influence of airframe translational component can be eliminated, the correct classification and identification rate of targets can be further improved. Ensemble Empirical Mode Decomposition (EEMD) is a noise-assisted data analysis method, which can separate the airframe translational component and the micro-motion component of aircraft echo. Based on the above analysis, EEMD and multifractal are used to analyze and extract the characteristics of aircraft target echo of conventional low resolution radar, and the effectiveness of features in aircraft target classification and identification is discussed.

2. THEORETICAL BASIS

2.1. Ensemble Empirical Mode Decomposition

Empirical mode decomposition (EMD), proposed by Huang et al. [18] in 1998, which is an analytical processing method suitable for distribution parameters or distribution law with time changes, nonlinear signals. Through time-scale features, the signal is decomposed into several intrinsic modal functions (IMFs) and a residual term. This method has been widely used in various fields for some time. However, with the application of many scholars, the defects of modal aliasing have been exposed. In the following research, Wu and Huang [19] improved EMD through the noise in 2009 to make up for the previous shortcomings. The improved new method, which is called ensemble empirical mode decomposition (EEMD), solves the defects of EMD by adding white noise with uniform distribution for many times. The specific steps of EEMD algorithm are as follows:

(1) Suppose the original signal to be $f(t)$, and set the amplitude of the added white noise to be a and the overall average number to be M;

(2) Add white Gaussian noise with amplitude a;

$$f_m(t) = f(t) + a \cdot n_m(t) \tag{1}$$

in the above formula, $f_m(t)$ represents the signal with the mth addition of noise, while $n_m(t)$ represents the Gaussian white noise with an amplitude of 1.

(3) With the EMD method, the signal is decomposed into a range of IMFs, $m = m + 1$;

(4) Cycle through steps (2) and (3), until $m = M$;

(5) The resulting series of intrinsic modal components are averaged over the whole population to obtain the final IMF. The calculation formula is as follows:

$$\overline{\mathrm{IMF}_i} = \sum_{m=1}^{M} \frac{\mathrm{IMF}_{i,m}}{M} \tag{2}$$

where $\mathrm{IMF}_{i,m}$ represents the ith intrinsic modal function obtained by EMD decomposition of the signal with the mth white noise added.

2.2. Doppler Spectrum and Its Waveform Entropy

The characteristic of the Doppler spectrum has great application potential. It can reflect the geometric structure, scattering characteristics, and motion characteristics of the target. The conventional radar targets in this paper have different physical parameters and working modes, so the corresponding target rotating parts will produce different periodic modulations to radar echo when they operate, which is reflected on the echo-Doppler spectrum.

The concept of entropy was first proposed by Clausius in 1865 and is widely used in thermodynamics. With the deepening of theoretical and applied research, the nature of entropy has been gradually recognized, and its application has also been stepwise expanded on other fields. In this paper, waveform entropy [20], which measures the evenness of signal energy distribution, is introduced to help the IMF in its selection. For the signal y, its waveform entropy is as follows:

$$\text{Entropy}\,(y) = -\sum_{i=1}^{N} p_i \log_2 p_i \tag{3}$$

where,

$$p_i = |y_i| \bigg/ \sum_{i=1}^{N} |y_i| \tag{4}$$

y_i is the ith value of the signal y. It can be seen from the definition of Equation (3): The smaller the waveform entropy is, the more concentrated the waveform distribution is. The higher the waveform entropy is, the more uniform the waveform distribution is.

2.3. Multifractal Theory

The fractal theory, which is proposed by Mandelbrot, is widely used to describe some complex phenomena [21] with nonlinear concepts such as scale invariance, self-similarity, self-affine property, and fractal dimension. However, there is no strict definition of multifractal, and its main idea can be described as follows: The fractal of a region is divided into many smaller regions, and the growth probability of the first small region is denoted as $p_i(\varepsilon)$. Generally speaking, the growth probabilities of different regions are different, which is usually represented by the index [22]:

$$P_i(\varepsilon)\infty\varepsilon^{\sigma_i} \quad i = 1, 2, \cdots, N \tag{5}$$

where the scale of each small region is denoted as ε; the total number of small regions is denoted as N_ε; and σ_i represents the growth probability of each small regional fractal. When different small regional fractal geometries have different local partial shape dimensions, the collection of these small regional fractal geometries can be called multifractal geometry. On the contrary, when different small regional fractal bodies have the same or similar local partial shape dimensions, the collection of these small regional fractal bodies can be called single fractal geometry. The multifractal can be divided into regular and irregular ones, and the corresponding multifractal spectrum can be obtained by statistical physics. Calculate both sides of Equation (4) to obtain a partition function [23]:

$$\Gamma(q, \varepsilon) = \sum_{i=1}^{N} P_i^q(\varepsilon) = \varepsilon^{\tau(q)} \tag{6}$$

