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Deep-Learning-Based Recovery of Frequency-Hopping Sequences for Anti-Jamming Applications

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Abstract: The frequency-hopping communication system has been widely used in anti-jamming communication due to its anti-interception and anti-jamming performance. With the increasingly complex electromagnetic environment, the frequency-hopping communication system needs more flexible frequency-hopping patterns to deal with interferences, which brings great challenges to the communication receiver. In this paper, an intelligent receiving scheme of frequency-hopping sequences is proposed, which combines time–frequency analysis with deep learning to realize an intelligent estimation of frequency-hopping sequences. A hybrid network module is designed by combining a convolutional neural network (CNN) with a gated recurrent unit (GRU). In the proposed network module, the combination of a residual network (ResNet) and squeeze and extraction (SE) improves the feature extraction and expression capabilities of the CNN network. The GRU network is proposed to solve the problem of dealing with signals with variant input lengths. A transfer learning scheme is further proposed to deal with communications systems with different frequency-hopping sets. Simulation results show that the proposed method has strong generalization ability and robustness, and the bit error rate (BER) performance of intelligent receiving is close to the receiving performance under ideal conditions.

Keywords: frequency-hopping communication; anti-jamming; convolutional neural network; gated recurrent unit; transfer learning

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1. Introduction

With the increasingly complex electromagnetic environment, intentional jamming has brought great challenges to the normal operation of wireless communication systems [1], so it is urgent to improve the anti-jamming capability. Traditional anti-jamming methods, such as filtering [2], direct sequence spread spectrum [3], and adaptive antenna [4], lack flexibility and have poor adaptability to the complex and changeable electromagnetic environment. Frequency-hopping communication [5] is widely used in common anti-jamming communications due to its strong anti-interference ability, ease of multi-access networking, and superior security. The frequency-hopping (FH) mechanism plays an important role in anti-jamming frequency-hopping communication, and the frequency-hopping sequence is the key to controlling frequency hopping. At present, the frequency-hopping sequence detection is mainly realized by the Bayesian detection algorithm [6], sequence prediction based on probability distribution algorithms [7], chaotic frequency-hopping sequence detection based on neural network algorithms [8], and frequency-hopping synchronous capture strategy based on subsequence search [9]. However, most of the sequence detection methods only consider the white Gaussian noise channel without jamming and also need prior information such as the frequency-hopping time and frequency-hopping set. In practical applications, frequency-hopping signals are usually accompanied by strong interference signals, and the above-mentioned methods will have limitations in this circumstance.

Artificial intelligence algorithms have been widely used in various fields of wireless communications at present, and intelligent anti-jamming communication systems based on artificial intelligence algorithms have also become a new research issue [10,11]. Intelligent decision making is used as the key technology in intelligent anti-jamming communication systems, which take into account the selection of parameters such as power [12] and frequency [13] and use the domain knowledge of pattern recognition [14] and multi-agent decision making [15] to adaptively search for the optimal solution of the objective function in a solution space to achieve efficient and reliable communication. For example, in NC-OFDM communication systems, radial basis function neural network algorithms [16], Q-learning algorithms [17], and BP neural network algorithms [18] are used to realize an intelligent decision-making process for communication parameters. In frequency-hopping systems, a double-deep Q-network (DDQN)-based anti-jamming scheme was proposed to solve anti-jamming communication [19]. In the proposed algorithm, the interactions between a radio transmitter and a follower jammer were formulated as a Markov decision process (MDP). The jammer was adjusted to improve the interference performance, and the radio terminal fed the state feedback information into the algorithm's input parameters and then selected the transmit power and hopping rate according to the output of the policy network. Song et al. [20] proposed a dynamic epsilon–DQN intelligent decision-making method to solve the problem of intelligent anti-jamming decision making in frequency-hopping communication systems. The proposed algorithm introduced experience replay and dynamic epsilon mechanism based on PHC under the framework of the DQN algorithm. Zhao et al. [21] designed a multi-agent fuzzy deep reinforcement learning algorithm based on centralized training and decentralized execution (MFDRL-CTDE) to improve the anti-jamming performance of frequency-hopping asynchronous networks in complex electromagnetic environments. Their simulation results showed that the algorithm has a great advantage in convergence speed and has good adaptability to a changeable complex electromagnetic environment. Kang et al. [22] proposed an intelligent fast frequency-hopping algorithm based on improved Q-learning with the goal of maximizing the information transmission rate and minimizing the frequency-hopping overhead simultaneously. Their simulation results showed that the proposed scheme can rapidly learn frequency-hopping strategies with faster convergence. Li et al. [23] constructed a long short-term memory (LSTM) neural network model for the frequency prediction of the frequency-hopping system with the intercepted massive frequency-hopping signal data. Their simulation results showed that parameter estimation methods could accurately estimate the frequency in the presence of a certain amount of noise. As a further study, a kind of robust long-term spectrum prediction scheme with missing values and sparse anomalies based on tensor completion was proposed in [24]. Due to the variation in the electromagnetic environment, the transmitter of the intelligent anti-jamming communication makes intelligent decisions on the frequency-hopping sequence, and the receiver cannot know the frequency-hopping sequence used by the transmitter in advance, which undoubtedly increases the difficulty of the receiver's information recovery. At present, the research of intelligent anti-jamming of frequency-hopping communication mainly focuses on the transmitter. Although there are some efforts on the detection and parameter estimation of FH signals [25–28] at the receiver side, these methods need to store frequency-hopping signals with a certain length of time for analysis and processing, which cannot be applied in real-time communication reception.

