Generative Adversarial Network for Generating Time-Frequency Images

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Abstract. To deal with the problem of de-noising and enhancement of radar signal time-frequency images, a method of secondary generating time-frequency images by generative adversarial network is proposed. Firstly, time-frequency analysis is used to generate the time-frequency image of the radar signal as the original data set 1. Then, after learning the data set 1 by using the generative adversarial network, a new data set 2 is generated, and the data set 2 has de-noising and enhancement effects relative to data set 1. Finally, the validity of the data set 2 generated by the time-frequency image singular value feature is checked. Experiments on the time-frequency images of five common radar signals are carried out. The results show that the method is effective in time-frequency image de-noising and increasing sample diversity.

Keywords: Radar emitter identification · Time-frequency image · GAN · Sample diversity · SVD

1 Introduction

Radar emitter identification refers to the process of analyzing radar system, usage and working status from the radar signal characteristic parameters obtained by processing, and is the key link of radar reconnaissance. The traditional radar emitter identification extracts the inter-pulse five parameters of the radar signal: pulse width (PW), carrier frequency (CF), pulse amplitude (PA), time of arrival (TOA), angle of arrival (AOA) forms the identified feature vector. However, with the increasing complexity of the electromagnetic environment and the continuous development of radar technology, various new radars with complex systems have emerged, such as multi-function phased array radars with functions of search, tracking, guidance, etc. As a result, traditional methods relying on inter-pulse parameter identification fail [1], and more and more researchers are turning their attention to the extraction of intra-pulse features of radar emitter signals. As a carrier of intra-pulse features, time-frequency images have more abundant radar information and robustness than inter-pulse features [2].

S. Shi et al. (Eds.): AICON 2020, LNICST 356, pp. 89–98, 2021.
https://doi.org/10.1007/978-3-030-69066-3_9

Preprocessing the time-frequency image can reduce the interference and redundant information and enhance the signal characteristics, which is of great significance for improving the recognition rate of the back-end classifier. The traditional method of preprocessing the time-frequency image is to use image pre-processing methods such as grayscale, standardization, binarization, cropping [3] to achieve the effect of denoising and weakening the cross-term interference of time-frequency distribution, and the processing process is cumbersome. At the same time, due to the extremely short interception time of the radar signal on the battlefield, it will result in: (1) the number of reconnaissance samples is limited enough to support the training of the radar emitter identification model; (2) the insufficient diversity of reconnaissance samples leads to the radar emitter identification model. Poor ability or training is easy to over-fit. Some commonly used digital image data enhancement methods, such as rotation, translation, etc. will destroy the time-frequency relationship of radar radiation source signals. Obviously, these methods are poorly processed for time-frequency images. In recent years, the generative adversarial network (GAN) has been successfully used in the image field because it can learn the true distribution of samples [4], eliminate interference, generate diverse samples. Therefore, this paper proposes a time-frequency image generation method based on generating an anti-network, which is effective in denoising time-frequency images [5], reducing cross-term interference, and increasing sample diversity.

2 Time-Frequency Analysis Generates Time-Frequency Images

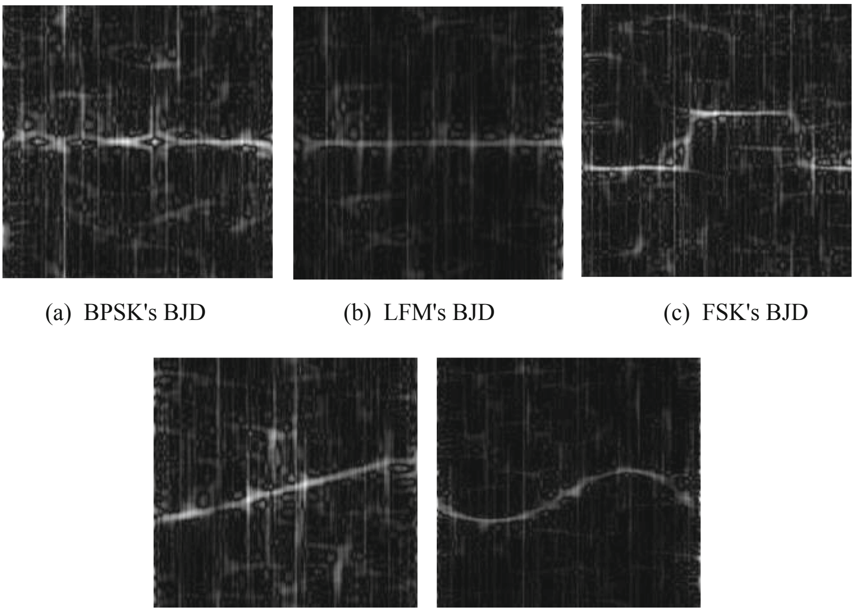
Time-frequency analysis is a powerful tool for dealing with non-stationary signals such as radar signals. It is essentially a combination of a two-dimensional joint function of time and frequency. For the radar signal x(t), the mathematical expression of the bord-jondan time-frequency distribution is as follows:

$$C_x(t,f) = \iint \varphi(t-t',\ \tau)x^*\left(t' - \frac{\tau}{2}\right)x\left(t' + \frac{\tau}{2}\right)e^{-j2\pi f\tau}dt'd\tau \tag{1}$$

$$\varphi(t,\tau) = \begin{cases} \frac{1}{|\tau|}, & \left|\frac{t}{\tau}\right| < \frac{1}{2} \\ 0, & \left|\frac{t}{\tau}\right| > \frac{1}{2} \end{cases} \tag{2}$$

Among them, $\varphi(t,\tau)$ is a kernel function [6]. Because it has better time-frequency aggregation while suppressing cross-term interference, this paper chooses bord-jondan distribution as the time-frequency analysis method of radar signal for five classics. The radar signal is simulated. As shown in Fig. 1, it can be seen that under the condition of

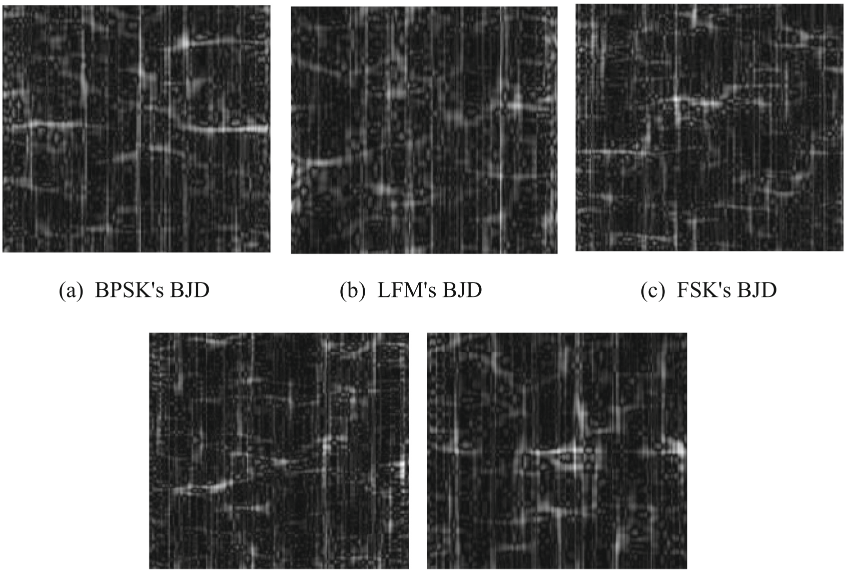
−5 dB SNR, the time-frequency diagrams of the five radar signals have certain identifiable time-frequency structural characteristics, but the signal-to-noise ratio is too low. And the bord-jondan distribution does not suppress the cross term incompletely, and still causes abnormal disturbances such as burrs, edge characteristics, and structural fractures in the time-frequency diagram of the radar signal, especially when the time-frequency structure characteristics of the radar signal are prominent. The influence of interference will also increase. Conversely, weakening the influence of interference will also obscure the time-frequency structure characteristics of the signal. When the signal-to-noise ratio is reduced to −10 dB (Fig. 2), the signal time-frequency structure has versely, weakening the influence of interference will also obscure the time-frequency structure characteristics of the signal. When the signal-to-noise ratio is reduced to -10 dB (Fig. 2), the signal time-frequency structure has been completely destroyed by noise and cannot be recognized by the naked eye.