In practical application, the value range of q can be determined according to the requirements of practical problems. If $q \geq 1$ in the above equation, the larger subset of $p_i(\varepsilon)$ in the fractal body plays a greater role. If $q \leq 1$ in the above equation, the smaller subset of $p_i(\varepsilon)$ in the fractal has a smaller role. The multifractal spectrum $f(\sigma)$, which is known as singular spectrum function, can further reflect the characteristics of the growth distribution probability of the fractal body on the whole.

3. SIGNAL ANALYSIS AND FEATURE EXTRACTION

After an in-depth understanding of EEMD and multifractal theory, the corresponding radar echo data model is established, and the EEMD and multifractal method are applied to the classification and identification of two kinds of aircraft targets.

Before EEMD, the initial values of the two parameters α and M need to be set. Whether the IMFs obtained by EEMD decomposition are reasonable depends on these two parameters. If the value of α is too small, the local extreme value distribution of the original signal will not be affected; if the value of α is too large, the actual signal will be submerged by α, resulting in less real signal extracted from the actual signal during decomposition. In theory, the larger the value of the overall average number of times is the better. However, increasing the value will lead to an increase in the running time of the program, so it is necessary to set an appropriate M. In addition, the purpose of increasing the average number of the population is to reduce the interference of the added white noise to the decomposition results. When the interference error of the added white noise to the final results is lower than the acceptable value, the increase of the average number of the population can be stopped. Wu and Huang [19] of Taiwan Central University believe that the value should conform to the following equation:

$$\ln\sigma + \frac{\alpha}{2}\ln M = 0 \tag{7}$$

In the above equation, σ represents the standard deviation of the original signal, and M represents the average number of population. In a general way, the weight coefficient is 0.2, and the decomposition effect is good when the average number of times is several hundred.

$$\alpha = 0.2\sigma \tag{8}$$

In this experiment, the ratio of the standard deviation of white noise to the original signal is set as 0.2. According to the mathematical formula and general conditions, the value of M is set as 100 on the premise of ensuring a good decomposition effect.

Taking the echo data of a group of civil aircraft flying towards the radar station as an example, this group of data was processed by EEMD to obtain a series of IMFs, and the Doppler spectrum of each IMF signal is analyzed. Figure 1 shows the IMFs obtained by EEMD. Figure 2 shows the Doppler spectrum of IMFs.

For each IMF obtained by EEMD as shown in Figure 1, waveform entropy Eq. (3) was used to calculate the waveform entropy in the Doppler domain, and IMF was selected according to the property of waveform entropy, in descending order IMF_2, IMF_3, IMF_4, IMF_5, IMF_6, IMF_7, IMF_8, IMF_9, IMF_1, and IMF_{10} It can be seen from the results that for the noise components introduced in the EEMD decomposition process, the Doppler spectrum distribution of IMF_2 is wide and uniform, and the waveform entropy is the largest. The waveform entropy of IMF_3 is the second, and IMF_3 is greatly affected by the noise introduced during the decomposition of EEMD. However, IMF_1, the translational component of echo body, and IMF_{10}, which reflects echo trend, have smaller waveform entropy and stronger DC component. In the following study, IMF_4, IMF_5, IMF_6, IMF_7, IMF_8, and IMF_9 are recombined, and the multifractal analysis of the reconstructed signals is performed. On this basis, choosing appropriate multifractal characteristic parameters as the classification criteria can improve the accuracy. In this study, the following multifractal feature parameters are defined as classification features.

