End-to-End Learning for RIS-Aided Communication Systems

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***Abstract*—From adapting to the propagation environment to reconstructing the propagation environment, reconfigurable intelligent surface (RIS) changes the design paradigm of wireless communications. To reconstruct the propagation environment, joint beamforming of RIS and multi-input multi-output (MIMO) is crucial. Unfortunately, due to the coupling effect of the active beamforming of MIMO and passive beamforming of RIS, it is difficult to find the optimal solution to the joint beamforming problem, so a serious performance loss will be caused. In this paper, inspired by the end-to-end (E2E) learning of communication system, we propose the E2E learning based RIS-aided communication system to mitigate the performance loss via deep learning techniques. The key idea is to simultaneously optimize the signal processing functions at base station (BS), RIS, and user, including active beamforming for BS and user, passive beamforming for RIS. This way is able to avoid the performance loss caused by alternately optimizing each function of the RIS-aided system. Specifically, we firstly utilize a deep neural network (DNN) to realize the modulation and beamforming for BS and utilize another DNN to realize the demodulation and combining for user. Then, the RIS passive beamforming is also represented by trainable parameters, which could be simultaneously optimized with the DNNs at BS and user. Simulation results show that the proposed E2E learning based RIS-aided communication system could achieve the better bit error rate (BER) performance than traditional RIS-aided communication systems.**

***Index Terms*—End-to-end learning, reconfigurable intelligent surface, bit error rate, deep neural network.**

I. Introduction

The *reconfigurable intelligent surface* (RIS) has been recently proposed as a promising technique for future 6 G communications [1], since it can improve the quality of the received signal by adding an extra reflected link [2]. As a result, RIS could be used to overcome the channel blockage, enrich the non-line-of-sight (NLoS) link, extend the coverage, and mitigate inter-user interferences. Different from the existing active massive multi-input multi-output (MIMO) and amplify-and-forwarding (AF) relay techniques, an RIS uses a large number of passive and low-cost elements to reflect the transmitted signal [3]. Since each element of RIS could change the phase and amplitude of the incident signal, RISs can realize passive beamforming by designing the phase shift and amplitude reflection coefficients of their elements.

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To achieve the passive beamforming gain, unlike conventional MIMO system, which mainly considers beamforming for base station (BS) and user, the RIS-aided communication system requires the joint design of active beamforming for BS and user as well as passive beamforming for RIS. Up to now, some joint beamforming methods for RIS-aided communication system have been proposed to optimize different performance metrics, such as outage probability [4], symbol error probability (SER) [5], weighted sum rate [6], [7], spectral efficiency [8], and so on. Unfortunately, due to the coupling effect between the active and passive beamforming, the closed-form solution to the joint beamforming problem of the RIS-aided communication system doesn't exist [5]. Therefore, some works [4]–[8] have proposed to alternately optimize the active and passive beamforming, i.e., the active beamforming is fixed when we optimize the passive beamforming, and vice versa. However, this kind of alternating optimization methods usually converge to the local optimum [5], which may cause an obvious performance loss for RIS-aided communication systems.

To compensate for the performance loss of the alternating optimization methods, in this paper, we propose an end-to-end (E2E) learning based RIS-aided communication system to avoid the local optimum via deep learning (DL) techniques.[1] Inspired by the concept of E2E learning, which simultaneously optimizes the transmitter and receiver by using deep neural network (DNN) [9], we develop the E2E learning for RIS-aided communication system. Specifically, we firstly utilize a DNN to realize the modulation and beamforming for BS and utilize another DNN to realize the demodulation and combining for user. Then, we represent the phase shift and amplitude reflection coefficients of each RIS element by trainable weights, which could be simultaneously optimized with the DNN weights at the BS and user. Finally, the signal processing functions at BS, RIS, and user are simultaneously optimized, the functions include the modulation and active beamforming for BS, passive beamforming for RIS, combining and demodulation for user. In this way, the proposed scheme is able to avoid the local optimum caused by alternating optimization methods. Simulation results show that the proposed E2E learning based RIS-aided communication system could achieve the better bit error rate (BER) performance than existing RIS-aided communication systems.

Notation: We denote the column vectors and matrices by boldface lower-case and upper-case letters, respectively. $(\cdot)^T$ denote the transpose of the matrix. x_i denote the ith element of the vector $\mathbf{x}$. $\{0,1\}^n$, $(0,1)^n$, and $\mathbb{C}^n$ denote the n-dimension number sampling from 0 and 1, 0 to 1 and complex number, respectively. $\|\cdot\|_2$ denote the l_2-norm.

