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SPECIAL ISSUE ON Intelligent Communication Technologies

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This special issue of Frontiers focuses on the recent progresses of the intelligent communication technologies. The research topics of the papers in this special issue include reconfigurable intelligent surface (RIS) aided user positioning, federated learning (FL) in wireless communications, deep reinforcement learning (DRL) enabled beamforming design, and deep learning (DL) based channel estimation techniques.

The first paper presented an overview of the RIS-assisted positioning techniques. Specifically, the authors first reviewed several representative researches which focused on combining the RIS with the millimeter-wave (mmWave), the received signal strength (RSS) and the ultra-wideband (UWB) technologies to localize the mobile users, and then summarized the potential challenges on the joint active and passive beamforming design and the practical phase shift adjustment.

The second paper presented a brief review for the FL in wireless communications, focusing on a recently proposed FL scheme which aimed to optimize the transmission performance in consideration of the user selection, the resource allocation and the impact of packet transmission errors. Results verified the feasibility and effectiveness of the proposed approach, and showed the significance of establishing the relationship between communication factors and FL performance.

The third paper presented an overview of the beamforming design achieved by the DRL. To maximize the sum rate by optimizing the transmit power and the beamforming vector, the authors first presented a deep Q-learning (DQN) algorithm which applied to the time-varying channel conditions, and presented a deep deterministic policy gradient (DDPG) framework to realize the continuous representation of the beamformers. The proposed DQN/DDPG-based beamforming design was validated to be able to outperform the conventional RL-based approaches.

The fourth paper presented an overview of the channel estimation approaches based on the DL, where the authors first described a general DL framework for channel estimation and introduced its applications in image processing fields and RIS-aided wireless communication scenarios, and then discussed the future challenges on exploring the internal mechanism and improving the dataset utility and the update rate.

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High-precision Positioning with the Help of Reconfigurable Intelligent Surface

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Abstract： With the rapid development of the wireless network, the demand for positioning-based applications such as navigation, location monitoring, medical care, indoor positioning, etc., continues to grow, leading to high-precision positioning related fields that have attracted widespread attention. Among them, the reconfigurable intelligent surface (RIS), also known as the intelligent reflecting surface (IRS), can provide highly efficient and flexible communication services, thus attracting considerable attention. The RIS is able to change the electromagnetic environment, which is beneficial to signal propagation and can be used for device positioning in communication systems. The use of RIS for device positioning involves a series of application scenarios and positioning methods, including the positioning of millimeter-wave (mm wave) multiple input multiple output (MIMO) communication systems, positioning technology based on the combination of received signal strength (RSS) and RIS, and UWB technology utilizes RIS indoor positioning. This article provides a comprehensive summary of these applications.

Index Term： reconfigurable intelligent surface (RIS), ultra-wideband (UWB), positioning, millimeter-wave (mmWave), massive MIMO, received signal strength (RSS).

1.Introduction

The reconfigurable intelligent surface (RIS) is composed of a large number of low-cost passive intelligent reflecting units. Each intelligent reflecting unit can independently make certain changes to the physical properties of the incident signal, e.g. phase, amplitude, etc. In essence, since the RIS can be easily and conveniently deployed and can make the wireless propagation environment electromagnetically controllable, it can enhance the signal transmission when the direct signal quality is poor. At the same time, RIS uses passive components to redirect the signal propagation, so that no additional thermal noise is introduced [1].

Because RIS has the ability to change the electromagnetic environment in wireless communication systems, it has been used to assist the wireless communications, such as cell-edge communications, by performing passive beamforming, to improve the quality of the received signals. The most notable applications of the RIS include: (1) When the user is in a dead zone ,the appropriate use of the RIS can create a reflection path so that the user can still receive the signal. (2) Assuming that the base station-user and the eavesdropper-user links are on the same straight line, no matter how to design the transmit beamforming, the eavesdropper will inevitably receive a better signal. For this reason, the reflection factor of the RIS can be appropriately designed, so that the signal reflected to the eavesdropper and the signal from the base station directly to the eavesdropper are offset as much as possible, and the signal reflected to the user and the direct signal are superimposed and enhanced as much as possible. (3) When the user is located at the edge of the cell, the signal from the base station of the cell is attenuated seriously. At the same time, it will be interfered by signals from neighboring cells. Then by designing the RIS reflection, the signal of the cell can be enhanced and the interference of neighboring cells can be reduced. (4) In the D2D (device to device) communication scenario, multiple devices communicate with each other, resulting in multiple transmitters and multiple receivers. At the same time, communication will obviously interfere with each other. By designing the RIS reflection, the interference signal can be eliminated as much as possible and the desired signal can be enhanced. (5) During the long-distance signal/energy transmission, the RIS can enhance the transmission effect.

According to the researches on the potential functions of RIS, RIS has gradually been applied to the field of positioning. Through investigation, under different signal measurement processes, the current positioning technologies used in cellular networks mainly include: (1) the trilateration measurement, which aims to measure the time of arrival (ToA), time difference of arrival (TDoA) and the received signal strength (RSS) information for device positioning; (2) the triangulation positioning, achieved by measuring the angle of arrival/departure(AoA/AoD); (3) the proximity, assisting positioning by monitoring the ID of the nearest cell [2]; (4) the fingerprinting approaches [3]. But in different application scenarios, these technologies usually require the cooperation of many BSs for positioning, and the positioning accuracy is not very precise. Therefore, in this article, in the field of RIS-assisted positioning, we briefly summarize some of the high-precision positioning methods and their applications.

The contributions of this paper mainly include:

- Introducing three application scenarios and positioning technologies from a more macro perspective,

and summarizing the characteristics of each technology.

- Putting forward some challenges that may be faced by RIS assisted positioning.

The rest of this article is organized as follows. Section II introduces the positioning method with dual RISs in the millimeter-wave MIMO system, and summarizes the characteristics and positioning accuracy of the technology. Section III introduces the positioning technology based on the combination of the RSS and the RIS, and summarizes the characteristics of the technology. Section IV introduces the indoor positioning technology using the RIS with the aid of the ultra-wideband (UWB) technology, and summarizes the characteristics of the technology. Section V analyzes and evaluates the performance of RIS-assisted positioning. Section VI summarizes some of the challenges that may be faced by RIS assisted positioning and provides some suggestions and opinions. Finally, Section VII concludes the paper.

2. RIS-assisted Positioning in Millimeter-wave MIMO Systems

The combination of the RIS and millimeter-wave MIMO communication system has attracted widespread attention. For the traditional cellular positioning technology in the 5G system, because the large bandwidth of the millimeter-wave band has high time resolution and the large-scale antenna array has high spatial resolution, device positioning can be achieved using single BS. However, this requires that the user equipments (UE) also needs to be equipped with large-scale antenna arrays, which is infeasible for mobile devices [2]. In order to solve the above problems, there have been some studies on the device positioning in millimeter-wave MIMO systems.

In [3], Hu et al. derived the Fisher-information matrix (FIM) and Cramer-Rao lower bounds (CRLB) for positioning with RIS. At the same time, they compared RIS centralized deployment and distributed deployment, and found that distributed deployment has the potential to expand the coverage of terminal positioning and can provide a better average CRLB for all dimensions. In [4], He et al. studied the limit of mmWave MIMO positioning, and studied the influences of the number and the phases of the reflecting units on the channel parameters, which was helpful to analyze the error limits of positioning and direction. Moreover, they compared the accuracy of the positioning system with or without RIS, and found that the introduction of RIS can help improve the positioning accuracy. On this basis, in [2], Zhang et al. proposed a two-stage positioning method with dual RISs, which studied the point-to-point uplink transmission. The main idea of this method was that in the first stage, the angle information such as AoA and AoD was estimated, and an appropriate RIS was selected to redirect the signal. Then in the second stage, the positioning reference signal (PRS) was sent through the UE, and was received by the BS through the direct path and the RIS reflection path. According to the estimated angle information and delay information, the location of the UE could be deduced using the geometric laws. Therefore, it was very suitable for the positioning of lightweight devices.

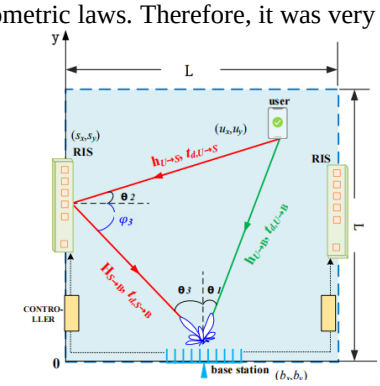


Fig. 1. Positioning system [2]

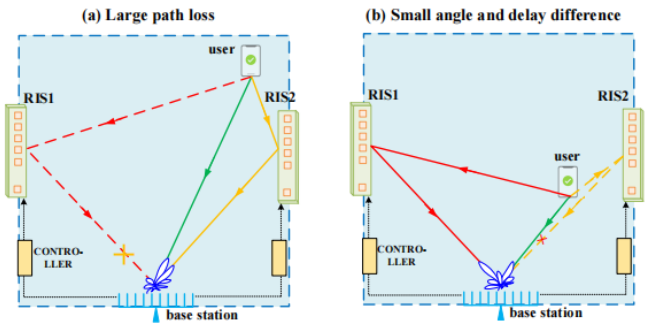


Fig. 2. Problems [2]

The model of this technology is shown in Figure 1. A single-antenna UE is randomly distributed anywhere in the scene, and two RISs are located at the boundary of the scene. At the same time, each RIS is connected to the BS through a programmable controller, and the UE transmits a reference signal to the BS, and then locates by the geometric theorem.