(1) Width of generalized fractal dimension

$$\Delta D = D_{q\max} - D_{q\min} \tag{9}$$

in the formula, the general dimension, D_q, is defined as [24]:

$$D_q = \frac{\tau(q)}{q-1} \tag{10}$$

in addition, $D_{q\max}$ represents the maximum value of generalized dimension, and $D_{q\min}$ represents the minimum value of generalized dimension.

(2) Mass index symmetric degree

$$R_\tau = \left|\frac{\max\tau(q)}{\min\tau(q)}\right| \tag{11}$$

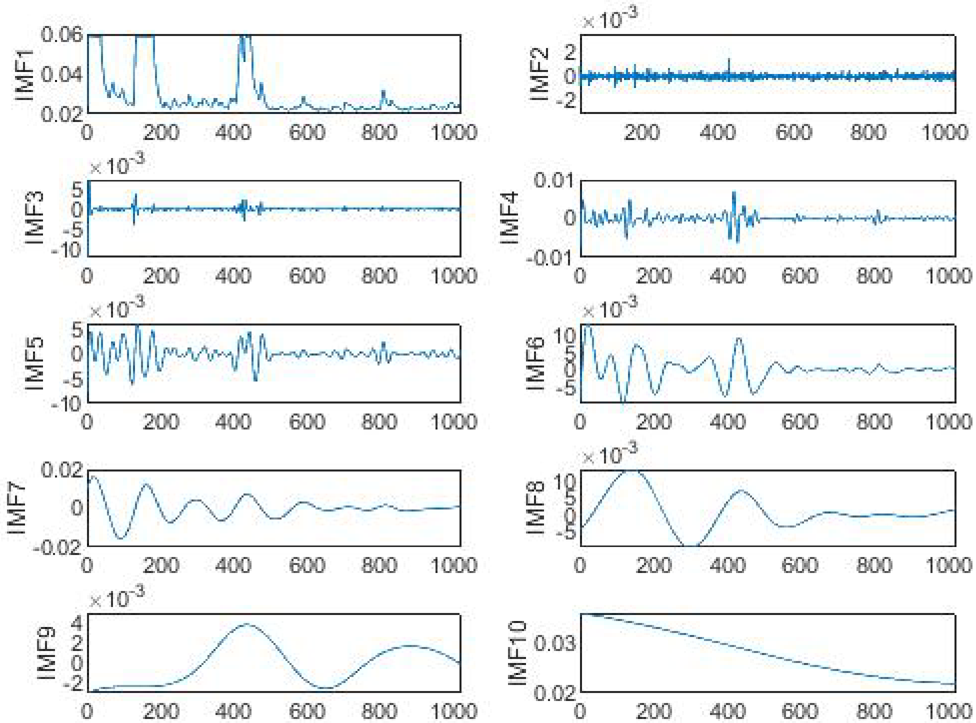

Figure 1. IMFs obtained by EEMD.