II. Traditional RIS-Aided System Model and Problem Formulation

We consider an RIS-aided downlink MIMO wireless communication system as shown in Fig. 1, where the BS is deployed with N_t antennas to sever one user with N_r antennas, with the aid of an N-element RIS. The signal $\mathbf{y}$ received at the user from both the direct link without RIS and the indirect link with RIS can be denoted by

$$\mathbf{y} = (\mathbf{H}^T + \mathbf{F}^T \mathbf{\Theta} \mathbf{G})\mathbf{x} + \mathbf{n}, \tag{1}$$

where $\mathbf{y} \in \mathbb{C}^{N_r \times 1}$ is the received signal at user; $\mathbf{H} \in \mathbb{C}^{N_t \times N_r}$ is the channel between BS and user; $\mathbf{G} \in \mathbb{C}^{N \times N_t}$ is the channel between

[1]Simulation codes are provided to reproduce the results in this paper: http://oa.ee.tsinghua.edu.cn/dailinglong/publications/publications.html.

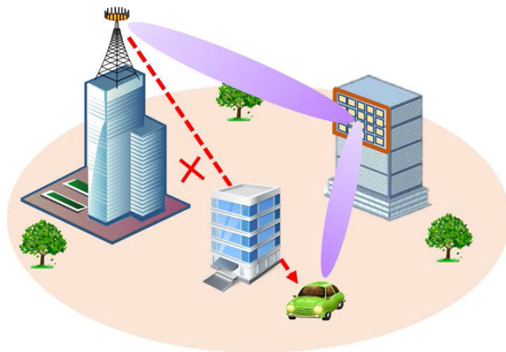

Fig. 1. RIS-aided downlink MIMO system.

BS and RIS; $\boldsymbol{\Theta} \in \mathbb{C}^{N \times N}$ is the passive beamforming matrix of RIS; $\mathbf{F} \in \mathbb{C}^{N \times N_r}$ is the channel between RIS and user; $\mathbf{x} \in \mathbb{C}^{N_t \times 1}$ is the transmitted signal of BS denoted by $\mathbf{x} = \mathbf{p}s$, where $\mathbf{p} \in \mathbb{C}^{N_t \times 1}$ is the precoder of BS, $s \in \mathbb{C}$ is the transmitted symbol; $\mathbf{n} \in \mathbb{C}^{N_r \times 1}$ is the received additive white Gaussian noise (AWGN).

During the downlink signal transmission, the bit stream $\mathbf{b} = [b_1, b_2, \ldots, b_k] \in \{0,1\}^k$ is firstly modulated to the symbol s at the BS. Then, the symbol s is digitally precoded by the precoder $\mathbf{p}$ for transmission. The channel between the BS and user is modeled as the combination of two components, i.e., direct BS-user link and indirect BS-RIS-user link. In indirect BS-RIS-user link, the phase and amplitude of incident signal of RIS can be adjusted by the phase shift and amplitude reflection coefficients of RIS, which could be modeled by multiplying the incident signal with a passive beamforming matrix $\boldsymbol{\Theta}$ represented as

$$\boldsymbol{\Theta} = \mathrm{diag}(\beta_1 e^{j\theta_1}, \beta_2 e^{j\theta_2}, \cdots, \beta_N e^{j\theta_N}), \tag{2}$$

where $\theta_n \in [0, 2\pi)$ and $\beta_n \in [0,1]$ denote the phase shift and amplitude reflection coefficients of the nth element of the RIS, respectively.[2]

At the user, the transmitted symbol can be estimated by combining the received signal $\mathbf{y}$ with the combiner $\mathbf{q} \in \mathbb{C}^{N_r \times 1}$, which yields the estimated complex signal

$$z = \mathbf{q}^T \mathbf{y}. \tag{3}$$

Note that the combiner $\mathbf{q}$ is designed by some classical algorithm, such as zero-forcing (ZF), minimum mean square error (MMSE), etc. Then, we recover the transmitted symbol using hard decision algorithm. The bit stream $\widehat{\mathbf{b}} = [\hat{b}_1, \hat{b}_2, \cdots, \hat{b}_k] \in \{0,1\}^k$ is eventually demodulated according to the corresponding modulation scheme.