It is worth mentioning that the two RISs used in this technology are used for UE positioning. This is because the use of one RIS will cause a larger error, resulting in two situations as shown in Figure 2. The first problem is that when the UE is far away from the RIS, the reflection path will also be farther, resulting in severer path loss, weaker signal strength received by the BS, and lower positioning accuracy [2]. The second problem is that when the UE is located near the connection line between the BS and the RIS, the delay difference and angle between the direct path and the reflected path are slight. If the angle between the two paths is small, it is difficult to distinguish the two paths, leading to higher estimation errors [2]. Based on the above reasons, this

technology chooses dual-RIS to assist positioning. According to the experimental results, the accuracy of this method can reach 10^{-5}~ 10^{-4} meter, which is an order of magnitude lower than using a single RIS [2].

3. RSS-based Positioning Scheme

The technology based on the RSS is widely used for positioning because of its simplicity and ease of implementation. It can be widely implemented on Wi-Fi compatible devices with few hardware requirements [5]. There are many researches on RSS-based technology. In [6] Bahl et al. proposed a radar radio frequency system based on RSS technology to realize user positioning and tracking in buildings. In [7] Youssef et al. designed Horus WLAN location determination system. The system recognized the different causes of changes in the wireless channel and solved them to achieve high accuracy. The location clustering technology was used to reduce the computational complexity, and the lightweight location positioning could be achieved. However, the above-mentioned technology highly depends on the RSS distribution, i.e., if the RSS is unfavorable, it will seriously affect the positioning accuracy. In practice, it is difficult to distinguish the RSS values of adjacent positions, so that the positioning accuracy is not very high. Because the RIS can easily adjust the state of the unit to change the reflection coefficient, and is easy to be deployed in a wireless environment, it can be combined with RSS-based technology to achieve high positioning, which means that integrating the RIS in the positioning system to improve the positioning accuracy [8].

In [8], Zhang et al. proposed a RSS-based RIS positioning scheme. The idea of this scheme was to increase the numerical difference of adjacent RSS by modifying the reflection coefficient of RIS, thereby improving the accuracy of positioning. In [8], due to the number of RIS and the complex relationship between RIS and RSS, choosing the right configuration had certain challenges. In order to solve the problems of choosing a suitable reflection coefficient to improve the accuracy of positioning, the problem of RIS-assisted positioning was formulated to minimize the weighted probability of the incorrect positioning, and an iterative algorithm was designed to solve this problem.

The positioning scene of this method is shown in Figure 3, including an AP (transmitting the signal reflected by the RIS and the RSS measured by the user), a RIS, and multiple users which need to know their locations. The AP is connected to the RIS controller to control the RIS. The entire positioning process can be described as follows: the AP sends a signal through the carrier frequency f_c, and the signal reaches the RIS and is reflected to the user. At the same time, the user will also measure the RSS information. This solution can also be extended to other scenarios by changing the location of the RIS and placing an AP nearby [8].

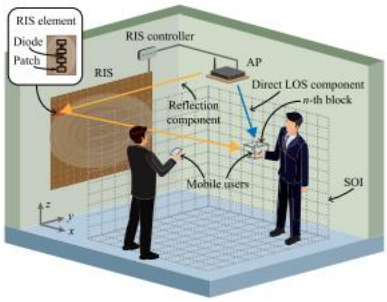


Fig. 3. System model for the RIS-aided multi-user positioning [8].

In [8], the experimental results show that when the standard deviation of RSS, the distance between RIS and space of interest (SOI), and the number of users increase, or the number of RIS elements, the number of element states, and the number of cycles decrease, the positioning error will increase.

4. Positioning with UWB Technology

In recent years, the RIS has been widely used in wireless communication systems because of its ability to manipulate multi-path signals. Inspired by the degree of freedom that the RIS can control wireless signals, in [9], Ma et al. extended the application of RIS to indoor positioning with the help of ultra-wideband (UWB) technology, and elaborated on the feasibility of using RIS to achieve high-precision indoor positioning. In [10], Qi et al. proposed a ToA-based positioning method in a multi-path environment, and studied whether processing the delay estimation of multi-path components can improve the positioning accuracy in addition to the first arrival. In [11], Qi et al. analyzed the time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA) and the positioning methods based on the signal strength (SS) in the NLOS environment. Note that there are many other researches on positioning, but the premise is that the outdoor environment has a rich spatial size and a multi-path propagation. Obviously, it is not suitable to use traditional positioning

methods in the indoor environment. At the same time, GPS signals and signals from cellular BSs often have blind spots, so that they are not suitable for indoor positioning [9]. Therefore, using wireless fidelity (WiFi) fingerprints is a trend of indoor positioning, which is the RSS-based technology mentioned in Section 3, but the positioning accuracy of this technology significantly depends on the modeling accuracy of the indoor electromagnetic propagation environment.

In this context, in [12], Xiang et al. studied the positioning scheme in the multiple input multiple output orthogonal frequency division multiplexing (MIMO-OFDM) system, and proposed a model-free positioning technology using a deep learning framework. On this basis, a Wi-Fi system positioning scheme based on logistic regression was proposed, which greatly improved the accuracy of positioning. It is worth mentioning that the UWB technology with extremely high multi-path resolution has also attracted considerable attention. However, as far as the authors know, some current studies have not fully utilized the ability of RIS to mark multi-path channels [9]. Therefore, in [9], Ma et al. developed a novel indoor RISP scheme, which could connect the UWB signals with high multi-path resolution and the RIS with the ability to mark multi-path channels. Specifically, in this indoor positioning scenario, RIS can mark channels, and UWB signals can be used for multi-path identification. The combination of RIS and UWB can improve the accuracy of indoor positioning of a single access point, and because this solution only requires one access point and some low-cost RIS units, it greatly reduces the cost and provides a more accurate and economic indoor positioning solution [9].

5. Performance Evaluation and Analysis

In this section, through the evaluation and analysis of the indoor positioning technology using RIS mentioned in the third section of the paper, to demonstrate the superiority of using RIS for positioning.

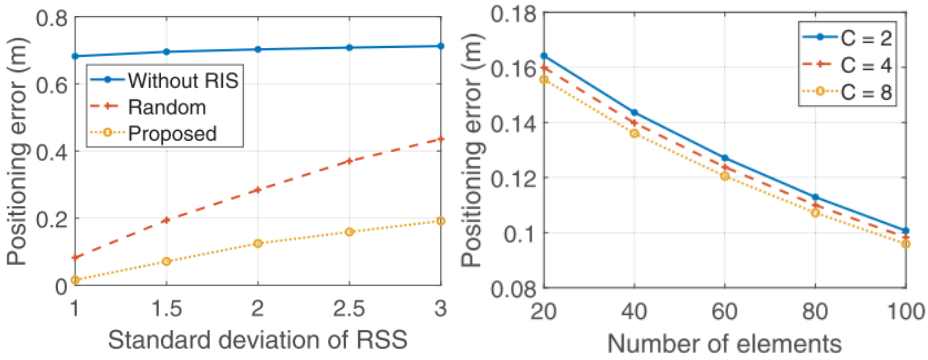
The scenario layout of the scheme is shown in Figure 3. Some basic parameters are set as follows. RIS lies in the plane of x = 0, and its center is located at the origin. The size of SOI is $1\times1\times1$ m^3, and it is divided into 1000 blocks, and its center is located at (1.5, 0, 0) m. The AP is located at (0.5, -0.5, 0) m, the transmit signal power is $s^t = 0$ dB, and the frequency $f_c = 2.4$ GHz [8].The RIS consists of 64 units, the interval between units is 0.06 m, and each unit has four states, i.e., $C = 4$, and the amplitude of each state is set according to the phase shift model in [13]. Assuming that the antennas equipped by the AP and users are omnidirectional and their power gains are equal to 1 [8].

In [8], in order to better analyze the experimental results, a positioning error l_e is defined as

$$l_e = \frac{1}{I}\sum_{i\in\ell} || r_i^e - r_i^g || \qquad (1)$$

where r_i^e is the location of the estimated block's center, and r_i^g is the truth.

At the same time, for comparison, in [8], two other schemes are provided. (1) Without RIS scheme: this scheme obtains the user's location by comparing the different signal patterns of AP with the RSS [14]. (2) Random configuration scheme.



(a) (b)

Fig. 4. (a) The positioning error l_e versus the standard deviation σ; (b) The positioning error l_e versus the number of elements [8].

The results in Figure 4 are obtained through simulations. It can be seen from Figure. 4 (a) that the l_e obtained by using the scheme proposed in Section 3 is smaller than the other two schemes, which proves the feasibility of using the RIS for indoor positioning [8]. It can be seen from the figure that the positioning errors of the three schemes all increase with the increase of the standard deviation. This is because the standard deviation and the measurement time are negatively correlated, so that the positioning accuracy can be improved by increasing the measurement time [15].

It can be seen from Figure. 4 (b) that the positioning error l_e decreases with the increase of the number of elements and the number of element states. Therefore, the method of increasing the number of elements and the number of element states can be used to improve the positioning accuracy [8].
Consequently, it can be seen from the above results that the use of the RIS for positioning can achieve higher positioning accuracy, and the positioning accuracy can be further improved by designing the RIS parameters.

6. Challenges and Future Extension

In summary, it can be seen that the RIS is playing an increasingly important role in positioning, especially in indoor positioning scenarios. Accurate indoor positioning can improve the quality of life, especially in large shopping malls or large exhibition halls. One of the most accurate examples is the indoor positioning system for the Shanghai World Expo, which greatly improves people's viewing experience. Of course, outdoor positioning is also of great significance to people's lives. However, whether it is indoor positioning or outdoor positioning, precise positioning systems still need continuous explorations. Here are some challenges that may be faced by RIS-assisted positioning. (1) How to jointly design the beamformer at the BS and the phase shifter at the RIS to achieve a more precise positioning [4]. (2) How to make corresponding adjustments to the configuration coefficients of RIS in time to deal with different positioning scenarios. (3) In different signal propagation environments, how to adjust the deployment of the RIS to achieve higher positioning accuracy.
According to the survey, most of the existing researches on the RIS-assisted wireless communications adopt the far-field assumption when modeling the channel, which implies that the incident signal reaching the RIS surface can be regarded as a plane wave, thereby reducing the complexity of the analysis on the phase effect. However, as RIS is gradually applied in various positioning scenarios, especially in indoor positioning scenarios where traditional methods cannot be applied, the use of the RIS for positioning becomes extremely important. Besides, in the indoor environment, to a large extent, the modeling of the channel should be more in line with the near-field assumption. Therefore, in the future research, the study of near-field hypothesis in RIS-assisted channel modeling will be a research hotspot.

