HYBRID INTELLIGENT REFLECTION SURFACE STRUCTURE ASSISTED MILLIMETER WAVE COMMUNICATION CHANNEL ESTIMATION

Navitha CH Department of Electronics and Communication Engineering Chaitanya Bharathi Institute of Technology, Gandipet, Telangana 500075 : navitha_ece@cbit.ac.in

Abstract: In response to the addition of mm wave communication, auxiliary communication is compared to obtain the challenge of the system, which is difficult to obtain channel status information (CSI), using a mixed intelligent reflection surface structure, ie IRS, a large number of passive components and limited radiofrequency (RF) Chain, which is limited to the channel between the base station \/ terminal and the IRS. Based on this structure, a channel estimation scheme is proposed. The scheme is based on a limited RF chain, first using an improved multi-signal classification algorithm to simultaneously estimate the leaving angle of the channel and the arrival angle, and then proposes a plurality of parallel depth neural networks to estimate the path gain. The superiority of the proposed program is proved by simulating the proposed schedule and other methods.
Keywords: Mix intelligent reflection surface, millimetre wave, channel estimation, multi-signal classification algorithm, depth neural network.

I. Introduction

5G communication system uses large-scale multi-input multi-output (MIMO) technology to compensate for millimeter wave propagation loss [1], but high-power consumption caused by the large-scale MIMO system brings challenges for its actual implementation [2]. At the same time, pushing is also caused, thereby affecting the accuracy of channel estimation. Document [3] proposes a channel estimation scheme based on interference cancellation. To further improve system performance, assist communication is performed using intelligent reflective surfaces (IRS, Intelligent Reflecting Surface). IRS is formed by a large number of passive reflective elements, on the one hand, by intelligent adjustment amplitude and phase, achieving the effect of reconfiguring the propagation environment [4]; on the other hand, by controlling the propagation environment, improve the spectral efficiency and energy efficiency of wireless communication [5-7]. However, since the IRS is added to make the channel complex, the channel estimate brings a certain difficulty; mainly the passive characteristics of the IRS make it difficult to estimate the channel between the base station (BSE Station) and IRS and IRS to mobile station. Channel between MS, Mobile Station.

In order to overcome the above difficulties, there is some research to design the IRS. Document [8] proposes a new IRS hardware structure, randomly distributed active reflective elements in passive reflective elements, and then proposes channel estimation based on compressed sensible (CS, Compressed Sensing) and deep learning (DL, Deep Learning) plan. However, the CS algorithm mentioned in this approach requires a large amount of active elements to improve performance and has not utilized the sparseness of the channel, resulting in an increase in cost and complexity; the neural network mentioned in the other hand is not Considering the effect of the phase, and the actual data is complex, the accuracy of the channel estimation is reduced. Document [9-10] proposes a channel estimation strategy based on switching state control. Each time slot opens only an IRS element, and the user's reflective channel can be channel without being reflected by other IRS components. estimate. However, the scheme needs to be individually controlled to the amplitude of each reflective element, resulting in an increase in cost.

There are also some programs that studies the level of the level channel. Document [11] proposes a depth denoising neutrio network assisted CS broadband channel estimation method to reduce training overhead. Document [12] proposes an algorithm based on sparse matrix decomposition and complete

ISSN: 2278-4632
Vol-12 Issue-05 No.03 May 2022

matrix. Although the programs used by the Cascading Channel estimation in the literature [11-12] are actually easy to channel estimates, there is a limit that it is difficult to obtain separate information of the BS-IRS channel and IRS-MS channel. For this, the literature [13] establishes a tensor model and uses its algebraic structure, and two simple and effective algorithms that perform separate estimates for 2 channels are proposed. However, due to pseudo-inverse operations in the algorithm, there will be results divergent or converge. Slow situation, thereby reducing the accuracy of channel estimation.