After recovering the transmitted bit stream, the BER performance is calculated by comparing the error rate between $\mathbf{b}$ and $\widehat{\mathbf{b}}$. We consider minimizing the BER with the transmitted power constraint, i.e., $||\mathbf{p}||_2^2 = 1$, and the passive beamforming matrix constraints, i.e., $\theta_n \in [0, 2\pi)$ and $\beta_n \in [0,1]$. The optimal precoder $\mathbf{p}^{\mathrm{opt}}$, the optimal combiner $\mathbf{q}^{\mathrm{opt}}$, and the optimal passive beamforming matrix $\boldsymbol{\Theta}^{\mathrm{opt}}$ could be found with the assumption that global CSI is known. The optimization problem is formulated as

$$\begin{aligned} \min_{\mathbf{p}^{\mathrm{opt}}, \mathbf{q}^{\mathrm{opt}}, \boldsymbol{\Theta}^{\mathrm{opt}}} \quad & \frac{1}{k} \sum_{i=1}^{k} P_e\{b_i \neq \hat{b}_i\} \\ \text{s.t.} \quad & ||\mathbf{p}||_2^2 = 1, \\ & \theta_n \in [0, 2\pi), n = 1, 2, \cdots, N, \\ & \beta_n \in [0, 1], n = 1, 2, \cdots, N. \end{aligned} \tag{4}$$

[2]Note that the phase shift and amplitude reflection coefficients of RIS elements can be independently controlled at the same time [10], [11].

Unfortunately, due to the coupling effect of the precoder, combiner, and RIS passive beamforming matrix, the close-form solution of the $\mathbf{p}^{\mathrm{opt}}$, $\mathbf{q}^{\mathrm{opt}}$, and $\boldsymbol{\Theta}^{\mathrm{opt}}$ don't exist [5]. To this end, existing works [4]–[8] have to alternately optimize these three variables. For example, $\mathbf{p}$ and $\mathbf{q}$ are fixed when we optimize $\boldsymbol{\Theta}$, and so on. However, this kind of alternating optimization method is easy to converge to a local optimum [5], which causes a performance loss.

III. Proposed E2E Learning Based RIS-Aided Communication System

In this section, to compensate for the performance loss of alternating optimization methods, we propose the E2E learning based RIS-aided communication system to avoid the local optimum via DL techniques.

A. *Overview of E2E Learning of Communication System*

3To solve the problem that the optimization of individual modules doesn't mean the global optimization of the whole communication system [9], [12], the E2E learning of communication system has been proposed recently [9], [13]. Unlike the conventional communication system which could be divide into multiple individual modules, the E2E communication system implements the transmitter, channel, and receiver as an autoencoder, where the transmitter and receiver are used to encode the input and decode the output, respectively [9]. Specifically, both transmitter and receiver are implemented by DNNs, in which many trainable weights are used to connect adjacent layers in DNNs. Then, the DNN weights of the transmitter and receiver are simultaneously optimized to reconstruct the transmitter input at the receiver output. In addition, mini-batch gradient descent (MBGD) algorithm could be used to avoid the local optimum and accelerate convergence. As stated above, the E2E learning of communication system regards the whole communication system as an autoencoder, in which both the transmitter and receiver are constructed by DNNs. For the transmitter DNN, the input bit stream $\mathbf{b} \in \{0,1\}^k$ is mapped to the complex baseband signal $\mathbf{x} \in \mathbb{C}^{N_t}$. To study a more practical transmitter, the signal $\mathbf{x}$ should be normalized to satisfy the power constraint $||\mathbf{x}||_2^2 \leq P$, where P is the maximum power. Then, the signal $\mathbf{x} \in \mathbb{C}^{N_t}$ is transmitted by N_t antennas. The channel acts as a statistic system, whose output $\mathbf{y}$ follows the conditional probability distribution $P(\mathbf{y}|\mathbf{x})$. At the receiver DNN, the distorted signal $\mathbf{y}$ could be observed and mapped to the estimated soft bit stream $\widetilde{\mathbf{b}} \in (0,1)^k$. The soft bit stream denotes the probabilities that the bits are 1 over the k bits, which could be obtained by the sigmoid function [14]. In addition, $\mathbf{W}_T$ and $\mathbf{W}_R$ are used to parameterize transmitter and receiver DNN weights, respectively.

