Secret Key Generation for FDD Systems Based on Complex-Valued Neural Network

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***Abstract*—Secret key generation based on wireless channel reciprocity has received widespread attention. However, in frequency division duplexing (FDD) systems, since the carrier frequencies of the uplink and downlink are different and the channel coefficients are no longer reciprocal, key generation for FDD systems is challenging. In this paper, a Complex-Valued neural Network (CVNet) is proposed to predict the downlink channel and generate reciprocal channel characteristics. Then, based on the trained CVNet, we propose a key generation protocol for FDD systems. Numerical results show that the CVNet achieves better performance in terms of prediction accuracy, bit disagreement rate, and bit generation ratio than a traditional Real-Valued Network (RVNet) under high signal-to-noise ratios. Furthermore, the training parameters required by the CVNet account for only half of that required by the RVNet.**

***Index Terms*—Physical layer security, secret key generation, frequency division duplexing, complex-valued neural network.**

I. Introduction

As the rise of the fifth-generation mobile communication (5G), massive amounts of sensitive and confidential data will be transmitted over wireless channels [1]. Currently, the security of the wireless air interface from the mobile communication base station to the mobile phone terminal is solved by encrypting and transmitting data with a pre-shared key. However, with the explosive growth of the number of network connections, the cost of key distribution has increased dramatically. Researches in recent years have shown that the physical layer secret key generation based on the reciprocity characteristics of the wireless channel can provide a new type of highly secure and convenient physical layer key distribution method.

Although this method can satisfy security well, the prerequisite for effective key generation is the ability to obtain channel features with high similarity. In time division duplexing (TDD) systems, the uplink and downlink channels work in different time slots, and only when the time difference is controlled within the coherence time, the extracted channel features can obtain better similarity. Therefore, in a high-speed mobile scene with a short coherence time, the reciprocity of the channel characteristics of the TDD system is not ideal. In frequency division duplexing (FDD) systems, the uplink and downlink are simultaneously transmitted on two different carrier frequencies, which are not affected by the moving speed, but it is difficult to extract highly similar channel characteristics due to the uplink and downlink are on the different frequency bands.

At present, only a handful of literatures have studied the key generation for FDD systems. Some works have explored the extraction of frequency-independent reciprocity features for FDD systems to generate keys, e.g., the angle and delay of path [2], channel covariance matrix [3], etc. However, there are many limitations in accurately estimating these features, such as multiple antennas, large bandwidth, and special antenna arrays. Besides, some works have adopted different methods to construct reciprocal channels to generate keys. One type of methods uses a loop-back mechanism, which is to generate a reciprocal channel through additional reverse channel training [4]–[7]. However, this type of methods not only adds extra overhead, but also brings security risks [8]. Another type of methods constructs a reciprocal channel by separating the paths, but it is difficult to divide the paths correctly [9].

Since deep learning is data-driven and excellent in performance, it has been widely used in the physical layer in recent years [10]. In [11], a fully connected neural network was proposed for uplink/downlink channel calibration. To further improve the performance, a sparse complex-valued neural network (SCNet) was proposed for downlink channel prediction [12]. Recently, deep learning has also been introduced to the physical layer key generation for FDD systems. In [13], a real-valued key generation neural network (KGNet) was proposed for key generation. In order to promote the performance, we propose a Complex-Valued neural Network (CVNet) for reciprocal features construction and key generation in FDD systems. Since the complex-valued representation is more suitable for representing channel characteristics and can avoid the loss of information, CVNet can better learn the feature correspondence between different frequency bands, and further improve the reciprocity of the constructed channel features.

In summary, this paper makes the following contributions:

- We propose a CVNet for reciprocal features construction, which can reduce the loss of channel information and better learn the channel feature mapping function between different frequency bands. The simulation results prove that using the CVNet under high signal-to-noise ratios (SNRs) can improve performance.

