Research on IRS-assisted communication optimization method based on federated learning

Chenguang He, Jing Li, Shengxian Huang, Yuchuan Ma
Department of Communication Engineering
Harbin Institute of Technology
Harbin, China
hechenguang@hit.edu.cn, lijing1123lv@163.com, 21s105173@stu.hit.edu.cn, yuchuan_ma@163.com

***Abstract*—In recent years, intelligent reflective surfaces (IRS) have been widely used to improve communication quality. IRS has the characteristics of low cost and no delay, and can be densely deployed to meet the communication needs of a large number of devices. In this paper, IRS is applied to the downlink multi-user communication system, and a central optimization algorithm is proposed for rate optimization design. At the same time, with the increasing demand of users for privacy, this paper designs a federated learning (FL) optimization algorithm to establish a rate optimization model for multi-user systems under the premise of ensuring data security.**

***Index Terms*—intelligent reflecting surface, federated learning, deep learning, multi-user communication**

I. Introduction

With the increase in communication equipment, our requirements for improving the data transmission rate and transmission efficiency continue to increase. However, related technologies often have problems of high design complexity and high energy consumption.We now have a high demand for channel bandwidth resources, and hardware design, cost, and energy consumption limit the bandwidth increase. This paper improves the system information transmission rate from the perspective of improving the signal-to-noise ratio of the receiver.

In the process of signal propagation, obstacles are often encountered, resulting in poor communication link performance. In the downlink communication system model designed in this paper, the base station and the user are connected by deploying the IRS reflection unit to create a communication link so that the signal can bypass the obstacle. The IRS is a plane composed of a large number of passive reflective elements. The IRS controller adjusts the incident signal by controlling the reflection element, so that the IRS transmits the signal with the characteristics of no delay and low power consumption. In addition, the IRS has a simple structure, is easy to deploy, and can be intensively deployed.

The design goal of this paper is to configure the IRS reflection unit to obtain the optimal transmission rate. In order to obtain the optimal IRS configuration scheme, the training for deep learning (DL) is required. Traditional centralized data training has a great risk of data leakage and cannot meet the needs of users and institutions for data privacy protection. In the case of data silos, it is difficult for institutions to complete model establishment and optimization. This paper uses FL to enable multiple users to jointly build a model without uploading data. In FL, users perform model training locally, upload the local model to the central server, and obtain the global model through aggregation. After simulation verification, the effect of the final global model is basically the same as that of the model trained on the central data.

II. IRS-assisted Communication Model

In this paper, an IRS-assisted multi-user downlink communication system is designed, including a base station, multiple users, and an IRS with M reflection elements, as shown in Figure 1. When the communication signal between the user and the transmitter is blocked by an obstacle, a reflection link is established through the IRS to realize normal communication. The signal received by each user is composed of the signals reflected by all the reflecting elements of the IRS. We assume that the channel state information of all users is independent and identically distributed (IID).The following is a system model for individual users.

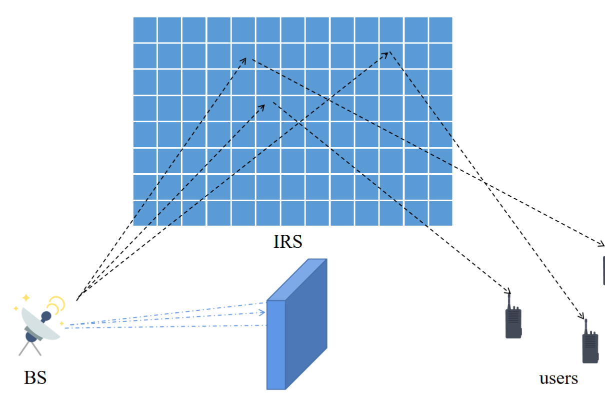

Fig. 1: System model.

A. System Model

In the single-user system, the orthogonal frequency division multiplexing (OFDM) technology including K subcarriers is adopted.This paper defines the communication channel $h_{R,k}$, $h_{T,k}$ from the transmitter to the receiver at the k^{th} subcarrier, which is the communication channel from the user and the base station to the IRS. The straight-line link from the base station to the user is ignored. Transmit signal s_k, noise v_k, the received signal can be expressed as:

$$y_k = h_{R,k}^T \Psi_k h_{T,k} s_k + v_k = (h_{R,k} \odot h_{T,k})^T \psi_k s_k + v_k \quad (1)$$

Ψ_k is the reflection matrix of the IRS, and ψ_k is the reflection beamforming vector, $\Psi_k = diag(\psi_k)$. The reflection matrix only changes the phase of the signal.

