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Research Article

A Robust Channel Estimation Scheme for 5G Massive MIMO Systems

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Channel state information (CSI) feedback in massive MIMO systems is too large due to large pilot overhead. It is due to the large channel matrix dimension which depends on the number of base station (BS) antennas and consumes the majority of scarce radio resources. To solve this problem, we proposed a scheme for efficient CSI acquisition and reduced pilot overhead. It is based on the separation mechanism for the channel matrix. The spatial correlation among multiuser channel matrices in the virtual angular domain is utilized to split the channel matrix. Then, the two parts of the matrix are estimated by deploying the compressed sensing (CS) techniques. This scheme is novel in the sense that the user equipment (UE) directly transmits the received symbols from the BS to the BS, so a joint CSI recovery is performed at the BS. Simulation results show that the proposed channel estimation scheme effectively estimates the channel with reduced pilot overhead and improved performance as compared with the state-of-the-art schemes.

1. Introduction

Massive multiple-input multiple-output (MIMO) systems are equipped with a large number of antennas at the base station (BS), which can significantly improve the spectrum efficiency and energy efficiency of the system. It is regarded as the most promising technology in the fifth-generation (5G) wireless communication system [1–6]. In order to obtain the performance gain of a massive MIMO system, the BS side needs to know the channel state information (CSI). However, due to a large number of antennas at the BS end, a large amount of system resources is consumed for channel estimation [7–10]. In order to avoid the problem of excessive channel estimation pilot overhead, many researchers' works mainly focus on the time division duplex (TDD) mode [11] to reduce channel overhead by using channel reciprocity. Due to complex calibration and limited coherence time, the CSI obtained through the uplink in the TDD system may be inaccurate for the downlink, while the FDD system has low latency characteristics and dominates the current wireless communication system [12]. Therefore, it is necessary to conduct an in-depth study of the large-scale MIMO system under FDD. Although the FDD massive MIMO system faces the problem of large pilot overhead, it is expected that the FDD system will be backward compatible with the current network. It is worth noting that the channel matrix of a massive MIMO system has a sparse structure and compressed sensing (CS) technology can be utilized to reduce the pilot overhead [13]. The literature [14, 15] detailed the principle of orthogonal tracking matching (OMP) and subspace pursuit (SP) algorithm in the CS recovery algorithm to reconstruct sparse signals, which shows the application of CS technology. It is feasible to estimate the sparse channel. Reference [16] details the application of CS in pilot-assisted channel estimation and further studies the application of CS in multicarrier underwater acoustic communication channel estimation. In [17], the channel estimation of multiuser massive MIMO systems is studied, and the temporal correlation and spatial correlation of the channels are fully utilized. A low-rank matrix approximation method based on CS is proposed. In [18], the channel estimation in the beam domain is studied, and the amplitude and phase of the received signal are quantized, respectively, and the channel matrix is recovered from the quantized signal, thereby reducing the pilot overhead. The literature [19–21] uses the common support information between the channel matrices to reduce the pilot overhead and improve the estimation performance. The literature [18–24] uses the temporal correlation of the channel path to use the support information of the previous frame into the current frame, and the literature [23, 24] separates the current frame into two parts based on the channel information of the previous frame. Different methods are used for estimation, which further reduces the pilot overhead, but all consider a single-user system. In the literature [25–27], a distributed compressed sensing channel estimation and a feedback scheme are proposed for large-scale MIMO multiuser systems and a higher performance gain is obtained.

Based on analyzing the channel estimation of existing FDD multiuser massive MIMO systems, this paper proposes a new channel estimation scheme to further reduce the pilot overhead. The main feature of the proposed algorithm is it utilizes the common sparse structure between multiple channel matrices, the channel matrix is split into two parts, and the channel estimation problem is transformed into the signal recovery problem in the CS model. The simulation results show that the channel estimation performance is improved.

2. System Model

2.1. Channel Model. This paper considers a narrowband flat block fading multiuser massive MIMO system. The system comprises a BS and K multiantenna user equipment (UE) operating in the FDD mode, wherein the BS is equipped with M ($M \gg 1$) antenna and each UE is equipped with N ($N > 1$) antenna. Through the common downlink channel, the BS broadcasts a pilot training symbol of length T on its M antennas, as shown in Figure 1.

