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Iterative Joint Detection and Channel Estimation Algorithm for Large-scale MIMO System

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Abstract

Large-scale Multiple-Input Multiple-Output (MIMO) can promise high spectrum efficiency and low multi-user interference. But the pilot contamination of the uplink channel estimation is the obstacle to acquire the great performance gains. A novel iterative joint channel estimation and detection algorithm is proposed. First, the initial channel information is estimated with the uplink pilots. Then the receiver detects the receiving signals with Match Filter (MF) precoding and Minimum Mean Square Error (MMSE) criterion based on the initial channel estimation. The receiving signal acquires the great large-scale MIMO detection gains and is more lightly interfered than the multiplexed uplink pilots because of the non-coherence of the transmitted data. Thus, it is in turn applied to suppress the pilot contamination in the channel estimation. In the iteration, the updated channel estimation is used for the data detection in the next loop. The theoretical analysis shows that the interference items in the detected signals and the channel estimation are continually decreased with the number of the iteration increasing. At last, the numerical results prove that, the proposed algorithm has significant performance gains comparing with the conventional algorithms. After only one iteration in light pilot contamination cases and three iteration in severe pilot contamination cases, it can obtain the detected data and the channel estimation information with the required performance. The proposed algorithm effectively improves the detection performance and suppress the pilot contamination of the uplink channel estimation, and can be worthy for the large-scale MIMO system.

Keywords*: Large-scale MIMO, Channel estimation, Data detection, Pilot contamination*

1. Introduction

LARGE-SCALE MIMO (Massive MIMO) has emerged as an attractive technique which can dramatically increase the capacity and robustness of the fifth generation wireless communication system. Given perfect channel state information (CSI), the received signals of every antenna can be combined coherently, and the array gain ascends linearly with the increment of the number of antenna elements at the Base Station (BS). Moreover, the large dimension channels of different users are asymptotically orthogonal and the multi-user interference is expected to be finally vanished in Large-scale MIMO system [1]. However, in practice, such benefits may be difficult to acquire for that the BS can't acquire perfect channel state information [1-2]. This is especially severe when the non-orthogonal or same training sequences used in adjacent cells for uplink training, which is named as the pilot contamination.

The channel estimation algorithms have been extensively investigated and some approaches have been proved effective in suppressing and even eliminating the pilot contamination [3-13]. In Reference [3], a Bayesian estimation approach was presented. It was shown to offer a powerful way of mitigating the pilot contamination by enabling the pilot assignment coordination among the adjacent cells. The coordination approach made

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use of the additional second-order statistical information of the user channels, thus needed to exchange mass interfering channel information among multiple cells. Ref. [4] proposed the blind channel estimation derived from the eigenvalue decomposition of the received signals. This approach exploited the asymptotic orthogonality of large-scale MIMO channel. But the orthogonality was not guaranteed in any environment nor with arbitrary antenna number. In Ref. [5], the conventional channel estimation was corrected by the partially decoded data with the prior data information. The cross-contamination in the channel estimation was caused by the transmitted signals from other users, and was finally suppressed in data-aided channel estimation because the data part of every frame was typically less coherent than the pilot part in a practical system. On the other hand, the self-contamination was caused by the dependency between the channel estimation and the estimation error, and was also suppressed by four or more iterations of data-aided channel estimation. But the data detection wasn't completely designed. Ref. [6] exploited the Space-Alternating Generalized Expectation-maximization (SAGE) iterative process to iteratively estimate the channel information. It focused to reduce the complexity and mitigate the pilot contamination. Unfortunately, the data detection wasn't be completely designed in Ref. [5] and [6]. Above all, the large-scale MIMO processing gains are not fully utilized in the above mentioned algorithms.

