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Massive MIMO System with Sparse Channel Estimation and Pilot Optimization

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Abstract: Aiming at the number of user pilots in Multiple-Input Multiple-Output (MIMO) uplink is small and the distribution is uneven, which leads to the error interpolation layer in conventional interpolation channel estimation method, a sparse channel estimation and pilot optimization are proposed. Based on the theory of Compressed Sensing (CS), the sparse channel impulse response is estimated. According to the principle of minimization of measurement matrix cross-correlation in CS theory, a pilot algorithm based on random search and pilot power optimization algorithm is proposed. Simulation results show that the performance of proposed method is better than the least squares estimation based on linear interpolation, with CS channel estimation without pilot optimization, and the CS channel estimation based on pilot pattern optimization. The simulation verifies that the uplink massiveMIMO performance with interleaved and generalized subcarrier allocation achieves reliable communication between two users when the received signal-to-noise ratio is higher than 20 dB.

Keywords: *Massive MIMO communication, compressive sensing, and channel estimation.*

1. Introduction

With the deepening of marine development, massive communication technology has also been developed from traditional point-to-point mode to multi-user MIMO information network [1, 2]. The commonly used multiple access technology in massive network mainly includes TDMA (time division Multiple access), CDMA (code division multiple access) and FDMA (frequency division multiple access), etc. In recent years, orthogonal frequency division multiple access with flexible resource allocation, high spectrum utilization, and strong multipath resistance (The technology has been paid more and more attention to the design of the massive MAC (Media Access Control) protocol [3, 4]. The MIMO system can allocate a continuous subcarrier for the user, that is, the sub band mode. Sub band Carrier Assignment Scheme (subband CAS) to implement spectrum resource sharing; The channel frequency diversity gain can also be improved by using an interleaved subcarrier allocation (interleaved CAS); the spectrum resources can be flexibly allocated according to channel conditions and user requirements, and the non-equal interval generalized subcarrier allocation (generalized CAS) is further improved. System performance[5]. However, the flexible subcarrier allocation method also causes the user pilots to be unevenly distributed in the entire communication frequency band, which brings challenges to the pilot-assisted channel estimation method in MIMO uplink communication. In uplink communication, multiple users experiencing different channels access simultaneously, especially for a water-acoustic channel with limited spectrum resources and severe multipath expansion, and how the uplink receiving end uses a small amount of uneven pilots allocated by each user to implement a multi-user channel. It is estimated that it is a key technology that needs to be solved in MIMO uplink communication.

The traditional method based on polynomial interpolation is widely used in channel estimation of GFDM systems. However, the interpolation performance of this algorithm is very sensitive to the number of pilots and pilot pattern distribution, and is not applicable to MIMO systems with flexible subcarriers and pilot distribution. A large number of literatures have been developed for this problem [6] In the MIMO system of subband subcarrier allocation, the joint linear and base expansion model (BEM) is used to describe the time-frequency distribution characteristics of the channel in each subband. Channel estimation is implemented by two-dimensional interpolation. In order to adapt to the flexible subcarrier allocation method of MIMO system, the literature [7] proposes a pilot-assisted channel estimation algorithm based on irregular sampling, which improves the channel estimation performance and reduces the performance of the number of pilots. Reference [8] proposes a parametric channel estimation algorithm for non-uniform pilot distribution. Based on the shift-invariant characteristics of the uplink MIMO stack structure in the IEEE 802.16d/e standard, ESPRIT (estimation of Signal parameters via rotational invariance technique. The algorithm estimates the channel multipath delay. In order to improve the spectrum utilization, the literature [9] introduces virtual subcarrier technology, which uses the orthogonality of noise and signal subspace to achieve semi-blind channel estimation, but this method

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there are restrictions on the subcarrier allocation method, which is only applicable to sub band and interleaved MIMO systems.