7. Concluding Remarks

This paper investigates the RIS-assisted positioning method in the millimeter-wave MIMO system, the RIS and RSS based positioning technology, and the RIS-aided indoor positioning method combined with the ultra-wideband (UWB) technology. Although not all positioning methods have been included, some representative positioning methods have been introduced. We sorted out some of the characteristics of the three positioning technologies or positioning scenarios, discussed the challenges to be solved in the future, and analyzed and discussed the meaning and value of precise positioning.

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Federated Learning Over Wireless Communication Networks

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Abstract: The traditional cloud-based machine learning methods are gradually unable to meet the more and more stringent requirements put forward by some complex learning application scenarios on transmission delay and data privacy, thus encouraging the emergence of federated learning (FL). FL integrates two originally separated fields, namely wireless communication and machine learning, where the communication factor becomes the key bottleneck due to the limitation of communication resources. Over-the-air computation (AirComp) provides an efficient communication framework for FL by utilizing waveform stacking characteristics of multi-access channels. Furthermore, reconfigurable intelligent surface (RIS) can artificially alter wireless conditions, thus effectively improving the communication environment for FL. This paper first outlines the need to study the impact of wireless communication factors on FL, followed by the analyze of three representative works, and finally discusses the future challenges of federated learning.
Index Terms: Federated Learning, Wireless Communication, Over-the-air Computation, Reconfigurable Intelligent Surface

1. Introduction

On the basis of the 5G wireless communication system, which is transforming from "connected people" to "connected everything", the future 6G wireless communication system is envisioned to provide ubiquitous wireless connectivity to billions of smart devices and sensing devices with the capabilities of sensing, communication, computing and control. In the 6G era, advanced machine learning (ML) technologies will achieve a paradigm shift from "connected things" to "connected intelligence". However, cloud-based centralized machine learning approaches face three challenges: 1) the limitation of frequency resources may lead to network congestion and excessive network delay when a large amount of raw data is gathered via the wireless channel for model learning, 2) the transmission of privacy-sensitive data over wireless channels may result in privacy leakage or data modification, 3) a large number of edge devices with powerful computing power are not fully utilized to coordinately train the complex models with high performance and accuracy requirements, which brings about potential resource waste. Federated learning (FL), first proposed by Google in 2016, is a promising solution for privacy-sensitive and low-latency smart Internet of Things (IoT) applications, and has the ability to take full advantage of distributed computing resources.

A typical FL framework allows each distributed user equipment (UE) to compute its local model updates based on local dataset and upload the updated parameters to a parameter server (PS). The global model is aggregated in PS and shared with the UEs. Simultaneously, iterations are carried out until the algorithm converges. Therefore, the FL framework can reduce the communication overhead of the network while ensuring the security of privacy data. Since all model parameters are transmitted through wireless channels, the learning quality will be affected by wireless communication factors potentially. At the same time, the energy consumption (EC) restriction of devices and the strict delay requirements of the system make FL systems need to select an appropriate subset of UEs to perform the learning algorithm. In order to obtain efficient FL network and reduce system EC, it is necessary to fully study the relationship between the performance of FL algorithm and the underlying wireless network. Therefore, a new framework for implementing efficient federated learning

algorithms on wireless networks by considering federated learning and wireless communication indexes and factors needs to be proposed.

To this end, a promising solution is over-the-air computation (AirComp), which uses the superposition of multiple access channel (MAC) to support the simultaneous transmission of all UEs, and completes the cooperative execution of local parameter calculation, communication and global model calculation. AirComp can effectively improve learning performance under limited communication bandwidth and strict delay requirements. In broad terms, AirComp can be seen as a non-orthogonal multiple access (NOMA) technology whose bandwidth requirements and communication latency do not increase with the number of UEs. Therefore, AirComp greatly reduces the required communication resources, thus improving the completion time and spectral efficiency of FL system, and alleviating the communication bottleneck in federated learning to a large extent.

Channel conditions can also be artificially improved by deploying reconfigurable intelligent surface (RIS), which is a technology for intelligent reconstruction of wireless signals during propagation. Specifically, the reconfigurable intelligent surface is composed of many passive editable components, which can control the amplitude and phase shift of wireless signal in real time by programming, that is, it can actively modify the wireless channel, thus providing a favorable wireless environment for FL to transmit parameters on the wireless channel.

Recently, several strategies have been done on FL implementation in wireless communication networks [1-7]. However, most of the work assumes that wireless networks can easily integrate FL algorithms and does not consider the impact of unreliability of wireless channels on FL algorithm performance. Practically, the unreliability of wireless network will make FL algorithm encounter transmission error during parameter transmission, which will affect the quality and correctness of FL parameter update between UEs, and further affect the performance and convergence rate of FL algorithm. In addition, although the work in [8] proposes a model by considering the impact of packet transmission errors on FL performance, it does not address the problem of optimizing user selection and resource allocation to optimize FL performance. As the matter of fact, the strict limitations of wireless bandwidth, device power consumption and FL propagation delay require FL algorithm to make reasonable device selection and resource allocation. Chen et al. [9] develop a new framework for implementing FL in wireless networks by taking into account not only the impact of packet transmission errors on FL performance, but also user selection and resource allocation. Yang et al. [10] propose a fast global model aggregation method based on AirComp, which realizes fast model aggregation of FL by combining equipment selection and receiver beamforming design problems, and meanwhile improves model accuracy and training speed. Liu et al. [11] propose to solve the straggler problem of AirComp based FL by using RIS technology. They develop a unified communication-learning optimization problem to jointly optimize device selection, AirComp transceiver design and RIS configuration.

In this paper, we first discuss the importance of studying the influence of communication factors on FL performance. Secondly, the basic framework in FL is modeled, and the communication problems in FL are briefly described. Thirdly, this paper provides a review of three representative papers on communication issues in FL. These three papers correspond to three fundamental communication problems in FL and propose constructive

solutions. Finally, the three representative papers are summarized and the future research directions in FL learning are discussed.

The rest of this paper are organized as follows. Section II provides a general framework for FL and describes the communication issues. Section III describes in detail three representative papers on studying the communication problems in FL. Section IV gives a conclusion and future extension of this paper.

2. System Model and Problem Formulation

FL enables the PS and the UEs to collaboratively learn a shared learning model while keeping all of the training data at the device of each UE. In an FL algorithm, each UE will use its collected training data to train an FL model. For UEs, the goal of local training is to find the optimal learning model parameter $\boldsymbol{w}^*$ that minimize its training loss. Without losing the generality, the *local loss function* of the model $\boldsymbol{w}_i$ on $\mathcal{D}_i$ measuring the learning performance is defined as follows

$$F(\boldsymbol{w}_i) = \frac{1}{|\mathcal{D}_i|}\sum_{(\boldsymbol{x}_i,y_i)\in\mathcal{D}_i} f(\boldsymbol{x}_i, y_i; \boldsymbol{w}_i) \tag{1}$$

where $f(\boldsymbol{x}_i, y_i; \boldsymbol{w}_i)$ denotes the sample loss. The i-th user has its own local data set of size $\mathcal{D}_i$, consisting of labeled data samples $\{(\boldsymbol{x}_i, y_i)\} \in \mathcal{D}_i$, where $\boldsymbol{x}_i$ denotes the input unlabeled data vector of the FL algorithm and y_i the associated label (output of $\boldsymbol{x}_i$). A global FL model, represented by the parameter vector $\boldsymbol{w}$, is trained collaboratively across the edge UEs, orchestrated by the PS. The *global loss function* on all the distributed datasets can be written as

$$F(\boldsymbol{w}) \triangleq \frac{\sum_{i=1}^{I}\sum_{(\boldsymbol{x}_i,y_i)\in\mathcal{D}_i} f(\boldsymbol{x}_i,y_i;\boldsymbol{w}_i)}{\sum_{i=1}^{I}|\mathcal{D}_i|} \tag{2}$$

where I represents the number of UEs. The training process of an FL algorithm is then done via minimizing the global loss function, i.e.,

$$\min_{\boldsymbol{w}\in\mathbb{R}} F(\boldsymbol{w}) = \min_{\boldsymbol{w}\in\mathbb{R}} \frac{\sum_{i=1}^{I}\sum_{(\boldsymbol{x}_i,y_i)\in\mathcal{D}_i} f(\boldsymbol{x}_i,y_i;\boldsymbol{w}_i)}{\mathcal{D}} \tag{3}$$

where $\mathcal{D} = \sum_{i=1}^{I}|\mathcal{D}_i|$ is total size of training data of all devices.