In this paper, a novel iterations algorithm is proposed by the joint optimization of the channel estimation and the data detection. The detection of receiving signals combines MF receiving precoding and MMSE detection to acquire the large-scale MIMO array gains, thus the detected data acquires better detection performance. Moreover it is more lightly interfered than the multiplexed pilots because the transmitted data from different users is non-coherent. For those reasons, the detected data is in turn applied to suppress the pilot contamination in the channel estimation. After only one iteration in high SNR cases and three iteration in low SNR cases, the proposed algorithm can obtain the detected data and the channel estimation information with the required performance, so that it can effectively reduce the complexity of mitigating the impact of the pilot contamination in contrast with [5] and [6]. Finally, the simulation results prove that the proposed algorithm has significant performance gain than that of the tradition algorithms with respect to the channel estimation and data detection.

Notations: we use bold font variables to denote vectors and matrices, C denote the complex number field, $(.)^H$ denote the conjugate transpose and $(.)^{-1}$ denote the inverse operation. $E\{.\}$ and $||a||_F$ stand for the expectation and two-norm, respectively.

2. System Model

Consider a multi-cell MIMO system with L time-synchronized cells. Each cell includes one single-antenna user and one base station with M antennas. Let the average transmitting power of each user equipment be p_r. $\boldsymbol{H}_{jl}$ denotes the propagation channel information from the base station of j-th cell to the user of the l-th cell and $\boldsymbol{H}_{jl} = \sqrt{\beta_{jl}}\boldsymbol{h}_{jl}$, $j,l = 1,2\cdots L$, dimensioned $M \times 1$. Where β_{jl} represents the large-scale fading coefficient which accounts for path-loss and shadowing fading. Furthermore, $\boldsymbol{h}_{jl}$ is the fast fading factor which is the complex Gaussian vector following independent identical distribution (i.i.d.) and $CN(0,1)$.

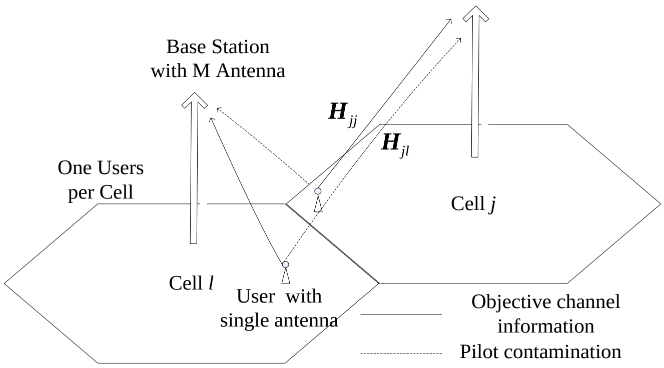

Figure 1. Uplink System Model of Large-Scale MIMO

To investigate the impact of the pilot contamination, the same uplink pilot sequences are reused by all cells. Let $\boldsymbol{x}$ be the pilot signals transmitted by all users, which is a row vector with τ length and $\boldsymbol{x}\boldsymbol{x}^{\mathrm{H}} = \tau$. In the uplink training phase as shown in Figure 1, all the users synchronously transmit the same pilot sequence to their serving BSs, then the signal received at the base station of j-th cell can be expressed as:

$$\boldsymbol{R}_j = \sqrt{p_r}\boldsymbol{H}_{jj}\boldsymbol{x} + \sqrt{p_r}\sum_{l=1,l\neq j}^{L}\boldsymbol{H}_{jl}\boldsymbol{x} + \boldsymbol{n} \tag{1}$$

Where, $\mathbf{R}_j \in C^{M\times\tau}$ denotes the received signal of the base station of j-th cell, and $\boldsymbol{n} \in C^{M\times\tau}$ are the additive noises which are the complex-Gaussian random variables with independent and identically distributed (*i.i.d.*) zero-mean and unit-variance, $\mathcal{CN}(0,1)$.

3. Iterative Algorithm with Joint Channel Estimation and Detection

In this section, we present an iterative joint channel estimation and detection algorithm that the detected data is used to update the channel estimation. The uplink transmission signals are divided into several blocks as shown in Figure 2. Each block contains the pilot and data symbols. The length of pilot symbols and the data symbols is τ and κ, respectively. Assume that every block experiences the same channel fading.

