Research on Active/Passive Hybrid IRS Assisted Communication Method Based on Deep Learning

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***Abstract*—With the rapid development of mobile communication technology, wireless communication systems have higher and higher requirements for spectral efficiency and energy efficiency. However, in the optimization process of many technologies, the wireless communication environment is still an uncontrollable factor, and is increasingly becoming a bottleneck for improving communication quality. Intelligent Reflecting Surface can reflect incident signals through a large number of low-cost reflective units, thereby improving the wireless communication environment. This paper introduces a solution based on deep learning method with the goal of maximizing the achievable rate of the system under the condition of intelligent reflecting surface hardware architecture of hybrid active/passive units. Firstly, the performance of communication system with intelligent reflecting surface and relay is compared. After that, the hardware architecture of intelligent reflecting surface with hybrid active/passive units is introduced, and the research scheme of intelligent reflecting surface based on deep learning is designed and simulated. The results show that the proposed scheme can approach the upper limit of the achievable rate of the system as much as possible while reducing the overhead of beam training.**

***Index Terms*—wireless communication, intelligent reflecting surface, deep learning**

I. Introduction

With the rapid development of mobile communication technology, wireless communication systems have higher and higher requirements for spectral efficiency and energy efficiency. However, in the optimization process of many technologies, the wireless communication environment is still an uncontrollable factor, and is increasingly becoming a bottleneck for improving communication quality [1]. Under the condition that the wireless environment is uncontrollable, the existing technology can improve the communication quality to a sufficient level [2], but with the popularization of 5G and the accelerating research and development of 6G, improving this problem is becoming a promising job.

For these reasons, in recent years, Intelligent Reflecting Surface (IRS) have attracted the interest of academia. IRS is a plane composed of a large number of low-cost passive reflective elements and one or more controllers, which are placed between the transmitter and receiver of the wireless channel, and can usually produce some changes to the incident signal, generally including: phase, amplitude, frequency and even polarization state, and it plays a role in changing the wireless communication environment. Deep Learning (DL) is an important way to realize artificial intelligence. Its core idea is to train a pre-built neural network through a large amount of sample data, and finally obtain the inherent rules and representations of the data, and then use this neural network to achieve some specific functions. Although the effect of the IRS is ideal, the difficulty lies in how to make a large number of reflective units on this configurable surface work together in different scenarios, that is, how to deal with the large amount of data generated during the working process of the reflective surface, so as to achieve the desired goal. Since deep learning requires a large amount of data to train its neural network, the deep learning method can be used to process the large amount of data on the IRS.

The main purpose of the theoretical research of wireless communication system based on IRS is to grasp the reflection characteristics of IRS and make use of it. In [3], author constructs a broadband IRS system model to maximize the average rate of the system. The research in [4] shows that channel estimation can be realized by using the characteristics of Khatri-Rao product and Kronecker product and the inherent sparsity of millimeter wave channel. The hardware structure of IRS determines that using traditional signal processing methods to study IRS will inevitably lead to huge amount of calculation and high hardware complexity. Using deep learning method to solve the key signal processing problems in IRS communication can achieve higher efficiency than traditional technology. A federated learning framework for channel estimation is proposed in [5], which greatly reduces the amount of data transmission between the user and the base station. In [6], the author developed an algorithm based on Deep Reinforcement Learning to generate the optimal beamforming matrix of IRS, which requires a lot of data for training, and its main disadvantage is the high training cost.

The main research content of this paper is to use deep learning method to configure the IRS surface reflection unit in the IRS assisted communication system, so as to achieve the highest achievable rate at the receiver. This paper uses the structure of two parallel lines to introduce, and the article is organized as follows. Section II introduces the models of IRS assisted communication system and relay assisted communication system, then describes the system architecture of IRS combined with deep learning. Section

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III describes and models the communication system model introduced previously. The simulation results of the two parts are shown in the Section IV. Section V gives the conclusion of the work.

