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Deep Learning Based MIMO Transmission with Precoding and Radio Transformer Networks

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Abstract

In this paper, we study MIMO transmission schemes based on deep learning (DL). We propose a novel DL-based MIMO communication structure by combing a beamforming network at the transmitter side and a radio transformer network (RTN) at the receiver side. Compared with the classical DL-based MIMO communication systems, the interference is potentially mitigated by a precoding network and a RTN network, which is thus beneficial to improve the performance of signal detection. Simulation results show that the proposed scheme outperforms the classical MIMO transmission schemes in terms of bit error rate (BER).

Keywords: Deep Learning; Multiple-Input Multiple Output (MIMO); Precoding; Radio Transformer Network

1. Introduction

Multiple-input multiple-output (MIMO) technology has been widely used in modern wireless communication systems due to its potential in improving throughput and coverage via spatial multiplexing [1, 11, 5]. Since multiple data streams are transmitted in parallel in a spatial multiplexing MIMO system[2, 3, 4], it is critical to precode transmitted signals at the transmitter side and post-process received signals at the receiver side[7, 6, 19]. Many classical spatial multiplexing methods have been proposed and widely adopted in MIMO transmissions, such as zero-forcing (ZF) precoding and minimum mean-squared error (MMSE) receiver, etc.

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In recent years, deep learning (DL) technology has gained considerable attention in wireless communication areas, due to its capability in representing complex communication systems that are indescribable with explicit mathematical models [12, 13]. It is becoming a hot topic to design wireless communication systems based on DL [15, 18, 20], such as signal classification, channel estimation and performance optimization, etc. Due to the same reason, it is also promising to apply DL in MIMO systems.

The pioneer work on DL-based MIMO communications was presented in [14] and [17], where the autoencoders were used to optimize the encoding and decoding processes through end-to-end deep learning. It was demonstrated that DL-based methods have the potential to approach, or even exceed the performance of classical methods. This sheds new lights on the system design of MIMO communication systems. However, the end-to-end learning MIMO communication systems based on the autoencoder is data-driven, where communication systems are treated as black boxes. Correspondingly, the transceivers are optimized without considering the expert knowledge, such as the channel state information (CSI) [9]. To incorporate expert knowledge for performance improvement, the radio transformer networks (RTN) was first proposed in [16] for modulation recognition, and lately used for DL-based receiver design in [13]. The RTN is regarded as a model-driven DL network, which is capable of enhancing signal processing ability and accelerating convergence. The experiment results in [14] and [9] demonstrated that the MIMO systems were also beneficial from RTN structures with respect to convergence speed and BER performance.

In this paper, we propose an improved DL-based MIMO transmission structure with a precoding network at the transmit side and an RTN at the receive side. In the proposed transmission structure, the transmitter consists of two sequentially connected neural networks (NNs). The former one accepts the transmitted symbols and performs basic encoding, while the later one incorporates the encoded symbols and channel state information to conduct precoding. Such a structure is a mimic to the traditional precoding module, which is able to effectively suppress inter-stream interference. This is different from the classical end-to-end DL MIMO structure proposed in [14], where the output of the encoder at the transmitter side is sent to the antennas directly. At the receiver side, we adopt the RTN structure for decoding enhancement. The simulation results show that the proposed DL-based MIMO transmission structure outperforms the classical schemes.

2. Deep Learning Based MIMO Transmission

In this section, we propose a DL transceiver optimization structure by combing the idea of RTN with precoding.

2.1. Basic Structure of DL-based MIMO

A basic end-to-end DL MIMO signal processing model is shown by Fig. 1. This model is originally proposed in [14]. In such a model, transmitted symbols $\{s_k, \forall k = 0, 1, \ldots, d-1\}$ are mapped to one-hot vectors. For example, if the QPSK constellation is adopted, the symbols s_0, s_1, s_2 and s_3 can be mapped to $[1\ 0\ 0\ 0]^T$, $[0\ 1\ 0\ 0]^T$, $[0\ 0\ 1\ 0]^T$ and $[0\ 0\ 0\ 1]^T$, respectively. Those one-hot vectors are then fed into a neural network (NN) with multiple layers, the output of which is further en-powered by a power amplifier (PA) and sent to the transmit antennas for transmitting. At the receiver side, the baseband output of the receive antennas is sent to another NN, the output of which is used to recover the symbols.

This classical and basic DL-based MIMO end-to-end signal processing model has not taken the CSI information into considerations. It is interesting to explore improved DL structure for MIMO transmission. In [16] and [14], it has been shown that the RTN structure has the potential to improve the performance of MIMO systems. It is also shown that the CSI is helpful for improving the performance of the NNs in MIMO systems. Inspired by the work of [16] and [14], we propose a novel DL-based MIMO end-to-end processing structure by combining a NN-based precoding network and an RTN.