In order to accurately recover the original bit stream $\mathbf{b}$ in time-varying channels, the E2E learning of communication system uses very deep and wide DNNs for transmitter and receiver to ensure good performance. Besides, to adapt to the change of the channel, the transmitter DNN and receiver DNN are trained according to the real channels over a period of time, where a legacy communication system is needed to realize the forward calculation and backward propagation. Then, the trained DNNs are fixed to do the actual bit stream transmission for the channels in other time. In the training process, we aim to minimize the cross-entropy (CE) loss function, which is represented by

$$(\mathbf{b}, \widetilde{\mathbf{b}}) = -\frac{1}{B} \sum_{i=1}^{B} \sum_{j=1}^{k} \left(b_j^{(i)} \ln \tilde{b}_j^{(i)} + \left(1 - b_j^{(i)}\right) \ln(1 - \tilde{b}_j^{(i)}) \right), \tag{5}$$

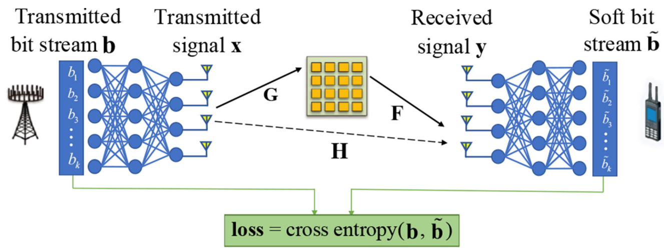

Fig. 2. The E2E learning based RIS-aided communication system.

where B is the batch size (the number of training samples to estimate the loss function). The CE loss function is used to measure the closeness between the transmitted bit stream $\mathbf{b}$ and the estimated soft bit stream $\widetilde{\mathbf{b}}$. Due to $0 \leq \widetilde{b}_j^{(i)} \leq 1$, the CE loss function $l(\mathbf{b}, \widetilde{\mathbf{b}}) \geq 0$, the equal sign is true if and only if $\mathbf{b} = \widetilde{\mathbf{b}}$, which implies that the smaller CE loss function means more accurate recovery of bit stream. To obtain the accurate recovery of bit stream, the transmitter DNN weights $\mathbf{W}_T$ and receiver DNN weights $\mathbf{W}_R$ are updated offline by the MBGD algorithm, which calculates the gradient of weights from the derivative of the CE loss function as follows:

$$\mathbf{W}_T^{(i+1)} = \mathbf{W}_T^{(i)} - \eta \nabla_{\mathbf{W}_T} l(\mathbf{b}, \widetilde{\mathbf{b}}), \tag{6}$$

$$\mathbf{W}_R^{(i+1)} = \mathbf{W}_R^{(i)} - \eta \nabla_{\mathbf{W}_R} l(\mathbf{b}, \widetilde{\mathbf{b}}), \tag{7}$$

where η denotes the learning rate, which affects the number of iterations for the CE loss function to reach convergence. Note that the transmitter DNN weights and receiver DNN weights are simultaneously optimized offline to recover the transmitted bit stream $\mathbf{b}$ at the receiver.

After the training process, we deploy the trained weights $\mathbf{W}_T$ and $\mathbf{W}_R$ to do the actual bit stream transmission. At the receiver, the estimated soft bit stream $\widetilde{\mathbf{b}}$ is decided by the principle of proximity, i.e., the corresponding $\hat{b}_j$ is demapped to 1 if $\tilde{b}_j > 0.5$, otherwise $\hat{b}_j$ is demapped to 0.

B. Proposed E2E Learning Based RIS-Aided Communication System

In this section, to compensate for the performance loss caused by existing alternating optimization methods, we improve the RIS-aided communication system via DL techniques. Specifically, inspired by the concept of E2E learning of communication system introduced in Section III-A, the signal processing functions in RIS-aided communication system are simultaneously optimized to avoid the local optimum, the functions include the modulation, active beamforming, RIS passive beamforming, combining, and demodulation.

First of all, we design an RIS-aided communication system via DL techniques as shown in Fig. 2. Specifically, we utilize a DNN to realize the modulation and beamforming functions for the BS, and utilize another DNN to realize the corresponding demodulation and combining functions for the user. Then, we represent the phase shift and amplitude reflection coefficients of each element of RIS by using trainable weights, which could be simultaneously optimized with the DNNs at BS and user. Before the actual bit stream transmission, the proposed E2E learning based RIS-aided communication system should be optimized online to realize the high BER transmission performance. For this purpose, we train the system at the BS by taking advantage of the powerful computing power of BS. Next, the four basic parts of the system including BS DNN, channels, RIS, and user DNN, are introduced as follows:

1) *BS DNN:* It maps the transmitted bit stream $\mathbf{b}$ to the transmitted signal $\mathbf{x} \in \mathbb{C}^{N_t}$. The modulation and beamforming of BS could be realized by a BS DNN. Note that the signal $\mathbf{x}$ should satisfy the power constraint $||\mathbf{x}||_2^2 = 1$. $\mathbf{W}_{\mathrm{BS}}$ is used to denote the BS DNN weights.