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- Based on the CVNet, we propose a key generation protocol for FDD systems, including training and deployment stages, which can achieve higher bit generation rate (BGR) and lower bit disagreement ratio (BDR) under high SNRs.
- The complexity analysis of the CVNet and the real-valued network (RVNet) shows that the number of FLOPs required by the CVNet and the RVNet are almost the same, and the training parameters required by the CVNet account for only half of that required by the RVNet, which means that less memory is required for saving the CVNet.

The rest of this paper is organized as below. In Section II, we introduce channel model and problem formulation. Then, we propose the CVNet based key generation protocol in Section III. Section IV provides simulation results to evaluate the performance of the proposed protocol. Section V concludes this paper.

II. Channel Model and Problem Formulation

A. Channel Model

Considering a FDD system, with a stationary person Alice and a person Bob with different candidate locations, where Alice and Bob are both equipped with a single antenna. Alice and Bob send signals to each other at different centering frequency f_{AB} and f_{BA}, respectively. If there are L discrete multipath components, the wireless multipath channel impulse response (CIR) can be defined as

$$h(f,\tau)=\sum_{l=0}^{L-1}\alpha_l e^{(-j2\pi f\tau_l+j\phi_l)}\delta(\tau-\tau_l), \tag{1}$$

where f is the center carrier frequency, α_l, τ_l, and ϕ_l are the attenuation, delay, and phase shift of the l^{th} path, respectively.

In an orthogonal frequency-division multiplexing (OFDM) systems with N subcarriers and bandwidth B MHz, the frequency of n^{th} subcarrier relative to the center frequency f is written as $f_n=(n-\frac{N}{2})\Delta f$, where $\Delta f=\frac{B}{N}$ is the frequency difference between two adjacent subcarriers. Thus, the channel frequency response (CFR) of n^{th} subcarrier can be given as

$$H(f,n)=\sum_{l=0}^{L-1}\alpha_l e^{(-j2\pi f\tau_l+j\phi_l)}e^{(-j2\pi\tau_l f_n)}. \tag{2}$$

Based on the channel model, we can get the CFR of channels with frequencies of f_{AB} and f_{BA}, which can be written as

$$\begin{cases}\mathbf{H}_{AB}=\{H(f_{AB},1),...,H(f_{AB},N)\}\\ \mathbf{H}_{BA}=\{H(f_{BA},1),...,H(f_{BA},N)\}\end{cases}. \tag{3}$$

B. Problem Formulation

According to (2), it can be seen that the CFR of frequency f is made up of multipath channel parameters which include α_l, τ_l, ϕ_l and f_n. Among them, α_l is affected by the frequency f; $\tau_l=\frac{d_l}{c}$, where d_l is the distance of the l^{th} path propagated

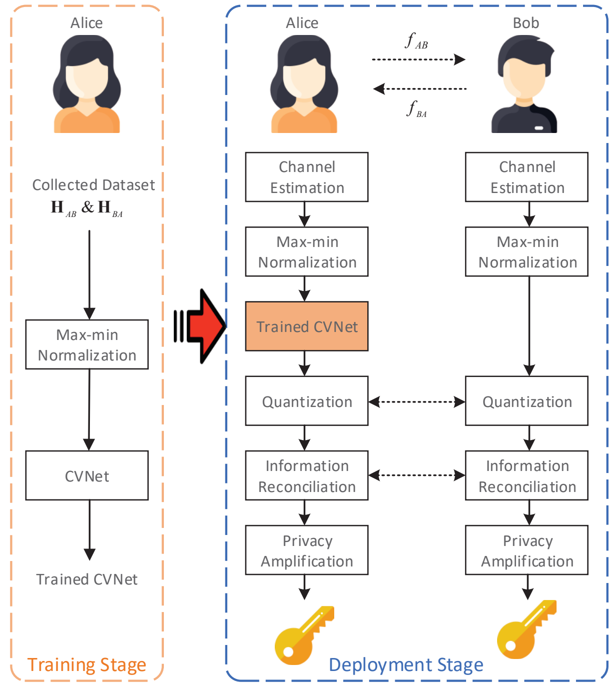

Fig. 1. The CVNet based key generation protocol for FDD systems.

between Alice and Bob, is frequency independent; ϕ_l and f_n is also frequency independent [9]. Some studies have used these frequency-independent parameters (e.g., τ_l) to generate keys for FDD systems [2]. However, these accurate estimates of these parameters require too much system performance. Therefore, extracting or constructing a reciprocal characteristic parameter to generate keys for FDD systems is still an unsolved problem.

