



Article

A Satellite Individual Identification Method Based on a Complex-Valued Conditional Generative Adversarial Network

Jun He , Can Xu, Canbin Yin, Pengju Li , Jishun Li , Shuailong Zhao and Yasheng Zhang *

Graduate School, Space Engineering University, Beijing 101416, China; hj1997@stu.xjtu.edu.cn (J.H.); canxu1985@163.com (C.X.); expressesp@126.com (C.Y.); lipengju@nuaa.edu.cn (P.L.); lijishun9981@163.com (J.L.); zsl20002021@163.com (S.Z.)

* Correspondence: zhangyspublic@163.com

Abstract: With the help of specific emitter identification (SEI), the control efficiency of the satellite communication systems can be effectively improved by discriminating the individual satellite. In recent years, deep learning has been introduced into SEI to enhance identification performance because of its powerful classification capability. However, classical real-valued neural networks exhibit some limitations in extracting the radio frequency fingerprint (RFF) features from complex signals, limiting the improvement of identification accuracy. Thus, we proposed a complex-valued conditional adversarial generative network (CC-GAN) which can directly deal with complex signals. Through adversarial learning between the generator and the discriminator, the generator implements direct mapping from the dynamic noisy signals to the noise-free signals. In addition, an auxiliary classifier is introduced into the discriminator to make the discriminator able to label the sample, which effectively compress the proposed model. The experimental results for a signal dataset collected in a real environment demonstrated that the proposed model is superior to the traditional denoising methods in denoising performance, which effectively improves the identification accuracy under dynamic noises. Furthermore, the proposed model outperforms other deep learning models in terms of identification performance under various SNRs, which can effectively improve the robustness and adaptability of the SEI system for communication satellites in dynamic noisy environments.

Keywords: specific emitter identification (SEI); dynamic noisy environment; complex-valued neural network (CVNN); generative adversarial network (GAN); auxiliary classifier



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1. Introduction

Satellite communication, as a crucial component of the space-ground integration information network, has the advantages of large spatial span, wide coverage, and high robustness, which provides wide-area coverage, high-quality communication services and is widely used in national defense, commercial communication, emergency rescue, and global navigation [1]. With the rapid increase in the number of communication satellites, satellite communication systems are facing various challenges. The high-dynamic characteristics of satellites lead to a great Doppler frequency shift in the process of satellite-to-ground communication, which increases the demodulation difficulty of ground terminals [2]. Furthermore, to ensure the continuity of satellite-ground communication, ground terminals will switch frequently between multiple satellites, which has negative impacts on the quality of service for users and system capacity. Additionally, in severe cases, it will also lead to communication interruptions, degradation of communication quality, and security risks [3,4]. Thus, effectively managing and controlling satellite communication systems

is a pressing issue that needs to be addressed. Accurately identifying the identity of the target communication satellite is a key step in ensuring the efficiency of space–ground communication [5]. To achieve the crucial step, some scholars have proposed applying specific emitter identification (SEI) technology to the efficient and accurate identification of communication satellites.

Specific emitter identification [6], also known as emitter individual identification or radio frequency fingerprint (RFF) identification, which directly extracts RFF features from RF signals that are difficult to be imitated and cloned for identifying different emitters, helps to improve the security of the authentication system. The RFF features of each emitter is inherent and unique, as it is derived from the imperfection of the emitter's hardware [7]. SEI can be mainly categorized into identification methods based on the transient signal and the steady-state signal [8]. The transient signal is generally generated during the transmitter turning on or off and has a short duration. However, the steady-state signal appears during the regular operation of the transmitter, features a longer duration, and is easier to capture compared to the transient signal. Thus, SEI based on the steady-state signal is the main research direction at present [9]. In summary, the target satellite can be uniquely identified with the help of SEI technology in order to enhance the management efficiency of satellite communication systems.

Identification of the individual satellite still faces many challenges in practical applications. Due to dynamic changes in weather, equipment location, and transmission channels, it is not possible to maintain stable and good quality for a long time during receiving the RF signals of satellites on the ground. The RF signals we received even over a short continuous period of time usually have various SNRs [10]; thus, there is an urgent need for the robust SEI system of the satellites which can adapt to the dynamic noisy environment and does not require a good quality dataset. Recently, deep learning (DL) has been introduced into SEI technology for improving identification performance [11]. Deep learning methods are driven by signal data and extract specific RFF features from signals for identification, thereby achieving higher identification accuracy than traditional feature engineering methods. However, most of the general deep learning methods split complex signals into in-phase (I) and quadrature (Q) components before processing due to the fact that real-valued neural networks (RVNNs) cannot directly process complex signals. The split preprocessing ignored the correlation between the in-phase and quadrature components of complex signals, which result in the degradation of identification performance [12].

Inspired by the widespread application of generative adversarial networks (GANs) in the field of image denoising [13], we proposed a satellite individual identification method based on complex-valued conditional generative adversarial networks (CC-GANs). The method aims to address the high difficulty of signal preprocessing and the low quality of the RF signal dataset of the SEI system in the task of identifying the identity of the target satellite in a dynamic noisy environment. The SEI system we designed for communication satellites consists of a signal acquisition module, a signal preprocessing module, and an RFF features extraction and classification network adapted to dynamic noisy signals (CC-GANs), as shown in Figure 1. The main steps of the system are as follows:

1. For communication satellites that need to be controlled, RF signals with labels are captured by the signal acquisition module and converted into a format that can be processed by the proposed model through preprocessing in order to generate the signal dataset.
2. The denoising network for dynamic noisy samples and the feature extraction and classification network for denoised samples are obtained by training and validating on the signal dataset.

3. For the satellite without a label, we first input its RF signals into the denoising network after preprocessing and then into the feature extraction and classification network after denoising. If the system determines that the probability of a signal originating from a satellite within the satellites that need to be controlled exceeds 90%, it is classified as belonging to that satellite. Conversely, the signal is regarded as originating from an unknown satellite or as interference.

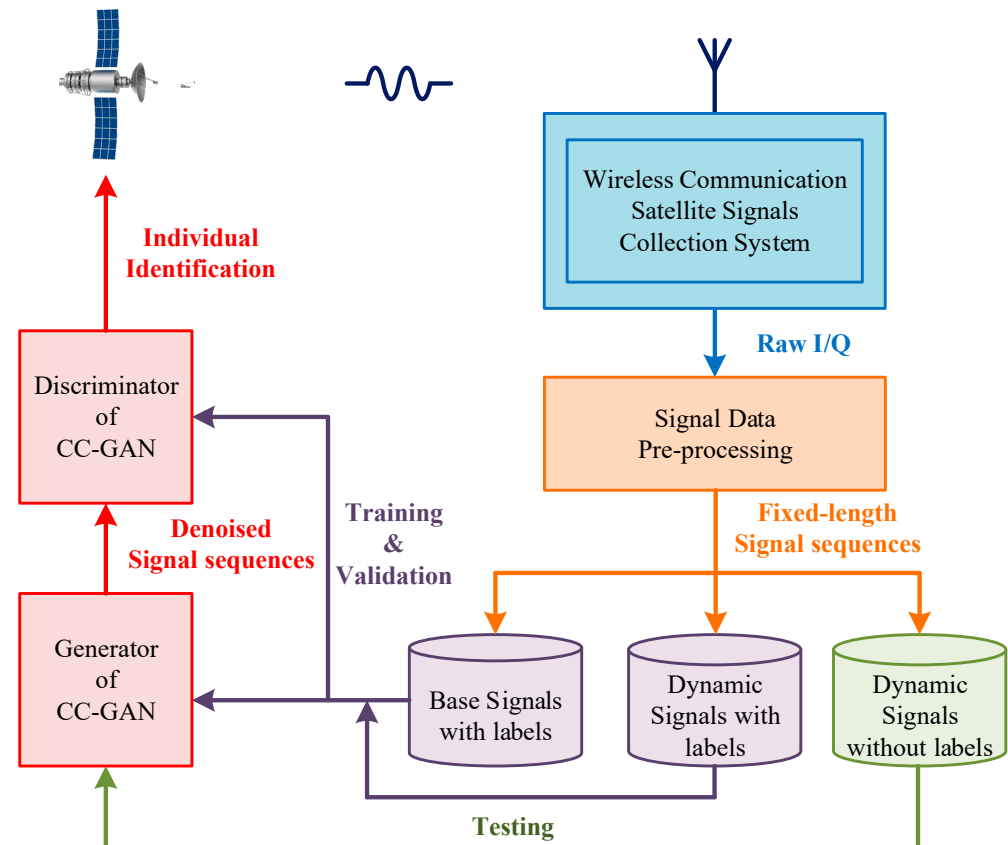


Figure 1. The view of our designed SEI system for communication satellites.