II. System Model

A. IRS Assisted Communication System Model

To study the IRS assisted communication system, it is necessary to compare it with the system without IRS deployment and the classical relay technology, and discuss the circumstances under which IRS is best placed to assist wireless communications. Consider a communication system from a single antenna transmitter to a single antenna receivier. In the first case, an IRS with M passive reflection units is deployed between the transmitter and the receiver to assist communication, as shown in Fig. 1, the second case is to deploy a relay between the transmitter and the receiver to assist communication, as shown in Fig. 2.

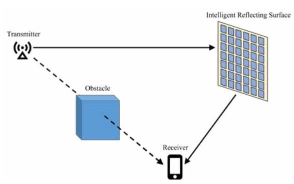

Fig. 1. IRS assisted communication system.

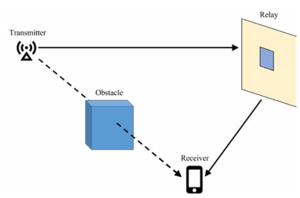

Fig. 2. Relay assisted communication system.

The channel from the transmitter to the IRS/relay is denoted by $\mathbf{h}_{\mathrm{T}} \in \mathbb{C}^M$, and the channel between the IRS/relay and the receiver channel is denoted by $\mathbf{h}_{\mathrm{R}} \in \mathbb{C}^M$, the blocked direct channel between the sender and the receiver is denoted by h_{D}. For brevity, suppose IRS only changes the phase of the incident signal, while does not change the amplitude of the signal. The received signal at the receiver is

$$y = \left(h_{\mathrm{D}} + \mathbf{h}_{\mathrm{T}}^{\mathrm{T}} \boldsymbol{\Theta} \mathbf{h}_{\mathrm{R}}\right) \sqrt{p} s + n \tag{1}$$

where p is the transmit power, s is the unit-power information signal, and n is the receiver noise.

Suppose the relay works in two stages in the relay assisted communication system. In the first stage, the transmitter sends signals, the relay and receiver receive signals from the transmitter. The first stage received signal at the receiver is

$$y_{1\mathrm{d}} = h_{\mathrm{D}} \sqrt{p_1} s + n_{1\mathrm{d}} \tag{2}$$

In the second stage, the relay sends signals and the receiver receives signals from the relay. The second stage received signal at the receiver is

$$y_{2d} = h_{\mathrm{R}} \sqrt{p_2} s + n_{2\mathrm{d}} \tag{3}$$

B. IRS Combined With Deep Learning Communication Model

In order to use deep learning method to study IRS assisted communication system, it is necessary to consider the architecture of IRS assisted communication system, and at the same time, it is essential to design the communication model appropriately according to the characteristics of deep learning method. Assume that the IRS has M reconfigurable reflective elements. In the same time, both the transmitter and receiver are single antenna. An orthogonal frequency division multiplexing (OFDM) system with K subcarriers is adopted. The overall architecture of the IRS assisted communication system combined with deep learning is shown in Fig. 3.

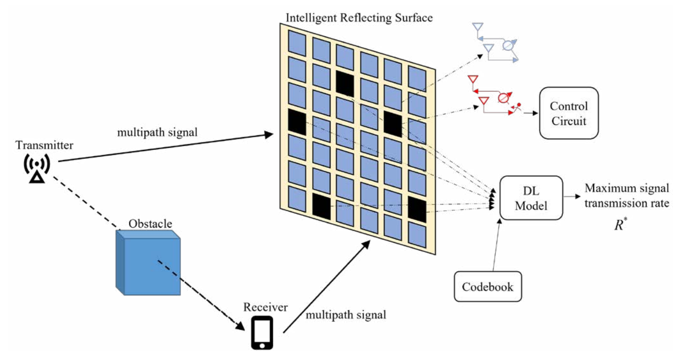

Fig. 3. Overall architecture of DL-IRS communication model.