B. Channel Model

The channel between the IRS and the transmitter, $h_{T,k}$, consists of Q paths. the delay of the q^{th} is τ_q . The azimuth angle of the arriving signal is $\phi_q \in [0, 2\pi)$, and the elevation angle is $\theta_q \in [0, \pi)$. The path loss is ρ_T , and the channel coefficient α_q . Let denote $p(\tau)$ the pulse-shaping function of a signal of interval T_s computed at τ second.

Define the array response vector of the arriving signal on the IRS reflector . Using the tap delay model for multipath channels, let D be the number of channel taps, $d = 1, 2, \ldots, D$, then the channel with delay d can be expressed as:

$$h_{T,d} = \sqrt{\frac{M}{\rho_T}} \sum_{q=1}^{Q} \alpha_l p(dT_s - \tau_q) a(\phi_q, \theta_q) \quad (2)$$

So:

$$h_{T,k} = \sum_{d=0}^{D-1} h_{T,d} e^{-j\frac{2\pi k d}{K}} \quad (3)$$

This paper predefines a codebook $\mathcal{R}$, which contains all reflected beamforming vectors. The frequency band utilization at the receiver is:

$$r = \frac{BW}{K} \sum_{k=1}^{K} \log_2(1 + SNR \left| (h_{T,k} \odot h_{R,k})^T \Psi \right|^2) \quad (4)$$

SNR is the signal-to-noise ratio, and BW is the system bandwidth. The optimal reflection vector corresponding to the optimal velocity is:

$$\Psi^* = \arg\max_{\Psi \in \mathcal{R}} \sum_{k=1}^{K} \log_2(1 + SNR \left| (h_{T,k} \odot h_{R,k})^T \Psi \right|^2) \quad (5)$$

In this article, the IRS contains N active units, $N \ll M$. In addition to simply reflecting the signal, the active unit can also receive and transmit pilot signals. The active unit receives the pilot signal of the base station, and obtains the transmit channel information after processing. At the same time, the active unit transmits a pilot signal to the user, and the user obtains the receiving channel information through analysis.

Define the channel vector from the transmitter to the IRS active unit as the sampling channel:

$$\overline{h}_{T,k} = \mathrm{H}_N h_{T,k} \quad (6)$$

H_N is to select the part corresponding to the IRS active unit from the original channel.

Then the IRS sampling channel at the k_{th} subcarrier is:

$$\overline{h}_k = \overline{h}_{T,k} \odot \overline{h}_{R,k} \quad (7)$$

III. Centralized Optimization Algorithm

A. Algorithm Structure

In this paper, the training data of each user is acquired in the same way, that is, the sampling channel is acquired by transmitting pilot signals from the IRS active unit and the base station. Then, the sampled channel information is transmitted to the cloud server for centralized training.

This algorithm uses DL and supervised learning (SL) methods for model training. The input (feature) of the deep learning dataset $\mathcal{S}$ is the sampled channel vector $\widehat{h}$, and the output (label) is the system rate r .

DL chooses the multilayer perceptron as the neural network and the root mean square error (RMSE) as the error function. According to the mathematical model obtained by training, the corresponding optimal rate can be predicted through the input channel vector, and then the corresponding reflection vector can be obtained, and finally the configuration of the IRS is completed.

The specific algorithm structure is shown in Algorithm 1.