Consider both the BS side and the UE side antennas are uniform linear array (ULA) models. Usually, channel $\mathbf{H}$ is sparser under the virtual angle domain [25], and the channel matrix from BS to k ($k = 1, 2, \ldots, K$) UEs can be expressed as follows [19, 20]:

$$\mathbf{H}_k = \mathbf{R}\widetilde{\mathbf{H}}_k\mathbf{T}^{\mathbf{H}}, \qquad (1)$$

where $\mathbf{R} \in \mathbb{C}^{N\times N}$ and $\mathbf{T} \in \mathbb{C}^{M\times M}$, respectively represent the unitary matrix under the angular transformation of the UE

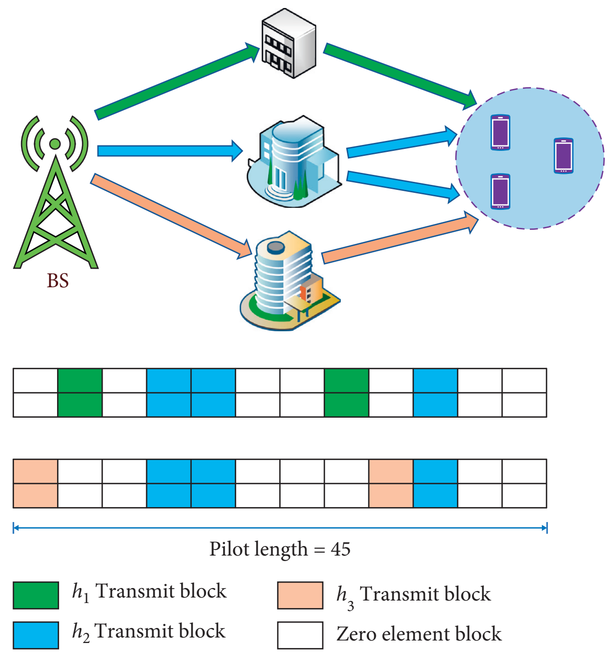

Figure 1: System model of joint channel sparse structure.

and BS ends and $\widetilde{\mathbf{H}}_k \in \mathbb{C}^{N\times M}$ represents the angular domain matrix, whose (n, m)th term is nonzero. It indicates that there is a spatial path from the mth transmission direction of the BS to the nth reception direction of the UE.

It is worth noting that in massive MIMO systems, due to the limited scattering environment at the BS, the angular domain channel $\widetilde{\mathbf{H}}_k$ has a large sparsity; that is, a large number of elements in $\widetilde{\mathbf{H}}_k$ are zero or approximately zero. At the same time, considering that the distance between multiple UEs is much smaller than the distance from each UE to the BS, this indicates that there is a spatial correlation between multiple channels; that is, there is partial common support between channels [14]. Generally, the local scattering environment at the UE is relatively rich, so that the row vectors of $\widetilde{\mathbf{H}}_k$ have the same sparse support, so it can be considered to treat each column of $\widetilde{\mathbf{H}}_k$ as a unit. Based on this, there are the following assumptions:

Hypothesis 1. The row vector of the angular domain channel $\widetilde{\mathbf{H}}_k$ has the same sparsity support [21, 28]; i.e.,

$$\mathrm{sp}\left(\widetilde{\mathbf{h}}_{k1}\right) = \mathrm{sp}\left(\widetilde{\mathbf{h}}_{k2}\right) = \ldots = \mathrm{sp}\left(\widetilde{\mathbf{h}}_{kN}\right) \triangleq \Theta_k, \quad \forall k, \qquad (2)$$

where $\widetilde{\mathbf{h}}_{kn}$ ($n = 1, 2, \ldots, N$) denotes the nth row of $\widetilde{\mathbf{H}}_k$, $\mathrm{sp}(\widetilde{\mathbf{h}}_{kn})$ denotes the support index set of the nonzero term of the vector $\widetilde{\mathbf{h}}_{kn}$ and the support of the kth channel matrix $\widetilde{\mathbf{H}}_k$, and the index set is Θ_k.

Hypothesis 2 [29, 30]. There is partial common support between different $\widetilde{\mathbf{H}}_k$ values; i.e.,

$$\bigcap_{k=1}^{K} \Theta_k = \Theta_c, \qquad (3)$$

where Θ_c represents a common support set between the K channel matrices.

Hypothesis 3 [31, 32]. There is a statistical sparse boundary for channel sparsity $S = \{s_c, \{s_k : \forall k\}\}$; i.e.,

$$\begin{aligned} |\Theta_c| &\geq s_c, \\ |\Theta_k| &\leq s_k, \\ &\forall k, \end{aligned} \tag{4}$$

where s_c represents the number of identical sparse locations between K channel matrices and s_k represents the number of sparse locations of the kth channel matrix.

