Model-Driven GAN-Based Channel Modeling for IRS-Aided Wireless Communication

Yi Wei, Ming-Min Zhao, and Min-Jian Zhao

***Abstract*—Intelligent reflecting surface (IRS) is a promising new technology that is able to create a favorable wireless signal propagation environment by collaboratively reconfiguring the passive reflecting elements, yet with low hardware and energy cost. In IRS-aided wireless communication systems, channel modeling is a fundamental task for communication algorithm design and performance optimization, which however is also very challenging since in-depth domain knowledge and technical expertise in radio signal propagations are required, especially for modeling the high-dimensional cascaded base station (BS)-IRS and IRS-user channels (also referred to as the reflected channels). In this paper, we propose a model-driven generative adversarial network (GAN)-based channel modeling framework to autonomously learn the reflected channel distribution, without complex theoretical analysis or data processing. The designed GAN (also named as IRS-GAN) is trained to reach the Nash equilibrium of a minimax game between a generative model and a discriminative model, where the special structure of the reflected channels is incorporated to improve the modeling accuracy. Simulation results are presented to validate the effectiveness of the proposed IRS-GAN framework for IRS-related channel modeling.**

***Index Terms*—Intelligent reflecting surface (IRS), generative adversarial network (GAN), deep learning, channel modeling, multiple-output single-input (MISO).**

I. Introduction

Recently, intelligent reflecting surface (IRS) has been proposed as a promising new paradigm to enhance the spectral and energy efficiency of wireless communication systems with low hardware cost and energy consumption [1]. To reap the performance gains offered by IRS, the acquisition of the channel state information (CSI) is of significant importance, but it is a difficult task since the IRS is generally not equipped with any transmit/receive radio frequency (RF) chains and thus not capable of performing complex baseband signal processing tasks. To alleviate the demand for full instantaneous CSI, some prior knowledge of the IRS-related channels, e.g., the underlying channel model or the statistical CSI, are considerably vital, which can be utilised to design advanced active and passive beamforming algorithms with reduced channel estimation overhead [2].

Since the wireless channels have a crucial impact on the design and practical implementation of wireless communication systems, it is of great interest and significance to study and model them. Accurate channel models can help us build and deploy feasible and efficient communication technologies that are suitable for various wireless propagation environments. In the literature, various works have been conducted to develop efficient channel modeling methods for different communication systems. Specifically, the parameter-based channel sounder is a popular channel modeling method, and it was adopted in [3] to measure a set of channel parameters such as angles of departure (AoDs), angles of arrival (AoAs), Doppler shift, etc. These parameters are further combined to reconstruct the channel impulse response. Also, data mining technologies can be employed to extract the hidden information embedded in the historical channel samples and thereby solve the channel modeling problem. For example, in [4], the principal component analysis (PCA) method was exploited to extract hidden features from channel data and characterize the underlying channel models. Furthermore, geometry-based stochastic channel models (GSCMs) [5] have been found well suited for non-stationary environments, which build on placing scatterers at random according to certain statistical distributions and assigning them (scattering) properties. However, the abovementioned channel modeling methods usually require in-depth domain knowledge and practical experience in wireless communications, and they are generally very complex especially when a large number of unknown parameters are involved in the corresponding models.

As a powerful technique which has revolutionized many computer vision tasks, deep learning (DL) techniques have been employed for channel distribution learning and regarded as promising candidates to address the abovementioned issues caused by traditional non-DL techniques, see e.g., [6]–[8]. To circumvent complex theoretical analysis and data processing, the work [6] exploited the generative adversarial network (GAN) framework [9] for channel modeling, where the channel distributions are estimated via an adversarial process. In particular, a generative model (captures the data distribution) and a discriminative model (estimates the probability that a sample is from the training data) are trained simultaneously and they compete against each other during the training process. Furthermore, the works [7] and [8] developed end-to-end wireless communication systems using deep neural networks (DNNs), where a conditional GAN is exploited to represent the channel effects and bridge the transmitter and receiver DNNs, such that the gradients of the end-to-end loss can be back-propagated to the transmitter DNN through the conditional GAN.

In the abovementioned works, only a limited number of channel parameters of the presumed channel model or the one-dimensional channel impulse response are learned, while how to characterize the distribution of a high-dimensional channel matrix is still unsolved, as in our considered case. Specially, due to the passive nature of IRS, its signal processing capability is limited and hence the BS-IRS and IRS-user channels cannot be measured independently in general. Besides, only a certain number of cascaded BS-IRS and IRS-user channel (also referred to as *reflected channel*) samples can be estimated and collected [10], which makes the channel modeling task more stringent. To tackle this challenge and

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motivated by the recent success of applying DL techniques to solve communication problems, we propose a novel model-driven GAN-based channel modeling framework, also referred to as *IRS-GAN*, to characterize the distribution of the reflected channel for an IRS-aided multiple-input single-output (MISO) communication system. The IRS-GAN framework, which consists of a generative model and a discriminative model, corresponds to a minimax two-player game, where these two models are competing with each other during the training procedure. In particular, to simply the training of IRS-GAN, we exploit the idea of model-driven DL in this work, where the special structure of the reflected channels is taken into consideration in the generative model. Besides, inspired by the Wasserstein GAN (WGAN) in [11], we propose to employ a Wasserstein distance based loss function which is able to guarantee the steady convergence, and a gradient penalty term and a moment penalty term are further added to the loss function to accelerate the training process. Numerical results are given to validate the effectiveness of the IRS-GAN.