In order to obtain the minimum global loss function, FL algorithm needs to carry out round after round of parameter transmission and iteration process. In n-th communication round of learning, the i-th user computes a local gradient of the loss function using its local dataset $\mathcal{D}_i$ and the current global FL model parameter vector $\boldsymbol{w}_i^{[n]}$, i.e.,

$$\boldsymbol{g}_i^{[n]} = \frac{1}{|\mathcal{D}_i|}\sum_{(\boldsymbol{x}_i,y_i)\in\mathcal{D}_i} \nabla f\left(\boldsymbol{x}_i, y_i; \boldsymbol{w}_i^{[n]}\right) \tag{4}$$

where ∇ represents the gradient operator. Then, the local model parameter can be updated via gradient descent based on the following equation

$$\boldsymbol{w}_i^{[n+1]} = \boldsymbol{w}_i^{[n]} - \lambda \cdot \boldsymbol{g}_i^{[n]} \tag{5}$$

where λ denotes the learning rate. If the local model parameter can be transmitted reliably to the PS, the global model parameter would be computed as follows

$$\boldsymbol{w}^{[n+1]} = \frac{1}{\mathcal{D}}\sum_{i=1}^{I} \mathcal{D}_i\, \boldsymbol{w}_i^{[n+1]} \tag{6}$$

The process in the n-th communication round above keeps iterating until the convergence condition is satisfied.

Since all of the local FL models are transmitted over wireless cellular links, once they are received by the PS, they may contain erroneous signals due to the unreliable nature of the

wireless channel, which, in turn, will have a significant impact on the performance of FL. Here are three representative papers that delve into how communication factors affect FL performance. They describe this process as different optimization problems, and then propose constructive schemes and algorithms to optimize FL performance in wireless communication environment.

3. Work Review

3.1 FL without AirComp or RIS

In work [9], first, a joint wireless FL system model is established, which includes transmission packet error rate, user selection and resource allocation. The learning model framework is shown in Figure 1.

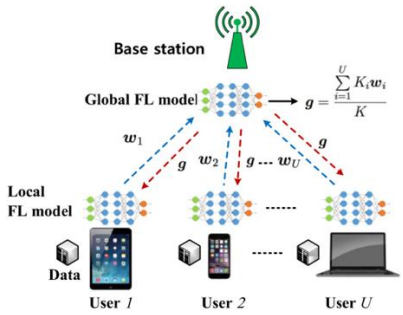

Fig. 1. The architecture of an FL algorithm that is being executed over a wireless network with multiple UEs and a single base station.

A UE with cellular connection transmits its local FL model parameters to the base station (BS) (BS is generally regarded as PS), and then the BS generates a global FL model and broadcasts it back to the UEs. The way of wireless transmission of model parameters is chosen to use orthogonal frequency division multiple access (OFDM) technology, where each UE occupies one resource block (RB) ($\boldsymbol{r}_i = [r_{i,1}, r_{i,2}, \dots, r_{i,R}]$). The transmission rate ($c_i^U(\boldsymbol{r}_i, P_i)$、$c_i^D$) and delay ($l_i^U(\boldsymbol{r}_i, P_i)$、$l_i^D$) on uplink and downlink are calculated respectively in the transmission model, where P_i is the transmission power of the i-th user. In this paper, the packet error rate, i.e.,

$$q_i(\boldsymbol{r}_i, P_i) = \sum_{n=1}^{R} r_{i,n} q_{i,n} \tag{7}$$

is used as a communication performance factor to establish the relationship between wireless channels and the performance of FL algorithm, where $q_{i,n} = \mathbb{E}_{h_i}\left(1 - exp\left(-\frac{m(I_n + B^U N_0)}{P_i h_i}\right)\right)$ is the packet error rate over RB n with m being a waterfall threshold. The selection mechanism of parameter data is established based on packet error rate, i.e., the global FL model can be written as

$$\boldsymbol{g}(\boldsymbol{a}, \boldsymbol{P}, \boldsymbol{R}) = \frac{\sum_{i=1}^{U} K_i a_i w_i C(w_i)}{\sum_{i=1}^{U} K_i a_i C(w_i)} \tag{8}$$

where

$$C(w_i) = \begin{cases} 1, with\ probability\ 1 - q_i(\boldsymbol{r}_i, P_i) \\ 0, with\ probability\ q_i(\boldsymbol{r}_i, P_i) \end{cases} \tag{9}$$

$\boldsymbol{a} = [a_1, a_2, \dots, a_U]$ is the vector of the user selection index with $a_i = 1$ indicating that user i performs the FL algorithm and $a_i = 0$, otherwise. $\boldsymbol{R} = [r_1, r_2, \dots, r_U]$, $\boldsymbol{P} = [p_1, p_2, \dots, p_U]$, $\sum_{i=1}^{U} K_i a_i C(w_i)$ is the total number of training data samples, which depends on the user selection vector $\boldsymbol{a}$ and pocket transmission $C(w_i)$. $\sum_{i=1}^{U} K_i a_i w_i C(w_i) = 0$ indicates that the local FL model of user i contains data errors and, hence, the BS will not use it to generate

the global FL model, and $\boldsymbol{g}(\boldsymbol{a}, \boldsymbol{P}, \boldsymbol{R})$ is the global FL model that explicitly incorporates the effect of wireless transmission.

In addition, the energy consumption model ($e_i(\boldsymbol{r}_i, P_i)$) of each UE is established. In this paper, the problem that combines the influence of communication factors, user selection and resource allocation is defined as an optimization problem with the goal of minimizing training losses while satisfying the requirements of latency and energy consumption. Therefore, this paper fully demonstrates the importance of high transmission reliability, low energy consumption and low delay for FL algorithm.

Subsequently, in order to solve the proposed joint optimization problem, a closed expression of the expected convergence rate of FL algorithm is derived. By analyzing this, it is found that the transmission power, RB allocation and user selection will significantly affect the convergence rate and performance of FL algorithm. Then, the optimization problem is transformed into a mixed integer nonlinear programming problem based on this relationship. After solving the optimal transmitting power by giving user selection and RB block allocation, the original problem is transformed into a binomial matching problem, and an optimal user selection and resource allocation strategy is obtained by solving the problem via Hungarian algorithm.

Finally, the feasibility and effectiveness of the proposed joint optimization algorithm are verified by experiments. Three baselines are set up: a) an FL algorithm that optimizes user selection with random resource allocation, b) an FL algorithm that randomly determines user selection and resource allocation, which can be seen as a standard FL algorithm, c) a wireless optimization algorithm that minimizes the sum packet error rates of all UEs via optimizing user selection, transmit power while ignoring FL parameters. Firstly, the algorithm is applied to the linear regression task, and the experimental results show that the proposed algorithm can achieve similar performance to the optimal FL. Compared with the three baselines, it can be concluded that the proposed algorithm can fit data samples more accurately, which verifies the feasibility of the proposed joint optimization algorithm. Next, the algorithm is applied to handwritten digit identification task. When measuring the relationship between the recognition accuracy and total number of UEs, the accuracy of the proposed algorithm can achieve up to 1.2%, 1.7% and 2.3% respectively compared with three baselines. When measuring the relationship between the accuracy and the number of RBs, the gain in identification accuracy of the proposed algorithm can achieve up to 1.4%, 3.5% and 4.1%, respectively. The reason is that the proposed algorithm can jointly optimize the wireless factor, RB allocation, transmitting power and user selection to minimize the training loss.

3.2 FL with AirComp

As mentioned before, limited communication bandwidth is the main bottleneck for aggregating local model parameter calculation updates. Therefore, in work [10], the author focuses on designing a fast model aggregation method of FedAvg algorithm. Considering computing and communication, by studying the superposition characteristics of wireless multiple access channels, they propose a cooperative transmission scheme using the principle of AirComp to achieve fast model aggregation. Compared with the traditional communication and computing separation scheme, AirComp can improve communication efficiency and reduce bandwidth requirements. The AirComp framework is shown in Figure 2.

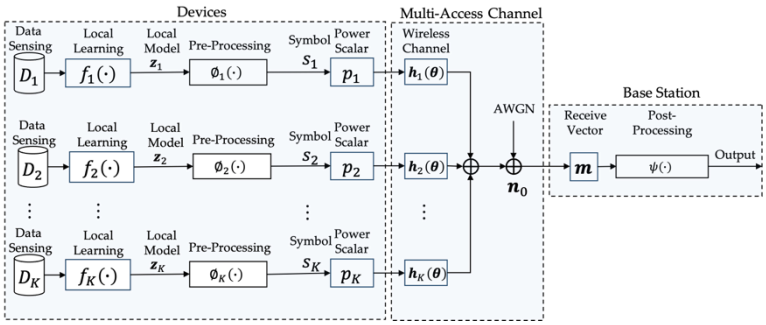

Fig. 2. The AirComp framework.

Specifically, the target vector for aggregating local updates in FedAvg algorithm is given by

$$\boldsymbol{z} = \psi(\textstyle\sum_{i\in\mathcal{S}} \emptyset_i(\boldsymbol{s}_i)) \tag{10}$$

where $\boldsymbol{s}_i$ is the updated local model at the i-th user, $\emptyset_i = |D_i|$ is the pre-processing scalar at user i, $\psi = \frac{1}{\sum_{k\in\mathcal{S}}|D_k|}$ denotes the post-processing scalar at the BS, and $\mathcal{S}$ represents the selected set of UEs. They denote

$$g = \textstyle\sum_{i\in\mathcal{S}} \emptyset_i(s_i) \tag{11}$$

as the target function to be estimated through AirComp. Thus, the received signal at the BS is given by

$$\boldsymbol{y} = \textstyle\sum_{i\in\mathcal{S}} \boldsymbol{h}_i b_i s_i + \boldsymbol{n} \tag{12}$$

where b_i is the transmitter scalar, $\boldsymbol{h}_i$represents the channel vector between user i and the BS, and $\boldsymbol{n}\sim\mathcal{CN}(\boldsymbol{0}, \sigma^2\boldsymbol{I})$ denotes the noise vector.

