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RESEARCH

Downlink Transmission and Channel Estimation for Cell-Free Massive MIMO-OFDM with Symbol Time Offset

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Abstract

In a cell-free massive MIMO system, multiple users arrive at multiple access points at separate times, while in an OFDM system, different delays can be equivalent to symbol timing offsets (STOs). Since symbol timing offsets are not all the same, in the downlink transmission process, it is necessary to consider its impact on transmission techniques, such as channel estimation and downlink precoding. In this paper, aiming at the performance loss caused by STO in cell-free massive MIMO-OFDM system, we propose a multi-RB precoding optimization algorithm that maximizes the downlink sum rate. We derive the sum rate maximization problem into an iterative second-order cone programming (SOCP) form to achieve convex approximation. Then, considering the impact of STO on the accuracy of cell-free massive MIMO-OFDM channel estimation, we propose a downlink channel estimation method, which jointly uses channel state information reference signal (CSI-RS) and demodulation reference signal (DMRS). Simulation results show that the proposed multi-RB optimal precoding can effectively improve the downlink sum rate, and the proposed downlink channel estimation can obtain accurate multi-RB frequency domain channel parameters.

Keywords: cell-free massive MIMO-OFDM; symbol timing offset; downlink channel estimation; second-order cone program; convex approximation

Introduction

A cell-free system is a new concept of mobile communication system architecture derived from distributed MIMO, in which the antenna unit is separated from the processing unit. Multiple remote antenna units (RAUs) are connected to the central processing unit (CPU) through optical fibres, and joint signal processing is performed through the CPU. Compared with the cellular system that eliminates the interference between antennas by allocating different frequencies, the joint signal processing of the cell-free system can eliminate the interference between antennas on the same frequency by means of simultaneous equations that make it possible to improve spectrum efficiency, coverage capability and cell boundary performance [1]-[4].

However, due to the distributed characteristics of cell-free systems, similar to coordinated multipoint (CoMP) systems, different user equipment (UE) and RAUs have separate propagation delays. These variations will cause the receiver to synchronize with the transmitted signal that arrives first, and the symbol timing offset (STO) will be generated on the asynchronous transmitted signal that arrives later.

Especially in the OFDM system, accurate symbol time synchronization is an important prerequisite for removing the cyclic prefix (CP) and completing correct demodulation. STO will cause the received signal to produce a phase rotation that varies with the subcarrier index during the demodulation process, which will have a negative impact on system performance [5]-[8].

Since per subcarrier precoding is not supported in the current 5G NR protocol [9], to reduce the performance loss of STO to broadband precoding as the number of subcarriers increases, we designed a multi-RB precoding optimization algorithm to maximize the system sum rate under the total RAU power constraint. In addition, since STO causes the channel matrix to vary significantly in the time and frequency domains, UE demodulation requires accurate downlink channel estimation. We propose a DMRS channel estimation method using the existing single-port CSI-RS assistance, aiming to obtain a multi-RB demodulation channel matrix such that UEs can correctly complete demodulation.

The following notations are used. All boldface letters represent vectors (lower case) or matrices (upper case). The $P \times P$ identity matrix is denoted $\mathbf{I}_P$. The notations $\mathbb{C}^N$ and $\mathbb{C}^{M \times N}$ refer to complex N -dimensional vectors and $M \times N$ matrices, respectively. The operators $\text{diag}(\cdot)$, $(\cdot)^T$ and $(\cdot)^H$ denote diagonalization, transpose and conjugate transpose, respectively. A random vector $x \sim \mathcal{CN}(\mathbf{m}, \Phi)$ is a complex Gaussian distribution with a mean vector $\mathbf{m}$ and covariance matrix Φ .