τ Pilots	κ Data	....	τ Pilots	κ Data

Figure 2. The Structure of Each Block

3.1. Initial Channel Estimation

Given $\boldsymbol{R}_j$ as Eq. (1), the LS channel estimation of the channel $\boldsymbol{H}_{jj}$ is:

$$\hat{\boldsymbol{H}}_{jj} = \frac{\boldsymbol{R}_j\boldsymbol{x}^H}{\sqrt{p_r}} = \boldsymbol{H}_{jj} + \sum_{l=1,l\neq j}^{L}\boldsymbol{H}_{jl} + \frac{\boldsymbol{n}\boldsymbol{x}^H}{\sqrt{p_r}} \tag{2}$$

As shown in Eq. (2), the estimated channel information contains not only the desired channel but also the pilot contamination $\sum_{l=1,l\neq j}^{L}\boldsymbol{H}_{jl}$ and the noise. So the traditional LS channel estimation suffers from significant estimation errors due to the interference of non-orthogonal uplink pilots transmitted by the adjacent cells.

3.2. Receiving Precoding for Received Data Signals

For the transmission of the uplink data, the received data signals at the base station of j-th cell can be written as:

$$\boldsymbol{y}_j = \sqrt{p_r}\boldsymbol{H}_{jj}\boldsymbol{S}_j + \sqrt{p_r}\sum_{l=1,l\neq j}^{L}\boldsymbol{H}_{jl}\boldsymbol{S}_l + \boldsymbol{n}_1 \tag{3}$$

Where, $\boldsymbol{S}_j \in C^{1\times\kappa}, j = 1\cdots L$ are the data symbols transmitted by the user with $\boldsymbol{S}_j\boldsymbol{S}_j^{\;H} = \kappa$. $\boldsymbol{n}_1 \in C^{M\times\kappa}$ denotes the Gaussian white noise with $\boldsymbol{n}_1^H\boldsymbol{n}_1 = \sigma_n^2\boldsymbol{I}_\kappa$ and $\boldsymbol{y}_j \in C^{M\times\kappa}$ is the received signals at j -th cell.

To acquire the large-scale MIMO array gains, the received signals in the target cell are uplink receiving pre-coded with MF algorithm. So let the $1\times M$ receiving pre-coding matrix of cell j be $\boldsymbol{u}_j^{(1)} = \hat{\boldsymbol{H}}_{jj}^H$ and the upper-lift corner (1) of $\boldsymbol{u}_j^{(1)}$ denotes the first detection. Then the receiving pre-coded signals $\boldsymbol{Y}_j^{(1)} \in C^{1\times\kappa}$ in the first detection are expressed as:

$$\boldsymbol{Y}_j^{(1)} = \boldsymbol{u}_j^{(1)}\boldsymbol{y}_j = \boldsymbol{u}_j^{(1)}(\sqrt{p_r}\boldsymbol{H}_{jj}\boldsymbol{S}_j + \sqrt{p_r}\sum_{l=1,l\neq j}^{L}\boldsymbol{H}_{jl}\boldsymbol{S}_l + \boldsymbol{n}_1) \tag{4}$$

The fast channel information from different users is statistically independent, and the noise $\boldsymbol{n}_1$ is also independent of the channel impulse response $\boldsymbol{H}_{jj}$. With the number of antenna increasing, the following results can be derived on the large number theorem:

$$\lim_{M->\infty}\frac{\boldsymbol{H}_{jj}^H\boldsymbol{H}_{jl}}{\beta_l\boldsymbol{M}} \overset{a.s.}{=} \delta_{jl}, \lim_{M->\infty}\boldsymbol{H}_{jj}^H\boldsymbol{n}_1 \overset{a.s.}{=} \mathbf{0}, \lim_{M->\infty}\mathbf{n}^{\boldsymbol{H}}\boldsymbol{n}_1 \overset{a.s.}{=} \mathbf{0}$$

Substitute $\boldsymbol{u}_j^{(1)} = \hat{\boldsymbol{H}}_{jj}^H$ and input the above-mentioned results into Eq. (4), $\boldsymbol{Y}_j^{(1)}$ can be deduced to the following expression:

$$\boldsymbol{Y}_j^{(1)} \overset{a.s.}{=} \lim_{M->\infty}\boldsymbol{Y}_j^{(1)} = \sqrt{p_r}\boldsymbol{M}(\beta_j\boldsymbol{S}_j + \sum_{l=1,l\neq j}^{L}\beta_l\boldsymbol{S}_l) \tag{5}$$

