Deep Leaning Aided NOMA Combining Different NOMA Schemes

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Abstract. Non-orthogonal multiple access (NOMA) is a promising technique for future wireless communication. Compared with orthogonal multiple access (OMA), it provides high spectral efficiency and the ability to support a large number of users. A novel DNN-NOMA scheme is proposed in this paper. Both the encoder and decoder of it are composed of deep neural networks (DNN). This DNN-NOMA scheme combines power-domain NOMA, sparse code multiple access (SCMA) and multi-user shared access (MUSA), which means all of these NOMA schemes can be regarded as a special case of it. DNN-based encoders and decoders are able to generate appropriate codebooks and decode received signals automatically. The orthogonal resources (OR) used by each user are automatically determined in the process of optimizing network parameters. The simulation results prove that the BER of this novel DNN-NOMA scheme is lower than other NOMA schemes. Moreover, because there is no need to design the codebook manually, it can easily adapt to different numbers of users and ORs.

Keywords: NOMA · Deep learning · SCMA

1 Introduction

As one of the most important and key technologies, multiple access has always been a focus of mobile communication. With the number of users increasing rapidly, non-orthogonal multiple access NOMA [1] becomes an inevitable choice. Although it has higher computational complexity compared with OMA, it improves the spectrum efficiency greatly [2].

SCMA evolved from low density signature (LDS) [3]. This scheme uses codebooks to complete spreading and constellation mapping. Signals from multiple users are overlaid on the same time-frequency resources sparsely. At the receiver, message passing algorithm (MPA) is the most commonly used decoding algorithm. Codebook design is a key problem and has a strong influence on the performance of SCMA. In [4], a basic codebook design method using lattice rotation technique is proposed. According to the lattice theory, SCMA receiver achieves better performance in higher dimensions [5]. Thus, in [5] and [6], new SCMA codebook design methods which could construct large size codebooks have been proposed.

Power domain NOMA distinguishes data of different users by allocating different transmitting power. Compared to OMA, the spectral efficiency of power domain

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NOMA can be improved by 30% [7]. In [8], the optimal power allocation under different conditions and constraints has been studied.

MUSA uses complex sequences as spreading sequences [9]. Each user chooses a spreading sequence and carry out spreading. The choice of spreading sequences and the algorithm used at the receiver have great impact on the performance of MUSA scheme [10]. In [11], a multi-stage partial parallel interference cancellation detection algorithm which does not require repeated ordering and repeated matrix inversion has been proposed. It can reduce the computational complexity with a good error rate when the overload rate is low. In [12], a blind multi-user detection without reference signal has been proposed.

In recent years, deep learning has developed rapidly, and its application in the physical layer has become more and more widespread. In [13], a belief propagation algorithm based on deep learning aiming to decode high-density parity check (HDPC) code was proposed. In [14], a DNN based encoder and decoder was used in SCMA. This encoder is able to generate codebooks automatically.

The key to all NOMA schemes is serving multiple users in the same time frequency resource. Thus, in this paper, a novel DNN-NOMA model is proposed, which is a generalized NOMA model. Multiple NOMA schemes (power-domain NOMA, SCMA, MUSA) can be regarded as special cases of it. They can be implemented by adjusting the parameters in the DNN or simply changing the network structure. The simulation shows that the proposed DNN-NOMA model performs better than other NOMA schemes.

The rest of this paper is organized as follows. The system model of DNN-NOMA is described in the second section. In the third section, we discussed the structure and training method of it in detail. The simulation results are shown in the fourth section. Finally, the conclusion is given in the fifth section.

2 System Model and DNN-NOMA Structure

2.1 System Model

Assume that the signals of J users is transmitted to the receiver through K ORs, e.g. OFDMA tones. In NOMA schemes, set $K < J$ so that non-orthogonal resource allocation is inevitable. The user overload rate (OR) is defined as $\mathrm{OR} = \frac{K}{J}$. More than one user's data is transmitted simultaneously on each resource. The received signal can be expressed as below.

$$\mathbf{y} = \sum_{j=1}^{J} \sqrt{p_j}\, diag(\mathbf{h}_j)\mathbf{x}_j + \mathbf{n} \tag{1}$$

where $\mathbf{x}_j \in \mathbb{C}^{K\times 1}$ indicates the normalized signal of the jth user, p_j is the transmit power of the jth user, $\mathbf{h}_j = (h_{1j}, h_{2j}, \ldots, h_{Kj})$ is the channel vector between the jth user and the receiver, and $\mathbf{n}$ is the additive white Gaussian noise (AWGN). The total power of the transmit signals for all users is $P = \sum_{j=1}^{J} p_j$ and the number of multiplexed layers is J.