Problem Formulation

Impact of the STO

In an OFDM system, obtaining accurate sampling of the transmitted signal within the symbol period is the prerequisite for the receiver to perform FFT. For this reason, it is necessary to perform symbol timing synchronization after removing CP. However, in the cell-free system as shown in Fig. 1, because the distances from RAUs to UEs are different, the receiver performs symbol timing synchronization with the signal that arrives first, and the signal that arrives subsequently will produce τ samples STO during the sampling process, as shown in Fig. 2. After FFT, τ samples STO result in a phase rotation of $e^{-j2\pi n\tau/N_c}$ on the n -th subcarrier, where N_c is the number of FFT points. It can be seen that phase rotation increases with the increase of subcarrier index, and the impact of phase rotation will be superimposed in the coherence bandwidth, causing additional frequency selective fading of the channel.

System Model

We consider a cell-free massive MIMO-OFDM system, including M multi-antenna RAUs and K single-antenna UEs, where each RAU has L antennas. The locations of RAUs and UEs are randomly distributed within the coverage area. The total number of subcarriers in the system is N , UEs are grouped into N_{RB} resource blocks (RBs), and each RB contains $\lambda_{RB} = N/N_{RB}$ subcarriers. The number of UEs in each RB is much smaller than the total number of RAUs.

The frequency-domain symbol sequence sent by RAU m on the t -th OFDM symbol is $\mathbf{x}_m = [x_{m,0}, \dots, x_{m,n}, \dots, x_{m,N-1}]^T$. The time-domain symbol sequence obtained after the N_c -point IFFT at the transmitter is $\mathbf{x}_m[t] = [x_{m,0}[t], \dots, x_{m,n}[t], \dots, x_{m,N-1}[t]]^T$,

where $x_{m,n'}[t] = \frac{1}{N} \sum_{n=0}^{N-1} x_{m,n} e^{j2\pi n n' / N_c}$. According to the derivation in [6], when the signal arrives at the receiver, due to the STO of τ samples, $x_{m,n'}[t] \rightarrow x_{m,n'}[t - \tau]$, after N_c -point FFT, a phase rotation $\Theta = e^{-j2\pi n \tau / N_c}$ is generated on the frequency domain symbol of the n -th subcarrier. Under the impact of the STO, the channel vector $\mathbf{h}_{m,k,n} \in C^{L \times 1}$ of the m -th RAU and the k -th UE on the n -th subcarrier can be expressed as

$$\mathbf{h}_{m,k,n} = \beta_{m,k}^{1/2} \mathbf{g}_{m,k,n} \Theta_{m,k,n} \quad (1)$$

where $\beta_{m,k} = (d_{m,k})^{-l}$ is the large-scale fading coefficient independent of frequency, $d_{m,k}$ is the distance between the m -th RAU and the k -th UE, and l is the path loss exponent. $\Theta_{m,k,n} = e^{-j2\pi n \tau_{m,k} / N_c}$ is the phase rotation caused by STO, where $\tau_{m,k} = d_{m,k}/c - \tau_k^{syn}$ is the delay spread difference (DSD) between the m -th RAU and the k -th UE, where $\tau_k^{syn} = \min_m \tau_{m,k}$ is the reference synchronization time and c is the speed of light.

Considering the downlink transmission, we model the received signal of UE k on the n -th subcarrier as

$$y_{k,n} = \mathbf{h}_{k,n}^H \mathbf{w}_k s_{k,n} + \sum_{u \neq k}^K \mathbf{h}_{k,n}^H \mathbf{w}_u s_{u,n} + z_{k,n} \quad (2)$$

where

$$\mathbf{h}_{k,n} = [\mathbf{h}_{1,k,n}, \dots, \mathbf{h}_{M,k,n}]^T \in \mathbb{C}^{ML \times 1} \quad (3)$$

represents the frequency domain channel vector on the n -th subcarrier from all RAUs to downlink UE k , $s_{k,n} \sim \mathcal{CN}(0, 1)$ is the data symbol sent by all RAUs to downlink UE k , $z_{k,n} \sim \mathcal{CN}(0, \sigma_{k,n}^2)$ is additive white Gaussian noise,

$$\mathbf{w}_k = [\mathbf{w}_{1,k}, \dots, \mathbf{w}_{M,k}]^T \in \mathbb{C}^{ML \times 1} \quad (4)$$

