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Target Classification by Conventional Radar Based on Bispectrum and Deep CNN

Huajuan Zhu[1, 2] and Qiusheng Li[1, 2, *]

Abstract—Due to the restriction of the low-resolution systems and the interference of background clutter and environmental noise in the exploration process, the traditional classification and recognition algorithms of conventional radar for aircraft targets have low accuracy and poor feature stability. To solve the above problems, this paper proposes to apply high-order cumulant spectrum and deep convolutional neural network (CNN) to feature the extraction and classification of aircraft target radar echoes. Firstly, analyze the high-order statistical characteristics of aircraft echoes, calculate their bispectrum, and then enhance the generated bispectrum dataset. Finally, use the augmented dataset to train and test the deep CNN, and obtain the final classification and recognition results. Experimental results show that the proposed method can accurately classify and identify multiple aircraft targets in the dataset, indicating that the bispectral features can better reflect the target characteristics, and the classification method combined with the deep learning model has good classification and identification performance and noise robustness.

1. INTRODUCTION

Radar target recognition refers to the use of various acquired target echo signals to judge the type of target and give the judgment results by extracting stable and meaningful features or directly using all the effective echo data. Due to the problems of complex structure, high research cost, and short detection distance, the traditional low-resolution radar system is used in most of the air defense warning radars in service. However, the limitations of the low-resolution design and the system performance make it difficult for conventional warning radars to achieve further classification and recognition of detected targets [1–3]. Therefore, it is of great practical significance and application value to study the target recognition technology that can adapt to conventional low-resolution radars.

Most conventional low-resolution radars use target recognition methods based on feature extraction. Firstly, they use echo signals to detect targets. On this basis, they extract features that can be used for target classification and recognition according to phase, amplitude, and other feature information and in combination with changes in feature space. Finally, they use machine learning methods such as support vector machine (SVM) to classify and recognize targets. For example, Zhang and Li [4] used multifractal correlation theory to extract the features of radar target echoes, and on this basis, combined with SVM to study the classification performance of conventional low-resolution radars for various types of aircraft. To solve the problem that traditional low-resolution radar target recognition is greatly affected by environmental clutter, Hu et al. [5] proposed an aircraft target classification method based on ensemble empirical mode decomposition (EEMD) and multifractal, which achieved the classification of targets such as civil aircraft and fighter aircraft. Xia et al. [6] proposed a joint multi-feature classification method based on the micro-Doppler effect caused by the micro-motion of targets,

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* Corresponding author: Qiusheng Li (bjliqiusheng@163.com).
[1] Research Center of Intelligent Control Engineering Technology, Gannan Normal University, Ganzhou 341000, Jiangxi, China.
[2] School of Physics and Electronic Information, Gannan Normal University, Ganzhou 341000, Jiangxi, China.

which extracted features from the time domain and frequency domain, respectively, and then combined with SVM for target classification. Chen et al. [7] proposed a jet engine modulation (JEM) feature extraction method based on eigenvalue decomposition to analyze JEM echo characteristic spectrum of three types of aircraft, and then classify them. Li and Xie [8] analyzed and defined multifractal features of various aircraft targets, which can achieve classification of targets effectively. Most of the above feature extraction methods focus on estimating spectral line interval, and the calculation is relatively complex, which often requires a high pulse repetition rate and long observation time. At the same time, the traditional low-resolution radar is often challenging to meet the requirements of a high pulse repetition rate and long observation time. Therefore, the estimation accuracy of this kind of method is often not high, and it is greatly limited in practical application.

