# End-to-End Learning of Communication System without Known Channel

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***Abstract*—Leveraging powerful deep learning techniques, the end-to-end (E2E) learning of communication system is able to outperform the classical communication system. Unfortunately, this communication system cannot be trained by deep learning without known channel. To deal with this problem, a generative adversarial network (GAN) based training scheme has been recently proposed to imitate the real channel. However, the gradient vanishing and overfitting problems of GAN will result in the serious performance degradation of E2E learning of communication system. To mitigate these two problems, this paper proposes a residual aided GAN (RA-GAN) based training scheme. Particularly, inspired by the idea of residual learning, we propose a residual generator to mitigate the gradient vanishing problem by realizing a more robust gradient back propagation. Moreover, to cope with the overfitting problem, we reconstruct the loss function for training by adding a regularizer, which limits the representation ability of RA-GAN. Simulation results show that the trained residual generator has better generation performance than conventional generator, and the proposed RA-GAN based training scheme can achieve the near-optimal block error rate (BLER) performance.**

***Index Terms*—End-to-end learning, residual neural network, generative adversarial network (GAN), regularization.**

## I. Introduction

In the history of wireless communications developed from 1G to 5G, the fundamental wireless system design paradigm remains unchanged, i.e., the whole complicated wireless system can be divided into multiple simpler individual modules, such as source encoder, channel encoder, modulator, demodulator, channel decoder, source decoder, etc [1]. However, the optimization of each module doesn't mean the global optimization of the whole system [2], e.g., the separate design of modulation and coding is known to be sub-optimal [3]. Thus, such a classical design paradigm becomes the bottleneck that limits the globally optimal performance of the wireless communication system.

To break through this bottleneck, the paradigm of end-to-end (E2E) learning of communication system has been recently proposed to jointly optimize the whole system by leveraging deep learning techniques [2], [4]. It is well known that deep learning is usually realized by using multi-layer neural network (NN), in which the adjacent layers are connected by trainable weights. For the E2E learning of communication system, the transmitter and receiver are constructed by multi-layer NNs, both of which are trained by the standard back propagation (BP) algorithm to update the weights. In contrast to the classical signal processing algorithms, which are usually complex in wireless communication systems [5], E2E learning can realize the modulation and other functions by simple addition and multiplication operations. Thus, the E2E learning of communication system could reach or even outperform the conventional system with lower complexity [2], [6].

However, the E2E learning of communication system faces a challenging problem not considered in [2], i.e., the transmitter cannot be trained by the BP algorithm without known channel, since the E2E learning of communication system doesn't have a explicit channel estimation module [7]. More specifically, the receiver should compute the loss function value, which represents the difference between the receiver output and the transmitted message. After that, the weights of receiver and transmitter NNs are updated by the gradient calculated from the loss function. The gradient could be obtained directly at the receiver. However, at the transmitter, the gradient is unavailable due to the unknown channel. Consequently, the transmitter could not be trained, which prevents the practical realization of the E2E learning of communication system [4].

To deal with the unknown channel in E2E learning of communication system, different machine learning techniques have been recently proposed [8]–[11]. Firstly, the simultaneous perturbation stochastic optimization algorithm was used in [8] to update the transmitter by utilizing the loss function fed back from the receiver. Moreover, reinforcement learning (RL) was utilized at the transmitter in [9], which regarded the loss function value as a reward. In addition, [10] optimized the transmitter by maximizing the mutual information between the transmitted signal and the received signal. Note that all schemes mentioned above require a large amount of information transmitted from receiver to transmitter. To avoid the burden of feeding back a large amount of information, a generative adversarial network (GAN) was used in [11] to imitate real received signal. The multi-layer generator in GAN generated fake received signal to approximate the distribution of real received signal, so that the transmitter could be trained reliably through the generator. Unfortunately, there are two problems causing performance degradation for GAN based training schemes. Firstly, the gradient vanishing problem may happen for a multi-layer generator. Secondly, the overfitting problem usually occurs when a mass of parameters



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are iteratively trained for transmitter, receiver, and GAN.