In order to solve the problems in the complex electromagnetic jamming environment, in this paper, an intelligent anti-jamming frequency-hopping communication system model is established, and the intelligent recovery of frequency-hopping sequences using deep learning is proposed. In the proposed method, a convolutional neural network (CNN) was used to extract the high-dimensional features of time–frequency diagrams of frequency-hopping signals, and a gated recurrent unit (GRU) was used to learn the time correlation between the signals in the presence of jamming. Then, simulations were conducted to analyze the performance of the proposed method. Specifically, the main objectives and contributions of the paper are mainly as follows:

(1) We propose a deep-learning-based recovery method of frequency-hopping sequences. In the proposed method, we used the short-time Fourier transform (STFT) diagram of the received frequency-hopping signal as the input of the network. We designed a hybrid CNN and GRU network architecture for learning and adaptation to variant signal input length. The combination of the two networks ensured the accuracy of frequency-hopping sequence estimation under a complex electromagnetic environment. Simulation results showed that in both the single and mixed jamming scenarios, the proposed method achieved high accuracy in estimating the frequency-hopping sequences.

(2) We used transfer learning to deal with new frequency-hopping systems with different frequency-hopping sets. We changed the last fully connected layer of the network so as to make the size of its output dimension correspond to the number of frequency points of the new frequency-hopping system. The simulation results showed that with transfer learning, the number of training samples could be reduced to a large extent.

(3) We analyzed the BER performance of the frequency-hopping system. Our results showed that the BER performance of the proposed hybrid network was close to that of the frequency-hopping receiving system under ideal conditions, in both the single and mixed jamming environments.

The rest of the paper is organized as follows: In Section 2, we introduce the intelligent anti-jamming frequency-hopping communication system model. Section 3 presents the details of the proposed method. In Section 4, extensive simulation experiments are conducted to verify the performance of the algorithm. Section 5 summarizes the paper.

2. System Model

In traditional frequency-hopping communication systems, the transmitter and the receiver use the predetermined frequency-hopping sequence for communication. The jammer intercepts and analyzes the frequency-hopping signal of the transmitter and uses different types of jamming signals to interfere with the communication process [29]. The system model of an intelligent anti-jamming frequency-hopping communication system is shown in Figure 1. The upper part of Figure 1 is the transmission system. An anti-jamming decision-making module is added on the basis of the traditional transmission system. This module makes decisions on the optimal frequency-hopping pattern (i.e., frequency-hopping sequence) according to the perception of the current interference environment and generates frequency-hopping signals for transmission. The lower part is the receiving system. The FH sequence estimation module recovers the frequency-hopping sequence from the received signal, which is then used to de-hop the signal and thus realize intelligent signal reception. An intelligent estimation module based on CNN-GRU is designed in this paper, which will be discussed in detail in the next section. Therefore, the transmitter can intelligently generate the frequency-hopping sequence through an anti-jamming decision, and the receiver can recover the frequency-hopping sequence through the proposed CNN-GRU module to achieve reliable and intelligent anti-jamming communication.

The mathematical model of the frequency-hopping signal is represented as

$$\begin{cases} X(t) = \sum\limits_{i=0}^{N-1} x_i(t) = \sqrt{2E} \sum\limits_{i=0}^{N-1} rect(t - iT_{FH}) \cos(2\pi f_i (t - iT_{FH}) + \phi), 0 \le t \le NT_{FH} \\ rect(t) = \begin{cases} 1, t \in [0, T_{FH}] \\ 0, others \end{cases} \end{cases} \tag{1}$$

where $x_i(t)$ represents the i-th frequency-hopping signal component, $rect(\cdot)$ represents a rectangular window with a width of T_{FH}, E represents the signal power, T_{FH} represents the frequency-hopping period, f_i represents the hopping frequency, and N represents the number of hopping frequencies.

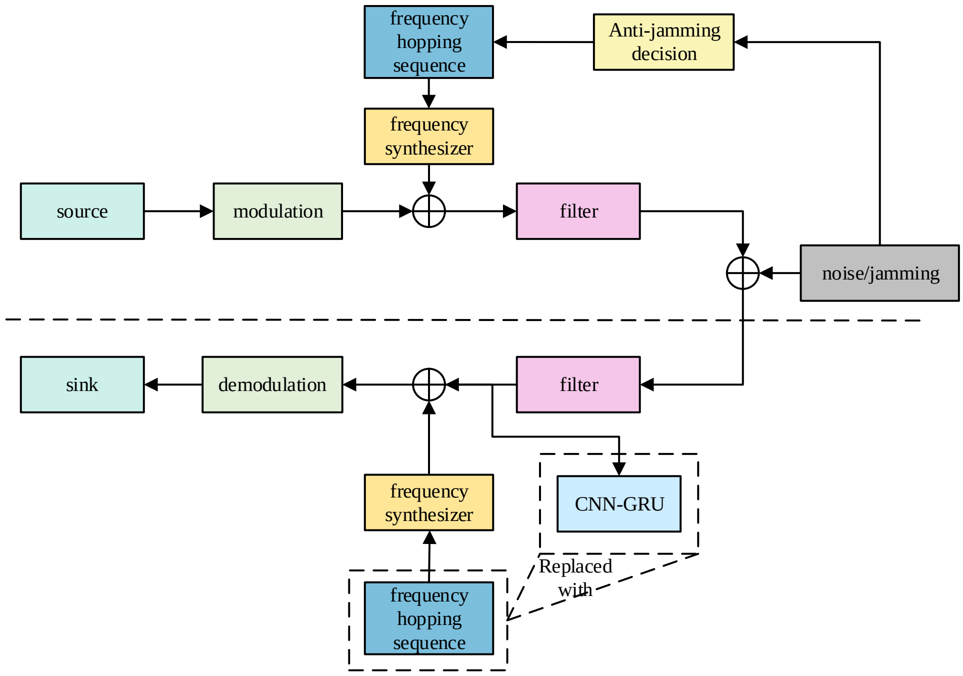


Figure 1. Structure diagram of intelligent anti-jamming frequency-hopping communication system.