Then, the author indicates that selecting more UEs can improve the convergence speed of federated learning, but at the same time, more UEs may bring more communication errors, and the greater the aggregation error, the worse the model accuracy. Therefore, it is necessary to simultaneously minimize communication error and maximize the number of UEs participating in the FL algorithm. In order to ensure high FL performance while improving FL communication efficiency, a joint user selection and receiver beamforming design method is proposed in this paper. By using AirComp fast aggregation model, the maximum user selection with mean square error (MSE) requirement is found. In work [10], the maximum number of participating UEs is selected given any channel coefficient, and the problem is modeled as a sparse low-rank optimization problem to establish an efficient FL algorithm.

Finally, aiming at the limitations of existing sparse and low-rank optimization algorithms, the author proposes a unified DC representation method to recognize sparse and low-rank structures, and finally obtains the optimal user selection scheme under MSE constraints by solving the proposed optimization problem. Experiments show that the sparsity and low-rank induction methods based on the proposed algorithm can select more UEs than the existing methods, and the proposed algorithm has lower training loss and higher prediction accuracy.

3.3 FL with AirComp and RIS

From the review of the second paper, we know that in order to improve the communication efficiency in FL model aggregation, the superposition characteristics of wireless channels can be fully used by introducing AirComp to support a large number of local model parameters with upload. However, there is heterogeneity among edge UEs, including not only the data heterogeneity, but also the channel heterogeneity of different edge UEs.

Therefore, under the AirComp framework, the edge UEs with the weakest communication ability restrict the aggregation performance of FL system, which is called straggler problem. Although the straggler problem can be mitigated to some extent by optimizing user selection, this approach still requires a trade-off between parameter calculation and model communication. The work in [11] proposes to alleviate the straggler problem, that is, to break the dilemma of trade-offs between parameter calculation and model communication, by depolying RIS, thus artificially adjusting the channel state of edge UEs. The communication system framework based on RIS is shown in Figure 3.

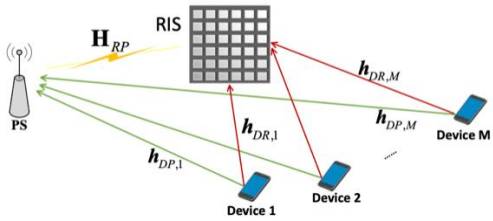

Fig. 3. The communication system framework based on RIS.

Specifically, let $\boldsymbol{h}_{DP,i}$, $\boldsymbol{H}_{RP}$, and $\boldsymbol{h}_{DR,i}$ denote the direct i-th-user-BS, the RIS-BS, and the i-th-user-RIS channel coefficient vector or matrix, respectively. Denote the RIS phase-shift vector as $\boldsymbol{\theta}$ with $|\theta_l| = 1$ for $l = 1,2,\dots,L$, where the RIS has L phase shift elements. Thus, the effective i-th-user-BS channel coefficient could be defined as

$$\boldsymbol{h}_i(\boldsymbol{\theta}) = \boldsymbol{h}_{DP,i} + \boldsymbol{H}_{RP} diag(\boldsymbol{\theta}) \boldsymbol{h}_{DR,i} \tag{13}$$

and the corresponding received signal at the BS is the superposition of the signals from the direct channel and the user-RIS-BS cascaded channel, i.e.,

$$\boldsymbol{y} = \sum_{i\in\mathcal{S}} \boldsymbol{h}_i(\boldsymbol{\theta}) b_i s_i + \boldsymbol{n} = \sum_{i\in\mathcal{S}} \left(\boldsymbol{h}_{DP,i} + \boldsymbol{H}_{RP} diag(\boldsymbol{\theta}) \boldsymbol{h}_{DR,i}\right) b_i s_i + \boldsymbol{n} \tag{14}$$

It is worth mentioning that the transmission scheme used in this work is also AirComp.

Then, the author in [11] also develop an analysis framework to quantitatively analyze the effects of user selection and model aggregation errors on the performance of AirComp based FL. Using MSE as the communication error performance index, a unified learning-communication optimization problem was developed to jointly optimize equipment selection, BS receiving beamforming design and RIS parameter configuration.

Finally, authors use Gibbs sampling for user-selected optimization, and the successive convex approximation (SCA) for the co-optimization of receiver beamforming and RIS phase shifts. The experiment in this paper sets up two different scenarios: a) all UEs are evenly distributed in the same area with the same number of training samples, and b) UEs are divided into two different areas with different numbers of training samples. Experiments in the former scenario show that, compared with FL algorithm without RIS, the FL algorithm with RIS can overcome the adverse effects of channel conditions by configuring RISs phase shift. For the latter scenario, the straggler problem should be considered. The experimental results show that when straggler problems need to be considered, the FL algorithm with RIS has more obvious advantages than the one without RIS, which can make the FL algorithm converge faster and obtain better test accuracy.

4. Conclusion and future extension

This paper provides a discussion of the impact of communication factors on FL performance, as well as a review of several representative ideas for solving communication problems in FL. First, the communication issues introduced when transmitting the parameters are the key bottleneck in FL, and we need to establish the relationship between communication factors and FL performance. Second, to improve communication efficiency in FL networks,

AirComp was introduced so that UEs could transfer their local model updates to PS in parallel. At the same time, AirComp allows more UEs to participate in FL tasks, which enables faster convergence of the learning network. Finally, RIS can be used to artificially improve the channel status of UEs, which can solve the straggler problem to some extent and break the dilemma of tradeoff between computing and communication.

Establishing the relationship between communication factors and FL performance is important and a promising research direction. At the same time, to achieve efficient FL network, user selection and resource allocation should be jointly considered. As far as we know, the study of communication factors, user scheduling and resource allocation in FL is now at a critical stage of development. Therefore, it is of great significance to design reasonable communication performance improvement scheme, fair user scheduling strategy and resource allocation scheme to improve FL learning performance for practical applications in future 6G intelligent wireless networks.

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Beamforming Design Based on Deep Reinforcement Learning

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Abstract: Beamforming design, known as a signal processing technique, can be applied to the wireless time-varying downlink channels. Due to the time-varying property of the downlink channels and the continuous values of the beamforming vectors, there are two challenges when optimizing the sum rate, i.e. real-time data processing and continuous representations. In view of these challenges, deep reinforcement learning (DRL) algorithms are adopted in the wireless communication systems. The deep Q-learning (DQN) is able to process the real-time data and the deep deterministic policy gradient (DDPG) is capable of outputing the continuous beamforming vectors.
Index Terms: Beamforming design, time-varying channel, deep reinforcement learning (DRL), continuous output

1. Introduction

Wireless technologies have offered a large-scale data transmission in order to meet the high demand of the communication field. Pertaining to the wireless communications, researches on the sum-rate optimizations during the downlink transmission have attracted considerable interests [1]. To optimize the sum-rate, a cellular network is adopted to model the channels, including base stations (BS) and user equipments (UE). At the BS side, beamforming is a common technique adjusting directional signals [2]. Through the beamforming design, the optimization of the sum rate at the UE side is able to be extended towards practical applications. In the practical situations, the channels change over time due to the varying impulse responses of signals during the transmission, i.e. the time-varying property.

There exist two main problems in the beamforming design at the downlink channels. First, due to this time-varying property, a real-time analysis of the channel matrices comes at a high cost. Second, the beamforming design requires the precise representation because of the continuous values of the beamforming vectors in the practical situations.

Regarding the real-time analysis problem, reinforcement learning (RL) is a machine learning technique processing real-time data interaction through the memoryless property, termed Markov property [3]. To obtain a more approximate solution to the optimization, deep learning (DL) techniques are adopted in the RL to perform deep reinforcement learning (DRL) [4]-[5]. For example, deep Q-learning (DQN), a traditional DRL algorithm, combines a RL algorithm with two neural networks and adds an experience buffer [6]. The DQN based beamforming design improves the sum rate performance in the time-varying problem. However, the output of DQN is limited as the discrete value.

To realize the precise continuous representations, some DRL algorithms, such as the deep deterministic policy gradient (DDPG) based on the DQN algorithm and the Actor-Critic algorithm [7], are able to output continuous values. In [8], the DDPG based beamforming design approaches the performance of the best benchmarks at the time-varying downlink problem.

In this paper, we present a comprehensive overview of the recently developed beamforming design based on DRL methods, dealing with the sum rate optimization problems in the wireless time-varying downlink channels. The contributions of this paper are summarized as follows:

- We summarize two main challenges at the channels. The influence of the time-varying property is analyzed and the continuous representation of the beamforming is considered.
- For the time-varying property, we propose a DQN-based beamforming design. The DQN algorithm is able to process the real-time data from the time-varying channel matrices. Compared with tabular Q-learning, the DQN improves the sum-rate performance in the downlink channels.
- To realize the precise continuous representation, we propose a DDPG-based beamforming design. The DDPG algorithm is capable of outputing continuous beamforming vectors and performs better than the DQN algorithm in terms of the sum rate.

The rest of this paper is organized as follows. Section II presents the system model and beamforming design. Section III introduces the DQN algorithm for beamforming design. Section IV elaborates the DDPG algorithm for beamforming design. Section VI concludes this paper.

2. System Model and Beamforming Design

2.1 System Model

A cellular network is an architecture of communication network consisting of a set of transmitters and receivers. In this paper, we adopt the cellular network in order to simulate the time-varying downlink channels. In this cellular network, L ($L \geq 2$) BSs are employed as the transmitters and the l-th BS with M antennas serves d_l UEs in a serving cell with the radius $R/2$. These cells are able to overlap and interfere with each other. Therefore, the received signal-to-interference-plus-noise ratio (SINR) $\gamma_{(l,i)}[t]$ at the i-th UE served by the l-th BS at the time step t is able to be expressed as:

$$\gamma_{(l,i)}[t] = \frac{P_{(l,i)}[t]|\mathbf{h}_{l,(l,i)}^T[t]\mathbf{f}_{(l,i)}[t]|^2}{\sigma_n^2 + \sum_{j\neq l} P_{(l,j)}[t]|\mathbf{h}_{l,(l,i)}^T[t]\mathbf{f}_{(l,j)}[t]|^2 + \sum_{b\neq l}\sum_{j=1}^{d_b} P_{(b,j)}[t]|\mathbf{h}_{b,(l,i)}^T[t]\mathbf{f}_{(b,j)}[t]|^2} \quad (2)$$

where $P_{(l,i)}[t]$ is the transmitted power and $\mathbf{f}_{(l,i)}[t] \in C^{M\times 1}$ denotes the beamforming vector at the l-th BS side applied to the i-th UE at the time step t. $\mathbf{h}_{b,(l,i)}[t] \in C^{M\times 1}$ represents the channel vector from the b-th BS to the i-th UE served by the l-th BS at the time step t.