What is exciting is that although the channel changes with frequency, the underlying physical path and scattering clusters remain unchanged [14], [15]. Furthermore, the existence of a certain mapping relationship between channels in different frequency bands is proved in [16]. Inspired by this, this paper uses the mapping relationship between different frequency bands to generate keys for FDD systems. We define the channel mapping function $\mathbf{\Psi}_{f_{BA}\to f_{AB}}$, i.e.,

$$\mathbf{\Psi}_{f_{BA}\to f_{AB}}=\mathbf{H}_{BA}\to\mathbf{H}_{AB}. \tag{4}$$

However, the frequency has an impact on the amplitude and phase of the CFR, and the CFR gap of different frequencies is more obvious under the superposition of multiple paths. Therefore, the existing mathematical methods are difficult to solve the mapping function. To solve this problem, this paper proposes the CVNet to obtain the mapping function, and uses the trained CVNet to generate reciprocal channel features for key generation in FDD systems. The proposed FDD key generation protocol as shown in Fig. 1. The protocol has two stages, i.e., training stage and deployment stage. In the training

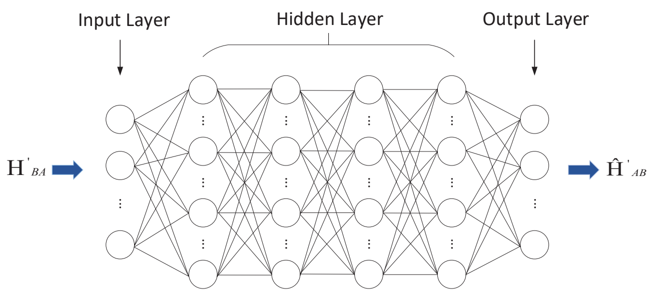

Fig. 2. The CVNet architecture.

stage, Alice uses the collected dataset for training the CVNet. In the deployment stage, the trained CVNet can be used for reciprocal features construction and key generation. The proposed key generation protocol will be described in detail in Section III. To our knowledge, this paper is the first time to apply the complex-valued neural network for key generation in FDD systems.

III. The Proposed CVNet based Key Generation Protocol

In this section, we first introduce the architecture of the CVNet and how to train it. Then, we discuss how to use it for key generation in FDD systems.

A. CVNet Architecture

The proposed CVNet is used to enable Alice and Bob to obtain reciprocal channel characteristics, and its structure is shown in Fig. 2. The CVNet includes four hidden layers, an input layer and an output layer. Compared with the traditional real-valued networks, the CVNet avoids the separation of the real and imaginary parts, which can better learn the mapping function between the complex-valued CFRs of different frequency bands.

As can be seen from Fig. 2, the input of the CVNet is $\mathbf{H}^{'}_{BA}$ obtained after a max-min normalization of $\mathbf{H}_{BA}$, the output of the CVNet is a representation $\hat{\mathbf{H}}^{'}_{AB}$ obtained by mapping $\mathbf{H}^{'}_{BA}$, i.e.,

$$\hat{\mathbf{H}}^{'}_{AB} = \mathbf{CVNet}_{\mathbf{\Omega}}(\mathbf{H}^{'}_{BA}), \tag{5}$$

where $\mathbf{CVNet}_{\mathbf{\Omega}}(\cdot)$ denotes the CVNet, and $\mathbf{\Omega}$ denotes the network parameters to be trained. Moreover, except for the output layer, the activation functions of other layers are the complex rectified linear unit (CReLU), i.e.,

$$\text{CReLU}(x) = \text{ReLU}(\Re(x)) + j\ \text{ReLU}(\Im(x)), \tag{6}$$

where $\Re(\cdot)$ and $\Im(\cdot)$ are the real and imaginary parts of the value x, $\text{ReLU}(\cdot)$ can be written as,

$$\text{ReLU}(z) = \begin{cases} z & z \geq 0 \\ 0 & z < 0. \end{cases} \tag{7}$$

The activation of the output layer is complex sigmoid function. Similar to (6), only change ReLU to sigmoid function.

