IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 5 January 2024, accepted 21 January 2024, date of publication 29 January 2024, date of current version 2 February 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3359419

RESEARCH ARTICLE

Small Sample Target Recognition Based on Radar HRRP and SDAE-WACGAN

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ABSTRACT The high resolution range profile (HRRP) of radar targets is commonly used for target recognition, and the recognition of non-cooperative targets is one of the urgent problems to be solved in radar target recognition. In order to address the noise impact and small sample issues in non-cooperative target recognition, this paper proposes a radar target HRRP recognition method based on SDAE-WACGAN. This method combines Stacked Denoising Auto-encoders (SDAE) and Weighted Auxiliary Classifier Generative Adversarial Networks (WACGAN). In this networks, the decoder of SDAE is used as the generator of WACGAN and the weight coefficients is introduced on the basis of ACGAN, so that the network can generate high-quality data that is more consistent with the real sample distribution, and can be more robust to noise. Experimental results show that compared with other commonly used models, the proposed method achieves higher recognition accuracy in scenarios with small samples and high noise, and demonstrates certain advantages in different SNRs and different number of sample sets.

INDEX TERMS High resolution range profile (HRRP), non-cooperative target recognition, stacked denoising auto-encoders (SDAE), weighted auxiliary classifier generative adversarial networks (WACGAN).

I. INTRODUCTION

Radar Target Recognition (RTR) refers to the use of electromagnetic waves emitted by radar to illuminate targets, obtain echoes for analysis, to determine the number and type of targets. It is an important direction in radar research, especially in the military field, has received significant attention.

Fig.1 shows the HRRP of the target detected by the radar. HRRP is a one-dimensional projection vector sum of the target in the line-of-sight direction obtained by broadband radar, which contains rich target information, such as the target size, structure, shape, and scattering distribution, etc., and is relatively easy to obtain and process. Therefore, it has become an important basis for radar targets recognition [1], [2], [3], [4], [5].

In recent years, radar target recognition based on HRRP has been sufficient research at home and abroad. The research mainly focuses on the recognition of cooperative targets and non-cooperative targets. It is easier to obtain data for cooperative targets, which of-ten have a huge amount of data; However, the acquisition of non-cooperative target data is often difficult, affected by the detection distance, detection environment, and target attributes, the number of samples of robust and sound non-cooperative target HRRP is relatively small. So, the corresponding study can be regarded as a small-sample recognition problem, which is also one of the problems to be solved urgently in the current radar target recognition based on HRRP.

The recognition of radar non-cooperative targets mainly faces the following problems: first, there is a signal-to-noise ratio mismatch between the training samples and the test samples [6]; second, the number of samples in the aspect angle are incomplete [7]; third, the HRRP has sensitivity to azimuth, translation, and amplitude, how to overcome the effects of these sensitivities on the recognition is a major difficulty.

Typical methods used for cooperative target recognition are often prone to overfitting or poor generalization performance

The associate editor coordinating the review of this manuscript and approving it for publication was Junjie Wu.

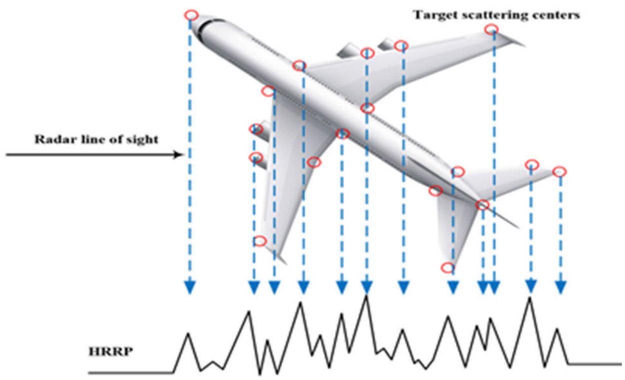

FIGURE 1. Schematic of HRRP of radar target.

when used for non-cooperative target recognition. Therefore, when recognizing non-cooperative targets, it is important to focus on extracting features with clear meanings that deeply reflect the nature of the target, and study methods that are specifically designed for small-sample target recognition to improve the recognition performance of the radar system.

The original data can be expanded by data augmentation methods to increase the number of samples and improve the data diversity. In recent years, it has been widely used in small sample recognition of radar targets [8], [9]. Traditional data generation methods mainly utilize various transformations of existing data (such as rotation, flipping, scaling and translation, etc.) to augment the data. However, these methods cannot expand the inherent information of the sample at the feature level [10]. Generative Adversarial Network (GAN) [11], as a deep generative model, has been widely used in data augmentation to generate new samples consistent with the given data distribution by fitting its distribution to a given small sample dataset via deep neural networks, which can expand the inherent information of the sample data.

In the field of radar target HRRP recognition, GAN can solve the problem of insufficient data samples and improve the recognition rate of small samples by using CNN as a classifier [12]. Combining GAN with the attention mechanism allows the model to pay more attention to the orientation change of HRRP and generate multi-view HRRP data [13]. Auto-encoder (AE) can reconstruct the data as much as possible by extracting the important features of that data. Improving it by adding some constraints can make the features extracted by AE more generalized and robust. It is shown that the reconstructed HRRP signals using the improved AE have a smoother and more concise signal forms, and can extract more abstract and higher-level hierarchical features [14], [15], [16], [17], [18]. Combining the auto-encoder or improved auto-encoder with GAN for small sample recognition can also improve the recognition accuracy [19], [20]. However, the objective value function of the original GAN may cause mode collapse and training instability, that makes the original GAN perform poorly when used to data augmentation. Therefore, many scholars have proposed some methods to solve this problem [21], [22], [23]. Original GAN can be extended into a conditional model such as deep convolutional GAN (DCGAN), Auxiliary Classifier GAN (ACGAN), Least Squares Conditional GAN (LSCGAN) and Wasserstein Conditional GAN (WCGAN) [24]. The comprehensive experimental results show that the ACGAN is more suitable for HRRP data augmentation than other models. By using data augmentation and Weighted Auxiliary Classification Generate Adversarial Networks(WACGAN) for radar target recognition, the original data is first expanded using time mirroring method, and then high-quality generative samples are generated and automatically selected by WACGAN, which can effectively improve the recognition performance of the model under small sample conditions [25]. However, WACGAN does not take into account the interpretability of the generator's input latent variables of the generated data and is sensitive to noise. If the input data contains a large amount of noise, the quality of the generated data often tends to be very low. Stacked Denoising Auto-Encoders (SDAE) [26], [27], [28] can effectively filter out noise and extract deep hidden features that are less susceptible to noise, and the decoder of SDAE can be used as a generator for GANs.