represents the precoding vector on the n -th subcarrier for the data stream of downlink UE k , where $w_{m,k} \in \mathbb{C}^{L \times 1}$. Assume that the precoding granularity is φ , the same precoding vector is used on the adjacent $N_\varphi = \varphi \lambda_{RB}$ subcarriers, and there are a total of $R = N/N_\varphi$ different precoding vectors in the system bandwidth. That is, for any $n = (r-1)N_\varphi + 1, \dots, rN_\varphi$, where $r = 1, \dots, R$, we have $\mathbf{w}_{k,n} = \mathbf{w}_k$. Therefore, the received signal of downlink UE k within the system bandwidth can be modelled as

$$y_k = \sum_{n=1}^N \mathbf{h}_{k,n}^H \mathbf{w}_k s_{k,n} + \sum_{u \neq k}^K \sum_{n=1}^N \mathbf{h}_{k,n}^H \mathbf{w}_u s_{u,n} + z_{k,n} \quad (5)$$

Proposed Approach

Proposed Precoding Design

In this paper, we are interested in the problem of the sum rate maximization under total RAU power constraints. On the n -th subcarrier, the SINR of downlink UE k is

$$\gamma_{k,n} = \frac{|\mathbf{h}_{k,n}^H \mathbf{w}_k|^2}{\sum_{u \neq k}^K |\mathbf{h}_{k,n}^H \mathbf{w}_u|^2 + \sigma_k^2} \quad (6)$$

Then, the design problem is given by

$$\begin{aligned} & \max_{\mathbf{w}_k} \sum_{n=1}^N \sum_{k=1}^K \log_2(1 + \gamma_{k,n}) \\ & s.t. \sum_{k=1}^K \|\mathbf{w}_k\|^2 \leq P_{\max}, \forall k \end{aligned} \quad (7)$$

Since problem (7) is NP-hard, the globally optimal design mainly acts as a theoretical benchmark rather than a practical solution. Herein, motivated by [10]-[11], we

develop a low-complexity algorithm that satisfies the necessary optimal conditions of (7).

According to the monotonicity of the logarithmic function, (7) is equivalent to

$$\begin{aligned} & \max_{\mathbf{w}_k} \prod_{n=1}^N \prod_{k=1}^K (1 + \gamma_{k,n}) \\ & s. t. \sum_{k=1}^K \|\mathbf{w}_k\|^2 \leq P_{\max}, \forall k \end{aligned} \quad (8)$$

which can be equivalently rewritten as

$$\max_{\mathbf{w}_k, \mathbf{t}_{k,n}} \prod_{n=1}^N \prod_{k=1}^K f_{k,n} \quad (9a)$$

$$s. t. \sum_{k=1}^K \|\mathbf{w}_k\|^2 \leq P_{\max}, \forall k \quad (9b)$$

$$\gamma_{k,n} \geq f_{k,n} - 1, \forall k \quad (9c)$$

$$f_{k,n} \geq 1, \forall k \quad (9d)$$

Note that the objective function in (9) admits an SOC representation. Since (9b) and (9d) are already convex forms, we mainly focus on dealing with the constraints in (9c).

Firstly, (9c) can be rewritten as

$$\sum_{u \neq k}^K |\mathbf{h}_{k,n}^H \mathbf{w}_u|^2 + \sigma_k^2 \leq \frac{\mathbf{w}_k^H \mathbf{\Lambda}_{k,n} \mathbf{w}_k}{f_{k,n} - 1} \quad (10)$$

where $\mathbf{\Lambda}_{k,n} = \mathbf{h}_{k,n}^H \mathbf{h}_{k,n}$. We can see that (10) is also non-convex, since the right side of (10) has the form of quadratic-over-linear, it can be replaced by its first-order expansions [12]. Thus, we define

$$J(\mathbf{w}, f, \mathbf{\Lambda}) = \frac{\mathbf{w}^H \mathbf{\Lambda} \mathbf{w}}{f - \alpha} \quad (11)$$