B. Training Stage

Since the various subcarriers of CFRs are of different magnitudes, and for the convenience of subsequent quantification, a max-min normalization is indispensable before training the network. We perform the max-min normalization on the real part and the imaginary part, respectively. The minimum and maximum values of the real and imaginary in each subcarrier of $\mathbf{H}_{BA}$ and $\mathbf{H}_{AB}$ in the training dataset are used and saved for the max-min normalization, i.e.,

$$\Re(\mathbf{H}^{'}) = \frac{\Re(\mathbf{H}) - min(\Re(\mathbf{H}_{Train}))}{max(\Re(\mathbf{H}_{Train})) - min(\Re(\mathbf{H}_{Train}))}, \tag{8}$$

where $\mathbf{H}^{'}$ is the normalized complex value of $\mathbf{H}$. The operation of normalizing the imaginary part is similar to the above.

Then, the dataset $\{\mathbf{H}^{'(m)}_{AB}, \mathbf{H}^{'(m)}_{BA}\}_{m=1}^{M}$ including M samples can be used for training the network. The goal of the proposed CVNet is to obtain the mapping function between $\mathbf{H}'_{AB}$ and $\mathbf{H}'_{BA}$. Therefore, The loss function of CVNet can be expressed as

$$Loss(\mathbf{\Omega}) = \frac{1}{N * M} \sum_{m=1}^{M} \parallel \hat{\mathbf{H}}^{'(m)}_{AB} - \mathbf{H}^{'(m)}_{AB} \parallel_2^2, \tag{9}$$

where $\parallel \cdot \parallel_2$ denotes the ℓ_2 norm. After training the CVNet, the parameters are fixed, CVNet can be used in the deployment of key generation in FDD systems.

C. Deployment Stage for Key Generation

Similar to the traditional key generation process, the deployment stage for key generation consists of the following steps.

1) Channel Estimation: Channel estimation is the first step to obtain channel randomness characteristics. Unlike the TDD system where Alice and Bob need to send pilots alternately, Alice and Bob send pilots to each other simultaneously and perform channel estimation based on the received signal to obtain channel measurement values in FDD systems. Therefore, the FDD mode does not need to meet the premise of coherence time, and is not affected by mobility. Additionally, since this paper mainly explores the channel reciprocity in FDD systems, it is assumed that the channel estimation is completely correct.

2) Reciprocal Features Construction: Although the FDD system is not affected by mobility, the characteristics obtained after channel estimation are not reciprocal since Alice and Bob transmit on different frequency bands. This paper uses the trained CVNet to construct the reciprocal channel characteristics. For Alice, she first performs a max-min normalization on the features obtained by channel estimation, and then uses CVNet to predict the channel features obtained by Bob. For Bob, he only needs to perform a max-min normalization on the features obtained by channel estimation.

3) Quantization: Quantization is the process of converting highly reciprocal channel characteristics into binary values. In this paper, we focus on the mean value μ and standard deviation σ based quantization method. Different from [17], [18] which estimate the mean and variance of the amplitudes of measured values in a time series, this paper estimate the mean and variance of the real and imaginary parts of the CFRs across subcarriers, i.e.,

$$\mu = \frac{1}{2N}\sum_{n=1}^{N}(|\Re(H(f,n))| + |\Im(H(f,n))|), \tag{10}$$

$$\sigma^2 = \frac{1}{2N-1}\sum_{n=1}^{N}\{(|\Re(H(f,n))| - \mu)^2 + (|\Im(H(f,n))| - \mu)^2\}. \tag{11}$$

Then, the thresholds are determined as

$$\eta_+ = \mu + \alpha \cdot \sigma, \tag{12}$$

$$\eta_- = \mu - \alpha \cdot \sigma, \tag{13}$$

where α is the quantization factor. The values above η_+/ below η_- will be converted to 1/0, and between η_+ and η_- will be converted to -1. Alice and Bob both quantize the real and imaginary parts of the features according to this quantization method to obtain a sequence with a length of $2N$. After that, Alice and Bob exchange all indexes with the value of -1 and drop them. Through this step, Alice and Bob can obtain the initial keys Q_A and Q_B, respectively.