3. Proposed FH Sequence Recovery Method

3.1. Overall Framework

In an intelligent anti-jamming frequency-hopping communication system, the transmitter intelligently generates the optimal frequency-hopping sequence during the confrontation with the jammer. Due to unknowing it in advance, the receiver needs to intelligently estimate the frequency-hopping sequence according to the received signal to complete the de-hopping processing. The problem of estimating frequency-hopping sequences can be transformed into the problem of frequency point classification by using deep learning. A CNN-GRU module is designed for an intelligent estimation of frequency-hopping sequences in this paper. The strong learning ability of the neural network is used to learn the characteristics of the frequency-hopping signals in the presence of jamming and complete the estimation of the frequency-hopping sequence, and thus realize the intelligent reception of frequency-hopping signals.

The structure diagram of the proposed method is shown in Figure 2. The input data are the time–frequency diagrams of the frequency-hopping signals. The output is the frequency-hopping sequence, which is obtained from the coordinates and frequency-hopping patterns of the signal pixels detected on the time–frequency diagram. The basic network structure is composed of an SE (squeeze and extraction) ResNet network and a GRU network, and the output is the frequency-hopping sequence. SE ResNet is the basic module of the CNN-GRU network, which is composed of deep residual networks [30] (ResNet) followed by the SE module, which is used to extract high-dimensional features of the time–frequency graph of received signals. The GRU [31] module jointly deduces the frequency-hopping sequence value of the current frequency-hopping cycle according to the currently extracted features and the previous memory.

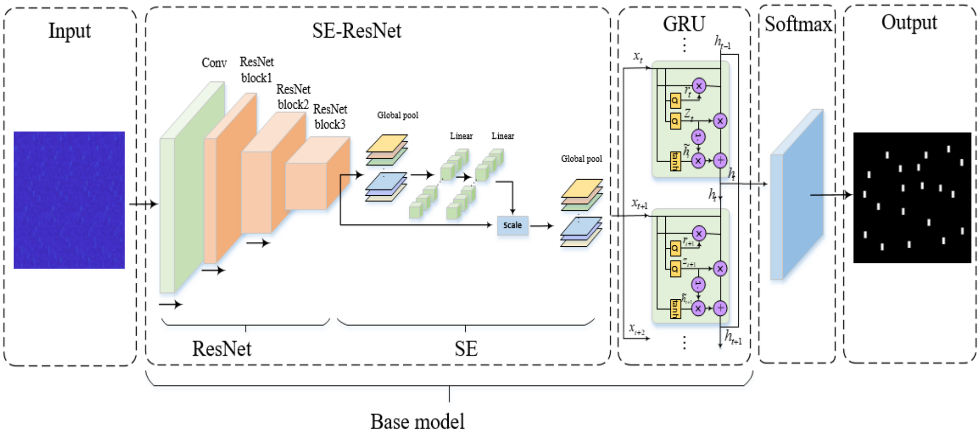


Figure 2. Structure diagram of frequency-hopping sequence classification.

3.2. Input Data Format

The frequency-hopping signal is non-stationary in nature. As the frequency-hopping signal may occupy a wide frequency range, the length of the sampled signal will be very long, which makes learning with the raw time domain signal as the input difficult. In this paper, we transform the frequency-hopping signal from the time domain to the time–frequency domain via STFT. STFT is used to preprocess the received signal, and the processed time–frequency diagram is used as the input of the neural network. The mathematical expression of the STFT is

$$\begin{cases} STFT_Y(t,f) = \int_{-\infty}^{+\infty} Y(\tau)\varpi^*(\tau - t)\exp(-j2\pi f\tau)d\tau \\ Y(t) = X(t) + J(t) \end{cases} \tag{2}$$

where $\varpi^*(t)$ represents the conjugate form of the window function, and $Y(t)$ represents the received signal, which is composed of the frequency-hopping signal $X(t)$ and the jamming $J(t)$ in the channel.

The receiver can take the frequency-hopping period as a known condition. It divides the received signal according to the frequency-hopping period and inputs the time–frequency diagram of each hopping signal into the network consecutively, and the output of the network at the current moment is the frequency-hopping sequence value of the hopping signal.

3.3. Designed Network Structure

The designed CNN-GRU network structure is composed of a SE-ResNet network and a GRU network, as shown in Figure 3. The SE-ResNet module is composed of a ResNet followed by an SE module, which is used to extract the high-dimensional features of the time–frequency diagram of the received signal. The GRU module jointly derives the frequency-hopping sequence value of the current frequency-hopping cycle according to the currently extracted features and the previous memory.

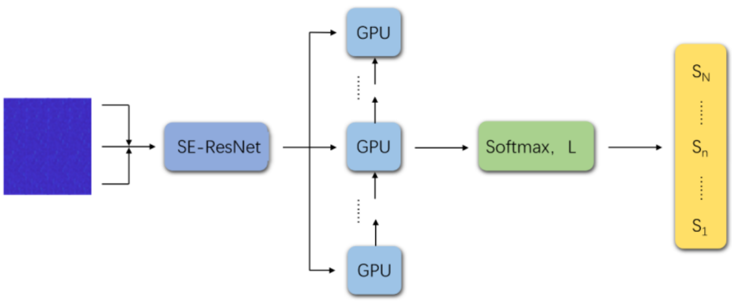


Figure 3. Structure diagram of CNN-GRU.