In power-domain NOMA, the vector $\mathbf{x}_j$ usually contains only one nonzero element, which means each user only transmits signals on one resource. In SCMA, $\mathbf{x}_j$ is a sparse vector containing zero elements. $x_{kj} = 0$ means the jth user does not transmit signals on the kth resource. In MUSA, each user transmits signals on all resources, so there is no zero element in $\mathbf{x}_j$. Moreover, p_j is transmit power allocated to the jth user. p_j is 1 in SCMA and MUSA, because these two schemes are usually implemented without power allocation.

2.2 DNN-NOMA Model

We built DNN encoder and decoder at the transmitter and receiver respectively. The input of the encoder is the data from users, which is binary. The encoder consists of a few DNN units and each DNN unit serves one user. The output of DNN encoder is the modulated signals which can be used to transmit on the channel. Then, the signals reach the receiver through the channel and binary data reconstructed in the decoder.

$f(\cdot)$ and $g(\cdot)$ are used to denote the encoder and decoder respectively. Suppose that $\mathbf{r}$ represents users' data and $\hat{\mathbf{r}}$ represents the reconstructed data after encoding and decoding. Then, the relationship between $\mathbf{r}$ and $\hat{\mathbf{r}}$ can be expressed as $\hat{\mathbf{r}} = g(f(\mathbf{r}))$. By minimizing the Euclidean distance between $\mathbf{r}$ and $\hat{\mathbf{r}}$, the network parameters can be optimized.

3 Proposed Scheme

In this part, the DNN-NOMA network structure, the physical meaning of each part in DNN and training procedure is explained in detail. The structure of DNN-NOMA is shown in Fig. 1. Data from users are encoded in the encoder and transmit on the orthogonal resources, and the decoder reconstruct them according to the received signals.

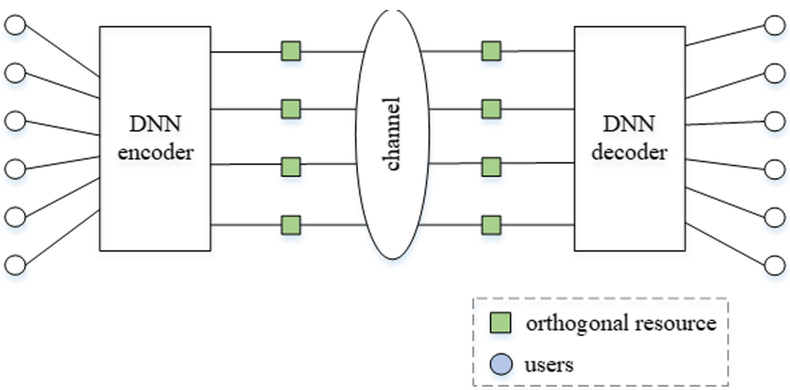

Fig. 1. DNN-NOMA structure.

3.1 DNN Encoder

The structure of DNN encoder is shown in Fig. 2. The encoder consists of multiple DNN units and each DNN unit is connected to a user. User data is encoded by the DNN unit connected to it. Hence, the number of DNN units equals to the number of users. Unlike [14], each DNN unit is connected to all ORs in this scheme, so the users can choose the ORs they use and find the best scheme during training.

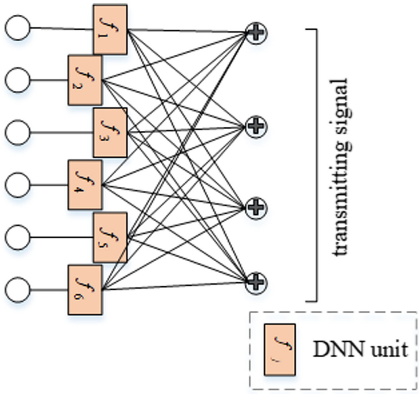

Fig. 2. The structure of DNN encoder.

The structure of each DNN unit is depicted in Fig. 3. Each DNN unit is composed of many fully connected layers. There are M input nodes because the encoder is M-ary. The number of hidden layers is 4 and each hidden layers consists of 32 nodes. Since DNN cannot calculate complex numbers, we split the real and imaginary parts of the signal. Thus, there are $2K$ output nodes in the output layer. Each part corresponds to one node in the output layer of the unit.

