Joint Channel Estimation Based on Compressive Sensing for Multi-User Massive MIMO-OFDM Systems

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Abstract

With the number of transmit antennas increases largely in Massive MIMO systems, the training and feedback overhead for the acquisition of channel state information (CSI) at the transmitter becomes rather overwhelming. In order to solve the problem of huge overhead of channel estimation, this paper utilizes a new CSI estimation scheme and the hidden joint sparsity structure in multi-user channel impulse response vectors and thus proposes a joint channel estimation algorithm based on compressive sensing (CS) technique for orthogonal frequency division multiplexing systems. In this scenario, after the base station transmits training signals to each user, the users directly send back the observed signals to the base station and then the joint CSI acquisition problem could be realized at the base station. Then, by using the distributed sparse property of Massive MIMO-OFDM systems, the recovery of the CSI of all users can be realized by the joint channel estimation algorithm. Simulation results show that the proposed algorithm can achieve accurate CSI with lower overhead and complexity.

Keywords: *Massive MIMO-OFDM, channel state information, joint channel estimation,*

1. Introduction

Massive MIMO (multiple-input multiple-output) refers to the idea of equipping base stations with hundreds of antennas and has become one of the key techniques of 5G wireless communication[1]. It can boost the system capacity and energy efficiency by orders of magnitude through effectively utilizing of the space resources. To fully realize the technological superiority of massive MIMO as well as for signal detecting and precoding, the accurate CSI is essential both in uplink and downlink channels. For the system of time division duplexing (TDD), the CSI can be obtained from uplink channel by using the channel reciprocity[2]. While TDD has the advantage on channel estimation, the frequency division duplexing (FDD) can provide more efficient communications with symmetric traffic and low latency than TDD[3], which is more popular in current cellular networks. Hence, it is important to provide efficient solution of CSI estimation for FDD massive MIMO systems.

In conventional channel estimation for FDD MIMO systems, the BS firstly sent pilot signals to users in the downlink and each user then conduct their own channel estimation by using least square (LS) or minimum mean square error (MMSE). And then the estimated channel is fed back to the BS via dedicated uplink channels. Since the number of pilots grows with the same scale of transmit antennas at the BS, the pilot overhead for channel estimation is prohibitively high which will be a big challenge for massive MIMO-OFDM systems. In recent years, as many studies have shown that the channel impulse response (CIR) in wireless communication systems is sparse, that is, most of the energy of CIR is focused on fewer paths. Thus, it is natural to combining the compressive reconstruction algorithm with the sparse channel estimation, which can achieve better estimation performance than traditional channel estimation methods by using the same number of pilot symbols.

At present, different compressive sensing based approaches have been proposed in recent years. Many researches[4,5] applied greedy pursuit algorithms for sparse channel estimation as it can recovery the original channel frequency domain response with high probability, but it may also cause the large pilot overhead with the increase of the number of antennas in massive MIMO-OFDM systems. Besides, some other researches utilized the hidden sparsity in CIR vectors and thus improve the estimation performance than traditional greedy pursuit algorithms. For instance, in [6], a new model of massive MIMO-OFDM system is considered by utilizing the temporal correlation in different OFDM symbols and proposes the local common sparsity channel estimation algorithm (LCS) to achieve the higher estimation efficiency and accuracy than traditional LMMSE algorithm and greedy pursuit algorithms.

The existing algorithms for channel estimation of MIMO-OFDM systems have indeed improved the performance of channel estimation, however, most of the proposed algorithms fail to take into account the hidden joint sparsity among different users which lead to the overwhelming pilot overhead as the transmit antennas increases largely. Thus, this paper proposes a space-time channel estimation method by using the joint sparsity for multi-user MIMO-OFDM systems.

The rest of this paper is structured as follows: In the second part is the establishment of multi-user MIMO-OFDM systems; the second part is the design of joint sparsity channel estimation algorithm; the fourth part is the scheme of the simulation analysis. Finally, we conclude the paper in part 5.

Notations: Uppercase and lowercase boldface denote matrices and vectors respectively. The operators $(\cdot)^T$, $(\cdot)^H$ $(\cdot)^{-1}$, $(\cdot)^{\dagger}$, $|\cdot|$, $I_{\{\}}$, $O(\cdot)$ are the transpose, conjugate transpose, inverse, pseudo inverse, cardinality, indicator function, big-O notation operator respectively. And $rank(\boldsymbol{H})$ denotes the rank of matrix $\boldsymbol{H}$; $\|\cdot\|_F$ denotes the Frobenius norm.