(a) SE-ResNet structure

The structure of SE-ResNet is shown in Figure 4. The left side of the dotted line is ResNet, which is mainly composed of three groups of residual modules. The first group adopts the identity shortcut mapping, and the latter two groups adopt the linear projection method, i.e., using the convolution kernel of size 1*1 to downsample the feature map. In Figure 4, "7*7 conv,64,/2" of Conv_1 indicates that the convolution kernel size is 7*7, the number is 64, and the stride is 2 (the default is 1). "Maxpool,/2" in Pool_1 indicates that the pooling method is maximum pooling, and the stride of the pooling core is 2. At the same time, a batch normalization (BN) layer is added after each convolutional layer, and the output of the convolutional layer is normalized so that the input of each layer maintains the same distribution. In this way, the requirements for the initialization of network parameters can be reduced, the difficulty of network training can be reduced, and the convergence speed of the network can be accelerated.

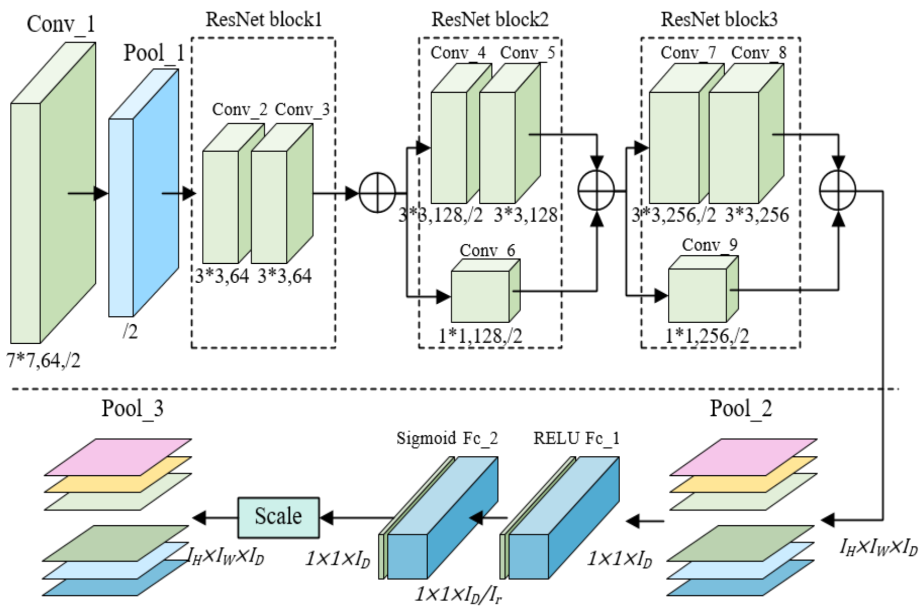


Figure 4. Structure diagram of SE-ResNet.

The right side of the dotted line is the SE module, where I_H, I_W, and I_D are the height, width, and number of channels of the input data, respectively, the pooling method is average pooling, FC is the fully connected layer, ReLU and Sigmoid are activation functions, D is the dimension reduction factor, and the dimension reduction factor is 16. The SE module uses two fully connected layers to achieve dimensionality reduction operations, which reduces the number of parameters and calculations. After the output of ResNet passes through the SE module, a set of weights corresponding to the output channels is obtained, which is used to perform weighted calculations on each channel, so as to realize the key information in the prominent features, suppress the useless information, and enhance the expressive ability of the model.

Finally, a global pooling layer is used at the output to replace the fully connected layer to avoid feature loss. This fully convolutional network-like structure can use the deconvolution layer to upsample the feature map of the last convolutional layer to achieve the same size as the input, so more feature information can be preserved by using this method. At the same time, the amount of network parameters can be further reduced, and the training difficulty and computing time of the network can be reduced.

(b) Gated recurrent unit

SE-ResNet is used to process the time–frequency diagram of the received signal, and the network can extract the high-dimensional features of the signal through training. At the same time, because the frequency of the frequency-hopping signal or jamming has different characteristics with time, we use GRU to learn the information in the time dimension of the high-dimensional features of the signal. The specific structure of the GRU is shown in Figure 5.

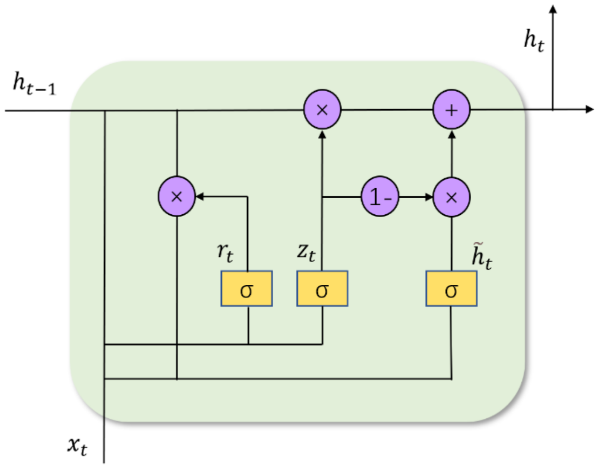


Figure 5. Schematic diagram of GRU.

The forward propagation mathematical expression of GRU is

$$\begin{cases} r_t = \sigma(\boldsymbol{W}_{ir}x_t + b_{ir} + \boldsymbol{W}_{hr}h_{t-1} + b_{hr}) \\ z_t = \sigma(\boldsymbol{W}_{iz}x_t + b_{iz} + \boldsymbol{W}_{hz}h_{t-1} + b_{hz}) \\ \widetilde{h}_t = \tanh(\boldsymbol{W}_{in}x_t + b_{in} + r_t \times (\boldsymbol{W}_{hn}h_{t-1} + b_{hn})) \\ h_t = (1 - z_t) \times \widetilde{h}_t + z_t h_{t-1} \end{cases} \tag{3}$$

where $\boldsymbol{W}_{iz}$ and $\boldsymbol{W}_{hz}$ are the updated gate's weight coefficients, and b_{iz} and b_{hz} are the bias coefficients. $\boldsymbol{W}_{ir}$ and $\boldsymbol{W}_{hr}$ are the reset gate's weight coefficients, and b_{ir} and b_{hr} are the bias coefficients. $\boldsymbol{W}_{in}$ and $\boldsymbol{W}_{hn}$ are the weight coefficients of the candidate hidden layers, b_{in} and b_{hn} are the bias coefficients, σ is the Sigmoid function, x_t is the input at time t, and h_t is the output at time t.