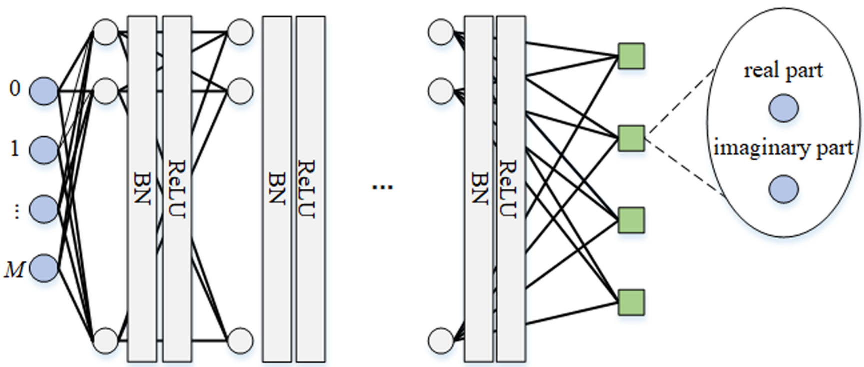

Fig. 3. The structure of DNN unit.

Then, the received signal can be written as below:

$$\mathbf{y}_{\mathrm{DNN}} = \sum_{j=1}^{J} \mathbf{h}_j f_j(r_j) + \mathbf{n}_j \tag{2}$$

3.2 DNN Decoder

In some NOMA schemes, each user may transmit signals on more than one OR, and the signals of different users are multiplexed over orthogonal resources. Hence, when decoding the signal of a certain user, the signals of the users which use the same ORs will affect the decoding result.

In order to combine the information scattered on all resources, we use a fully connected (Fully Connected, FC) network as decoder. The structure is shown in Fig. 4. The input layer is connected to all ORs. The input of the decoder is the received signals and the output represents the decoding results. The result of each user is represented by the value of M output nodes. There are 4 hidden layers and each layers has 64 neural nodes in the decoder.

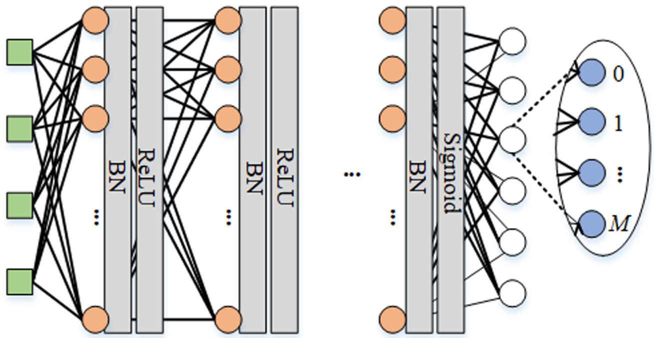

Fig. 4. The structure of decoder.

3.3 Training

Obviously, it is difficult to express the principle of optimal codebook design, so we train the network by minimizing the BER. The encoder and decoder are regarded as one network when training. We use randomly generated binary data stream as training set and test set. The training process of the network can be regarded as an optimization process according to the least square.

$$\min_{\lambda} \|\mathbf{r} - g(\mathbf{y}_{\mathrm{DNN}})\| = \min_{\lambda} \left\| \mathbf{r} - \sum_{j=1}^{J} \mathbf{h}_j f_j(r_j) + \mathbf{n}_j \right\|_2 \tag{3}$$

where λ represents the parameters of encoder and decoder, $\mathbf{r}$ is the original data, $g(\mathbf{y}_{\mathrm{DNN}})$ is the reconstructed data, and $\|\cdot\|_2$ represents the Euclidean distance.

The loss function can be defined as

$$L(\mathbf{r}, \hat{\mathbf{r}}; \lambda_f, \lambda_g) = L(\mathbf{r}, g(\mathbf{h}f(\mathbf{r}; \lambda_f) + \mathbf{n}; \lambda_g) = \left\|\mathbf{r} - g(\mathbf{h}f(\mathbf{r}; \lambda_f) + \mathbf{n}; \lambda_g)\right\|_2 \tag{4}$$

where λ_f and λ_g represent the parameters in DNN encoder and DNN decoder respectively.

According to the loss function, we use mini-batch gradient descent (MBGD) algorithm to update the parameters. The update process can be expressed as

$$(\lambda_f, \lambda_g)^+ := (\lambda_f, \lambda_g) - \alpha \nabla L(\mathbf{r}, \hat{\mathbf{r}}; \lambda_f, \lambda_g) \tag{5}$$

where α is the learning rate, determining the step size of updating in each iteration. Here we set $\alpha = 0.0001$.

