Machine Copy for Proofreading, Vol. x, y–z, 2013

CLASSIFICATION OF AIRCRAFT TARGETS WITH SURVEILLANCE RADARS BASED ON FUZZY FRACTAL FEATURES

Qiusheng Li[1, 2, *] and Weixin Xie[1]

[1]ATR Key Laboratory of National Defense Technology, Shenzhen University, Shenzhen, Guangdong 518060, China

[2]School of Physics and Electronic Information, Gannan Normal University, Ganzhou, Jiangxi 341000, China

Abstract—The fuzzy fractal characteristics of return signals from aircraft targets in conventional radars offer a description of dynamic features which induce the echo structure of targets, therefore they can provide a new way for aircraft target classification and recognition with low-resolution surveillance radars. On basis of introducing fuzzy fractal theory, the paper analyzes the fuzzy fractal characteristics of return signals from aircraft targets in a VHF-band surveillance radar by means of the fuzzy fractal analysis, and puts forward a fuzzy-fractal-feature-based classification method for aircraft targets with a low-resolution radar from the viewpoint of pattern recognition. The analysis shows that the fuzzy fractal characteristic parameters such as the local fuzzy fractal dimension (LFFD) and local degree of fractality (LGF) can be used as effective features for aircraft target classification and recognition. The results of classification experiments validate the proposed method.

1. INTRODUCTION

Most of active surveillance radars adopt the conventional low-resolution radar system, and their main functions are detecting and tracking targets. If they can provide target attribute information such as class and model, it certainly will have important practical significance. However, due to restrictions brought by the low-resolution radar system, for example, the physical characteristics of targets cannot be excited completely by a transmission signal with

Received 16 December 2012.

* Corresponding author: Qiusheng Li (bjliqiusheng@163.com).

low-bandwidth and single-polarization, or the excited characteristic information may be limited by the low-performance radar system, target classification and recognition with low-resolution radars has not been solved effectively for a long time [1, 2].

So far, the features extracted in methods with respect to target classification and recognition with low-resolution radars can be divided into three kinds basically: the first kind of features is extracted based on the fluctuation characteristics of return signals from targets, such as the target radar cross-section (RCS), echo amplitude undulation, echo phase undulation, echo vision effect or its 2-D gray-level map [3–6]; the second kind of features is extracted based on the target motion characteristics, for example, the motion parameters such as the flight height, velocity, acceleration, and time-spectrum (the dynamic trends that target space position as well as its motion state varies with the time is referred to as time-spectrum) [7, 8]; the third kind of features is extracted based on the rotational modulation spectra (also called jet engine modulation (JEM) features), which are generated by target rotating parts, such as the rotor, empennage, propeller and turbine fan [9–15]. JEM features lie on the leaf number and rotary speed of the rotating parts of a target, and are independent with the target attitude if no LOS-sheltering, i.e., the rotating parts can be seen by the radar. Currently, the related research work is mostly concentrated on the extraction of JEM features, and proposed methods mainly contain the complex cepstrum method, self-correlation method, autoregressive (AR) model power spectrum method, singular value decomposition (SVD) eigenvalue decomposition method, etc., however most of these methods have high computational complexity, and often demand a higher pulse repetition frequency (PRF) as well as a longer observation time, therefore it is difficult to put them to use [16].

In fact, as a kind of complex targets, the dimension of an aircraft is generally far longer than the wavelength of a conventional radar, therefore its echo scattering is in the optical area, i.e., the general scattering echo is the linear superposition of the scattering echo from each independent and equivalent scattering center. The research shows that the echo fluctuation reflects the complicated nonlinear modulation effect induced by the nonrigid vibration and attitude change of the target as well as the rotation of the target rotating parts, and contains some target information such as the fine geometry structure and material composition [17, 18]. Different types of aircraft targets often have different structure and rotating parts, and have different nonrigid vibration and JEM modulation characteristics. If these nonlinear modulation features which reflect the physical characteristics of an aircraft target can be extracted, then one may apply them to aircraft target classification and recognition directly [19–21]. Therefore, the paper plans to adopt the nonlinear research method — fuzzy fractal theory to analyze the characteristics of conventional radar return signals from aircraft targets, and on this basis puts forward a fuzzy-fractal-feature-based classification method so as to identify different types of aircraft targets in condition of no compensation for airframe echo components.