4) Information Reconciliation and Privacy Amplification: After quantization, there are still inconsistent bits between Alice and Bob, information reconciliation (e.g., Cascade [19], low-density parity-check (LDPC) [20]) needs to be used to reconcile these error bits. Furthermore, privacy amplification uses hashing function to reduce information leakage during information reconciliation. Information reconciliation and privacy amplification can greatly reduce the disagreement bits between the two parties. However, the focus of this paper is on the initial key consistency in the FDD system, so we only observe the key generation performance without this step.

IV. Simulation Results

In this section, the proposed method is simulated and verified. We focused on comparing the performance of the RVNet and the CVNet.

A. Dataset Generation and Simulation Setup

We generate dataset by using the indoor scene 'I1' provided by the DeepMIMO dataset [21] and is generated based on the accurate 3D ray-tracing simulator Wireless InSite [22]. As depicted in Fig. 3, the number of BS and users are set to 1 and 100,000, respectively. We assume that the BS is Alice, and 100,000 users are considered as possible locations for Bob. Additionally, the number of the paths is 5, the number of subcarriers is 64. f_{AB} and f_{BA} are 2.5 GHz and 2.4 GHz, respectively. Among the 100,000 samples of CFR data, 80,000 samples are used for training, 20,000 samples are used to test and evaluate the performance of the CVNet and the initial keys. Additionally, in order to improve the robustness of the system, we randomly select 20,000 samples in the training dataset and add Gaussian white noise to make the SNR 0 dB.

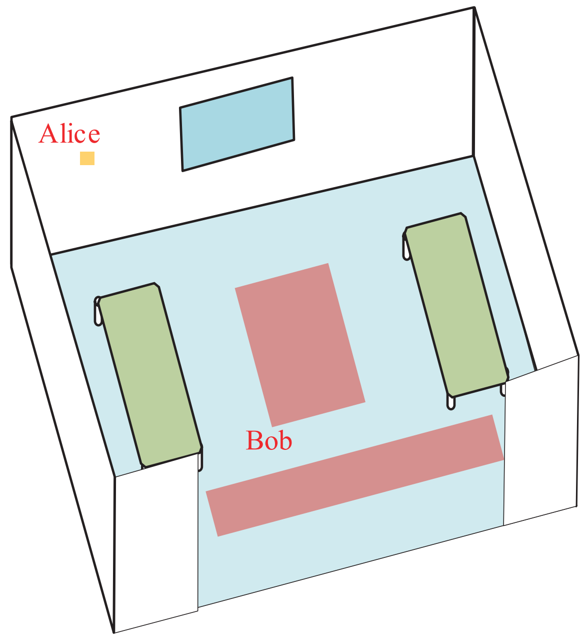

Fig. 3. The simulation scenario. The yellow little box on the ceiling represents Alice, the two red rectangles are the possible user locations of Bob.

TABLE I
Parameters for the CVNet

Parameter	Value
Number of neurons in Input/Output layers	64
Number of neurons in hidden layers	(256,512,512,256)
Optimization	ADAM [23]
Learning rate	1e-3
Number of epochs	500
Batch size	128
Number of training samples	80,000
Number of testing samples	20,000

We combine these 20,000 samples with SNR of 0 dB and the original 60,000 samples without adding noise to form the training dataset. Gaussian white noise is also added to the testing dataset to generate datasets with different SNRs to test the robustness of the proposed method.