In order to combine with the deep learning model, a new IRS hardware architecture is considered. Unlike the traditional IRS, which all use passive parts as reflection units, this architecture adopts a hybrid active/passive reflection unit structure. The passive unit is realized by a phase shifter, which simply shifts the received incident signal and then sends it out. The active unit has two working modes. It can either send the received incident signal to the baseband control processing circuit through the RF link for operation, or it can work in the same state as the passive unit and send the incident signal only by phase shifting. In the same time, the active unit can sense the channel and obtain the channel state, so as to input it into the deep learning model for training.

Every element in the reflected beamforming vector $\boldsymbol{\theta}$ of IRS is realized by using phase shifters, which usually have a set of quantized angles, so they can't change the signal at any phase. In order to adapt to this constraint, it is assumed that every element in the reflected beamforming vector $\boldsymbol{\theta}$ must be selected from a predefined codebook B, and every reflected beamforming codeword in the codebook B is assumed to be implemented using a quantized phase shifter.

III. Problem Formulation

A. Performance Analysis of IRS Assisted Communication System

According to the signal expression at the receiver of IRS/relay assisted communication system obtained by Section II-A, the channel capacity of IRS assisted communication system is represented as follows

$$R_{\text{IRS}}(M) = \log_2\left(1 + \frac{p\left(|h_{\text{D}}| + \sum_{m=1}^{M} |[\mathbf{h}_{\text{T}}]_m[\mathbf{h}_{\text{R}}]_m|\right)^2}{\sigma^2}\right) \tag{4}$$

The capacity of relay assisted communication system [7] is

$$R_{\text{RL}} = \frac{1}{2}\log_2\left(1 + \min\left(\frac{p_1|h_{\text{T}}|^2}{\sigma^2}, \frac{p_1|h_{\text{D}}|^2}{\sigma^2} + \frac{p_2|h_{\text{R}}|^2}{\sigma^2}\right)\right) \tag{5}$$

When obstacles block the direct channel between the transmitter and the receiver, the channel quality of the transmitter-IRS/relay-receiver is better than that of the transmitter-receiver. At this time, if the channel capacity of the system with the IRS deployed is larger than that of the system with the relay deployed, the number of reflection units of the IRS needs to meet the following conditions

$$M > \frac{\sqrt{\left(\sqrt{1 + \frac{2p|h_{\text{R}}|^2|h_{\text{T}}|^2}{\left(|h_{\text{T}}|^2+|h_{\text{R}}|^2-|h_{\text{D}}|^2\right)\sigma^2}} - 1\right)\frac{\sigma^2}{p}} - |h_{\text{D}}|}{\frac{1}{M}\sum_{m=1}^{M} |[\mathbf{h}_{\text{T}}]_m[\mathbf{h}_{\text{R}}]_m|} \tag{6}$$

B. IRS Combined With Deep Learning Model Setup

In this paper, because the required reflection beamforming codewords are obtained from a predefined codebook, the construction of the codebook plays an important role, and the reflection beamforming vector codebook B is in the form of Discrete Fourier Transform (DFT) codebook.

The Discrete Fourier Transform can be written as

$$X[k] = \sum_{m=0}^{M-1} x[m]e^{-j\frac{2\pi}{M}km}, 0 \leq k \leq M-1 \tag{7}$$

Based on this, we can have the following DFT matrix $\mathbf{F}$:

$$\mathbf{F} = \begin{pmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & \xi & \xi^2 & \cdots & \xi^{m-1} \\ 1 & \xi^2 & \xi^4 & \cdots & \xi^{2(m-1)} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & \xi^{m-1} & \xi^{2(m-1)} & \cdots & \xi^{(m-1)(m-1)} \end{pmatrix} \tag{8}$$

where $\xi = e^{-j\frac{2\pi}{M}}$. In essence, IRS is a special uniform planar array (UPA), for a UPA with M antennas spaced at half wavelength, the antenna response is related to the two parameters of incident azimuth angle θ and elevation angle ϕ. The response formula of UPA can be expressed as follows

$$\begin{aligned} a_{UPA}(\theta,\phi) = \tfrac{1}{\sqrt{M}}\big[1,\ldots,e^{j\pi(q\sin(\phi)\cos(\theta)+p\cos(\phi))}, \\ \ldots,e^{j\pi((Q-1)\sin(\phi)\cos(\theta)+(P-1)\cos(\phi))}\big]^T \end{aligned} \tag{9}$$