2. FUZZY FRACTAL THEORY

Since Mandelbrot introduced the concept of fractal geometry in the seventh decade of the 20th century, fractal theory has been widely applied to many realms such as natural science, social science and engineering. However, there is not a proper fractal object in the nature, and the calculation of fractal dimensions depends on the observed scale-free interval. Actually, to what degree a discrete time series has fractal characteristics or self-similarity is a fuzzy attribute. Therefore, on basis of combining fuzzy theory and fractal theory, K. Kamijo and A. Yamanouchi proposed fuzzy fractal theory [22], and introduced the local fuzzy fractal dimension (LFFD) and local degree of fractality (LGF) to describe the fuzzy fractal structure hidden in a dynamic system in the form of self-similarity. This theory deems that characteristics in all kinds of time series can be treated as "fuzzy fractal phenomena" from the viewpoint of fuzzy system; therefore one can process them by means of the fuzzy fractal analysis without exception. Below, the text will introduce LFFD and LGF which are the two main concepts in fuzzy fractal theory.

2.1. LFFD

Assume that there is a discrete time series $Y = \{y_i,\ i = 1,\ 2,\ \ldots,\ N\}$ and M is the length of a processing unit, then the k-th processing unit $\mathbf{y}_k$ can be expressed as

$$\mathbf{y}_k = \{y_k, y_{k+1}, \ldots, y_{k+M-1}\} \tag{1}$$

with $k = 1,\ 2,\ \ldots,\ N - M + 1$. If defining the accumulated change $N_k\,(r,\ M)$ of $\mathbf{y}_k$ as

$$N_k\,(r, M) = \frac{1}{r} \sum_{i=0}^{M-r-1} |y_{k+r+i} - y_{k+i}|, \tag{2}$$

where r denotes the sampling interval (i.e., scale), then one can get

$$N_k\,(r, M) \propto r^{-D_k}, \tag{3}$$

where D_k is known as the LFFD of $\mathbf{y}_k$, which can be obtained from the slope of the $\ln N_k(r, M) - \ln r$ curve through a regression analysis.

Obviously, LFFD describes the extent to which the time series pattern is complex in a processing unit on the long time series, and it is an extension of the fractal dimension. It is believed that the dimension is a function of the observation scale, so LFFD can be applied to non-proper fractal objects. In addition, LFFD has a series of favorable properties: The value of LFFD is invariable if adding a constant value or multiplying a factor to each value in the discrete time series; If the length of a processing unit M is sufficiently large so that the processing unit retains the same properties in the long time series, then LFFD is almost a constant without depending on M.

2.2. LGF

[23] has proposed the Six-Point Evaluation Method to calculate the LFFD of a processing unit, and further introduced the concept of LGF to indicate how well the regression line fits. LGF is composed of the degree-of-freedom-adjusted contribution ratio, and it is defined according to the variance analysis results for the regression procedure shown by Table 1. In Table 1, if noting $z = \ln N_k(r,\ M)$ and $x = \ln r$, then one can get

$$S_R = \sum_{i=1}^{n} (\hat{z}_i - \bar{z})^2 \tag{4}$$

and

$$S_e = \sum_{i=1}^{n} (z_i - \bar{z})^2, \tag{5}$$

where, $\bar{z} = \sum_{i=1}^{n} z_i$, $\hat{z}_i$ is the Y-coordinate corresponding to the X-coordinate x_i in the regression line $\hat{z} = \hat{a}x + \hat{b}$, and z_i denotes the actual measure corresponding to $\hat{z}_i$.

Table 1. Variance analysis for single-factor test.

Source of variance	Sum of squares	Degree of freedom	Mean square	Observed F value
Regression	S_R	1	$V_R = S_R/1$	
Error	S_e	$n-2$	$V_e = S_e/(n-2)$	$F = V_R/V_e$
Total	$S_T = S_R + S_e$	$n-1$	$V_T = S_T/(n-1)$	

*Note: For Six-Point Evaluation Method, n equals to 6.