Based on the above assumptions, this paper considers decomposing the channel matrix into two parts [17, 18], as shown in Figure 2. The grey blocks show the nonzero sparse channel transmit blocks while the white block represents zero elements. After the channel is decomposed, the channel of each part will have more sparsity and the channel estimation based on CS will further reflect its recovery advantage. Based on this idea, this paper decomposes the channel into partial common support channels $\widetilde{\mathbf{H}}_{k,c}$ and their respective unique support channels $\widetilde{\mathbf{H}}_{k,i}$, namely, as follows:

$$\begin{aligned} \widetilde{\mathbf{H}}_{k,c} &= (\widetilde{\mathbf{H}}_k)_{\Theta_c} (\mathbf{I}_M)^T_{\Theta_c}, \quad \forall k, \\ \widetilde{\mathbf{H}}_{k,i} &= (\widetilde{\mathbf{H}}_k)_{\Theta_{k,i}} (\mathbf{I}_M)^T_{\Theta_{k,i}}, \quad \forall k, \end{aligned} \tag{5}$$

where $\Theta_{k,i}$ denotes support set unique to the kth channel matrix, $\mathbf{I}_M \in \mathbb{C}^{M\times M}$ denotes an identity matrix, and $(^*)_\Theta$ denotes a submatrix composed of corresponding columns in the matrix * by index Θ.

2.2. Pilot Transmission. The transmitted pilot sequence is $\mathbf{X} \in \mathbb{C}^{M\times T}$ and stratifies $\mathrm{tr}(\mathbf{X}\mathbf{X}^{\mathbf{H}}) = PT$, where P is the signal-to-noise ratio (SNR) transmitted by each slot of the BS. Therefore, the signal received by the kth UE can be expressed as follows:

$$\mathbf{Y}_k = \mathbf{H}_k \mathbf{X} + \mathbf{N}_k, \quad \forall k, \tag{6}$$

where $\mathbf{Y}_k \in \mathbb{C}^{N\times T}$, $\mathbf{H}_k \in \mathbb{C}^{N\times M}$ is the quasistatic channel matrix of the BS to the kth UE, and $\mathbf{N}_k \in \mathbb{C}^{N\times T}$ is the complex Gaussian noise with zero mean and unit variance.

In order to utilize the CS technique for sparse channel estimation, the following new variables are defined to match the standard CS measurement model [10]:

$$\begin{cases} \overline{\mathbf{Y}}_k = \sqrt{\dfrac{M}{PT}} \mathbf{Y}_k^{\mathbf{H}} \mathbf{R}, \\ \overline{\mathbf{X}}_k = \sqrt{\dfrac{M}{PT}} \mathbf{X}^{\mathbf{H}} \mathbf{T}, \end{cases} \tag{7}$$

$$\begin{cases} \overline{\mathbf{H}}_k = \widetilde{\mathbf{H}}_k^{\mathbf{H}}, \\ \overline{\mathbf{N}}_k = \sqrt{\dfrac{M}{PT}} N_k^{\mathbf{H}} R. \end{cases} \tag{8}$$

Substituting equations (7) and (8) into equation (6) yields

$$\overline{\mathbf{Y}}_k = \overline{\mathbf{X}}\,\overline{\mathbf{H}}_k + \overline{\mathbf{N}}_k, \quad \forall k. \tag{9}$$

Thus, the channel estimation problem is transformed into the CS recovery problem, where $\overline{\mathbf{Y}}_k \in \mathbb{C}^{T\times N}$ represents the measured value, $\overline{\mathbf{X}} \in \mathbb{C}^{T\times M}$ represents the measurement matrix and satisfies $\mathrm{tr}(\overline{\mathbf{X}}^{\mathbf{H}}\overline{\mathbf{X}}) = M$, and $\overline{\mathbf{H}}_k \in \mathbb{C}^{M\times N}$ represents the sparse matrix that needs to be recovered.

3. Proposed Algorithm

3.1. Algorithm Design. In order to overcome the problem of excessive pilot overhead and feedback overhead in channel estimation of massive MIMO systems and to alleviate the resource consumption of the UE, this paper considers the distributed joint channel estimation scheme [25]; that is, after the UE receives the compressed measurement $\mathbf{Y}_k$, the channel estimation is performed immediately, and the received signal is directly fed back to the BS, and the $\{\mathbf{H}_1, \mathbf{H}_2, \ldots, \mathbf{H}_K\}$ is jointly restored at the BS. This paper assumes perfect CSI measurement feedback from the UE to the BS.

According to the spatial correlation of the channel matrix of multiuser massive MIMO systems, unlike the literature [25], this paper considers splitting the channel matrix into two parts in order to reduce the pilot overhead for channel estimation. The proposed channel estimation scheme is divided into two phases. The first phase first identifies their common support set according to the spatial correlation between the K channel matrices; the second stage identifies each support set unique to each channel matrix.

