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Research on Analysis of Aircraft Echo Characteristics and Classification of Targets in Low-Resolution Radars Based on EEMD

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Abstract—As a kind of complex targets, the non-rigid vibration of an aircraft as well as its attitude change and the rotation of its rotating parts will induce complex nonlinear modulation on its echo from low-resolution radars. If these nonlinear modulation features which reflect the physical characteristics of an aircraft target can be extracted effectively, then they are helpful to target classification and recognition. However, the echo translational component and background clutter have a very adverse effect on the extraction of such features. On basis of introducing the ensemble empirical mode decomposition (EEMD) algorithm, the paper firstly performs the decomposition of real recorded aircraft echo data from a low-resolution radar by EEMD and distinguishes the false component, body translational component and micro-motion component by calculating waveform entropy in the Doppler domain. Secondly, it carries out characteristic analysis and feature extraction further on the echo micro-motion component separated and extracts three features of the micro-motion component, including Doppler domain waveform entropy E_{mc}, normalized equivalent Doppler spectrum width BW_0, and normalized frequency interval between the adjacent maximum spectral peaks on both sides of the spectrum center Δf_0. The analysis results show that EEMD can be used to separate the body translational component and micro-motion component of an aircraft echo effectively, and the proposed features (E_{mc}, BW_0 and Δf_0) can be used as effective features for aircraft target classification and recognition.

1. INTRODUCTION

Most of active surveillance radars adopt the conventional low-resolution radar system. The restrictions brought by the low-resolution system and performance, such as low pulse repetition frequency (PRF), narrow frequency bandwidth, and short irradiation time, always make it a key and difficult point in the field of radar target recognition to classify and identify all kinds of important military targets under conventional radar systems [1]. As an important kind of targets surveilled by aircraft-warning radars, aircraft has complex shape. On the one hand, the non-rigid vibration or attitude change of aircraft relative to the observation radar will induce complicated nonlinear modulations on the echo amplitude and its phase [2]. On the other hand, the jet engine modulation (JEM) induced by the rotation of the aircraft rotating parts, such as the rotor, empennage, propeller, and turbine fan, is also a typical nonlinear modulation, which embodies in the echo characteristics, such as amplitude, phase, frequency, and polarization [3–5]. These kinds of nonlinear modulations reflect the complicated micro-motion modulation effects of various parts of aircraft and contain target attribute information, such as geometric structure and material composition. If these nonlinear modulation signatures which reflect the physical characteristics of an aircraft target can be extracted effectively, it is undoubtedly very useful for further classification and identification of aircraft targets [6, 7].

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So far, some scholars have proposed several theoretical models for aircraft echoes from low-resolution radars [8–12]. However, due to the complexity of the nonlinear modulation induced by the nonrigid vibration or attitude change, most models have paid more attention to the modeling of the JEM echo section, and simplified the modeling of the airframe echo section; so in some cases they are unsatisfactory in analyzing the nonlinear modulation characteristics of aircraft echoes from low-resolution radars. In recent years, some nonlinear analysis methods, such as mono-fractal, fuzzy fractal, and multifractal, have been introduced into the characteristic analysis of aircraft echoes from low-resolution radars. The proposed nonlinear features are used for target classification and recognition, and better classification and recognition results are obtained under specific experimental conditions [13–18]. However, in a strong clutter background, due to relatively weak target echo, the echo nonlinear characteristics will be more about the characteristics of clutter. In addition, the body translational components, which have little effect on target classification and identification, account for most of the echo energy. If the effects of body translational components can be eliminated before the feature extraction of the target echoes, it will undoubtedly be helpful for further increase of the correct classification rate of aircraft targets. Ensemble empirical mode decomposition (EEMD) [19] is a noise-assisted data analysis method proposed aiming at the shortcomings of empirical mode decomposition (EMD). It can overcome the modal aliasing problem of EMD method and separate the body translational components and micro-motion components of aircraft echoes. Based on the above analysis, the paper uses EEMD as the analytical method to analyze the characteristics of the conventional low-resolution radar echoes from aircraft, extracts the echo features on basis of the characteristic analysis, and investigates the application of the extracted features in aircraft target classification and recognition.