2. System Model

2.1 MIMO-OFDM system model

As is shown in Figure 1, we consider a MIMO-OFDM system with N_T transmit antennas and N_R receive antennas, and assume the channel between the i_T *th* transmit antenna and the i_R *th* receive antenna is a frequency selective fading channel.

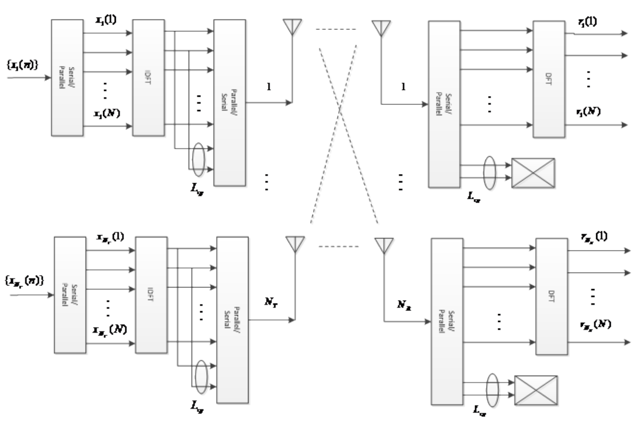

Figure1. MIMO-OFDM system model

Assume that each OFDM symbol contains N_{FFT} subcarriers, where the number of pilot subcarriers is N_P and the number of data subcarriers is $N_{FFT}-N_P$. The position of the pilot subcarriers in the first OFDM symbol is expressed as $\mu_n=\{c_{n,1},c_{n,2},\dots,c_{n,N_P}\}$, which is randomly selected from the sequence of $\{1,2,\dots,N_{FFT}\}$. During the data transmission procession, the OFDM modulation signal $\boldsymbol{p}_{i_T}(k), k\in\{1,2,\dots N_{FFT}\}$ is sent by the i_T transmit antenna, and then after the inverse discrete Fourier transform (IDFT), the pilots are multiplexed with data in the frequency domain. In addition, a cyclic prefix (CP) is finally added to each signal to avoid inter-symbol interference (ISI). At the receive antenna, each user firstly removes the CP and then performs the DFT transformation to get the received pilot signals.

Assuming that the channel parameters are constant during an OFDM symbol, then the signal received by the each user is expressed as:

$$\boldsymbol{r}_{i_R}=\sum_{i_T=1}^{N_T}\boldsymbol{P}_{i_T}\boldsymbol{f}_{i_Ti_R}+\boldsymbol{z}_{i_R} \quad (1)$$

where $\boldsymbol{P}_{i_T}=diag[\boldsymbol{p}_{i_T}(1),\boldsymbol{p}_{i_T}(2),\dots,\boldsymbol{p}_{i_T}(N_{FFT})]$, and $\boldsymbol{f}_{i_Ti_R}$ is the discrete channel frequency response of the i_T *th* transmitting antenna and the i_R *th* receiving antenna; $\boldsymbol{z}_{i_R}\in\mathbb{C}^{N_{FFT}\times 1}$ is the Gaussian white noise $\sim\mathcal{CN}(\boldsymbol{0},\sigma_n^2)$.

In the Rayleigh fading channel, the traditional channel estimation method requires that the pilots of the different antennas of the MIMO-OFDM system should be orthogonal to each other, for simplicity, we assume that only one antenna transmit pilots in the time-frequency recourse elements[7]. Then the pilot symbols received by the i_R *th* receiving antenna can be expressed as:

$$\begin{aligned}\boldsymbol{r}_{pilot}&=\boldsymbol{P}_{pilot}\boldsymbol{f}_{pilot}+\boldsymbol{z}_{pilot}\\&=diag(\boldsymbol{p}_{pilot})\boldsymbol{F}_{N_P}\begin{bmatrix}\boldsymbol{h}\\\boldsymbol{0}_{N_{FFT}-N_{CIR}}\end{bmatrix}+\boldsymbol{z}_{pilot}\\&=\underbrace{diag(\boldsymbol{p}_{pilot})\boldsymbol{F}_{N_P}\boldsymbol{\Pi}}_{\boldsymbol{U}}\boldsymbol{h}+\boldsymbol{z}_{pilot}\end{aligned} \quad (2)$$