II. System Model

We consider an IRS-aided MISO system, where an N-element IRS is deployed to improve the communications from an M-antenna BS to a single-antenna user, as shown in Fig. 1. Let $\mathbf{h}_d \in \mathbb{C}^{M\times 1}$, $\mathbf{h}_r \in \mathbb{C}^{N\times 1}$ and $\mathbf{G} \in \mathbb{C}^{N\times M}$ denote the baseband equivalent channels from the BS to the user, from the IRS to the user, from the BS to the IRS, respectively.

In the considered system, each reflecting element at the IRS is able to induce an independent phase-shift change of the incident signal sent by the BS. Thus, by properly adjusting the IRS reflection coefficients at different reflecting elements, a preferable wireless signal propagation environment between the transmitter and receiver can be created to enhance the communication performance. Let $\boldsymbol{\theta} \in \mathbb{C}^{N\times 1}$ denote the reflection coefficient vector, where the n-th element θ_n satisfies

$$|\theta_n| = \begin{cases} 1, & \text{if element } n \text{ is on,} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

and let $\boldsymbol{\Theta} = \mathrm{diag}([\theta_1, \cdots, \theta_N])$ denote the $N \times N$ diagonal reflection coefficient matrix, then the received signal at the user can be written as

$$y = (\mathbf{h}_r^H \boldsymbol{\Theta} \mathbf{G} + \mathbf{h}_d^H)\mathbf{x} + n, \tag{2}$$

where $n \sim \mathcal{CN}(0, \sigma^2)$ is the additive white Gaussian noise (AWGN), and $\mathbf{x} = \mathbf{w}s$ is the complex signal transmitted by the BS with s and $\mathbf{w}$ denoting the information symbol and active precoding vector, respectively. Due to the fact that the IRS is generally not equipped with any RF chains and thus not capable of performing any complex signal processing tasks, the acquisition of the BS-IRS and IRS-user channels is very difficult. To address this issue, we define the reflected channel from the BS to the user via the IRS as

$$\mathbf{H} \triangleq \mathbf{G}^H \mathrm{diag}(\mathbf{h}_r) \in \mathbb{C}^{M\times N}, \tag{3}$$

then the received signal in (2) can be equivalently rewritten as

$$y = (\boldsymbol{\theta}^H \mathbf{H}^H + \mathbf{h}_d^H)\mathbf{x} + n. \tag{4}$$

It can be observed that based on the knowledge of the instantaneous CSI of the BS-user and BS-IRS-user links, the active transmit precoding vectors at the BS and/or passive phase shifts at the IRS can be separately or jointly optimized to realize the potentials of IRS-aided wireless systems.

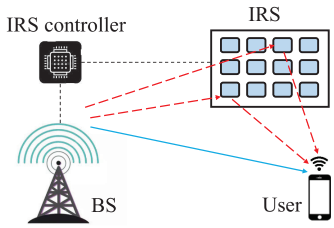

Fig. 1: An IRS-aided MISO communication system.

In the literature, various types of channel models are considered in IRS-aided communication systems, such as the Rayleigh fading channel model, the Rician fading channel model and the clustered delay line (CDL) model, etc. However, in practice, the actual channel may not follow the above-mentioned classical channel models. In this work, for ease of illustration, we consider the general spatially correlated Rician fading channel [12] as an example since both line-of-sight (LoS) and non-LoS (NLoS) components may exist in practical channels. As a result, $\mathbf{h}_d$, $\mathbf{h}_r$ and $\mathbf{G}$ can be modeled as follows:

$$\mathbf{h}_d = \sqrt{\eta_{\mathrm{BU}}}\bar{\mathbf{z}}_d + \sqrt{1-\eta_{\mathrm{BU}}}\tilde{\mathbf{z}}_d, \tag{5a}$$

$$\mathbf{h}_r = \sqrt{\eta_{\mathrm{IU}}}\bar{\mathbf{z}}_r + \sqrt{1-\eta_{\mathrm{IU}}}\tilde{\mathbf{z}}_r, \tag{5b}$$

$$\mathbf{G} = \sqrt{\eta_{\mathrm{BI}}}\bar{\mathbf{F}} + \sqrt{1-\eta_{\mathrm{BI}}}\tilde{\mathbf{F}}, \tag{5c}$$

where $\eta_{\mathrm{BU}} \triangleq \beta_{\mathrm{BU}} l_{\mathrm{BU}}/(1+\beta_{\mathrm{BU}})$, $\eta_{\mathrm{UI}} \triangleq \beta_{\mathrm{UI}} l_{\mathrm{UI}}/(1+\beta_{\mathrm{UI}})$ and $\eta_{\mathrm{BI}} \triangleq \beta_{\mathrm{BI}} l_{\mathrm{BI}}/(1+\beta_{\mathrm{BI}})$ with β^{BU}, β^{BI} and β^{IU} denoting the Rician factors of the BS-user, BS-IRS and IRS-user channels, respectively; l^{BU}, l^{BI} and l^{IU} denoting the corresponding pass loss. $\bar{\mathbf{z}}_d \in \mathbb{C}^{M\times 1}$, $\bar{\mathbf{z}}_r \in \mathbb{C}^{N\times 1}$ and $\bar{\mathbf{F}} \in \mathbb{C}^{M\times N}$ represent the LoS components, while $\tilde{\mathbf{z}}_d \in \mathbb{C}^{M\times 1}$, $\tilde{\mathbf{z}}_r \in \mathbb{C}^{N\times 1}$ and $\tilde{\mathbf{F}} \in \mathbb{C}^{M\times N}$ represent the corresponding NLoS components.