Therefore, this paper combines WACGAN and SDAE to propose a radar HRRP target recognition method based on SDAE-WACGAN. SDAE can compress and extract the features of high-dimensional scattering data such as HRRP at a deeper level, while also performing noise reduction on the data, providing stronger noise robustness and generalization capabilities than traditional auto-encoders. Firstly, the model introduces Gaussian noise that conforms to the standard normal distribution into the original input data, making the data contain more hidden feature information. SDAE is added to the WACGAN framework as a feature extractor of HRRP, which can map the original data into the potential representation space and obtain low-dimensional hidden features that can better reflect the nature of the data. Then, the hidden features and the category in-formation are input into the generator to strengthen the ability to associate the hidden features with the category, so that the data category features can be effectively maintained during the model training stage and recognition stage, improving the performance of the discriminator. In summary, SDAE-WACGAN can capture the intrinsic distribution of HRRP data, optimize the model's ability to learn features, improve the quality of the generated data, enhance the robustness to noise, and ultimately enable the model to achieve efficient recognition performance under small sample conditions.

The contributions of this article are shown as follows:

1) Focusing on the practical problems of non-cooperative target recognition with small samples and higher noise, a small-sample HRRP recognition method based on SDAE-WACGAN is proposed, which is robust to noise and has superior recognition performance when the number of target samples is small and the noise is high, and has certain application value.

2) The model proposed in this article combines SDAE and WACGAN, which introduces label constraints, transforms

unsupervised learning into supervised learning, and improves the problems of pattern crashing and unstable training, compared to SDAE or GAN model.

3) The model proposed in this article introduces label constraints in the data generation stage, enhancing the correlation between data categories and hidden features; In the discrimination stage, weight coefficients are introduced to enable the model to automatically select high-quality generated samples based on the weights size. Therefore, the model can effectively improve the quality of generated data and improve the model's ability to generate data.

This paper is organized as follows. In Section II, the basic theoretical knowledge of SDAE-WACGAN is introduced in detail. The framework and detailed information of the model are proposed in Section III. Section IV conducts experimental analysis and gives the results of comparative experiments. Finally, the conclusion and summarizes are outlined in Section V.

II. BASIC THEORETICAL

A. STACKED DENOISING AUTO-ENCODERS

Auto-encoder (AE) is an unsupervised neural network model that learns the hidden features of input data, and then reconstructs the original data with the learned features to achieve data compression. A general AE network contains a three-layer structure: the input layer, the hidden layer, and the output layer, which is shown in Figure 2. The algorithm consists of two processes: encoding and decoding.

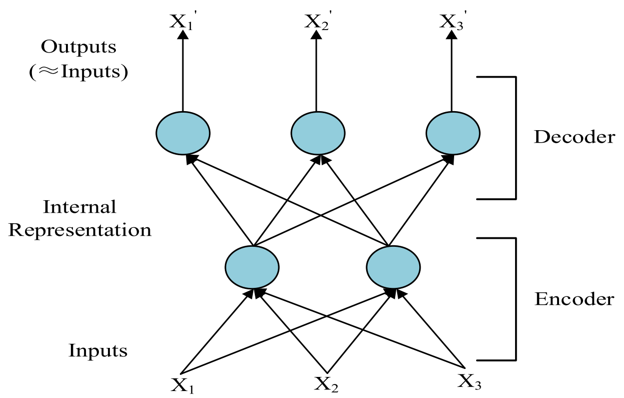

FIGURE 2. The basic architecture of AE.

For a given n-dimensional training set: $D = (x_1, x_2, \ldots, x_{n-1}, x_n)$, where x_n is the nth vector of D, In the training stage, x_n is first encoded to obtain the feature y_n, and then the decoder reconstructs the original input x_n from the features y_n to the output vector x'_n as much as possible. The processes of encoder and decoder are expressed as:

$$\begin{cases} y_n = f\,(Wx_n + b) \\ x'_n = h(W'y_n + b') \end{cases} \tag{1}$$

where *f, h* represents the neuronal activation function during encoding and decoding respectively; *W, b* represents the weight and bias during encoding, and *W', b'* represents the weight and bias during decoding.

Commonly used loss functions in AE include minimizing the negative log-likelihood function, sigmoid, Relu function, and so on. AE obtains the reconstructed vector x'_n through the encoding and decoding processes, with the core aim of ensuring that the error between the output vector x'_n and the input vector x_n is sufficiently small. Its reconstruction error can be expressed as:

$$\sigma = \sum ||x'_n - x_n||_2^2 \tag{2}$$

When the reconstruction error is small enough, the reconstructed output vector x'_n is an implicit characteristic representation of x_n.

Denoising auto-encoder(DAE) is based on auto-encoder which adds random noise to the input signal to train the whole network. Introducing a degradation process in AE to reconstruct the original data without noise from the noisy data can make the hidden layer extracted features less susceptible to noise and make the encoder have better robustness and stability.

Stacking multiple DAEs can form a stack denoising auto-encoder. The deepening of the layers can extract higher-level and deeper feature representations. In SDAE, the hid-den features output by the upper DAE hidden layer are used as the input to the next DAE layer, as shown in Figure 3.