where $\boldsymbol{r}_{pilot}=[\boldsymbol{r}(1),\boldsymbol{r}(2),\dots\boldsymbol{r}(N_P)]^T\in\mathbb{C}^{N_P\times 1}$ is the received pilot signal in single antenna, $\boldsymbol{p}_{pilot}\in\mathbb{C}^{N_P\times 1}$ is the transmitted pilot signal; $\boldsymbol{h}$ is the time-domain CIR vector with size of $N_{CIR}\times 1$ and is assumed to be sparse, $\boldsymbol{F}\in\mathbb{C}^{N_{FFT}\times N_{FFT}}$ is a DFT matrix and its (m,n) element is $\exp(-j2\pi mn/N_{FFT})$, $\boldsymbol{F}_{N_P}\in\mathbb{C}^{N_P\times N_{FFT}}$ is a partial DFT matrix which is selected from the N_P rows from the DFT matrix with its index corresponding to the μ_n, $\boldsymbol{\Pi}\in\mathbb{C}^{N_{FFT}\times N_{CIR}}$ is the coordinate matrix corresponding to the N_{CIR} columns selected from the unit matrix, $\boldsymbol{z}_{pilot}\in\mathbb{C}^{N_P\times 1}\sim\mathcal{CN}(\boldsymbol{0},\sigma_z^2\boldsymbol{I})$ is the Gaussian white noise, $\boldsymbol{U}$ is the observation matrix and is defined as $\boldsymbol{U}=diag(\boldsymbol{p}_{pilot})\boldsymbol{F}_{N_P}\boldsymbol{\Pi}$. In addition, to ensure that the observation matrix satisfies the random matrix theory and the RIP condition, the position matrix of the pilot

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subcarriers $\boldsymbol{\mu}_n = \{c_{n,1}, c_{n,2}, \ldots, c_{n,N_P}\}$ is randomly selected from the sequence $\{1, 2, \ldots, N_{FFT}\}$, and the pilot signal is a Gaussian random matrix.

2.2. Joint sparsity of Multi-user MIMO-OFDM System

Suppose there are *K* users in massive MIMO-OFDM system, as the number of scatters is limited near the base station, the transmitted signals from the base station to different users often passes through the common scatters, especially for the users with similar distance. So the CIR vectors of different users have the similar channel delay and thus their CIR vectors exhibit the common sparsity. Besides, due to the rich scatters near each user, when the signal arrives at different users through different scatters, each channel of user has a different arrival delay, thus their CIR vectors exhibit the individual sparsity. Figure 2 shows the joint structure of multi-user system, where the scatter 1 and the scatter 3 in the Figure 2(a) are the individual scatter for user 1 and user K, respectively, and the scatter 2 is the common scatter for all users. Therefore, the CIR vectors in Figure 2(b) has both the common sparse location and individual sparse location.

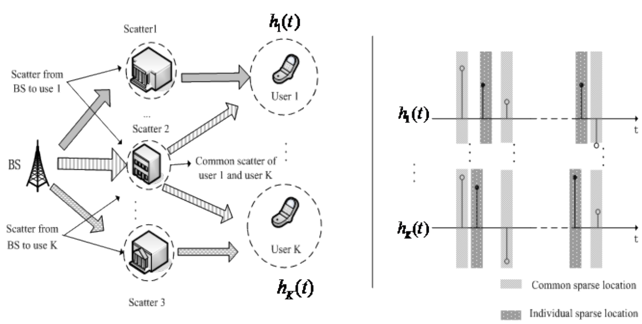

Figure2. Joint sparse model of Multi-user systems

Due to the time correlation of MIMO-OFDM systems, that is, the locations of domain locations usually vary slowly in time which can be considered as constant during certain time duration. Thus, in several continuous OFDM symbol time, the time common sparsity of time-domain CIR vector can be expressed as:

$$\mathrm{supp}(\boldsymbol{h}_1) = \mathrm{supp}(\boldsymbol{h}_2) = \cdots \mathrm{supp}(\boldsymbol{h}_R) \triangleq \boldsymbol{\Omega} \qquad (3)$$

where $\boldsymbol{h}_n$ $(n \in \{1, 2, \ldots, R\})$ is the CIR vector for each user in *R* continuous OFDM symbols.

Besides, during each OFDM symbol, the common sparsity of CIR vectors among different users can be expressed as:

$$\bigcap_{k=1}^{K} \mathrm{supp}(\boldsymbol{h}^{(k)}) \triangleq \boldsymbol{\Omega}_C,\ 1 \le k \le K \qquad (4)$$

As shown in Figure 3, except for the common sparsity $\boldsymbol{\Omega}_C$ in different CIR vectors for all users, the remaining sparse locations of them are different. The total sparse support of different users is expressed as $\{\boldsymbol{\Omega}_k, \forall k\}$ and the size of common support set and the individual support set satisfy $|\boldsymbol{\Omega}_k| \sim U(S_k - 2, S_k)$ and $|\boldsymbol{\Omega}_c| \sim U(S_C, S_C + 2)$, respectively.