In this paper, the overall sum-rate optimization problem in this wireless time-varying downlink channel is formulated as:

$$\begin{aligned} &maximize_{P_{(l,i)}[t],\mathbf{f}_{(l,i)}[t],\forall l,i} \sum_{l=1}^{L}\sum_{i=1}^{d_l} log_2(1 + \gamma_{(l,i)}[t]) \\ &subject\ to \quad \mathbf{f}_{(l,i)}[t] \in \mathbf{F}, \quad \forall l,i \end{aligned} \quad (3)$$

where $\mathbf{F}$ is the codebook of beamforming design.

2.2 Beamforming Design

Beamforming is a common technique adjusting signals directionally through the antennas of the BS. In this paper, we assume that the beamforming vectors depend on the constant-modulus phase shifters, i.e. $[\mathbf{f}_l]_m = e^{j\theta_m}$. For the discrete selection, the beamforming vector is able to be selected from the codebook **F**. Therefore, the *n*-th element in the codebook **F** is expressed as:

$$\mathbf{f}_n = \frac{1}{M}[1, e^{jkdcos(\theta_n)}, \ldots, e^{jkd(M-1)cos(\theta_n)}]^T \quad (4)$$

where *d* is the antenna spacing and *k* is the wave number. θ_n denotes the steering angle varying from 0 to π.

2.3 Challenges

In this problem formulation, there exist two main challenges due to the time-varying property of the downlink channels and the continuous values of the beamforming vectors.

First, in order to optimize the sum rate, the channel matrices are required to be processed at each time step *t*. However, the matrices are high dimensional with a large amount of elements and vary over time. Therefore, the real-time data processing comes at a cost due to a high calculation power and a huge memory at each time step *t*. This high cost hinders the realization of common optimization algorithms. Hence, the DRL algorithms such as DQN are able to play an important role in this time-varying problem.

Second, in the beamforming design, the beamforming vectors are continuous. Therefore, a precise continuous representation of the vectors is able to bring a better performance in the optimization. However, the traditional DRL algorithms are limited by the discrete output. Hence, the continuous DRL algorithms such as DDPG are proposed to improve the performance in this paper.

3. DQN based Beamforming Design

Algorithm 1 DQN

Require: α, γ, θ, C, B

Ensure: optimized θ

Intialize the current network $Q(s, a|\theta)$ with weights θ
Intialize the target network $\widehat{Q}\left(s, a|\widehat{\theta}\right)$ with weights $\widehat{\theta} \leftarrow \theta$
Initialize replay experience buffer Ω
for episode from 1 to *Limit* **do**
  Receive the initial observation state s_1.
  for t=1 to T **do**
    Select the action a_t according to the ϵ-greedy policy
    Execute action a_t, observe reward r_{t+1} and new state s_{t+1}
    Store transition $(s_t, a_t, r_{t+1}, s_{t+1})$ in Ω
    Sample a random minibatch of B transitions $(s_i, a_i, r_{i+1}, s_{i+1})$ from Ω
    set

$$y_i = \begin{cases} r_{i+1} & \text{if terminate at the step j+1} \\ r_{i+1} + \gamma \widehat{Q}\left(s_i, \underset{a^* \in A}{arg\max} Q\left(s_i, A\right)\right) & \text{else} \end{cases}$$

    Perform the BP process with respect to θ, update θ
    Every C steps reset $\widehat{Q} = Q$
  end for
end for

3.1 DQN

DQN is a traditional DRL algorithm with an experience buffer, combining the tabular Q-learning with two neural networks. The tabular Q-learning is able to generate Q-values. The Q-values assist to select the adjusting method based on the situations so that the optimization goal can be achieved.

According to the architecture of the DQN, the stability of the DQN model is protected from the disturbance of the training data. There are two main reasons as follows. First, these two neural networks are able to be denoted as current and target network. The target network is updated through copying the parameters from the current ones per *N* time steps. Second, the experience buffer is able to store the experience of previous transitions. When performing back propagation in the neural networks, a batch of the transitions are randomly selected in order to calculate the loss function.

3.2 DQN based Beamforming Design

[9] applied the DQN-based beamforming design. Considering the system model in this paper, some basic elements such as states, actions and rewards are set as follows.

First, the states have the capacity to represent the situations of the channels. These channel matrices vary depending on the time-varying positions of the UEs. Therefore, the position tracks are applied in the state settings to map the channel matrices. Second, the actions are taken to achieve the task. The beamforming design as the signal adjusting technique is treated as the actions. However, due to the limitation of discrete outputs in DQN, the beamforming vectors are designed to be selected from the codebook **F** discretely. Third, the rewards as the optimization goal guide the learning direction. Regarding the sum rate optimization problem, the value of the sum rate is set as the reward at each time step *t*.

As shown in Fig.1, the DQN algorithm performs best in terms of the complementary cumulative distribution function (CCDF) of the effective SINR γ_{eff}. The effective SINR γ_{eff} increases so that the sum rate grows.

4. DDPG based Beamforming Design

Algorithm 2 DDPG

Require: α, τ, θ^Q, θ^μ

Ensure: optimized θ^Q, θ^μ

Randomly initialize critic network $Q\left(s, a|\theta^Q\right)$ and actor network $\mu\left(s|\theta^\mu\right)$ with weights θ^Q and θ^μ

Initialize target network Q' and μ' with weights $\theta^{Q'} \leftarrow \theta^Q$, $\theta^{\mu'} \leftarrow \theta^\mu$

Initialize replay experience buffer Ω

for episode from 1 to *Limit* **do**

  Initialize a random process(noise) N for action exploration

  Receive initial observation state s_1

  for t=1 to T **do**

    Select action $a_t = \mu\left(s_t|\theta^\mu\right) + N_t$ according to the current policy and exploration noise

    Execute action a_t, observe reward r_{t+1} and new state s_{t+1}

    Store transition $(s_t, a_t, r_{t+1}, s_{t+1})$ in Ω

    Sample a random minibatch of B transitions $(s_i, a_i, r_{i+1}, s_{i+1})$ from Ω

    set $y_i = r_{i+1} + \alpha Q'\left(s_{i+1}, \mu'(s_{i+1}|\theta^{\mu'})|\theta^{Q'}\right)$

    Update critic by minimizing the loss:

$$L = \frac{1}{B}\sum_i \left(y_i - Q(s_i, a_i|\theta^{Q'})\right)^2$$

    Update the actor policy using the sampled policy gradient:

$$\nabla_{\theta^\mu} J \approx \frac{1}{B}\nabla_a Q(s, a|\theta^Q)|_{s=s_i, a=\mu(s)} \nabla_{\theta^\mu}\mu(s|\theta^\mu)|_{s_i}$$

    Update the target networks:

$$\theta^{Q'} \leftarrow \tau\theta^Q + (1-\tau)\theta^{Q'}$$

$$\theta^{\mu'} \leftarrow \tau\theta^\mu + (1-\tau)\theta^{\mu'}$$

  end for

end for

4.1 DDPG

DDPG is a DRL algorithm based on the DQN and Actor-Critic algorithms. When designing the target network, there are four neural networks from the Actor-Critic algorithms. Two of these neural networks as the Critic parts are able to output the Q-values assisting to select the actions. The other two neural networks as the Actor parts are responsible for interacting with the environment to generate the actions.

The actions can be continuous and are generated by an approximate function. This function is continuous due to the architecture of the Actor neural networks. Therefore, different from the Q-value tables in DQN, the actions are output from the approximate function with the Q-values as the input.

4.2 DDPG based Beamforming Design

[8] adopted the DDPG-based beamforming design. Considering the downlink system, the states, the actions and the rewards are set as follows.

First, for the state settings, the channel matrices are divided into the real part and imaginary part and are set as the states. Second, the beamforming design is treated as the actions. Different from the action settings in DQN, the beamforming vectors can be output directly due to the continuous actions in DDPG. Third, as the same as DQN, the value of the sum rate is set as the reward at each time step *t*.

As shown in Fig.2, the proposed DDPG algorithm improves the sum-rate performance, which approaches those of the other two best benchmarks.

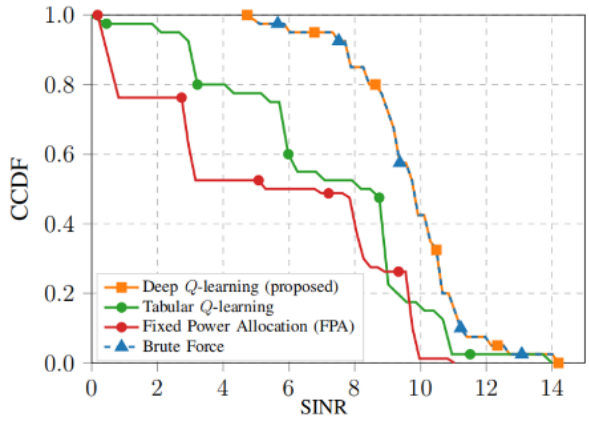

Fig. 1. The coverage CCDF plots of γ_{eff} for different algorithms.