(a) BPSK's BJD (b) LFM's BJD (c) FSK's BJD

(d) NLFM's BJD (e) CW's BJD

Fig. 1. Bord-Jondan time-frequency distribution of five radar signals (SNR = −5 dB)



(a) BPSK's BJD (b) LFM's BJD (c) FSK's BJD

(d) NLFM's BJD (e) CW's BJD

Fig. 2. Bord-Jondan time-frequency distribution of five radar signals (SNR = −5 dB)

3 Generative Adversarial Network Secondary Generation Time-Frequency Image

The principle of generating a time-frequency image of a radar signal by using an anti-network is as follows:

The GAN consists of two neural networks [7], which are the generation model (G) and the discriminant model (D). G is responsible for generating the radar signal time-frequency image. D is responsible for judging the time-frequency image and feeding the result back to G to continuously improve the quality of generating image. The objective function is defined as follows:

$$\mathrm{V}(D, G) = E_{\mathrm{X} \sim P_{data}(x)}[ln\mathrm{D}(\mathrm{x})] + E_{\mathrm{Z} \sim P_Z(Z)}[ln(1 - \mathrm{D}(\mathrm{G}(\mathrm{z})))] \tag{3}$$

The function $P_{data}(x)ln\mathrm{D}(\mathrm{x}) + P_G(x)ln(1 - \mathrm{D}(\mathrm{x}))$ in the integral term of the above formula is derived to be equal to 0, and the final expression of D is obtained as:

$$\begin{aligned} \mathrm{V}(D, G) &= E_{\mathrm{X} \sim P_{data}(x)}[ln\mathrm{D}(\mathrm{x})] + E_{\mathrm{Z} \sim P_Z(Z)}[ln(1 - \mathrm{D}(\mathrm{G}(\mathrm{z})))] \\ &= E_{\mathrm{X} \sim P_{data}(x)}[ln\mathrm{D}(\mathrm{x})] + E_{\mathrm{X} \sim P_G(x)}[ln(1 - \mathrm{D}(\mathrm{x}))] \\ &= \int [P_{data}(x)ln\mathrm{D}(\mathrm{x}) + P_G(x)ln(1 - \mathrm{D}(\mathrm{x}))]dx \end{aligned} \tag{4}$$

The function $P_{data}(x)ln\mathrm{D}(\mathrm{x}) + P_G(x)ln(1 - \mathrm{D}(\mathrm{x}))$ in the integral term of the above formula is derived to be equal to 0, and the final expression of D is obtained as:

$$D = \frac{P_{data}(x)}{P_{data}(x) + P_G(x)} \tag{5}$$

Next, substitute the obtained D into V(D, G) and continue to find the expression of G with the smallest V(D, G):

$$V(D,G) = \int P_{data}(x) ln \frac{P_{data}(x)}{P_{data}(x) + P_G(x)} dx + \int P_G(x) ln \frac{P_G(x)}{P_G(x) + P_{data}(x)} dx \tag{6}$$

Compare the Jensen-Shannon divergence formula:

$$JSD(P \parallel Q) = \int p(x) ln \frac{p(x)}{p(x) + q(x)} dx + \int q(x) ln \frac{q(x)}{q(x) + p(x)} dx \tag{7}$$

The expression of V(D, G) is written as:

$$V(D,G) = -ln(4) + 2 \times JSD(P_{data}(x) \parallel P_G(x)) \tag{8}$$

Since the JS divergence is non-negative, in order to minimize V(D, G), when $P_{data}(x) = P_G(x)$, the minimum is obtained, that is, the distribution of the time-frequency image of the final G-generated $P_G(x)$ and the real time-frequency The distribution of images $P_{data}(x)$ is consistent.