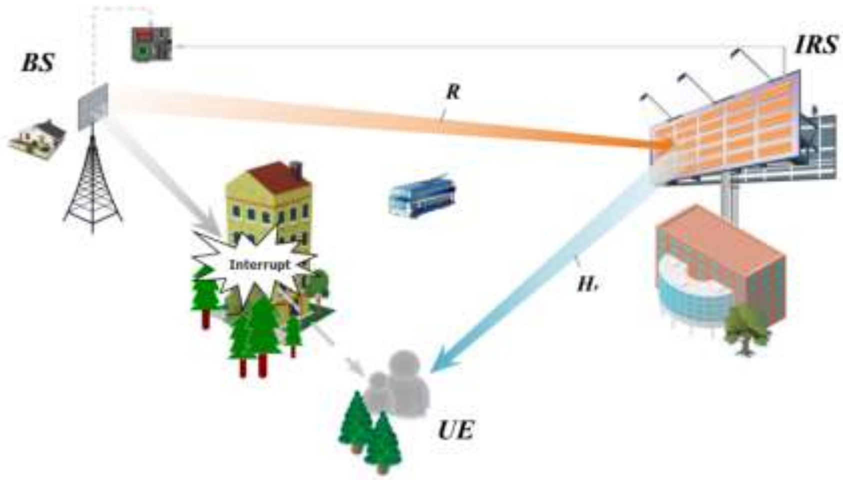

Fig 1. Hybrid IRS structure-assisted millimeter wave communication system model

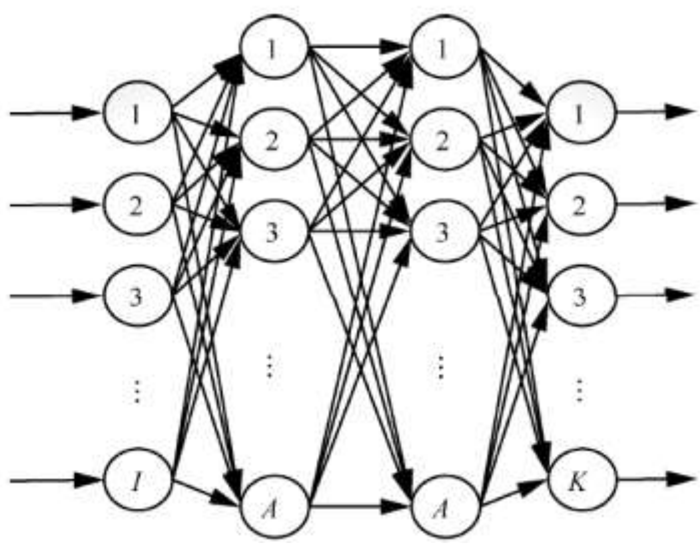

Fig 2. Deep neural network structure

This paper uses a mixed (passive ∨ active) IRS structure, i.e., the limited passive component on the IRS is equipped with a radio frequency (RADIO FREQUENCY) chain, and the structure is applied to the millimeter wave communication system. In order to avoid the problems of the two channels before and after IRS, this paper proposes a channel estimation plan based on improved multi-signal classification algorithm and multiple parallel depth neural networks, which only requires a small amount of active components to be implemented. Separate estimates of the BS-IRS channel and IRS-MS channels to reduce costs. Specifically, the scheme includes leaving angles, reaches angle and channel gain estimation, and conventional multi-signal classification algorithms can only be estimated to reach the angle, in order to achieve the simultaneous estimation of leaving angles and arrival angles, an improved multi-signal classification algorithm is used. For channel gain estimates, a plurality of parallel depth neural networks are proposed, and the real part and virtual sections are estimated thereby no loss of phase information, and the threshold determination is added to the output, and the accuracy of the estimation is further improved. The simulation results also verified the effectiveness of the proposed program.

II. System model and channel model

2.1.System Model

In this paper, it is considered a mimmerometer wave communication system that is auxiliary IRS structure. IRS consists of NIRS passive reflective elements and can independently adjust the phase and amplitude, then select the NRF component each equipped with an RF chain to add a plus shape array, where NRF \u003C\u003C NIRS. Due to the presence of an NRF active element, IRS has two operating modes [8]: reception mode and reflection mode. In the receiving mode, the active element is used to estimate the channel; in the reflection mode, the active element and passive element are simply attached to the incident signal, and then reflect them. Therefore, the operating mode of the IRS can be switched between the two modes through the controller. The transmitting ends and receiving ends of the system are equipped with a plurality of antennas, i.e., BS and MS are configured with M roots and N roots. At this time, the communication system has two propagation paths, and BS is directly to MS, respectively, BS through IRS to MS. There are three channels on these two paths, and the channels H1 of the channels L, BS to IRS, respectively, channel H1, IRS to MS, respectively, channel H1 of the channels l, BS to IRS, respectively. When the direct path is blocked, the path provided by IRS is used, which can help millimeter waves to transmit. This article is assumed to block the straight path is blocked, so the millimeter wave communication system assisted by mixed IRS structure is used, and the model is shown in Figure 1. Suppose that the training phase of a hybrid IRS structure-assisted millimeter wave communication channel consists of T consecutive time frames, each timeframe containing Q time slots. Thus in the q(q∈{1,...,Q}) time slot in the timeframe t, the model of the received signal at MS is

$$y_{t,q} = H_2 \Phi H_1 x_{t,q} + n_{t,q}$$

where, $H_1 \in C^{N_{IRS} \times M}$ is channel between BS and IRS, $H_2 \in C^{N \times N_{IRS}}$ is channel between IRS and MS; φ $\Phi = diag\left(\left[a_1 e^{j\theta_1}, \dots, a_n e^{j\theta_n}, \dots, a_{N_{IRS}} e^{j\theta_{N_{IRS}}}\right]^T\right) \in C^{N_{IRS} \times N_{IRS}}$ is the phase shift matrix of the element on the IRS, $a_n (n \in \{1, \dots, N_{IRS}\})$ is amplitude, $\theta_n \in (0, 2\pi]$ is the phase, in order to reduce the complexity of the study, this article only studies the phase change, the amplitude is 1, i.e., $a_n = 1 (n \in \{1, \dots, N_{IRS}\}); x_{t,q} \in C^{M \times 1}$ is in time frame the pilot symbol vector sent at the q time slot in t, $n_{t,q} \in^{N \times 1}$ is the additive white Gaussian noise (AWGN).

By equation (1) it is possible to derive the received signal at MS on the entire timeframe t, the expression is

$$Y_t = H_2 \Phi H_1 X + N_t$$

where, $X = [x_1, x_2, \dots, x_Q] \in C^{M \times Q}$ is the pilot symbol signal,$N_t = [n_{t,1}, \dots, n_{t,Q}] \in C^{N \times Q}$ is the entire time frame T Additive white Gaussian noise matrix.