where $\mathbf{\Lambda} \geq 0$ and $f \geq \alpha$. We obtain the first-order Taylor expansion of (11) about a certain point $(\mathbf{w}^{(a)}, f^{(a)})$ as

$$\begin{aligned} & J(\mathbf{w}, f, \mathbf{w}^{(a)}, f^{(a)}, \mathbf{\Lambda}, \alpha) = \\ & \frac{2\Re \left\{ (\mathbf{w}^{(a)})^H \mathbf{\Lambda} \mathbf{w} \right\} (f^{(a)} - \alpha) - (\mathbf{w}^{(a)})^H \mathbf{\Lambda} \mathbf{w}^{(a)} (f - \alpha)}{(f^{(a)} - \alpha)^2} \end{aligned} \quad (12)$$

From the above analysis, we can transform the constraint of (9c) into a convex form

$$\sum_{u \neq k}^K |\mathbf{h}_{k,n}^H \mathbf{w}_u|^2 + \sigma_k^2 \leq J(\mathbf{w}_k, f_k, \mathbf{w}_k^{(a)}, f_k^{(a)}, \mathbf{\Lambda}_k, 1) \quad (13)$$

Finally, the original problem (8) can be reformulated as a convex approximate problem (14) which can be solved in Algorithm 1.

$$\begin{aligned} & \max_{\{\mathbf{w}_k, \mathbf{t}_{k,n}\}} \prod_{n=1}^N \prod_{k=1}^K f_{k,n} \\ & s. t. (9b), (9d), (13) \end{aligned} \quad (14)$$

Algorithm 1 Iterative Convex Approximate Algorithm.

- 1: **Initialization:**
 - 2: Generate initial points for $\mathbf{w}_k^{(0)}$ and $f_{k,n}^{(0)}$ for $k = 1, \dots, K$, $n = 1, \dots, N$.
 - 3: Set $a = 0$.
 - 4: **Iterative procedure:**
 - 5: **Repeat**
 - 6: Solve (14) to find optimal solutions $\mathbf{w}_k^*$, $f_{k,n}^*$ for $k = 1, \dots, K$, $n = 1, \dots, N$.
 - 7: Set $a = a + 1$.
 - 8: Update: $\mathbf{w}_k^{(a)} = \mathbf{w}_k^*$; $f_{k,n}^{(a)} = f_{k,n}^*$.
 - 9: **until** Convergence.
 - 10: **return** The optimal solution $\mathbf{w}_k^*$.
 - 11: **Finalization:**
-

Downlink Channel Estimation

In this section, considering the impact of STO on the accuracy of cell-free massive MIMO-OFDM system channel estimation, we propose a high-precision multi-RB downlink channel estimation scheme, which provides the necessary channel information for multi-RB precoding optimization. In the pilot design of the 5G NR [13], CSI-RS is mainly used for channel sounding to obtain the path loss and DSD between UEs and RAUs. DMRS is mainly used for the demodulation of uplink and downlink data. The least squares (LS) algorithm is usually used to estimate the initial channel response of the pilot position, and then interpolation filtering is performed in the frequency domain to obtain the channel response of the data position [14]. The specific steps of the multi-RB channel estimation we proposed are as follows:

First, all RAUs transmit orthogonal CSI-RS, UE k estimates large-scale fading, $\beta_1^{1/2}, \beta_2^{1/2}, \dots, \beta_M^{1/2}$ and DSD, $\tau_1, \tau_2, \dots, \tau_M$ of the overall channel with all RAUs based on the reference signal. It is worth mentioning that all RAUs can also send the same CSI-RS pilot, that is, the CSI-RS pilot adopts a single-port design. At this time, the receiver only estimates the composite signal from all RAUs to the UE. Specifically, multiple RAUs are regarded as multipath signals, and the power and delay of each path are estimated on UE k based on the distinguishable time-domain multipath signals. The single-port design can effectively reduce the pilot overhead and design complexity, but it will produce additional channel time/frequency selectivity.

In the case of sufficient estimation accuracy, these two methods are theoretically equivalent.