As an important kind of target monitored by conventional low-resolution radar, the non-rigid oscillation or attitude change of the airframe relative to the radar will generate complex nonlinear modulation on the echo amplitude and its phase [9]. In addition, the JEM caused by the rotation of flight-rotating parts such as rotors, tails, propellers, and turbofans is also a typical nonlinear modulation, which is reflected in the echo amplitude, phase, frequency, and other characteristics [10]. However, besides the target echo, there are also various kinds of interference signals contained in the target echo signal of the aircraft, such as noise and clutter. How to eliminate clutter and other interference and extract characteristic signals is a significant issue to be considered. The high-order cumulant spectrum has good noise suppression ability for colored Gaussian noise. It can maintain the phase information of the nonlinear system, so it can extract rich feature information and provide accurate feature samples for target classification and recognition. Numerous scholars have studied the application of bispectrum, as the lowest order high-order cumulant spectrum, in the field of radar target recognition. Walton and Jouny [11] analyzed the details of the interaction of multiple reflection mechanisms of a bispectral representation object as a robust feature for radar target classification and applied it to commercial aircraft model classification. Ji et al. [12] proposed a bispectral estimation method for auto-regressive (AR) model parameters, aiming at the suppression effect of bispectrum on Gaussian noise, and selected reasonable bispectral characteristics to classify aircraft targets. Jouny et al. [13] obtained the time domain bispectral features of radar targets and then used two classification methods, Cross Correlation and Nearest Neighbor Rule, to identify the radar targets. All the aforementioned studies proved the effectiveness of the bispectral feature; therefore, it is well documented to employ this kind of features as the recognition features for aircraft targets. Although the above feature extraction methods can achieve target classification and recognition to a certain extent, most features are artificially designed and belong to shallow features, which is not conducive to further improvement of target classification and recognition rate. In recent years, target recognition technology based on convolutional neural network (CNN) and other deep learning networks has been rapidly developed and applied to radar target recognition [14]. The introduction of the deep learning methods into the field of radar target detection and recognition is helpful in solving the problems of difficulty in manually defining features and insufficient model expression ability in traditional methods [15]. For this reason, this paper intends to propose a radar target classification and recognition method combining bispectrum and deep CNN, aiming at exploring and designing excellent feature representation for low-resolution radar targets and using deep learning methods to complete target recognition.

2. DEFINITION AND CALCULATION OF BISPECTRUM

2.1. Definition of Bispectrum

The cumulant higher than the second order is called the higher order cumulant, and the bispectrum is called the third order cumulant spectrum, which is the two-dimensional discrete Fourier transform of the third order cumulant. The bispectral expression defined by the third-order cumulant is as follows.

If the higher-order cumulants of random sequences $x(t), x(t+\tau_1), \ldots, x(t+\tau_{k-1})$ can be summed absolutely, that is to say [16]:

$$\sum_{\tau_1=-\infty}^{\infty} \cdots \sum_{\tau_{k-1}=-\infty}^{\infty} |c_{kx}(\tau_1, \ldots, \tau_{k-1})| < \infty, \tag{1}$$

then the k-order spectrum of the signal can be defined as the $(k-1)$ dimensional discrete Fourier transform of the k-order cumulant, which is expressed as [16]:

$$s_{kx}(\omega_1,\ldots,\omega_{k-1}) = \sum_{\tau_1=-\infty}^{\infty}\cdots\sum_{\tau_{k-1}=-\infty}^{\infty} c_{kx}(\tau_1,\ldots,\tau_{k-1})e^{-\mathrm{j}(\omega_1\tau_1+\ldots+\omega_{k-1}\tau_{k-1})} \tag{2}$$

where $|\omega_i| \leq \pi,\ i=1,2,\ldots,k-1, |\omega_1+\omega_2+\ldots+\omega_{k-1}| \leq \pi$.

Bispectrum is the third-order spectrum, expressed as follows [16]:

$$B_x(\omega_1,\omega_2) = \sum_{\tau_1=-\infty}^{\infty}\sum_{\tau_2=-\infty}^{\infty} c_{3x}(\tau_1,\tau_2)\mathrm{e}^{-\mathrm{j}(\omega_1\tau_1+\omega_2\tau_2)} \tag{3}$$

According to the additivity of cumulants, the third-order cumulants of the gained signal $y(n) = x(n)+g(n)$ can be expressed as

$$\begin{aligned} C_{3y}(\tau_1,\tau_2) &= E\{[x(n)+g(n)][x(n+\tau_1)+g(n+\tau_1)][x(n+\tau_2)+g(n+\tau_2)]\} \\ &= C_{3x}(\tau_1,\tau_2)+C_{3g}(\tau_1,\tau_2)+E[x(n)]\{C_{2g}(\tau_1)+C_{2g}(\tau_2)+C_{2g}(\tau_2-\tau_1)\} \\ &\quad +E[g(n)]\{C_{2x}(\tau_1)+C_{2x}(\tau_2)+C_{2x}(\tau_2-\tau_1)\} \end{aligned} \tag{4}$$