The main contributions of this article are summarized as follows:

1. A complex-valued conditional generative adversarial network is proposed for eliminating dynamic noise from the original signals while extracting RFF features from the noise-free signals for satellite individual identification by this article. The generator network is regarded as a denoising network, which implements a direct mapping from the dynamic noisy signals to the noise-free signals. The discriminator network is mainly used to determine whether the output from the generator comprises noise-free signals or not while also achieving classification of the individual satellite.
2. The complex-valued structure is introduced into the generative adversarial network, which enables it to extract RFF features directly from complex signals, thereby avoiding the feature loss during the preprocessing and transformation of original signals. Furthermore, an auxiliary classifier is incorporated into the discriminator network, endowing it with the classification capability while realizing the control of the attributes of the generated samples, thereby, to some extent, reducing the complexity of the CC-GAN.
3. We generated two datasets to train and evaluate the CC-GAN. In generating the labeled datasets, we received the real-world RF signals and divided the RF signal datasets into a reference signal dataset and a dynamic signal dataset based on the

strength of the signals. We completed the performance evaluation of the CC-GAN with the two datasets mentioned above.

The rest of the article is organized as follows: Section 2 briefly describes some related work. Section 3 describes the architecture and loss function of the CC-GAN in detail. Section 4 describes the detailed experimental procedure for evaluating the CC-GAN. Finally, Section 5 summarizes the article and states some prospects.

2. Related Work

Here, we focus on radio frequency fingerprint identification methods using steady-state signals. The main methods can be divided into two categories: an identification method based on expert features and classifiers and an identification method based on deep learning. The feature engineering method is supported by domain-specific expertise to extract interpretable features, but hand-crafted features are time-consuming, labor-intensive, and rely on complex and protocol-specific knowledge, lacking flexibility [14]. The deep learning method is data-driven and is able to learn features automatically, adjusting quickly and flexibly with the task; however, the performance of deep learning models degrades rapidly when there is a large discrepancy between the distribution of training data and test data [15]. However, the deep learning method faces some difficulties, and extensive experiments have demonstrated that its performance in various identification tasks has surpassed the feature engineering method. Thus, we pay more attention to the research development of RFF identification methods based on deep learning.

Cui et al. [16] proposed a convolutional neural network structure based on IQ correlation features (IQCNet) on the basis of traditional convolutional neural networks (CNNs). The model uses 32 convolutional kernels with a size of 2×1 to extract the correlated features of I/Q paths, effectively reducing the parameters and computation, making it more suitable for lightweight deployment. Experimental results demonstrated that specific transmitters can be identified by variable power signals from 21 transmitters, with an identification accuracy of 94% for fixed variable power packets and an accuracy of 86% for random variable power packets. Zhang et al. [17] proposed an adaptive radio frequency fingerprints fusion network (ARFNet), which is based on dual attention convolution (DA-Conv), to extract and adaptively fuse multiple radio frequency fingerprints in a data-driven manner. Experimental results demonstrated that combining ARFNet with data augmentation can achieve an identification accuracy of 99.5% on five USRP X310 devices and 95.7% on 56 ADS-B devices. Zhao et al. [18] proposed a classification network (FSig-Net) based on deep learning in the case of a small number of signal samples, which can reduce the dependence of the model on big data by adaptively extracting the distance metric between features. The FSig-Net achieves an average identification accuracy exceeding 90% with a signal-to-noise ratio (SNR) ranging from 20 to 32 dB and a sample size of only 10 for each class. Zeng et al. [19] used a multi-channel attentive feature fusion (McAFF) method to extract the RFF features of radio signals and utilized the convolution-based ResNeXt module to accomplish device identification. Experimental results on 72 commercial WiFi end devices show that the McAFF significantly outperforms the single-channel-based RFF method in terms of identification accuracy and robustness and is more robust in noisy environments.

However, the RF signals collected directly are mostly complex-valued data in practical applications which cannot be directly processed by RVNNs. Thus, complex-valued neural networks (CVNNs) have been applied to the scenarios of RFF identification due to their excellent performance and ability to directly process complex-valued data.

Cekic et al. [20] employed complex-valued deep neural networks to investigate the effects of various confounding factors, such as data collected with different times (training

and testing on different days), clock drift, and wireless channel variations on RFF features. Experimental results demonstrated that the networks will tend to learn notable features reflecting mixed factors instead of the nonlinear device-specific characteristics of hardware without implementing some strategies, also showing that the use of data augmentation methods can be effective in improving the generalization performance of the networks. Wang et al. [21] proposed a compression method to reduce the complexity of CVNNs, but the performance of the compressed network decreases drastically at low SNRs. Chen et al. [22] conducted ablation experiments on real LoRa (Long Range) and WiFi datasets with different network layers, components of the network layers (convolutional filters or their outputs), and real and imaginary components of the network layer outputs. The experimental results confirm that, when the number of model parameters is approximately equal, the complex-valued deep neural networks (DNNs) utilize the joint features of the in-phase and quadrature components of the signal more effectively and the performance of the complex-valued DNNs are always better than the real-valued DNNs.

The above-mentioned deep learning-based RFF identification methods have demonstrated good identification performance in stable environments with high SNRs, but the identification efficiency of the deep learning models decreases rapidly in high-dynamic-noise and low-SNR environments. To address these issues, recent studies have introduced GANs into the applications of RFF identification. The basic modules of GANs still consist of convolutional layers, fully connected layers, and activation functions, which are commonly used for data augmentation and denoising.

Zeng et al. [23] proposed a preprocessing algorithm improving synchrosqueezed wavelet transforms by energy regularization (ISWTE) and an unsupervised neural-network-noise-feature-extracting GAN (NEGAN). ISWTE improves the robustness of RFF by simplifying the process of signal preprocessing. NEGAN extracts RFF features directly from the structure of signal waveform and obtains more stable RF fingerprint features by subtracting noise features learned. Experimental results on a dynamic test set with an SNR range of -20 – 10 dB show that the method achieves 96% (SNR of 10 dB), 85% (SNR of 0 dB), and 25% (SNR of -20 dB) identification accuracy, respectively. Wang et al. [24] proposed a novel deep denoising network for TEM signals (TEM-NLnet) which is inspired by noise-learning. Specifically, the method first learns the noise present in real-world signals through GANs and then applies a denoiser based on DNNs to learn the mapping from the noisy TEM signals to the corresponding noise-free signals. Experiments on simulated and real-world geological datasets have shown that TEM-NLnet performs better both quantitatively and visually compared to other state-of-the-art denoising methods for TEM signals. Du et al. [25] proposed a generative adversarial denoising and classification network (GADNet) for denoising radar signals and identifying intra-pulse modulations. The network comprises three components: a generator, a discriminator, and a classifier. The generator has the structure of an encoder–decoder which extracts high-order feature vectors from the input radar signals through symmetric upsampling and downsampling operations and recovers clean signals from noise. The discriminator is used to determine the authenticity of the denoised output generated by the generator. Then, a cascading classifier with a generator and discriminator is used to ensure that the denoising results meet the semantic information required for classification. The experimental results show that GADNet possesses a high-quality signal denoising effect and high identification accuracy in dense noise environments, as well as a certain superiority in regard to the transferability of data with low SNRs.