To address the gradient vanishing and overfitting problems of GAN-based training scheme, we propose a residual aided GAN (RA-GAN) based training scheme by using the residual neural network (Resnet) to change the layer structure of generator. Unlike the layer-by-layer structure of conventional generator, we build a skip connection that links the input and output layers of the generator to provide extra gradient. Thus, the proposed scheme is able to mitigate the gradient vanishing problem. In addition, we reconstruct the loss function for the proposed RA-GAN to solve the overfitting problem of conventional GAN. Moreover, comparing the generated fake signal with the real received signal, we verify that the trained residual generator has better generation performance than conventional generator.

## II. Preliminaries for E2E Learning of Communication System

In this section, we will firstly introduce the principle of E2E learning of communication system and the corresponding problem caused by unknown channel. Then, we will show how GAN could solve this problem, where the associated problems of gradient vanishing and overfitting will be discussed.

### A. The principle of end-to-end communication system

The architecture of E2E learning of communication systems is shown in Fig. 1, which is composed of three parts: transmitter, channel, and receiver. Both transmitter $\boldsymbol{T}$ and receiver $\boldsymbol{R}$ are implemented by multi-layer NNs, with the trainable weights denoted by $\boldsymbol{\theta_T}$ and $\boldsymbol{\theta_R}$, respectively. Note that the input information $s$ to the transmitter is mapped to a one-hot vector $\mathbf{1}_m$, which is an $M$-dimensional vector taken from set $\mathcal{M}$, where only the $m$-th element is one, while the rest $M-1$ elements are zeros. Then, the transmitter acts as a function $\boldsymbol{f_{\theta_T}}: \mathcal{M} \mapsto \mathbb{C}^n$, which maps the one-hot vector $\mathbf{1}_m$ to the signal $\mathbf{x} \in \mathbb{C}^n$ to be transmitted through $n$ channels. Correspondingly, the receiver acts as a function $\boldsymbol{f_{\theta_R}}: \mathbb{C}^n \mapsto \{\mathbf{p} \in \mathbb{R}_+^M \mid \sum_{i=1}^M p_i = 1\}$, which maps the received signal $\mathbf{y} \in \mathbb{C}^n$ to a probability vector $\mathbf{p} \in \mathbb{R}_+^M$. The final decision of $\hat{s}$ will correspond to the one-hot vector $\mathbf{1}_{\widehat{m}}$, where $\widehat{m}$ is the subscript of the maximum in the probability vector $\mathbf{p}$. In general, the hardware of the transmitter introduces the power constraint on the transmitted signal $\mathbf{x}$, i.e., $\|\mathbf{x}\|^2 = 1$. The purpose of transmitter-receiver is to recover the one-hot vector $\mathbf{1}_m$ as accurately as possible from the received signal $\mathbf{y} = h\mathbf{x} + \mathbf{w}$, where $h \in \mathbb{C}$ and $\mathbf{w} \in \mathbb{C}^n$ are channel and Gaussian noise, respectively. The difference between the transmitted one-hot vector $\mathbf{1}_m$ and the recovered probability vector $\mathbf{p}$ is measured by a loss function [9] as follows:

$$\mathcal{L}(\boldsymbol{\theta_T}, \boldsymbol{\theta_R}, h) \triangleq \mathbb{E}\left\{\int l(\boldsymbol{f_{\theta_R}}(\mathbf{y}), \mathbf{1}_m) p_h(\mathbf{y} | \boldsymbol{f_{\theta_T}}(\mathbf{1}_m)) d\mathbf{y}\right\}$$
$$\approx \frac{1}{B}\sum_{i=1}^{B} l\left(\boldsymbol{f_{\theta_R}}\left(\mathbf{y}^{(i)}\right), \mathbf{1}_m^{(i)}\right) \quad (1)$$

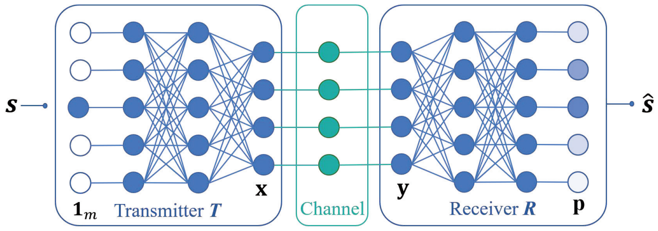


Fig. 1. The architecture of E2E learning of communication system.