The above literature is modeled under the conventional radio channel, although some results have been obtained, the sparse characteristics of the massive channel have not been fully studied. In recent years, Compressed Sensing (CS) theory has been widely used in massive multi-carrier communication system [10-13]. Using the natural sparse characteristics of massive channel, based on CS theory, the reconstruction of sparse channel impulse response can be realized by a small number of pilots [10]. [13] Cross-matching tracking algorithm, inserting uniform pilots in sub-band and interleaved subcarrier allocation MIMO systems to achieve sparse channel estimation, and performing band-pass filtering on the GFDM signals collected by sea trials to verify sub-band subcarrier allocation MIMO communication performance. The above literature [10-13] assumes that the comb pilots are evenly distributed over the entire frequency band, and the CS estimation performance under the irregular pilot distribution is not discussed. The CS theory usually uses the random measurement matrix to reconstruct the sparse signal [14, 15] There is no special limitation on the pilot distribution when applied to channel estimation. This paper proposes a CS-based sparse channel estimation method in massiveMIMO uplink communication, and implements pilot optimization based on the principle of measurement matrix cross-correlation minimization in CS theory. Finally, for the uplink MIMO communication of interleaved and generalized subcarrier allocation with high frequency diversity gain, numerical simulation and pool experiments are carried out under different multipath extended channels to verify the performance of the proposed method.

Compared with the results of other channel estimation studies in MIMO uplink communication, the differences in this paper are as follows: 1) Using the sparse characteristics of massive channels, using CS-based channel estimation algorithm to overcome the error generated by traditional interpolation methods under a small number of non-uniform pilots. Ping ping phenomenon; 2) According to the principle of minimization of measurement matrix cross-correlation in CS theory, a joint optimization algorithm based on random search for pilot pattern and pilot power is proposed, which is better than the method based on pilot pattern optimization.

2. Massivemimo Uplink Communication Channel Estimation

2.1 System Model

Consider a massiveMIMO uplink communication system with U users. The total number of system subcarriers is K, and user u allocates Ku non-overlapping subcarriers, satisfying$\sum_{u=1}^{U} K_u = K$. Let GFDM symbol period be T, Cyclic prefix (Cyclic Prefix, CP) the length is T_{cp}, the subcarrier spacing is 1/T. The system carrier frequency is fc, then the k[th] subcarrier frequency $f_k = f_c + \frac{k}{T}, k = -\frac{K}{2}, \dots, \frac{K}{2} - 1$. The definition $d_u[k]$ is the coded information symbol transmitted by the user u on the k^{th} subcarrier, and the symbol mapping manner thereof may be QPSK or 16QAM,etc.

$$x_u(t) = \mathrm{Re}\{\sum_{k \in S_u} d_u[k] \exp(j2\pi f_k t)\}, t \in [0, T] \quad (1)$$

Su is a set of subcarrier indices of user u, including data subcarrier index set S_u^D and comb pilot index set $S_u^P, S_u = S_u^D \cup S_u^P$.

Considering the linear time-invariant massive multipath channel model in a CP-OFDM block, the channel impulse response of user u to the receiving end can be expressed as

$$h_u(\tau) = \sum_{p=1}^{N_{p,u}} A_{p,u} \delta(\tau - \tau_{p,u}) \quad (2)$$

Where $N_{p,u}$ is number of multipaths of u users; $A_{p,u}$ is the attenuation coefficient of a constant path p in a CP-OFDM block; $\tau_{p,u}$ is the delay corresponding to path p. Assume that the cyclic prefix T_{cp} is greater than the channel maximum, the sum of multipath delay and the maximum access time difference between users, the uplink MIMO is a quasi-time synchronization system, and the signals of each user reaching the receiving end is

$$y(t) = \sum_{u=1}^{U} \sum_{p=1}^{N_{p,u}} A_{p,u} x_u(t - \tau_{p,u}) + w(t) \quad (3)$$

