GAN-based Wireless Channel Recognition Enhancement in Aerospace Communication System

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Abstract. In the field of communications, wireless channel identification is of great significance for spectrum identification and spectrum resource scheduling, and is an indispensable link in cognitive radio technology. However, the poorness of the aerospace data set will affect the recognition accuracy. This paper studies the application of neural network in aerospace communication wireless channel recognition scenarios. Then, we propose a sample set expansion method based on GAN (Generative Adversarial Networks) to enhance the cognitive ability of neural network. Finally, we compare the accuracy of the channel recognition model before and after the data set expansion. The results show that in the case of small sample data sets, the use of GAN-based data expansion method helps to improve the accuracy of the channel recognition model.

1. Introduction
In the complex electromagnetic environment, the signal in the wireless communication field changes rapidly [1], [2]. Especially in the space communication system, as the aircraft launches, the wireless communication channel will experience rapid switching between different environments such as the ground, sea and deep space. Therefore, it is necessary to study an advanced intelligent method to comprehensively identify the complex communication environment. Literature [3][4] pointed out the importance of cognition in wireless networks. In order to solve the problem of channel identification under additive noise channel environment, Literature [5] introduced a method to realize wireless channel classification combined with convolutional neural network, and successfully applied this technique to modulation recognition. However, in the aerospace communication system, there are certain difficulties in channel data acquisition [6]. The impoverishment of the training set leads to the poor generalization ability of the classification and recognition method based on the artificial intelligence neural network model and the low recognition accuracy. Based on the channel recognition method of recurrent neural network, this paper proposes an improved method based on generative confrontation network to enhance the generalization ability of neural network. Through experiments, it can be concluded that the recognition accuracy of several classical noise channels has been improved.

2. System Model

2.1. Channel Model
This article is based on the digital frequency band communication system model, and also considers the channel environment of aerospace communication link. The typic digital communication model generally consists of three parts: source, sink and channel. The transmitting end transforms the
information source into an electrical signal, which is transformed into a form suitable for transmission in the channel medium through an encoder, a modulator, etc. After receiving, the signal is restored by inverse transformation at the receiving end.

Aerospace communication link is more complicated. Generally, the working frequency band of the entire system is about 500MHz. Each spacecraft is equipped with several transceivers, and each transceiver is allocated a certain working frequency band, like Fig.1. Therefore, aerospace communication link mostly uses FDMA. This article considers the channel part of the digital communication system of aerospace communication link, and it is an additive noise channel.

Due to the channel fading characteristics, this paper divides the wireless channel into several time slots in the time domain, and the channel gain of each time slot can be expressed as \( h, h \sim \mathcal{CN}(0,1)[7] \). Transmission data can be expressed as a set of transmission sequence \( x = [x_1, ..., x_n]^T \). Then the receiving sequence can be expressed as

\[
y_n = h_k x_n + w_n
\]

Among them, \( h_k \) represents the channel gain of the kth time slot, and \( w = [w_1, ..., w_n]^T \) represents the channel noise sequence.

2.2. Noise model

The communication channel noise of aerospace communication system is usually divided into ground clutter, sea clutter and Gaussian noise after lift-off according to the location of the spacecraft. Generally, there are nonlinear transformation methods and spherical invariant random process methods to generate related random sequences that obey a certain probability distribution law. The former is to first generate a Gaussian sequence that meets certain correlation characteristics, and then a clutter sequence to the relevant target distribution through a certain nonlinear change; the latter also first generate a Gaussian sequence of correlation characteristics, and then generate a sequence that meets the target distribution through modulation. The nonlinear transformation method is relatively simple, classic, and has a small amount of calculation. For several noise distributions in the wireless communication channel of aerospace communication system, such as coherent correlation Rayleigh distribution, Weibull distribution, and logarithmic distribution \[8\], the corresponding nonlinear transformation process can be found, so the nonlinear transformation method is used.