where

$$l(\mathbf{p}, \mathbf{1}_m) = -\sum_{i=1}^{M} (\mathbf{1}_m)_i \ln \mathbf{p}_i + (1 - (\mathbf{1}_m)_i) \ln(1 - \mathbf{p}_i) \quad (2)$$

is the cross-entropy (CE) function representing the distance between one-hot vector $\mathbf{1_m}$ and probability vector $\mathbf{p}$, $B$ is the batch size (the number of training samples to estimate the loss function). The weights $\boldsymbol{\theta_T}$ and $\boldsymbol{\theta_R}$ are updated to make smaller loss function values with respect to the channel $h$. In order to get the optimal weights $\boldsymbol{\theta_T^*}$, $\boldsymbol{\theta_R^*}$ for transmitter and receiver, the gradient of the loss function $\mathcal{L}(\boldsymbol{\theta_T}, \boldsymbol{\theta_R}, h)$ in (1) is required to be calculated by the BP algorithm. However, from (1), only $\boldsymbol{\theta_R}$ could be updated by applying the gradient defined as follow:

$$\nabla_{\boldsymbol{\theta_R}} \widetilde{\mathcal{L}}(\boldsymbol{\theta_R}) = \frac{1}{B}\sum_{i=1}^{B} \nabla_{\boldsymbol{\theta_R}} l\left(\boldsymbol{f_{\theta_R}}\left(\mathbf{y}^{(i)}\right), \mathbf{1}_m^{(i)}\right), \quad (3)$$

where $\widetilde{\mathcal{L}}$ is an approximation of the loss function, which could be computed from (1). To fully exploit the performance of E2E learning, the transmitter NN weights $\boldsymbol{\theta_T}$ also need to be optimized [2]. However, the gradient $\nabla_{\boldsymbol{\theta_T}} \widetilde{\mathcal{L}}$ with respect to $\boldsymbol{\theta_T}$ is unavailable [4], since the unknown channel $h$ blocks the back propagation procedure as follows:

$$\begin{aligned}
\nabla_{\boldsymbol{\theta_T}} \widetilde{\mathcal{L}}(\boldsymbol{\theta_T}) &= \frac{1}{B}\sum_{i=1}^{B} \nabla_{\boldsymbol{\theta_T}} l\left(\boldsymbol{f_{\theta_T}}\left(\mathbf{y}^{(i)}\right), \mathbf{1}_m^{(i)}\right) \\
&= \frac{1}{B}\sum_{i=1}^{B} \frac{\partial l}{\partial \boldsymbol{f_{\theta_R}}} \frac{\partial \boldsymbol{f_{\theta_R}}}{\partial \mathbf{y}^{(i)}} \frac{\partial \mathbf{y}^{(i)}}{\partial \mathbf{x}^{(i)}} \nabla_{\boldsymbol{\theta_T}} \boldsymbol{f_{\theta_T}}\left(\mathbf{1}_m^{(i)}\right) \\
&= \frac{1}{B}\sum_{i=1}^{B} h \frac{\partial l}{\partial \boldsymbol{f_{\theta_R}}} \frac{\partial \boldsymbol{f_{\theta_R}}}{\partial \mathbf{y}^{(i)}} \mathbf{I_n} \nabla_{\boldsymbol{\theta_T}} \mathbf{f}_{\boldsymbol{\theta_T}}\left(\mathbf{1_m}^{(i)}\right).
\end{aligned} \quad (4)$$

To address this problem, a GAN based training scheme was proposed in [11] to generate a surrogate gradient to update the transmitter NN weights $\boldsymbol{\theta_T}$, which will be discussed in the next subsection.