The response vectors corresponding to M different incident angles can be written in a matrix $\mathbf{A}$, as shown in (10). Assuming that at this time, let

$$[\theta_0, \theta_1, \cdots, \theta_{M-1}] = [\frac{\pi}{2}, \frac{\pi}{2}, \cdots, \frac{\pi}{2}] \tag{11}$$

$$\begin{aligned} &[\cos(\phi_0), \cos(\phi_1), \cdots, \cos(\phi_{M-1})] = \\ &\left[0, -\tfrac{2}{M}, \ldots, -\tfrac{M}{M}, -\tfrac{M+2}{M}+2, \ldots, -\tfrac{2(M-1)}{M}+2\right] \end{aligned} \tag{12}$$

Comparing (8) and (10), we can find that $\mathbf{A} = \mathbf{F}$. Based on this, all ϕ_m can be derived, where $\mathbf{A}$ is the DFT codebook obtained based on the DFT matrix. Each column of $\mathbf{A}$ represents the antenna response corresponding to an incident angle. The biggest feature is that the antenna responses of each incident angle are orthogonal to each other, which is caused by the mutual orthogonality of each column of the DFT matrix.

With the above communication model, the goal of this paper is to maximize the transmission rate of the signal received by the receiver by designing the reflection beamforming vector $\boldsymbol{\theta} \in \mathbb{C}^{M\times 1}$. The signal transmission rate of the receiver can be expressed as

$$\begin{aligned} R &= \frac{1}{K}\sum_{k=1}^{K}\log_2\left(1 + SNR\left|\mathbf{h}_{T,k}\boldsymbol{\Theta}\mathbf{h}_{R,k}\right|^2\right) \\ &= \frac{1}{K}\sum_{k=1}^{K}\log_2\left(1 + SNR\left|\left(\mathbf{h}_{T,k}\odot\mathbf{h}_{R,k}\right)\boldsymbol{\theta}\right|^2\right) \end{aligned} \tag{13}$$

where $SNR = \frac{P_T}{K\sigma_n^2}$ is the signal-to-noise ratio of the signal.

Based on the above assumption of DFT codebook, the goal is to find the best reflected beamforming codeword from the codebook and finally get the maximum signal transmission rate at the receiver R^*, which is defined as follows

$$R^* = \max_{\boldsymbol{\theta}\in\text{B}} \frac{1}{K}\sum_{k=1}^{K}\log_2\left(1 + SNR\left|\left(\mathbf{h}_{T,k}\odot\mathbf{h}_{R,k}\right)\boldsymbol{\theta}\right|^2\right) \tag{14}$$

IV. Simulation Results

A simple modeling of the scene in Sections II-A is shown in Fig. 4. The transmitter and the IRS/relay are deployed in a fixed location, while the position of the receiver varies with variables. A LOS propagation channel is assumed between IRS/relay and transmitter and between receiver and IRS/ relay, while there is a poor quality NLOS propagation

$$
\mathbf{A}=\begin{pmatrix}
1 & \cdots & 1 \\
e^{j\pi\left(\sin(\phi_0)\cos(\theta_0)+\cos\left(\phi_{(j)}\right)\right.} & \cdots & e^{j\pi(\sin(\phi_{M-1})\cos(\theta_{M-1})+\cos(\phi_{M-1}))} \\
e^{j\pi(2\sin(\phi_0)\cos(\theta_0)+2\cos(\phi_0))} & \cdots & e^{j\pi(2\sin(\phi_{M-1})\cos(\theta_{M-1})+2\cos(\phi_{M-1}))} \\
\vdots & \vdots & \vdots \\
e^{j\pi((Q-1)\sin(\phi_0)\cos(\theta_0)+(P-1)\cos(\phi_0))} & \cdots & e^{j\pi((Q-1)\sin(\phi_{M-1})\cos(\theta_{M-1})+(P-1)\cos(\phi_{M-1}))}
\end{pmatrix} \tag{10}
$$

channel between the transmitter and the receiver. Table I shows the settings of the specific simulation parameters in this paper.