Second, considering that there are P equally spaced DMRS in the coherent bandwidth, after UE k is estimated by the LS algorithm, the collected frequency domain signal can be expressed as $\mathbf{h}_1, \mathbf{h}_2, \dots, \mathbf{h}_P$. Assuming the pilot precoding vector $\hat{\mathbf{w}}_{\mathbf{m}} = [\hat{\mathbf{w}}_1, \dots, \hat{\mathbf{w}}_M]^T$ is known to UE k , the frequency domain signal collected by UE k can be modelled as (15).

$$\begin{bmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \\ \vdots \\ \mathbf{h}_P \end{bmatrix} = \begin{bmatrix} \beta_1^{1/2} \mathbf{g}_{1,1} e^{\frac{-j2\pi\Delta\tau_1}{N_c}} & \beta_2^{1/2} \mathbf{g}_{2,1} e^{\frac{-j2\pi\Delta\tau_2}{N_c}} & \dots & \beta_M^{1/2} \mathbf{g}_{M,1} e^{\frac{-j2\pi\Delta\tau_M}{N_c}} \\ \beta_1^{1/2} \mathbf{g}_{1,2} e^{\frac{-j2\pi(2\Delta)\tau_1}{N_c}} & \beta_2^{1/2} \mathbf{g}_{2,2} e^{\frac{-j2\pi(2\Delta)\tau_2}{N_c}} & \dots & \beta_M^{1/2} \mathbf{g}_{M,2} e^{\frac{-j2\pi(2\Delta)\tau_M}{N_c}} \\ \vdots & \vdots & \vdots & \vdots \\ \beta_1^{1/2} \mathbf{g}_{1,P} e^{\frac{-j2\pi(P\Delta)\tau_1}{N_c}} & \beta_2^{1/2} \mathbf{g}_{2,P} e^{\frac{-j2\pi(P\Delta)\tau_2}{N_c}} & \dots & \beta_M^{1/2} \mathbf{g}_{M,P} e^{\frac{-j2\pi(P\Delta)\tau_M}{N_c}} \end{bmatrix} \begin{bmatrix} \hat{\mathbf{w}}_1 \\ \hat{\mathbf{w}}_2 \\ \vdots \\ \hat{\mathbf{w}}_M \end{bmatrix} + \begin{bmatrix} \mathbf{z}_1 \\ \mathbf{z}_2 \\ \vdots \\ \mathbf{z}_P \end{bmatrix} \quad (15)$$

Assuming that the frequency domain channel remains unchanged on these P resource elements, we have (16).

$$\underbrace{\begin{bmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \\ \vdots \\ \mathbf{h}_P \end{bmatrix}}_{\mathbf{H}_p} = \underbrace{\begin{bmatrix} \beta_1^{1/2} e^{\frac{-j2\pi\Delta\tau_1}{N_c}} & \beta_2^{1/2} e^{\frac{-j2\pi\Delta\tau_2}{N_c}} & \dots & \beta_M^{1/2} e^{\frac{-j2\pi\Delta\tau_M}{N_c}} \\ \beta_1^{1/2} e^{\frac{-j2\pi(2\Delta)\tau_1}{N_c}} & \beta_2^{1/2} e^{\frac{-j2\pi(2\Delta)\tau_2}{N_c}} & \dots & \beta_M^{1/2} e^{\frac{-j2\pi(2\Delta)\tau_M}{N_c}} \\ \vdots & \vdots & \vdots & \vdots \\ \beta_1^{1/2} e^{\frac{-j2\pi(P\Delta)\tau_1}{N_c}} & \beta_2^{1/2} e^{\frac{-j2\pi(P\Delta)\tau_2}{N_c}} & \dots & \beta_M^{1/2} e^{\frac{-j2\pi(P\Delta)\tau_M}{N_c}} \end{bmatrix}}_{\Omega_p} \underbrace{\begin{bmatrix} \mathbf{g}_1 \hat{\mathbf{w}}_1 \\ \mathbf{g}_2 \hat{\mathbf{w}}_2 \\ \vdots \\ \mathbf{g}_M \hat{\mathbf{w}}_M \end{bmatrix}}_{\mathbf{g}} + \underbrace{\begin{bmatrix} \mathbf{z}_1 \\ \mathbf{z}_2 \\ \vdots \\ \mathbf{z}_P \end{bmatrix}}_{\mathbf{z}_p} \quad (16)$$