### B. GAN based training scheme

In order to update the transmitter NN weights $\boldsymbol{\theta_T}$, a GAN was used to produce the surrogate gradient [11], as shown in Fig. 2. Generally, a GAN contains a generator $\boldsymbol{G}$ and a discriminator $\boldsymbol{D}$, both of which are implemented by multi-layer NNs, with trainable weights denoted by $\boldsymbol{\theta_G}$ and $\boldsymbol{\theta_D}$, respectively. The generator $\boldsymbol{f_{\theta_G}}: \mathbb{C}^n \mapsto \mathbb{C}^n$ produces fake received signal $\widetilde{\mathbf{y}}$ according to the transmitted signal $\mathbf{x}$ and random noise $\mathbf{z}$ following the standard Gaussian distribution. To

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simplify the representation, the random noise $\mathbf{z}$ is considered as a built-in variable in the generator, and it is not expressed explicitly in this paper. At the same time, the discriminator $\boldsymbol{f}_{\boldsymbol{\theta_D}} : \mathbb{C}^n \mapsto (0,1)$ is used to train the generator so as to generate the signal as similarly to the distribution of the real received signal as possible.

The objective of the discriminator $\boldsymbol{D}$ is to accurately distinguish real and fake received signals. Particularly, if the input data of the discriminator are sampled from real received signal distribution $p_h(\mathbf{y}|\mathbf{x})$, the expected output of discriminator is 1. On the contrary, if the input data are sampled from fake received signal distribution $p_{\tilde{h}}(\widetilde{\mathbf{y}}|\mathbf{x})$ generated by the generator, the expected output is 0. For the generator $\boldsymbol{G}$, in order to generate a signal as similarly to the real received signal as possible, its output $\widetilde{\mathbf{y}}$ must make the discriminator output $\boldsymbol{f}_{\boldsymbol{\theta_D}}(\widetilde{\mathbf{y}})$ as close to 1 as possible. Based on the working procedure of GAN discussed above, the generator weights $\boldsymbol{\theta_D}$ and the discriminator weights $\boldsymbol{\theta_G}$ are alternately updated according to the following two loss functions:

$$\widetilde{\mathcal{L}}(\boldsymbol{\theta_D}) = \frac{1}{B}\sum_{i=1}^{B}\left\{ l\left(\boldsymbol{f}_{\boldsymbol{\theta_D}}\left(\mathbf{y}^{(i)}\right),1\right) + l\left(\boldsymbol{f}_{\boldsymbol{\theta_D}}\left(\widetilde{\mathbf{y}}^{(i)}\right),0\right)\right\}, \tag{5}$$

$$\widetilde{\mathcal{L}}(\boldsymbol{\theta_G}) = \frac{1}{B}\sum_{i=1}^{B} l\left(\boldsymbol{f}_{\boldsymbol{\theta_D}}\left(\boldsymbol{f}_{\boldsymbol{\theta_G}}\left(\mathbf{x}^{(i)}\right)\right),1\right). \tag{6}$$

Where the functional $l(\cdot)$ is defined similarly to (2). The discriminator loss function (5) contains two items. Specifically, the first item in right side denotes the loss function of the real received input $\mathbf{y}$, while the second item denotes the loss function of the fake received input $\widetilde{\mathbf{y}}$. Then, the gradients could be computed by $\nabla_{\boldsymbol{\theta_G}}\widetilde{\mathcal{L}}(\boldsymbol{\theta_G})$ and $\nabla_{\boldsymbol{\theta_D}}\widetilde{\mathcal{L}}(\boldsymbol{\theta_D})$, and Adam gradient descent algorithm can be used to minimize the loss functions (5) and (6). Since the generator can be trained to imitate the real received signal, the surrogate gradient as close to the gradient (4) as possible could be passed back through the generator to transmitter from the link of transmitter-generator-receiver as follows:

$$\begin{aligned}\nabla_{\boldsymbol{\theta_T}}\widetilde{\mathcal{L}}(\boldsymbol{\theta_T}) &= \frac{1}{B}\sum_{i=1}^{B}\nabla_{\boldsymbol{\theta_T}} l\left(\boldsymbol{f}_{\boldsymbol{\theta_R}}\left(\boldsymbol{f}_{\boldsymbol{\theta_G}}\left(\boldsymbol{f}_{\boldsymbol{\theta_T}}\left(\mathbf{1}_m^{(i)}\right)\right)\right),\mathbf{1}_m^{(i)}\right)\\ &= \frac{1}{B}\sum_{i=1}^{B}\frac{\partial l}{\partial \boldsymbol{f}_{\boldsymbol{\theta_R}}}\frac{\partial \boldsymbol{f}_{\boldsymbol{\theta_R}}}{\partial \boldsymbol{f}_{\boldsymbol{\theta_G}}}\frac{\partial \boldsymbol{f}_{\boldsymbol{\theta_G}}}{\partial \boldsymbol{f}_{\boldsymbol{\theta_T}}}\nabla_{\boldsymbol{\theta_T}}\boldsymbol{f}_{\boldsymbol{\theta_T}}\left(\mathbf{1}_m^{(i)}\right).\end{aligned} \tag{7}$$