2) *Channels:* The channels between RIS and user, BS and RIS, BS and user could be denoted by $\mathbf{H}$, $\mathbf{F}$, and $\mathbf{G}$, respectively, which could be obtained by the RIS channel estimation method [15], [16].

3) *RIS:* It transfers the incident signal $\mathbf{r}_{\mathrm{in}} = \mathbf{G}\mathbf{x} \in \mathbb{C}^N$ to the reflected signal $\mathbf{r}_{\mathrm{out}}$. The reflection could be modeled by multiplying the incident signal $\mathbf{r}_{\mathrm{in}}$ with a passive beamforming matrix $\mathbf{\Theta}$, i.e., $\mathbf{r}_{\mathrm{out}} = \mathbf{\Theta}\mathbf{r}_{\mathrm{in}}$, where $\mathbf{\Theta}$ is a diagonal matrix in (2).

4) *User DNN:* It maps the received signal $\mathbf{y} \in \mathbb{C}^{N_r}$ described by (1) to the estimated soft bit stream $\widetilde{\mathbf{b}}$. The combining and demodulation at the user could be realized by a user DNN. $\mathbf{W}_{\mathrm{user}}$ is used to denote the user DNN weights.

Then, to achieve the optimal BER performance, $\mathbf{W}_{\mathrm{BS}}$, $\mathbf{\Theta}$, and $\mathbf{W}_{\mathrm{user}}$ should be trained online to obtain the robust representation against channels. The training is similar to the E2E learning of communication system introduced in Section III-A. By calculating the gradient from the CE loss function in (5), the MBGD optimization of the weights in BS DNN, RIS, and user DNN could be represented as

$$\begin{aligned} \mathbf{W}_{\mathrm{BS}}^{(i+1)} &= \mathbf{W}_{\mathrm{BS}}^{(i)} - \eta \nabla_{\mathbf{W}_{\mathrm{BS}}^{(i)}} l(\mathbf{b}, \widetilde{\mathbf{b}}), \\ \mathbf{\Theta}^{(i+1)} &= \mathbf{\Theta}^{(i)} - \eta \nabla_{\mathbf{\Theta}^{(i)}} l(\mathbf{b}, \widetilde{\mathbf{b}}), \\ \mathbf{W}_{\mathrm{user}}^{(i+1)} &= \mathbf{W}_{\mathrm{user}}^{(i)} - \eta \nabla_{\mathbf{W}_{\mathrm{user}}^{(i)}} l(\mathbf{b}, \widetilde{\mathbf{b}}). \end{aligned} \tag{8}$$

When the maximum number of iterations has been reached, the training process is completed. In addition, to satisfy the amplitude constraint of the passive beamforming matrix $\mathbf{\Theta}^{(i+1)}$, i.e., $\beta_n^{(i+1)} \in [0, 1]$, we normalize the optimized $\mathbf{\Theta}^{(i+1)}$ in every iteration as follows:

$$\beta_n^{(i+1)} = \beta_n^{(i+1)} / \beta_{\max}^{(i+1)}, \tag{9}$$

where $\beta_{\max}^{(i+1)}$ is the largest value in $\beta_1^{(i+1)}, \beta_2^{(i+1)}, \cdots, \beta_N^{(i+1)}$.

After the training process, we deploy the trained $\mathbf{W}_{\mathrm{BS}}$, $\mathbf{\Theta}$, and $\mathbf{W}_{\mathrm{user}}$ of the system to the BS, RIS, and user, respectively. The BS DNN weights are directly deployed within BS, while the phase shift and amplitude reflection coefficients of each RIS element is adjusted according to the trained $\mathbf{\Theta}$, which could be transmitted to RIS by wired or wireless manner [6]. For example, a control line connected to the BS could be used to transmit the trained $\mathbf{\Theta}$ to RIS. By pruning and quantifying user DNN weights, several DNN weights with a small number of bits are transmitted to the user through the wireless manner. The training parameters of the E2E learning based RIS-aided communication system is described in Table I and the parameters of weights $\mathbf{W}_{\mathrm{BS}}$, $\mathbf{\Theta}$, and $\mathbf{W}_{\mathrm{user}}$ is shown in Table II.