If noting the LGF of the k-th processing unit as μ_k, then

$$\mu_k = 1 - \frac{V_e}{V_T}, \tag{6}$$

can be got, where V_e and V_T denote the error variance and total variance respectively. Evidently, $0 \le \mu_k \le 1$. Moreover, the more μ_k is close to 1, the better the $\ln N_k(r, M) - \ln r$ regression line fits, i.e., the more distinct the fractal characteristics of the processing unit are; contrarily, the more μ_k is close to 0, the worse the $\ln N_k(r, M) - \ln r$ regression line fits, i.e., the more indistinct the fractal characteristics of the processing unit are. Therefore, LGF has the characteristic of "grade" in fuzzy theory, and it describes to what extent a processing unit has the property of self-similarity.

From (6), one can get further

$$\mu_k = \frac{V_T - V_e}{V_T} = \frac{S_T - (n-1)\,V_e}{S_T} = \frac{S_T - S_e - V_e}{S_T} = \frac{S_R - V_e}{S_T}. \tag{7}$$

In other words, LGF can also be defined as the ratio of the difference between the sum of the regression squares S_R and the error variance V_e, i.e., $S_R - V_e$, and the total sum of squares S_T. As a result, the definition given by (6) can avoid the over-evaluation of the regression-based contribution ratio to a certain extent.

Altogether, both LFFD and LGF are obtained by processing the short time series in a processing unit. For a long time series, one can analyze its fuzzy fractal characteristics through sliding the processing unit successively.

3. FUZZY FRACTAL ANALYSIS FOR RETURN SIGNALS FROM AIRCRAFTS

Below real recorded echo data from a large civil aircraft and a feeder liner on a VHF-band surveillance radar will be taken to perform the analysis. To raise the dependability of target classification, firstly one should do some preprocessing on the raw echo data, such as attitude partitioning (flying towards the radar station, flying in side direction, and flying off the radar station), energy normalizing, so as to minish the influence of factors such as flying attitude and distance.

In surveillance radars, a single irradiation time towards a target is very short (often 20 to 30 ms), so the target echo series is a sub-series of the long echo series obtained in the beam-park mode. If using the Six-Point Evaluation Method to perform the regression analysis with a pulse repetition interval (PRI) as the length of a processing unit, and assuming that there is no overlap between two adjacent processing

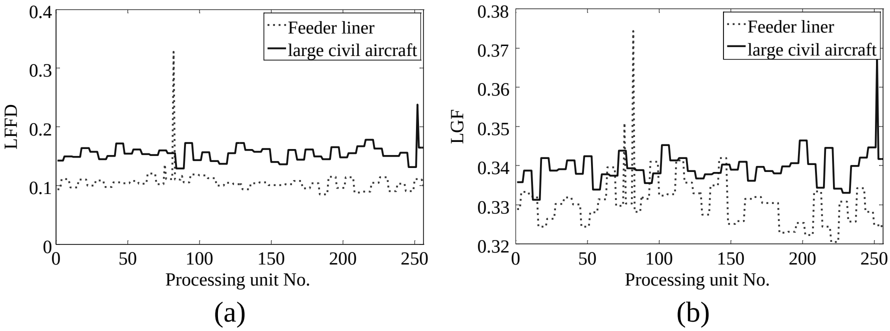

Figure 1. Fuzzy fractal analysis for aircraft returns in a VHF-band radar. (a) LFFD. (b) LGF.

units, then the LFFD and LGF of the k-th processing unit can be expressed as

$$D_k = f\left(r, N_k\left(r, M\right)\right) \tag{8}$$

and

$$\mu_k = g\left(r, N_k\left(r, M\right)\right) \tag{9}$$

respectively, where $r = 1, 2, \ldots, 6$. From the viewpoint of limit, each value of r corresponds to an infinitesimal scale interval and a LFFD can be got without exception, thus D_k is the average of the six LFFDs, and reflects the manner of change in the processing unit from the whole. In addition, from the analysis in the above section one can know, $0 \leq \mu_k \leq 1$, therefore $g(r, N_k(r, M))$ is a complex and special "membership function" from the concept of fuzzy fractal, which describes the extent to which the sub-series in the processing unit satisfies self-similarity.