Where w(t) is additive noise, the user subcarriers of the quasi-synchronous uplink MIMO system are orthogonal, so the received signals can be taken out and processed separately after DFT conversion. Substituting (1) into (3), after removing the cyclic prefix and undergoing DFT transformation, the frequency domain baseband received vector z_u of user u is obtained as

$$z_u = H_u d_u + v \quad (4)$$

where z_u and d_u respectively represents the K-dimensional receiving and transmitting vectors formed by the subcarriers of u users, and the subcarrier positions outside the index set S_u is set to zero. v is the frequency domain additive noise vector. The frequency domain channel matrix H_u is $K \times K$-dimensional diagonal array, regardless of the subcarrier interference caused by channel timing or synchronization error

$$H_u = \sum_{p=1}^{N_{p,u}} A_{p,u} \Lambda_{p,u} \quad (5)$$

where $\Lambda_{p,u}$ is a diagonal matrix, and the diagonal elements are satisfied.

$$[\Lambda_{p,u}]_{m,m} = \exp(-j2\pi\tau_{p,u}m/T) \quad (6)$$

2.2 Sparse Channel Estimation on Compressed Sensing

In order to overcome the problem of small number of user pilots and uneven distribution in MIMO uplink communication, in this paper compressed sensing is used to implement channel estimation. By establishing a measurement matrix containing enough path delay samples, using CS theory to estimate sparse path Delay $\tau_{p,u}$ and the non-zero attenuation coefficient of path $A_{p,u}$, define the path delay parameter set $\left\{\frac{T}{\lambda K}, \frac{2T}{\lambda K}, \dots, \frac{N_\tau T}{\lambda K}\right\}$, Its time resolution is $\frac{T}{\lambda K}$, which is $\frac{1}{\lambda}$ of the baseband sampling rate, λ is the time oversampling factor, and N_τ is the maximum search range of delay [10]. According to the delay parameter set and (6), a measurement matrix of $K \times N_\tau$ dimension is constructed

$$A = [\Lambda_{1,u}d_u, \Lambda_{2,u}d_u, \dots, \Lambda_{N_\tau,u}d_u] \quad (7)$$

Let the column vector in A is $a_j = \Lambda_{j,u}d_u, j = 1, 2, \dots, N_\tau$. The non-zero elements in the vector d_u are the comb pilots of the user u in the corresponding index set S_u^P, and the rest of elements are placed Zero. Define the path attenuation coefficient vector corresponding to the delay parameter set

$$x_A = [\xi_{1,u}, \xi_{2,u}, \dots, \xi_{N_\tau,u}]^T \quad (8)$$

where x_A is a sparse vector with a small number of non-zero elements. A new channel estimation model is obtained.

$$z_u = Ax_A + v \quad (9)$$

(9) is a mathematical model that satisfies CS theory, i.e., reconstructing the N_τ dimensional sparse vector x_A from the observation vector z_u , where A is a known measurement matrix. When the known number of pilots is less than N_τ, the solution vector x_A is an underdetermined problem. If the number of non-zero elements in the sparse vector x_A is much smaller thanN_τ; and the measurement matrix A satisfies the restricted isometric Property (RIP) [16], the sparse vector can be accurately recovered. The sparse signal reconstruction algorithm mainly includes base tracking algorithm and matching tracking algorithm. The matching tracking algorithm can recover highly sparse signals quickly and effectively, and the calculation amount is lower than that of the base tracking algorithm, which is more suitable for real-time processing systems [17]. Therefore, in this paper the matching pursuit algorithm is used to perform sparse channel estimation.

The following is a brief introduction to the channel estimation process based on the matching pursuit algorithm by the model (9) [18, 19].

1. Algorithm initialization, number of iterations $q = 0$, residual vector $r_0 = z_u$, index set $I_0 = \Phi$, q^{th}iteration, $q \geq 1$;
2. Determine the best matching index:
$$s_q = \arg \underbrace{\max}_{j=1,\dots,N_\tau, j\notin I_{q-1}} \frac{|a_j^H r_{q-1}|^2}{\|a_j\|_2^2} \ ;$$
3. Update index set: $I_q = \{I_{q-1}, s_q\}$;
4. Calculate non-zero estimation coefficients:$\hat{x}_q = \frac{|a_{s_q}^H r_{q-1}|}{\|a_{s_q}\|_2^2}$;
5. Update residual vectors: $r_q = r_{q-1} - \hat{x}_q a_{s_q}$.