(c) Classifier design

In this paper, the problem of frequency-hopping sequence estimation is regarded as a sequence classification problem. Assuming that the length of the frequency-hopping sequence is N, and the number of frequency bins is L, then the number of all possible classes is L^N, so it can be solved by using a single classifier with L^N classes. However, as the sequence length and the number of frequency bins increase, the number of categories increases exponentially, which increases the time and space complexity of the network. Secondly, the number of training samples required to train this classifier will be much larger than L^N. It is uneconomical to generate such a large number of training samples because it is difficult to converge in a limited time. Finally, when the length of the frequency-hopping sequence changes, the number of categories will change, at which time it is necessary to change the output size of the classifier and retrain the network. In order to solve the above problems, we input the time–frequency diagram of the received signal into the network according to the frequency-hopping period and use a classifier with L categories to process the output of the GRU. The output at each moment is used as the frequency-hopping sequence value of each hop. This not only can ensure that the network converges in a limited time but also adapt to the change in the length of the input signal. When signals of different lengths are input to the network, the network can obtain the frequency-hopping sequence of the corresponding length through the GRU.

Let the signal received by the receiver be $y(t) = [y_1, y_2, y_3, \cdots y_N]$, where y_i represents the signal sequence of the i-th hop. After STFT processing, a time–frequency matrix

$M = [m_1, m_2, m_3, \cdots, m_N]$ can be obtained, where m_i is the time–frequency matrix of the i-th hop signal. The output of the network is the estimated frequency-hopping sequence $\hat{S} = [\hat{s}_1, \hat{s}_2, \hat{s}_3, \cdots, \hat{s}_N]$. The optimization of the network can be expressed as

$$\min_{Q} ||\hat{S} - S||_1, \hat{S} = F(M : Q) \tag{4}$$

where Q represents the model parameters of the network, and $F(\cdot : Q)$ represents the functional mapping of the network from input to output. As we treat the problem as a classification problem, we adopt the cross entropy as the loss function in training the network

$$\xi = -\frac{1}{N_B} \sum_{i=1}^{N_B} \sum_{t=1}^{l} \sum_{k=1}^{q} label_{itk} \log(p_{itk}) \tag{5}$$

where N_B represents the number of samples in the batch, p_{itk} represents the output probability of the k-th class of the i-th sample at the t-th time of the classifier, and $label_{itk}$ represents the k-th label of the frequency-hopping sequence value corresponding to the t-th hop of the i-th sample.

3.4. Network Transfer Learning

For different frequency-hopping communication systems, due to different communication bandwidths, the number of frequency points in the frequency set may be different. When the number of frequency points changes, the corresponding frequency-hopping sequence should also change, and the network trained will no longer be directly applicable to the system. In order to train a new network with better performance under a small number of datasets, we adopted the method of transfer learning (TL), as shown in Figure 6.

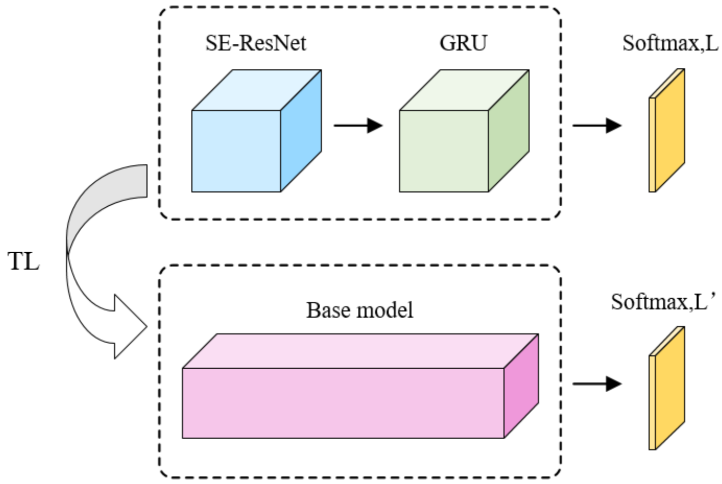


Figure 6. Schematic diagram of transfer learning.

For the trained network, it was able to perform correct feature extraction on the input data. The basic characteristics of artificial jamming on the time–frequency diagram will not change due to the change in the frequency band, so for the frequency-hopping system with different frequency-hopping sets, the input data of the network have similar characteristics to a certain extent. When the number of frequency points of the communication system changes, only the last fully connected layer of the network needs to be changed. The size of its output dimension corresponds to the number of frequency points of the current frequency-hopping system. The network architecture of other layers remains unchanged, and the trained parameters are used as initial values. On this basis, parameter fine-tuning through training is more effective than training the network directly.

4. Performance Analysis

4.1. Simulation Settings

We considered five kinds of jamming signals in this paper: single-tone jamming, single partial-frequency band-blocking jamming, multiple partial-frequency band-blocking jamming, frequency sweeping jamming, and sweeping collision-blocking jamming, which are denoted as jamming 1 to jamming 5, respectively. Parameters such as the frequency and bandwidth of the jamming signal were randomly selected within the allowable value range. The number of frequencies in the frequency-hopping set of the frequency-hopping signal was 16. The number of hops in each signal was 60. The frequency points of the frequency-hopping sequence were randomly selected. The received signal samples were frequency-hopping signals with or without jamming. The signal-to-jamming ratio was −10 dB to 10 dB with an interval of 2 dB. There were 2200 groups of frequency-hopping received signals under each jamming situation and thus a total of 13,200 groups of received signals. Each received signal was subjected to STFT with a window length of 1024 points, and finally, 13,200 time–frequency images were obtained, and the label corresponding to each image is a frequency-hopping sequence with a length of 60. The ratio of the training set to the validation set in the final generated dataset was 8:2. An Adam optimizer was used in training the network. The mini-batch size was 60. The initial learning rate was 0.001. A total of 6 rounds of training were carried out, and the learning rate of each round of training was reduced to 0.5 times that of the previous round. The physical parameters required are shown in Table 1.