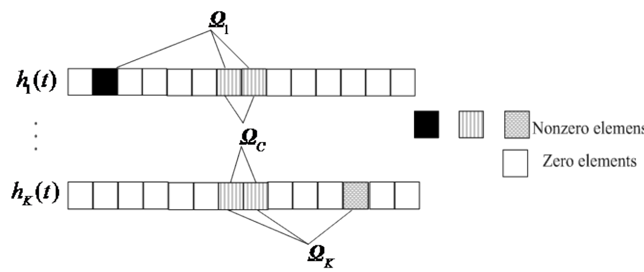

Figure3. Joint sparsity structure of CIR vectors

Based on the system model of equation(2) and the above sparse properties, the joint multi-user massive MIMO-OFDM system model in can be formulated as:

$$\tilde{\boldsymbol{r}}_n^{(k)} = \underbrace{diag(\boldsymbol{p}_n)\boldsymbol{F}_{N_P}\boldsymbol{\Pi}}_{\boldsymbol{U}_n}\boldsymbol{h}_n^{(k)} + \boldsymbol{z}_n^{(k)},\ \ (1 \le k \le K, 1 \le n \le R) \quad (5)$$

where $\boldsymbol{h}_n^{(k)} \in \mathbb{C}^{N_{CIR} \times 1}$ is the channel impulse response vector of the *k-th* user in the *n-th* OFDM symbol.

In order to take advantage of the joint sparse features of multi-user massive MIMO-OFDM systems and to reduce the pilot overhead, we adopt an improved estimation scheme that each user directly feeds back the pilot observation after they receives the pilot signal, then we can get the stacked receive pilot vectors for each user as:

$$\bar{\boldsymbol{r}}^{(k)} = \underbrace{diag(\boldsymbol{U}_1, \ldots, \boldsymbol{U}_R)}_{\text{Sensing matrix}} \begin{bmatrix} \boldsymbol{h}_1^{(k)} \\ \vdots \\ \boldsymbol{h}_R^{(k)} \end{bmatrix} + \begin{bmatrix} \boldsymbol{z}_1^{(k)} \\ \vdots \\ \boldsymbol{z}_R^{(k)} \end{bmatrix},\ \ 1 \le k \le K \quad (6)$$

Since the CIR vectors within different OFDM symbols have the same sparsity (see Eq. (3)), the combined CIR vectors can be reorganized into a block sparse matrix:

$$\boldsymbol{d}_i^{(k)} = [(\boldsymbol{h}_1^{(k)})_i, \ldots, (\boldsymbol{h}_R^{(k)})_i]^T,\ (1 \le k \le K, 1 \le i \le N_{CIR}) \ (7)$$

As $\mathbf{d}_i^{(m)} \in \mathbb{C}^{R \times N_{CIR}}$ is a sparse block matrix, and its nonzero elements correspond to that of CIR vectors during R OFDM symbols. Then, the equation (5) can be expressed as the following model:

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$$\tilde{\boldsymbol{r}}^{(k)} = [\boldsymbol{\Psi}_1 \ldots \boldsymbol{\Psi}_{N_{CIR}}] \begin{bmatrix} \boldsymbol{d}_1^{(k)} \\ \vdots \\ \boldsymbol{d}_{N_{CIR}}^{(k)} \end{bmatrix} + \begin{bmatrix} \boldsymbol{z}_1^{(k)} \\ \vdots \\ \boldsymbol{z}_R^{(k)} \end{bmatrix}, \quad 1 \le k \le K \qquad (8)$$

where $\boldsymbol{\Psi}_i \in \mathbb{C}^{RN_P \times R}$, $(i = 1, 2, \ldots, N_{CIR})$ is the observation matrix corresponding to reordered vector $[\boldsymbol{d}_1^{(k)}, \ldots, \boldsymbol{d}_{N_{CIR}}^{(k)}]^T$.

Considering the Rayleigh fading channel model with the maximum Doppler frequency as f_d, then the temporal correlation of complex gain is given as:

$$E[\boldsymbol{d}_i^{(k)} \boldsymbol{d}_j^{(k)H}] = \begin{cases} P_i^{(k)} \boldsymbol{J}_{R\times R} & for\ i = j \\ \boldsymbol{0}_{R\times R} & for\ i \ne j \end{cases} \quad (1 \le i, j \le N_{CIR}) \quad (9)$$

where $P_i^{(k)} = E[|(\boldsymbol{h}_n^k)_i|]^2$ is the variance of the *i-th* element of CIR vector, $\boldsymbol{J}_{R\times R}$ is the covariance matrix with its (m,n) element as $J_0(2\pi f_d T_s(m-n))$.