Specifically, in the first stage, this paper uses the orthogonal matching pursuit (OMP) algorithm [8] with low computational complexity to identify the common support set. For the kth channel matrix $\overline{\mathbf{H}}_k$, by calculating the correlation between the jth ($j = 1, 2, \ldots, M$) column of the matrix $\overline{\mathbf{X}}$ and the residual signal $\mathbf{R}_k$, i.e., $\|\overline{\mathbf{X}}(j)^{\mathbf{H}}\mathbf{R}_k\|_{\mathrm{F}}$, the support index is selected, where $\overline{\mathbf{X}}(j)$ represents the jth column of $\overline{\mathbf{X}}$. For the identification of the common support index, the selection of the common support index j is determined according to the maximum number of statistics corresponding to the support index of the K channel matrices; i.e.,

$$\Theta_c = \Theta_c \bigcup \arg_j^{\max} \sum_{k=1}^{K} \mathbf{I}_{\{j: j\in \Theta_k'\}}, \tag{10}$$

where Θ_k' represents the selected supporting index of the kth channel matrix set and $\mathbf{I}_{\{\cdot\}}$ represent the base.

Thus, after iterative calculation, the common supporting index set of the K channel matrices can be identified. It is worth noting that the common sparse structure between channels, in turn, ensures the accuracy of the identified common support set. Furthermore, the least square (LS) method can be used to obtain the channel estimate for this part:

$$\overline{\mathbf{H}}_{k,c}^{e} = \left(\overline{\mathbf{X}}_{\Theta_c}\right) + \overline{\mathbf{Y}}_k, \quad \forall k. \tag{11}$$

At this point, part of the common support channel can be expressed as

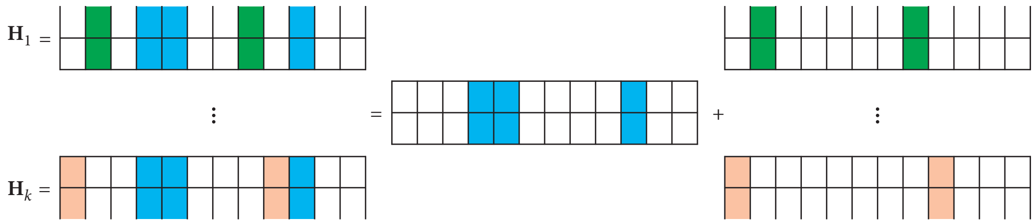

Figure 2: Illustration of channel matrix decomposition into two parts.

$$\overline{\mathbf{H}}_{k,c} = (\mathbf{I}_M)_{\Theta_c}\left(\overline{\mathbf{H}}_k^T\right)_{\Theta_c}^T, \quad \forall k. \tag{12}$$

After the common support index set between the channels is identified, the second stage is to identify the respective support sets of $\{\overline{\mathbf{H}}_k : \forall k\}$. According to the common support set that has been identified in the first stage, the values of the corresponding index positions of the channel $\{\overline{\mathbf{H}}_k : \forall k\}$ are all set to zero, and the unique support channel portion of the kth channel matrix can be expressed as

$$\overline{\mathbf{H}}_{k,i} = \overline{\mathbf{H}}_k - \overline{\mathbf{H}}_{k,c}, \quad \forall k. \tag{13}$$

Compared with the original channel matrix $\overline{\mathbf{H}}_k$, the channel matrix $\overline{\mathbf{H}}_{k,i}$ has more sparsity and is more suitable for channel recovery using CS technology. For the identification of unique support index sets, the subspace pursuit (SP) algorithm [15] is used here and its backtracking idea improves the correctness of the selected elements in each iteration. The core idea of the SP algorithm is to update the supporting index set after selecting multiple elements in each iteration and then update the supporting index set again by backtracking calculation. In this paper, the element selection is updated again by calculating the norm of the row vector of $(\overline{\mathbf{X}}_{\Theta_{k,i}}) + \overline{\mathbf{Y}}_{k,i}$ and then adding the corresponding index to the index set $\Theta_{k,i}$ or deleting the error from it. After the iteration stops, the unique support channel portion can be estimated based on the identified unique support set, namely,

$$\overline{\mathbf{H}}_{k,i}^e = \left(\overline{\mathbf{X}}_{\Theta_{k,i}}\right) + \overline{\mathbf{Y}}_{k,i}, \quad \forall k, \tag{14}$$

where $\overline{\mathbf{Y}}_{k,i} = \overline{\mathbf{Y}}_k - \overline{\mathbf{Y}}_{k,c}, \quad \forall k$.