Based on the modular code for complex-valued neural networks in [24], [25], the proposed CVNet employs Keras with the TensorFlow backend as the deep learning framework. The CVNet is implemented on a workstation with one Nvidia GeForce GTX 1660Ti GPU. The parameters of the CVNet are given in Table I.

B. Results

1) Results of The CVNet: The performance of the CVNet determines the quality of the feature reciprocity of the structure. In order to better observe the performance of the CVNet, we compare the CVNet with two benchmarks. A benchmark is *a direct method* that does not require the use of a network for channel feature mapping like a TDD system. The second benchmark is *a RVNet based key generation method* for FDD

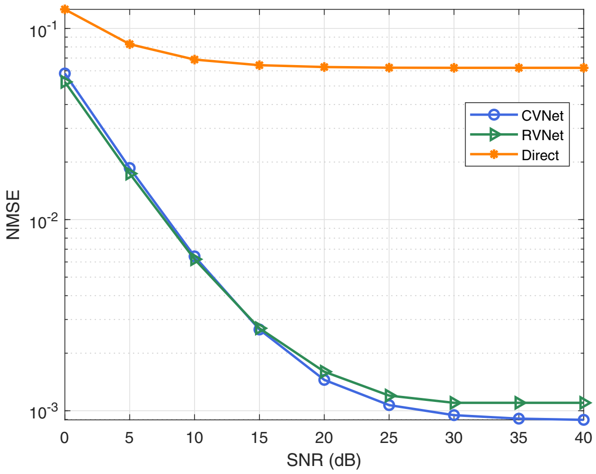

Fig. 4. The NMSE performance versus SNR

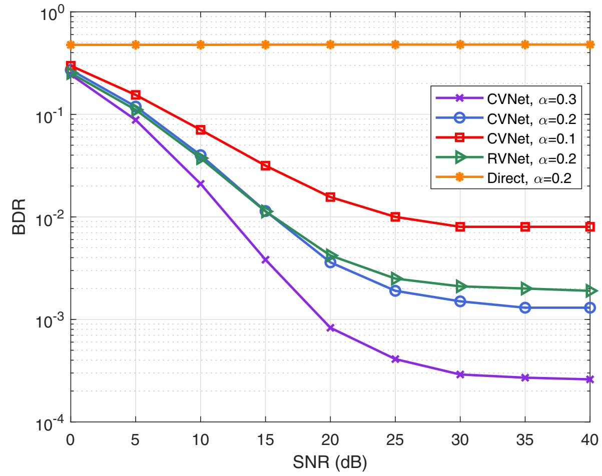

Fig. 5. The BDR performance versus SNR

systems. Since the complex number needs to be split into the real part and the imaginary part as the input of the RVNet, the input and output dimensions of the RVNet are 128, and we choose the number of neurons in the hidden layer as (512, 1024, 1024, 512).

Normalized Mean Square Error (NMSE) is used to evaluate the performance of the CVNet, which is defined as

$$\mathrm{NMSE} = E\left[\frac{\| \widehat{\mathbf{H}}'_{AB} - \mathbf{H}'_{AB} \|_2^2}{\| \mathbf{H}'_{AB} \|_2^2}\right], \tag{14}$$

where $E[\cdot]$ represents the expectation operation. As shown in Fig. 4, the reciprocity of the channel characteristics obtained after using the network is far superior to the performance after not using the network. This also means that the methods used in TDD systems are completely unusable in FDD systemsss. Furthermore, comparing the NMSE performance of CVNet and RVNet, the performance of CVNet is better when the SNR is higher than 15 dB, and the performance of RVNet is slightly better than that of CVNet when the SNR is lower than 15 dB.

2) Results of The Initial Keys: We evaluate the initial key in terms of BDR and BGR. BDR is defined as the inconsistent bit rate in the initial keys Q_A and Q_B. BGR is defined as the number of bits of the initial keys Q_A and Q_B divided by the number of subcarriers, i.e., the average number of bits that can be generated by the channel characteristics on one subcarrier.