In the actual situation, the distribution of the radar signal $P_{data}(x)$ is unknown, and only the limited time-frequency image X of the sample is obtained, and the noise distribution $P_Z(Z)$ is known, so that the existing limited time-frequency image can be passed. The training of X on GAN causes G to map the known noise Z to the unknown X, expand the degree of freedom of generating time-frequency images, increase the diversity of the generated time-frequency images and suppress the image noise that does not belong to the $P_{data}(x)$ distribution (unknown The generation of noise). The original GAN has the defects of unstable training and slow convergence [8, 9]. The Deep Convolutional Generative Adversarial Network (DCGAN) [10] has been improved on GAN and has a significant effect on high quality image generation.

4 Validity Test Using Singular Values

Singular Value Decomposition (SVD) is an extension of the feature decomposition of the matrix matrix and is widely used in the field of image and signal processing [11]. Since the singular value can well characterize the image features, this paper extracts the singular value feature of the time-frequency image as the criterion for verifying the validity of the time-frequency image generated by DCGAN. The SVD is defined as follows:

The matrix $A \in R^{m \times n}$, if there is an orthogonal matrix $U = [u_1, u_2, \ldots, u_m] \in R^{m \times m}$, $V = [v_1, v_2, \ldots, v_n] \in R^{n \times n}$, let $A = U\Sigma V^T$, $\Sigma = diag[\sigma_1, \sigma_2, \ldots, \sigma_p]$, p = min$(m, n)$, $\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_p \geq 0$, then say $A = U\Sigma V^T$ is the singular value decomposition of A, $\sigma_1, \sigma_2, \ldots, \sigma_p$ is the singular value of A, and is the square root of AA^T or A^TA eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_p$, That is, $\sigma_i = \sqrt{\lambda_i}$.

The change of singular value can represent the change of time-frequency image. The diversity of singular value can represent the diversity of samples. The change of position of time-frequency image cannot increase the diversity of time-frequency image samples. Only by using DCGAN to learn the true distribution of samples, it is possible to generate more time-frequency images with different characteristics. At the same time, the singular value can reflect the composition of the time-frequency image energy. The closer to the front, the singular value reflects the energy of the signal [12, 13], and the closer the singular value reflects the energy of the noise. Therefore, the distribution of singular values can be used to judge the denoising ability of DCGAN for time-frequency images.

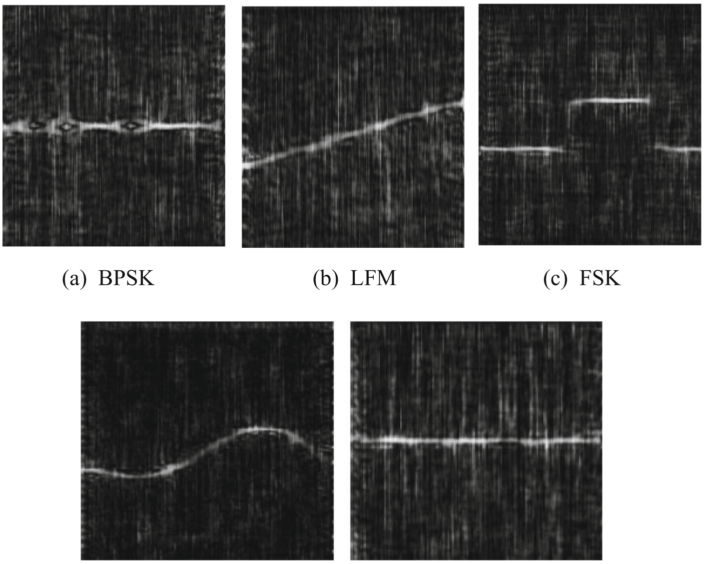
5 Experiment and Analysis

In order to verify the validity of the method for generating time-frequency images, five kinds of radar signals are used in the experiment: binary phase shift keying (BPSK), linear frequency modulation (LFM), frequency shift keying (FSK), nonlinear frequency modulation (NLFM) and conventional radar (CW). Among them, BPSK uses 7-bit Barker code, LFM bandwidth is 17 MHz, pulse width is 10 μs, NLFM uses sine wave frequency modulation, CW carrier frequency is 25 MHz, sampling frequency is 100 MHz, and Gaussian white noise is added. A time-frequency analysis method is generated every 1 dB between the signal-to-noise ratio of −10 dB to −5 dB, and a total of 600 time-frequency images are used as the training set of DCGAN.