At this point, the recovered two parts of the channel are added to obtain the channel estimation in the angular domain:

$$\begin{aligned}\widetilde{\mathbf{H}}_k^e &= \left((\mathbf{I}_M)_{\Theta_c}\overline{\mathbf{H}}_{k,c}^e\right)^{\mathbf{H}} + \left((\mathbf{I}_M)_{\Theta_{k,i}}\overline{\mathbf{H}}_{k,i}^e\right)^{\mathbf{H}} \\ &= \overline{\mathbf{H}}_{k,c}^e + \overline{\mathbf{H}}_{k,i}^e, \quad \forall k.\end{aligned} \tag{15}$$

The specific steps of the proposed algorithm are shown in Algorithm 1.

4. Simulation Results

For a multiuser FDD massive MIMO system, this paper considers the case of one BS and K UEs, where the BS is equipped with M antennas and each UE is equipped with N antennas. For the sake of simplicity, it is assumed that the sparsity of different channels is the same, that is, $s_k = s$, and the common sparsity between channels is s_c. In order to show the performance of the proposed channel estimation scheme, this paper selects the extension algorithm MMVOMP of OMP algorithm in the literature [8], OB-OMP [18], CS-aided [23], DCS-aided [24], J-OMP algorithm in [25], and the Genie-aided LS algorithm as the upper bound of performance. In this paper, the normalized mean square error (NMSE), bit error rate (BER), and sum rate are used to compare the performance. The NMSE is defined as follows:

$$E_{\text{NMSE}} = \frac{1}{G}\sum_{k=1}^{G}\frac{\left\|\mathbf{H}_k - \mathbf{H}_k^e\right\|_F^2}{\left\|\mathbf{H}_k\right\|_F^2}, \tag{16}$$

where $\mathbf{H}_k$ represents the kth channel matrix, $\mathbf{H}_k^e$ represents the recovered kth channel matrix, and G represents the number of simulation implementations. The simulation parameters used in the MATLAB simulator for the experimental results analysis are shown in Table 1.

Figure 3 compares the NMSE performance of each algorithm under different pilot length conditions. As can be seen from Figure 3, the proposed M-JOMP algorithm NMSE performance is much better than the algorithm for estimating each channel separately. When the number of pilots is small, the proposed algorithm reduces the NMSE by about 5 dB compared to the J-OMP algorithm in [25]. The reason is that the channel splitting makes each part of the channel have more sparsity. Furthermore, the proposed M-JOMP algorithm shows better NMSE performance the other state-of-the-art algorithms [8, 18, 23, 25] for different pilot conditions which makes it more effective for channel estimation. When using CS technology for signal recovery, the higher the sparse the signal, the less the training overhead is required. Since the channel matrix after splitting has more sparsity, channel recovery using CS technology will consume fewer pilots and backtracking selection will keep the correct rate when the number of pilots is small. When the pilot length increases to a certain value, the proposed M-JOMP and J-OMP algorithms reach the performance upper bound and the advantage of the channel joint recovery scheme can be seen, which is due to the spatial correlation of the channel between multiple UEs. By means of the channel structure with common support between different channels, the correctness of elements selection is greatly improved, that is, the accuracy of support set identification.

Figure 4 compares the NMSE of channel recovery between different algorithms under different SNRs. It can be seen from Figure 4 that under the conditions of low and high

Input: $\{\mathbf{Y}_k : \forall k\}$, $\mathbf{X}$, S, according to Equation (7), calculate the measured value $\{\overline{Y}_k : \forall k\}$ and the measurement matrix $\overline{X}$, and initialize the residual signal $\{\mathbf{R}_k = \overline{Y}_k : \forall k\}$. Let the common support set of the channels $\Theta_c = \phi$, and set the number of iterations l_c to 1.

(1) From $\|\overline{X}(j)^{\mathbf{H}}\mathbf{R}_k\|_{\mathrm{F}}$ $(j = 1, 2, \ldots, M)$, the BS selects the position corresponding to the previous $(s_k - |\Theta_c|)$ maximum values as the support index to join the support set Θ_k'.
(2) The BS update the common support set Θ_c by Equation (10).
(3) Let $\mathbf{R}_k = \overline{Y}_k - (\overline{X}_{\Theta_c})(\overline{X}_{\Theta_c}) + \overline{Y}_k$ if $l_c < s_c$, then $l_c = l_c + 1$, return to Step 1, otherwise go to Step 4.
(4) BS obtains partial joint support channel estimation by Equation (13) transmitted by the UE.
(5) Let the unique support set of the channel $\Theta_{k,i} = \phi, \overline{Y}_{k,i} = \overline{Y}_k - \overline{Y}_{k,c}, \forall k$, the residual signal $\mathbf{Q}_k = \overline{Y}_{k,i}$, set the number of iterations l_i to 1.
(6) From $\|\overline{X}(j)^{\mathbf{H}}Q_k\|_{\mathrm{F}}$ $(j = 1, 2, \ldots, M)$, the position corresponding to the previous $(s_k - s_c)$ maximum values is selected by the BS as a supporting index and added to the support set $\Theta_{k,i}$.
(7) Let $\overline{X}_p = (\overline{X}_{\Theta_{k,i}}) + \overline{Y}$, according to $\overline{X}_p(j)_F$ $(j \in \Theta_{k,i})$, the position corresponding to the previous $(s_k - s_c)$ maximum values is added as a supporting index to the support set $\Theta_{k,i}$ at the BS.
(8) Let $Q_k = \overline{Y}_{k,i} - (\overline{X}_{\Theta_{k,i}})(\overline{X}_{\Theta_{k,i}}) + \overline{Y}_{k,i}$, if $l_i < (s_k - s_c)$, let $l_i = l_i + 1$, return to Step 6, otherwise, go to Step 9.
(9) The BS obtains a unique support channel estimate by Equation (14).