At this time, the received signal at the element equipped with the RF chain on the IRS can be written as

$$\overline{H}_1 = G H_1$$

$$Y_t^{IRS} = \overline{H}_1 X + N_t^{IRS}$$

Where g is an $N_{RF} \times N_{IRS}$ selection matrix for selecting active components on the IRS; $\overline{H}_1 \in C^{N_{RF} \times M}$ is the channel of the N_{RF} active component on the BS to IRS; $N_t^{IRS} \in C^{N_{RF} \times Q}$ It is an additive white Gaussian noise matrix.

2.2.Channel Model

Since the scattering path of the millimeter wave channel is limited, its channel model has a rich geometric feature, so each scattering path should determine a single propagation path based on the geometry channel model. Under this model, the channel between the BS-IRS and the IRS-MS may be expressed as

$$H_1 = \sqrt{\frac{MN_{IRS}}{L_1}} \sum_{l_1=1}^{L_1} \alpha_{l_1} a_{IRS}(\gamma_{l_1}, \phi_{l_1}) a_{BS}^H(\theta_{l_1})$$

$$H_2 = \sqrt{\frac{NN_{IRS}}{L_2}} \sum_{l_2=1}^{L_2} \beta_{l_2} b_{MS}(\theta'_{l_1}) b_{IRS}^H(\gamma'_{l_2}, \phi'_{l_2})$$

Wherein L_1 and L_2 are the number of scattering paths on channel H_1 and channel H_2, $\alpha_{l_1} \sim CN\left(0, \sigma_{l_1}^2\right)$ is path gain on the path of the first l_1 , $\beta_{l_2} \sim CN\left(0, \sigma_{l_2}^2\right)$ is the path gain on the second L path. The previous part of the literature is simple, so that IRS uses a Uniform linear array (ULA), but this does not meet the actual situation, so this article uses a uniform square array (UPA), BS and MS the ULA structure is used, and the response vector of the antenna array in the channel H_1 is

$$a_{IRS}(\gamma_{l_1}, \phi_{l_1}) = \frac{1}{\sqrt{N_{IRS}}}\left[1, \dots, e^{\frac{j2\pi}{\lambda} d\left(m sin(\gamma_{l_1}) \sin(\phi_{l_1}) + n cos(\phi_{l_1})\right)}, \dots, e^{\frac{j2\pi}{\lambda} d\left(\left(\sqrt{N_{IRS}}-1\right) sin(\gamma_{l_1}) \sin(\phi_{l_1}) + \left(\sqrt{N_{IRS}}-1\right) cos(\phi_{l_1})\right)}\right]$$

$$a_{BS}(\theta_{l_1}) = \frac{1}{\sqrt{M}}\left[1, \dots, e^{j\frac{2\pi}{\lambda} dmsin(\theta_{l_1})}, \dots, e^{j\frac{2\pi}{\lambda} d(M-1) sin(\theta_{l_1})}\right]^T$$

where, λ is millimeter wave wavelength; d is the spacing between the antenna array or the pitch between the components on the IRS, usually takes $\frac{\lambda}{2}$; γ_{l_1} and ϕ_{l_1} are the azimuth at the IRS on the first l_1 path, respectively. The elevation angle, θ_{l_1} is the leaving angle at the BS on the first l_1 path.
In order to make the structure more compact, the following changes can be made

$$\alpha = \sqrt{\frac{MN_{IRS}}{L_1}} [\alpha_1, \alpha_2, \dots, \alpha_{L_1}]$$

$$A_{BS} = \left[a_{BS}(\theta_1), a_{BS}(\theta_2), \dots, a_{BS}(\theta_{L_1})\right]$$

$$A_{IRS} = [a_{IRS}(\gamma_1, \phi_1), a_{IRS}(\gamma_2, \phi_2), \dots, a_{IRS}(\gamma_L, \phi_L)]$$

Equation (4) can be rewritten by formula (8) to formula (10).

$$H_1 = A_{IRS} diag(\alpha) A_{BS}^H$$

Channel H_2 and channel H_1 are similar, so they can be rewritten in the formula (5)

$$H_2 = B_{MS} diag(\beta) B_{IRS}^H$$

Where,

$$\beta = \sqrt{\frac{NN_{IRS}}{L_2}} [\beta_1, \beta_2, \dots, \beta_{L_2}]$$

$$B_{MS} = \left[b_{MS}(\theta'_1), b_{MS}(\theta'_2), \dots, b_{MS}(\theta'_{L_2})\right]$$

$$B_{IRS} = \left[b_{IRS}(\gamma'_1, \phi'_1), b_{IRS}(\gamma'_2, \phi'_2), \dots, b_{IRS}(\gamma'_{L_2}, \phi'_{L_2})\right]$$

III. Channel Estimation Methods

The above-mentioned mixed IRS structure assisted millimeter wave communication system model performs channel estimation. Since there is active elements on the IRS, the channel $\overline{H}_1$ between the active elements on the IRS can be easily estimated in the reception mode. Common channel estimates are estimated with the least squares (LS) method, so this article uses the LS method to estimate the channel $\overline{H}_1$. It estimates that the expression is

$$\overline{H}_1 = Y_t^{IRS} X^H (XX^H)^{-1}$$

By studying (11), it is found that the channel H_1 includes an array in response to A_{IRS}, A_{BS}, and path gain α, that is, it is necessary to estimate the above information to obtain an estimate of channel H_1.