The symbol $\|.\|_2$ represents the L_2 norm of the vector, and the superscript H represents the conjugate transpose of the vector. Repeat step 2-5 until the residual vector L_2 norm is less than the noise threshold to be iteratively terminated. At this time, the final index set I_q can determine the multipath delay estimation value, and the non-zero coefficient $\hat{x}_q$ corresponds to the multipath attenuation coefficient. Then the channel frequency response estimation can be obtained by (5).

2.3 Pilot Optimization Design

In this paper, the pilot optimization design is carried out under the CS theory framework. The sparse signal reconstruction theorem under the noisy model is given in [20]. According to the formula (9), the frequency domain noise vector $\|v\|_2 \leq \varepsilon$. The problem of solving the sparse vector x_A under conditions can be described as

$$\underbrace{\min}_{x_A} \|x_A\|_0 \quad s.t \ \ \|z_u - Ax_A\|_2 \leq \delta$$
(10)

where $\|.\|_0$ represents the L_0 norm of the vector, $\delta \geq \varepsilon$. Defines the cross-correlation of the measurement matrix A

$$M = M(A) = \underbrace{\max}_{1\leq m,n\leq N_\tau, m\neq n} \frac{|a_m^H a_n|}{\|a_m\|_2 \|a_n\|_2} \quad (11)$$

If the sparse signal $x_A$is satisfied (meets)

$$\|x_A\|_0 = N < (1/M + 1)/2, \quad (12)$$

where N is the number of non-zero elements in the sparse signal x_A. Then the approximate solution $\hat{x}_A$ of x_A obtained from the noisy observation signal zu is satisfied.

$$\|\hat{x}_A - x_A\|_2 \leq \Theta_0.(\varepsilon + \delta), \ \ \forall\, \delta \geq \varepsilon > \ 0, \quad (13)$$

which defines the stability coefficient$\Theta_0 = \frac{1}{(1-M(2N-1))}$. From (13), it can be seen that the upper limit of the estimation error of the sparse signal is related to the stability coefficient Θ_0 and the observed signal noise. The cross-correlation M of the signal sparsity N and the measurement matrix is determined. If the cross-correlation M is reduced by rationally designing the measurement matrix, the upper limit of the estimation error of the sparse signal will be greatly reduced.

Substituting (6) and (7) into (11), the measurement matrix cross-correlation of the MIMO uplink communication user u under the CS channel estimation model is obtained.

$$M = M(A) = \underbrace{\max}_{1\le m,n\le N_\tau, m\ne n} \frac{\left|\sum_{k\in S_u^P} |d_u[k]|^2 \exp\left(\frac{j2\pi(m-n)k}{\lambda K}\right)\right|}{\sum_{k\in S_u^P} |d_u[k]|^2}$$
(14)

In practical applications, the multipath delay search range Nr and the oversampling factor that determines the delay resolution can be selected as the fixed value. According to (14), the cross correlation M of the measurement matrix is only composed of the pilot pattern index set. S_u^P and pilot power set Pu are determined. By properly designing the pilot pattern and pilot power, the measurement matrix cross correlation can be reduced, and the channel estimation error can be reduced. Therefore, MIMO uplink communication Pilot optimization problems can be translated into the following objective functions

$$\underbrace{\min}_{S_u^P, P_u} M(A) = \underbrace{\min}_{S_u^P, P_u} M(S_u^P, P_u) \quad (15)$$

(15) is a complex two-dimensional optimization problem. Let user u place KP in Ku available subcarriers; u comb pilots. When pilot power is determined, CKP still needs to be searched; $C_{K_u}^{K_{P,u}} = \frac{K_u!}{K_{P,u}!(K_u - K_{P,u})!}$ The combination of the global optimal solution of the pilot pattern can be obtained, and the calculation is too high to be realized. Therefore, the joint optimization of pilot pattern and pilot power based on random search is proposed. The algorithm randomly selects a set of pilot patterns and pilot powers in the set of subcarrier indices and the set of candidate pilot powers, repeats the steps within a given number of searches, and finally localizes the objective function (15). The optimal solution is used as an optimization scheme for the pilot pattern and pilot power. The pilot pattern and pilot power joint optimization algorithm are described in detail below.