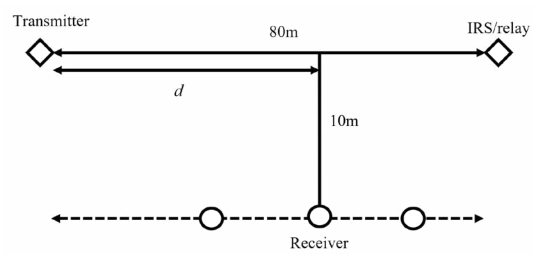

Fig. 4. IRS/relay comparison simulation scenario.

TABLE I
EXPERIMENT SIMULATION PARAMETER

Parameter	Value
Frequency	28GHz
Bandwidth	100MHz
Reflection coefficient amplitude gain	1
IRS reflection units	[500;1000;1500;2000]
Number of hidden layers	4

Fig. 5 shows the relationship between the required minimum transmission power of the transmitter and the horizontal distance d between the receiver and the transmitter when the data reception rate required by the receiver is $\overline{R} = 6\text{bps/Hz}$.

When $\overline{R} = 6\text{bps/Hz}$, the transmission power required by the scheme with IRS deployed decreases with the increase of the number of reflection units, and when the receiver is closer to the transmitter or the IRS, the transmission power required can obtain a smaller value. At the same time, the results show that when the communication system needs the receiving signal rate of the receiver to be as large as possible, it is a better solution to choose the IRS instead of the relay.

Fig. 6 shows the change of transmit power with the increase of the total number of reflective units on the IRS when $\overline{R} = 6\text{bps/Hz}$ and $d = 80\text{m}$ are fixed. On the premise that the receiver position and receiving signal rate are fixed, with the increase of the number of reflection units M, the required transmitting power of the transmitter also decreases gradually.

For the IRS assisted communication simulation combined with the deep learning method, first consider the selection

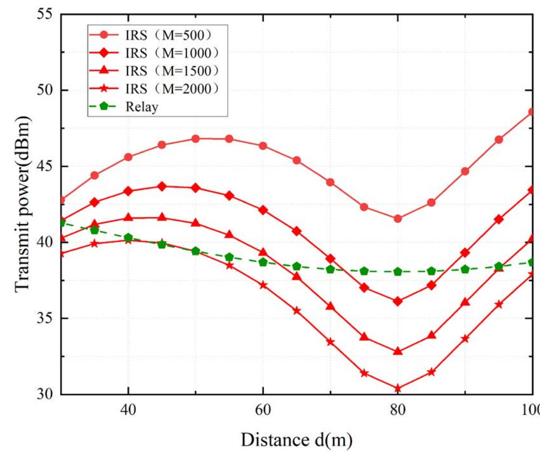

Fig. 5. Relationship between transmission power and distance d in case $\overline{R} = 6\text{bps/Hz}$.

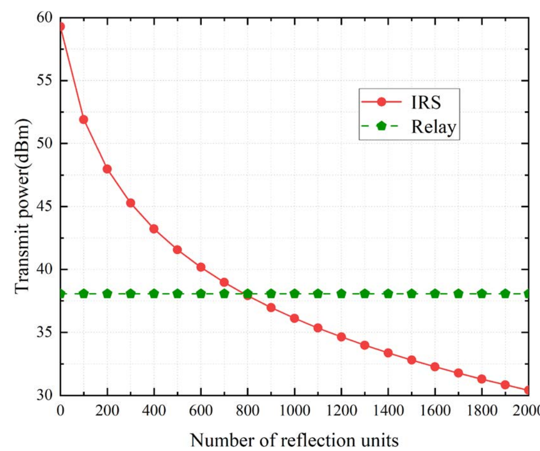

Fig. 6. Relationship between the transmit power and the number of IRS reflection units when $\overline{R} = 6\text{bps/Hz}$.

of the number of active units on the surface of the IRS. Fig. 7 shows the predicted rate output by the model as a percentage of the maximum achievable rate.