3.1.Channel estimation H_1 for the angle of arrival

Traditional Multi-Signal Classification Algorithm [14] can only be estimated to reach the angle by spectrum search, but in fact, on the one hand, leave the angle to estimate, on the other hand, because the IRS uses a uniform square array structure The arrival angle includes two types of information of the azimuth and elevation angle, that is, the array of the L1 path at the IRS response IRS A contains two kinds of information including azimuth and elevation angle. At this time, the traditional MUSIC algorithm has not been met to estimate the above three kinds of information. . To avoid three-dimensional estimation, the improved MUSIC algorithm estimates three-dimensional to two-dimensional estimation. According to the active element equipped with an RF chain on the IRS, it can be estimated to estimate the elevation angle and the uniform linear array estimated azimuth and vertical direction, respectively, and only estimates 2 information in various directions. It is assumed here that N_{RF} is odd, the number of components on the horizontal array is n_x, and the number of components on the vertical array is $n_y = N_{RF} - n_x + 1$. Therefore, IRS can get an array response vector in horizontal and vertical directions.

$$a_{IRS}^x(\gamma_{l_1}) = \frac{1}{\sqrt{n_x}}\left[1, e^{j\frac{2\pi}{\lambda}d\sin(\gamma_{l_1})}, \dots, e^{j\frac{2\pi}{\lambda}d(n_x-1)\sin(\gamma_{l_1})}\right]^T$$

$$a_{IRS}^x(\gamma_{l_1}) = \frac{1}{\sqrt{n_y}}\left[1, e^{j\frac{2\pi}{\lambda}d\cos(\gamma_{l_1})}, \dots, e^{j\frac{2\pi}{\lambda}d(n_y-1)\cos(\phi_{l_1})}\right]^T$$

In the horizontal direction at the IRS, the received signal at the uniform linear array of the active elements of the RF chain is configured.

$$Y_{t,x}^{IRS} = A_{IRS}^x diag(\alpha) A_{BS}^H X + N_{t,x}^{IRS}$$

where, $A_{IRS}^x = [a_{IRS}^x(\gamma_1), \dots, a_{IRS}^x(\gamma_{l_1}), \dots, a_{IRS}^x(\gamma_{L_1})]$. At this time, only the conventional MUSIC algorithm can only be estimated to the angle γ_{l_1}, but the leaving angle θ_{l_1} cannot be estimated, and the improved MUSIC algorithm can make it simultaneously estimate through spatial spectrum simultaneously estimate the leaving angle of each path and Arrival angle. In order to construct a suitable direction matrix, it is necessary to perform a quantization operation on the formula (19), and its expression is

$$y_x = vec(Y_{t,x}^{IRS}) = [(A_{BS}^H X)^T \otimes A_{IRS}^x] vec(diag(\alpha)) + vec(N_{t,x}^{IRS})$$

where, $W \in C^{Qn_x \times L_l^2}$ is a direction matrix, including leaving angles and reaching angle information. Then you need to ask for a covariance matrix of y_x and perform the characteristic value decomposition, the expression is

$$R = E(y_x y_x^H) = U\boldsymbol{\Lambda}U^H$$

$$[U_s \ \ U_n]\begin{bmatrix}\boldsymbol{\Lambda}_s & 0\\ 0 & \boldsymbol{\Lambda}_n\end{bmatrix}\begin{bmatrix}U_s^H\\ U_n^H\end{bmatrix} = U_s\boldsymbol{\Lambda}_s U_s^H + U_n\boldsymbol{\Lambda}_n U_n^H$$

Where, U is the characteristic value vector, which can be broken down into the signal sub-space U_s and the noise sub-space U_n [15-16], respectively, the characteristic vector corresponding to the L_1 maximum feature value $\boldsymbol{\Lambda}_s$ and $Qn_x - L_1$ small feature value $\boldsymbol{\Lambda}_n$ composition. Finally, the directional spectrum function is obtained

$$P(\theta,\gamma) = \frac{1}{\{[a_{BS}^H(\theta)X]^T \otimes a_{IRS}^x(\gamma)\}^H U_n U_n^H \{[a_{BS}^H(\theta)X]^T \otimes a_{IRS}^x(\gamma)\}}$$

ISSN: 2278-4632
Vol-12 Issue-05 No.03 May 2022

The θ and γ on the L_1 path can be estimated by searching L_1 poles in the direction spectrum function. The estimation in the estimation and horizontal direction in the vertical direction is similar, and the elevation angle φ on the L_1 path can also be estimated by an improved MUSIC algorithm. Finally, the estimates of A_{BS} and A_{IRS}, $\hat{A}_{BS}$ and $\hat{A}_{IRS}$ can be obtained.

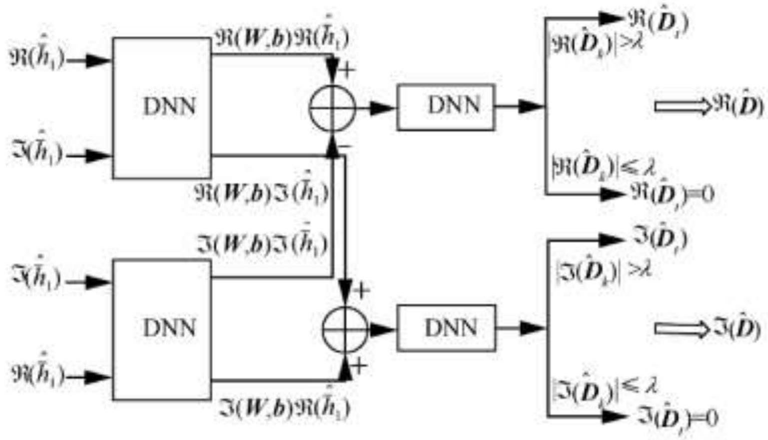

Fig 3. Multiple parallel depth neural network structure

3.2.Path Gain Estimate for H1 Channel

The path gain α is important information in channelH_1, which can be estimated by channel$\widehat{H}_1$. The expression of channel $\widehat{H}_1$ is