2. ENSEMBLE EMPIRICAL MODE DECOMPOSITION

Empirical mode decomposition (EMD) [20] is a time frequency analysis and processing method especially suitable for nonlinear and non-stationary signals, which is presented by Huang et al. in the late 1990s. This method gives a signal with its intrinsic time scale characteristics and decomposes the complex signal into several intrinsic mode functions (IMF) and a remainder. It is an adaptive signal processing method. However, due to the problem of modal aliasing, EMD is limited in many applications. For this reason, Wu and Huang put forward an improved algorithm of EMD in 2009, namely ensemble empirical mode decomposition (EEMD) [19], which is a noise-assisted data analysis method.

By adding Gaussian white noise to the original signal and using the adaptive dynamic filtering characteristics of white noise in the decomposition, EEMD overcomes the modal aliasing problem of EMD. Its calculation method is as follows [21]:

1) Assume that the original signal is $f(t)$ and N the number of decomposition, and set m as 1.

2) Generate a new test signal

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

by adding a Gaussian white noise with an amplitude coefficient of a in $f(t)$.

3) Decompose $f_m(t)$ into a series of intrinsic mode functions (IMFs) by using the EMD method.

4) When $m < N$, repeat Steps 2) and 3), and set m as $m + 1$. However, here the new Gaussian white noise is required to be different from that of the previous several times.

5) After the Nth decomposition, several groups of IMFs can be obtained. The mean value of each IMF is

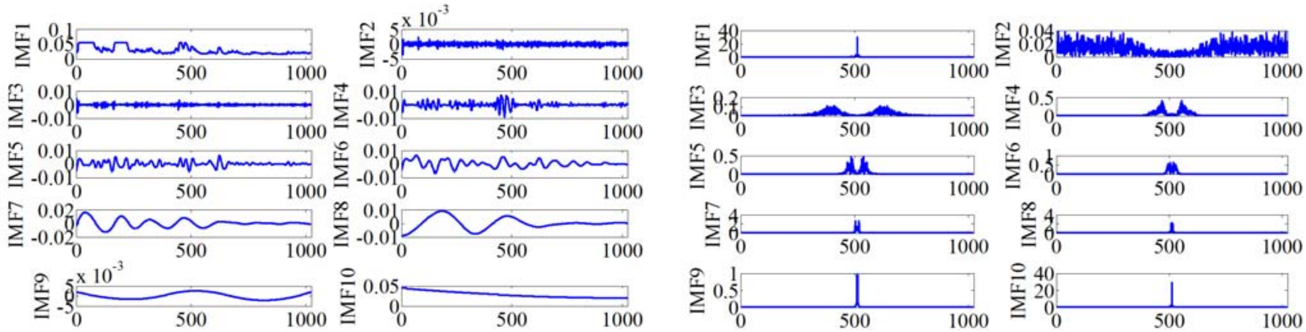
$$\overline{IMF_i} = \sum_{m=1}^{N} IMF_{i,m}/N \tag{2}$$

where $IMF_{i,m}$ is the ith IMF of the mth decomposition.

Each of the final IMFs is the mean of the corresponding IMFs in the above N times of decomposition.

3. CHARACTERISTIC ANALYSIS OF AIRCRAFT ECHOES BASED ON EEMD

The echo data used in this section are recorded from a surveillance radar, and they are from a number of different types of aircraft targets. The radar operates in the VHF band with its PRF 100 Hz and pulse width 25 μs, and the flight attitude of each type of aircraft targets has two kinds: towards the radar station and off the radar station. Fig. 1(a) shows the IMFs obtained by EEMD of a group of normalized echo data from a civil aircraft when it flies off the radar station, and Fig. (b) gives their Doppler spectra. As a contrast, Fig. 2 shows the Doppler spectrum of the original signal. Ideally, each IMF component is a simple stationary signal, which represents one of the characteristic components of the original signal. However, because the decomposition results will be influenced by the parameter selection, such as envelope estimation function, white noise amplitude coefficient and number of decomposition iterations, it is hard to avoid false composition. As can be seen from the intrinsic mode function waveforms of Fig. 1(a) and the corresponding Doppler spectra of Fig. 1(b), the first IMF should mainly reflect the body translational component of the echo. The second IMF should be the noise component introduced by the EEMD decomposition process, because its Doppler spectrum is almost uniformly distributed throughout the spectrum analysis range. The third IMF is still influenced by the noise induced by the EEMD decomposition process, because its Doppler spectral width is still wider than that of the original signal shown by Fig. 2. The fourth to ninth IMFs should mainly reflect the micro-motion components of the echo. What the tenth IMF reflects should be the echo trend.