As can be seen from the above equation, when the mean value of the target echo signal $x(n)$ and Gaussian noise $g(n)$ is 0, Equation (4) can be simplified as

$$C_{3y}(\tau_1,\tau_2) = C_{3x}(\tau_1,\tau_2)+C_{3g}(\tau_1,\tau_2) \tag{5}$$

Since $g(n)$ is Gaussian noise, its third-order cumulant is zero. Therefore, the bispectrum feature of the received signal can restrain the influence of Gaussian colored noise. That is,

$$B_y(\omega_1,\omega_2) = B_x(\omega_1,\omega_2) \tag{6}$$

Because the phase information of radar echo reflects the radiation and scattering characteristics of aircraft target to a electromagnetic wave and contains the physical characteristics such as the structure and material composition of aircraft target, when analyzing the radar target echo signal, it is generally required that the extracted signal features should have timeshift invariance, scale variability, and phase preservation. The bispectrum in the higher-order spectrum has the above three properties, for the third-order cumulant and bispectrum maintain the amplitude and phase information of the signal, are time-invariant, and can suppress any colored Gaussian noise [17]. Given this, this paper takes bispectrum as an example to study the application of high-order spectrum in the characteristic analysis and feature extraction of conventional low-resolution radar target echo signals.

2.2. Bispectrum Estimation

Bispectral analysis methods of actual signals are generally divided into two categories: the first category is the parametric model estimation method, and the second is the nonparametric estimation method, in which the nonparametric estimation method includes the direct estimation method and indirect estimation method [18]. Here we mainly introduce the direct estimation method of bispectrum. The calculation steps are as follows.

(1) Divide $x(n)$ into K segments, and each component contains M observed samples, denoted as

$$x^k(0), x^k(1), \ldots, x^k(M-1), \quad (k=1,\ldots,K) \tag{7}$$

(2) Calculate the Fourier transform coefficients

$$X^{(k)}(\lambda) = \frac{1}{M}\sum_{n=0}^{M-1} x^{(k)}(n)\cdot \mathrm{e}^{-\mathrm{j}\frac{2\pi n\lambda}{M}} \tag{8}$$

where $\lambda = 0,1,\ldots,M/2$.

(3) Calculate the triple correlation of the discrete Fourier transform coefficients

$$b_k(\lambda_1, \lambda_2) = \frac{1}{\Delta_0^2} \sum_{i_1=-L_1}^{L_1} \sum_{i_2=-L_1}^{L_1} X^{(k)}(\lambda_1 + i_1) \cdot X^{(k)}(\lambda_2 + i_2) \cdot X^{(k)}(-\lambda_1 - \lambda_2 - i_1 - i_2) \tag{9}$$

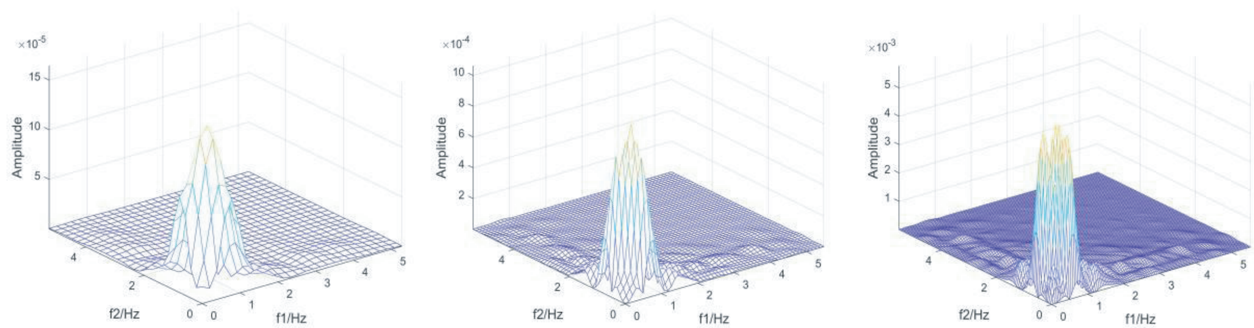
where $\Delta_0 = f_s/N_0$.