$$\widehat{H}_1 = G\, \hat{A}_{IRS} diag(\alpha)\, \hat{A}_{BS}^H + N_1$$

where, $diag(\alpha)$ is the required estimated path gain matrix, $\hat{A}_{BS}$ and $\hat{A}_{IRS}$ are array response estimates of the L_1 paths at the BS and IRS, respectively, $N_1 \in C^{N_{RF}\times M}$ is an additive white Gaussian noise matrix . In order to facilitate the following estimation, the channel $\widehat{H}_1$ is needed to quantize, and its expression is

$$\hat{h}_1 = vec(\widehat{H}_1) = (\hat{A}_{BS}^H)^T \otimes (G\, \hat{A}_{IRS}) vec(diag(\alpha)) + vec(N_1) = (\hat{A}_{BS}^H)^T \otimes (G\, \hat{A}_{IRS}) D + vec(N_1)$$

where, $\hat{h}_1 \in C^{MN_{RF}\times 1}, D = vec(diag(\alpha)) \in C^{L_1 L_1 \times 1}, vec(N_1) \in C^{MN_{RF}\times 1}$ is an additive white Gaussian noise vector. According to the formula (24), this paper proposes a solution based on the depth neural network (DNN) to estimate the path gain, which is less than the LS method, and the one-way estimated information is small, only needs Get channel information between the base station to the IRS; on the other hand, the LS method involves the process of counterfeiting, and if the matrix is dissatisfied, the unique solution is not unique, and eventually, the estimation result is errors. Although the number of network layers in DNN can increase the effectiveness of training, there will be problems with fit, and the training complexity is also increased. In order to find a folding scheme between these two points, the number of layers of the DNN has been made, and finally the training effect and complexity is obtained when the number of network layers is four layers.

As shown in Figure 2, the depth neural network has four layers, and the input layer has I neurons. There are A neurons in the two hidden layers. The output layer has K neurons, and the layers are all connected between the layered structures. Therefore, the weight matrix between the four-layer neural network layers and the layers is $W_1 \in R^{A\times I}, W_2 \in R^{A\times A}$ and $W_3 \in R^{K\times A}$, the bias vector is $b_1 \in R^4, b_2 \in R^A$ and $b_3 \in R^k$ respectively. In order to improve the performance of the neural network, the gradient dissipation is mitigated, and the nonlinear hyperthrosis is used in two hidden layers ($\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$). According to the actual situation, the data processed is a plural. Some of the previous neural network programs only extracted the real part and the imaginary part, all as a real input neural network, and the

 ISSN: 2278-4632
Vol-12 Issue-05 No.03 May 2022

final output is real, which causes the multiple phase information missing. This article proposes a solution that uses multiple DNN parallel structures on real and virtual parts to realize. Depending on the nature of neural network and complex calculation, you can get

$$\begin{bmatrix} Re(\widehat{D}) \\ Img(\widehat{D}) \end{bmatrix} = \begin{bmatrix} Re(W,b) & -Img(w,b) \\ Img(W,b) & Re(W,b) \end{bmatrix} \begin{bmatrix} Re(\hat{h}_1) \\ Img(\hat{h}_1) \end{bmatrix}$$

where, $Re\,(\cdot)$ and $Img(\cdot)$ indicate the complex real and imaginary parts, respectively. According to formula (25), the specific structure of the proposed complex parallel neural network is shown in Figure 3.

In this scheme, the neural network is trained using the ADAM algorithm, and the purpose is to minimize the loss functions of the real and imaginary parts of the path gain matrix D, and the loss functions of the real and imaginary parts are respectively

$$Loss\left(Re(\widehat{D})\right) = \frac{1}{PK}\sum_{p=1}^{p=P}\left\|Re(\widehat{D})^p - Re(D)^p\right\|_F^2$$

$$Loss\left(Img(\widehat{D})\right) = \frac{1}{PK}\sum_{p=1}^{p=P}\left\|Img(\widehat{D})^p - Img(D)^p\right\|_F^2$$

where P is the number of training samples, $Re(D)^p$ and $Img(D)^p$ are the real and imaginary parts of the p sample, respectively. The proposed neural network only needs to obtain the channel information between the base station and the source element on the IRS, open the input of the real and imaginary parts in the input layer, and then combine them according to equation (25), calculate by calculating with the weight matrix and bias vector of each layer, obtain the value of the neurons in the output layer and calculate it according to the loss function shown in formula (26) and equation (27), in order to minimize it, through the ADAM algorithm continuously optimize iteration, it is necessary to continuously update the weight matrix and bias vector, when the loss function reaches the minimum loss Out of the results. Since there are some 0 elements in the channel gain matrix D, it is difficult for the trained neural network to accurately estimate 0, and only a small value can be estimated. In order to further reduce the error, a threshold judgment is added to the final output of the real and imaginary estimates, and the threshold judgment criterion is

$$Re(\widehat{D}_k) = \begin{cases} Re(\widehat{D}_k), & \left|Re(\widehat{D}_k)\right| > \lambda \\ 0\,, & \left|Re(\widehat{D}_k)\right| \le \lambda \end{cases}, k = 1,2,\dots,K$$

$$Img(\widehat{D}_k) = \begin{cases} Img(\widehat{D}_k), & \left|Img(\widehat{D}_k)\right| > \gamma \\ 0\,, & \left|Img(\widehat{D}_k)\right| \le \gamma \end{cases}, k = 1,2,\dots,K$$

where $Re(\widehat{D}_k), Img(\widehat{D}_k)$ is the kth element of the output vector $Re(\widehat{D}_k), Img(\widehat{D}_k)$; λ and γ are judging thresholds, and the values in this article are 0.001.