Further, Eq. (5) can be normalized in the vector $\overline{\boldsymbol{Y}}_j^{(1)}$:

$$\overline{\boldsymbol{Y}}_j^{(1)} = \frac{\boldsymbol{Y}_j^{(1)}}{\sqrt{p_r}M\beta_j} = \boldsymbol{S}_j + \sum_{l=1,l\neq j}^{L}\frac{\beta_l}{\beta_j}\boldsymbol{S}_l = \boldsymbol{S}_j + \mathbf{P}_1 \tag{6}$$

3.3. Data Detection

The desired data $\boldsymbol{S}_j$ could be detected from Eq. (6) on the MMSE criterion as following:

$$\hat{\boldsymbol{S}}_j^{(1)} = \boldsymbol{A}^{(1)}\overline{\boldsymbol{Y}}_j^{(1)} \tag{7}$$

Where, $\hat{\boldsymbol{S}}_j^{(1)}$ is the detected signals in the first detection and the number (1) of the upper-lift corner denotes the index of the detection. $\boldsymbol{A}^{(1)}$ is the weighting vector satisfying MMSE criterion that the mean square error is minimum, and could be expressed as following:

$$\boldsymbol{A}^{(1)} = \mathrm{argminE}\left\{\| \hat{\boldsymbol{S}}_j^{(1)} - \boldsymbol{S}_j \|_F^2\right\} = \mathrm{argminE}\left\{\| A^{(1)}\overline{\boldsymbol{Y}}_j^{(1)} - \boldsymbol{S}_j \|_F^2\right\} \tag{8}$$

Base on the mean value theorem of differential, the mean square error reaches minimum when its partial derivative with respect to $A^{(1)}$ is equal to zero. That is, the following formula is established:

$$\frac{\partial \mathrm{E}\left\{\| \mathbf{A}^{(1)}\overline{\mathbf{Y}}_j^{(1)} - \boldsymbol{S}_j \|_F^2\right\}}{\partial \mathbf{A}^{(1)}} = \frac{\partial \mathrm{E}\left\{\mathbf{A}^{(1)}\overline{\mathbf{Y}}_j^{(1)}\left(\mathbf{A}^{(1)}\overline{\mathbf{Y}}_j^{(1)}\right)^H - \mathbf{A}^{(1)}\overline{\mathbf{Y}}_j^{(1)}\boldsymbol{S}_j^H - \boldsymbol{S}_j\left(\mathbf{A}^{(1)}\overline{\mathbf{Y}}_j^{(1)}\right)^H + \boldsymbol{S}_j\boldsymbol{S}_j^H\right\}}{\partial \mathbf{A}^{(1)}} = 0$$

Through the derivation, we have:

$$\mathbf{A}^{(1)} = E\left[(\boldsymbol{S}_j\boldsymbol{S}_j^H + \boldsymbol{S}_j\mathbf{P}_1{}^H)(\boldsymbol{S}_j\boldsymbol{S}_j^H + \boldsymbol{S}_j\mathbf{P}_1{}^H + \mathbf{P}_1\boldsymbol{S}_j^H + \mathbf{P}_1\mathbf{P}_1{}^H)^{-1}\right]$$

On the other hand, when κ is much greater than 1, we can assume the data symbols transmitted from different users are i.i.d, and the data and noise are independent.