2.2. Improved DL MIMO Transmission Structure

We propose an improved DL-based MIMO transmission structure by combining a precoding network at the transmitter and a RTN network at the receiver. The proposed signal processing structure is shown by Fig. 2. Compared with the classical structure Fig. 1, a precoding network and an RTN network are combined into the signal processing process in the proposed structure.

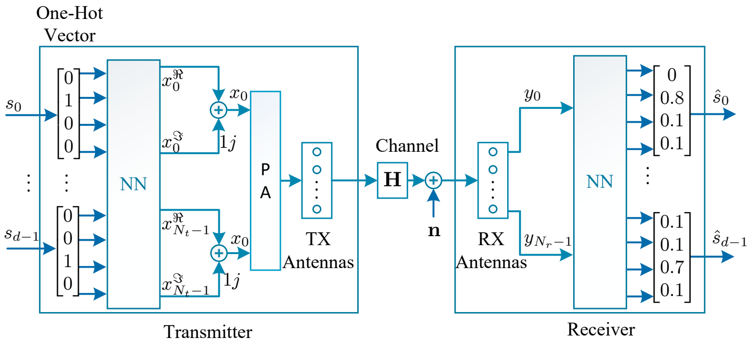

Fig. 1. Block Diagram of DL-based MIMO System

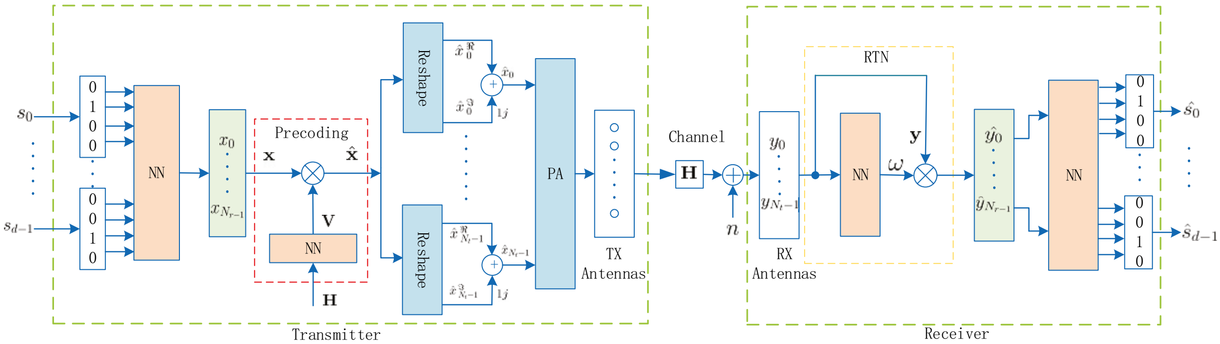

Fig. 2. Block Diagram of the Improved DL MIMO Transmission Structure Combining the Precoding and RTN networks.

As shown in Fig. 2, the transmitted symbols $\{s_k, \forall k = 0, 1, \ldots, d-1\}$ are mapped to one-hot vectors. Those one-hot vector are sent to a NN for encoding, which consists of one input layer of $M \times d$ nodes, 3 hidden layers of 128,128 and 64 nodes, one output layer of $N_t \times d$ nodes. The activation function in hidden layers is *ReLU* and the activation function of the output layer is the linear function. The output of the NN is sent to the precoding network and power amplifier, transmitting signal $\hat{x}$ to the receiver through the channel.

The received symbols $\mathbf{y}$ are sent to the RTN network where the received symbols can be calibrated as $\hat{\mathbf{y}}$. Then the calibrated signal $\hat{\mathbf{y}}$ are send to a NN which with 4 dense layers for decoding, the number of nodes in each dense layer is 128, 64, 64 and $M \times d$. Using *tanh* and *ReLU* as the activation functions, which enables non-linear transformations. The output of NN can be noted as $\hat{s}$ which means recovered symbols, does the inverse - mapping the received symbols into every bit or code word that may have been transmitted. Based on the above, the goal of our DL model is to reduce the error between the transmitted symbol and the recovered symbol, which is also one of the criteria we refer to when choosing the loss function.

2.2.1. *Precoding Network*

The precoding network in Fig. 2 plays similar roles of the traditional precoders. The difference is that the precoding parameters are learned through the samples generated with perfect CSI $\mathbf{H}$. Specifically, the input of the precoding network is the vector that cascaded by the rows of $\mathbf{H}$. Hence, the dimension of the input data is determined by the size of $\mathbf{H}$, i.e., $N_t N_r \times 1$. Since the system performance changes with the number of hidden layers and the number of nodes, we repeat experiments to find optimal settings of those hyper parameters.

