Electromagnetic Signal Interference Based on Convolutional Autoencoder

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Abstract. At present, electromagnetic interference methods are mainly divided into traditional interference methods and intelligent interference methods. Traditional interference is currently dominated by barrage interference. Intelligent interference solves the shortcomings of barrage interference by sending out fixed-frequency and directional targeted interference waveform. However, most of the current intelligent interference methods require prior information and cannot deal with highly dynamic electromagnetic environments. Therefore, this study introduces an intelligent interference method without prior information. This study is based on a convolutional autoencoder model, which is used to extract high-order features of disturbed communication signal waveform without prior information. By covering some indistinct features and using a deconvolution network to generate similar signals to generate the best interference waveform, this method has an ideal bit error rate. The target signal is reconstructed by a convolutional autoencoder, and the optimal interference waveform is generated in the network by covering the high-order features of the input signal. Finally, the simulation is carried out using the method in this paper. In the BPSK communication system, a bit error rate of 48.7% can be achieved with a low signal-to-noise ratio. In practical engineering, the interference method in this paper can also realize covert jamming, which greatly improves the safety of jammer itself.

Keywords: Intelligent interference · Convolutional autoencoder · Signal to interference ratio

1 Introduction

Electromagnetic interference devices are widely used today. In terms of civilian use, electromagnetic interference equipment is used from signal shielding in the examination room to interference with unmanned aerial vehicle (UAV) communication. In the military field, electronic warfare and information warfare in modern warfare are becoming more and more important, and electromagnetic interference equipment is essential in electronic warfare. However, the traditional electromagnetic interference equipment has some shortcomings. The interference is less effective, and it cannot cope with the

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highly dynamic electromagnetic environment [1]. So experts and scholars from many countries began to study new interference methods.

In 2006, American Abel S. Nunez et al. proposed a transform-domain communication interference waveform generation method that relies on prior knowledge. The method can interfere with the communication of the other party under the condition of correctly analyzing the other party's modulation method and some other information [2]. In the field of signal interference, the prior knowledge is mainly based on the modulation mode of the signal. Yun Lin et al. [3] identified the modulation mode of the physical layer signal based on the contour star image and deep learning. Ya Tu et al. [4] used Generative Adversarial Networks for modulation classification of digital signals. Changbo Hou et al. [5] used sliding window detection and complex convolutional networks in the frequency domain for modulation classification of aliased multi-signals. In 2017, Xingyu Xia et al. proposed an intelligent interference optimization waveform design method centered on Cell-Averaging (CA-CFAR). According to the CA-CFAR anti-interference mechanism, this method designs the interference waveform whose amplitude follows the Rayleigh distribution and is random in a finite interval. The interval is designed as a random interval based on the minimum interval [6]. In 2020, Pan Zhang et al. proposed an electronic interference method inspired by bionic systems, based on the "cognitive electronic interference" method for electronic interference, so that the interference method has the ability of autonomous perception and rapid decision-making [7]. In 2021, Zhe Su et al. proposed a new method based on the Stackelberg game, which can effectively interfere with specific signals while interfering with own signals as little as possible [8].

In this study, the interference signal generation method based on convolutional autoencoder (CAE) is used to realize the intelligent interference waveform generation without prior knowledge. In the system, the transmitter and receiver of the communication system and the RF front-end of the interference system are realized through USRP. The interference system consists of a USRP and a computer. The computer determines the optimal interference waveform and sends the interference signal by the software radio platform to achieve the interference effect, and the receiver evaluates the interference effect.

2 Method

2.1 System Model

In order to change the shortcoming of the intelligent interference method with prior knowledge mentioned above, the system model of this section is proposed. In this study, the features of the signal are extracted by the CAE, and the error function is designed through the classification effect and the minimum mean square error to improve the signal reconstruction performance. After the model is trained, the feature parameters in some fully connected layers are changed by occlusion and replacement to generate interference waveform. After the interference is implemented, the effect of the interference is evaluated by the receiver.