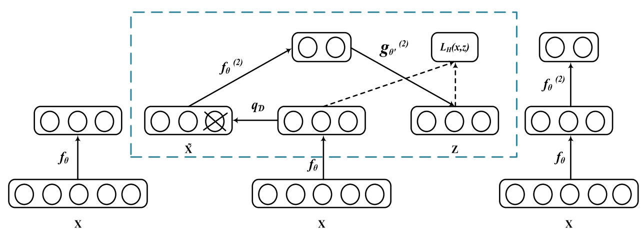

FIGURE 3. Architecture of SDAE.

The blue dashed boxed portion of Figure 3 shows the architecture of the *k-th* layer denoising auto-encoder. A sample x_{k-1} is stochastically corrupted via q_D (the process of noise addition) to get the corrupted version $\tilde{x}_{k-1}$:

$$\tilde{x}_{k-1} \sim q_D(\tilde{x}_{k-1}|x_{k-1}) \tag{3}$$

Then the reconstructed sample z_k is obtained after encoding (denoising process) and decoding according to equation (1).

The purpose of DAE training is to adjust parameters by minimizing reconstruction errors:

$$\sigma_{DAE} = \sum ||x_{k-1} - z_k||_2^2 \tag{4}$$

The working process of SDAE is as follows: first, train one layer of denoising auto-encoder, and use the learned encoding function f_θ for the clean input samples (left of Figure 3); then use the resulting representation for the second layer of denoising auto-encoder (middle of Figure 3) to learn the secondary encoding function $f_\theta^{(2)}$; finally, repeat the above work (right of Figure 3) until the auto-encoder network converges.

B. AUXILIARY CLASSIFIER GAN, ACGAN

The GAN generally consists of a generator and a discriminator, as shown in Figure 4(a). A random variable z in hidden space is input into generator G, which generates the samples $G(z)$ that obey the real data distribution as much as possible through forward propagation, in order to "trick" the discriminator D. Then the generated sample $G(z)$ and the real sample data x are input into D to determine the category of input sample, and the discriminative result is output through forward propagation. During the training process, based on the idea of "Nash equilibrium" in game theory, G and D play a game against each other, training the discriminator D by maximizing the difference in data distribution between real samples x and generated samples $G(z)$, and training the generator G by minimizing the difference in data distribution between the two, so that G and D can optimize their performance in constant confrontation to achieve "Nash equilibrium".

In the final training results, the generated sample $G(z)$ can be fake, making D unable to correctly distinguish between x and $G(z)$, and realizing the approximate estimation of the generator G to the real data distribution. The training process is shown as:

$$\min_G \max_D V(D,G) = E_{x\sim P_{\text{data}}}[\log D(x)] + E_{z\sim P_z(z)}[\log(1-D(G(z)))] \tag{5}$$

where $E[\cdot]$ is the expected value of the corresponding distribution.

However, the original GAN was trained based on a gradient descent algorithm, which is unstable and sometimes difficult to achieve Nash equilibrium between G and D. Meanwhile, the Loss function also has the problems of gradient disappearance and mode collapse, which makes GAN show poor performance when used to data augmentation.

Adding certain auxiliary information, such as class labels or tags, to the original GAN to get an improved GAN model can effectively solve the above problems. Among the many improved GANs. the Auxiliary Classifier GAN is more suitable for HRRP data augmentation than other models, and its architecture is shown in Figure 4(b).

ACGAN improves GAN in two aspects. First, by adding class labels c, the generator G takes both the latent variable z and the labels c as input, to guide G to generate category conditioned samples $G(c, z)$. Second, by adding an auxiliary classifier, usually a softmax classifier, to the discriminator D, which captures the probability distribution over the labels and distinguishes whether the samples come from real samples or generated samples.

The loss function of ACGAN consists of classification loss L_C and discrimination loss L_S, as shown in:

$$\begin{cases} L_C = E_{x\sim P_{data}}[L_D(c_x|x)] \\ \qquad + E_{z\sim P_z(z)}[L_D(c|G(c,z))] \\ L_S = E_{x\sim P_{data}}[\log_2(D_s(x))] \\ \qquad + E_{z\sim P_z(z)}[\log_2(1-D_s(G(c,z)))] \end{cases} \tag{6}$$

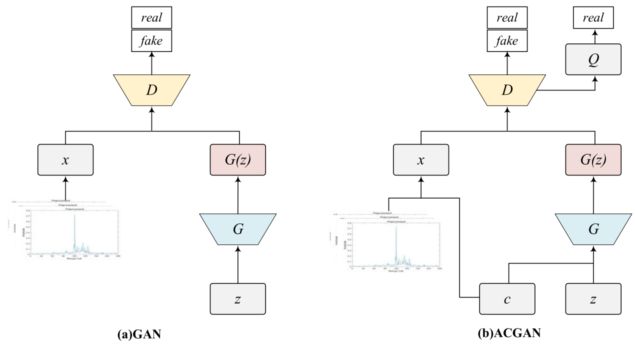

FIGURE 4. Architecture of GAN and ACGAN. (a) The architecture of GAN; (b) The architecture of ACGAN.

where $E[\cdot]$ is the expected value of the corresponding distribution; $L_D(c_x|x)$ is the classification loss of x by D, and c_x is the true class of x; $L_D(c|G(c,z))$ is the classification loss of D to $G(c,z)$, and c is the label of $G(c,z)$; $D_s(x)$ is the probability that D judges x to be the real sample; $D_s(G(c,z))$ is the probability that D determines that $G(c,z)$ is a real sample.

The training process is to train D by maximizing $L_C + L_S$ and train G by minimizing $L_C - L_S$. As shown in:

$$\begin{cases} \max_D V(D,G) = L_C + L_S \\ \min_G V(D,G) = L_C - L_s \end{cases} \tag{7}$$

C. WEIGHTED AUXILIARY CLASSIFIER GAN, WACGAN

The HRRP data generated by ACGAN has a high degree of similarity to the real sample data, but some features of the generated data will be corrupted or blurred, and the quality of the samples is uneven. Equation (4) that the classification loss of ACGAN adopts the cross-entropy, which accumulates the losses of each generated sample equally. Due to the varying quality of generated samples, the recognition effect may be reduced if those poor quality generated samples are fed into the discriminator D.