(a) (b)

Figure 1. The EEMD decomposition diagram of aircraft echo data. (a) The IMFs obtained by EEMD decomposition. (b) The Doppler spectra of the obtained IMFs.

Because the body translational components of aircraft echoes have little effect on target classification and recognition, it is necessary to eliminate the body translational components and false components introduced by EEMD, so as to facilitate the follow-up extraction of features for target classification and recognition. As we all know, entropy is a measure of the degree of disorder. The smaller the entropy is, the better the regularity will be; otherwise, the worse the regularity will be. Therefore, the concept of wave entropy [22] is introduced herein. For the signal $\mathbf{s} = \{s_i\}_{i=1}^{N}$, its waveform entropy is defined as

$$Entropy\left(\mathbf{s}\right) = -\sum_{i=1}^{N} p_i \log_2 p_i, \tag{3}$$

where, $p_i = |s_i| \Big/ \sum\limits_{i=1}^{N} |s_i|$.

As can be seen from Eq. (3):

1) When p_i tends to 0 or 1, $-p_i \log_2 p_i$ tends to 0. In other words, the more centralized the waveform is, the smaller its waveform entropy is.

2) $Entropy(\mathbf{s}) \leq \log_2 N$, where the equal sign is set up when and only when $\forall i = 1, 2, \ldots, N$, $p_i = 1/N$. In other words, the more uniform the waveform is, the greater its waveform entropy is.

The above characteristics of waveform entropy make it possible to separate the noise component introduced by EEMD, echo translation component and micro-motion component. For example, for IMFs shown in Fig. 1, calculating their waveform entropies in the Doppler domain and normalizing the results by the maximum value among them, we can get the normalized waveform entropies respectively 0.25628, 1, 0.82651, 0.53296, 0.53444, 0.43981, 0.22902, 0.34823, 0.084435, 0.15752, descending followed by the

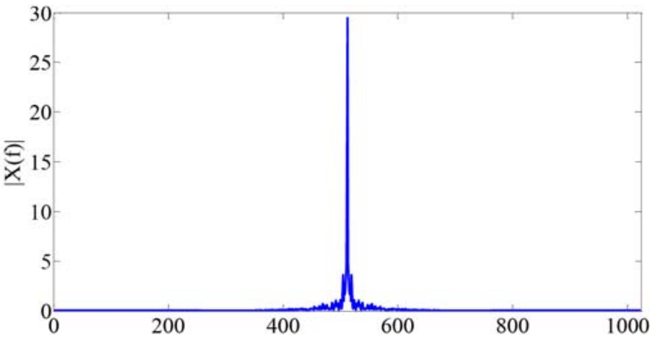


Figure 2. Doppler spectrum of real recorded aircraft echo data.

IMF_2, IMF_3, IMF_5, IMF_4, IMF_6, IMF_8, IMF_1, IMF_7, IMF_{10}, IMF_9. From the calculation results, it can be seen that for the noise component IMF_2 introduced by EEMD, the waveform entropy is maximal due to its wide and uniform Doppler spectrum distribution. Since IMF_3 is still greatly affected by the noise introduced by EEMD, its waveform entropy is the second largest and still significantly larger than that of the remaining IMFs. However, the echo body translational component IMF_1 and the IMF_{10} reflecting the echo trend have less waveform entropy, and both have stronger DC (direct current) components. Therefore, the waveform entropy of each IMF in the Doppler domain can be used to effectively identify the false components, body translational components and micro-motion components introduced in the decomposition process of EEMD, so as to separate the echo micro-motion components for further characteristic analysis and feature extraction.

4. ECHO FEATURE EXTRACTION BASED ON EEMD

According to the above analysis, for the recorded aircraft target radar echo data, firstly, we should decompose them with EEMD and calculate the normalized waveform entropies in the Doppler domain of the IMFs obtained by the decomposition. Secondly, we should determine which IMFs belong to the echo micro-motion components by using the waveform entropy and combine them into the echo micro-motion components. Finally, we can carry out echo feature extraction and target classification.