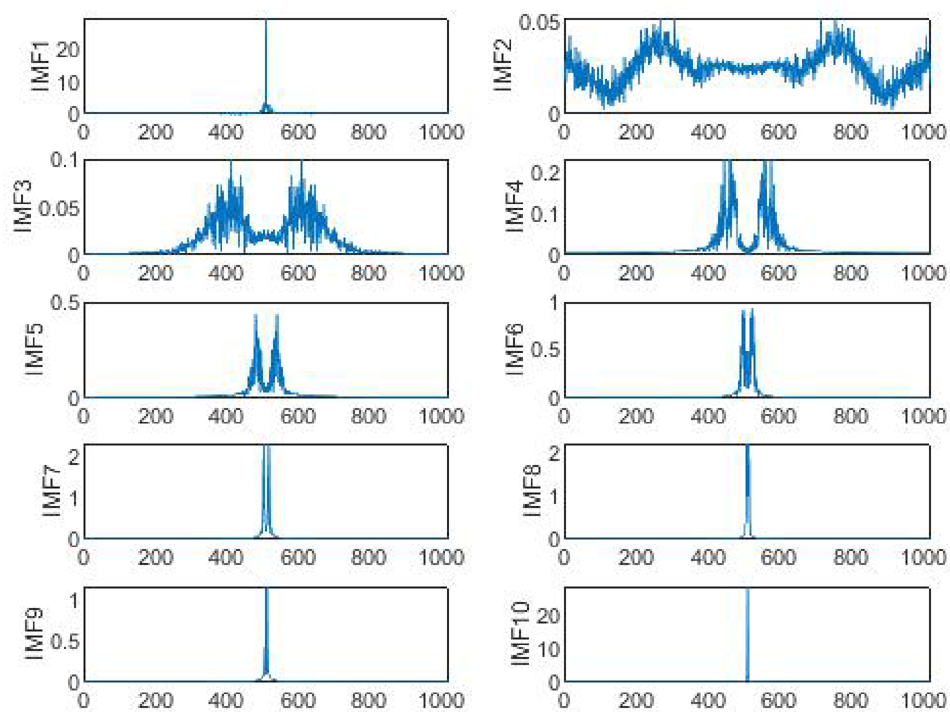

Figure 2. Doppler spectrum of IMFs.

where $\max \tau(q)$ is the maximum value of mass index curves, and likewise, $\min \tau(q)$ is the minimum value of mass index curves.

(3) Spectrum width

$$\Delta\sigma = \sigma_{\max} - \sigma_{\min} \tag{12}$$

in Equation (12), $\sigma_{\max}$ and $\sigma_{\min}$ are the maximum and minimum values of the exponent, respectively.

Figure 3 shows the scatter distribution of the three multifractal features. In this figure, the coordinates of the three dimensions are respectively three features (Width of generalized fractal dimension, Spectrum width, and Mass index symmetric degree). The blue points are represented according to the multi-fractal features of civil aircraft, while the red points are represented according to the multi-fractal features of fighter aircraft. As can be seen from the figure, the red points and blue points are clearly distinguished, with only a few points in staggered distribution. It can be seen that the difference between the two types of aircraft is obvious, and only a small part of them overlap. Therefore, based on these three multifractal features, the two kinds of aircraft targets can be classified effectively.

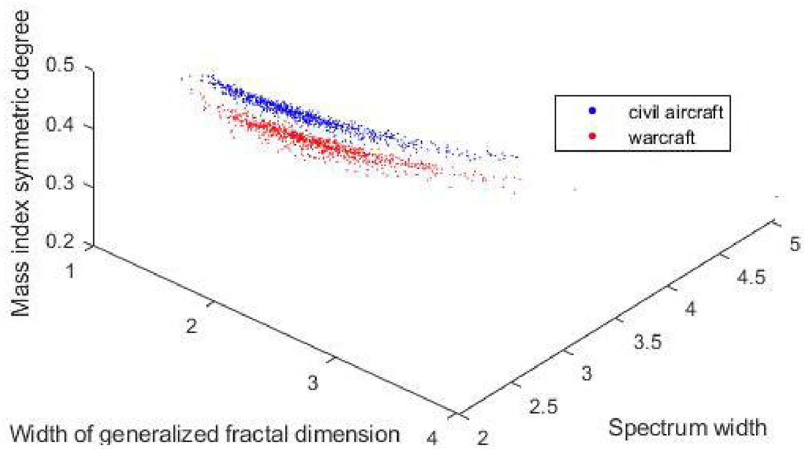

Figure 3. Scatter distribution of three multifractal features.

4. AIRCRAFT TARGET CLASSIFICATION EXPERIMENTS

The application of the above characteristics in aircraft target classification is discussed by using the measured target echo data below. The data used in the following experiments are radar echo data of a certain civil aircraft and fighter aircraft. The radar operated in the VHF band with a pulse width of 25 μs and a pulse repetition frequency of 100 Hz.

For two different kinds of aircraft, the recognition experiments were carried out according to two flight attitudes, namely, toward and off the radar station. In the toward-the-radar-station experiment, a total of 1536 groups of randomly scrambled echo data were selected, and the echo numbers of both targets were 768 groups. In the-off-the-radar-station experiment, 1536 groups of randomly scrambled echo data were also selected, and the echo numbers of both targets were 768 groups. Ref. [25] proposed a method to classify aircraft targets by using multifractal characteristics, which has the good overall performance. In the process of classification, support vector machine (SVM), which has strong generalization ability and fast convergence, is selected [26]. Wang [27] applied an SVM to news text classification model and proved the advantages and practicability of multi-kernel SVM with experimental results. A study on realizing the recognition of infrared ship targets using offline sample base training to obtain SVM classifier was done by Zhang et al. [28]. Geng et al. [29] used an SVM to establish a prediction model for air traffic flow prediction and concluded that the SVM model was superior to the polynomial model and robust model. When multifractal features are used for category, Gaussian kernel function is selected as the kernel function of SVM in this paper. To adjust each parameter within the range of computer running time, the accuracy of aircraft target classification is compared to determine whether the parameter setting is optimal. The following data are obtained based on the essential parameter chosen reasonably. Table 1 lists the correct classification rates (CCR) of two sets of data under two analysis methods.