Algorithm 1 Centralized Optimization Algorithm

Phase I : Dataset construction
for $s = 1$ to S **do**
  According to the pilot signal, get the sampling channel $\widehat{h}(s)$
  for $n = 1$ to $\mathcal{R}$ **do**
    Set IRS reflection vector ψ_n
    Get the corresponding rate $R_n(s)$
  end for
  At sample s, $r(s) = [R_1(s), R_2(s), \ldots, R_{|\mathcal{R}|}(s)]$
  Get the corresponding optimal reflection vector number $n^* = arg\max_n [r(s)]_n$, the optimal reflection vector is ψ_{n^*}
  Dataset creation $\mathcal{S} \leftarrow (\widehat{h}(s), r(s))$
end for
Data set $\mathcal{S}$ is divided into training data set $\mathcal{S}_t$, validation data set $\mathcal{S}_v$
Phase II : Deep learning training
Input: dataset $\mathcal{S}$
Neural Networks: Multilayer Perceptrons
Output: system model

B. Simulation Configuration

In this paper, the system scene model is constructed from the DeepMIMO dataset, as shown in Figure 2. Rows 1000 to 1300 of the grid are divided equally into 60 users, each occupying 5 consecutive rows. The location of the base station is (800,90) and BS3 is the location of the IRS.

Define the IRS reflected beam codebook as the discrete Fourier transform(DFT) codebook, $\mathsf{D} = \mathsf{D}_H \otimes \mathsf{D}_V$. The horizontal and vertical dimensions of the angle of incidence M_H, M_V are the number of uniform planar array(UPA) antennas in the horizontal and vertical directions. The range of the angle of incidence is 0π . The codebook in the horizontal direction is shown in Equation 8.

Each user is randomly located on an arbitrary grid in their area. The DL dataset consists of 54,300 sampling points of data from 60 users. The sampled channel vectors and corresponding rates are normalized to form a dataset. The dataset is divided into training dataset (45000 points) and validation dataset (9300 points).

Other parameters are shown in Table I.

TABLE I: System Simulation Parameters

Simulation Parameter	Value
Frequency band	28GHz
Bandwidth	200MHz
Number of OFDM subcarriers	512
Antenna gain	5dBi
Antenna spacing	0.5λ

C. Simulation Results

Set the size of the UPA antenna used by the IRS to M=[(1,32,32); (1,40,40); (1,48,48); (1,56,56)]. Set the number of active units to N=8, and the training dataset size to $\mathcal{S}$ =[2,2000,5000,9000,18000,27000,36000]. The simulation results are shown in Figure 2. The user's receiving rate increases with the increase of the training data set, and gradually approaches the target rate. As the size of the IRS increases, the reception rate increases significantly. When the IRS size is 56×56, the achievable receive rate is 896.52Mbps, which is 98.46% of the target rate. This illustrates the potential of this algorithm in realizing largescale smart reflectorassisted communication.

IV. Federated Learning Optimization Algorithm

A. Algorithm Structure

In the Section III, we discussed the method of training the system model through DL after all channel data is transmitted to the central server. However, this operation is unreliable for users who need privacy protection, because uploading data means there is a risk of privacy leakage.

This paper proposes an FL optimization algorithm to allow all users to participate in the training process,as shown in Figure 3. For each communication, the server randomly selects a certain percentage of users to receive the global model. After the user obtains the global model, local model training is performed. Multiple local models are uploaded to the server for integration to obtain a new global model. Repeat the communication process for E times to obtain a global model that can adapt to all participants.

Assuming that L users are selected to participate in training each time, in the i communication, the local model of the j user is w_i^j, and the global model is:

$$w_{i+1} = \frac{1}{L} \sum_{j=1}^{L} w_i^j \tag{9}$$

Users use DL for local training. DL uses a multilayer perceptron as the neural network and chooses the mean squared error (MSE) as the loss function. The data set acquisition method for DL is the same as the Section III.

The specific algorithm structure is shown in Algorithm 2.

Algorithm 2 Federated Learning Optimization Algorithm

for i in range(E) **do**
  The server randomly selects L users and sends the global model
  User updates local model w_i
  Validation rate $\widehat{r_i}$
  for j in range(L) **do**
    Load local dataset $\mathcal{S}_j$
    Local deep learning training, get local model parameters w_i^j
    $w_{i+1} = w_{i+1} + \frac{1}{n} w_i^j$
  end for
end for
Final model parameters w_E, validation rate $\widehat{r_E}$

B. Simulation Results

In the centralized data processing method, the maximum amount of sample data uploaded by all users and the cloud server is set to be D_C. The federated learning method processes data. The amount of parameter data uploaded in one communication is D_F .