The generalized subcarriers in MIMO uplink communication are more flexible, and may be concentrated in some frequency bands or scattered in a few distant frequencies. In order to overcome the frequency fading effect of the massive channel, the comb should be guaranteed as much as possible. The probabilities of pilots are scattered throughout the user subcarrier set. Therefore, the user subcarrier index is sorted and equally divided into multiple index subsets, and the index is selected in each subset to form a pilot pattern, which improves the frequency diversity gain. At the same time, the search range is narrowed down. The detailed steps of the pilot pattern and pilot power joint optimization algorithm are given below.

1) Initialize the subcarrier index set Su of user u in ascending order and divide it into KP; u index subsets as much as possible; Set the alternative pilot power set $P_u^0 = \{P_1, P_2, \dots, P_Q\}$ set size $Q > 1$, and the mean of the elements in the collection is 1.
i-th search, $i \ge 1$;
2) The pilot pattern is selected by randomly selecting an index value in the $K_{P,u}$ index subsets to generate a pilot pattern index set $S_u^{P,i}$ of the user u, and storing.
3) The pilot power is selected from the candidate set $P_u^0 = \{P_1, P_2, \dots, P_Q\}$ randomly selects $K_{P,u}$ elements (the same element can be repeatedly selected), and the pilot power set of user u is obtained $P_u^i = \{|d_u[k]|^2\}, k \in S_u^{P,i}$, and store.
4) According to the i-th randomly selected pilot pattern $S_u^{P,i}$ and the pilot power P_u^i, the measurement matrix cross-correlation $M(S_u^{P,i}, P_u^i)$ is calculated by (14).
5) Repeat steps 2) - 4) until the $M(S_u^{P,i}, P_u^i)$ value converges, or the number of cycles exceeds the preset value to stop the search. Select f arg min $f = \arg\min_{i=1,2,\dots} M(S_u^{P,i}, P_u^i)$ in the search range, obtain the corresponding optimal pilot pattern index set $S_u^{P,f}$ and pilot power set $P_u^f = \{|d_u[k]|^2\}, k \in S_u^{P,f}$.

Omitting step 3), setting the pilot power of the user to 1, can realize the method based solely on pilot pattern optimization, which is called "pilot optimization method one" in this paper; joint optimization algorithm of pilot pattern and pilot power It is called “Pilot Optimization Method 2”. Literature [21, 22] implements pilot pattern optimization in cognitive radio systems based on the principle of measurement matrix cross-correlation minimization, assuming all pilot powers are the same. 14) It can be seen that the pilot power also affects the cross-correlation size, and by changing the pilot power, the “Pilot Optimization Method 2” is lower than the “Pilot Optimization Method 1” cross-correlation M under the same number of searches, the channel estimation error is Smaller. This paper will verify this conclusion in Simulation results.