However, it is well known that the training instability problem that limits the performance of GAN, which results in the serious performance degradation for the E2E learning of communication system. Specifically, the gradient vanishing problem will happen in a multi-layer generator. Moreover, the overfitting problem always occurs because of a mass of weights are iteratively trained for transmitter, receiver, generator, and discriminator. These two problems will result in the serious performance degradation of E2E learning of communication system. To address these two problems of

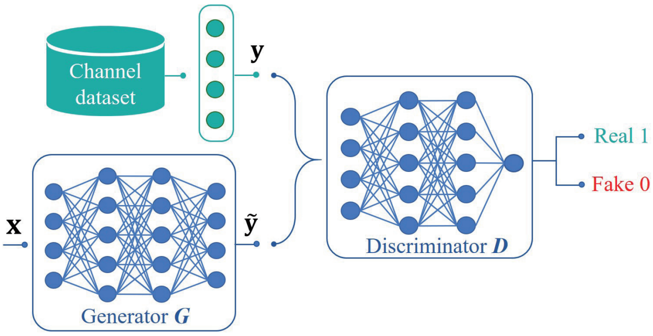


Fig. 2. The generator and discriminator in GAN.

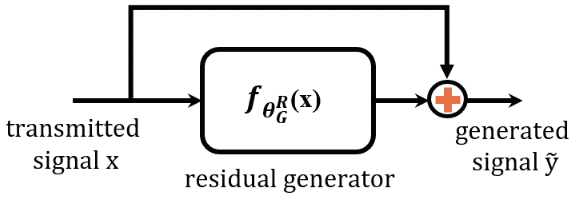


Fig. 3. The residual generator in proposed RA-GAN.

GAN-based training scheme in E2E learning of communication system, we will propose a residual aided GAN (RA-GAN) based training scheme in next section.

## III. RA-GAN Based Training Scheme

The training of transmitter is a challenging task because of the unknown channel. According to the GAN based training scheme, a surrogate gradient is produced in (7) to update transmitter. However, the generator output distribution $p_{\tilde{h}}(\widetilde{\mathbf{y}}|\mathbf{x})$ is inconsistent to the real received signal distribution $p_h(\mathbf{y}|\mathbf{x})$ due to the gradient vanishing and overfitting problems. Therefore, we propose a RA-GAN based training scheme to address these two problems.

### *A. Residual learning to mitigate gradient vanishing*

In conventional GAN, multi-layer generator always feeds forward the variables layer-by-layer and outputs fake samples at last. However, as the generator depth increases, the gradient may become very small. This is caused by the fact that the layer-by-layer gradient is obtained by multiplying the partial derivatives of loss functions layer-by-layer in the classical BP algorithm. If value of the partial derivative is close to 0, the final gradient will be very small. This gradient vanishing problem makes it difficult to train the multi-layer generator. Inspired by the idea of residual learning [12], we intentionally construct a skip connection between the input and output layers of the generator, which is shown by the residual generator in Fig. 3. For the residual generator, the residual generating function $\boldsymbol{f}_{\boldsymbol{\theta}_G^R} : \mathbb{C}^n \mapsto \mathbb{C}^n$ could be denoted by

$$\boldsymbol{f}_{\boldsymbol{\theta}_G^R}(\mathbf{x}) = \widetilde{\mathbf{y}} - \mathbf{x} = \boldsymbol{f}_{\boldsymbol{\theta_G}}(\mathbf{x}) - \mathbf{x}, \tag{8}$$

where $\mathbf{x}$ and $\widetilde{\mathbf{y}}$ are transmitted and generated signals, respectively, and $\boldsymbol{f}_{\boldsymbol{\theta}_G^R}(\mathbf{x})$ is a residual generator aiming to learn