(4) Calculate the average of the K-segment bispectrum estimates

$$B(\omega_1, \omega_2) = \frac{1}{K} \sum_{k=1}^{K} b_k(\omega_1, \omega_2) \tag{10}$$

where $\omega_1 = 2\pi f_s \lambda_1 / N_0$, $\omega_2 = 2\pi f_s \lambda_2 / N_0$.

Bispectrum contains signal information such as energy, amplitude, and phase, which can be used as an important tool to detect non-Gaussian and nonlinear characteristics of a signal. Extracting bispectrum features will be beneficial to signal classification [19]. Fig. 1 shows the three-dimensional bispectral estimation of a group of normalized radar echo data calculated when different fast Fourier transform (FFT) points are selected in the MATLAB environment. If the length of FFT is noted as $nfft$, $nfft$ is usually taken as an integer power of 2, and its default value is 128. As shown in Fig. 1, as the number of $nfft$ points increases, the bispectrum 3D graph curve becomes more and more detailed. In general, the larger $nfft$ is, the more accurate the bispectrum estimation is, and the higher the frequency resolution is. Therefore, the more detailed the convex peak is in the figure, the higher-order statistical characteristics of the signal are better highlighted. However, when the number of $nfft$ points increases, the bispectrum calculation amount will increase, so the calculation time will also increase accordingly. Considering the computational complexity and resolution, the bispectrum estimation map with $nfft = 1024$ is selected as the input of the neural network.



(a) (b) (c)

Figure 1. Estimated bispectral three-dimensional graph. (a) $nfft = 512$. (b) $nfft = 1024$. (c) $nfft = 2048$.

3. DEEP CONVOLUTIONAL NEURAL NETWORKS

Deep learning network has an excellent ability to capture the abstract expression of data automatically. In the current research, a great quantity of deep learning models have been applied to radar target recognition processing and have achieved relatively good recognition results [20–22]. The basic principle of feature selection based on neural networks is: in the process of neural network training, the weights of each input unit can be learned and obtained. These weights reflect the sensitivity of sample features in the classification task. Then, the weights are used as the quantitative standard to delete or weaken the influence of redundant features and noise features in the original feature set. The input weighting factors that are more beneficial to classification are constructed at the model input level to improve the classification accuracy.

Convolutional Neural Network (CNN) is a very representative deep neural network structure, which is excellent in processing two-dimensional image data and has strong spatial feature extraction ability. The basic structure of CNN consists of a convolution layer, a pooling layer, and a fully connected layer. The structure of CNN used in this paper is shown in Fig. 2.

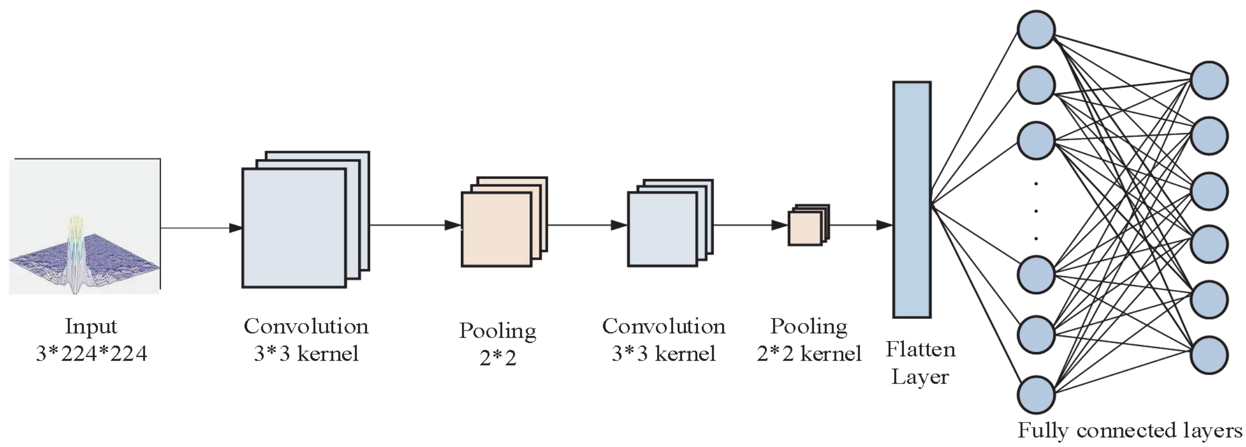


Figure 2. Structure of convolutional neural network.