Therefore, it is possible to improve the ACGAN model by introducing weight coefficients into the discriminator to obtain a Weighted auxiliary classification GAN(WACGAN). The weight coefficient enables D to automatically select high-quality generated samples according to the weight size during the training process to optimize the recognition model and improve the recognition performance of the network model. The discrimination probability $D_s(x)$ is introduced into the weight coefficient W, then the weighted discrimination loss L_S' of D in the WACGAN model is shown as:

$$L_S' = E_{x\sim P_{data}}[W_t(D_s(x))\log_2(D_s(x))] + E_{z\sim P_z(z)}[W_f(D_s(G(c,z)))\log_2(1-D_s(G(c,z)))] \tag{8}$$

where, $W_t(D_s(x))$ is the weight of the real sample determined by $D_s(x)$; $W_f(D_s(G((c,z))))$ is the weight of the generated sample determined by $D_s(G((c,z)))$.

In the training process of WACGAN, the weighted discriminative loss L_S' is used to encourage the discriminator

D to pay more attention to high-quality generated samples and real samples that are judged to be fake, and increase the corresponding weights; Try to ignore the generated samples of low quality and the real samples judged to be true, and reduce the corresponding weights.

The weight coefficient of the real sample can be expressed as:

$$W_t(D_s(x)) = (1 - D_s(x))^{\gamma} \tag{9}$$

The weight coefficient of the generated sample can be expressed as:

$$W_f(D_s(G(c, z))) = D_s(G(c, z))^{\gamma} \tag{10}$$

where, γ represents the parameter of weight attenuation degree.

The sample loss distribution is affected by the weight parameters γ. When $\gamma = 2$ the generated samples with low quality have the least influence on the discriminator [29]. The result is used in this paper, assuming that $\gamma = 2$. Therefore, the weighted discriminative loss of D in the WACGAN model can be expressed as:

$$\begin{aligned} L_S' = {} & E_{x \sim P_{data}}[(1 - D_s(x))^2 \log_2(D_s(x))] \\ & + E_{z \sim P_z(z)}[D_s(G(c, z))^2 \log_2(1 - D_s(G(c, z)))] \end{aligned} \tag{11}$$

The training process of WACGAN is to train D by maximizing $L_C + L_S'$ and G by minimizing $L_C - L_S$. As shown in:

$$\begin{cases} \max\limits_{D} V(D, G) = L_C + L_s \\ \min\limits_{G} V(D, G) = L_C - L_s \end{cases} \tag{12}$$

III. SDAE-WACGAN

WACGAN can learn the distribution structure of hidden features of samples based on class labels, but if the samples are directly used as inputs, the model may not be able to learn the effective features when learning the data distribution of real samples due to the influence of data perturbation. On the other hand, the model does not take into ac-count the link between the input latent variable z and the generated sample $G(z)$. SDAE can extract higher-level and deeper feature representations of samples, and the hidden features extracted from the hidden layer of SDAE can be input into the generator G as latent variable z, which can better generate high-quality data close to real samples. At the same time, the hidden features extracted by SDAE are not susceptible to noise and have better robustness to noise.

Therefore, this paper proposes a radar HRRP target recognition method based on SDAE-WACGAN to solve the small samples problem of non-cooperative radar targets.

In this method, the original sample is encoded by adding an auto-encoder, the standard normal distribution noise is added to the coding vector, and the latent variable containing real sample feature information and robust to noise is extracted by the hid-den layer of SDAE. Then the latent variable and its class information are input into the generator, which can effectively narrow the range of the feature space of the generator to learn the real sample, strengthen the ability of the latent variables to correlate with the features of their respective classes, effectively preserve the class features of the samples during the training and recognition stage, and further improving the recognition performance under small sample conditions.

A. NETWORK MODEL DESIGN

The network structure of SDAE-WACGAN is shown in Figure 5. The framework consists of SDAE, generator G, and discriminator D, and the decoder of SDAE is used as the generator of WACGAN. The method consists of the discriminator training stage and the test stage.

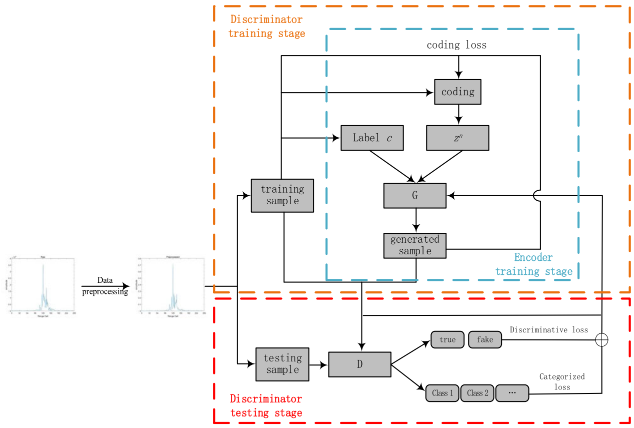

FIGURE 5. The Structure of SDAE-WACGAN.

In this method, the generated HRRP sample can be expressed as:

$$\left\{ y_{gen}^n \right\} = f(x_{true}^n, c) = f_\theta(z^n, c) = f_\theta[f_\phi(x_{true}^n), c] \tag{13}$$

where, $f(x_{true}^n, c)$ is the generated sample obtained by input HRRP sample $\{x_{true}^n\}_{n=1}^N$ and class label c; $f_\phi(\cdot)$ is the mapping function of SDAE, and ϕ is the coding parameter set of SDAE. $f_\theta(\cdot)$ is a generator whose decoded parameter set is θ. Implicit variables z^n and class label c are combined to form a joint feature (z^n, c), to generate a generated HRRP sample of the corresponding class $\left\{ y_{gen}^n \right\}_{n=1}^N$. Finally, the generated sample $\left\{ y_{gen}^n \right\}$ and $\{x_{true}^n\}$ are entered into discriminator D to discriminate the class of the input sample.