To reduce the channel training overhead, the statistical CSI can be exploited as it varies much slowly as compared to the instantaneous CSI [2], [13], [14]. By efficient channel modeling, we can re-generate a large number of channel samples, and accordingly obtain the statistical CSI, e.g., the statistical mean and covariance of the channel matrices, etc. However, accurate channel model is very difficult to obtain, since extensive knowledge and experiences in the wireless communication field are required, especially when MIMO communication systems are considered. To resolve this difficulty, we leverage the strong power of DL techniques to learn the reflected channel distribution, and accordingly propose a novel model-driven GAN-based channel modeling method, which will be introduced in the following.

III. IRS-GAN

In this section, we first introduce some preliminaries of GAN, which is a promising alternative for distribution learning, after which we present a detailed description of the proposed IRS-GAN framework and explain the intuition behind it. Finally, we provide the learning strategy for the proposed IRS-GAN framework.

A. Preliminaries of GAN

Recently, GAN has emerged as a novel framework for distribution learning via an adversarial process, which aims to learn a generative model that is able to produce samples close to some target distribution [9], [11], [15]. As shown in

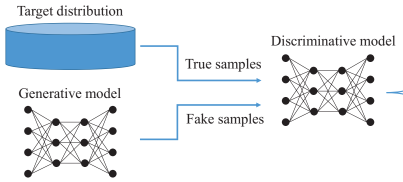

Fig. 2: Architecture of GANs.

Fig. 2, a typical GAN generally consists of a generative model and a discriminative model. These two models are trained simultaneously and competing with each other in the training stage. The discriminative model is trained to distinguish the true samples from the target distribution and the fake samples generated by the generative model, while the generative model learns to fool the discriminative model into making mistakes. This framework corresponds to a minimax two-player game, and the training process will end up with a Nash equilibrium, where the discriminative model cannot outperform random guessing when distinguishing the true and fake samples. In [9], it was demonstrated that this minimax game has a global optimum and GANs can accurately recover the target distribution as long as the generative and discriminative models have enough capacity.

Nevertheless, despite the abovementioned strengths of GANs, training them is known for being delicate and unstable, and hence it is difficult to ensure their convergence [9], [11]. Another problem is that the trained generative model may be lack of diversity, i.e., the generative model may concentrate on samples that only exhibit a few patterns instead of from the whole data space.

B. Proposed IRS-GAN Framework

In this subsection, we present the proposed IRS-GAN framework, where a specially designed GAN that takes the structure of the cascaded BS-IRS-user channel into consideration is applied to learn the channel distribution. The proposed framework consists of a generative model $\mathcal{F}_{\mathrm{G}}$, and a discriminative model $\mathcal{F}_{\mathrm{D}}$, where random noise is transformed by $\mathcal{F}_{\mathrm{G}}$ into a channel sample, and either this generated sample or a true channel sample is accepted by $\mathcal{F}_{\mathrm{D}}$ to produce a real value denoting the probability that the input sample is from the true channel distribution.

Note that in the traditional GAN framework, $\mathcal{F}_{\mathrm{D}}$ and $\mathcal{F}_{\mathrm{G}}$ are usually multi-layer perceptions (MLPs) [9], convolutional neural networks (CNN) [11] or residual networks [15], etc. These networks are trained as black boxes with a large number of training data, and it is difficult to understand their operational mechanisms and investigate how to modify their architectures to achieve better performance. Therefore, we can infer that it would very inefficient to simply adopt these canonical network structures for IRS-related channel modeling since the prior knowledge of the inherent channel property is not exploited. Motivated by this, we embrace the model-driven DL technique [16] in this work and propose to combine it with GAN to solve the considered IRS channel modeling problem. Specifically, the model-driven DL technique [16] is one of the most popular and promising methods for accelerating the training process of neural networks and it has been successfully applied in many other communication problems, such as the LcgNet for massive MIMO detection [17], the LampResNet for mmWave channel estimation [18], and the OFDM-autoencoder [19], etc. Inspired by model-driven DL, we design the network structure in the proposed IRS-GAN framework based on the prior knowledge that the reflected channel is the cascade of the BS-IRS and IRS-user channels.

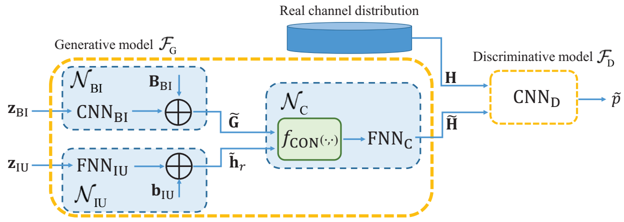

Fig. 3: Proposed IRS-GAN framework.