As can be seen from Table II, when the size of the reflective surface is 32×32 , 40×40 , 48×48 , the ratio of D_F to D_C is much smaller, which greatly reduces the frequency band pressure. When the size of the reflector is 56×56, D_F is slightly smaller than D_C, Not very good at mitigating band pressure.This shows that for small IRS reflective surfaces, the federated learning optimization algorithm can play a role in reducing the pressure on the bandwidth of a single communication. Considering that the training of federated learning requires multiple communications, the existing design requires local users to perform multiple data training and parameter uploading.

TABLE II: The Total Amount of Data Uploaded by Communication Users at One Time

Type of Data/ Size of IRS	Table Column Head			
	32×32	40×40	48×48	56×56
D_C	7.414e7	9.499e7	1.205e8	1.506e8
D_F	2.097e7	4.198e7	7.668e7	1.305e8

$$
\mathrm{D}_H = \begin{pmatrix} 1 & 1 & \cdots & 1 & \cdots & 1 \\ e^{-j\frac{2\pi}{M_H}} & e^{-j\frac{2\pi\times 2}{M_H}} & \cdots & e^{-j\frac{2\pi\times m_H}{M_H}} & \cdots & e^{-j\frac{2\pi\times M_H}{M_H}} \\ e^{-j\frac{2\pi}{M_H}} & e^{-j2\times\frac{2\pi\times 2}{M_H}} & \cdots & e^{-j2\times\frac{2\pi\times m_H}{M_H}} & \cdots & e^{-j2\times\frac{2\pi\times M_H}{M_H}} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ e^{-j(M_H-1)\frac{2\pi}{M_H}} & e^{-j(M_H-1)\frac{2\pi\times 2}{M_H}} & & e^{-j(M_H-1)\frac{2\pi\times m_H}{M_H}} & & e^{-j(M_H-1)\frac{2\pi\times M_H}{M_H}} \end{pmatrix} \tag{8}
$$

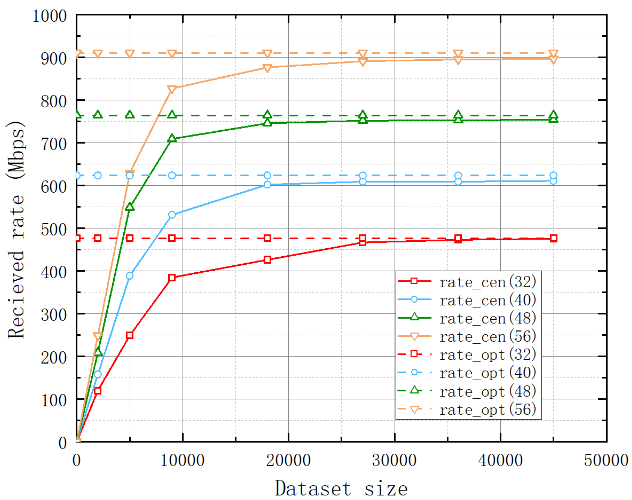

Fig. 2: Achievable rates for different reflector sizes.

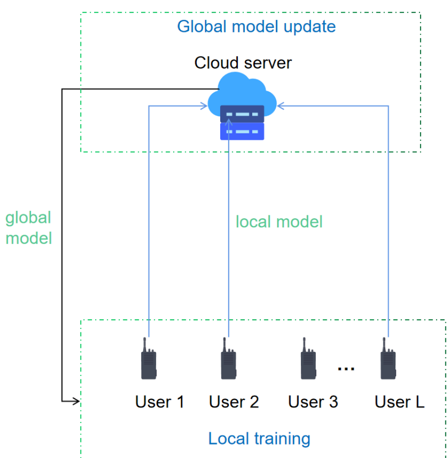

Fig. 3: Federated Learning Process.

As shown in Figure 4, under the premise that the location and number of sample collection points remain unchanged, and the number of users is set to be 20, 30, 50, and 90, respectively, the training data set for each user is 2250, 1500, 900, and 500. Set the number of communications to 800 times, the size of the IRS reflective surface to 56×56 , and do not change other parameter settings. It can be seen that in the process of 800 communications, the more the number of users, the lower the achievable receiving rate. This shows that in a sized IRS-assisted communication system, the higher the user density, the more difficult it is for the federated learning optimization method to achieve an overall high rate.