Subsequently, using minimum mean square error (MMSE) channel estimation, the cross-correlation matrix of $\mathbf{H}_p$ and $\mathbf{g}$ is

$$\mathbf{R}_{\mathbf{gH}_p} = \mathbb{E} [\mathbf{gH}_p^H] = \mathbf{C}_g \Omega_p^H \quad (17)$$

and the auto-correlation matrix of $\mathbf{H}_p$ is

$$\mathbf{R}_{\mathbf{H}_p\mathbf{H}_p} = \mathbb{E} [\mathbf{H}_p\mathbf{H}_p^H] = \Omega_p \mathbf{C}_g \Omega_p^H + \frac{\sigma^2}{A} \mathbf{I}_P \quad (18)$$

where $\mathbf{C}_g = \text{diag}([\sigma_{\mathbf{g}_1}^2, \dots, \sigma_{\mathbf{g}_M}^2]^T) = \text{diag}([\beta_1, \dots, \beta_M]^T)$ is the covariance matrix of $\mathbf{g}$, A is the pilot power.

Finally, the MMSE estimate of $\mathbf{g}$ is [15]

$$\hat{\mathbf{g}} = \mathbf{R}_{\mathbf{gH}_p} \mathbf{R}_{\mathbf{H}_p\mathbf{H}_p}^{-1} \mathbf{H}_p = \left(\frac{\psi}{\zeta} \mathbf{C}_g^{-1} + \Omega_p^H \Omega_p \right)^{-1} \Omega_p^H \mathbf{H}_p \quad (19)$$

where ψ is the average signal-to-pilot power ratio, and ζ is the average signal-to-noise ratio. Through DMRS interpolation, the MMSE estimate of UE k can be

obtained as

$$\hat{\mathbf{H}} = \Omega_n \hat{\mathbf{g}} = \Omega_n \left(\frac{\psi}{\zeta} \mathbf{C}_{\mathbf{g}}^{-1} + \Omega_p^H \Omega_p \right)^{-1} \Omega_p^H \mathbf{H}_p \quad (20)$$

where

$$\Omega_n = \begin{bmatrix} \beta_1^{1/2} e^{-\frac{j2\pi\tau_1}{N_c}} & \dots & \beta_M^{1/2} e^{-\frac{j2\pi\tau_M}{N_c}} \\ \vdots & \ddots & \vdots \\ \beta_1^{1/2} e^{-\frac{j2\pi N\tau_1}{N_c}} & \dots & \beta_M^{1/2} e^{-\frac{j2\pi N\tau_M}{N_c}} \end{bmatrix} \quad (21)$$

Through calculation, the mean square error of channel estimation is

$$\begin{aligned} MSE_{\hat{\mathbf{H}}} &= \frac{1}{K-1} \mathbb{E} \left[\left(\mathbf{H} - \hat{\mathbf{H}} \right)^H \left(\mathbf{H} - \hat{\mathbf{H}} \right) \right] \\ &= \frac{1}{K-1} \text{tr} \left(\mathbf{C}_{\hat{\mathbf{g}}} \Omega_{\mathbf{H}}^H \Omega_{\mathbf{H}} \right) \end{aligned} \quad (22)$$

where $\mathbf{C}_{\hat{\mathbf{g}}} = (\mathbf{C}_{\mathbf{g}}^{-1} + \frac{\zeta}{\psi} \Omega_p^H \Omega_p)^{-1}$ is the covariance matrix of the estimated channel $\hat{\mathbf{g}}$.

Numerical Results

In this section, some numerical examples are evaluated to show the performance of the proposed channel estimation and precoding optimization under various system settings. We consider a cell-free massive MIMO-OFDM system with detailed simulation parameters listed in Table 1.