Below is a brief introduction to the main encoder networks, decoder (generator) networks, and discriminator networks.

1) ENCODER NETWORK

As shown in Figure 6, the input data is passed through the hidden layers, fully connected layers and activation function to obtain the mean(μ) and variance(σ^2) of the hidden variables required for generating the HRRP samples. The activation function adopts the Leaky ReLU function, in order to avoid the problem of "dead neuron" in the ReLU function, and to accelerate the training of the model.

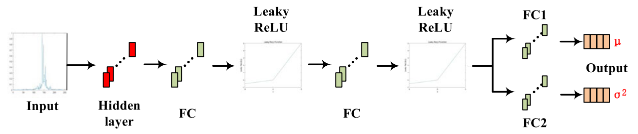

FIGURE 6. Encoder network schematic.

2) DECODER (GENERATOR) NETWORK

As shown in Figure 7, the purpose of the decoder is to generate corresponding HRRP samples by obtaining hidden features z^n and labels c. By adding labels, unsupervised learning is transformed into supervised learning, which can effectively control the category of generated samples. To obtain z^n, we first extract a vector z_0^n from the standard random distribution, then multiply it by the standard deviation(σ) and plus the mean(μ). Replace the final activation function with the sigmoid, keeping the output between 0 and 1.

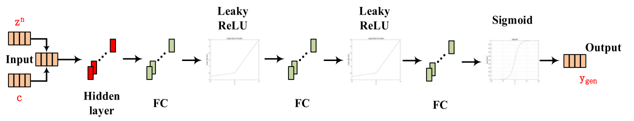

FIGURE 7. Decoder(generator) network schematic.

3) DISCRIMINATOR NETWORK

As shown in Figure 8, the discriminator is used to distinguish between "true" and "false" samples. The inputs are training samples, generating samples and testing samples. Firstly, a Squeeze-and-Excitation Block (SE-Block) is added to extract and weight the input feature information to improve the transmission of useful features.

Then, after passing through several convolutional layers, fully connected layers, batch normalization layers, and Leaky ReLU activation functions, the discrimination results are finally obtained through Softmax. The training process of the discriminator is constrained according to equations (6), (11), and (12).

B. THE IMPLEMENTATION PROCESS

The implementation process of the radar target recognition method based on SDAE-WACGAN under small sample conditions is shown in Figure 6. The specific steps are as follows:

Step 1 Obtain the real HRRP sample x_{true}^n of the radar target, perform L2 normalization and centroid alignment processing on it, and then divide it into training samples and test samples;

Step 2 Add random noises that conform to the normal standard distribution to the training samples, input them into SDAE, and obtain the latent variable z^n through coding;

Step 3 The class labels c and the latent variable z^n are combined to form a joint feature, which is input into the generator G to obtain the generated sample y_{gen}^n.

Step 4 The real sample x_{true}^n and the generated sample y_{gen}^n are input into the discriminator D to judge the authenticity and class of the samples, and then the loss value of the discriminator D is calculated, and the network parameters are updated with the Adam optimizer. Then the parameters of D are fixed, the parameters of SDAE and G are updated by the loss function.

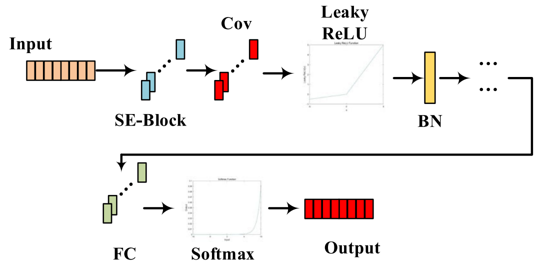

FIGURE 8. Discriminator network schematic.

Step 5 Repeat step 2 to step 4 through network adversarial learning until the network converges and the training of SDAE-WACGAN is completed.

Step 6 Use the trained discriminator D for target recognition, input the test samples into D for recognition, and output the recognition results.

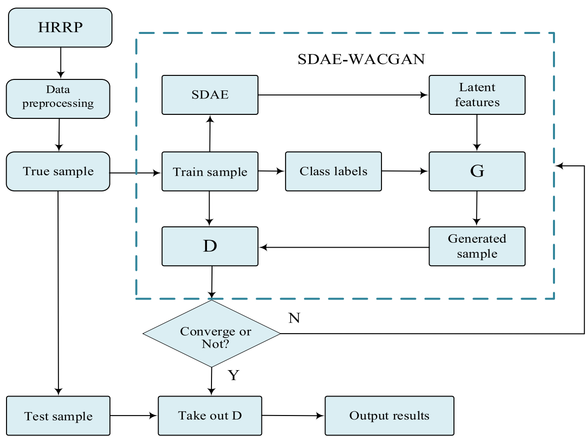

FIGURE 9. Flow Chart of SDAE-WACGAN.

IV. EXPERIMENTAL RESULTS AND COMPARATIVE ANALYSIS

A. THE DATA SET

In this paper, we use the HRRP data from three types of aircraft measured by a certain type of radar. Under the premise that the target does not migrate through resolution cells relative to the radar, the *k-th* (k=*1, 2,…,* K) distance cell in the *m-th* echo signal can be approximated as

$$x_k(t,m) \approx x_k(m) = e^{j\theta(m)} \sum_{i=1}^{V_k} \sigma_{ki} e^{j\varphi_{ki}(m)} \tag{14}$$

where $\theta(m)$ represents the initial phase of the *m-th* echo, V_k is the number of scattering points in the *k-th* distance cell, is the intensity of the *i-th* scattering point in the *k-th* distance cell, and $\varphi_{ki}(m)$ is the phase. The *m-th* distance image $x(m)$ can be obtained by arranging all the distance cells sequentially.