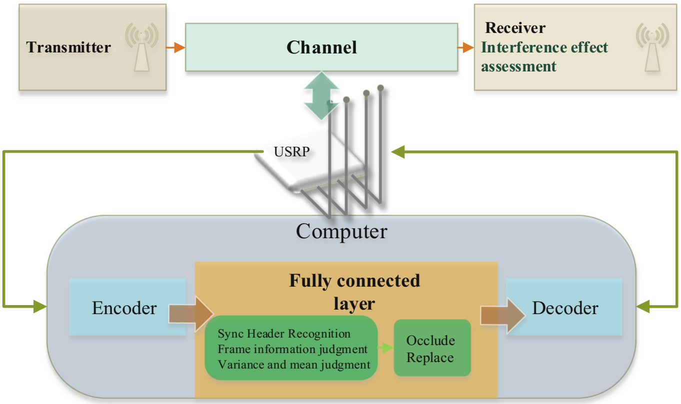


Fig. 1. System model structure diagram

2.2 Convolutional Auto-encoder

CAE [9–12] is based on autoencoder (AE) and introduces the idea of convolution into AE. In CAE, the encoder and decoder consist of convolutional layers and pooling layers. The convolutional layers in the encoder perform convolution operations, while the convolutional layers in the decoder perform deconvolution operations. Convolution is the process of multiplying and summing part of the data with the corresponding weights, while pooling is to extract invariant features. The structure of the CAE is shown in the following figure (Fig. 2):

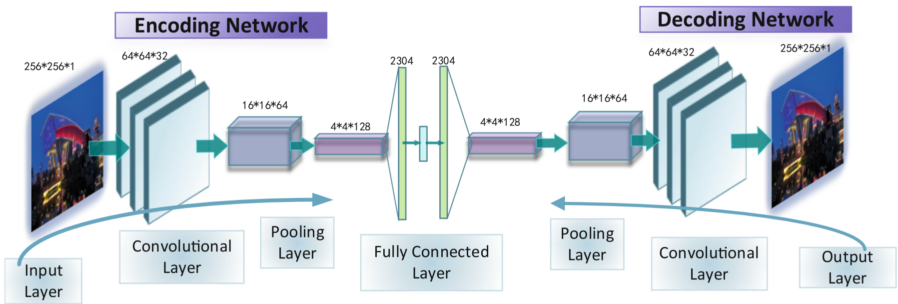


Fig. 2. CAE structure diagram

Assuming that there are k convolution kernels, each convolution kernel consists of parameters w^k and b^k, and h^k represents the convolution layer, then

$$h^k = \sigma(x * w^k + b^k) \quad (1)$$

where w^k represents is the weight, b^k represents the bias, x represents the input of the convolution kernel, and σ is the activation function.

Perform feature reconstruction on the obtained h^k, you can get:

$$y = \sigma\left(h^k * \hat{w}^k + c\right) \tag{2}$$

where y is the output of the network, and the bias in the reconstruction process is c.

Comparing the input and output of the network with Euclidean, and optimizing through the BP algorithm, a complete CAE can be obtained:

$$E = \frac{1}{2n}\sum_{i=1}^{n}(x_i - y_i)^2 \tag{3}$$

where n is the training times of CAE.

In the forward pass pooling layer, its output is:

$$a_{ij}^{l} = \max(a_{mn}^{l-1}), i \le m, n \le i + 2 \tag{4}$$

where m, n is the area covered by the pool core corresponding to a_{ij}^{l-1}.