3.3.H_2 Channel Estimation

According to the above scheme, the array response estimation matrix $\hat{A}_{BS}(\hat{A}_{IRS})$and path gain estimating matrix $\widehat{D}$ at the BS (IRS) at channel H_1 may be obtained, and the estimation value of channel $\widehat{H}_1$ can be obtained by H_1. In the receiving mode of the mixed IRS structure, the channel H_1 is estimated, and then the channel H_2 needs to be estimated at the MS in the reflection mode. At this time, the equation (2) can be rewritten as

$$\bar{Y}_t = H_2\phi_{RF}Y_t^{IRS} + N_t = B_{MS}diag(\beta)B_{IRS}^H\Phi_{RF}Y_t^{IRS} + \bar{N}_t$$

where $\bar{Y}_t \in C^{N\times Q}$ is received signal at MS, which is reflected from the element on the IRS with an RF chain. For channel H_2, the same channel estimation scheme may be used. Since the separation angle includes an azimuth angle and an elevation angle, it is still estimated separately with a uniform linear array equipped with the horizontal direction of the RF chain and a uniform linear array equipped with the vertical direction of the RF chain. The departure and arrival angles are estimated from the level and vertical directions using the improved MUSIC algorithm, and finally the estimated value of the array response $B_{MS}, \hat{B}_{MS}$ and the estimated value of the array response $B_{IRS}, \hat{B}_{IRS}$ can be obtained. The estimation of the channel gain is carried out by the proposed complex parallel deep neural network, before estimating the channel gain, the received signal t $\bar{Y}$ is vectorized, and its expression is as follows $\bar{y}_t = vec(\bar{Y}_t) = [(B_{IRS}^H \Phi_{RF} Y_t^{IRS})^T B_{MS}]\mathrm{vec}[\mathrm{diag}(\beta)] + vec(\bar{N}_t) = [(B_{IRS}^H \Phi_{RF} Y_t^{IRS})^T B_{MS}]\, \bar{\mathrm{D}} + vec(\bar{N}_t)$ where, $\bar{y}_t \in C^{NQ\times 1}$ is an additive white Gaussian noise vector. The $Re(\bar{y}_t),\ Img(\bar{y}_t)$ as the input of the multiple parallel depth neural network, and the training of the neural network can obtain the real and imaginary estimates of the channel gain $Re(\bar{D})$ and $Img(\bar{D})$, respectively. The estimated matrix M $\hat{B}_{MS}$ and $\hat{B}_{MS}, \hat{B}_{IRS}$ in which the above array responded, the estimation value of the channel H_2 can be obtained by $\hat{H}_2$.

IV. Simulation Results

In order to test the performance of the proposed program, the accuracy of the channel estimation is evaluated by normalized mean square error (NMSE, Normalized Mean Square Error), and the expression is

$$NMSE(\hat{H}) = \frac{1}{R}\sum_{r=1}^{R}\frac{\left\|H_r - \hat{H}_r\right\|_F^2}{\|H_r\|_F^2}$$

where, R represents the number of Monte Carlo operations, and R h represents the result of the completion of the entire channel estimation. This paper simulates the M 16, N 4, L1 L2 3, Q 20, T 50, NRF 5, R 5000. In order to analyze the effects of the components on the IRS on the channel estimation, the nirs∈ {16, 25, 36, 49}. 4 and 5 are performance simulations for channel H1 and channel H2 in the IRS number of elements of 16 and 49, wherein the number of RF chains in the horizontal and vertical direction NX NY 3, and double linear alternating least two The performance of channel H1 and channel H2 estimated by Bals, Bilinear Alternating Least Squares [11] The performance of channel H2 is compared. The simulation results show that the programs have excellent performance than the BALS algorithm.