The HRRP examples diagrams for three types of aircraft are shown in Figure 10, which are medium jet aircraft Z, small jet aircraft X, and medium propeller aircraft L. The radar operates in the C-band, with a signal bandwidth of 400MHz. The sampling points for each class of aircraft are 256, which includes 256 distance cells. Adaptive angular domain segmentation is used for angular domain segmentation of frames to obtain the HRRP data which is less sensitive to orientation. Each of the three classes of target samples contains 600 pieces of data, for a total of 1800 samples. They are divided into training sets and test sets ac-cording to the ratio of 0.7:0.3, that is, the training set has 420 samples of each class and the test set has 180 samples of each class.

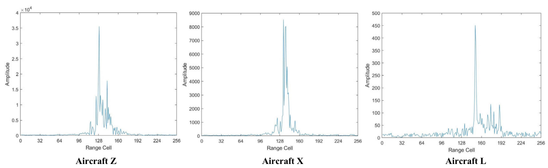

FIGURE 10. **HRRP example diagram for three types of aircraft.**

Data need to be processed before the experiment starts. Since the original HRRP data obtained contains intensity sensitivity and displacement sensitivity, these two sensitivities need to be processed before the HRRP samples are sent to the model to eliminate the instability caused by them to the network model.

The data needs to be processed before the experiment begins. Since the raw HRRP data contains intensity sensitivity and displacement sensitivity, these two sensitivities need to be processed before sending the HRRP samples to the model to eliminate their instability on the network model. First, L2 normalization is used to eliminate the influence of HRRP intensity sensitivity. Raw HRRP data $x_{raw} = [x(1), x(2), \ldots, x(N)]$, and L2 normalized data can be expressed as:

$$\underset{norm}{x} = \frac{x_{raw}}{\sqrt{\sum_{i=1}^{N} x(i)^2}} \tag{15}$$

where, N represents the total number of HRRP range units, that is, the dimension of x_{raw}; $x(i)$ is the I-th element of x_{raw}.

Then, the centroid alignment method is used to eliminate the influence of displace-ment sensitivity. By calculating the centroid position of the data, the HRRP data is then shifted left or right to obtain new HRRP data. The calculation process of the center of mass g is shown as:

$$g = \frac{\sum_{i=1}^{N} i \cdot x_{norm}(i)}{\sum_{i=1}^{N} x_{norm}(i)} \tag{16}$$

Finally, the HRRP data after L2 normalization and centroid alignment are shown in Figure 11. The processed HRRP samples have amplitudes ranging from 0 to 1, with the centroid near the center point.

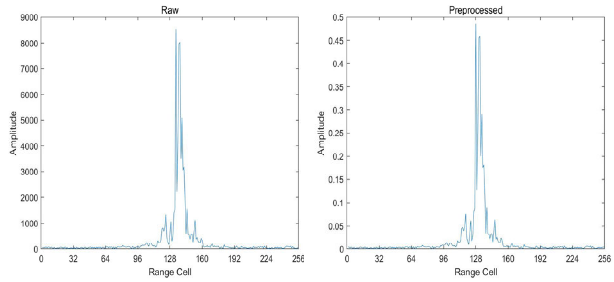

FIGURE 11. **Raw HRRP data (left) and processed data (right).**

B. EXPERIMENTAL RESULTS AND COMPARATIVE ANALYSIS

In this paper, we first give the comparison between generated samples by SDAE and real samples; Then we experimentally compare the recognition effects of CNN, ACGAN+CNN, SDAE, WACGAN, AE-ACGAN, and the SDAE-WACGAN method proposed in this paper under the condition of small samples; Finally, the original HRRP is noised by adding Gaussian white noise with different energies, so that the SNR of the input signals are 5dB, 10dB, 15dB, 20dB, 25dB and 30dB, respectively, to compare the recognition performance of the SDAE-WACGAN method at different SNRs, and to compare with the other several methods mentioned above.

1) COMPARISON BETWEEN GENERATED SAMPLES AND REAL SAMPLES

The original HRRP sample x_{true}^n is input into the encoder of SDAE to extract the deep latent features and get the latent variable z^n, and then the class information c_i of this sample is input into the decoder (which is both the decoder of SDAE and the gener-ator of WACGAN) along with the latent variable to get the generated sample y_{gen}^n through the decoder. Each type of target generates 420 samples at a ratio of 1:1, and a test sample is randomly selected to generate the generated sample through the trained SDAE model. The test sample and generated sample are shown in Figure 12.

Root Mean Square Error (RMSE) is used to give the error results of the test sample and the generated sample. RMSE is defined as:

$$\sigma = \sqrt{\frac{1}{N} \sum_{n=1}^{N} \frac{||\widehat{x}_n - x_n||_2^2}{||x_n||_2^2}} \tag{17}$$

where σ is root mean square error; N represents the number of test samples; x_n represents the N-th original sample; $\widehat{x}_n$ indicates the generated sample of x_n.

The root mean square error between the three target test samples and the generated samples is shown in Table 1. It can be seen from Figure 12 and Table 1 that the generated samples

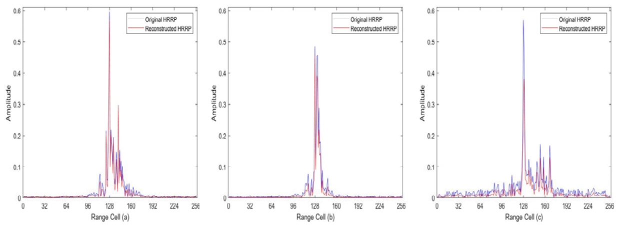

FIGURE 12. HRRP diagram of three types of test samples and generated samples.

TABLE 1. RMSE between three types of target test samples and generated samples.