In summary, we consider making full use of the advantages of CVNNs in the feature extraction of complex signals and GANs in denoising noisy signals, combining the two networks to realize the denoising of RF signals and the extraction of RF fingerprints. The

proposed CC-GAN is obtained by modifying the GAN. Firstly, we introduce complex-valued structures into the GAN so that both the generator and discriminator can fully leverage the inherent phase-related information in complex signals to extract RFF features with greater representational ability. Secondly, the generator of the CC-GAN effectively removes random dynamic noise from the signals and generates noise-free signals through symmetrical upsampling and downsampling structures. Finally, the discriminator of the CC-GAN extracts more robust and adaptive RFF features from the noise-free signals for identification. Consequently, the CC-GAN can significantly enhance the identification performance of target satellites in dynamic noisy environments.

3. Complex-Valued Conditional Generative Adversarial Network

To mitigate the impact of dynamic noise on satellite individual identification, we proposed a satellite individual identification method based on complex-valued conditional generative adversarial network (CC-GAN). The overall architecture of the model is shown in Figure 2, which is mainly composed of two parts: the generator and the discriminator. The model initially employed a specific generator to eliminate noise features in the noisy signals to generate the denoised signals. Subsequently, the denoised signals were fed into the modified discriminator with a classification capability for RFF features, ultimately achieving the function of identifying the identity of individual satellites.

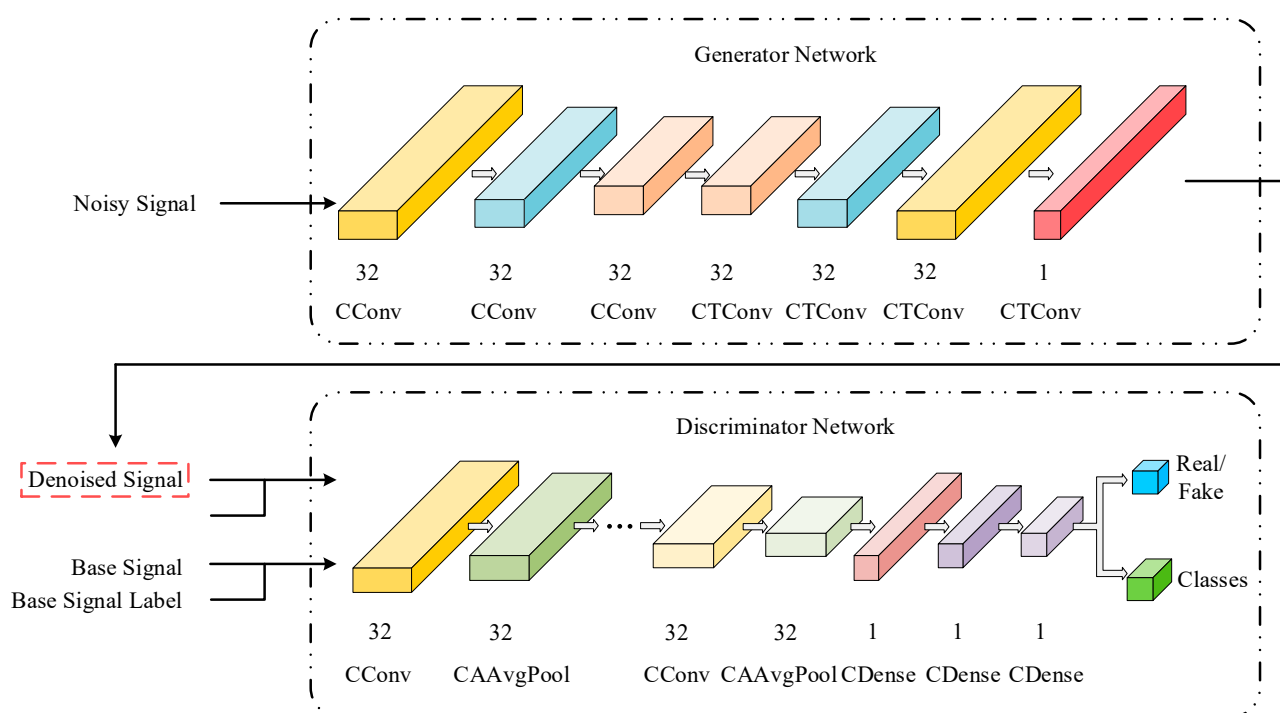


Figure 2. The architecture of the CC-GAN, where CConv, CTConv, CAAvgPool, and CDense represent a 1D convolution layer, 1D transposed convolution layer, 1D adaptive average pooling layer, and linear layer in the complex-valued domain, respectively.

3.1. Complex-Valued Components

CVNNs contain the same components as RVNNs, including convolutional layers, pooling layers, batch normalization layers, and activation functions. However, the components of the RVNNs cannot directly process complex-valued data, which need to be modified to adapt to complex data. CVNNs can be regarded as an extension of RVNNs

from the real-valued domain to the complex-valued domain, with both the input and network parameters presenting in complex-valued form [26].

$$\begin{aligned} W * z &= R(W * z) + I(W * z) \\ &= (A * x - B * y) + i(B * x + A * y) \end{aligned} \quad (1)$$

where x and y represent the real and imaginary part of a complex number, while A and B represent the real and imaginary part of a complex-valued convolution kernel, respectively. $R(W * z)$ and $I(W * z)$ represent the real and imaginary part of the complex-valued convolutional operation, respectively. $*$ represents the convolutional operation. The process of complex-valued convolutional operation is shown in Figure 3.

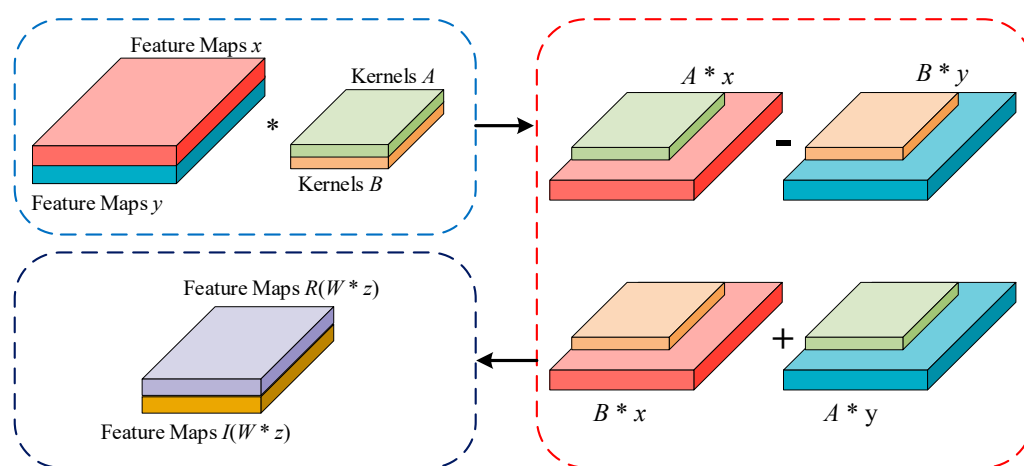


Figure 3. The process of complex-valued convolutional operation.