When the IRS size is $M = 32 \times 32$ and $M = 45 \times 45$, with the increase of the number of active units, the output rate of the deep learning model can reach about 90% and 95% of the maximum achievable rate. However, when the number of active units $\overline{M}$ reaches 8 or more, it is almost difficult to see the improvement in the output rate of the model by increasing the number of active units, indicating that the model has basically converged in this case. Although

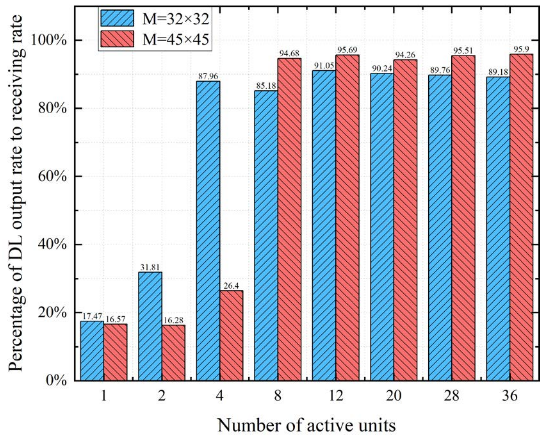

Fig. 7. Relationship between the percentage of predicted rate in the maximum achievable rate and the number of active units.

increasing the number of active units will improve the system performance, it will cause a lot of additional energy overhead. The increased performance and the overhead are seriously mismatched. According to the above analysis, considering the comprehensive performance and energy cost, active unit $\overline{M} = 8$ is the best choice.

After the above analysis, Fig. 8 shows the performance of the deep learning model when the IRS uses UPA of size 16×16, 32×32, and 45×45.

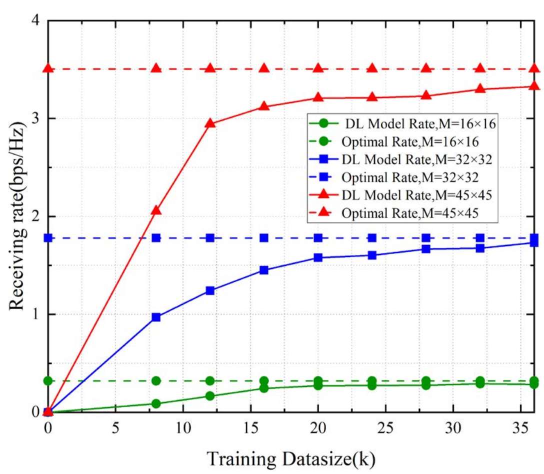

Fig. 8. Rate performance of deep learning model.

When there are only $\overline{M} = 8$ active reflection units, the output rate of the deep learning model can be very close to the maximum reachable rate in (14). At the same time, a large amount of beam training overhead is avoided because a certain amount of data sets are used to train the deep learning network, indicating the potential of this IRS hybrid active/passive unit hardware structure and deep learning approach in solving large size IRS problems.

V. Conclusions

This paper mainly studies the IRS assisted communication system using the method of deep learning, analyzes the characteristics of the wireless communication system with IRS deployed, and studies the specific performance relationship between the IRS assisted communication system and the communication system with relay deployed. It is concluded that IRS assisted communication can achieve better results than relay communication when the expected signal receiving rate of the receiver is high. At the same time, the communication system model of IRS combined with deep learning is established. Combined with the IRS hardware architecture of hybrid active/passive units, a deep learning scheme aiming at maximizing the achievable rate of the receiver is designed, and the system rate performance under different parameters is simulated and compared. The simulation results show that the proposed scheme can approach the upper limit of the achievable rate of the system as much as possible while reducing the overhead of beam training.

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