Simulation 1: Time-frequency image generation experiment based on DCGAN.

The experimental software environment: operating system Win10 64-bit, based on the open source deep learning framework Tensorflow1.5-GPU build model, VS2015 + CUDA8 + CUDNN7 provides support for GPU computing and improves the speed of graphics parallel computing. Hardware environment: CPU: Intel i7-7700K @ 4.20 GHz, GPU: GTX TITAN X. Training parameters: Mini-Batch is trained by 64 random gradient descent algorithm, and the Adam optimizer performs hyper parameter tuning with a learning rate of 0.0002, momentum β_1 of 0.5, and Epoch of 200. The experimental results are shown in Fig. 3 (only one generated sample is listed for each radar signal).

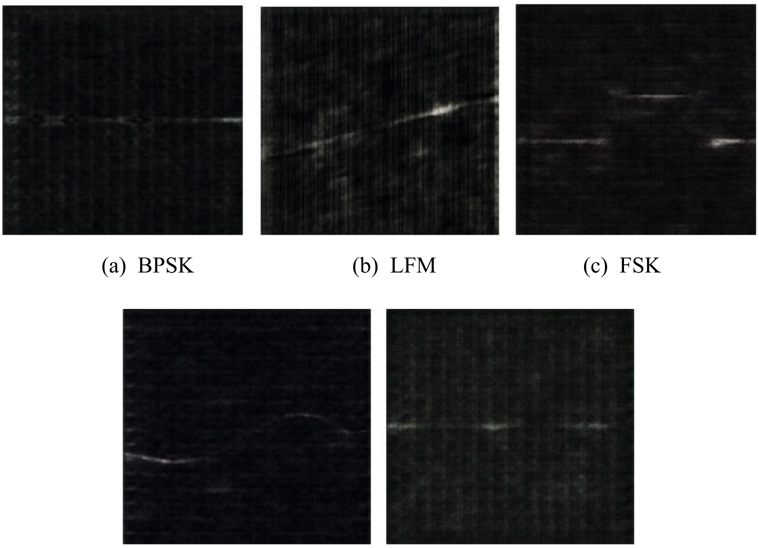
It can be seen from Fig. 3 that compared with the original image (Fig. 1), the generated time-frequency image has better time-frequency aggregation, and the phenomena such as burr, edge characteristic blur and structural fracture are all relieved to some extent, especially for the lower signal-to-noise ratio (Fig. 2). This effect is more obvious, and the ability to reconstruct the characteristics of the radar signal is stronger. However, DCGAN also has a common problem in the GAN model, namely the collapse mode. After a certain training phase, the generated model loses the ability to learn new features of the sample, and the discriminant model will only judge with the same standard, the repeated samples are continuously generated, and the sample features learned are incomplete. As shown in Fig. 4, DCGAN believes that the importance of the background is greater than the importance of the sample, so the background contour is more prominent, and the time-frequency structural features of the sample are diluted, losing the ability to generate new samples.



(a) BPSK (b) LFM (c) FSK

(d) NLFM (e) CW

Fig. 3. Five kinds of radar signal time-frequency images generated by DCGAN



(a) BPSK (b) LFM (c) FSK

(d) NLFM (e) CW

Fig. 4. Collapse mode

Simulation 2: Validity test based on singular value feature

In the experiment, the five kinds of radar signals with signal-to-noise ratios of −10 dB and −5 dB are taken from the average of the first 10 singular values of the 10 time-frequency images, and the time-frequency images of the five kinds of radar signals generated by DCGAN are also taken. Comparing the average singular values of the five radar signals for −10 dB, −5 dB, and DCGAN conditions, which can eliminate random interference and make the result more credible. The experimental results are shown in Fig. 5.