Thus, the channel estimation problem of the joint sparsity multi-user MIMO-OFDM system is the problem of using the observation matrix $\{\boldsymbol{\Psi}_i, 1 \le i \le N_{CIR}\}$ and the pilot observations of multiple users to obtain the combined time-domain CIR vector $\{\tilde{\boldsymbol{r}}^{(k)}, 1 \le k \le K\}$, which can be expressed as the following joint model:

$$[\tilde{\boldsymbol{r}}^{(1)}, \ldots, \tilde{\boldsymbol{r}}^{(K)}] = [\boldsymbol{\Psi}_1 \ldots \boldsymbol{\Psi}_{N_{CIR}}] \begin{bmatrix} \boldsymbol{d}_1^{(1)} & \boldsymbol{d}_1^{(2)} & \cdots & \boldsymbol{d}_1^{(K)} \\ \boldsymbol{d}_2^{(1)} & \boldsymbol{d}_2^{(2)} & \cdots & \boldsymbol{d}_2^{(K)} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{d}_{N_{CIR}}^{(1)} & \boldsymbol{d}_{N_{CIR}}^{(2)} & \cdots & \boldsymbol{d}_{N_{CIR}}^{(K)} \end{bmatrix} + \begin{bmatrix} \boldsymbol{z}_1^{(1)} \cdots \boldsymbol{z}_1^{(K)} \\ \vdots \ \ddots \ \vdots \\ \boldsymbol{z}_R^{(1)} \cdots \boldsymbol{z}_R^{(K)} \end{bmatrix} \qquad (10)$$

3. Joint Channel Estimation Algorithm

In order to solve the channel estimation problem of equation(10), we firstly use the temporal estimation algorithm to calculate the common support set $\boldsymbol{\Omega}_C$ of all CIR vectors, and then calculate the remaining individual support set of each user which we called the joint channel estimation algorithm (JCE).

3.1. Temporal channel estimation algorithm

The algorithm firstly uses the greedy pursuit method to calculate the correlation between the observation matrix $\boldsymbol{\Psi}_i$ and the residual matrix to find out the index of the largest correlation, with the common support set updated at each iteration, the common support set is utilized to calculate the LMMSE correlation coefficient which will finally obtain the estimated CIR vectors $\{\hat{\boldsymbol{d}}_{n,i}, \forall i\}$ after S times of iteration.

The specific steps are shown as follows:

1: Input: $\bar{\boldsymbol{r}}_n$, $\{\boldsymbol{\Psi}_i, \forall i\}$, $\{P_i, \forall i\}$, S, j,

2: Output: $\{\boldsymbol{d}_{n,i}, \forall i,\}$

3: Initialize $\boldsymbol{M} := \bar{\boldsymbol{r}}_n$, $\boldsymbol{\Omega} := \varnothing$, j=1

4: Repeat the following steps until the iteration index j=S :

5: Find the index of largest correlation:

$$i_{\max} := \arg\max_i \left\| \boldsymbol{\Psi}_i^H \boldsymbol{M} \right\|_F$$

6: Update the common support set: $\boldsymbol{\Omega} := \boldsymbol{\Omega} \bigcup \{i_{\max}\}$

7: Compute the LMMSE estimation:

$$\mathbf{W}_{n,i} := E[\boldsymbol{d}_{n,i}(\bar{\boldsymbol{r}}_n)^H] E^{-1}[\bar{\boldsymbol{r}}_n(\bar{\boldsymbol{r}}_n)^H], \ \forall i$$

$$E[\boldsymbol{d}_{n,i}(\bar{\boldsymbol{r}}_n)^H] := \begin{cases} P_i \boldsymbol{J}_{R\times R} \boldsymbol{\Psi}_i^H, & for\ i \in \boldsymbol{\Omega} \\ 0, & otherwise \end{cases}$$

$$E[\bar{\boldsymbol{r}}_n(\bar{\boldsymbol{r}}_n)^H] := \sum_{i\in\boldsymbol{\Omega}} P_i \boldsymbol{\Psi}_i \boldsymbol{J}_{R\times R} \boldsymbol{\Psi}_i^H + \sigma_w^2 \boldsymbol{I}_{RN_P \times RN_P}$$

8: Calculate the estimated CIR vector:

$$\hat{\boldsymbol{d}}_{n,i} := \mathbf{W}_{n,i} \bar{\boldsymbol{r}}_n, \ 1 \le i \le N_{CIR}$$

9: Update the residual and the iteration index, and then return to the step 5:

$$\boldsymbol{M} := \bar{\boldsymbol{r}}_n - \sum_{i\in\boldsymbol{\Omega}} \boldsymbol{\Psi}_i [\hat{\boldsymbol{d}}_{n,i}], \quad j = j + 1$$