Test data	Sample_1	Sample_2	Sample_3
σ_{RMSE}	0.0280	0.0414	0.0321

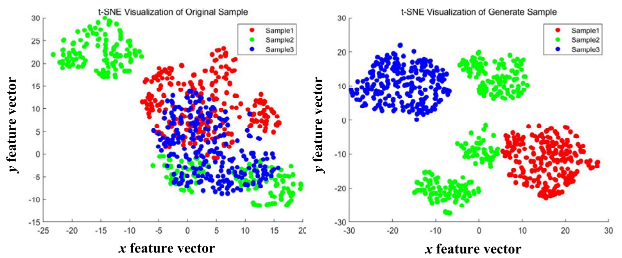

FIGURE 13. t-SNE Comparison of dimensionality reduction results.

obtained by this model can well reflect the data distribution of the original samples.

The t-Distributed Stochastic Neighbor Embedding (t-SNE) is used to visually com-pare the original HRRP dataset and the generated HRRP dataset. The results after reducing the extracted features to two dimensions are shown in Figure 13. Compared with the original dataset, the target features of each target of the generated dataset have a clearer boundary after dimensionality reduction, which is more conducive to the identification of the target. Therefore, the use of SDAE can improve the divisibility of the features.

2) RECOGNITION PERFORMANCE ANALYSIS

The generated samples and real samples are input into the discriminator D to determine the authenticity and category of the samples, and the loss value of D is calculated. The network parameters are updated by the Adam optimizer. Then fix the parameters of D, and use the loss function to adjust the parameters of SDAE and generator G. Then continuously update parameters to make the network converge and com-plete the training of SDAE-WACGAN. Finally, the trained discriminator D is used for target recognition, the test samples are input into D for recognition, and the recognition result is output.

The decoder generates 420 samples for each type of target in a 1:1 ratio and expands them to the training set, that is, the training set contains a total of 840 samples for each type of target. In this paper, we first compare the impact of training sets with different sample sizes on the final recognition results. Figure 14 shows the recognition effect of the SDAE-WACGAN method when each type of target in the training set contains 340/440/.../840 samples.

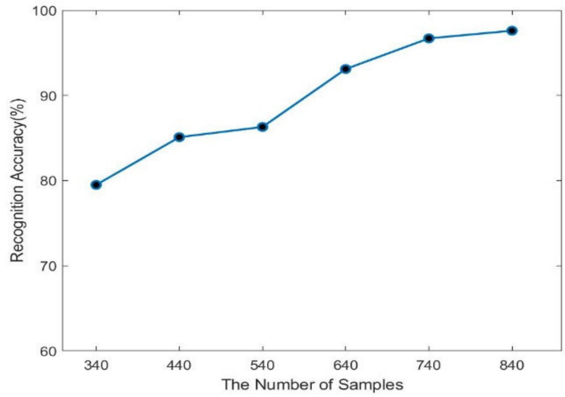

FIGURE 14. Comparison of recognition rate results under different numbers of samples.

Experiments show that when the number of original samples per class is 170 (the number of samples after expansion is 340), the method can achieve a recognition accu-racy of 79.5% on the test set, showing better recognition performance under small sample conditions. With the increase of the number of samples in the training set, the method's recognition accuracy on the test set gradually improves and levels off, showing the robustness of this method in radar HRRP data recognition.

Furthermore, in order to verify the recognition performance of SDAE-WACGAN for HRRP recognition under different SNR conditions, Gaussian white noise with different energies was added to the original data, resulting in signals with SNRs of 5dB, 10dB, 15dB, 20dB, 25dB, and 30dB. The definition of SNR is shown as:

$$SNR = 10\log_{10}\left(\frac{\overline{P}_{signal}}{P_{noise}}\right) \tag{18}$$

where, $\overline{P}_{signal}$ is the average power of HRRP, and P_{noise} is the noise power.

This paper compares the average recognition accuracies of the test set after training with the methods used in this paper when the number of original samples per class is 170 and 420, as shown in Table 2.

As shown in Table 2, the recognition accuracy of the model decreases as the SNR decreases. However, the SDAE method used in this paper can effectively extract hidden features that are not easily affected by noise, it has better robustness to noise

Therefore, even when the sample size is small and the SNR is low, the recognition accuracy of the method used in this paper is still 63.8%. When the sample size reaches a certain size and the SNR is low, the recognition accuracy of the method rises to 75.5%, as the SNR increases, the model

TABLE 2. Comparison of recognition accuracy of SDAE-WACGAN under different SNRs.

SNRs		5dB	10dB	15dB	20dB	25dB	30dB
Average accuracy (%)	Sample Size (170)	63.8	68.5	73.2	77.3	78.5	79.2
	Sample Size (420)	75.5	83.3	88.3	94.5	96.9	97.8

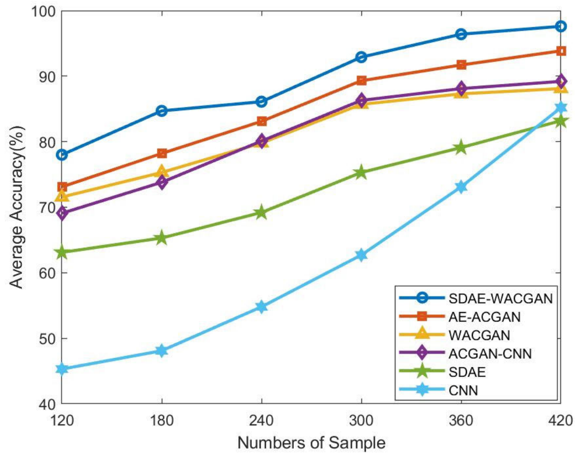

FIGURE 15. Comparison of recognition rates under different sample sizes for six methods.