It can be seen from Fig. 5 that since the time-frequency images of the BPSK signal and the CW signal themselves have great similarities, their singular value line graphs have similar similarities. The time-frequency image singular value line graph generated by DCGAN is roughly the same as the −5 dB time-frequency image singular value trend, indicating that the time-frequency image generated by DCGAN does represent such a signal, which is effective, but at the same time, the two fold lines are not complete. Coincidence, there are differences, indicating that DCGAN has produced a

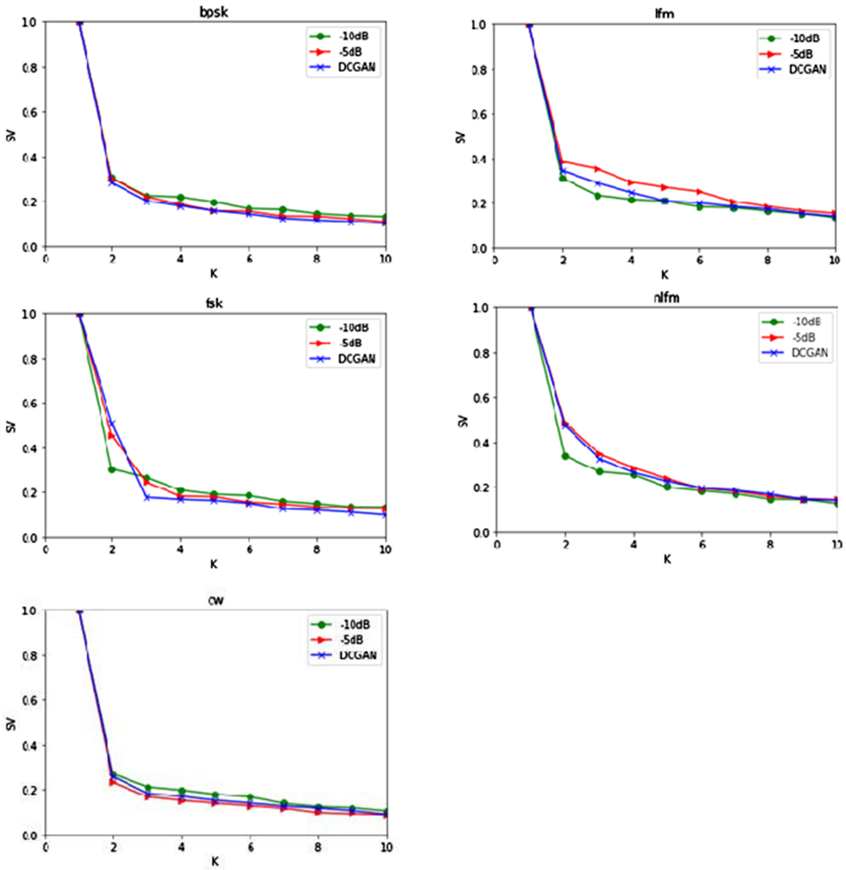


Fig. 5. Singular value line graph of five radar signals (singular value takes normalized value)

new sample after learning the true distribution of the original sample, expanding the diversity of training samples. Among the singular values, the large value reflects the signal energy, and the small value reflects the noise energy. Therefore, the suppression effect of DCGAN on the noise is reflected in the singular value line graph. The DCGAN of the first half of the X-axis is slightly closer. Above, the DCGAN's fold line in the second half of the X-axis is slightly below, that is, the signal has more energy and less noise.

6 Conclusion

Based on the in-depth analysis of the radar signal time-frequency image and the generative adversarial network, this paper proposes a method for denoising and enhancing the radar signal time-frequency image by generating the time-frequency image with generative adversarial network and using the image singular value feature to verify the validity. Different from traditional time-frequency image de-noising and enhancement methods, the generative adversarial network can learn the real distribution of samples and generate new effective samples, expand the freedom of generating samples, increase the diversity of original samples. Simulation experiments prove the effectiveness of the proposed method, but how to solve the problem of collapse mode, finding more robust time-frequency image feature representation methods and using the time-frequency image generated by this method for radar emitter signal recognition experiments One step that needs to be studied.

Acknowledgment. This work was funded by No. 2020Z0203B of the State Key Laboratory of Complex Electromagnetic Environment Effects on Electronics and Information System.

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