4 Simulation Results

The simulation results are shown in this section. Among the three non-orthogonal multiple access technologies (power-domain NOMA, SCMA, MUSA), SCMA has the best BER performance. Thus, we compare the results of proposed DNN-NOMA with conventional SCMA.

The simulation parameters are shown in Table 1.

It is noted that SNR of the training data needs to be carefully selected. On the one hand, if the SNR is too high, the anti-noise performance of codebooks designed by DNN-encoder will be bad. On the other hand, if the SNR is too low, noise in the received signal will seriously affect the training of decoder. We refer to literature [14] and choose SNR of training data after exhaustive searches.

Table 1. The simulation parameters for proposed DNN-NOMA scheme

Simulation parameters	Parameters configuration
Training algorithm	MBGD
Modulation	QAM
Loss function	mean-square error (MSE)
Learning rate	0.0001
Number of training samples	1000000
SNR of training data	4 dB, 6 dB, 8 dB
Channel	AWGN
Number of orthogonal resources	4, 8, 6
Number of users	6, 12, 24
Overloading rate	1.5

The results of proposed DNN-NOMA and conventional SCMA are shown in Fig. 5. The number of users and number of orthogonal resources are 6 and 4 in the simulation respectively. According to Fig. 5, the proposed DNN-NOMA scheme significantly outperforms the conventional SCMA.

The main reasons for the better performance of DNN-NOMA are summarized as follows.

1) Unlike SCMA, in DNN-NOMA scheme, the orthogonal resources used by each user is not fixed. They are automatically determined in the process of training.
2) In SCMA, the performance heavily depends on the codebook. In MUSA, it depends on the spreading code. In the proposed DNN-NOMA scheme, if the number of hidden layers and nodes of the neural network is sufficient, the best codebook and transmitted signal can be obtained theoretically.

The results of DNN-NOMA with different numbers of users and ORs are shown in Fig. 6. According to the Fig. 6, the performance of DNN-NOMA improves with the increase of the number of users and codebook dimensions. This phenomenon is similar to SCMA [5, 6].

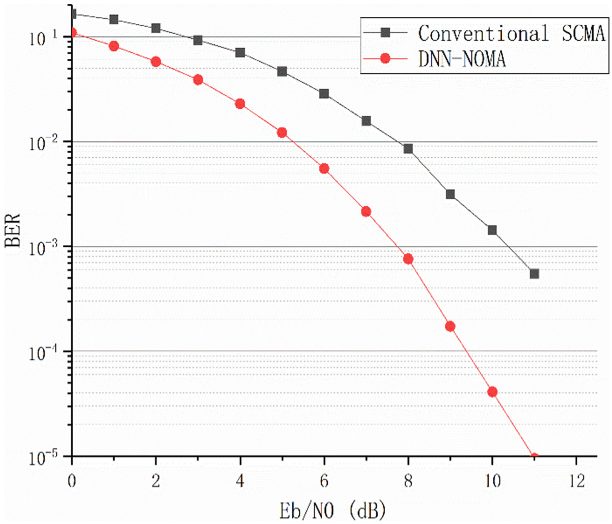

Fig. 5. BER of conventional SCMA and DNN-NOMA.

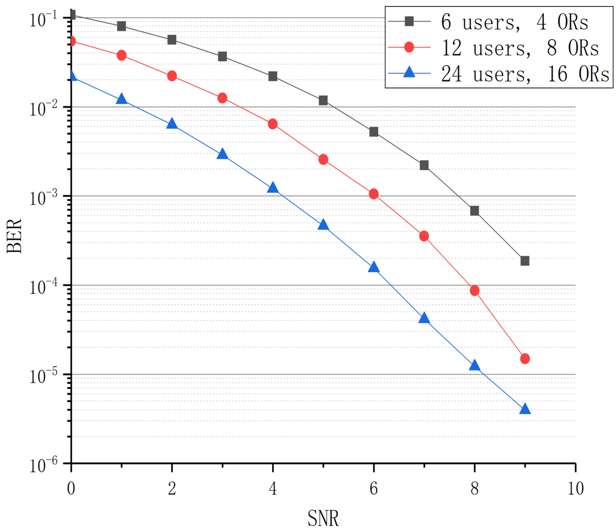

Fig. 6. BER of DNN-NOMA with different number of users.

5 Conclusion

We proposed a DNN-NOMA scheme and three NOMA schemes (power-domain NOMA, SCMA, MUSA) can be regarded as special cases of it. In this scheme, user data can be automatically encoded and decoded. The simulation results show that the DNN-NOMA scheme can achieve better BER performance than other NOMA schemes.

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