The precoding network consists of one input layer of $N_t \times N_r$ nodes, one dense layer of 64 nodes, one output layer of $N_t \times d$ nodes. The activation function in hidden layers is *ReLU* and the activation function of the output layer is the linear function. The outputs are reshaped to $\mathbf{V} \in C^{N_t \times d}$ when they are sent to the multiplier. The output of the precoding network is given by $\hat{\mathbf{x}} = \mathbf{V}\mathbf{x} \in C^{N_t \times 1}$, which is sent to the power amplifiers for transmitting over the air.

2.2.2. Radio Transformer Network

The radio transformer networks were introduced in [13] as a way to integrate expert knowledge into the DL model. RTNs are additional NNs that can transform the CSI or output signal into parameters, which can be fed to the end-to-end training process to calibrate the performance of system. We incorporate the RTN structure in the proposed MIMO signal processing system shown by Fig. 2.

The RTN network is a parameter estimator between the received signal and the signal detector. It accepts the received signal $\mathbf{y}$ and produces an estimated phase offset ω to counteract the signal distortion caused by the channel. Combined with ω, the received signal $\mathbf{y}$ is calibrated as $\hat{\mathbf{y}}$, which is further sent to the last NN for symbol detection. The RTN can simplify the discriminator's classification task, thereby improving the classification accuracy of the neural network.

We implement RTN as an NN with 3 dense layers and use *tanh* and *ReLU* as the activation functions for the hidden layers, and the final layer is still linear. The number of nodes in each dense layer is 64, 32 and $2 \times N_r \times 2 \times N_r$. We have integrated this module into the end-to-end system without adding any new objective function or loss term.

2.3. Training Process

The better the neural network is trained, the superior its performance will be. Based on the system model proposed in this paper, an MSE loss function is used to measure the error between the transmitted symbols at the transmitter side and the recovered symbols at the receiver side. It can be expressed as:

$$Loss_{mse} = \frac{1}{N}\sum_{k=1}^{N}(s_k - \hat{s}_k)^2 , \tag{1}$$

where N is number of samples, s_k is the transmitted symbol, $\hat{s}_k$ is the recovered symbol. As a tool to regulate the optimization of the loss function, we use the adam algorithm[10]. We set the learning rate to 0.001, which is a critical parameter for controlling the learning progress of the model. Large learning rates tend to cause oscillations, on the contrary, small learning rates may lead to slow convergence. The training data is randomly generated. The generated 10000 samples are divided into a training set, a validation set and a test set. The training set contains 60% of the total samples, which are used to adjust the network parameters. The validation set has 10% of the total samples. When the model achieves best performance over the validation set, the training process terminates. The rest 30% of the total samples are used to obtain the final performance of the model. The performance is evaluated under different signal-to-noise ratios (SNRs), ranging from -20db to 20db. For each SNR, the training goes 100 epochs.

3. Simulation and Experimental Results

In this section, we evaluate the proposed DL-based MIMO system. The proposed system is implemented using using the Keras deep learning library in Python [8]. Without loss of generality, the Rayleigh fading channel is adopted in this work. We assume the original signals $s_k, \forall k$ are standard QPSK symbols. The BER is used as the main performance evaluation criterion. We use the classical precoding schemes as the evaluation benchmarks. We also compared the performance of the systems when only the RTN network or the precoding network is considered. The performance of the basic DL-based MIMO transmission scheme shown by Fig. 1 is also compared.

Fig. 3 demonstrates the BER performance achieved by the proposed DL-based transmission scheme in a MIMO system with $N_t = 2$, $N_r = 2$ and $d = 2$. It can be observed that the proposed scheme (Precoding+RTN) outperforms all other schemes. Among all the schemes, the basic DL-based MIMO system perform the worst. Compared with the basic system, the SNR gain achieved by the proposed scheme is about 10dB at 10^{-3} BER.

To fully show the performance of the proposed scheme, we plot the BER performance curves for a 2×4 MIMO system and a 4×2 MIMO system in Fig. 4 and Fig. 5, respectively. Since more antennas will bring the diversity gain, the BER performance of all schemes will be improved compared with the 2×2 system. In the two cases, the proposed scheme still has advantages over other methods in terms of BER performance.

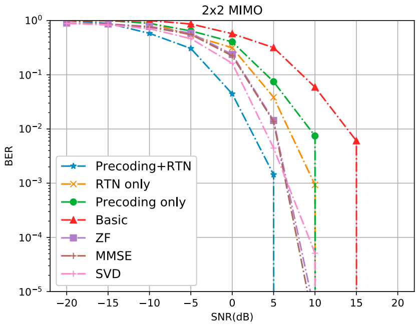

Fig. 3. BER of the MIMO transceiver and the traditional scheme consisting of QPSK modulation with $N_t = 2, N_r = 2, d = 2$.