(1) Convolution layer: The input image is a three-dimensional bispectrum image obtained by the direct estimation method. For the convenience of processing, the image size is uniformly processed as $224 \times 224 \times 3$, where 3 is the depth of the image (namely, red, green, blue, RGB), the size of the convolution kernel is 3×3; the number of convolution kernels is 2; and the moving step is 2. The convolution operation is done on the feature map output from the previous layer using a pre-defined convolution kernel. The convolution kernel is a multi-dimensional matrix, which moves over the feature map in specific steps. Each time it moves, a convolution operation is performed, and finally, a feature map is acquired, which is the feature map extracted by this convolution kernel. n convolution kernels can extract n feature maps. After the convolution operation, the output feature map is transformed into a new feature map through the nonlinear transformation of the ReLU activation function. Then the input of the next layer is obtained. The ReLU function is expressed as follows [23].

$$\mathrm{ReLU}(x) = \max(0, x) \tag{11}$$

(2) Pooling layer: The input vector of the previous layer is pooled to reduce the dimension, improve the calculation speed, and improve the robustness of the extracted features. Commonly used pooling methods involve maximum pooling, mean pooling, and random pooling. In classification tasks, the maximum pooling can make the network get better results and has a certain error screening function, so it is often used as the primary pooling method.

(3) Fully connected layer: In essence, the fully-connected layer is a classifier, where each neuron is connected to each value of the one-dimensional vector of the flat layer. After multi-layer convolution and pooling, the input data of the neural network are mapped to the hidden layer feature space. The feature map formed needs to be mapped with the output sample labels through the fully connection layer to complete the classification task.

In this paper, we intend to use the Softmax function [24] for classification. The Softmax function can normalize the output component of the previous layer and convert it into a value between $(0, 1)$. These values can be regarded as a probability distribution and used as the target prediction value of classification. The one with the highest probability is the final classification result. In order to prevent overflow, this paper intends to use the following method to obtain the final classification result: firstly get the maximum value of the input vector, and then subtract this maximum value from all vectors. The calculation is as follows:

$$M = \max(x_i) \tag{12}$$

$$\text{Softmax}(x_i) = \frac{e^{x_i - M}}{\sum_j e^{x_j - M}} \tag{13}$$

Figure 3 shows the flowchart of aircraft target classification and identification using deep CNN.

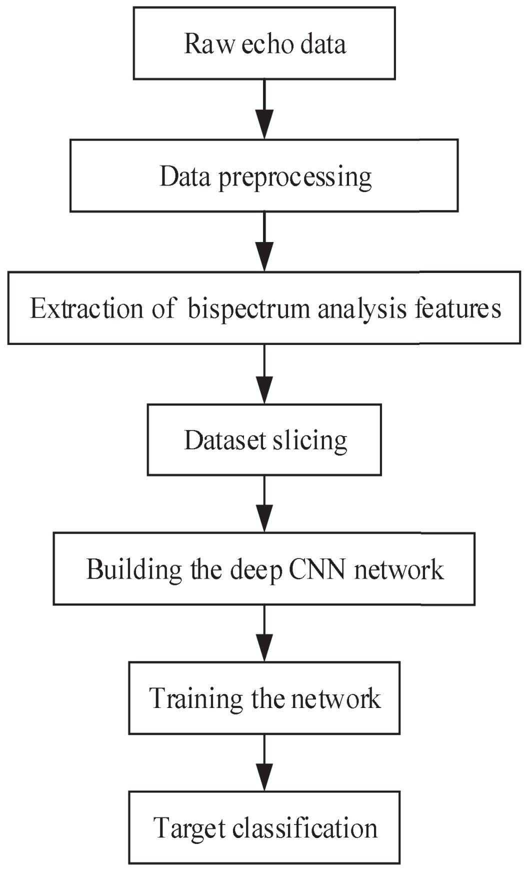


Figure 3. Classification and Recognition Process of Aircraft Targets.