Pooling operation is primarily utilized for downsampling and enhancing the generalization capability of features. Two of the most frequently employed pooling methods in deep learning are maximum pooling and average pooling. The maximum pooling operation on the complex-valued domain is performed based on the magnitude of the complex-valued nodes. The complex-valued average pooling involves averaging the real and imaginary parts of all complex-valued nodes within a local region separately, and the average of the real part and the average of the imaginary part are used as the real and imaginary parts of the pooled complex data, which represents the result of the average pooling operation in the selected local region. The computational process of the average pooling can be expressed as follows:

$$p = \frac{1}{|\mathcal{R}|} \sum_{(i,j) \in \mathcal{R}} q_{ij} \quad (2)$$

where p represents the average pooled output of the feature map in the rectangular region $\mathcal{R}$, q_{ij} represents the element in the rectangular region $\mathcal{R}$ located at (i, j) , and $|\mathcal{R}|$ represents the number of elements in the rectangular region $\mathcal{R}$.

Batch normalization plays a crucial role in speeding up the convergence of neural networks and mitigating gradient dispersion within deep networks, thereby facilitating stable training of the networks. The derivation of complex-valued batch normalization is based on real-valued batch normalization [27]; the process can be expressed as follows:

$$BN(\tilde{z}) = \gamma \cdot \tilde{z} + \beta \quad (3)$$

$$\tilde{z} = (V)^{-\frac{1}{2}}(z - E(z)) \quad (4)$$

$$V = \begin{pmatrix} V_{rr} & V_{ri} \\ V_{ir} & V_{ii} \end{pmatrix} = \begin{pmatrix} \text{Cov}(R\{z\}, R\{z\}) & \text{Cov}(R\{z\}, I\{z\}) \\ \text{Cov}(I\{z\}, R\{z\}) & \text{Cov}(I\{z\}, I\{z\}) \end{pmatrix} \quad (5)$$

where γ represents the scaling parameters for normalized data, β represents the translation parameters for normalized data, and V represents the covariance matrix.

Activation functions are mainly used to introduce nonlinearity into networks, but activation functions in the real-valued domain cannot be directly applied to the complex-valued domain. Complex-valued activation functions must take into account the two inherent degrees of freedom in complex numbers, which are represented by the real and imaginary parts, or magnitude and phase. Currently, there are three activation functions available for complex domains: modReLU, CReLU, and zReLU. The modReLU activation function processes only the magnitude of complex numbers while retaining their phase. In contrast, the zReLU activation function [28] manipulates only the phase, and the CReLU activation function operates separately on the real and imaginary parts of complex numbers. In consideration of the crucial role that phase plays in the process of extracting RFF features, the proposed model primarily incorporates the zReLU activation function, which can be expressed as follows:

$$\text{zReLU} = \begin{cases} z, & \theta_z \in [0, \frac{\pi}{2}] \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

where θ_z represents the phase of the complex-valued input.

3.2. Generator Network

The generator network is mainly used to generate noise-free signals and achieve direct mapping from noisy signals to noise-free signals, whose inputs are dynamic noisy signals. In order to suppress noise as much as possible without compromising the RFF features of the original signals, we incorporated complex-valued convolution and symmetric architecture [29] into the generator network. The complex-valued convolution can better characterize signals, while symmetric upsampling and downsampling structures can effectively remove random noise from the signals and restore the detailed RFF features in the original signals. The downsampling process was implemented through complex-valued convolutions without using pooling operations to avoid losing valuable information. The upsampling process is implemented by complex-valued inverse convolution operations, also known as complex-valued transposed convolution, which recovers the original signals from the higher-dimensional feature maps.

The generator network consists of seven network layers. The first to third layers are utilized for extracting latent characteristics from dynamic noisy signals, while the fourth to seventh layers are responsible for restoring the extracted features back into noise-free signals. The structures of the first to third layers of the generator network are consistent, each comprising complex-valued convolutional layers with a common kernel size of 3×1 , complex-valued batch normalization layers, and zReLU activation functions. The structures of the fourth to sixth layers of the generator network are consistent, each comprising complex-valued transposed convolutional layers with a common kernel size of 3×1 , complex-valued batch normalization layers, and zReLU activation functions. The last layer of the generator network consists of a complex-valued transposed convolution layer and a complex-valued Tanh activation function, which is mainly used to generate noise-free signals which are the same size as the dynamic noisy signals.

3.3. Discriminator Network

The discriminator network evaluates the generated noise-free signals and the corresponding reference signals so that the reference signals score higher, and the output of the

generator network will be closer and closer to the reference signals through the mutual game between the generator network and the discriminator network. In order to improve the identification accuracy of the CC-GAN by using as few labeled samples as possible and reducing the dependency on a large amount of labeled data for classification tasks, we integrated an auxiliary classifier into the discriminator network [30]. Compared with classical GANs, the discriminator of the CC-GAN can not only distinguish between real and fake samples but also assign the correct class labels to the samples.

The discriminator network consists of ten network layers. The first to sixth layers are feature extraction layers with a consistent structure. Each feature extraction layer consists of complex-valued convolutional layers, complex-valued batch normalization layers, zReLU activation functions, and complex-valued global average pooling layers. The convolutional kernel size is set as 3×1 , and the sizes of the pooling layers are 512, 256, 128, 64, 32, and 16 in sequence. The seventh layer is the flattening layer. The eighth and ninth layers are complex-valued dense layers with a unit number of 256 and 128, respectively. The last output layer of the discriminator network utilizes different activation functions based on the task requirements. A complex-valued sigmoid activation function is applied when distinguishing between real and fake samples, while a complex-valued softmax activation function is used for the classification task.

3.4. Loss Function

The generation capability of the generator network and the discriminative ability of the discriminator network need to be progressively improved in adversarial training. The training process can be described as involving the solving of the minimax optimization of a binary function [31], which can be expressed as follows:

$$\min_G \max_D V(D, G) = \min_G \max_D \mathbb{E}_{x \sim P_{data}(x)} [\log D(x)] + \mathbb{E}_{z \sim P(z)} [\log(1 - D(G(z)))] \quad (7)$$

where D represents the discriminator network, G represents the generator network, $V(D, G)$ represents the objective function, $\mathbb{E}(\cdot)$ represents the expectation of the distribution function, $P(x)$ represents the distribution of real samples, and $P(z)$ represents the low-dimensional distribution of noise.

The loss functions of the CC-GAN are different from that of classical GANs due to the inclusion of auxiliary classifiers [32]. For the generator network, its input is a dynamic noisy signal with a label, and the output is a denoised signal belonging to the label of the input. The generator network is designed to make it impossible for the discriminator network to distinguish the authenticity of the generated samples. The loss function of the generator network L_G is defined as follows:

$$L_{DF} = \mathbb{E}_{z \sim P_{noisy}(z)} [1 - \log D(G(z|y))] \quad (8)$$

$$L_{PF} = \mathbb{E}_{z \sim P_{noisy}(z)} [\log P(c|G(z|y))] \quad (9)$$

$$\begin{aligned} L_G &= L_{PF} + L_{DF} \\ &= \mathbb{E}_{z \sim P_{noisy}(z)} [\log P(c|G(z|y))] + \mathbb{E}_{z \sim P_{noisy}(z)} [1 - \log D(G(z|y))] \end{aligned} \quad (10)$$

where L_{DF} represents the loss function of the discriminator network to determine the authenticity of the denoised signals, L_{PF} represents the loss function of the discriminator network to predict the class of the samples of the denoised signals, D represents the discriminator network, G represents the generator network, $\mathbb{E}(\cdot)$ represents the expectation of the distribution function, and $P_{noisy}(z)$ represents the distribution of the samples of the dynamic noisy signals.