Since the n-th column of the reflected channel $\mathbf{H}$ is the scalar-vector multiplication of the n-th entry of $\mathbf{h}_r$ and the n-th row of $\mathbf{G}$ (see the reflected channel model given in (3)), we propose a three-node generative model $\mathcal{F}_{\mathrm{G}}$ which consists of a BS-IRS (BI) node $\mathcal{N}_{\mathrm{BI}}$, an IRS-user (IU) node $\mathcal{N}_{\mathrm{IU}}$ and a Cascading (C) node $\mathcal{N}_{\mathrm{C}}$, as shown in Fig. 3. First, $\mathcal{N}_{\mathrm{BI}}$ is utilised to transform the input random noise vector $\mathbf{z}_{\mathrm{BI}}$ from a fixed distribution (usually a uniform or Gaussian distribution) into a matrix $\tilde{\mathbf{G}}$ which approximates the BS-IRS channel $\mathbf{G}$. Note that in a typical CNN, each neuron in the current layer is only connected to a few nearby neurons in the previous layer and the same set of weights is shared by all the neurons in one layer. Based on this weight-sharing architecture and the translational invariance characteristics, CNNs can effectively extract high-level features from the input data. As a result, to approximate the distribution of the BS-IRS channel matrix $\mathbf{G}$ (which is generally high-dimensional and spatially correlated), we treat $\mathbf{G}$ as a two-dimensional natural image and employ a number of two-dimensional convolutional layers, denoted by $\mathrm{CNN}_{\mathrm{BI}}(\mathbf{z}_{\mathrm{BI}};\boldsymbol{\theta}_{\mathrm{BI}})$, to learn the intrinsic correlation among different elements in $\mathbf{G}$, where $\boldsymbol{\theta}_{\mathrm{BI}}$ denotes the network parameters included in $\mathrm{CNN}_{\mathrm{BI}}(\mathbf{z}_{\mathrm{BI}};\boldsymbol{\theta}_{\mathrm{BI}})$. Besides, it is noteworthy that a natural BGR image generally consists of three color channels each with real elements, while the wireless channel matrices usually have complex elements. Since most DL platforms require computing with real numbers, we propose to avoid handling complex-valued input channel samples by regarding the real and imaginary parts of $\mathbf{G}$ as two image color channels with real entries. Furthermore, since there is in general a LoS component exists in $\mathbf{G}$ that does not change much over time, an additional bias term $\mathbf{B}_{\mathrm{BI}} \in \mathbb{C}^{N\times M}$, is introduced into $\mathcal{N}_{\mathrm{BI}}$ to represent this LoS component and $\mathbf{B}_{\mathrm{BI}}$ is set to be independent of the input noise vector $\mathbf{z}_{\mathrm{BI}}$. Accordingly, the output of $\mathcal{N}_{\mathrm{BI}}$, denoted by $\tilde{\mathbf{G}}$, can be expressed as

$$\tilde{\mathbf{G}} = \mathcal{N}_{\mathrm{BI}}(\mathbf{z}_{\mathrm{BI}};\boldsymbol{\theta}_{\mathrm{BI}},\mathbf{B}_{\mathrm{BI}}) = \mathrm{CNN}_{\mathrm{BI}}(\mathbf{z}_{\mathrm{BI}};\boldsymbol{\theta}_{\mathrm{BI}}) + \mathbf{B}_{\mathrm{BI}}. \tag{6}$$

Second, $\mathcal{N}_{\mathrm{IU}}$ is designed to represent the IRS-user channel $\mathbf{h}_r$ by passing a random noise vector $\mathbf{z}_{\mathrm{IU}}$ though a multi-layer fully-connected network $\mathrm{FNN}_{\mathrm{IU}}$ and then adding a bias term $\mathbf{b}_{\mathrm{IU}} \in \mathbf{C}^{N\times 1}$, i.e.,

$$\tilde{\mathbf{h}}_r = \mathcal{N}_{\mathrm{IU}}(\mathbf{z}_{\mathrm{IU}};\boldsymbol{\theta}_{\mathrm{IU}},\mathbf{b}_{\mathrm{IU}}) = \mathrm{FNN}_{\mathrm{IU}}(\mathbf{z}_{\mathrm{IU}};\boldsymbol{\theta}_{\mathrm{IU}}) + \mathbf{b}_{\mathrm{IU}}, \tag{7}$$

where $\tilde{\mathbf{h}}_r$ denotes the output of $\mathcal{N}_{\mathrm{IU}}$ and $\boldsymbol{\theta}_{\mathrm{IU}}$ is the learnable parameters included in $\mathrm{FNN}_{\mathrm{IU}}$. It is noteworthy that since the IRS-user channel $\mathbf{h}_r$ is a vector, the FNN structure is employed for simplicity (the CNN structure can also be used in this node). Finally, the node $\mathcal{N}_{\mathrm{C}}$ is designed to first concentrate the outputs of $\mathcal{N}_{\mathrm{BI}}$ and $\mathcal{N}_{\mathrm{IU}}$, then pass these concentrated results though a few fully-connected layers, $\mathrm{FNN_C}$, to further approximate the reflected channel and finally output the generated reflected channel samples $\{\tilde{\mathbf{H}}\}$, i.e.,

$$\tilde{\mathbf{H}} = \mathcal{N}_{\mathrm{C}}(\tilde{\mathbf{G}}, \tilde{\mathbf{h}}_r; \boldsymbol{\theta}_{\mathrm{C}}) = \mathrm{FNN_C}\big(f_{\mathrm{CON}}(\tilde{\mathbf{G}}, \tilde{\mathbf{h}}_r); \boldsymbol{\theta}_{\mathrm{C}}\big), \quad (8)$$

where $f_{\mathrm{CON}}(\tilde{\mathbf{G}}, \tilde{\mathbf{h}}_r) = \tilde{\mathbf{G}}^H \mathrm{diag}(\tilde{\mathbf{h}}_r)$ and $\boldsymbol{\theta}_{\mathrm{C}}$ represents the network parameters of $\mathrm{FNN_C}$. Let $\boldsymbol{\Theta}_{\mathrm{G}} = \{\boldsymbol{\theta}_{\mathrm{BI}}, \mathbf{B}_{\mathrm{BI}}, \boldsymbol{\theta}_{\mathrm{IU}}, \mathbf{b}_{\mathrm{IU}}, \boldsymbol{\theta}_{\mathrm{C}}\}$ denote the overall learnable parameters in the proposed generative model $\mathcal{F}_{\mathrm{G}}$, then we can express $\mathcal{F}_{\mathrm{G}}$ based on (6), (7) and (8) as follows:

$$\tilde{\mathbf{H}} = \mathcal{F}_{\mathrm{G}}(\mathbf{z}_{\mathrm{BI}}, \mathbf{z}_{\mathrm{IU}}; \boldsymbol{\Theta}_{\mathrm{G}}) = \mathrm{FNN_C}\Big(f_{\mathrm{CON}}(\tilde{\mathbf{G}}, \tilde{\mathbf{h}}_r); \boldsymbol{\Theta}_{\mathrm{G}}\Big). \quad (9)$$

As for the discriminative model $\mathcal{F}_{\mathrm{D}}$, since the reflected channel $\mathbf{H}$ can be viewed as a matrix whose columns are scaled versions of those of the BS-IRS channel $\mathbf{G}$ (see (3)) and thereby inherits the spatial correlation in $\mathbf{G}$, we employ a multi-layer CNN, denoted by $\mathrm{CNN_D}$, to extract the features in the input channel samples $\{\hat{\mathbf{H}}\}$ and determine whether $\hat{\mathbf{H}}$ is from the true channel distribution or not. By letting $\boldsymbol{\Theta}_{\mathrm{D}}$ denote the network parameters in $\mathrm{CNN_D}$, $\mathcal{F}_{\mathrm{D}}$ can be represented by

$$\tilde{p} = \mathcal{F}_{\mathrm{D}}(\hat{\mathbf{H}}; \boldsymbol{\Theta}_{\mathrm{D}}) = \mathrm{CNN_D}(\hat{\mathbf{H}}; \boldsymbol{\Theta}_{\mathrm{D}}), \quad (10)$$

where the input $\hat{\mathbf{H}}$ can be the true channel sample $\mathbf{H}$ or the generated channel sample $\tilde{\mathbf{H}}$; and the output $\tilde{p}$ represents the probability that $\hat{\mathbf{H}}$ is drawn from the true channel distribution. To summarize, the proposed IRS-GAN framework is illustrated in Fig. 3.

C. Learning Strategy

In this work, to validate the effectiveness of the proposed IRS-GAN and for simplicity, the training data set is constructed by generating reflected channel samples according to a known channel model, i.e., the model introduced in Section II[1], and the reflection coefficient matrix is set as discrete Fourier transform (DFT) matrix. The Gaussian noise vectors $\mathbf{z}_{\mathrm{BI}}$ and $\mathbf{z}_{\mathrm{IU}}$ fed into $\mathcal{F}_{\mathrm{G}}$ follow complex normal distributions, i.e., $\mathbf{z}_{\mathrm{BI}} \sim \mathcal{CN}(0, \sigma_{z,1}^2 \mathbf{I})$ and $\mathbf{z}_{\mathrm{IU}} \sim \mathcal{CN}(0, \sigma_{z,2}^2 \mathbf{I})$. Besides, the biases in $\mathcal{N}_{\mathrm{BI}}$ and $\mathcal{N}_{\mathrm{IU}}$, i.e., $\mathbf{B}_{\mathrm{BI}}$ and $\mathbf{b}_{\mathrm{IU}}$, are randomly generated from $\mathcal{CN}(0, \sigma_{b,1}^2 \mathbf{I})$ and $\mathcal{CN}(0, \sigma_{b,2}^2 \mathbf{I})$, respectively. The noise variances $\sigma_{z,1}^2$, $\sigma_{z,2}^2$, $\sigma_{b,1}^2$ and $\sigma_{b,2}^2$ are hyper-parameters that determine the initial distribution of the generated channel samples from $\mathcal{F}_{\mathrm{G}}$.

Inspired by [11] and [15], we leverage the Wasserstein distance to construct the loss functions for training the generative and discriminative models, which are shown as follows:

$$\mathcal{L}_{\mathrm{G}} = \min_{\boldsymbol{\Theta}_{\mathrm{G}}} \mathbb{E}\Big[\max\big\{1 - \mathcal{F}_{\mathrm{D}}\big(\mathcal{F}_{\mathrm{G}}(\mathbf{z}_{\mathrm{BI}}, \mathbf{z}_{\mathrm{IU}}; \boldsymbol{\Theta}_{\mathrm{G}}); \boldsymbol{\Theta}_{\mathrm{D}}\big), 0\big\}\Big], \quad (11)$$

$$\mathcal{L}_{\mathrm{D}} = \min_{\boldsymbol{\Theta}_{\mathrm{D}}} \mathbb{E}\Big[-\mathcal{F}_{\mathrm{D}}(\mathbf{H}_k; \boldsymbol{\Theta}_{\mathrm{D}}) - \max\big\{1 - \mathcal{F}_{\mathrm{D}}\big(\mathcal{F}_{\mathrm{G}}(\mathbf{z}_{\mathrm{BI}}, \mathbf{z}_{\mathrm{IU}}; \boldsymbol{\Theta}_{\mathrm{G}}); \boldsymbol{\Theta}_{\mathrm{D}}\big), 0\big\}\Big], \quad (12)$$