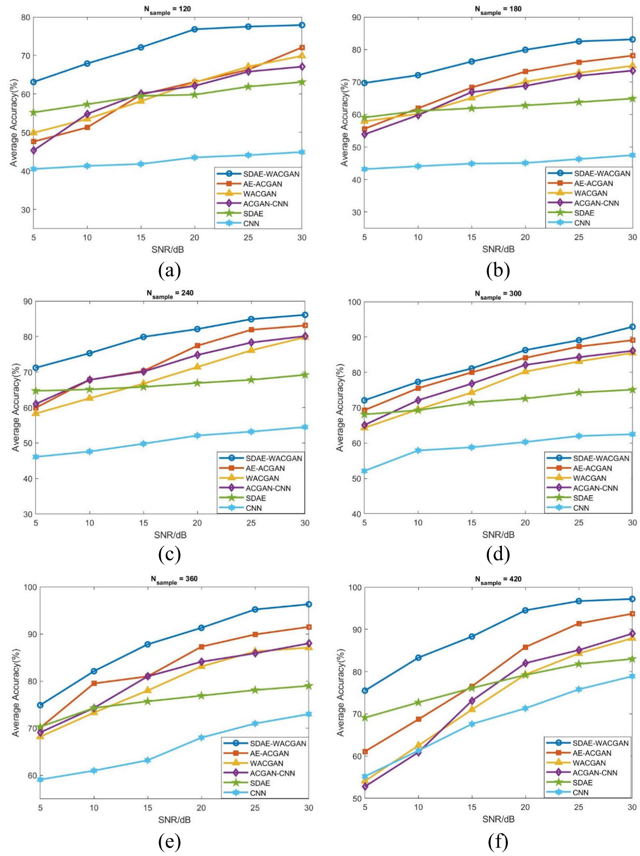

FIGURE 16. Comparison of recognition rate results of six methods with different numbers of samples and different SNRs. (a) /(b)/ (c) /(d)/ (e) /(f) represent the recognition accuracy of each model at different SNRs for different numbers of samples.

recognition accuracy gradually rises and tends to stabilize, indicating that the SDAE method is robust to noise.

3) COMPARISON AND ANALYSIS OF RECOGNITION PERFORMANCE WITH OTHER MODELS

To further illustrate the advantages of the radar target HRRP recognition algorithm based on SDAE-WACGAN under small sample conditions, a comparative analysis of six methods proposed in this paper, including SDAE-WACGAN, CNN, ACGAN+CNN, SDAE, WACGAN, and AE-ACGAN, is performed. The input data is the original data without noise processing. Comparing the impact of different sample sizes on the final recognition results, the average recognition accuracy of each method is shown in Figure 15.

As shown in Figure 15, the recognition accuracy demonstrated by each method is relatively low when the sample size is small, but the method used in this paper still manages to maintain more than 78%. When the number of original samples is 120, the recognition rate of the SDAE-WACGAN method is 78.0%, which is 8.92% higher than SDAE, 6.45% higher than WACGAN, and 4.89% higher than AE-ACGAN. However, the traditional CNN algorithm performs poorly under small sample conditions, with an average recognition accuracy of only 45.3%. As the sample size increases, the recognition accuracy of each method improves significantly, and the method used in this paper still has at least a 3.74% improvement over other recognition algorithms. The experimental results prove that the radar target recognition method used in this paper has obvious advantages under small sample conditions.

Furthermore, this paper compares the recognition performance of six recognition algorithms with different sizes of training sets and different SNRs, and the recognition accuracies of each method are shown in Figure 16 after noise addition to the original data.

The above experimental results show that when the number of samples is sufficient, with the improvement of the SNR, the recognition performance of SDAE-WACGAN is comparable to that of AE-ACGAN and is significantly better than that of the other four methods. However, when the SNR decreases, the features extracted by the SDAE are more robust to noise, so the method used in this paper has better recognition performance for radar targets.

Under the small sample dataset, the method used in this paper has significant ad-vantages both in the case of low SNR and high SNR, especially in comparison with AE-ACGAN. Due to the improvement made on the ACGAN model by introducing weight coefficients into the discriminator, the samples generated by WACGAN are of higher quality than those generated by ACGAN, and the distribution of these samples is closer to the real samples. Therefore, the recognition effect of SDAE-ACGAN under small sample conditions is more pronounced.

The results of the above multiple comparison experiments show that the SDAE-WACGAN method proposed in this paper exhibits good overall performance in small-sample scenarios and can effectively solve the problem of insufficient non-cooperative target samples in radar target recognition. Meanwhile, as the number of samples increases and the SNR decreases, the method still maintains high recognition performance and keeps good generalization performance and robustness to noise in both small-sample and sample-sufficient scenarios.

V. CONCLUSION

In this paper, a target recognition method based on the SDAE-WACGAN is pro-posed under the condition of small samples, aiming at the practical situation of radar non-cooperative target recognition with few samples and with more noise in the data. The method first uses SDAE to extract the hidden features that are not easily affected by noise from the noisy data and reconstruct the noise-free sample data; then introduces weight coefficients into the discriminator of ACGAN to obtain a WACGAN model, which enables the discriminator to automatically select high-quality generated samples based on the weight size during training process to optimize the recognition model and improve the recognition performance of the network model.

This paper conducts recognition experiments on the measured data from three types of aircraft targets, by comparing with several other methods, the method used in this paper achieves higher recognition accuracy in small-sample, high-noise scenarios, and demonstrates certain advantages in different SNRs and different numbers of sample sets. The results show that the SDAE-WACGAN method proposed in this paper has bet-ter performance in HRRP recognition of non-cooperative targets.

In practical radar applications, in addition to noise information, radar echo signals also contain a certain amount of ground clutter and meteorological clutter, which can interfere with the recognition of normal targets. In addition to using clutter suppression methods to filter out clutter, the next step is to study more robust and generalizable RTR algorithms to deal with clutter interference. In addition, he bandwidth and sampling rate of the radar system will also have an impact on the target echo signal. the bandwidth or sampling rate is too low will lead to the loss of signal details or inaccuracy, which in turn affects the depiction of the target structural details.The impact of radar bandwidth and sampling rate on radar target recognition is also a problem that needs to be considered in the next step. Finally, there is often a sample imbalance between the samples of non-cooperative targets, therefore, the sample imbalance problem in non-cooperative target recognition will also be investigated in the next step.

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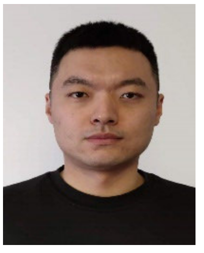

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