Unlike the conventional E2E learning of communication system, which just considers to simultaneously optimize the weights in transmitter and receiver DNNs, we extend the concept of E2E learning of communication system to the RIS-aided system to simultaneously optimize the weights in BS, RIS, and user. In this way, the proposed E2E learning based RIS-aided communication system could mitigate the performance loss caused by alternating optimization methods in existing RIS-aided communication systems.

C. Complexity Comparison

In this subsection, we compare the computational complexity of the proposed E2E learning based RIS-aided system with the alternating scheme in the traditional RIS-aided system [6]. Since the E2E learning based RIS-aided communication system is composed of trainable

TABLE I
TRAINING PARAMETERS AND SCENARIO PARAMETERS OF E2E LEARNING BASED RIS-AIDED SYSTEM

Training Parameters	**Value**
Loss function	Cross Entropy
Initialization	Xavier
Optimizer	Adam
Training epoch	200
Learning rate	1×10^{-3}
Training samples	1×10^{4}
Batch size	160
Performance metric	BER
Scenario Parameters	**Value**
Number of BS antennas: N_t	8
Number of user antennas: N_r	2
Number of RIS elements: N	128 or 256
BS location	(0 m, -40 m)
User location	from (0 m, 0 m) to (100 m, 0 m)
RIS location	(60 m, 10 m)
Length of bit stream: k	4

TABLE II
WEIGHT PARAMETERS IN E2E LEARNING BASED RIS-AIDED COMMUNICATION SYSTEM

	Layer	**Output dimension**
BS DNN	Input	k
	FC + ReLU	$8N_t$
	FC + ReLU	$8N_t$
	FC + Linear	$2N_t$
	Normalization	$2N_t$
	Real to complex	N_t
RIS	Input	N
	Reflection	N
User DNN	Input	N_r
	Complex to Real	$2N_r$
	FC + ReLU	$2N_t$
	FC + Sigmoid	k

weights and global CSI, the overall computational complexity comes from updating the trainable weights and calculating the multiplication between the transmitted signals and the CSI. Firstly, for the complexity of updating the trainable weights, the computational complexity is proportional to the number of weights. Therefore, according to Table II, the computational complexity for updating the trainable weights is in the order of $\mathcal{O}(kN_t + N_t^2 + N_r^2 + N_tN_r + N)$. Then, for the multiplication between the transmitted signals and the estimated channels, the computational complexity is proportional to the dimension of channels $\mathbf{H}$, $\mathbf{F}$, and $\mathbf{G}$. As a result, the computational complexity for calculating the multiplication between the transmitted signals and the estimated channels is in the order of $\mathcal{O}(N_tN_r + NN_t + NN_r)$. Therefore, the overall computational complexity of E2E learning based RIS-aided communication system is in the order of $\mathcal{O}(kN_t + N_t^2 + N_r^2 + N_tN_r + NN_t + NN_r)$.

As a comparison, the complexity of the existing alternating scheme, which alternately optimizes the active precoding at BS and passive precoding at RIS, is in the order of $\mathcal{O}(N_t^2 + N^2)$ [6]. Besides the ZF algorithm could be used to design a combiner at user, wherein the pseudo inverse of the effective channel $\mathbf{H}_e = \mathbf{H}^T + \mathbf{F}^T\mathbf{\Theta}\mathbf{G} \in \mathbb{C}^{N_r \times N_t}$ involves a complexity in the order of $\mathcal{O}(N_r^3 + N_r^2N_t)$. Therefore, the complexity of the existing alternating scheme is in the order of $\mathcal{O}(N_t^2 + N^2 + N_r^3 + N_r^2N_t)$. Note that the number of RIS elements is usually much larger than the number of BS antennas and user antennas, we can conclude that our proposed E2E scheme can greatly reduce

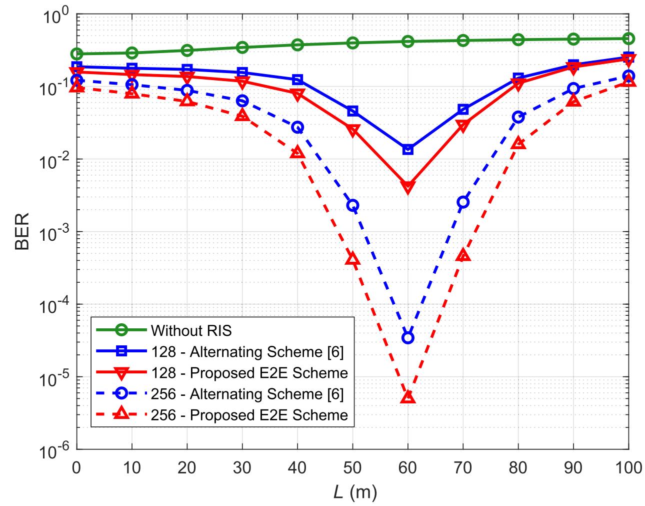

Fig. 3. BER performance against distance L.

the computational complexity compared with the existing alternating scheme.