Fig. 3 and Fig. 4 compare the achievable sum rate of the system when using traditional conjugate precoding and the proposed optimized precoding, where the precoding granularity is 2RB, 4RB, 6RB and 8RB respectively. In these two precoding schemes, the sum rate increases as the SNR increases, and decreases with increasing granularity of the precoding. In addition, as expected, our proposed optimized precoding always perform better than conjugate precoding in terms of sum rate. When the precoding granularity is 2RB and 4RB, the sum rate is increased by approximately 20 percent, and when the precoding granularity is 6RB and 8RB, the sum rate is increased by approximately 10 percent. This result is because as the number of subcarriers increases, the impact of STO on system performance becomes increasingly serious. Since the minimum granularity of precoding in the existing 5G NR protocol is 2RB, and is usually statically configured as 4RB, the proposed algorithm can reflect the robustness to STO in wideband precoding under the existing 5G NR protocol.

Fig. 5 shows the MSE vs. SNR performance comparison of the proposed downlink channel estimation when the channel estimation granularity is 2RB, 4RB, 8RB and 12RB. It can be observed that as the SNR increases, the MSE of the proposed channel estimation decreases, and the accuracy of the channel estimation increases. In addition, the accuracy of the proposed channel estimation improves with increasing channel estimation granularity. This result is due to the use of DMRS interpolation intervals of the same width. The larger the bandwidth of the estimated channel

is, the greater the number of DMRS participating in the channel estimation. Since the CSI-RS pilot can be designed in a single-port mode, the pilot overhead and design complexity are effectively reduced, thereby realizing low-complexity accurate estimation of the wideband channel with STO.

Fig. 6 shows the performance comparison when the UE estimates the path loss and time delay based on the single-port CSI-RS sent by all RAUs, and different numbers of RAUs send DMRS. Assuming that the number of RAUs sending DMRS is 2, 4, 6, and 8 and the granularity of frequency domain joint channel estimation is 2RB, 12RB, and 24RB, it can be seen that the mismatch of CSI-RS and DMRS has little effect on the accuracy of channel estimation. Especially when the signal-to-noise ratio is low and the channel estimation granularity is small, the loss caused by this mismatch can be ignored.

Table 1 Simulation Parameters

Number of RAUs	8
Number of UEs	4
Number of antennas per RAU	4
Number of subcarriers per RB	12
Granularity of precoding	2,4,6,8 (RBs)
Granularity of channel estimation	2,4,8,12,24 (RBs)
Radium of background	12(m)
Path loss exponent	-3.7
FFT points	4096
Power constraint for RAUs	10(W)
DMRS interpolation interval	4

Figure 3 Performance Comparison of the Multi-RB Precoding

Conclusion

In this paper, we have studied the STO problem in a cell-free massive MIMO-OFDM system due to its distributed characteristics, which causes the received signal to pro-

Figure 4 Performance Comparison of the Multi-RB Precoding

Figure 5 MSE Comparison of the Multi-RB Channel Estimation

duce phase rotation related to the subcarrier index during demodulation. Since the existing 5G NR protocol does not support per subcarrier precoding, to address the impact of STO, we designed a multi-RB precoding optimization problem and

Figure 6 MSE Comparison of the Multi-RB Channel Estimation

used convex approximation to solve the problem. Then, to cope with the influence of the STO on the accuracy of channel estimation, we propose a downlink channel estimation method, which uses CSI-RS and DMRS jointly to realize multi-RB channel estimation. Simulation results show that, compared with conjugate precoding, the proposed optimal precoding can effectively improve system performance. In addition, the proposed downlink channel estimation can obtain accurate channel information.

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Availability of data and materials

The datasets simulated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Ethics approval and consent to participate

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Authors' contributions

YG wrote the manuscript, simulated and modified the experiments; XX and DW helped to conceive the idea and revise the manuscript; PW and DL helped with article writing; ZF and AL contributed to the development of the ideas. All authors read and approved the final manuscript.

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