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the difference between transmitted and received signals with conditional input $\mathbf{x}$. The gradient in each iteration for the transmitter NN can be computed as:

$$\begin{aligned}\nabla_{\boldsymbol{\theta_T}}\widetilde{\mathcal{L}}\left(\boldsymbol{\theta_T}\right) &= \frac{1}{B}\sum_{i=1}^{B}\frac{\partial l}{\partial \boldsymbol{f}_{\boldsymbol{\theta_R}}}\frac{\partial \boldsymbol{f}_{\boldsymbol{\theta_R}}}{\partial \boldsymbol{f}_{\boldsymbol{\theta_G}}}\frac{\partial \boldsymbol{f}_{\boldsymbol{\theta_G}}}{\partial \boldsymbol{f}_{\boldsymbol{\theta_T}}}\nabla_{\boldsymbol{\theta_T}}\boldsymbol{f}_{\boldsymbol{\theta_T}}\left(\mathbf{1}_m^{(i)}\right)\\ &= \frac{1}{B}\sum_{i=1}^{B}\frac{\partial l}{\partial \boldsymbol{f}_{\boldsymbol{\theta_R}}}\frac{\partial \boldsymbol{f}_{\boldsymbol{\theta_R}}}{\partial \boldsymbol{f}_{\boldsymbol{\theta_G}}}\frac{\partial \boldsymbol{f}_{\boldsymbol{\theta}_{\boldsymbol{G}}^{\boldsymbol{R}}}}{\partial \boldsymbol{f}_{\boldsymbol{\theta_T}}}\nabla_{\boldsymbol{\theta_T}}\boldsymbol{f}_{\boldsymbol{\theta_T}}\left(\mathbf{1}_m^{(i)}\right)\\ &\quad+\frac{1}{B}\sum_{i=1}^{B}\frac{\partial l}{\partial \boldsymbol{f}_{\boldsymbol{\theta_R}}}\frac{\partial \boldsymbol{f}_{\boldsymbol{\theta_R}}}{\partial \boldsymbol{f}_{\boldsymbol{\theta_G}}}\nabla_{\boldsymbol{\theta_T}}\boldsymbol{f}_{\boldsymbol{\theta_T}}\left(\mathbf{1}_m^{(i)}\right).\end{aligned}\tag{9}$$

Note that (9) is the gradient for updating the transmitter NN weights of the proposed RA-GAN based training scheme. There are two items in the right side of (9). The first item is same to (7), while the second item denotes the gradient through the skip connection between the input and output layers of the generator. Compared with the conventional GAN, the RA-GAN could generate more powerful gradient to efficiently train the transmitter NN due to the extra second item in (9), thus the gradient vanishing problem could be mitigated.

### *B. Regularization method to mitigate overfitting*

In this subsection, we reconstruct the loss function for the E2E learning of communication system to mitigate the overfitting problem. As the generator and the discriminator in GAN are added to train the E2E learning of communication system, the representation ability increases substantially due to a mass of extra trainable NN weights, which results in the overfitting problem. In order to limit the representation ability of RA-GAN based training scheme, the regularizer is added in the loss function. Compared to the existing GAN based training scheme, the regularizer enables the RA-GAN based training scheme to generate a signal as similarly to the real received signal as possible by using the regularization method. Specifically, by adding a weight penalty item $\Omega\left(\boldsymbol{\theta}\right)$ in the loss function to restrict the representation ability of RA-GAN, we have

$$\widehat{\mathcal{L}}\left(\boldsymbol{\theta}_i\right) = \widetilde{\mathcal{L}}\left(\boldsymbol{\theta}_i\right) + \lambda\Omega\left(\boldsymbol{\theta}_i\right), i \in \left\{\boldsymbol{R},\boldsymbol{T},\boldsymbol{G},\boldsymbol{D}\right\}, \tag{10}$$