Figures 1(a) and (b) present the calculation results of the LFFD and LGF of a group of echo data from the two types of aircraft targets respectively, thereinto, both the aircrafts fly towards the radar station, and the length of a processing unit $M = 1024$. It can be seen from the figures, in condition of VHF-band and single-pulse, the LGFs of return signals from both types of aircrafts are less than 0.5 without exception, and their LFFDs are also very little, therefore their fractal characteristics are all not distinct. However, the LFFDs can classify the two types of aircraft targets preferably, and the LGFs still have some classification abilities though there are some overlaps between the LGFs of the two types of targets. Moreover, from the figures one can still see that the LFFDs and LGFs of the large civil aircraft are greater than those of the feeder liner as a whole, and the reason is

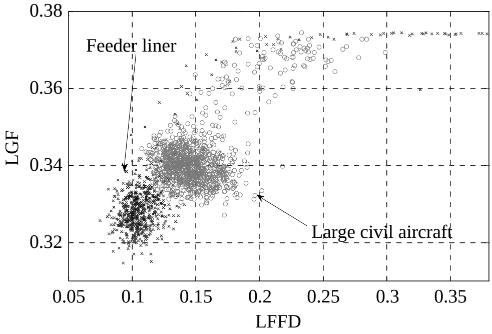

Figure 2. Distributing circumstances of 2-D features composed of LFFDs and LGFs of echo data from two types of aircraft targets.

that the large civil aircraft often has intenser nonrigid vibration and attitude change than the feeder liner, and its JEM effect is also more distinct than that of the feeder liner.

Figure 2 shows the distributing circumstances of the 2-D features composed of the LFFDs and LGFs of echo data from the two types of targets, with "×" and "o" denoting the feeder liner and the large civil aircraft respectively. Thereinto, the echo data from both the large civil aircraft and the feeder liner contain two kinds of attitudes (flying towards or off the radar station), with the echo group numbers of flying towards the radar station eight and seven respectively and those of flying off the radar station ten and five respectively, and each group of echo data includes 256 PRIs. As can be seen from Figure 2, although there are some overlaps between the 2-D features of the two types of aircraft targets, as a whole, the features belonging to different types of aircrafts still separate from each other distinctly. Consequently, if the two characteristic parameters are combined together to identify different types of aircraft targets, it is hopeful to obtain a better performance.

4. FUZZY-FRACTAL-FEATURE-BASED CLASSIFICATION EXPERIMENTS

Here the aforementioned echo data from two types of aircraft targets in a VHF-band radar will be adopted to do the experiments. On basis of analyzing the performance of methods using some typical low-resolution radar target classification features [15, 24–34], [16] indicates that the classification method based on dispersion situations of eigenvalue spectra (CMDSES) outgoes other methods remarkably.

[19] uses fractional Brown motion to model echo amplitude fluctuation, on this basis, puts forward a classification method based on fractional Brown fractal dimension of echo in time and frequency domain (CMFBFD) for low-resolution radars, and gains a better classification effect for helicopters and civil aircrafts using the proposed method. Therefore, here CMDSES and CMFBFD will be taken as the contrast to analyze the performance of the classification method based on fuzzy fractal features (CMFFF) in the following text.

In the experiments, the group numbers of echo data from the feeder liner are twelve (with the group numbers of flying towards the radar station seven and those of flying off the radar station five), those of echo data from the large civil aircraft are eighteen (with the group numbers of flying towards the radar station eight and those of flying off the radar station ten), and each group of echo data contains 256 PRIs. A PRI is taken as the length of a processing unit, and for each processing unit, the eigenvalue spectrum and fractional Brown fractal dimension features as well as the LFFD and LGF features are extracted. Withal, compared with other classifiers, support vector machine (SVM) has stronger generalization abilities [35], so here SVM using the Gaussian kernel $K(x_i, x_j) = \exp(-\|x_i - x_j\|^2/\sigma^2)$ as the kernel function will be taken as the uniform classifier in the experiments. By reason that there is no prior knowledge about the parameter σ^2, in the following experiments, different parameter values will be tried several times without going beyond the calculation burden and the parameters which can well classify different types of targets will be taken as the kernel function parameters. All the correct classification rates (CCRs, here CCR is defined as the ratio of the number of samples which are classified correctly and the corresponding total number of samples) given in the following are the classification results using the better kernel function parameters. For each type of aircraft targets, feature data extracted from two groups of echo data (thereinto, one group is recorded when the target flies towards the radar station, and the other is recorded when the target flies off the radar station.) will be selected as training samples, and the rest feature data will be taken as testing samples. Table 2 shows the classification results using CMDSES, CMFBFD, and CMFFF.