We have $\mathrm{E}\{\boldsymbol{S}_j^H\boldsymbol{S}_l\} = \delta_{jl}\mathbf{I}_\kappa, \mathrm{E}[\boldsymbol{S}_j\boldsymbol{n}_1] = \boldsymbol{0}, \mathrm{E}\{\boldsymbol{S}_l^H\boldsymbol{S}_j\} = \delta_{jl}$, So $\mathbf{A}^{(1)}$ could be reformed into the vector as following:

$$\boldsymbol{A}^{(1)} \overset{a.s.}{=} E\left[\boldsymbol{S}_j\boldsymbol{S}_j^H(\boldsymbol{S}_j\boldsymbol{S}_j^H + \sum_{l=1,l\neq j}^{L}(\frac{\beta_l}{\beta_j})^2\boldsymbol{S}_l\boldsymbol{S}_l^H)^{-1}\right] = \frac{1}{1+\sum_{l=1,l\neq j}^{L}(\frac{\beta_l}{\beta_j})^2} \tag{9}$$

Combing the results in Eq. (6) and Eq. (9), we arrive:

$$\hat{\boldsymbol{S}}_j^{(1)} = \boldsymbol{A}^{(1)}\overline{\mathbf{Y}}_j^{(1)} = \frac{1}{1+\sum_{l=1,l\neq j}^{L}(\frac{\beta_l}{\beta_j})^2}\frac{\mathbf{Y}_j^{(1)}}{\sqrt{p_r}M\beta_j} \tag{10}$$

3.4. Update the Uplink Channel Estimation Information with Detection Data $\hat{S}_j^{(1)}$

In practice the detected data acquires Large-scale MIMO processing and MMSE detection gains, and its performance is greatly improved. Moreover the data is less polluted than uplink pilots by the interfering cell because the data transmitted by different cells are independent. If the detected data symbols are used as the known transmitting signals to update the uplink channel estimation information, not only the channel estimation quality could be improved but also the pilot contamination could be suppressed. The channel estimation is calculated on the received signals $\boldsymbol{y}_j$ and the detected data signals $\hat{\boldsymbol{S}}_j^{(1)}$ as following:

$$\overline{\boldsymbol{H}}_{jj}^{(1)} = \frac{\boldsymbol{y}_j(\hat{\boldsymbol{S}}_j^{(1)})^H}{\sqrt{p_r}\kappa} \overset{a.s.}{=} \frac{1}{1+\sum_{l=1,l\neq j}^{L}(\frac{\beta_l}{\beta_j})^2}\left(\boldsymbol{H}_{jj} + \sum_{l=1,l\neq j}^{L}\frac{\beta_l}{\beta_j}\boldsymbol{H}_{jl}\right) \tag{11}$$

Further, simply the updated channel estimation as following:

$$\widetilde{\boldsymbol{H}}_{jj}^{(1)} = \frac{\overline{\boldsymbol{H}}_{jj}^{(1)}}{\left\|\overline{\boldsymbol{H}}_{jj}^{(1)}\right\|} = \boldsymbol{H}_{jj} + \sum_{l=1,l\neq j}^{L}\frac{\beta_l}{\beta_j}\boldsymbol{H}_{jl} \tag{12}$$

After the first iteration, the pilot contamination $\sum_{l=1,l\neq j}^{L}\frac{\beta_l}{\beta_j}\boldsymbol{H}_{jl}$ in Eq.(12) is less than $\sum_{l=1,l\neq j}^{L}\boldsymbol{H}_{jl}$ in (2) since the large-scale fading coefficient β_j of the target cell is larger than β_l of the interfering cells, So the channel estimation aided by the detected data will mitigate the pilot contamination of the traditional channel estimation approach.

When the pilot contamination is light, the large-scale fading rate β_l / β_j is much less than 1.Thus the pollution of Eq.(12) can be greatly reduced and its impact on the system performance would be negligible. When the contamination is severe, the pollution of Eq.(12) is approximately equal to LS channel estimation since the large-scale fading rate β_l / β_j is approximately equal to 1. Thus the impact of pilot contamination imposes a significant estimation error on desired channel estimation. To further suppress the pilot contamination in Eq.(12), the following iterative method is introduced.

3.5. Iterative Joint Detection and Channel Estimation Algorithm

The main idea of the iterative joint detection and channel estimation algorithm is introduced as following and shown in Figure. 3.

Step 1: Based on LS channel estimation algorithm, the initial channel estimation is performed on pilot symbols of each block as described in 3.1.