where $\mathcal{F}_{\mathrm{D}}(\mathbf{H}_k; \boldsymbol{\Theta}_{\mathrm{D}})$ represents the probability that $\mathcal{F}_{\mathrm{D}}$ decides that a true channel sample comes from the true channel data set, and $\mathcal{F}_{\mathrm{D}}\big(\mathcal{F}_{\mathrm{G}}(\mathbf{z}_{\mathrm{BI}}, \mathbf{z}_{\mathrm{IU}}; \boldsymbol{\Theta}_{\mathrm{G}}); \boldsymbol{\Theta}_{\mathrm{D}}\big)$ denotes the probability that $\mathcal{F}_{\mathrm{D}}$ determines that a generated fake channel sample is from the true channel date set; the $\max(\cdot)$ functions in (11) and (12) are introduced to confine the output of $\mathcal{F}_{\mathrm{D}}$ to lie in the interval [0,1]. By training $\mathcal{F}_{\mathrm{G}}$ and $\mathcal{F}_{\mathrm{D}}$ using the loss functions in (11) and (12), $\mathcal{F}_{\mathrm{G}}$ and $\mathcal{F}_{\mathrm{D}}$ are expected to play a two-player minimax game, i.e.,

$$\min_{\boldsymbol{\Theta}_{\mathrm{G}}} \max_{\boldsymbol{\Theta}_{\mathrm{D}}} \mathbb{E}[\mathcal{F}_{\mathrm{D}}(\mathbf{H}_k; \boldsymbol{\Theta}_{\mathrm{D}})] + \mathbb{E}[\max\big\{1 - \mathcal{F}_{\mathrm{D}}\big(\mathcal{F}_{\mathrm{G}}(\mathbf{z}_{\mathrm{BI}}, \mathbf{z}_{\mathrm{IU}}; \boldsymbol{\Theta}_{\mathrm{G}}), \boldsymbol{\Theta}_{\mathrm{D}}\big), 0\big\}], \quad (13)$$

where $\mathcal{F}_{\mathrm{D}}$ is expected to give a high value if the input sample belongs to the true channel data set and a low one if the input is generated by $\mathcal{F}_{\mathrm{G}}$, and $\mathcal{F}_{\mathrm{G}}$ is trained to fool $\mathcal{F}_{\mathrm{D}}$ to output a high probability value when the input is from $\mathcal{F}_{\mathrm{G}}$. Since (11) and (12) are based on the Wasserstein distance which is continuous and differentiable everywhere, the proposed IRS-GAN is easier to train and converge as compared to GANs trained with the Jensen-Shannon (JS) divergence based loss function [9], [11].

The training process of the proposed IRS-GAN framework mainly consists of two loops. In each of the outer loop, three inner loops (contains a generative loop, a discriminative loop and a testing loop) are executed sequentially. In the inner generative (discriminative) loop, $\mathcal{F}_{\mathrm{G}}$ ($\mathcal{F}_{\mathrm{D}}$) is trained with a fixed number of iterations denoted by I_{G} (I_{D}). In the testing loop, we calculate a coarse estimate of the Wasserstein distance $\bar{D}_{\mathrm{W}} \triangleq \mathbb{E}[\mathcal{F}_{\mathrm{D}}(\mathbf{H})] - \mathbb{E}[\mathcal{F}_{\mathrm{D}}(\tilde{\mathbf{H}})]$ between the true channel distribution and the generated channel distribution and save it for the next testing loop. Note that $\bar{D}_{\mathrm{W}}$ is related with the convergence and the generated sample quality of $\mathcal{F}_{\mathrm{G}}$. Let α_{I}, $\{\epsilon_1, \epsilon_2\}$ and l denote the initial learning rate, two threshold values, and the outer iteration index, respectively. When $|\bar{D}_{\mathrm{W}}^{(l)} - \bar{D}_{\mathrm{W}}^{(l-1)}| < \epsilon_1$, the training process is terminated, and if $|\bar{D}_{\mathrm{W}}^{(l)} - \bar{D}_{\mathrm{W}}^{(l-1)}| \in [\epsilon_1, \epsilon_2]$, the learning rate is set to $\tau\alpha_I$ with τ denoting a decaying factor, otherwise, the next outer loop directly starts with α_I.

Note that employing Wasserstein distance based loss functions can effectively improve the stability of learning, but this improvement usually comes at the cost of lower training speed. In this work, to speed up the training procedure, we employ the following three schemes in the proposed learning strategy.

- First, we train $\boldsymbol{\Theta}_{\mathrm{D}}$ by minimizing the sum of $\mathcal{L}_{\mathrm{D}}$ and a gradient penalty term $\lambda\mathbb{E}\big[(\|\Delta_{\bar{\mathbf{H}}}\mathcal{F}_{\mathrm{D}}(\bar{\mathbf{H}})\| - 1)^2\big]$, i.e., $\frac{1}{M}\sum_{m=1}^{M}\mathcal{L}_{\mathrm{D,GP}}^{(m)}$, where

$$\mathcal{L}_{\mathrm{D,GP}}^{(m)} = -\max\big\{1 - \mathcal{F}_{\mathrm{D}}(\tilde{\mathbf{H}}^{(m)}), 0\big\} - \mathcal{F}_{\mathrm{D}}(\mathbf{H}^{(m)}) + \lambda||\nabla_{\bar{\mathbf{H}}^{(m)}}\mathcal{F}_{\mathrm{D}}(\bar{\mathbf{H}}^{(m)})|| - 1)^2, \quad (14)$$