Furthermore, to improve training efficiency and reduce training complexity, we provide the received power based and transfer learning based training methods. First, we introduce the received power based training method which could adaptively adjust the training noise power according to the received signal power. Since the transmitted information is contained in the received signal of the user, low received power will not have a good training effect when the training noise power is large. A large received power will not make the E2E learning based RIS-aided communication adapt to the noise when the training noise power is low. So a suitable training SNR helps to improve the training efficiency and reduce training complexity. Therefore, from this point, we adaptively adjust the training noise power according to the received signal power to improve the training efficiency. Next, we also utilize the transfer learning based training method [17] to further speed up the training. In the transfer learning based method, the weights in BS, RIS, and user tried to learn generalized weights $\mathbf{W}_{\mathrm{BS},0}$, $\mathbf{\Theta}_0$, and $\mathbf{W}_{\mathrm{user},0}$ to realize the E2E communication in different channels. For this purpose, the E2E learning based RIS-aided system firstly is trained in K_s source tasks, in which each task denotes an E2E training. Then, for the target task of the E2E training, the transfer learning based method initializes the weights $\mathbf{W}_{\mathrm{BS}}$, $\mathbf{\Theta}$, and $\mathbf{W}_{\mathrm{user}}$ as the pre-trained weights $\mathbf{W}_{\mathrm{BS},0}$, $\mathbf{\Theta}_0$, and $\mathbf{W}_{\mathrm{user},0}$, respectively. Next, the weights are fine-tuned on this target task of E2E training via Adam updates.

IV. SIMULATION RESULTS

In this section, for the simulation of the proposed E2E learning based RIS-aided communication system, we consider an RIS-aided communication system scenario, where the scenario parameters are described in Table I. For the large-scale fading of the channel, the signal attenuation are set as 30 dB and 40 dB at the reference distance of 1 m for the BS-user link and BS-RIS-user link, respectively [6]. The path loss exponents are set as 2, 2, and 3 for the BS-RIS, RIS-user, and BS-user links, respectively [6]. For the small-scale fading of the channel, we consider the Rayleigh fading channel model. Finally, the channel can be represented as the product of the small-scale fading channel and the square root of the large-scale fading.

Fig. 3 shows the BER performance against the user movement distance L when $\mathrm{SNR} = 0$ dB in two RIS configuration scenarios, where

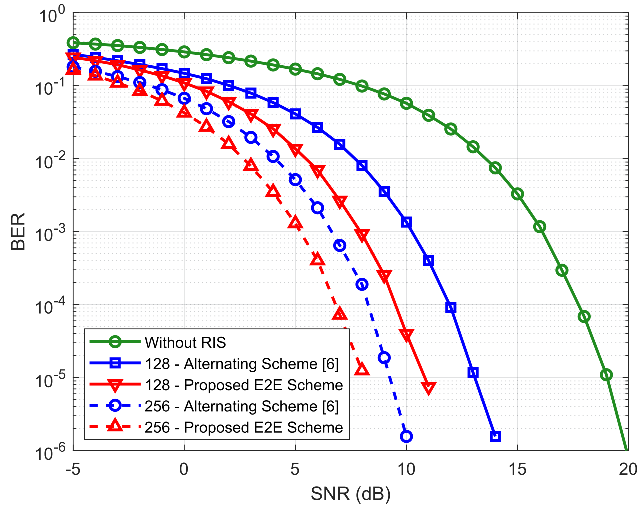

Fig. 4. BER performance against SNR.