Since the pooling layer of backpropagation has no parameters, the relevant gradients can be passed down:

$$\delta_{k,v}^{l-1} = \frac{\partial C}{\partial z_{k,v}^{l-1}} = \sum_{ij}^{i=3,j=3} \frac{\partial C}{\partial a_{ij}^{l}} \frac{\partial a_{ij}^{l}}{\partial a_{k,v}^{l-1}} \frac{\partial a_{k,v}^{l-1}}{\partial z_{k,v}^{l-1}} \tag{5}$$

The loss function applied in the network is designed below, the input pure data is denoted as x_c^*, the parameters of the hidden part in the network are denoted as h_c, and the Taylor expansion of the Lagrangian remainder of the feature function of the autoencoder is as follows:

$$f\left(x_c^*\right) = f(x) + \left(x_c^* - x\right)^T \nabla f\left[x + \rho\left(x_c^* - x\right)\right] \tag{6}$$

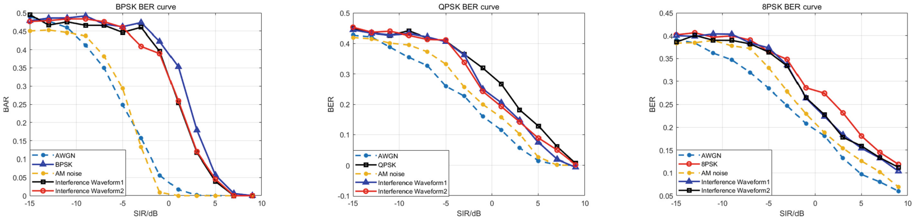
where $\nabla f\left[x + \rho\left(x_c^* - x\right)\right]$ is the first derivative of the coding part, and $\rho \in (0, 1)$, the loss function can be expressed as:

$$L\left(h_c, h_c^*\right) = L(h_c, f(g(h_c))) = \left\|h_c^* - h_c\right\| = \left\|f\left(x_c^*\right) - f(x)\right\|^2 \tag{7}$$

3 Interference Effect Analysis

Apply the interference method above, and evaluate the interference effect by evaluating the bit error rate (BER) of the receiver after implementing the interference. The influence of the signal itself and different interference signals on the BER of the receiver is shown in the figure below, in which the interference waveform 1 and the interference waveform 2 are the interference waveform generated by the method used in this study (Fig. 3):

It can be seen from Fig. 4 that in the BPSK communication system, when the SIR is lower than −10 dB, the BER can reach up to 48.7%; in the QPSK communication system, when the SIR is lower than −10 dB, the BER can reach up to 33%; in the 8PSK



(a) BER of BPSK Communication System under Five Kinds of Interference

(b) BER of QPSK Communication System under Five Kinds of Interference

(c) BER of 8PSK Communication System under Five Kinds of Interference

Fig. 3. BER Curve Under Interference Waveform (SNR = 10 dB)

communication system, when the SIR is lower than −10 dB, the BER can reach up to 38.4%. It can be seen from the above results that the interference signal generated by this method can effectively interfere with the communication system. The method in this paper uses the I/Q two-way signal components to interfere with the signal, and distributes the power to the I/Q two-way, while the quadrature power of the QPSK signal is zero, so the method in this paper has a poor interference effect on the QPSK signal.

4 Conclusion

This study constructs a communication and interference system. The system can be used to develop and verify the generation of interference waveform based on CAE, as shown in Fig. 1. It can be concluded that the interference effect of the interference waveform intelligent generation method based on the CAE in this study is better than that of Gaussian noise interference, noise amplitude modulation and other interference signals.

The waveform generation method of the CAE in this study does not require prior information of the communication signal, and achieves the highest BER of 48.7% in the simulation. Through the continuous iteration of many experiments, the optimal convolution and deconvolution networks were obtained. The optimal parameter selection for implementing Gaussian perturbation in the fully connected layer of the CAE was found, and finally a better interference effect was achieved.

However, the interference method in this study still has some shortcomings, such as the poor interference effect on BPSK modulated signals in the actual situation, and the high dimension of the fully connected layer in the CAE, resulting in a high amount of computation. The above shortcomings will also be improved in future research.

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