  M is batchsize, $\bar{\mathbf{H}} = \epsilon\mathbf{H} + (1-\epsilon)\tilde{\mathbf{H}}$ with $\epsilon \sim U(0,1)$ denoting a random coefficient, and λ is the gradient penalty coefficient which is fixed before training. Note that WGAN sometimes can still generate only poor samples or fail to converge, due to the use of weight clipping [11]. Adding this gradient penalty term, which is an alternative to clipping weights, can enable more stable training.
- Second, we propose to add a moment penalty term to $\mathcal{L}_{\mathrm{G}}$ such that $\mathcal{F}_{\mathrm{G}}$ is forced to focusing on learning

[1]In practice, we should construct the training data set by collecting the true reflected channel matrices obtained from channel measurements, where the channel estimation methods in [10], [20] can be used.

the statistical information contained in the true channel samples. Specifically, in the generative loop, the corresponding network parameters are learned by minimizing $\frac{1}{M}\sum_{m=1}^{M}\mathcal{L}_{\text{G,MP}}^{(m)}$, where

$$\mathcal{L}_{\text{G,MP}}^{(m)} = \mu\big(||\mathbf{H}^{(m)}||_{\text{F}} - ||\tilde{\mathbf{H}}^{(m)}||_{\text{F}}\big)^2 + \max\left\{1 - \mathcal{F}_{\text{D}}(\tilde{\mathbf{H}}^{(m)}), 0\right\}, \tag{15}$$

and $\mu\|\mathbb{E}[\mathbf{H}^{(m)}] - \mathbb{E}[\tilde{\mathbf{H}}^{(m)}]\|_{\text{F}}$ represents the moment penalty term with μ denoting the moment penalty coefficient. As such, $\mathcal{F}_{\text{G}}$ is expected to produce a distribution that has a similar expectation as the true channel distribution, which is helpful for accelerating of the training process especially when the channel has a large deterministic (LoS) component.

- Finally, the initial learning rate for training the bias terms (i.e., $\mathbf{\Theta}_{\text{B}} \triangleq \{\mathbf{B}_{\text{BI}}, \mathbf{b}_{\text{IU}}\}$) is set to be larger than that for training the other network parameters, (i.e., $\mathbf{\Theta}_{\text{O}} \triangleq \{\boldsymbol{\theta}_{\text{BI}}, \boldsymbol{\theta}_{\text{IU}}, \boldsymbol{\theta}_{\text{C}}\}$ and $\mathbf{\Theta}_{\text{D}}$). This modification enables the proposed IRS-GAN to learn the LoS component quickly and then gradually approximate the distribution of the NLoS component.

Besides, all the network parameters in the proposed IRS-GAN are updated by minimizing the corresponding loss functions using the Adam optimizer $\text{Adam}(\cdot,\cdot,\alpha,\beta_1,\beta_2)$, where α is the learning rate, and β_1 and β_2 are the exponential decaying rates for the first and second moment estimates [21].

IV. Simulation Results

In this section, we provide numerical results to evaluate the performance of the proposed IRS-GAN framework.

First, we assume a three-dimensional coordinate system where the BS equipped with a uniform linear array (ULA) is deployed on the x-axis and the IRS equipped with an $N_y \times N_z$ uniform planar array (UPA) is deployed on the $y - z$ plane. The reference antenna/element at the BS/IRS are located at (2 m, 0, 0) and (0, 45 m, 2 m), respectively. Specifically, the distance-dependent path losses of $\mathbf{h}_d$'s, $\mathbf{h}_r$'s and $\mathbf{G}$ are modeled as $l_m^{\text{BU}} = l_0\left(d_m/d_0\right)^{-\alpha^{\text{BU}}}$, $l_n^{\text{IU}} = l_0\left(d_n/d_0\right)^{-\alpha^{\text{IU}}}$, $l_{m,n}^{\text{BI}} = l_0\left(d_{m,n}/d_0\right)^{-\alpha^{\text{BI}}}$, respectively, where $l_0 = -30$ dB represents the path loss at the reference distance $d_0 = 1$ meter (m), d_m, d_n and $d_{m,n}$ denote the link distances from the user to the m-th BS antenna, from the user to the n-th reflecting element and from the n-th reflecting element to the m-th BS antenna, respectively. The path-loss exponents of the user-BS, user-IRS and IRS-BS links are fixed to $\alpha^{\text{BU}} = 3.4$, $\alpha^{\text{IU}} = 3$ and $\alpha^{\text{BI}} = 2.2$, respectively. Other system parameters are set as follows unless otherwise specified: $\sigma^2 = -80$ dBm, $\beta^{\text{BI}} = \beta^{\text{IU}} = 5$ dB, $\beta^{\text{BU}} = -5$ dB, $r_d = r_{r,k} = 0$ and $r_r = 0.5$.

Second, we introduce the detailed network architecture of the proposed IRS-GAN. For the generative model, CNN_{BI} in the BI node, consists of 4 convolutional layers, which produce 256, 128, 64 and 2 feature maps using 5×5, 3×3, 3×3 and 3×3 convolutional cores, respectively, and $\tanh(\cdot)$ is considered as the activation function. Besides, FNN_{IU} and FNN_{C} in the IU and C nodes consist of 3 and 2 fully-connected layers, respectively, where $\tanh(\cdot)$ is also employed as the activation function. For the discriminative model, CNN_{D} contains 3 convolutional layers, and they use convolutional cores of sizes 5×5, 3×3 and 3×3 to generate 128, 64 and 1 feature maps. Besides, the ReLU function, i.e., $\text{ReLU}(x) = \max(0,x)$, is served as the activation function. In our simulations, the training process is conducted offline on a Windows server with Intel Xeon Gold 6230 CPU and an Nvidia 2080Ti GPU. The proposed networks are implemented in Python using the TensorFlow library with the Adam optimizer.