The discriminator network takes denoised signals with labels and reference signals with labels as input, with the aim of assigning samples with correct labels and distinguishing between real and fake samples. The loss function of the discriminator network L_D is defined as follows:

$$L_{DR} = \mathbb{E}_{x \sim P_{\text{reference}}(x)} [\log D(x)] \quad (11)$$

$$L_{PR} = \mathbb{E}_{x \sim P_{\text{reference}}(x)} [\log P(c|x)] \quad (12)$$

$$\begin{aligned} L_D &= L_{PF} + L_{PR} + L_{DF} + L_{DR} \\ &= \mathbb{E}_{z \sim P_{\text{noisy}}(z)} [\log P(c|G(z|y))] + \mathbb{E}_{x \sim P_{\text{reference}}(x)} [\log P(c|x)] \\ &\quad + \mathbb{E}_{z \sim P_{\text{noisy}}(z)} [\log D(G(z|y))] + \mathbb{E}_{x \sim P_{\text{reference}}(x)} [\log D(x)] \end{aligned} \quad (13)$$

where L_{DR} represents the loss function of the discriminator network to determine the authenticity of the reference signals, L_{PR} represents the loss function of the discriminator network to predict the class of the samples of the reference signals, D represents the discriminator network, G represents the generator network, $\mathbb{E}(\cdot)$ represents the expectation of the distribution function, $P_{\text{reference}}(z)$ represents the distribution of the samples of the reference signals, and $P_{\text{noisy}}(z)$ represents the distribution of the samples of the dynamic noisy signals.

4. Experiments and Results

4.1. Data Collection and Preprocessing

To train and evaluate our proposed model, we used low-Earth-orbit (LEO) communication satellites as the subjects for individual identification research. By collecting and preprocessing the RF signals emitted by LEO communication satellites, we have established our own RF signal dataset for experiments. The whole process of collecting RF signals and building a dataset is shown in Figure 4.

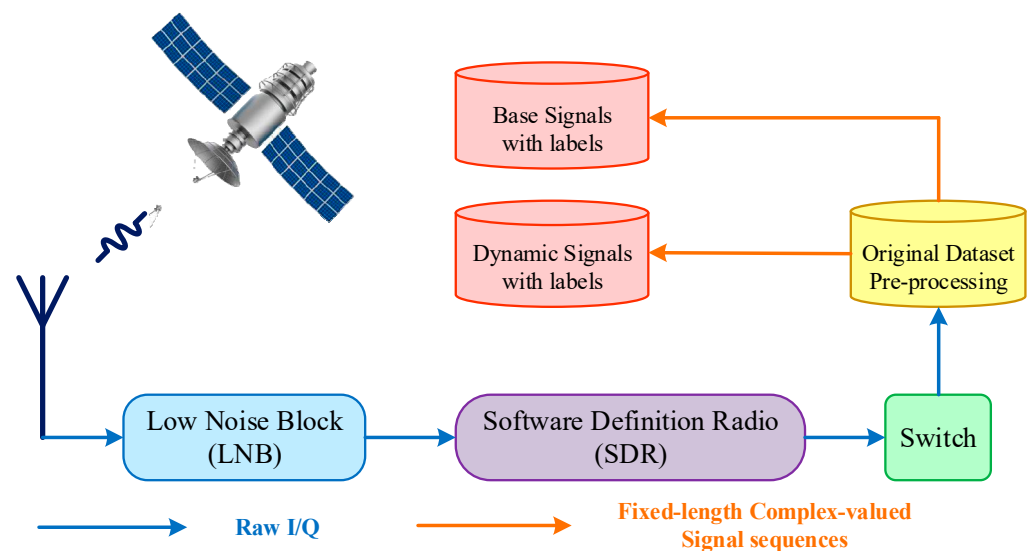


Figure 4. The process of collecting RF signals and building a dataset.

To achieve stable collection of signals and control the quality of signals, we have built a signal acquisition system. The hardware components of the system consisted of a parabolic antenna, a downconverter, and a software-defined radio (SDR) device. The software components of the system comprise antenna control software and SDRPlusPlus. The detailed process of signal acquisition is as follows:

- Firstly, the RF signals were received and amplified by a 60 cm parabolic antenna, then fed into the downconverter via RF feed lines;

- Subsequently, the RF signals were converted into intermediate frequency (IF) signals by the downconverter;
- Finally, the IF signals were converted to baseband signals by an SDR device and the data were stored in IQ format.

After obtaining the raw signals, we performed the following preprocessing operations: High-quality signal data files for 42 LEO communications satellites over different days were selected. The high signal-to-noise ratio segment (10 dB) from each satellite signal data was utilized as the reference signals $x_{reference}$, while the remaining signal segments (0–10 dB) were considered as dynamic noisy signals $x_{dynamic}$. Due to the potential presence of the RFF features at any position within the signal, it was necessary to perform signal segmentation on long signal data to facilitate feature extraction by deep learning models [33]. The specific process of signal segmentation is illustrated in Figure 5. Each sample in IQ format was sampled into a complex-valued signal sample of length 1024 after the segmentation.

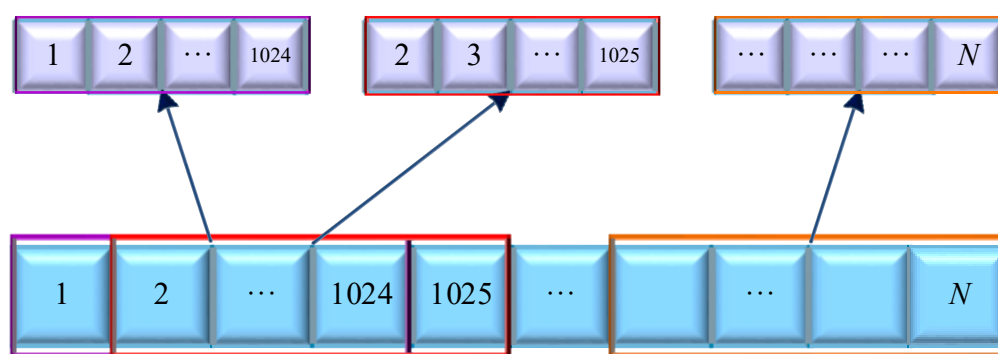


Figure 5. The segmentation process of the original signal sample.

After processing the signal data files from 42 LEO communication satellites, the final dataset we have built is described as follows:

- Each satellite has a reference signal set and a dynamic noisy signal set, both of which contain 4096 complex-valued signal samples;
- Each complex-valued signal sample corresponds to a label of the specific satellite;
- The SNR of the reference signal set is maintained at 10 dB, while the SNR of the dynamic noisy signal set varies between 0 and 10 dB;
- The signal dataset of LEO communication satellites comprises a total of 344,064 complex-valued signal samples labeled from 42 satellites.

4.2. Hyper-Parameters Setup

The experiments were conducted on a computer with an Ubuntu 20.04.6 LTS operating system, an Intel(R) i5-13600KF central processing unit (2.60 GHz), and a NVIDIA GeForce GTX 4090 (24 G) GPU. All models were implemented by PyTorch 1.9.1, which is a machine learning toolkit released by Facebook that can run on the graphic processing units (GPUs) for acceleration. All complex-valued components were implemented by Complex-Torch 1.0.0, which is a toolkit built on PyTorch with the intention of implementing lightweight interfaces for common complex-valued neural network operations and architectures [34].