3. Simulation Results

In order to verify the robustness of the algorithm, two different multipath extended Massive MIMO sparse channels are randomly generated for simulation. The channel 1 path number is 7, and the adjacent path delay difference satisfies the exponential distribution with a mean of 2 ms, and the average multipath time The delay spread is 14 ms, and the multipath amplitude obeys the Rayleigh distribution with a negative exponential decay of the average power delay [10]; the channel 2 path number is 11, the statistical law of the delay difference and amplitude is the same as that of channel 1, and the average multipath time The delay spread is increased to 22 ms. The noise is additive Gaussian noise in the signal passband. Without loss of generality, assuming that the number of massiveMIMO uplink communication access users is 2, a comb pilot auxiliary channel is inserted in the user subcarrier set. It is estimated that the subcarriers adopt QPSK mapping, and the low-complexity single-tap zero-forcing equalizer is used to implement frequency domain channel equalization. Other parameters are shown in Table 1. The time oversampling factor in CS channel estimation is 16, and the channel estimation is more Path delay resolution $\frac{T}{\lambda K} = 0\ 0156$ ms, multipath search range Nr floor(Tcp/0 0156)=1923

Defining the channel frequency domain response estimation mean square error

$$\mathrm{MSE} = 10\log\left(\frac{\mathrm{E}\left[\sum_{k\in S_u^D}\left|H[k]-\hat{H}[k]\right|^2\right]}{\mathrm{E}\left[\sum_{k\in S_u^D}\left|H[k]\right|^2\right]}\right) \quad (16)$$

Where H[k] and $\widehat{H}[k]$ are the channel frequency response values and estimated values on the kth subcarrier, respectively.

3.1 Performance Analysis of Different Pilot Optimization Schemes

Firstly, the convergence performance of the pilot optimization method 1 and method 2 is compared. Both optimization methods search for the pilot pattern in the interlaced allocated subcarrier set. All the pilot powers of the optimization method 1 are set to 1. To reduce the transmission and reception sides. The required pilot storage space, the alternative pilot power set of optimization method 2 is set to a binary set P0 u f1/2; 3/2g. Figure 1 shows two pilot optimization algorithms under different search times, 15) The comparison result of the objective function values obtained by the equation. It can be seen from Fig. 1 that by jointly optimizing the pilot pattern and the pilot power, the objective function value of the pilot optimization method 2 under the same search times is significantly lower than the optimization method. First, a better pilot transmission scheme can be obtained.

The performance of the CS channel estimation method under the Least Squares (LS) algorithm and the different pilot schemes in the interleaved subcarrier allocation MIMO uplink communication is as follows. The upper limit of the number of loops in the pilot optimization method 1 and method 2 is set. 2000. The traditional interpolation channel estimation performs optimally under uniform pilot. Therefore, the simulation only compares the performance of the LS channel estimation algorithm based on frequency domain linear interpolation under uniform pilot. Figure 2 shows the uniform pilot under simulation channel 1. LS channel estimation method, uniform pilot CS channel estimation method, and channel frequency response estimation mean square error comparison based on pilot optimization method 1 and method 2 CS channel estimation method.

It can be seen from Figure 2 that the performance of the CS channel estimation algorithm under the three pilot insertion modes is significantly better than that of the LS channel estimation algorithm. Compared with the CS channel estimation with uniform pilot insertion, both pilot optimization methods are further reduced. The channel estimation mean square error, in which the pilot optimization method 2 is about 2 dB lower than the estimation error of the first method under the same search times, and has the best estimation performance. The subsequent simulation and pool experiments all use method 2 as the pilot optimization. method.

3.2 Channel estimation performance analysis under different multipath delay spread

The performance of the CS channel estimation and pilot optimization method for interleaving subcarrier allocation uplink MIMO communication is verified under different multipath delay spreads. Figure 3 shows the CS based on uniform pilot and pilot optimization under simulated channel 1 and channel 2. Channel frequency response estimation mean square error comparison.

It can be seen from Table 1 that the number of comb pilots per user of MIMO uplink communication is 52, and the system baseband sampling rate is K/T=4000 Hz. Under the baseband sampling rate, the length of the simulated channel 1 is 56 points, and the length of channel 2 is 88 points. The length under the baseband sampling rate is approximately equal to the number of pilots. Therefore, the channel estimation error of the uniform pilot and pilot optimization algorithms in channel 1 in Figure 3 is approximately linearly decreasing with the increase of the SNR, and the pilot optimization algorithm is in the signal-to-noise. When the ratio is higher than 15 dB, the estimation error of the uniform pilot algorithm is lower than 4 dB. The length of channel 2 is 1.7 times of the pilot number. Therefore, the uniform pilot CS channel estimation error in Figure 3 is greatly increased, and the optimized pilot algorithm is on the channel. The estimation error under 2 is only about 3 dB lower than channel 1. It shows that the CS channel estimation of the optimized pilot scheme can reconstruct the sparse channel impulse response more stably under a small number of pilots.