where $\widehat{\mathcal{L}}\left(\boldsymbol{\theta}_i\right)$ and $\widetilde{\mathcal{L}}\left(\boldsymbol{\theta}_i\right)$ are the reconstructed and original loss functions, respectively, $\lambda$ is the hyper-parameter to balance the penalty item and original loss function $\widetilde{\mathcal{L}}\left(\boldsymbol{\theta}_i\right)$. $\boldsymbol{R}$, $\boldsymbol{T}$, $\boldsymbol{G}$, and $\boldsymbol{D}$ represent receiver, transmitter, generator, and discriminator in the RA-GAN based training scheme, respectively. In this paper, we use $\boldsymbol{l}_2$ regularization $\frac{1}{2}||\boldsymbol{\theta}||^2$ as the penalty item. The key simulation procedures of the RA-GAN based training scheme are described in **Algorithm** 1.

## IV. Simulation Results

In this section, we investigate the performance of the proposed RA-GAN based training scheme in terms of block error rate (BLER) for data transmission in AWGN channel. We compare the performance of the RA-GAN based training scheme with RL [9] and GAN based training scheme [11], and the optimal training method with known channel is also considered as the optimal performance bound. In the optimal training method, we assume the real channel are known at transmitter, which makes the gradient $\nabla_{\boldsymbol{\theta_T}}\widetilde{\mathcal{L}}$ available to train the transmitter. In addition, we analyze the ability of RA-GAN to generate fake received signal and compare it with GAN. Moreover, the parameter $E_b/N_0$ denotes the ratio of energy per bit ($E_b$) to the noise power spectral density ($N_0$), and the noise power $\delta^2$ equals to $\left(\frac{2E_b \log_2 M}{N_0 n}\right)^{-1}$ [2].

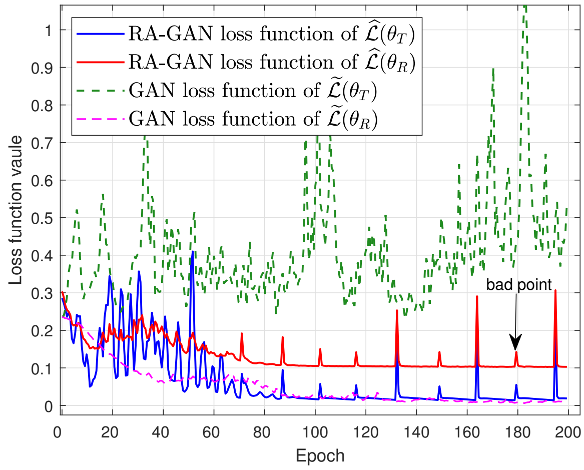


Fig. 4. Generation performance comparison between RA-GAN and GAN.

### *A. Generation capability comparison between RA-GAN and GAN*

At first, we compare the generation performance of RA-GAN and GAN for training the E2E communication system. Specifically, we consider the reconstructed loss function $\widehat{\mathcal{L}}\left(\boldsymbol{\theta_R}\right)$, $\widehat{\mathcal{L}}\left(\boldsymbol{\theta_T}\right)$ in (10) for RA-GAN based training scheme and the original loss function $\widetilde{\mathcal{L}}\left(\boldsymbol{\theta_R}\right)$, $\widetilde{\mathcal{L}}\left(\boldsymbol{\theta_T}\right)$ for GAN based training scheme.

In Fig. 4, we show the values of the corresponding loss functions against the training epoch in AWGN channel. The system is trained at $E_b/N_0 = 3$ dB. We can observe that the original loss function $\widetilde{\mathcal{L}}\left(\boldsymbol{\theta_T}\right)$ in the GAN based training scheme can not converge, and it is not close to the $\widetilde{\mathcal{L}}\left(\boldsymbol{\theta_R}\right)$. Note that in the training process, there are still some bad points due to the randomness of training, but the bad points could recover in next epoch. Thus, the proposed RA-GAN based training scheme could generate much more similar signal to the real received signal, which shows that the trained residual generator has better generation performance than the conventional generator.

### *B. BLER performance in AWGN channel*

Next, we compare the performance of the RA-GAN based training scheme with RL and GAN based training scheme, and the optimal training method in AWGN channel. The training parameters are the same as those in Subsection IV-A.