Setting hyper-parameters is essential for the training and optimization of the models. After several experiments to adjust the parameters, we selected the following hyper-parameter values to train the CC-GAN:

- The number of training iterations was set to 100 and the batch size was set to 128;
- The Adam optimizer was chosen for minimizing the loss function, featuring a learning rate of 2×10^{-4} , a mean exponential decay rate β_1 of 0.5, and a uncentered variance exponential decay rate β_2 of 0.999;

- Binary cross-entropy (BCE) loss was used to calculate the loss value for the discrimination of authenticity and categorical cross-entropy loss was used to calculate the loss value for classification.

4.3. Performance Evaluation for CC-GAN

To evaluate the performance of the CC-GAN, the reference signal set and the dynamic noisy signal set were fed into the discriminator network and the generator network for training, respectively. The training set and test set account for 90% and 10%, respectively, in the original dataset. The trends of the loss values for the generator network and the discriminator network during the training process are shown in Figure 6a, while the trend in the classification accuracy of the discriminator network is shown in Figure 6b. From Figure 6, we can see that the training loss values of the two networks continuously decrease and eventually are stabilized, indicating that both have learned effective feature representations and are better trained. Meanwhile, the classification accuracy of the discriminator network keeps increasing and eventually maintains a high level, indicating that the discriminator also possesses a strong classification capability.

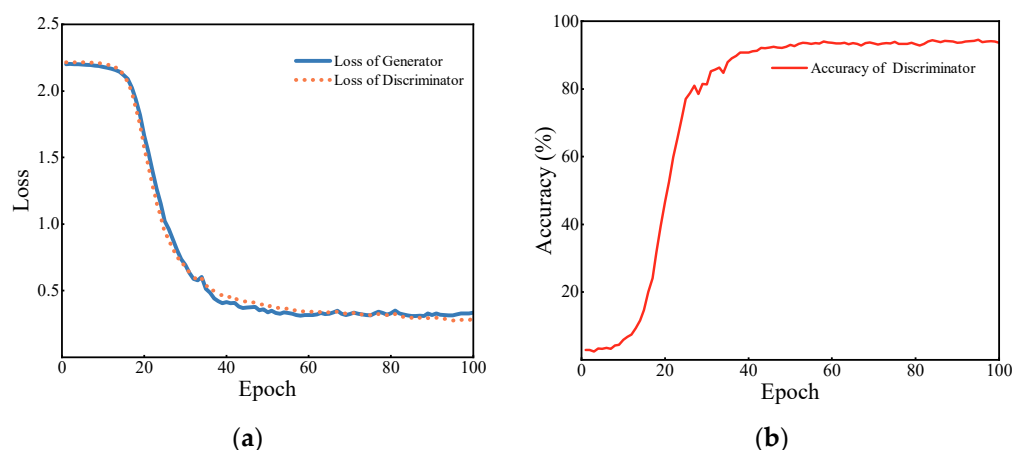


Figure 6. The training process of the CC-GAN. (a) The changing trend of the loss of the generator network and the discriminator network with the number of iterations; (b) the changing trend of the accuracy of the discriminator network with the number of iterations.

To evaluate the denoising effect of the proposed generator network, the structure of the discriminator network was kept unchanged, and the wavelet threshold denoising algorithm and the infinite impulse response (IIR) filter were used, respectively, to denoise the complex signals before the discriminator was used to realize the classification.

The wavelet threshold denoising algorithm has become a popular filtering method in recent years that first utilizes wavelet decomposition to ensure that the magnitude of the wavelet coefficients of the signal exceeds that of the noise coefficients (coefficients with larger magnitudes represent the signal, while those with smaller magnitudes largely represent noise); it then removes the coefficients below the threshold as noise and, finally, reconstructs the signal through wavelet reconstruction to achieve denoising. An IIR filter is a type of filter with an infinite unit impulse response and a feedback loop. The output of the IIR filter depends not only on the current inputs but also on previous inputs and outputs. An IIR filter has advantages in terms of improving the filtering efficiency and reducing the consumption of computational resources.

The changes in the amplitude of the sample after denoising the same complex-valued signal sample with different denoising algorithms are shown in Figure 7. After denoising the test set in the dynamic noisy signal set with different denoising methods, the discrimi-

nator was then utilized for identification. Comparison results of identification accuracy are shown in Figure 8.

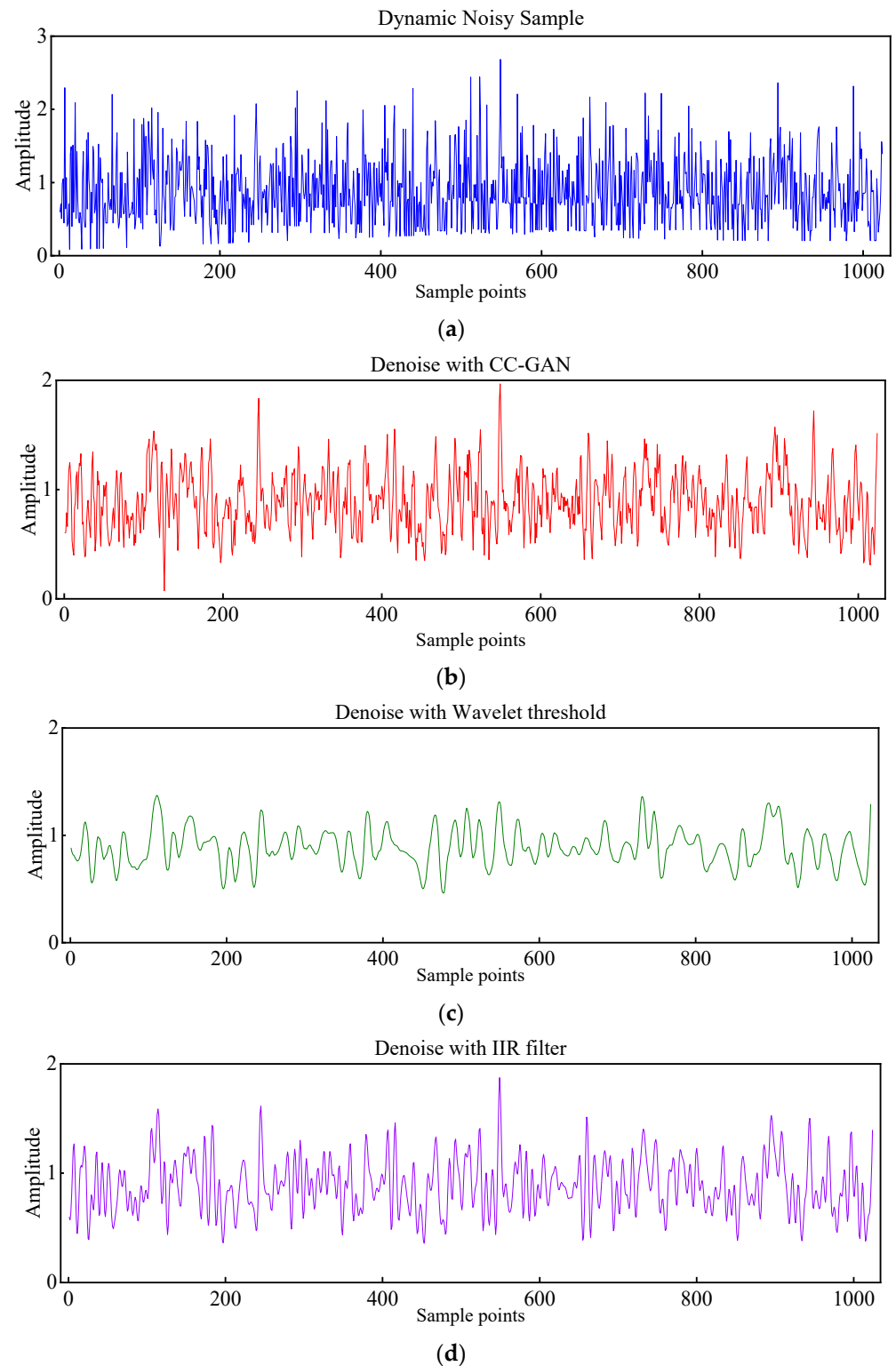


Figure 7. The amplitude of the complex signal sample changes with different denoising algorithms. (a) The raw dynamic noisy sample; (b) the sample denoised with the generator network of the CC-GAN; (c) the sample denoised with the wavelet threshold denoising algorithm; (d) the sample denoised with the IIR filter.