3.3 Performance Analysis of Channel Estimation for Interleaved and Generalized Subcarrier Allocation Systems

Figure 4 shows the channel-to-noise and generalized subcarrier allocation MIMO uplink communication under channel 1 and the channel frequency response estimation mean square error of different pilot allocation schemes. In the generalized subcarrier allocation system, the probability of two-user subcarriers is randomly distributed. In the communication band, the pilots are randomly distributed in the respective user subcarrier sets to compare the performance of the pilot optimization algorithm.

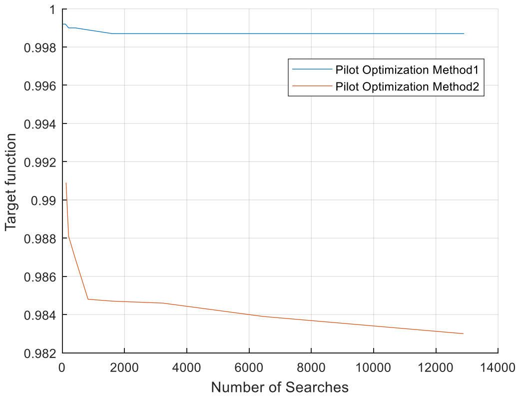

Fig. 1. Convergence comparison of two pilot optimization algorithms

Firstly, the simulation results of the four pilotless optimization algorithms in Fig. 4 are analyzed. The performance of the LS algorithm in the generalized system random pilot distribution is worse than that of the interleaved system with uniform pilot distribution, indicating the effect of non-uniform pilots. The channel estimation performance of the LS algorithm. Conversely, for the CS channel estimation algorithm, the generalized system random pilot channel estimation performance is better than the interleaved system uniform pilot channel estimation performance. The reason is that the generalized system pilots are randomly distributed in irregular users. Within the subcarrier set, the cross-correlation of the measurement matrix is smaller than that of the uniform pilot pattern, which is beneficial to the sparse signal reconstruction. The above results show that the CS channel estimation is more suitable for the communication system with non-uniform pilot distribution. Second, Figure 4 The pilot-optimized CS channel estimation algorithm obtains the minimum channel estimation error in both interleaved and generalized systems, indicating that the pilot estimation performance based on pilot optimization is not limited by the subcarrier allocation mode, and can be given at a given The channel estimation error is further reduced by optimizing the pilot within the user subcarrier set.

Figure 5 shows the results of the bit error rate comparison between different interleaved and generalized subcarrier allocation systems in channel 1. The channel less coding in the simulation. The LS channel of the random pilot distribution under the generalized subcarrier allocation. It is estimated that there is obvious error leveling phenomenon. The pilot-optimized CS channel estimation algorithm approximates the bit error rate curve under the known channel condition with high SNR in both subcarrier allocation modes.

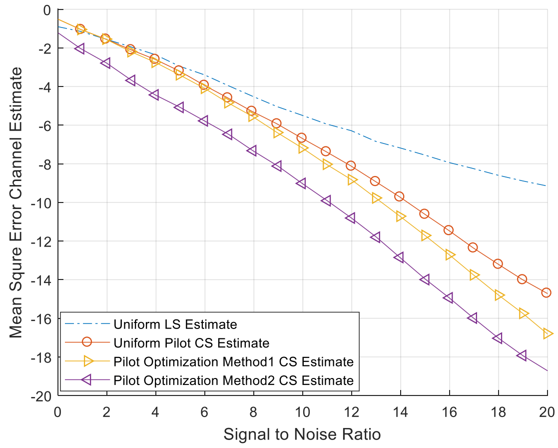

Fig. 2. Channel estimation performance comparison under different pilot insertion methods