4. EXPERIMENTAL RESULTS AND ANALYSIS

4.1. Experimental Dataset

The data used in this research have various types of aircraft target echo data recorded from an air defense warning radar. The radar operates in the VHF band, with a pulse repetition frequency of 100 Hz and a pulse width of 25 μs. The data used in the experiment are groups of radar echo data of six different aircraft types with varying attitudes of flight. The input image of the classification network is the bispectrum estimation image obtained from the original echo data. There are 512 samples of each category in the training set, and the quantity of six types of training samples is 3072 groups. Among them, Targets 1, 2, 4, and 5 are civil aircraft, and Targets 3 and 6 are fighter aircraft. Targets 1, 2, and 3 fly towards the radar station, and Targets 4, 5, and 6 fly away from radar. The statistical information of the training and test samples is given in Table 1, in which the order of the training and test sets is randomly scrambled.

Due to the complexity of the target flight state and environment, it is essential to preprocess the original measured data to reduce the impact of these interference factors. Here, energy normalization and attitude angle diversity are used to preprocess the original echo data [25]. For conventional low-resolution radars, the attitude angles of aircraft targets can be divided into three types: towards the

Table 1. Sample statistics of the training set and test set of various aircraft targets.

Flight attitude	Target Category	Training data	Testing data
Towards the radar station	Target 1	512	256
	Target 2	512	256
	Target 3	512	256
Off the radar station	Target 4	512	256
	Target 5	512	256
	Target 6	512	256

radar station, off the radar station, and in the side direction. Among them, the former two can be used for target classification, while the third hardly ever works for target classification. The energy normalization is mainly used to avoid the influence of the difference of target echo amplitude on target feature research and extraction.

The energy normalization calculation formula is as follows. Suppose that $\{x_n\}$ $(n = 0, 1, 2, \ldots, m-1)$ is the target echo signal sequence, then its signal energy is:

$$E_x = \sum_{n=0}^{m-1} |x_n|^2 \tag{14}$$

The normalized sequence is expressed as:

$$\hat{x}_n = \frac{x_n}{\sqrt{E_k}} \tag{15}$$

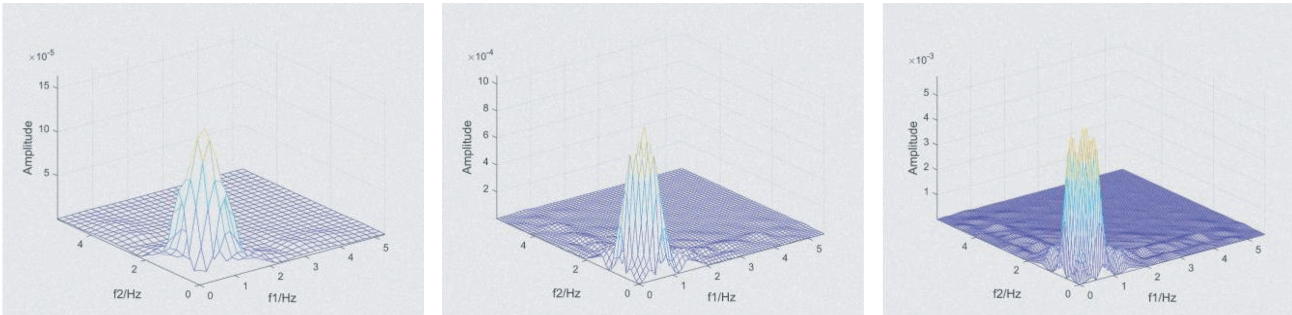
Then there is

$$E_{\hat{x}} = \sum_{n=0}^{N-1} |\hat{x}_n|^2 = 1 \tag{16}$$

4.2. Data Augmentation

The objective of data augmentation is to improve the universalization ability and robustness of the model via obtaining more available training samples [26]. Therefore, this paper obtains more training samples through data augmentation to train the CNN, which can reduce the overfitting phenomenon of the CNN model effectively. Specifically, this paper uses three ways of data augmentation: image flipping, random cropping, and adding noise. In the process of image flipping, the original bispectrum estimated image center is used as a reference, and the image is flipped 90 degrees clockwise. During random cropping, the generated cropping area should avoid the feature prominent areas in the original image as much as possible to avoid losing the pixel blocks of prominent areas in the newly generated samples, which can improve the classification performance of the model to a certain extent [27]. When adding noise, the complicated approach is by dropping pixels on a rectangular region with optional area size and random position to produce black rectangular blocks, thus generating some colored noise, represented by the Coarse Dropout method. It is even possible to randomly select an area on the image and erase the image information. In this study, we choose the method of adding Gaussian noise. Fig. 4 shows some examples of bispectral images of aircraft target radar echo after adding Gaussian noise.