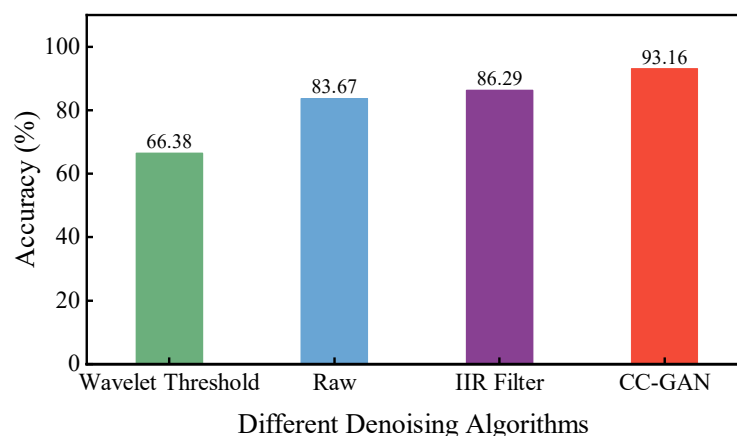


Figure 8. The individual identification accuracies with different denoising algorithms.

From Figures 7 and 8, we can see that the accuracy of individual identification is only 66.38% after processing the complex-valued signal samples with the wavelet threshold denoising algorithm, which indicates that the original signal samples were severely distorted during the process of denoising, resulting in the loss of signal features and decreased accuracy compared to scenarios where no denoising algorithm was applied. After processing the complex-valued signal samples with an IIR filter for denoising, the accuracy of individual identification is improved compared to that without using the denoising algorithm, but the improvement is not significant, which indicates that the IIR filter cannot effectively adapt to dynamic noise. Compared with the above two denoising methods, the best accuracy of individual identification of 93.16% is achieved by using the CC-GAN, which indicates that the generator of the CC-GAN can better adapt to dynamic noisy signals, effectively eliminating random dynamic noise in the original signals and, consequently, improving the accuracy of individual identification.

4.4. Experimental Comparison with Other Deep Learning Models

To evaluate the identification performance of the proposed CC-GAN, we conducted comparative experiments with several RVNNs and CVNNs. The architectures and parameters of the models to be compared were designed to be as consistent as possible with the CC-GAN. The RVNNs include a real-valued conditional adversarial generation network (RC-GAN), real-valued generative adversarial denoised network (RGADNet) [25], real-valued deep residual network (RResNet) [35], and a real-valued deep residual shrinkage network (RDRSN) [36]. The CVNNs include a generative adversarial network based on deep complex U-net (DCU-net-GAN) [37] and a complex-valued deep residual shrinkage network (CDRSN). The detailed architectures of these models are shown in Table 1.

The RC-GAN consist of two components, a generator and a discriminator, with a architecture identical to that of the CC-GAN. In detail, the 1D complex-valued convolutional layer, the 1D complex-valued transposed convolutional layer, and the 1D complex-valued global average pooling layer in the generator and the discriminator are replaced with a 2D real-valued convolutional layer, a 2D real-valued transposed convolutional layer, and a 2D real-valued global average pooling layer, respectively. The complex-valued batch normalization layer, complex-valued dense layer, zReLU activation function, complex-valued Tanh activation function, complex-valued sigmoid activation function, and complex-valued softmax activation function were replaced with the corresponding real-valued components. The RGADNet consists of two components: a generator and a discriminator. The residual unit A, as shown in Figure 9a, has been incorporated into the generator in addition to the upsampling and downsampling structures. The structure of the discriminator is consistent with the RC-GAN.

Table 1. Detailed architectures of the CC-GAN and other deep learning models.

Model	Architecture
CC-GAN	Generator: (CConv1d, CBN, zReLU) $\times$ 3 (CConvTranspose1d, CBN, zReLU) $\times$ 2 (CConvTranspose1d, CTahn) Discriminator: (CConv1d, CBN, zReLU, CAdaptiveAvgPool1d) $\times$ 6 Flatten CDense $\times$ 3 (256, 128, 42)
RC-GAN	Generator: (Conv2d, BN, ReLu) $\times$ 3 (ConvTranspose2d, BN, ReLu) $\times$ 2 (ConvTranspose2d, Tahn) Discriminator: (Conv2d, BN, ReLu, AdaptiveAvgPool2d) $\times$ 6 Flatten Dense $\times$ 3 (256, 128, 42)
RGADNet	Generator: Residual Block A $\times$ 2 (ConvTranspose2d, BN, ReLu) Residual Block A (ConvTranspose2d, BN, ReLu) (ConvTranspose2d, Tahn) Discriminator: (Conv2d, BN, ReLu, AdaptiveAvgPool2d) $\times$ 6 Flatten Dense $\times$ 3 (256, 128, 42)
RResNet	Residual Block $\times$ 6 Flatten Dense $\times$ 3 (256, 128, 42)
RDRSN	Residual Shrinkage Block $\times$ 6 Flatten Dense $\times$ 3 (256, 128, 42)
CDRSN	Complex-valued Residual Shrinkage Block $\times$ 6 Flatten CDense $\times$ 3 (256, 128, 42)
DCUnet-GAN	Generator: Modified DCUnet Discriminator: (CConv1d, CBN, zReLU, CAdaptiveAvgPool1d) $\times$ 6 Flatten CDense $\times$ 3 (256, 128, 42)

The architectures of the RResNet and the RDRSN are consistent with the structure of the discriminator of the CC-GAN. Most importantly, the feature extraction unit in the original discriminator needed to be replaced with the respective residual unit B and residual shrinkage unit of each network, and the specific structures of the two units are shown in Figure 9b,c. The remaining components of the two networks refer to the RC-GAN, replacing the complex-valued components in the original discriminator with the corresponding real-valued components.

The architecture of the CDRSN is consistent with that of the RDRSN, which merely requires replacing the components in the original real-valued model with their corresponding

complex-valued counterparts. The DCUnet-GAN consists of two components: a generator and a discriminator. The generator employs a deep complex U-Net (DC-Unet) without the complex-valued ratio mask (cRM) layer [38]. The structure of the discriminator is consistent with the CC-GAN.