3.2. Joint channel estimation algorithm

The algorithm flow is shown as follows:

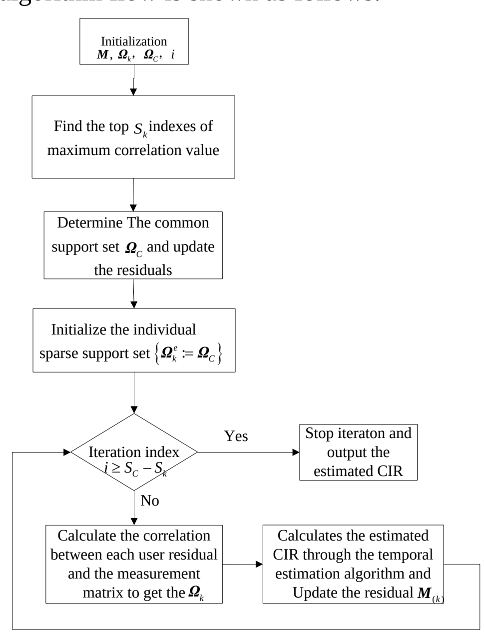

Figure4. JCE algorithm flow

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In the algorithm flow, the specific step for calculate common sparsity $\boldsymbol{\Omega}_C$ of all users are explained as follows:

Firstly, we initialize the residual $\boldsymbol{M}_{(k)} := \tilde{\mathbf{r}}^{(k)}$, individual sparse support set $\{\boldsymbol{\Omega}_k := \varnothing, \forall k\}$, common sparse support set $\boldsymbol{\Omega}_C := \varnothing$, and the number of iterations $s = 1$.

Secondly, compute the iteration calculation for S_C times:

1. Using the greedy pursuit method to calculate the correlation between each user's residual $\boldsymbol{M}_{(k)}$ and the observation matrix $\{\boldsymbol{\Psi}_i, \forall i\}$, and then find the top $S_k - |\boldsymbol{\Omega}'_C|$ index of maximum correlation value:

$$\boldsymbol{\Omega}'_k := \arg\max \left\| \boldsymbol{\Psi}_\Lambda^H \boldsymbol{M}_{(k)} \right\|_F^2 ,\ |\Lambda| = S_k - |\boldsymbol{\Omega}_C^e| \qquad (11)$$

2. Find out the index j with the largest number of occurrences for different users and then update the estimated common support set:

$$\boldsymbol{\Omega}_C^e = \boldsymbol{\Omega}_C^e \bigcup \arg\max_j \sum_{k=1}^{K} I_{\{j \in \boldsymbol{\Omega}'_k\}} \qquad (12)$$

where $I_{\boldsymbol{\Omega}'_k}(x)$ is the indicator function and is defined as:

$$I_{\Omega'_k}(x) = \begin{cases} 1 \ , if \ \ x \in \boldsymbol{\Omega}'_k \\ 0 \ , if \ \ x \notin \boldsymbol{\Omega}'_k \end{cases} \qquad (13)$$

3. Update the residual of all users, and estimate the channel frequency domain with the indexes corresponding to common sparse support set by using the temporal channel estimation algorithm:

$$\boldsymbol{M} := [\tilde{\boldsymbol{r}}^{(1)}, \cdots, \tilde{\boldsymbol{r}}^{(K)}] - \sum_{i \in \boldsymbol{\Omega}_C^e} \boldsymbol{\Psi}_i [\tilde{\boldsymbol{d}}_i^{(1)}, \cdots, \tilde{\boldsymbol{d}}_i^{(K)}] \qquad (14)$$

Thirdly, after S_C times of the iteration, we can obtain the common sparse support set, then carry out the update of each user's sparse support set $\boldsymbol{\Omega}_C$, and then use the temporal channel estimation to obtain the final channel estimation $\{\hat{\boldsymbol{d}}_i^{(k)}, \forall i, k\}$.

5. Simulation analysis

In this part, we use the Matlab simulation platform to fully verify the performance of the proposed algorithm. In order to prove that our proposed JCE algorithm is feasible and effective, we compare it with typical greedy pursuit algorithm and the LCS algorithm proposed in [6], and set the Oracle algorithm as the low bound. Besides, we also verify the effect of common sparsity and individual sparsity on estimation performance. Through the simulation, it can show that the proposed JCE algorithm has better channel estimation performance than traditional estimation algorithms, which is of great usefulness for multi-user massive MIMO-OFDM systems.

The main parameters are shown in Table 1.