As can be seen from Fig. 4, the image with Gaussian noise is presented as random blocks of black and white pixels propagating in the image, and overfitting generally happens when the model tries to learn high-frequency features that may be unnecessary. Gaussian noise with zero mean has data points in all frequencies, thus it can distorting high-frequency features effectively, so adding an appropriate amount of noise can enhance the learning ability of the network and effectively prevent the network from overfitting.



(a) (b) (c)

Figure 4. Bispectral image after adding Gaussian noise. (a) $nfft = 512$, variance $= 0.05$. (b) $nfft = 1024$, variance $= 0.05$. (c) $nfft = 2048$, variance $= 0.05$.

After data augmentation, there are 1024 samples of each type in the training set, and the total number of six types of training samples is 6144 groups. Table 2 shows the statistical information of training samples and test samples after data enhancement.

Table 2. Sample statistics of the training set and test set of various aircraft targets after data augmentation.

Flight attitude	Target Category	Augmented training data	Testing data	Total Sample number
Towards the radar station	Target 1	1024	256	1280
	Target 2	1024	256	1280
	Target 3	1024	256	1280
Off the radar station	Target 4	1024	256	1280
	Target 5	1024	256	1280
	Target 6	1024	256	1280

4.3. Model Training

The training of the deep learning model is carried out on the CPU. Based on the Python programming environment, a CNN is built under the Tensorflow and Keras frameworks. The value of iterations epochs is set to 100 in the training process, and the batch_size of each iteration is set to 20. The network training process is as follows:

(1) Initialize the network structure and parameters. Use the Adamax optimizer to optimize the network, and set the initial learning rate lr to 0.001. The learning rate attenuation mechanism is set to take the accuracy of the validation set as a reference. If the accuracy is not optimized after ten iterations, multiply the current learning rate by the attenuation coefficient to get a new learning rate, and the attenuation coefficient is set to 0.95.

(2) Build the network. Randomly select samples from the training data set and input them into the network, calculate the output of each layer of the convolution network, and output the category prediction probability of samples.

(3) Conduct iterative training and continuously optimize the network model. Set the training stop conditions, and judge whether to continue training by referring to accuracy and loss function value. If the accuracy of the model training is improved by less than 1% after any ten iterations, or the accuracy of the model is not improved when the value of the loss function decreases, the training is stopped.

In the process of network training, each parameter is constantly adjusted, and the setting of parameters is determined to be optimal by comparing the accuracy of aircraft target classification. When the training conditions are met, the network training process is ended. The calculation method of classification accuracy [28] is as follows:

$$Accuracy = \frac{\text{Number of correctly predicted samples}}{\text{Total number of samples}} \tag{17}$$

4.4. Analysis of Experimental Results

Some fundamental literatures on bispectrum (Ref. [7], Ref. [8], Ref. [12], etc.) have been directly or indirectly compared with Ref. [4], and the experimental results show that the classification performance of [4] is better than that of fundamental literature. To verify the effectiveness of the extracted features, we finally choose to compare and analyze the classification performance of the classification method based on deep learning proposed in this paper (abbr. as CMDL) on the same data set with the three traditional classification methods proposed in [4–6]. The classification results of aircraft targets under the two flight attitudes of towards the radar station and off the radar station are given in Table 3 and Table 4, respectively.

Table 3. Classification accuracy of attitude towards the radar station.

Method	Target 1	Target 2	Target 3	Accuracy
Ref. [4]	90.72%	88.87%	94.96%	91.52%
Ref. [5]	93.57%	91.88%	88.70%	91.38%
Ref. [6]	94.96%	92.66%	92.19%	93.27%
CMDL	96.20%	95.47%	96.48%	96.05%

Table 4. Classification accuracy of attitude off the radar station.