Table 1. CCR of classification and recognition.

item compared	Multifractal characteristics		EEMD and multifractal characteristics	
	Toward the radar station	Off the radar station	Toward the radar station	Off the radar station
civil aircraft	95.05%	96.09%	98.05%	99.22%
fighter aircraft	95.96%	97.01%	98.44%	98.31%
Average CCR	95.51%	96.55%	98.25%	98.77%

The data obtained by the two categories of comparison items in Table 1 are based on the same data set. The accuracy rate obtained by using the EEMD and multifractal feature is shown on the right side of Table 1, and the accuracy rate obtained by using the multifractal feature of the data not processed by EEMD is shown on the left side of Table 1. It can be found that in the absence of EEMD, the recognition rate of the two types of aircraft is about 95%. In contrast, after the EEMD, the recognition rate of the two types of aircraft has been improved, with the accuracy reaching more than 98%. The recognition rate of the correct classification has been improved by more than two percentage points. As the same algorithm has different effects in different data sets, experiments with similar data sets are selected for comparison. Wu et al. [30] used self-affine fractal features to classify similar data sets, and the overall recognition accuracy was about 91%. When Li et al. [31] processed similar data sets by using fractional Fourier domain multifractal features, the average recognition rate of flight toward the radar station was 93.23%, while that of flight off the radar station was 99.28%. Through the comparison of these three methods, it can be considered that the method in this paper has a certain validity. The specific confounding matrices based on EEMD and multifractal feature experiments are shown in Table 2 and Table 3.

Table 2. Confusion matrix when flying toward the radar station.

item compared	civil aircraft	fighter aircraft
civil aircraft	753	15
fighter aircraft	12	756

Table 3. Confusion matrix when flying off the radar station.

item compared	civil aircraft	fighter aircraft
civil aircraft	762	6
fighter aircraft	13	755

As can be seen from the data in Table 2 and Table 3, the classification effect of the civil aircraft and fighter aircraft is relatively good, but about 1.5% of data are still misclassified. The reasons for the loss are as follows: although the target of the civil aircraft in this experiment is larger than the target of the fighter, the nonlinear modulation of the target echo is more intense, but because the echo data of the civil aircraft are recorded in the distance range of $100 \sim 130$ km, and the echo data of the fighter aircraft are recorded in a distance range of $60 \sim 90$ km, so that their echo signal-to-clutter ratios may be equivalent, resulting in a certain degree of confusion in echo data samples. In addition, the parameters of the EMD of the set in this paper are selected as empirical estimates, which may not be the optimal parameters applicable to the data set, and the fractal features in this paper are artificially defined, so there may be better fractal features. From the experimental process, the first derivative of the fractal dimension after EEMD processing as the eigenvalue can also be used to classify aircraft targets. Furthermore, we intend to combine deep learning with signal processing in an attempt to find a more intelligent processing system.

5. CONCLUSIONS

According to the principle of EEMD, each component of the target aircraft can be decomposed reasonably. According to the fractal theory, the multifractal characteristics of aircraft targets can be extracted. In this paper, EEMD is first used to process the data to separate the fuselage translational component and the fretting component of the aircraft echo. Then, according to the waveform entropy in the Doppler domain, the optimal IMFs of aircraft target echo are selected again, and the components that have little effect on target classification and identification are removed. Then the multifractal characteristics of the reconstructed signal are extracted. Taken together, these results suggest EEMD can enhance the multifractal characteristics of target echo data of these two types of aircraft. The average classification recognition rate of the two types of aircraft data obtained by using the multifractal feature processed by EEMD is improved by about 3%. Although this method performs well in this experimental data set, it has not been tested in other data sets. Therefore, the generalization ability of this method needs to be verified in subsequent studies.

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