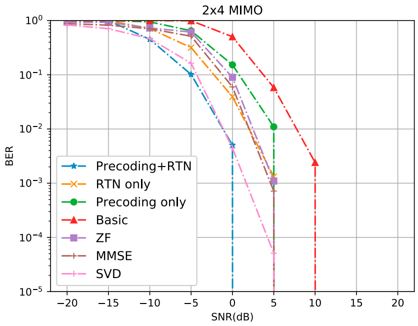

Fig. 4. BER of the MIMO transceiver and the traditional scheme consisting of QPSK modulation with $N_t = 2, N_r = 4, d = 2$.

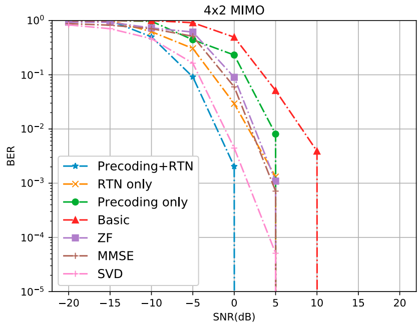

Fig. 5. BER of the MIMO transceiver and the traditional scheme consisting of QPSK modulation with $N_t = 4, N_r = 2, d = 2$.

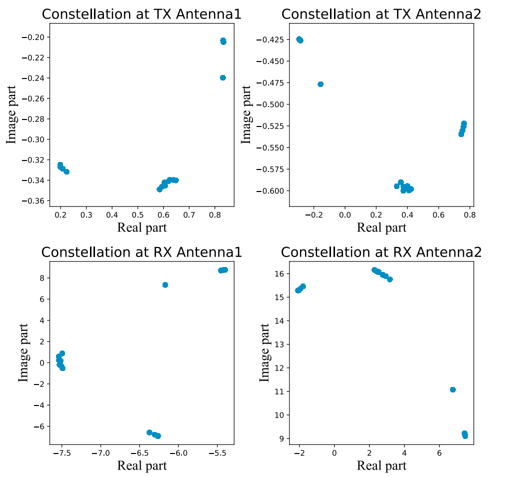

Fig. 6. Learned transmit constellations at each antenna with QPSK modulation and $N_t = 2, N_r = 2, d = 2, SNR = 20db, epoch = 1$.

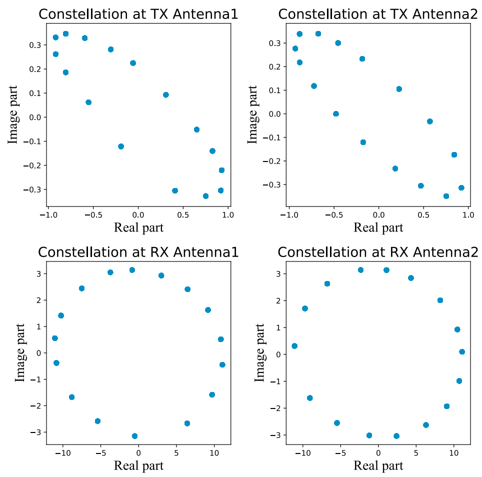

Fig. 7. Learned transmit constellations at each antenna with QPSK modulation and $N_t = 2, N_r = 2, d = 2, SNR = 20db, epoch = 100$.

How does the proposed scheme achieve better BER performance? To unveil the answer, we demonstrate the constellations of the signals at each antenna in Fig. 6 and Fig. 7, at different training epochs, say $epoch = 1$ and $epoch = 100$. In the experiments, the original signals are QPSK modulated, and the MIMO system is set as $N_t = 2$, $N_r = 2$, $d = 2$ and $SNR = 20$dB.

In Fig. 6, we plot the scatter diagram of the signals at the antennas after on epoch of training over one channel realization. It can be observed that those signals are huddled with each other. This means that there is not enough decision space to distinguish the signals.

However, after enough epochs of training (for example, $epoch = 100$), the signals at the antennas are scattered, as shown in Fig. 7. Specifically, at the transmit antennas, the two data streams at any one of the two transmit antennas, each of which is QPSK, constitute a constellations of size $4 \times 4 = 16$. These constellation points are scatters around an ellipse. At the same time, at the receive antennas, the received signals scatters almost uniformly around a circle. Therefore, the received signals are separated with each other. This is the reason why the proposed DL-based MIMO system with precoding and RTN networks achieves good BER performance.

4. Conclusion

In this paper, we have proposed a novel MIMO transmission scheme based on deep learning. The results show that MIMO communication model based on deep learning technology has achieved better performance than traditional algorithms. It implies that deep learning will lead a promising direction in wireless communication. The combination of traditional communication model and deep learning technology will be an important topic in this new frontier. In our future work, we will extend the current model to multi-user MIMO scenarios and explore the potential of deep learning in wireless communications.

Acknowledgments

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