Table 1. The physical parameters.

Parameter	Value
Jamming signal	five kinds of jamming signals
The number of frequencies	16
The number of hops of each signal	60
signal-to-jamming ratio	−10 dB to 10 dB
The frequency-hopping received signals	2200
The window length of STFT	1024
The number of time–frequency images	13,200
The mini-batch size	60
The initial learning rate	0.001
convolution kernel size	7*7
Stride	2
The number of convolution kernels	64

4.2. Performance of FH Sequence Recovery

In order to evaluate the performance of the proposed method, the network that only used the convolutional part of the CNN-GRU network in this paper was selected as a comparison, which was recorded as a CNN network. The two networks were trained under the same dataset and hyperparameter settings. The test samples were generated as follows: The signal-to-jamming ratio ranged from −18 dB to 0 dB with an interval of 2 dB. In total, 500 time–frequency diagrams under single jamming and mixed jamming were generated, respectively. In each case, a total of 30,000 frequency bins had to be classified. The results are shown in Figure 7. It can be seen that the estimation accuracy of the frequency-hopping sequence of the CNN-GRU network was higher than that of the CNN network under single jamming or mixed jamming which did not appear in training. This proves that the CNN-GRU network can correctly learn the features of different jamming signals, and its learning ability is stronger than that of the CNN network.

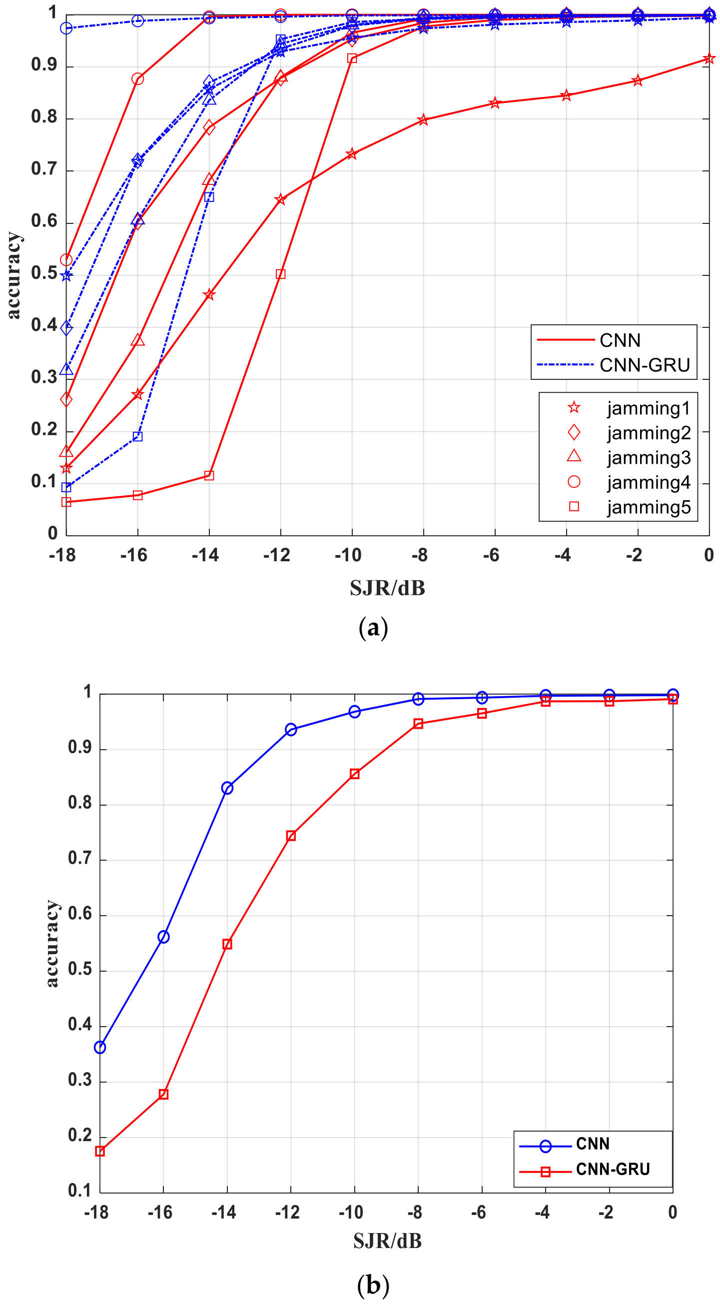


Figure 7. Frequency-hopping sequence estimation accuracy: (**a**) single jamming; (**b**) mixed jamming.

To be more specific, as can be seen from Figure 7a, when the signal-to-jamming ratio was greater than −6 dB, the estimation accuracy of the frequency-hopping sequence of the CNN-GRU network under various single jamming scenarios was close to 100%. Compared with other jamming signals, the CNN-GRU network had a lower estimation accuracy of the frequency-hopping sequence under jamming 5 (sweeping collision-blocking jamming). This was due to the case of the same signal-to-jamming ratio, the frequency band of the swept-frequency collision-blocking jamming was narrower than in other jamming scenarios, and the energy was more concentrated. Moreover, the swept-frequency collision-blocking jamming also had the characteristics of frequency hopping, which was closer to the frequency-hopping signal than other jamming scenarios in the time–frequency diagram, which increases the difficulty of the CNN-GRU network to extract the characteristics of the frequency-hopping signals. Similarly, it can be seen from Figure 7b that when the signal-to-jamming ratio was greater than −8 dB, the estimation accuracy of the frequency-hopping sequence of the CNN-GRU network was close to 100%. The trend observed in the estimation accuracy curve of the frequency-hopping sequence of the CNN-GRU network under mixed jamming was the same as that under single jamming, which indicates that the CNN-GRU network has good generalization ability.