In general, the micro Doppler modulation effect is mainly induced by the motion of the rotating parts on the aircraft. When the radar operates at a certain wavelength, the Doppler spectral width of the echo micro-motion components mainly depends on the equivalent blade length of the rotating parts and the number of blades, while the spectral line spacing depends on the number of blades and blade speed [9]. Ref. [5] pointed out that for jet aircraft, due to shorter equivalent blade length and more number of blades, it is difficult to observe their JEM modulation effect under the conventional low-resolution radar system, because they often require that the observation radar has a higher operating frequency band and higher pulse repetition frequency. Hence, aircraft target classification method based on JEM features is generally only applicable to the identification of helicopters and propeller aircraft. However, due to the inherent differences in the geometric structure and material composition, the Doppler spectra of echo micro-motion components of different types of aircraft targets still have distinctly different distribution characteristics. Figs. 3(a) and (b) give the Doppler spectra of the echo micro-motion components of a civil aircraft and a fighter aircraft when they fly off the radar station. Obviously, they have significant differences in aspects such as the sag width of the spectral center, spectral width and spectral distribution.

To this end, this paper proposes three-dimensional EEMD-based features for classification of different types of aircraft targets.

The three-dimensional features extracted based on EEMD decomposition are as follows:

Feature 1: The waveform entropy E_{mc} of the echo micro-motion component $s_{mc}(n)$ in the Doppler domain, which is defined as in Eq. (3).

E_{mc} reflects the energy distribution characteristics of $s_{mc}(n)$ in the frequency domain. The more dispersed the energy distribution, the larger E_{mc} will be, and vice versa. It can be seen from Fig. 3

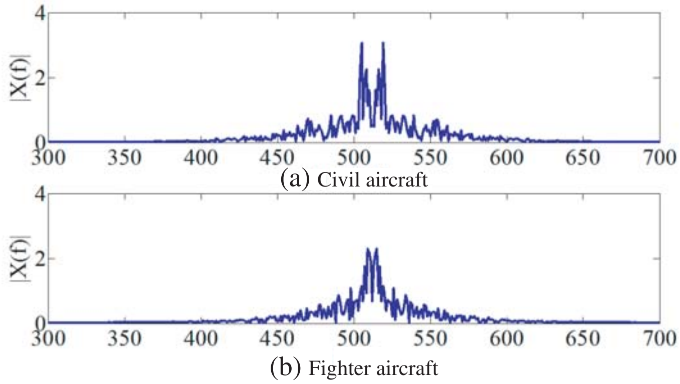


Figure 3. Comparison of Doppler spectra of echo micro-motion components of both types of aircraft targets.

that the frequency domain energy distribution of the echo micro-motion component of the civil aircraft is more decentralized than that of the echo micro-motion component of the fighter aircraft; therefore, its E_{mc} is larger than that of the fighter aircraft echo.

Feature 2: The normalized equivalent spectral width BW_0 of the echo micro-motion component $s_{mc}(n)$ in the Doppler domain. It is assumed that the discrete Fourier transform of $s_{mc}(n)$ is $S_{mc}(k)$, $k = 0, \dots, N-1$, then BW_0 is defined as

$$BW_0 = \sum_{k=0}^{N/2-1} k \cdot |S_{\mathrm{mc}}(k)| \Bigg/ \left[\frac{N}{2} \cdot \sum_{k=0}^{N/2-1} |S_{\mathrm{mc}}(k)| \right]. \tag{4}$$

BW_0 reflects the complexity of the micro-motion modulation effect of an aircraft echo. The richer the echo micro-motion components, the greater BW_0 will be, and vice versa. As can be seen from Fig. 3, compared to the fighter aircraft echo, the civil aircraft echo contains more abundant micro-motion components, so its BW_0 is larger than that of the fighter aircraft echo.

Feature 3: The normalized frequency interval Δf_0 of the highest spectral peak adjacent to the left and right of the Doppler domain spectral center of the echo micro-motion component $s_{mc}(n)$. Assuming that k_1 and k_2 are the spectral numbers of the left and right peaks of the spectral center, then Δf_0 is defined as

$$\Delta f_0 = \frac{|k_1 - k_2|}{N}, \tag{5}$$

where N is the number of discrete Fourier transform points.