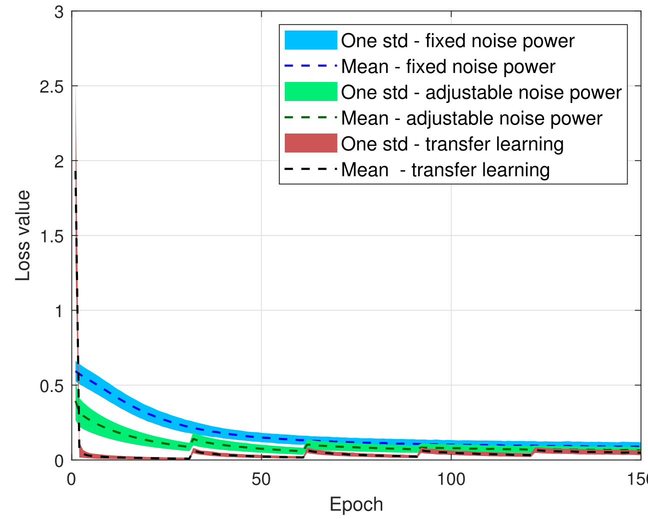

Fig. 5. Learning curve of different training methods.

we compare the proposed E2E learning based RIS-aided communication system with the existing RIS-aided communication system. For the traditional RIS-aided communication system, the joint beamforming is realized by utilizing the fractional optimization [6], which optimizes the precoder vector $\mathbf{p}$ and passive beamforming matrix $\mathbf{\Theta}$ in an alternating way. At the same time, the ZF algorithm is used to calculate the combiner $\mathbf{q}$. In contrast, the proposed E2E scheme optimizes the whole system via MBGD algorithm. We can observe that the proposed scheme is able to achieve lower BER than the existing alternating scheme in both 128 RIS elements and 256 RIS elements configurations.[3] Besides, we can observe that the BER performance improves as the number of the RIS elements increases. Moreover, since the RIS provides more degrees of freedom for communications, the RIS-aided communication system outperforms the system without RIS.

In addition, Fig. 4 shows the BER performance against the SNR when $L = 20$ m. We can observe that the proposed E2E learning based RIS-aided communication system outperforms the traditional RIS-aided communication system in both 128 RIS elements and 256 RIS elements configuration. The 1.3 dB and 2.4 dB gains could be achieved with 128 RIS elements and 256 RIS elements, respectively, when the BER is 10^{-4}. The BER performance gain above comes from two aspects. First, unlike the alternating optimization methods, the proposed E2E learning of communication system can simultaneously optimize the signal processing functions in BS, RIS, and user. So that the local optimization caused by alternating optimization methods could be avoided by the E2E learning scheme. Secondly, the existing RIS-aided communication systems only design a common precoder $\mathbf{p}$ for all transmitted symbols in BS, while the proposed E2E learning scheme could adaptively learn different transmitted signals for different transmitted bit streams. Thus, the transmitted signals are not limited by a common vector, such as the precoder $\mathbf{p}$ in the existing RIS-aided system, and BS achieves a similar effect to precoding the different bit streams with different precoders. We guess that the joint modulation and precoding make transmitted signals adaptively exploit the rich scattering environment with the assistance of RIS, such that the spatial multiplexing gain could be maximized.

As shown in Fig. 5, we train the E2E learning based RIS-aided communication system with the training SNR of 8 dB. The loss value roughly decreases as the number of epochs increases. Note that the learning curve achieves the near-optimal performance at epoch 62. To avoid the increase of the loss value, we could stop optimization once the number of epochs reaches 62. Compare with the fixed noise power shown in blue color, the smaller training standard deviation and faster training could be realized. We also show the learning curve of the transfer learning based method, which also considered the adjustable noise power. We can observe that the transfer learning based method can realize the smallest standard deviation and fastest training speed. Though the loss value is higher than other methods at the beginning, it quickly converges to the near-optimal performance within 10 epochs and remains largely stationary after that.

[3] Since the optimized RIS elements have amplitudes equal to 1, the results of alternating optimization for the continuously controllable amplitude reflection coefficient remain unchanged [6].

V. Conclusion

In this paper, to compensate for the performance loss of the alternating optimization methods in traditional RIS-aided communication systems, we have proposed the E2E learning based RIS-aided communication system to mitigate performance loss via DL techniques. Specifically, inspired by the concept of E2E learning of communication system, the signal processing functions in RIS-aided communication system are simultaneously optimized to avoid the local optimum, which include the modulation, active beamforming, RIS passive beamforming, combining, and demodulation. Simulation results showed that the SNR gain of about 2.4 dB can be achieved by the proposed E2E learning based RIS-aided communication system compared with the alternating optimization in a traditional RIS-aided communication system. For future research, we will focus on the E2E learning for multi-user wideband RIS-aided systems.

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