We now analyze the robustness of the CNN-GRU network to various frequency-hopping sequence lengths. The CNN-GRU network was tested by using the frequency-hopping received signals with lengths of 30 hops, 60 hops, 90 hops, and 120 hops, respectively. Other parameter settings remained unchanged. The results are shown in Figure 8. It can be seen that the estimation accuracy curves of the CNN-GRU network for the frequency-hopping sequences of different lengths were very close and had good robustness. This is because the network architecture of recurrent connections was adopted in designing the network, which enabled the network to handle sequence inputs of arbitrary length. In order to achieve more flexible and efficient anti-jamming communication, the frequency-hopping system had to adjust the frequency-hopping sequence in time according to the jamming. Therefore, when the length of the frequency-hopping received signal changed, the network in this section could be used directly without retraining, which greatly increases the scope of application of the network.

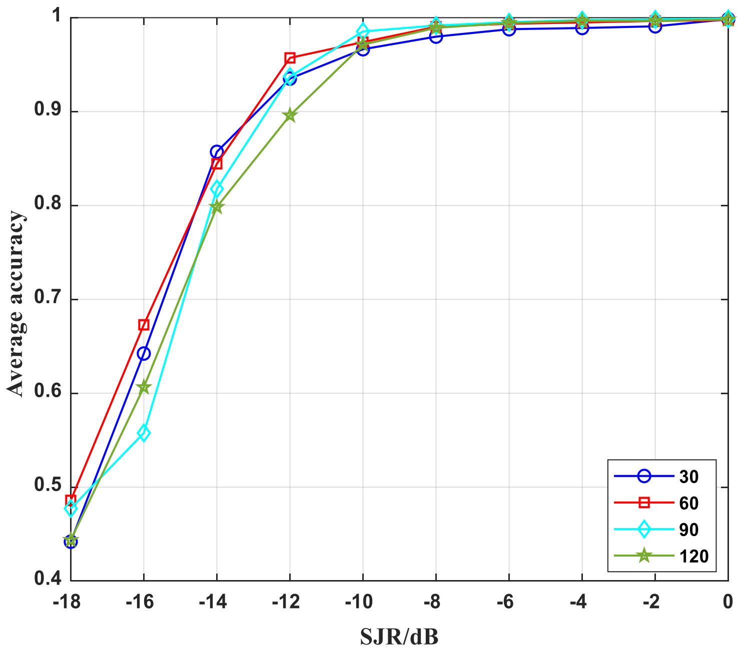


Figure 8. Estimation accuracy of sequences of different lengths.

4.3. Performance of Transfer Learning

In this section, the frequency-hopping communication system with 20 frequency points is used as the object of CNN-GRU network transfer learning. We adopted transfer learning and non-transfer learning, respectively, and the learned network models are denoted as network1 and network2, respectively. We conducted the experiments by choosing different numbers of training samples, and the results are shown in Figure 9.

It can be seen from Figure 9 that the performance of the network model obtained by using the same number of datasets for transfer learning training was better than that of the network model trained without transfer learning. By sharing the parameters of the trained model, the network's ability to extract some basic features of the received signal can be preserved, and training on this basis will greatly improve the performance. With the transfer learning method, when the number of datasets reached 3300 or more, the performance of the trained network model was not significantly improved. Notably, 7700 samples were needed to train the network model without transfer learning to approximate the performance of the network model trained by transfer learning with 3300 samples.

Transfer learning reduced the data demand by 57.1%, which shows that transfer learning has more advantages under the condition of a few-shot scenario.