Table 1Simulation parameters

Simulation parameters	value
number of users	20
number of subcarriers	20
spacing of subcarriers	15kHz
Doppler frequency	70Hz
maximum delay spread	4.88μs
time interval of OFDM symbols	0.5ms
length of CIR vector	150
channel sparsity	S_C=7, S=15
signal to noise ratio(SNR)	20dB
iteration times	500

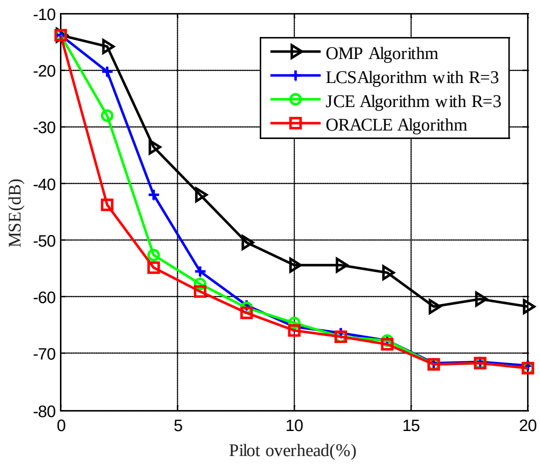

Figure5. Proportion of total energy consumption

Figure5 compares the mean square error (MSE) of several algorithms to verify the feasibility and effectiveness of JCE algorithm. It can be seen from the figure that the JCE algorithm is slightly better than the LCS algorithm and is far superior to the OMP algorithm. This is because the LCS algorithm and the OMP algorithm perform the recovery of separate support set for each user without using the common sparsity of all users which leads to the poor ability to recover the original signal with less observation.

In order to verify the efficiency and time complexity of different algorithms, we compute the operating time of various algorithms. For the typical OMP algorithm, to solve the problem of channel estimation in the model (10), it utilizes iteration estimation based on the direct selection of the support set which has the time complexity of $O(R^3KSN_P)$. The LCS algorithm proposed in [6] estimate the individual support set of each user and has the time complexity of $O(R^3KSN_P + R^3N_{CIR}SN_P^{\ 3})$. The proposed JCE algorithm firstly estimate the common sparsity and then estimate the remaining individual support set and has the time complexity of $O(R^3KSN_P + R^3SN_P{}^3)$. The comparison of time complexity of different algorithms is shown in Table 2:

Table 2 Comparison of time complexity of different algorithms

Algorithms	Time complexity
OMP	$O(R^3KSN_P)$
LCS	$O(R^3KSN_P + R^3N_{CIR}SN_P{}^3)$
JCE	$O(R^3KSN_P + R^3SN_P{}^3)$

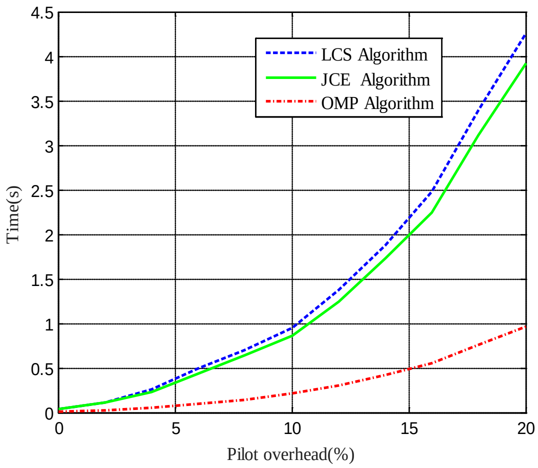

Figure6. node mobility rate *vs* packet delivery ratio

Figure 6 verifies the operating time of various algorithms. It can be seen from the figure that the JCE algorithm has slightly less computational complexity than the LCS algorithm as the JCE algorithm compute the LMMSE estimation based on the obtaining of common sparsity. The LCS algorithm separately recoveries the support set for each user which requires higher number of calculations. For the OMP algorithm, even though it has a lower computing time due to the simple structure, it has a big gap to the oracle algorithm as shown in Figure5 which confirms that the overall performance is still poor. Combining the Figure 5 and Figure 6, it can get the conclusion that the proposed JCE algorithm has the big advantages for the channel estimation in joint sparse model.

Figure 7 verifies the effect of common sparsity on the channel estimation performance of different algorithms with the pilot overhead set to 4%. It can be seen from the figure that when the user's individual sparseness remains a constant and the common sparsity S_C keeps increasing, the estimation performance of JCE algorithm and LCS change better, whereas the estimation performance of OMP algorithm does not change with the increasing of S_C. This is because the JCE algorithm takes advantage of the common sparsity of different users, and the probability of correct recovery becomes higher with the increasing of the number of common support set. However, the OMP algorithm is related to the overall sparsity S and has nothing to do with the common sparsity and therefore does not change with the increasing of S_C..