Method	Target 4	Target 5	Target 6	Accuracy
Ref. [4]	85.55%	95.90%	94.56%	92.00%
Ref. [5]	87.54%	90.21%	92.75%	90.17%
Ref. [6]	91.41%	96.48%	88.67%	92.19%
CMDL	96.86%	95.65%	95.20%	95.90%

As can be grasped from Tables 3 and 4, the average classification accuracy (Accuracy) of the method in this paper outperformed the traditional methods in the comparison experiments in both flight attitudes. Among them, compared with the three traditional methods, the classification accuracy of Target 2 in the flight toward the radar station is more than 6% higher than the method in [4]. Compared with the method in [5], the classification accuracy of Target 3 has been improved by more than 7%. In the flight off the radar station, although the classification accuracy of Target 5 is almost the same as that of the comparative methods, the accuracy of Target 4 is more than 11% higher than that of the method in [4], more than 9% higher than that of the method in [5]. The accuracy of Target 6 is more than 6% higher than that of the method in [6]. The experimental results show that the model established in this paper can effectively handle the classification task of multiple categories of aircraft targets.

The reason that the proposed method performs relatively well is that the high-order cumulant spectrum can suppress Gaussian noise. This paper uses bispectrum features to classify targets, which improves the signal-to-noise ratio (SNR) of aircraft echoes and helps to improve the classification and recognition rate. In [4], Zhang and Li use the fractional Fourier transform to perform multifractal correlation analysis in the optimal fractional Fourier domain, but their multifractal correlation features are artificially defined. Therefore, it may be necessary to define other better fractal features for the data set in this experiment. In [5], EEMD is used to reconstruct the micro-motion component of aircraft echoes, but its experimental parameter settings do not seem to find the optimal solution. If better parameters are used, better performance may be obtained. In addition, the EEMD algorithm achieves the goal of noise reduction by repeatedly adding the Gaussian white noise with zero mean value for auxiliary analysis. Such reconstructed signal features are not robust in a low SNR environment. Although [6] extracts multiple features from the time domain and frequency domain, the final classifier selected is still the traditional machine learning method, with weak generalization ability.

To sum up, the fundamental reason for the better performance of the method proposed in this paper is that bispectral processing can make full use of the possible interrelationships of the data and help to explore the deep multidimensional features of the aircraft target, which is more discriminative than the traditional statistical features. At the same time, the proposed method based on bispectrum is not affected by Gaussian noise in the environment and has strong anti-interference performance.

Tables 5 and 6 show the confusion matrix of classification results under the two flight attitudes. The main diagonal of the confusion matrix is the correct sample for classification, and the rest are the wrong samples. It is observed that although the classification accuracy of various types of aircraft targets is comparatively good, in the prediction results of Table 5 and Table 6, about 3% $\sim$ 5% of the test samples are wrongly classified. The main reason for classification loss is that the acquisition distance of civil aircraft echo data is $90 \sim 140\,\text{km}$, while the acquisition distance of fighter aircraft echo data is $50 \sim 100\,\text{km}$. Their signal-to-noise ratios may not differ much, causing confusion of some data samples in classification experiments.

Table 5. Confusion matrix of attitude towards the radar station.

	Target 1	Target 2	Target 3
Target 1	246	0	10
Target 2	0	244	12
Target 3	0	9	247

Table 6. Confusion matrix of attitude off the radar station.

	Target 4	Target 5	Target 6
Target 4	248	0	8
Target 5	5	245	6
Target 6	0	12	244

5. CONCLUSIONS

Aiming at the difficulties faced by the traditional low-resolution radar target classification methods in practical applications, this paper proposes an aircraft target classification method based on bispectrum and deep CNN. In view of the characteristics that the network structure of the CNN model requires a large number of data sets, the data sets are constructed by calculating the bispectrum of the radar echo of aircraft targets and performing image flipping and random cropping, and other data augmentation processing. Experiments show that the radar target recognition model based on bispectrum features and CNN can accurately classify and recognize targets such as civil aircraft and fighter aircraft, and has better robustness and generalization than traditional methods. Although the proposed method has good classification performance, due to the increasing variety and number of radar targets in practical applications, how to design more ingenious and more generalized classification models is a focus of future research. In addition, since radar signals are typical cyclostationary signals, the inherent characteristics of aircraft targets in the cyclostationary domain may not be fully characterized. In the follow-up work, it can be considered to analyze the property of these nonlinear modulation characteristics reflecting the physical characteristics of aircraft targets in the cyclostationary domain and study their characterization methods.

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