Output: According to Equation (15), the channel estimate (CSI) at the BS $\overline{H}_k^e$ in the angular domain can be obtained, and then, $\mathbf{H}_k^e = \mathbf{R}\widetilde{H}_k^e\mathbf{T}^{\mathbf{H}}, \forall k$.

Algorithm 1: M-JOMP algorithm.

Table 1: Simulation parameters.

Parameter	Value
Number of BS antennas, M	128
Number of UE antennas, N	2–12
Number of UE, K	20
Channel sparsity, s	15
Interchannel common sparsity, s_c	6
SNR	28 dB
Pilot length, T	45
Channel model	Narrowband flat block fading

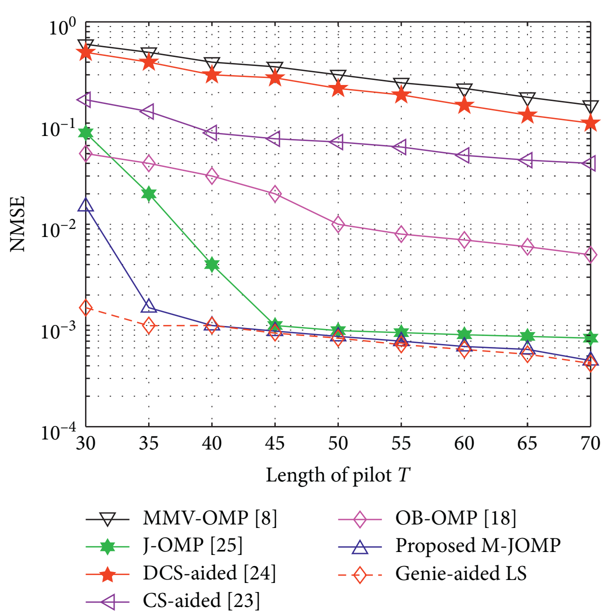

Figure 3: Performance comparison of NMSE with a pilot length under different algorithms.

SNR, the proposed algorithm has better performance gain than the literature [8, 18, 23–25], because, at the high SNR, the element recognition accuracy of the common support is higher, that is, it is well recognized. The common support set will have a beneficial effect on the splitting of the latter channel and the identification of another part of the channel support.

Figure 5 compares the variation of NMSE with number of users K of each algorithm. Here, the number of antennas at the BS is selected to be $M = 128$, the number of antennas at the users is $N = 12$, the channel sparsity is $s = 15$, the common sparsity between channels is $s_c = 6$, the pilot length is $T = 45$, and the BS transmits SNR = 28 dB. As can be seen from Figure 5, when the number of users increases, the NMSE can be effectively reduced. This is because the common support structure between the channels is utilized, the correctness of the element selection is improved, and the channel recovery performance is improved. Compared with the literature [8, 18, 23–25] algorithms, the proposed M-JOMP algorithm has a large performance improvement. The reason is that the SP algorithm is adopted for the second part of the split channel, which further improves the correctness of the selected element. As the number of users increases, the NMSE performance of the proposed algorithm hardly changes. It is seen that this algorithm is robust. It can be seen from the simulations results that the proposed scheme has better channel estimation performance under the condition of less pilot or low and high SNR (Figures 3 and 4). It is worth mentioning that the M-JOMP algorithm is especially suitable for channel estimation in multiuser situations.