Δf_0 reflects the structural characteristic parameters such as the distance of the blade inner end from the blade center and the blade rotation speed [5, 8]. Generally speaking, for helicopters, the distance of their blade inner end from their blade center is the smallest, and their blade rotation speed is the lowest; for propeller aircraft, the distance of their blade inner end from their blade center is the largest, and their blade rotation speed is in the middle; for jet aircraft, the distance of their blade inner end from their blade center is in the middle, and their blade rotation speed is the highest. Even for the same category of aircraft targets, the structural characteristic parameters, such as the distance of the inner and outer ends of the blades from the blade center, blade length and rotational speed are generally different from each other. Therefore, Δf_0 has certain classification and identification ability for different types of aircraft targets.

5. TARGET CLASSIFICATION EXPERIMENTS

Below we will discuss the application of aforementioned features in the classification of aircraft targets by using the real recorded echo data. The echo data used in the experiment are from two different types of aircraft targets with one civil aircraft and the other fighter aircraft. The radar operates in the

VHF band with its PRF 100 Hz and pulse width 25 μs, and the flight attitude of both types of aircraft targets has two kinds: towards the radar station and off the radar station. In the working band of the experimental radar, the RCS values of the two kinds of aircraft targets fluctuate slowly.

Due to complexities of the actual target state as well as the environment, the target attitude, distance, background, etc. often change, so the raw target echo data cannot be directly used for feature analysis and extraction, and therefore, we must do some data preprocessing to reduce the influence of these factors. Here the following two kinds of preprocessing will mainly be done: one is attitude partition, and the other is energy normalization. The specific method can be found in [23]. In addition, when an aircraft target flies in side direction, echo modulation induced by its nonrigid vibration is not easy to be observed, and for most jet aircraft, the JEM phenomenon which is important for target classification is also difficult to be observed [9]. Therefore, the echo data used in the following classification experiments are mainly recorded when aircraft targets fly towards or off the radar station. In the experiment, we have selected 5120 groups of echo data from the two different types of aircraft targets, and the group number for each type of aircraft targets is 2560 (with the group number of each of the flight attitude equal to 1280). For each type of aircraft targets, the feature data extracted from 512 groups of echo data are chosen as training samples (the group number for each of the two flight attitudes useful for classification is 256), with the rest feature data as testing samples. Moreover, compared to other classifiers, support vector machine (SVM) has stronger generalisation abilities and a faster convergence rate [24], so in the experiment SVM using the Gaussian kernel function is taken as the classifier, and the kernel function parameters are selected rationally without going beyond the calculation burden.

Table 1 shows the classification results for the two types of aircraft targets. As can be seen from Table 1, for the training data, the correct classification rate (CCR) and the average CCR of the two types of aircraft targets are both more than 99%, and for the testing data, the CCRs of the two types of aircraft targets are also over 91%, and the average CCR is more than 92%. Therefore, the classification effect is satisfactory. In addition, it should be pointed out that here only three features of E_{mc}, BW_0 and Δf_0 are used for the classification experiments. If the Doppler domain features of the echo micro-motion components, such as the spectral line spacing and the second-order central moment, can be further mined, the average CCR could still have an increase to a certain degree.

Table 1. Classification results.

	Training data	Testing data
Civil aircraft	99.03%	91.58%
Fighter aircraft	99.80%	94.40%
Average CCR	99.41%	92.94%

6. CONCLUSIONS

Non-rigid vibration and attitude change of aircraft as well as JEM will induce complicated nonlinear modulations on the radar echoes, but the strong background clutter will have extremely adverse effects on the characteristic analysis of the target echoes. To solve this problem, this paper uses EEMD to decompose aircraft echoes from conventional low-resolution radars from the viewpoint of ensemble empirical mode decomposition, separates the body translational components and micro-motion components for further characteristic analysis and feature extraction, and investigates the application of the extracted features in target classification with low-resolution radars. The experimental results show that:

(1) The use of EEMD can effectively separate the body translational components and micro-motion components of aircraft echoes.

(2) Using the micro-motion component of aircraft echoes for characteristic analysis and feature extraction, the extracted features can be used as effective features for aircraft target classification with low-resolution radars.

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