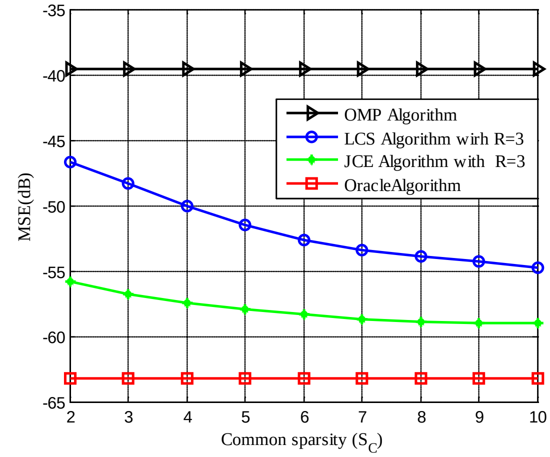

Figure7. node mobility rate *vs* packet network lifetime

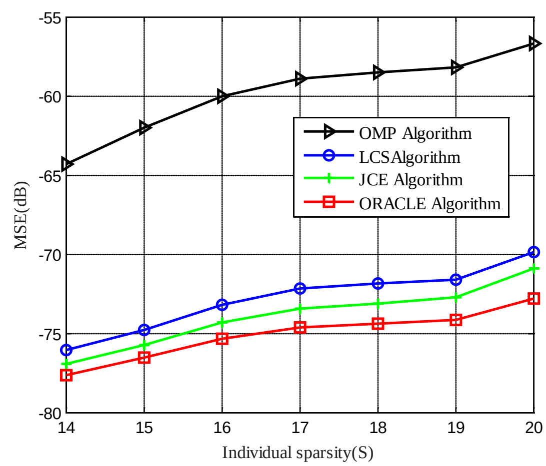

Figure8. node mobility rate *vs* network throughput

Figure 8 verifies the effect of individual sparsity on the channel estimation performance of different algorithms with the pilot overhead set to 4%. As can be seen from the figure, with the individual sparsity increasing, the estimation performance of the various algorithms becomes worse. The reason can be derived from the theory of compressive sensing, which illustrates that if the sparsity increases, the required observations should be increased in order to ensure the channel estimation performance. Therefore, the estimated performance of the system will become worse with the increase of S under the same dimension of pilot observation.

5. Conclusions

To solve the problem of overwhelming estimation overhead in massive MIMO-OFDM systems, this paper utilizes the hidden sparsity in channel impulse response vectors for multi user systems and proposes a joint sparsity channel estimation algorithm. Experimental results show that the proposed algorithm reduces the estimation overhead as well as time complexity and obtain the better estimation performance with comparison to the typical greedy pursuit algorithm.

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References

[1] L. Lu, G. Y. Li, A. L. Swindlehurst, A. Ashikhmin, and R. Zhang "An overview of massive MIMO: Benefits and challenges," IEEE Journal of Selected Topics in Signal Process., vol. 8, no. 5, pp. 742-758, Oct. 2014.

[2] T. L. Marzetta, "Noncooperative cellular wireless with unlimited numbers of BS antennas," *IEEE Trans. Wireless Commun.*, vol. 9, no. 11, pp. 3590–3600, Nov. 2010.

[3] F. Rusek, D. Persson, B.K. Lau, and F. Tufvesson, "Scaling up MIMO: Opportunities and challenges with very large arrays," IEEE Signal Process. Mag., vol. 30, no. 1, pp. 40-60, Jan. 2013.

[4] Karabulut G Z, Youngacoglu A. Sparse channel estimation using orthogonal matching pursuit algorithm [C]// IEEE 60th Vehicular Technology Conference. Los Angeles: IEEE Press, 2004: 3880-3884.

[5] Donoho D L, Tsaig Y, Drori I, et al. Sparse solution of underdetermined linear equations by stagewise orthogonal matching pursuit[J]. IEEE Transactions on Information Theory, 2012, 58(2): 1094-1121.

[6] Jun W C, Byonghyo S, Seok H C. Downlink Pilot Reduction for Massive MIMO Systems via Compressed Sensing[J]. IEEE communication Letters, 2015, 19(11): 1889-1892.

[7] Qi C, Wu L. A hybrid compressed sensing algorithm for sparse channel estimation in MIMO OFDM systems[C]//IEEE International Conference on Acoustics, Speech and Signal Processing. Prague: IEEE Press, 2011: 3488-3491.