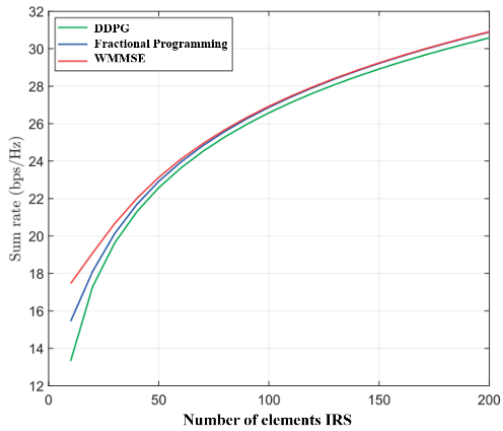

Fig. 2. Sum rate with the proposed DDPG algorithm as well as two best benchmarks

7. Conclusion

This paper presented an overview of the beamforming design based on DRL algorithms. The beamforming design was applied in the wireless time-varying downlink channels in order to optimize the sum rate. In view of the time-varying property of the downlink channels and the continuous values of the beamforming vectors, we summarized two challenges on the real-time data processing and the continuous representation. In order to address these challenges, DQN as a discrete DRL algorithm and DDPG as a continuous DRL algorithm were adopted. The DQN performed better than the traditional RL algorithms, and the DDPG approached the best performance. Based on these DRL algorithms, the

beamforming design could play an important role in adjusting the signals at the wireless channels.

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Deep Learning Based Wireless Communication Channel Estimation

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Abstract: Recently, more and more attention has been paid to deep learning (DL) based channel estimation. In this paper, we introduce several researches on the DL based channel estimation. Based on a DL based channel estimation model, we introduce the mathematical analysis of the error of DL estimator by Hu Qiang et al at [6]. It is concluded that the DL estimator has the performance comparable to MMSE estimator but it does not require any statistical prior information. Two typical application scenarios of DL estimator are introduced and analyzed. DL estimator based on image processing method has better performance and lower computational complexity than the traditional estimators. DL estimator can help the intelligent reflecting surface (IRS) aided communication system obtain accurate channel state information (CSI). In terms of the data set, mechanism and update speed, the DL based channel estimation may have many challenges, but it has the advantages of superior performance, convenient deployment and great development prospects.
Index Terms: channel estimation, deep learning (DL), convolutional neural network (CNN), residual learning, intelligent reflecting surface (IRS).

1. Introduction

Channel estimation is a vital component in the wireless communication system. Channel estimation is based on a branch of statistics known as Estimation Theory [1]. Channel state information (CSI) can be estimated utilizing the known pilot signals and the received signals. Using the estimated CSI, the receiver can accurately recover the received signals. Traditional channel estimation methods include the least squared (LS) estimation method and the minimum mean squared error (MMSE) estimation method. The LS estimation method does not need priori information of channel statistics, and its computational complexity is low. However, the estimation accuracy of the LS estimation method is relatively poor [2]. MMSE estimation takes the second-order statistics of the wireless channel as a priori information. The estimation accuracy is rather ideal, but the computational complexity is high. In some application scenarios, the CSI changes rapidly. Thus, it is difficult to accurately obtain the prior information required for MMSE estimation.

In recent years, deep learning (DL) has been widely applied in the field of wireless communication, and has received ideal application results. More and more researchers employ DL technology to improve the wireless communication performance in the physical layer. In [3], DL was first used in orthogonal frequency division multiplexing (OFDM) systems to implicitly estimate CSI and directly recover transmitted symbols. The results show that the DL estimator is more robust than the traditional estimators under the circumstance of nonlinear distortion. An enhancing LS channel estimation based on DL was proposed in [4], and the channel estimation effect has been significantly improved. These studies show that the DL estimator can obtain the accuracy comparable to the traditional channel estimators by establishing the mapping relationship between the pilot signal and the received signal.

The contributions of this paper mainly include:

- We introduce several researches on the DL based wireless channel estimation, including the mathematical analysis of and the practical application scenarios of the DL estimator. Combined with the simulation results of relevant papers, the advantages of DL estimator are verified.
- We analyze the future development of the DL estimator and propose several challenges that will be encountered in the future. In view of these challenges, feasible suggestions for the future development of the DL estimator are provided.

2. Performance of the DL Estimator

When estimating the CSI, the base station (BS) first transmits pilot signals to the receiver. The pilot signal, represented by $\boldsymbol{x}$, is completely known. The received signal at the receiver is denoted as $\boldsymbol{y}$. If the channel function is denoted as $\boldsymbol{h}$, then the received signal can be expressed as:

$$y = h \circ x + n \tag{1}$$

where n denotes the additive white Gaussian noise (AWGN). What the DL estimator needs to do is calculating the channel function $\boldsymbol{h}$ under the condition that the pilot signal and the received signal are known.

The DL estimator generally adopts deep neural networks (DNN), whose model structure is shown in Figure 1 [5]. The overall network framework consists of an input layer, multiple hidden layers and an output layer. The network adopts full connection structure. For the input X_i of layer i and the bias term b_i, the following equation is satisfied:

$$S_i = W_i X_i + b_i \tag{2}$$

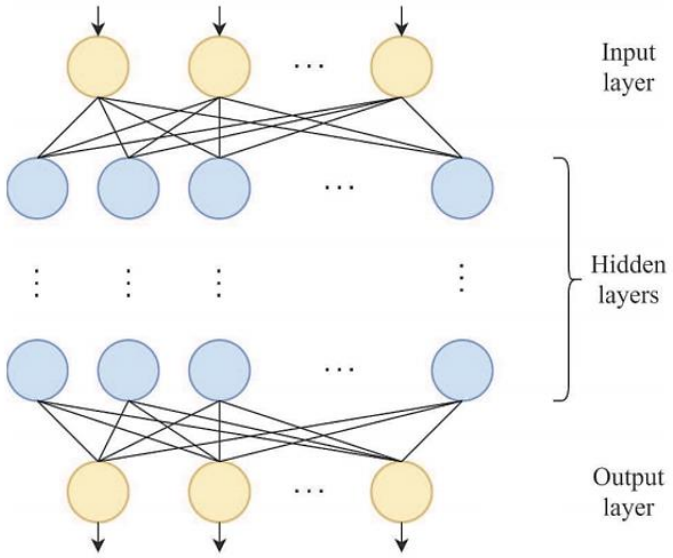

Fig. 1. The structure of deep neural network

In the DNN, in order to avoid pure linear combination, an activation function $relu(x)$ is adopted:

$$relu(x) = \max(x, 0) \tag{3}$$

Hence, the output Y_i of layer i is given by:

$$Y_i = relu(S_i) \tag{4}$$

Set the received signal $\boldsymbol{y}$ as the input of the DNN and the estimated channel function $\hat{\boldsymbol{h}}$ as the output. Set the real channel function $\boldsymbol{h}$ as the training label. The loss function is defined as:

$$J = \sum (h - \hat{h})^2 \tag{5}$$

According to [6], as the DNN with rectified linear unit (relu) activation function is mathematically equivalent to a piecewise linear function, the DL estimator can approximate the MMSE estimator by making efficient use of piecewise linearity. The approximation error can be effectively reduced if the scale of neural network is larger and more linear units are adopted.

In conclusion, when the scale of the neural network is large enough, the estimation error of DL estimator can approximate the error of MMSE estimator. However, the DL estimator does not need channel prior information, so it is more flexible and convenient to be deployed in practical applications. It should be noted that larger neural networks are not always better. Too complex network design will greatly increase the computational burden. Therefore, it is necessary to reasonably select the network scale in the process of practical application.

3. Application of the DL Estimator

Image Processing Technique Based DL Estimator

In [7], Soltani et al. proposed a new DL estimator based on image processing techniques, namely ChannelNet estimator. Considering the time frequency response of a fading channel as a 2D-image, the channel response

in the pilot positions and the estimated channel response are treated as low resolution (LR) images and high resolution (HR) images, respectively. ChannelNet estimator combines two convolutional neural networks (CNN) designed for 2D-image processing (SRCNN and DnCNN) to accurately estimate the CSI and denoise [8]. The simulation results show that the error of ChannelNet estimator is comparable to the error of MMSE estimator. Compared with the DL estimator based on fully connected DNN, ChannelNet estimator uses image processing method to estimate the channel, and is more advantageous in terms of the estimation performance and computational complexity.

However, ChannelNet estimator still has some drawbacks. The ChannelNet Estimator performs large-scale interpolation before data operation, and the network size is large, which undoubtedly increases the burden of data calculation and network optimization [10]. At the same time, SRCNN and DnCNN are trained separately, and the network lacks internal connectivity.

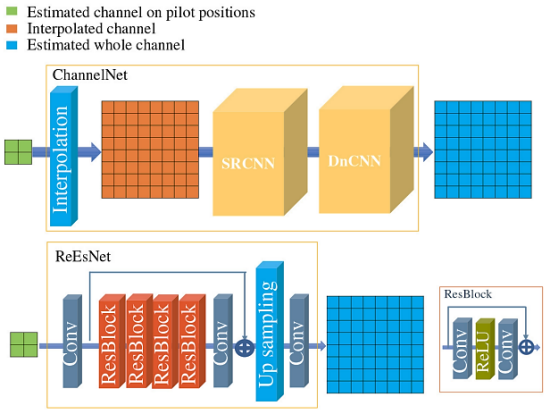

Fig. 2 The architecture of ChannelNet estimator and ReEsNet estimator

In view of these shortcomings, Lianjun Li et al. introduces residual learning into DL estimator and builds a deep residual channel estimation network (ReEsNet) estimator [9]. ReEsNet estimator modifies the super-resolution model proposed in [10]. ReEsNet estimator analyzes the channel estimation as smooth image processing and adjusts the up-sampling function and network parameters which greatly reduce the computational complexity and obtain smaller errors. The architectures of the ChannelNet estimator and the ReEsNet estimator are shown in Figure 2 [9]. ReEsNet estimator can realize end-to-end network training, and its network scale is smaller than that of the ChannelNet estimator. Thus, the ReEsNet estimator is easier to be deployed in practical application scenarios.