Figure 6 compares the BER of the proposed M-JOMP algorithm with the state-of-the-art [8, 18, 23–25] algorithms against the SNR. The linear precoding technique MMSE is used at the BS, while ZF is used at the UEs at it does not require postcoding. The QAM modulation is used and considers a narrowband flat block fading channel model. As can be seen from Figure 6, when the SNR increases, the BER can be effectively reduced. This is because the common support structure between the channels is utilized, the correctness of the element selection is improved, and the

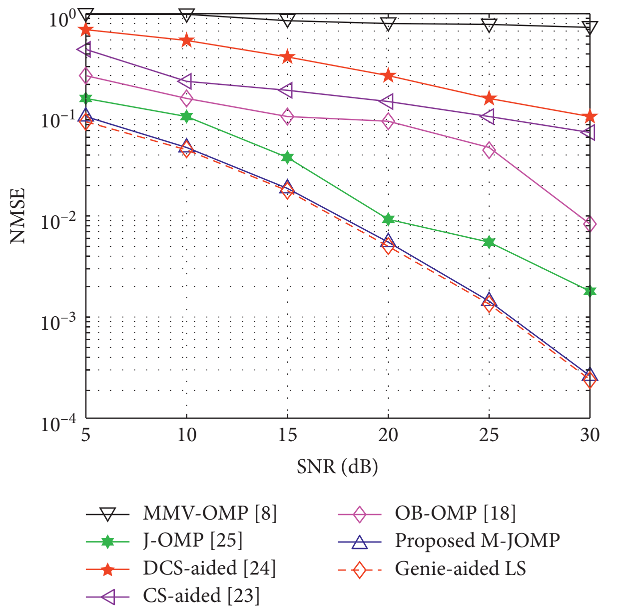

FIGURE 4: Performance comparison of NMSE with SNR under different algorithms.

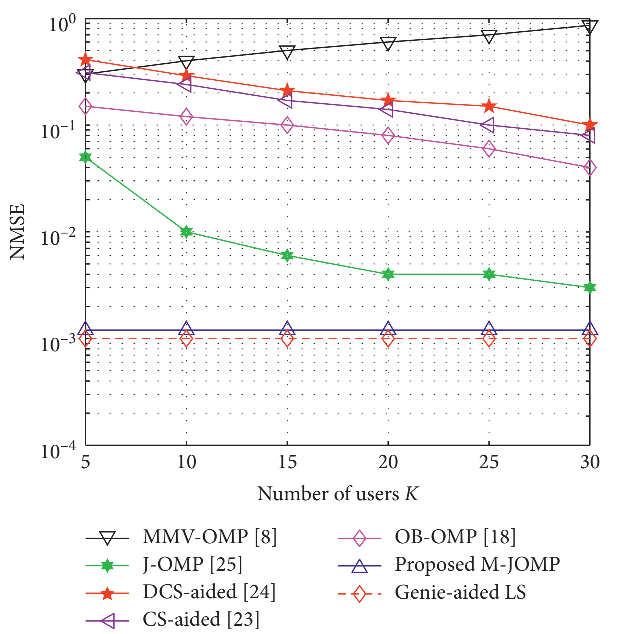

FIGURE 5: Performance comparison of NMSE with a number of users under different algorithms.

channel recovery performance is improved. It can be seen from Figure 6 that the proposed M-JOMP algorithm outperforms the existing algorithms under low and high SNR regime which makes it more robust than the existing algorithms. Moreover, the proposed algorithm shows close performance with the Genie-aided LS algorithm.

Figure 7 compares the achievable sum rate of the proposed algorithm with the state-of-the-art [8, 18, 23–25] algorithms against the SNR variations considering the same transceiver model parameters. As can be seen from Figure 7, the sum rate of the proposed M-JOMP algorithm is better

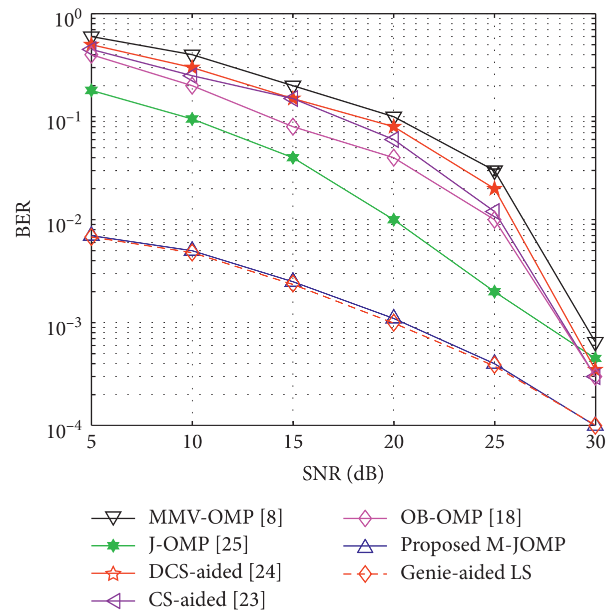

FIGURE 6: Performance comparison of BER with SNR under different algorithms.