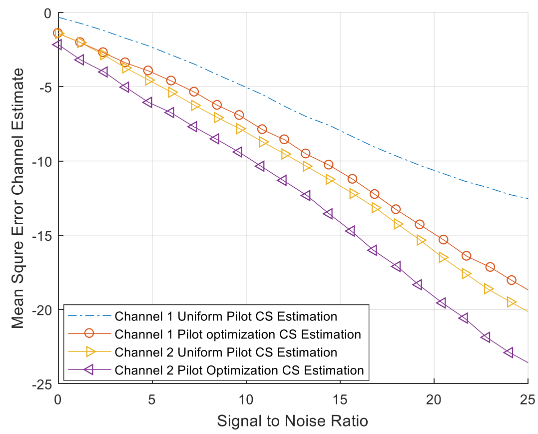

Fig. 3. Comparison of CS channel estimation performance between uniform pilot and pilot optimized under different multipath channels

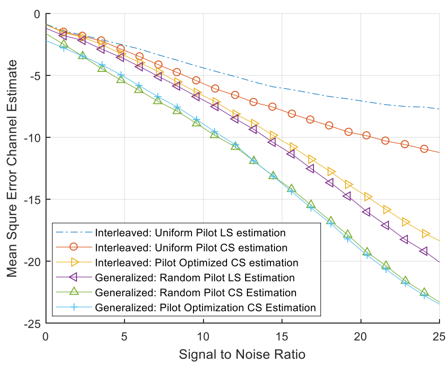

Fig. 4. Performance comparison of interleaved and generalized subcarrier allocation of MIMO uplink communication channel estimation methods

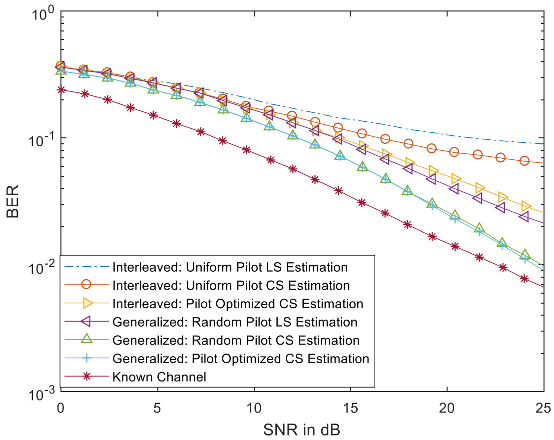

Fig. 5. Comparison of bit error rate under each channel estimation method of interleaved and generalized subcarrier allocation MIMO uplink communication

4 Conclusion

In this paper, in view of the problem that the traditional interpolation method in Massive MIMOMIMO upstream communication has a large interpolation error in a small amount and non-uniform conductivity, a sparse channel estimation and pilot optimization method are proposed. Based on the upstream communication application of Massive MIMOMIMO, a CS channel estimation model is established, and the sparse channel impulse response is reconstructed by matching tracking algorithm. According to the principle of measuring matrix intercorrelation minimization in CS theory, the frequency pattern and the frequency power joint optimization algorithm are proposed to further improve the estimated performance of CS channel. The simulation results show that the performance of the text-proposed method is superior to the traditional LS estimation and the CS estimation without the frequency optimization in different multi-path extension channels and different subcarrier distribution methods, and the convergence performance and channel estimation performance of the pilot pattern and the frequency power joint optimization algorithm are better than the optimization algorithm based solely on the pilot pattern. The upstream communication performance of MIMO is verified by pool experiments, and reliable communication between the two users is achieved using the pilot-optimized CS estimation. The performance of the method proposed in this paper is not limited by the subcarrier distribution method, which provides a stable and feasible channel estimation scheme for the upstream communication of Massive MIMOMIMO.

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