It is worth noting that when the number of communications is more than 300 times, the achievable rate difference between 50 and 20 users is very small, and can reach 92% of the optimal rate. This shows that when the number of users is within a certain range, the federated learning optimization algorithm has a good effect.

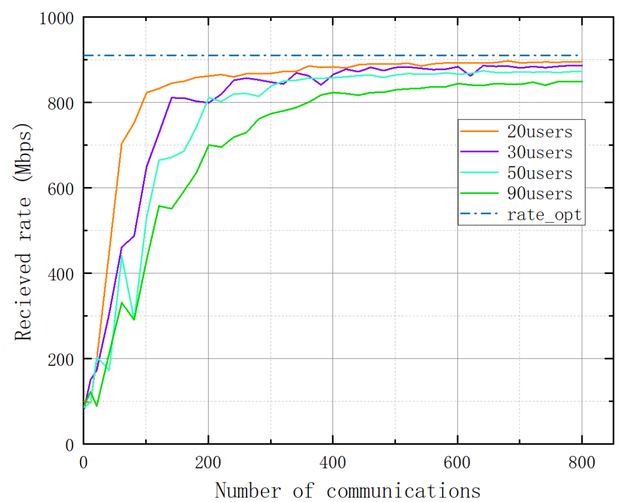

Fig. 4: Achievable rates for scenarios with different numbers of users.

V. Conclusion

In this paper, a centralized optimization algorithm and a joint learning optimization algorithm are proposed based on the IRS assisted downlink multi-user communication system. The centralized optimization algorithm conducts centralized deep learning training on the sampling data of all users, maps the sampling channel to the maximum receiving rate, and finally realizes the configuration of IRS reflector. Considering the data security problem, this paper proposes a federated learning optimization algorithm, which allows users to jointly build system models without providing underlying data. Comparing the two algorithms, when the reflection surface size is small, the amount of data uploaded by the federated learning optimization algorithm is small, which can reduce the bandwidth pressure to a certain extent. Federated learning optimization algorithm has broad prospects in multi-user scenarios.

Acknowledgment

This paper is supported by the National Key R&D Program of China(No.2020YFE0205800) and the National Natural Science Foundation of China(41861134010).

References

[1] Q. Wu and R. Zhang, ”Towards Smart and Reconfigurable Environment: Intelligent Reflecting Surface Aided Wireless Network,” in IEEE Communications Magazine, January 2020,vol. 58, no.1, pp.106-112.

[2] S. Zhang and R. Zhang, ”Intelligent Reflecting Surface Aided Multiple Access: Capacity Region and Deployment Strategy,” 2020 IEEE 21st International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), 2020, pp. 1-5, doi: 10.1109/SPAWC48557.2020.9153884.

[3] D. Chang, H. Jiang, J. Zhou, H. Zhang and M. Mukherjee, ”Capacity optimization using augmented lagrange method in intelligent reflecting surface-based MIMO communication systems,” in China Communications, vol. 17, no. 12, pp. 123-138, Dec. 2020, doi: 10.23919/JCC.2020.12.009.

[4] Y. Wei, M. -M. Zhao, M. -J. Zhao and Y. Cai, ”Channel Estimation for IRS-aided Multiuser Communications with Reduced Error Propagation,” in IEEE Transactions on Wireless Communications, doi: 10.1109/TWC.2021.3115161.

[5] M. Cui, G. Zhang and R. Zhang, ”Secure Wireless Communication via Intelligent Reflecting Surface,” in IEEE Wireless Communications Letters, vol. 8, no. 5, pp. 1410-1414, Oct. 2019, doi: 10.1109/LWC.2019.2919685.

[6] M. Fu, Y. Zhou and Y. Shi, ”Intelligent Reflecting Surface for Downlink Non-Orthogonal Multiple Access Networks,” 2019 IEEE Globecom Workshops (GC Wkshps), 2019, pp. 1-6, doi: 10.1109/GCWkshps45667.2019.9024675.M. Fu, Y. Zhou and Y. Shi, ”Intelligent Reflecting Surface for Downlink Non-Orthogonal Multiple Access Networks,” 2019 IEEE Globecom Workshops (GC Wkshps), 2019, pp. 1-6, doi: 10.1109/GCWkshps45667.2019.9024675.