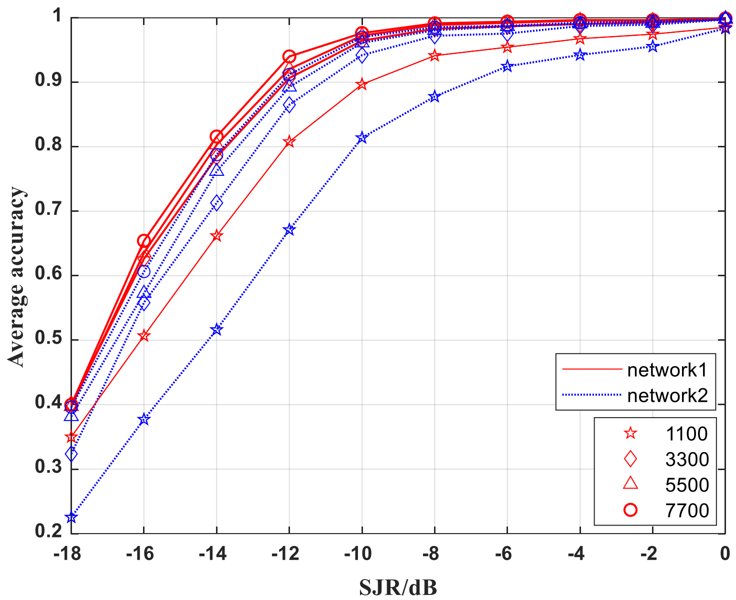


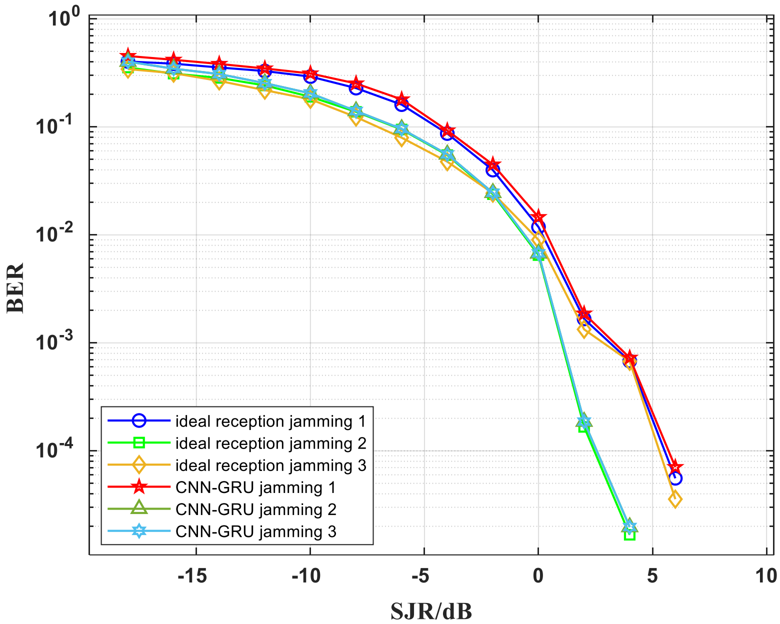
Figure 9. Frequency-hopping sequence estimation accuracy.

4.4. Performance of FH Reception

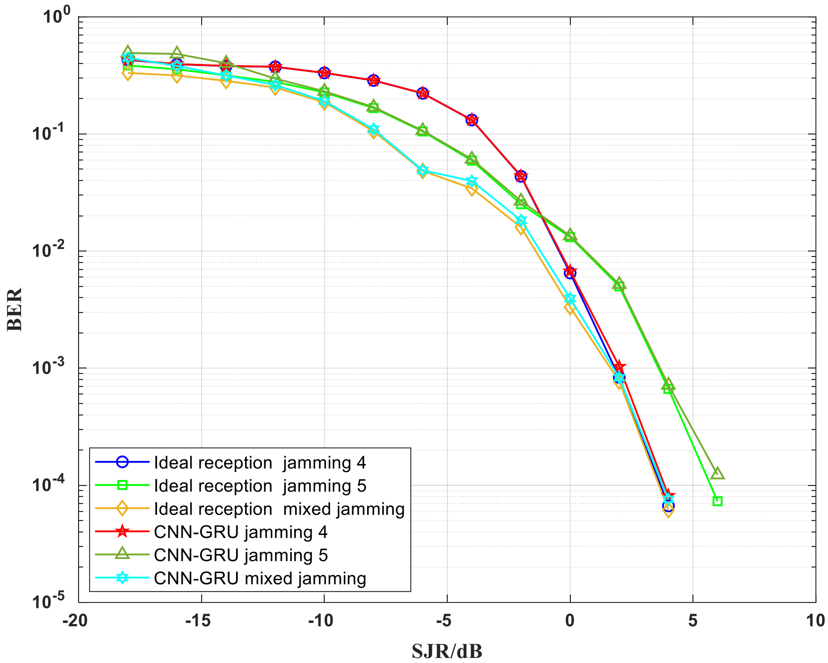
Now, we analyze the bit error rate (BER) of the frequency-hopping receiving system. The CNN-GRU network built in this paper was applied to the receiver of the frequency-hopping communication system, and the 100,000-bit source code sequence was received under five kinds of single jamming and mixed jamming. The BER of the frequency-hopping signal intelligent receiving system based on CNN-GRU is shown in Figure 10, where the ideal frequency-hopping reception refers to an ideal situation in which the receiver knows the frequency-hopping sequence used by the transmitter in advance.

We can see from Figure 10 that the BER performance of the intelligent receiving system was generally close to the ideal frequency-hopping reception. When the signal-to-jamming ratio was lower than −14 dB, because the CNN-GRU-based frequency-hopping signal intelligent receiving system estimated the accuracy of the frequency-hopping sequence at about 80%, the BER was slightly higher than that of the ideal frequency-hopping reception. When the signal-to-jamming ratio was greater than 0 dB, the BER of the frequency-hopping signal intelligent receiving system based on CNN-GRU was slightly higher than that of ideal frequency-hopping reception. This is because the GRU module of the CNN-GRU network had no signal features that could be used to assist inference when estimating the frequency of the first hop, so it was possible to misestimate the frequency of the first hop, resulting in bit errors in the intelligent receiving system.

It should be indicated that when the intelligent frequency-hopping transmitting system adjusted the frequency-hopping sequence according to the electromagnetic environment, the actual conventional frequency-hopping receiving method could not know the frequency-hopping sequence in advance. Therefore, the BER of conventional frequency-hopping reception was close to 50%, while the intelligent receiving system of the frequency-hopping signal based on CNN-GRU could reach the BER close to the ideal conditional reception under the constraints of the known frequency-hopping period.



(**a**)



(**b**)

Figure 10. BER of the receiving systems: (**a**) jamming 1, jamming 2, and jamming 3; (**b**) jamming 4, jamming 5, and mixed jamming.

5. Conclusions

In view of the fact that the transmitter of the frequency-hopping communication system adopts the intelligent frequency-hopping sequence, we designed a CNN-GRU network by combining a convolutional neural network (CNN) with a gated recurrent unit (GRU) for the communication receiving end, which realized the intelligent recovery of the frequency-hopping sequences. Our simulation results showed that the proposed method can estimate the frequency-hopping sequence of any length with high flexibility. With the designed method, the frequency-hopping receiving system achieved a BER performance close to that of the receiving system with known frequency-hopping patterns. In the future, we need to consider the proposed algorithm's performance and compare it with other algorithms. At the same time, we need to design a large number of comparative experiments in the future, including the jamming effects in different scenarios and the effects of algorithm parameters.

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