It can be seen from Table 2, the CCRs of CMFFF (with each CCR more than 90%) are far higher than those of CMDSES and CMFBFD whether for the CCR of each type of aircraft targets or the average CCR, while the CCRs of CMFBFD excel those of CMDSES markedly. The reasons are as follows: Firstly, the feature data used in the experiments are extracted from a single PRI, and JEM features within a PRI are subject to clutters and noises; Secondly, a

Table 2. CCRs of CMDSES, CMFBFD, and CMFFF.

	CMDSES	CMFBFD	CMFFF
Feeder liner	57.07%	76.68%	98.22%
Large civil aircraft	78.22%	81.81%	94.39%
Average CCR	66.38%	80.03%	95.75%

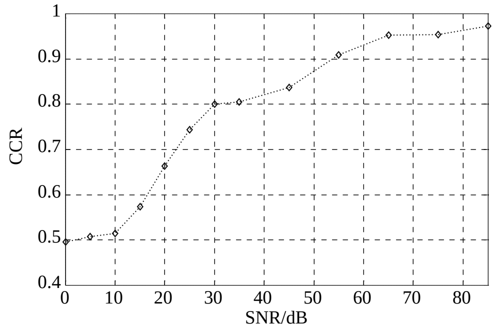

Figure 3. Variational curve of average CCR of CMFFF with SNR.

pure radar clutter (a return signal without target) may agree with a fractal model commendably, but the existence of a target will change its fractal characteristics remarkably even if being in a environment with strong clutters; Thirdly, generally speaking, a man-made target can be depicted by some regular geometric cells, and its surface and spatial structure have intrinsic discrepancies with the laws expressed by fractal model, so fractal model is not suitable to describe a man-made target, however, fuzzy fractal model may describe the target preferably. Therefore, CMFFF outstrips CMDSES and CMFBFD in the total performance.

Below Gaussian noises with different intensities will be added to the real recorded echo data to investigate the performance of CMFFF in condition of different signal-to-noise ratios (SNRs). Figure 3 shows the variational curve of the average CCR of CMFFF with SNR ranging from 0 to 85 dB. As can be seen from Figure 3: when SNR is less than 10 dB, CMFFF still has some classification abilities, but the average CCR of CMFFF (around 50%) is lower, and after this, CCR rises quickly along with the increase of SNR; when SNR rises to 30 dB, CCR leaves behind 80% and continues to rise relaxedly with the increase of SNR; when SNR reaches 65 dB, CCR exceeds 95% and tends towards invariableness hereafter. It is obvious that CMFFF is hopeful to achieve a satisfactory classification effect only when SNR is greater than 30 dB. Investigating the reasons, one may find that LFFDs of noises are often larger and their fractal characteristics are more distinct than those of target echoes, so along with the decrease of SNR, the extracted fuzzy fractal features mainly embody the characteristics of noises, as a result, the classification performance will decrease.

What should be pointed out is that the used data are return signals from aircraft targets within a single PRI. If one combines pulse echo data recorded in multiple PRIs, the average CCR of CMFFF could still have a larger increase. In addition, it can be seen from the above simulation process, CMFFF has a series of merits such as lower feature dimension, lesser algorithmic load, and it is suitable for engineering application.

5. CONCLUSIONS

The paper introduces fuzzy fractal theory into the characteristic analysis of return signals from aircraft targets as well as the classification and recognition of targets in surveillance radars. Firstly, it introduces fuzzy fractal theory. Secondly, on basis of the foregoing introduction, it analyzes the fuzzy fractal characteristics of return signals from aircraft targets, and puts forward a fuzzy-fractal-feature-based classification method for aircrafts. Finally, it does classification experiments with the real recorded echo data, and takes the classification methods proposed in [16, 19] as the contrast to analyze the classification performance of the proposed method. The experimental results show that in the conventional low-resolution radar system, the fuzzy-fractal-feature-based SVM classifier can classify different types of aircraft targets effectively and has an excellent classification performance in condition of no compensation for airframe echo components. Moreover, the proposed method is simple and effective, and it can be applied to engineering preferably.

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