Fig. 5 and Fig. 6 compare the BDR and BGR performance of the initial keys generated by the three methods. As the SNR increases, the BDR of the initial keys generated by the three methods will decrease, and the BGR will increase. Obviously, the performance of the direct method is poor, and the BDR of the generated initial key is about 0.5 under different SNRs, which means that the keys generated by Alice and Bob are basically irrelevant. The performance of the initial keys generated based on CVNet and RVNet is roughly similar.

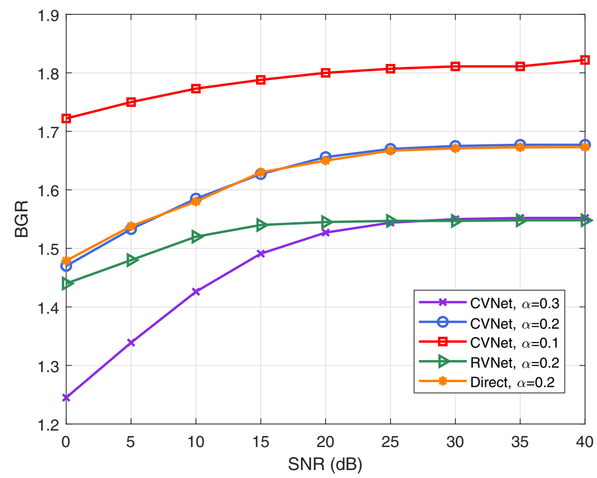

Fig. 6. The BGR performance versus SNR

In the case of high SNR, the performance of the method based on CVNet is better than that based on RVNet.

Through the above results, we can find that the performance of the CVNet based key generation method and the RVNet based key generation method are similar. Only in the case of high SNR, the CVNet based key generation method will be better than the RVNet based method. Next, we mainly analyze the complexity of the two methods.

C. Complexity Analysis

Firstly, we analyze the required number of floating point operations (FLOPs). Denote K_r as the number of neurons in the r^{th} layer, K_0 as the number of neurons in the input layer, and R is the total number of layer including input and output layers. For RVNet, the total number of FLOPs required is $\sum_{r=1}^{R-1}(K_{r-1}+1)K_r$. Since the FLOPs performed by complex multiplication is 4 times that of real multiplication, the total number of FLOPs required is $4*\sum_{r=1}^{R-1}(K_{r-1}+1)K_r$ for the

CVNet. In this paper, the number of neurons in each layer of the CVNet is (64, 256, 512, 512, 256, 64), and the number of neurons in each layer of the RVNet is (128, 512, 1024, 1024, 512, 128). After calculation, the FLOPs required by the CVNet are 2,234,624, and the FLOPs required by RVNet are 2,231,424. The FLOPs required for the CVNet and the RVNet are almost the same.

Next, we analyze the number of trained parameters required for training in these two methods. For the RVNet, the number of trained parameters required is $\sum_{r=1}^{R-1}(K_{r-1}+1)K_r$. Since the trained complex number parameters are divided into real and imaginary parameters for the CVNet, the number of trained parameters required is $2*\sum_{r=1}^{R-1}(K_{r-1}+1)K_r$. Although it seems that the CVNet needs to store more parameters, it needs to be emphasized that the number of neurons in each layer of the CVNet is only half of that of the RVNet. After calculation, the trained parameters required by the CVNet are 1,117,312, and the trained parameters required by the RVNet are 2,231,424. The trained parameters required by the CVNet are only half of those required by the RVNet. This means that saving the CVNet requires only half of the memory space required by the RVNet.

V. Conclusion

In this paper, we proposed the CVNet to construct the reciprocal features of the communication parties. Then, we proposed the CVNet based key generation protocol for FDD systems. The simulation results show that the traditional key generation methods used in TDD systems cannot be directly used in FDD systems, and the proposed CVNet-based key generation method achieves better performance than the RVNet-based method in terms of NMSE, KDR, KGR under high SNRs. Furthermore, through complexity analysis, it can be found that the number of FLOPs required by the CVNet and the RVNet is almost the same, while the training parameters required by the CVNet are only half of those required by the RVNet. In the future, we will evaluate this method on experimental dataset.

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