DL Based Channel Estimation for Intelligent Reflecting Surface (IRS)

Recently, the IRS has attracted considerable attention from experts and scholars, and has been widely used in 5G wireless communication field to reconfigure the communication environment and improve the communication quality [11]. The actual application scenario of the IRS aided communication system is shown in Figure 3 [12].

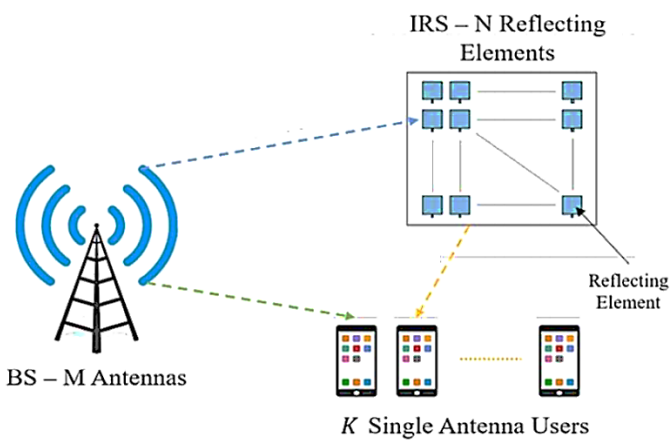

Fig. 3. The application scenario of the IRS aided communication system

When using the IRS to assist wireless communication, the IRS controller must first obtain sufficient CSI from the BS. Especially, when the channel state changes rapidly or the number of the IRS units is significantly large, it is difficult to accurately estimate the channel state using the traditional estimators. In this case, DL estimator can estimate the data accurately. When the channel state meets some laws, reinforcement learning (RL) and other DL technologies can be used to continuously improve the performance of the estimator and predict the subsequent channel function, so as to improve the performance of the overall communication system. Using the training data to optimize the DL estimator which adopts adaptive motion estimation (ADAM) optimizer, we can obtain extremely accurate CSI and effectively improve the performance of the communication system [12].

4. Simulation Results

In this section, the simulation results of different estimators are displayed, and the results are compared and analyzed to evaluate the performance of the DL based wireless channel estimation approaches.

Simulation of Fully Connected Neural Network Based Estimator

In [6], Qiang Hu et al. simulated the DL estimator based on the fully connected neural network, and calculated the mean squared error (MSE) of channel estimation. The MSE performance of the LS, LMMSE, and DL estimators versus signal-to-noise ratio (SNR) under linear signal mode is shown in Figure 4 [6] and the MSE performance of the MMSE, LMMSE, and DL estimators versus SNR under nonlinear signal model is shown in Figure 5 [6].

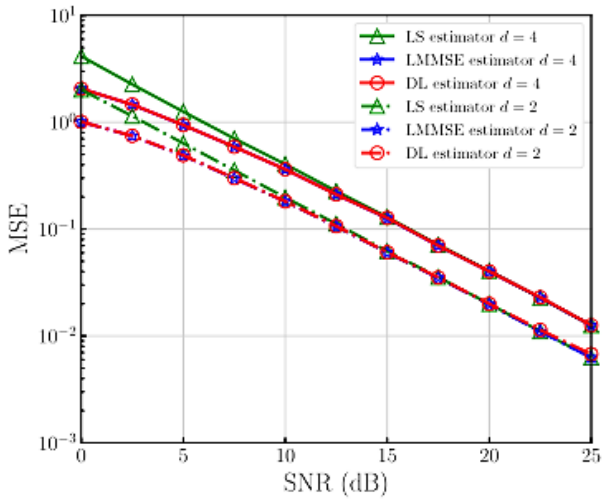

Fig. 4. The MSE performance of the LS, LMMSE, and DL estimators versus SNR under linear signal model

In Figure 4, *d* represents the dimension of the signal. Obviously, the estimation error is directly proportional to the dimension of the signal. The greater the dimension of the signal, the greater the error of the channel estimator. When the SNR of the system is higher, the performance of all kinds of estimators will be better. When the SNR is low, the performance of LS estimator is obviously worse than that of other estimators. When the training data set is large enough, the performance of DL estimator is always close to that of the LMMSE estimator, which verifies the feasibility of the DL based channel estimation approaches.

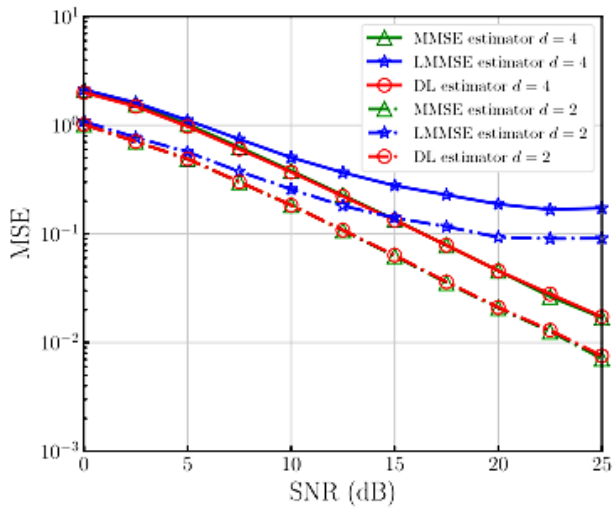

Fig. 5. The MSE performance of the MMSE, LMMSE, and DL estimators versus SNR under nonlinear signal model

From Figure 5, when the SNR is low, the performance of the LMMSE estimator can be compared with MMSE estimator and DL estimator, but when the SNR is high, the performance of the LMMSE estimator degrades significantly. In nonlinear systems, the MSE of the DL estimator is always close to that of the MMSE estimator, which shows that the DL estimator can well combat the nonlinear distortion of the system.

ChannlNet and ReEsNet Estimator

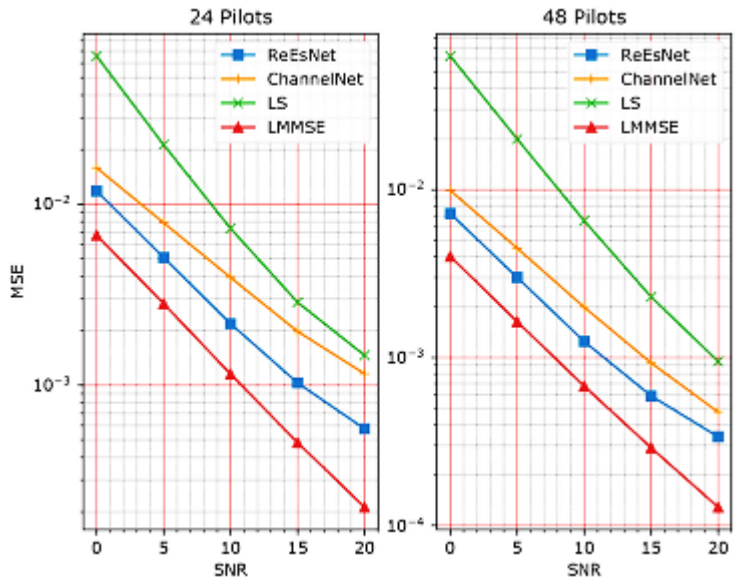

Fig. 6. The MSE performance of the LS, LMMSE, ChannelNet and ReEsNet estimators versus SNR

In [9], Lianjun Li et al. compare the MSE performance of the LS, LMMSE, ChannelNet and ReEsNet estimators versus SNR, and the simulation results is shown in Figure 6 [9]. Obviously, the performance of ChannelNet and ReEsNet estimators is much better than that of traditional LS estimators, and the performance of ReEsNet estimators is always better than that of ChannelNet estimators. When the number of pilots increases, the performance of the ChannelNet estimator is significantly improved, because the super resolution problem difficulty is reduced [9].

5. Future & Challenges

It can be predicted that with the continuous progress of the DL, the performance of the DL estimator will continue to improve. The development prospect of DL based channel estimation techniques is very glorious on the whole, but there are still some challenges.

- **Dataset:** Most of the existing studies focus on supervised learning neural networks, and rarely involve unsupervised learning and self-supervised learning. As a result, the data set used for DL estimator training is very small, and a lot of valuable unlabeled data are wasted.
- **Mechanism:** The DL estimator overturns the traditional communication model and realizes accurate estimation through a large amount of data training. So far, few studies have analyzed the internal mechanism of the DL estimator. There are few studies dealt with how the DL estimator learns from the training data, and how the lack of expert knowledge affects the system performance [6]. In our opinion, we can combine expert knowledge and DL to establish a channel estimation model based on the combination of data-driven and knowledge-driven models, so as to make full use of their respective advantages.
- **Update speed**: Most of the existing studies first use a large amount of data for off-line training, and then actually deploy for on-line training to improve the update rate of neural network. However, in practical application scenarios, the update speed of neural network is generally insufficient when the channel changes rapidly. Therefore, the reinforcement learning needs to be introduced to improve the adaptability of the DL estimator to the rapidly changing environment.

6. Conclusion

In this paper, we summarize some researches on the DL based channel estimation. Based on a DL based channel estimation model, we introduce the mathematical analysis of the error of the DL estimator according to the work of Hu Qiang et al. We also introduce two popular application scenarios of the DL estimator, and analyze their performance and advantages in combination with the simulation results of relevant papers. We also analyze three possible challenges in the development of the DL based channel estimation, and provide feasible suggestions. It can be predicted that although there are still some challenges ahead, the development prospect of the DL based channel estimation is very bright.

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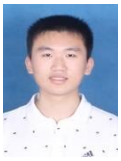

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