We test the BLER performance with a validation dataset including 100,000 random one-hot vectors. As shown in Fig. 5, we can observe that the BLER performance gap between the

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**Algorithm 1:** RA-GAN based E2E training scheme

**Input:**
1) Maximum number of iterations Epoch;
2) Real channel dataset $\mathcal{H}$;

**Output:**
Trained transmitter and receiver NNs weights $\boldsymbol{\theta_T}$ and $\boldsymbol{\theta_R}$;

Initialization:
$M = 16,\ n = 7,\ B = 320,\ N_{\text{train}} = 10000,$
$\delta^2 = (\frac{2E_b \log_2 M}{N_0 n})^{-1},\ \lambda = 0.01,$
$\text{Index} = \lfloor N_{\text{train}}/B \rfloor$;

Generate $N_{\text{train}}$ training data samples at random;

Initialize weights $\boldsymbol{\theta_D}, \boldsymbol{\theta_G}, \boldsymbol{\theta_R}$ and $\boldsymbol{\theta_T}$ according to Xavier initialization method;

**for** *epoch* $= 1, 2, \cdots,$ Epoch **do**

  **for** *index* $= 1, 2, \cdots,$ Index **do**

    Take $B$ one-hot vectors as training samples;

    Caculate transmitted signals: $\mathbf{x}^{(1)}, \cdots, \mathbf{x}^{(B)}$;

    Take $B$ channel samples: $\mathbf{h}^{(1)}, \cdots, \mathbf{h}^{(B)}$;

    Get real received signals: $\mathbf{y}^{(1)}, \cdots, \mathbf{y}^{(B)}$;

    Generate fake received signals: $\widetilde{\mathbf{y}}^{(1)}, \cdots, \widetilde{\mathbf{y}}^{(B)}$;

    **for** $i \in \{\boldsymbol{D}, \boldsymbol{G}, \boldsymbol{R}, \boldsymbol{T}\}$ **do**

      Caculate the loss function $\widehat{\mathcal{L}}(\boldsymbol{\theta}_i)$ according to (10);

      Use $\nabla_{\boldsymbol{\theta}_i} \widehat{\mathcal{L}}(\boldsymbol{\theta}_i)$ to update $\boldsymbol{\theta}_i$ according to Adam method;

    **end**

  **end**

**end**

Return $\boldsymbol{\theta_R}$ and $\boldsymbol{\theta_T}$.

existing GAN based training scheme [11] and optimal training scheme with known channel is large. This performance gap is caused the gradient vanishing and overfitting problem when training GAN. On the contrary, the proposed RA-GAN based training scheme almost approaches the optimal training method.

## V. Conclusions

In this paper, we proposed RA-GAN based training scheme for the E2E learning of communication system without known channel. Specifically, we improved the surrogate gradient method with residual learning so as to transform the conventional GAN into RA-GAN. Based on the proposed RA-GAN based training scheme, more powerful and robust gradients can be achieved to solve the gradient vanishing problem. Furthermore, regularizer was utilized in the RA-GAN to limit the representation ability, which is able to solve the overfitting problem. Simulation results verified the near-optimal BLER performance of the proposed RA-GAN based training scheme in terms of BLER, which outperforms other deep learning methods.

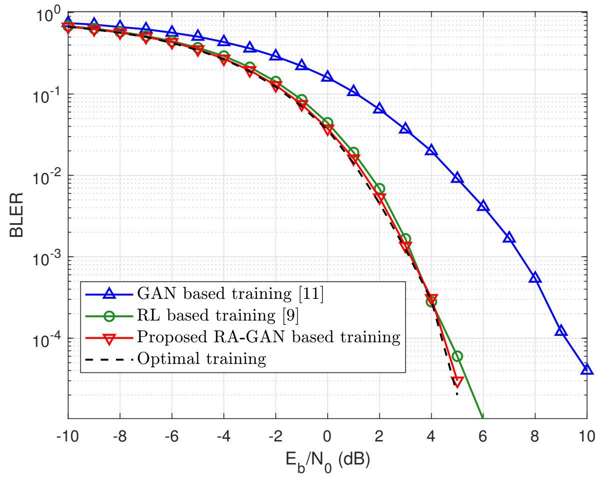


Fig. 5. BLER performance comparison in AWGN channel.


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