In the analysis of the clutter distribution characteristics, in addition to considering that the amplitude of the clutter must conform to the above specific distribution characteristics, the correlation must also be considered, and the correlation is reflected in the power spectrum. The power spectrum models used commonly are: Gaussian spectrum model, Cauchy spectrum model and cubic spectrum model. The normalized form of the Gaussian spectrum model is as

\[
W(f) = \exp \left( -\alpha \left( \frac{f - f_0}{f_{3dB}} \right)^2 \right)
\]

The expression forms of Cauchy spectrum and cubic spectrum are as follows:
\[ W(f) = \frac{1}{1 + \left(\frac{f-f_0}{f_{3\text{dB}}} \right)^n} \quad (3) \]

Among them, \( n=2 \) represents Cauchy spectrum, \( n=3 \) represents cubic spectrum. \( f_{3\text{dB}} \) is the 3db bandwidth of the clutter and becomes the characteristic frequency. \( f_0 \) is the Doppler frequency shift caused by the clutter velocity, but due to the high altitude and high velocity of the spacecraft, it is generally treated as zero. For ground clutter, the center frequency of the spectrum is generally 0, and \( f_{3\text{dB}} \) is about 3% of the speed of wind. The center frequency of sea clutter is a function of the wind speed and the angle between the wind direction and the line of sight, which can be expressed as:

\[ f_{3\text{dB}} = \frac{2\sigma_w}{\lambda} \quad (4) \]

3. Channel recognition model

Literature [9] uses convolutional neural network to establish corresponding channel scene recognition models for outdoor, indoor and mixed interference scenes. Based on this research, this paper establishes a corresponding additive noise channel model for aerospace communication link, and this work is a classification problem based on RNN (Recursive Neural Network). Then we use GAN to improve the model.

3.1. Generative adversarial networks model

GAN is a data enhancement method proposed in recent years [10]. GAN does not simply transform data, but learns the distribution of existing data sets to generate new data that matches the characteristics of the data set. GAN uses random noise to generate fake data similar to the real data distribution, thereby achieving data expansion. Generally speaking, GAN is divided into the following two parts:

Generator network (G): Generally speaking, it is a regression network. The generator network in GAN learns the distribution of real data sets and generates fake data from random noise input. As the noise changes, the data generated is also very diverse. The trained generator can generate data consistent with the original data set distribution.

Discriminator network (D): It is usually a classification network. Send the generated data with fake labels and original data with real labels to the recognizer for training, and learn how to judge whether the data comes from the original data set. The activation function of the last layer of D is generally a sigmoid function, which is used to output a scalar representing the probability of true or false.

The ultimate goal of the network is that while D is very powerful, the fake sample generated by G is sent to D and its output value becomes 0.5, indicating that G has completely deceived D, that is, D has no way to distinguish whether the input sample is \( X_{\text{fake}} \) or \( X_{\text{real}} \), thus get a G with very good effect.

Loss function design:

\[ V(G, D) = E_{X \sim P_{\text{data}}} \left[ \log D(x) \right] + E_{X \sim P_{G}} \left[ \log \left(1 - D(x)\right)\right] \quad (5) \]

It can be seen from the above formula that the loss function is the expected sum of the two distributions, where \( P_{\text{data}} \) is the probability distribution of the real data, and \( P_{G} \) is the probability distribution of the fake samples generated by the generator. For D, its purpose is to make the output result of the sample in \( P_{\text{data}} \) as large as possible, that is, \( P_{G} \) becomes larger, and the output result of the generated sample x is as small as possible. So the objective function can be obtained as:

\[ \min_G \max_D V(G, D) = E_{X \sim P_{\text{data}}} \left[ \log D(x) \right] + E_{Z \sim P_{G}(z)} \left[ \log \left(1 - D(G(z))\right)\right] \quad (6) \]

This is a maximum and minimum optimization problem, which corresponds to the above two optimization processes. First optimize D, then optimize G. The essence is two optimization problems, which can be broken down into two formulas:

Optimization D:

\[ \max_D V(G, D) = E_{X \sim P_{\text{data}}} \left[ \log D(x) \right] + E_{Z \sim P_{G}(z)} \left[ \log \left(1 - D(G(z))\right)\right] \quad (7) \]
Optimization G:

\[
\min_G V(D, G) = \mathbb{E}_x \sim p_G(x) \left[ \log \left( 1 - D(G(x)) \right) \right]
\]  

(8)

When optimizing D, that is, the optimization of the discriminant network, the input x is the true sample set, and G(z) is the false sample set after the generation network. For the true sample set, the larger the optimization result is, the better; for the generated false sample set, the smaller the optimization result is, the better, which corresponds to the first and last two items in formula (7) respectively.