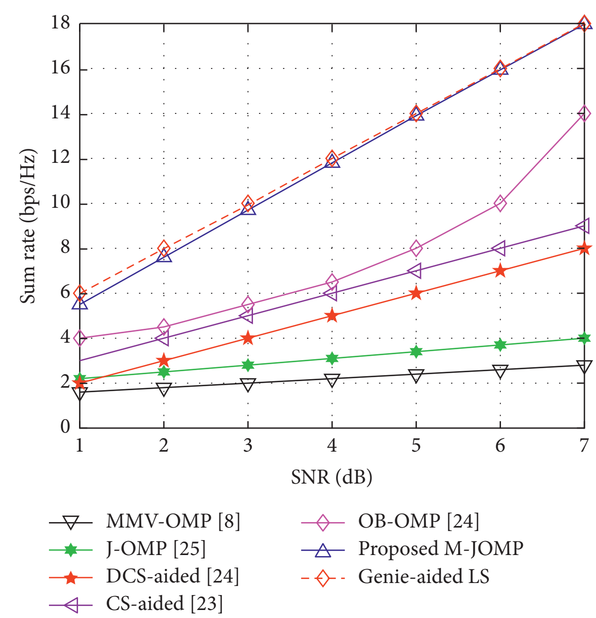

FIGURE 7: Performance comparison of sum rate with SNR under different algorithms.

than the other algorithms which make it suitable for low and high SNR and multiuser environments.

Figure 8 evaluates the sum rate versus feedback bits of the proposed and traditional state-of-the-art [8, 18, 23–25] algorithms. As can be seen from Figure 8, the proposed M-JOMP algorithm gives overall better sum rate performance as compared with the other state-of-the-art schemes for a different number of feedback bits. Moreover, the rate gap between the proposed M-JOMP algorithm and the reference benchmark Genie-aided LS algorithm is close enough which shows its improved performance over the

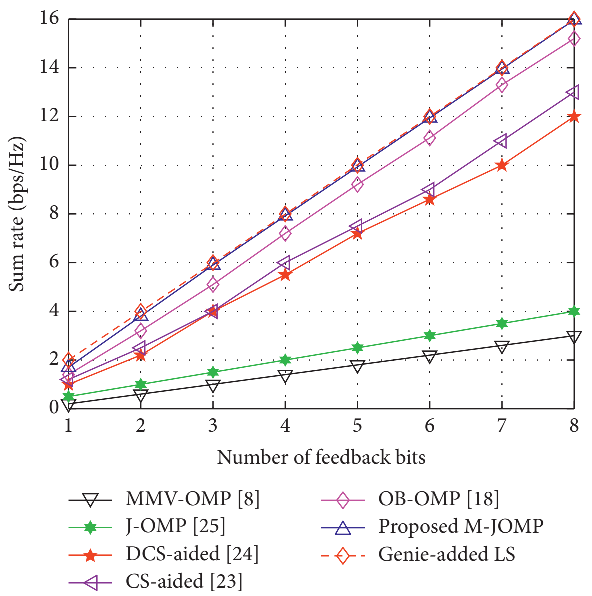

Figure 8: Spectral efficiency versus feedback bits: a comparison of the algorithms.

other algorithms. The rate gap between the proposed M-JOMP and the other algorithms increases with increasing feedback overhead which indicates that the proposed algorithm gives better spectral efficiency performance for the same number of feedback bits than the other algorithms which makes it suitable for massive MIMO systems.

5. Conclusions

This paper studies the channel estimation problem in 5G FDD multiuser massive MIMO systems. In order to reduce the pilot overhead, this paper proposes to use the spatial correlation between multiuser channels to split the channel matrix into two more sparse channel matrices and then use compressed sensing technology to estimate the two parts of the channel separately. Different from the traditional channel estimation scheme, this paper considers that multiple UE do not perform channel estimation locally after receiving the pilot signal from the BS but directly provide feedback the received signal to the BS, and perform joint recovery of the channel at the BS end. The simulation results show that the proposed scheme can effectively reduce pilot overhead while ensuring good channel estimation performance. Compared with the algorithm in [25], the improved algorithm can obtain better channel estimation performance under the condition of less pilot number. The pros of this method are that it splits the channel which has more sparsity and then uses the subspace pursuit algorithm which further provides correct sparse elements and it has good estimation performance in low and high SNR regime. The cons of this method are that it assumes perfect CSI measurement feedback from the UE to the BS which is not possible in practice and a nonideal CSI measurement approach needs to be considered. This work can further be extended by incorporating mmWave with massive MIMO and performing the analysis of beamspace channel estimation using the CS paradigm.

Data Availability

The data (figures) used to support the findings of this study are included within the article. Further details can be provided upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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