Furthermore, notice that different from the generative models/networks designed for computer vision tasks (such as those in [9], [11]) whose performance can be directly demonstrated by observing the generated images, it is challenging to evaluate the performance of a generative model/network for the channel modeling problem, especially when the channel matrix is high-dimensional. To address this issue, we design the following metrics in this work.

- Probability distribution function (PDF) of the average singular value of reflected channel matrices: In random matrix theory [22], the average eigenvalue of a random matrix, i.e., the linear eigenvalue statistic, is usually employed to characterize a random square matrix. Inspired by this, we regard the PDF of the average singular value (also referred to as *linear singular value statistics (LSVS)*) as an essential metric to characterize the distribution of the reflected channels.
- Average achievable rate achieved by the TTS beamforming scheme: The authors in [2] proposed a TTS beamforming optimization scheme for an IRS-aided communication system, where the sum-rate maximization problem was solved by using randomly generated channel samples (under the assumption that the BS-user, BS-IRS and IRS-user channel models are perfectly known). Motivated by this, we take the achievable rate achieved by the TTS beamforming scheme as the second performance metric, where the required channel samples are generated from the trained IRS-GAN, and all the results are averaged over 1000 independent channel realizations.

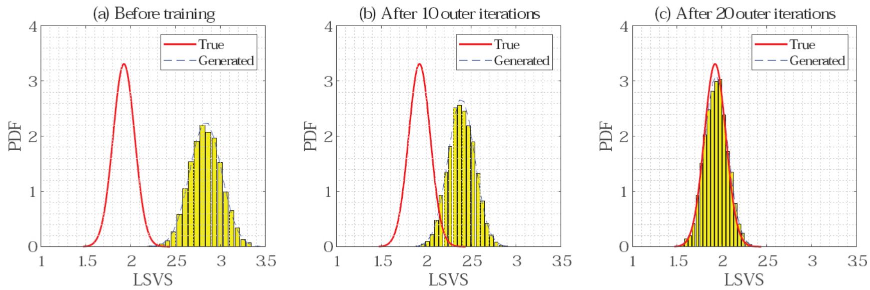

Fig. 4: PDFs of the LSVS of the true channel samples and the generated channel samples by $\mathcal{F}_{\text{G}}$ during the training process.

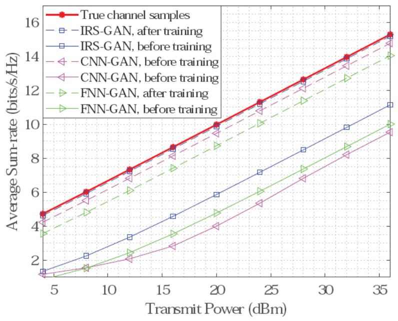

Fig. 5: Average sum-rate performance with different power budgets.

In Fig. 4, we illustrate the PDFs of the LSVS of the reflected channel samples generated by $\mathcal{F}_{\mathrm{G}}$ during the training process and compare them with that of the true channel samples. It is can be observed from Fig. 4 (a) that at the beginning of the training process, the LSVS of the generated channel samples is very different from that of the true channel samples due to the random initialization of the proposed IRS-GAN. Then, the proposed network gradually learns to approximate the LSVS of the true channel samples, as can be observed from Fig. 4 (b). After training, the LSVS distributions of the generated channel samples and the true channel samples are almost identical (shown in Fig. 4 (c)), which indicates that the proposed IRS-GAN has successfully learned the reflected channel distribution at least in terms of LSVS.

In Fig. 5, we plot the average achievable rates achieved by the TTS beamforming scheme [2] based on the true and generated channel samples, under various transmit power budgets. For comparison, we also provide the performance achieved by two benchmark GANs, i.e., a CNN-based GAN and a FNN-based GAN (abbreviated as CNN-GAN and FNN-GAN in the following), where the conventional CNN and FNN are regarded as the generative models, respectively. Specifically, the CNN therein consists of 4 convolution layers, which produce 256, 128, 64 and 2 feature maps using kernels of sizes 5×5, 3×3, 3×3 and 3×3, respectively, and the FNN consists of 4 fully-connected layers, which contains $5MN$, $10MN$, $5MN$ and $2MN$ neurons respectively. Besides, $\tanh(\cdot)$ is employed as the activation function of each layer. It can be observed from Fig. 5 that the average achievable rate achieved based on the generated channel samples is almost identical to that achieved based on the true channel samples, and it is higher than those achieved by the CNN-GAN and FNN-GAN. This indicates that the proposed IRS-GAN framework can effectively learn the true reflected channel distribution, and by exploiting the special structure of the reflected channel, IRS-GAN shows a better performance as compared to other canonical network structures.

V. Conclusions

In this paper, we studied the channel modeling problem in an IRS-aided MISO system. A model-driven GAN-based channel modeling framework, called IRS-GAN, was proposed to learn the reflected channels, and the proposed framework does not require in-depth domain knowledge in wireless signal propagation and complex data processing. The special structure of the reflected channel was exploited to design the generative model, which helps to capture the reflected channel distribution effectively. Simulation results demonstrated the effectiveness of the proposed GAN-based channel modeling method. Further extension to the general multiuser case will be left for future work.

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