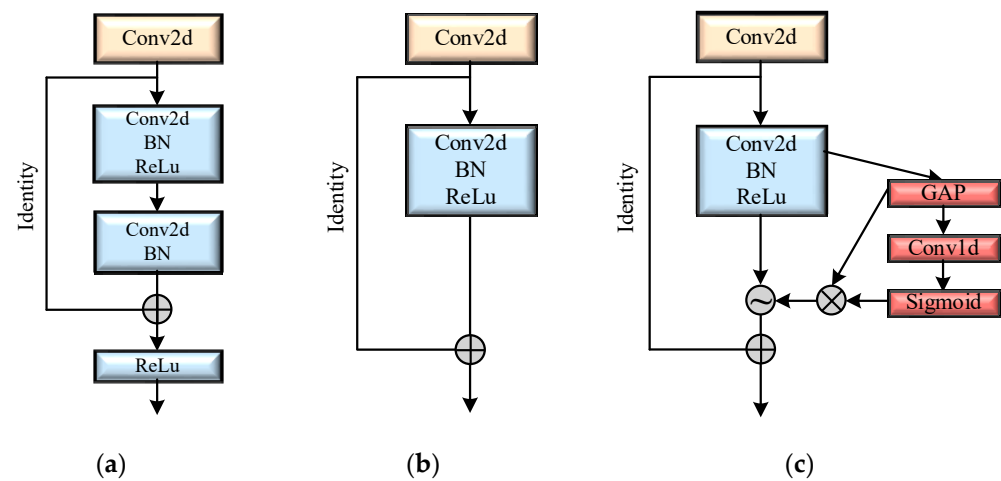


Figure 9. The structures of the core components of the RGADNet, the RResNet, and the RDRSN. (a) The structure of the residual unit A; (b) the structure of the residual unit B; (c) the structure of the residual shrinkage unit.

The RVNNs are unable to directly process the complex-valued signal samples. To ensure the consistency of the input data, each complex-valued signal sample was extracted and recombined into real-valued 2D vectors comprising the components of in-phase and quadrature. The size of each reconstructed sample was 1024×2 . The test set from the reconstructed dynamic noisy signals set and the original test set were input into the above models, respectively, and the results of the number of parameters, training time, and identification accuracy of the models compared with the CC-GAN are shown in Table 2.

Table 2. Comparison results of the parameters, training times, and identification accuracies of different deep learning models.

Model	Parameters	Training Time	Accuracy (%)
CC-GAN	408,706	1 h 47 min 12 s	93.16
DCUnet-GAN	563,925	2 h 28 min 07 s	92.87
RGADNet	394,713	1 h 52 min 18 s	90.61
RC-GAN	254,764	1 h 6 min 35 s	89.03
CDRSN	373,578	1 h 41 min 26 s	84.95
RDRSN	201,264	1 h 2 min 27 s	82.72
RResNet	104,778	50 min 39 s	79.34

From Table 2, we can see that the RC-GAN and the RGADNet have better identification performance compared with other RVNNs and the CDRSN, indicating that the generator in their architectures can eliminate the random noise of the original 2D IQ vectors to a certain extent, which is conducive to completing the feature extraction of the signals and individual identification by the subsequent discriminator. However, the identification accuracy of the RGADNet is slightly superior to that of the RC-GAN, which indicates that the incorporation of residual units in the generator of the GADNet enhances its capability of feature extraction compared to the RC-GAN.

The identification accuracies of the CVNNs are higher than the RVNNs in the case of consistent architectures, indicating that the phase-related features in the complex signals are better able to characterize satellite individuals. Thus, the key features can only be

extracted from the complex signals by using complex-valued structures to achieve better identification performance. The identification accuracy of the DCUnet-GAN is close to that of the CC-GAN, but it is more complex, with more training parameters and longer training times.

To evaluate the identification performance of the above models under different SNRs, we constructed a new test set by extracting signal samples of a single SNR (0~10 dB, in 2 dB steps) from the test set of the dynamic noisy signals set. The new test set was input into the different models that have been trained, respectively, and the identification accuracies of the different models under different SNRs are shown in Figure 10.

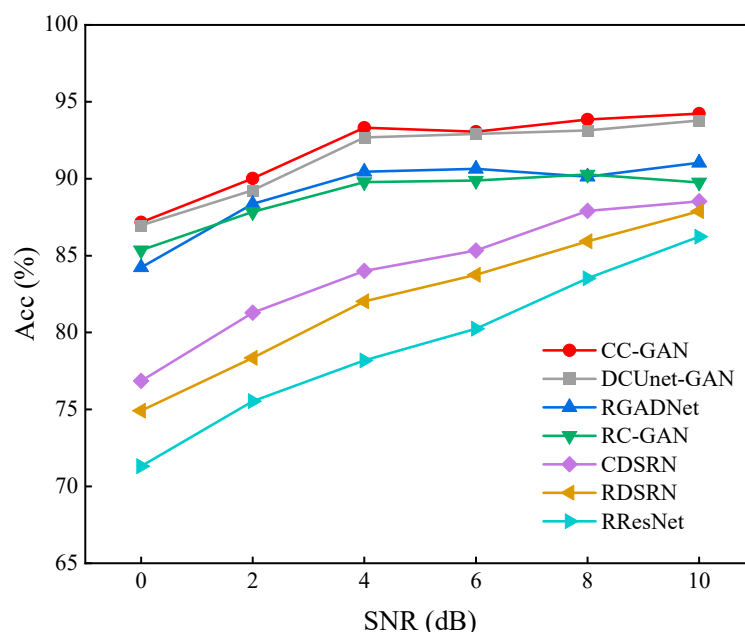


Figure 10. The identification accuracies of the different models under different SNRs.

From Figure 10, we can see that the identification accuracies of the models based on CNN continuously increase with the increase in the SNR, indicating that their identification performances are significantly affected by the quality of the signals. The identification accuracies of the models based on GANs are essentially maintained at good and stable values when the SNR is greater than 2 dB, which indicates that these models have mitigated the impact of noise on identification performance to a certain extent through adversarial training. The CC-GAN has the best identification performance under different SNRs compared with other models based on GANs, indicating that the CC-GAN can better adapt to signals with different SNRs and extract a more ideal distribution of RFF features in dynamic noisy signals. Consequently, the CC-GAN can significantly enhance the robustness and adaptability of the SEI system in dynamic noisy environments and achieve high identification accuracy for individual satellites.

5. Conclusions

To address the problem of dynamic noise affecting the identification effectiveness of individual satellites, we proposed an identification method based on the CC-GAN that is outlined as follows:

- (1) Taking the reference signal as a benchmark, the generator network of the CC-GAN outputs the denoised signals that approximate the reference signals through adversarial learning with the discriminator network of the CC-GAN, while the ability of the

discriminator to distinguish whether the dynamic noise from the output signals of the generator has been eliminated also improves over time.

- (2) We enhanced the discriminator by incorporating conditional control so that it has the function of auxiliary classification while realizing the control of the attributes of the generated samples, which reduces the complexity of the model to a certain extent and enhances the relevance and practicality of the generator.

The experimental results on a signal dataset collected in a real environment illustrate that the proposed model outperforms traditional methods in terms of denoising, thereby enhancing the identification accuracy of the discriminator to a certain extent. Meanwhile, the complex-valued structure adopted in the proposed model can directly extract the phase-related features in the complex signals, which can better characterize the satellite individuals, and thus demonstrates superior identification performance. Furthermore, the CC-GAN does not require an evaluation in regard to noise intensity and maintains identification accuracies well under different SNRs, which effectively improves the robustness and adaptability of the SEI system for communication satellites in dynamic noisy environments.

Our future work will concentrate more on the following aspects:

- (1) The CC-GAN demonstrates superiority in controlling the attributes of the generated denoised samples, but it faces challenges in terms of training difficulty and conditional dependence. The new training strategies and model architectures need to be developed to improve its training efficiency and stability.
- (2) The CVNNs can directly process complex signals and extract key individual characteristic features, but the complex structure limits their deployments and applications. Subsequent work on lightweight optimization of the CVNNs is needed.
- (3) We consider introducing the CC-GAN into the scenario of cross-receiver specific emitter identification, which aims to address the impact of RFF features induced by the receivers on identification performance, under the condition of eliminating dynamic noises.

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