3.2. GAN-based Recognition Enhancement

The wireless channel scene of aerospace communication system has the characteristics of fast time change and wide bandwidth. Due to various factors such as hardware and sudden interference, it is difficult for the system to collect complete wireless channel sequence data [6]. As a result, the neural network only pays attention to when doing recognition training. Because of the local characteristics of the data set, it is impossible to learn all the information of the sample set, so that the trained recognition model cannot accurately distinguish various channel data types.

Overfitting of training is related to the dimensions of the problem and the model, as well as the size and distribution of the training set data. Training with a model higher than the problem dimension will lead to over-fitting; uneven sampling or small scale of the data set will also lead to over-fitting. The literature [11] discusses measures to prevent overfitting in deep convolutional network training, including Data Augmentation and Dropout. Among them, Data Augmentation uses the transformation of translation and horizontal flipping of the image, thereby expanding the data set and reducing the phenomenon of overfitting, but the simple transformation makes the data have a strong correlation.

To solve this problem, this paper uses GAN’s ability to learn the distribution of data characteristics, and proposes a GAN-enhanced wireless channel noise recognition method. The specific process is: divide the training set into a test set and a training set. Then the training set is used as the original data for generating the confrontation network, and it is input to D to judge whether it is similar to the simulated data generated by G, and the result is fed back to G. The G and D networks reach the Nash equilibrium through a continuous game process like Fig.2.

![Fig.2 The process of model](image)

Assuming that G can reach the optimal, its optimal discriminator is \(D^*(x)\):

\[
D^*(x) = \frac{P_{data}(x)}{P_{data}(x) + P_G(x)}
\]

(9)

When D reaches the optimum, the objective function of G is transformed into:

\[
\min_G V(D, G) = \min_G \left\{ \frac{2JS(p_{data}\parallel p_G) - \log 4} \right\}
\]

(10)

It can be seen that the ultimate goal of training G is to minimize the JS divergence between the generated distribution and the target distribution, and reach the optimal when \(p_{data} = p_G\). Therefore, this paper uses GAN to generate a multiplied sample data set that meets the characteristics of the original data, and enters the recurrent neural network for training. Finally, the accuracy of the model is evaluated through the testing set.

4. Experiment Results

The experiment obtains Gaussian and Weibull noise data through simulation, and adds it to the DSB modulation of the sinusoidal signal in the form of additive noise. The frequency domain signal is
obtained by Fourier transform. After uniform sampling, the training data is obtained. The processed data is input to the RNN model for classification training, which is specifically divided into Gaussian noise channels, Weibull noise channels and mixed channels. Since the frequency domain characteristics of the modulated signal are more obvious and single, a small-scale data amount is initially selected, each of which is 100. Take 1/5 of the data set as the test set for cross-validation, and the results obtained after 8000 training are as Fig.3.

As can be seen from Fig.3, in a data set with relatively simple features, the RNN model has been more convergent after training 4000 epochs, but the accuracy can be improved. Input the Gaussian and Weibull noise data set above into the GAN model for training. The structures and parameters of GAN model are listed in Table.1.

| Parameters                  | Values         |
|-----------------------------|----------------|
| Generator hidden layers     | 256, 128, 128  |
| Discriminator hidden layers | 256, 128, 1    |
| Learning rate               | 0.0001         |

The mean variance curve of the generated data are as Fig.4.

The mean value of the original data set of Gaussian noise is 0 and the variance is 1, the mean value of the original data of Weibull noise is 0.9, and the variance is 0.6. It can be seen from Fig.4 that although the training of the GAN model has unstable characteristics, the generated data after convergence is basically stable at the target value. We use the generator model obtained by training to output 100 times the amplified data set, and input 1W of each type into the RNN model for retraining. The accuracy results obtained are as Fig.5.
Fig. 5 Accuracy comparison before and after training set expansion

It can be seen that the model after the augmented data set fluctuates greatly in the early stage of training, but the recognition accuracy of the model after stability has improved.

5. Conclusion
This paper first discusses the channel recognition of aerospace communication link, and points out the problem of overfitting of neural network training caused by poor training set. Finally, we propose an enhancement method based on GAN. Experiments have proved that the accuracy of channel recognition of aerospace communication link can be improved.

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