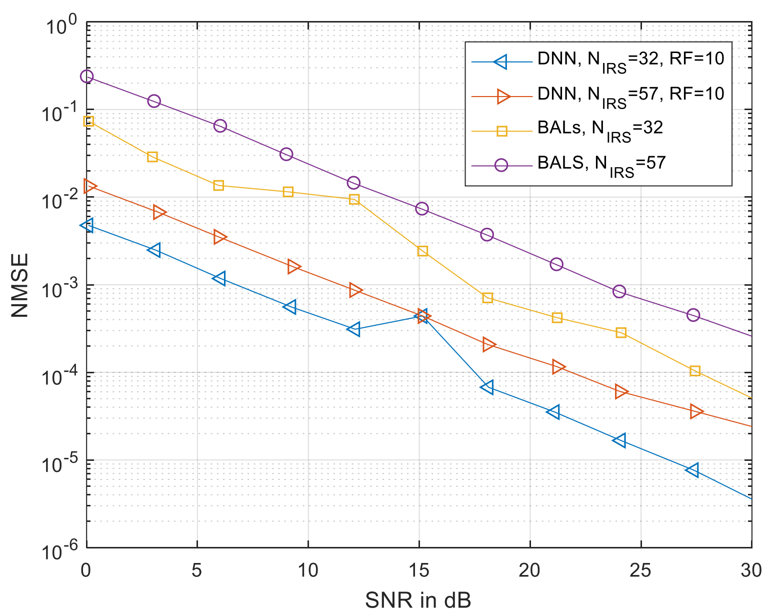

Figure 4. NMSE performance comparison for channel H_1

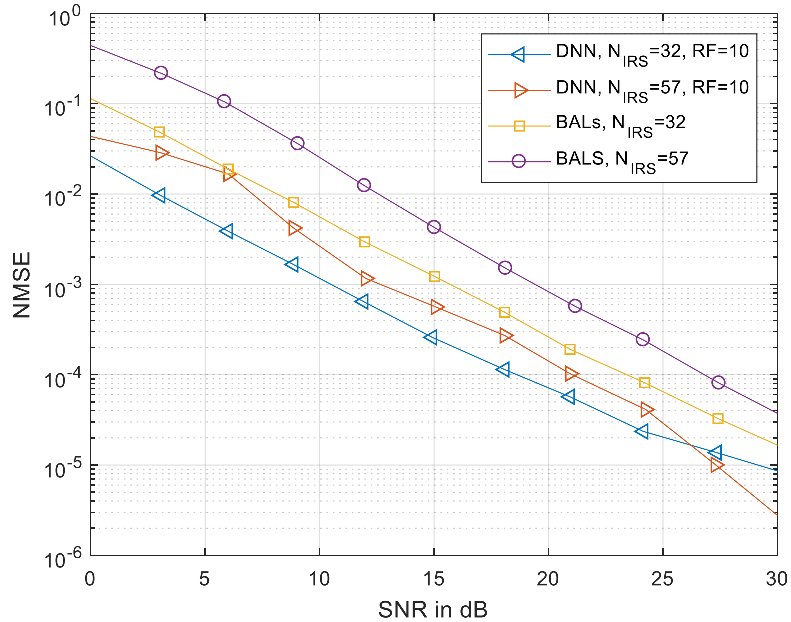

Figure 5. NMSE performance comparison for channel H_2

Figure 6 is a simulation of the performance of full channel H at 16, 25, 36, and 49 components on the IRS, where the number of horizontal and vertical upward RF chains nx ny 3. As can be seen from Figure 6, as the number of components on the IRS increases, its performance decreases, because as the number of components on the IRS increases, the channel coefficient that needs to be estimated also increases, that is, the unknown term increases. To compensate for this, you can increase the length of the pilot symbol sequence or increase the number of timeframes.

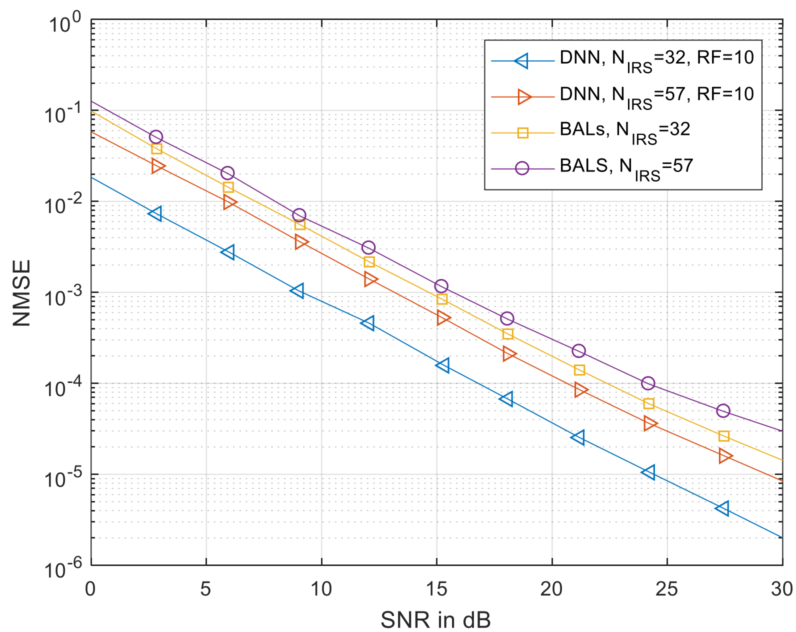

Figure 6. NMSE performance comparison of channel H with different component counts on the IRS

ISSN: 2278-4632
Vol-12 Issue-05 No.03 May 2022

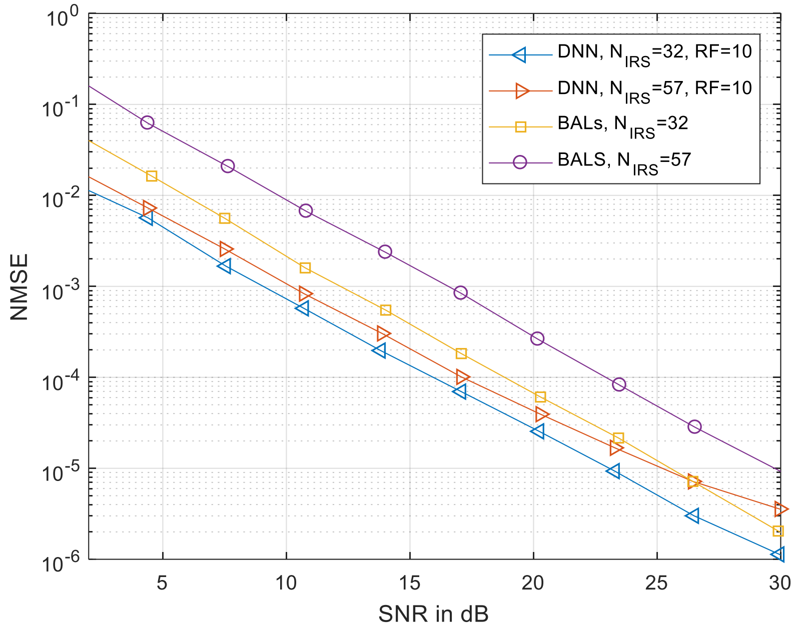

Figure 7. NMSE performance of the proposed scheme is compared with algorithms

Figure 7 is a comparison of the performance of the channel estimation algorithm (MusicDN), BALS algorithm, and LS algorithm in NIRS 16. As can be seen from Figure 7, the performance of the channel estimation calculation proposed herein is superior to the remaining BALS algorithm and the LS algorithm. Figure 7 also compares the combination of improved MUSIC algorithms and traditional DNN. By comparison, the accuracy of the program channel estimate is lower than this paper, so it can be proved that the plural parallel depth neural network mentioned in this paper. The phase factor does improve the accuracy of the channel estimate.

V. Conclusion

In this paper, a hybrid IRS structure-assisted millimeter wave channel estimation scheme is proposed, which estimates the departure angle, arrival angle and channel gain by equipping the IRS with a limited RF chain. The traditional MUSIC algorithm can only estimate the angle of arrival, so the INNOVATIVE algorithm that extends the improvement estimates both the exit angle and the arrival angle at the same time. Then the complex parallel deep neural network is proposed to estimate the channel gain, the network structure can avoid the loss of phase when training the complex numbers. Simulation proves the feasibility of the proposed scheme, and compares with other algorithms to reflect the superiority of the proposed scheme.

REFERENCES:

1. HASSAN K, MASARRA M, ZWINGELSTEIN M, et al. Channel estimation techniques for millimeter-wave communication systems: achievements and challenges[J]. IEEE Open Journal of the Communications Society, 2020, 1: 1336-1363.
2. SUN B L, ZHOU Y Q, YUAN J H, et al. High order PSK modulation in massive MIMO systems with 1-bit ADCs[J]. IEEE Transactions on Wireless Communications, 2021, 20(4): 2652-2669.
3. SUN B L, ZHOU Y Q, YUAN J H, et al. Interference cancellation based channel estimation for massive MIMO systems with time shifted pilots[J]. IEEE Transactions on Wireless Communications, 2020, 19(10): 6826-6843.

4. WU Q Q, ZHANG R. Towards smart and reconfigurable environment: intelligent reflecting surface aided wireless network[J]. IEEE Communications Magazine, 2020, 58(1): 106-112.
5. BASAR E, RENZO M D, ROSNY J D, et al. Wireless communications through reconfigurable intelligent surfaces[J]. IEEE Access, 2019, 7: 116753-116773.
6. LIASKOS C, NIE S, TSIOLIARIDOU A, et al. A new wireless communication paradigm through software-controlled metasurfaces[J]. IEEE Communications Magazine, 2018, 56(9): 162-169.
7. YUAN X J, ZHANG Y J A, SHI Y M, et al. Reconfigurable-intelligent-surface empowered wireless communications: challenges and opportunities[J]. IEEE Wireless Communications, 2021, 28(2): 136-143.
8. TAHA A, ALRABEIAH M, ALKHATEEB A. Enabling large intelligent surfaces with compressive sensing and deep learning[J]. IEEE Access, 2021, 9: 44304-44321.
9. MISHRA D, JOHANSSON H. Channel estimation and low-complexity beamforming design for passive intelligent surface assisted MISO wireless energy transfer[C]//Proceedings of ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). Piscataway: IEEE Press, 2019: 4659-4663.
10. YANG Y F, ZHENG B X, ZHANG S W, et al. Intelligent reflecting surface meets OFDM: protocol design and rate maximization[J]. IEEE Transactions on Communications, 2020, 68(7): 4522-4535.
11. LIU S C, GAO Z, ZHANG J, et al. Deep denoising neural network assisted compressive channel estimation for mmWave intelligent reflecting surfaces[J]. IEEE Transactions on Vehicular Technology, 2020, 69(8): 9223-9228.
12. HE Z Q, YUAN X J. Cascaded channel estimation for large intelligent metasurface assisted massive MIMO[J]. IEEE Wireless Communications Letters, 2020, 9(2): 210-214.
13. ARAÚJO G T D, ALMEIDA A L F D. PARAFAC-based channel estimation for intelligent reflective surface assisted MIMO system[C]//Proceedings of 2020 IEEE 11th Sensor Array and Multichannel Signal Processing Workshop (SAM). Piscataway: IEEE Press, 2020: 1-5.
14. SCHMIDT R. Multiple emitter location and signal parameter estimation[J]. IEEE Transactions on Antennas and Propagation, 1986, 34(3): 276-280.
15. DASTGAHIAN M S, GHOMASH H K. MUSIC-based approaches for hybrid millimeter-wave channel estimation[C]//Proceedings of 2016 8th International Symposium on Telecommunications (IST). Piscataway: IEEE Press, 2016: 266-271.
16. GHAUCH H, KIM T, BENGTSSON M, et al. Subspace estimation and decomposition for large millimeter-wave MIMO systems[J]. IEEE Journal of Selected Topics in Signal Processing, 2016, 10(3): 528-542.