Step 2: Then the received signals are precoded by the MIMO receiver with Matched filter, whose weighting vectors are calculated based on the uplink channel estimation of the last step.

Step 3: Further, the desired data of the target cell is detected with MMSE detector from MF filtered signals.

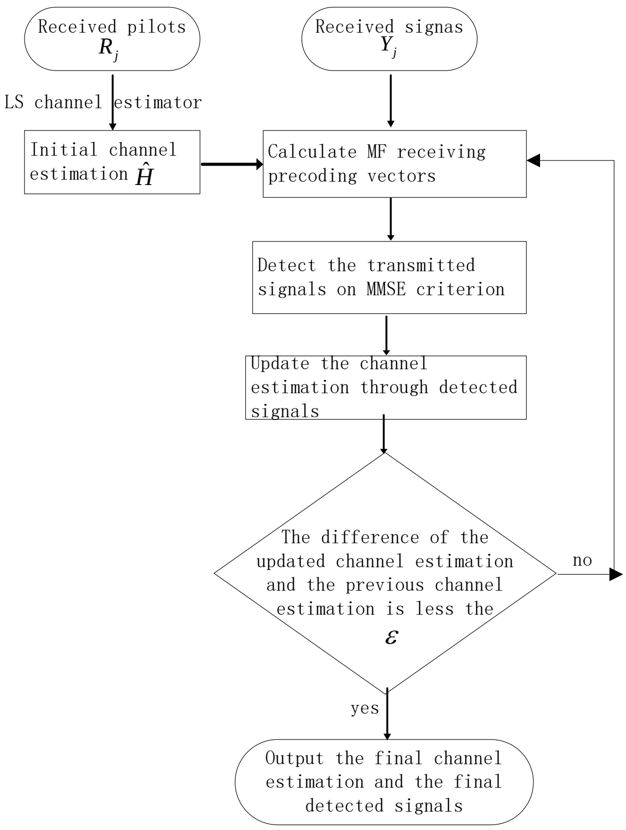

Figure 3. Iterative Channel Estimation Aided with Detected Data

Step 4: The detected data is used as the known signals to update the uplink channel information.

Step 5: Continual iteration can suppress the pilot contamination of the channel estimation further, and its approach and the performance analysis are explained as the following.

Described as step 2, we calculate the receiving precoding matrix based on the channel information acquired in the first loop in the second loop, $\boldsymbol{u}_j^{(2)} = (\widetilde{\boldsymbol{H}}_{jj}^{(1)})^H$. The BS will use $\boldsymbol{u}_j^{(2)}$ to multiply the received signal $\boldsymbol{y}_j$ as in Eq.(4). Then, repeat the deducing approach of the above Eq.(4) to Eq.(12) to detect the desired data and update the channel estimation. At the second iteration, the receiving precoded signals is deduced as Eq.(5):

$$\boldsymbol{Y}_j^{(2)} = \boldsymbol{u}_j^{(2)}\mathbf{y}_j \overset{a.s.}{=} \sqrt{p_r}\boldsymbol{M}(\beta_j \boldsymbol{S}_j + \frac{\beta_l}{\beta_j}\sum_{l=1,l\neq j}^{L}\beta_l \boldsymbol{S}_l) \tag{13}$$

The interference item of the precoded signals in Eq.(13) could be remarkable reduced compared with Eq.(5). The interfering item $\sum_{l=1,l\neq j}^{L}\frac{\beta_l}{\beta_j}\boldsymbol{H}_{jl}$ of the previous channel estimation $\widetilde{\boldsymbol{H}}_{jj}^{(1)}$ is decreased and the precoding matrix is more accurate. Further, the normalized receiving precoding signals can be denoted as following:

$$\overline{\boldsymbol{Y}}_j^{(2)} = \frac{\boldsymbol{Y}_j^{(2)}}{\sqrt{p_r}M\beta_j} = \boldsymbol{S}_j + \sum_{l=1,l\neq j}^{L}\left(\frac{\beta_l}{\beta_j}\right)^2 \boldsymbol{S}_l = \boldsymbol{S}_j + P_2 \tag{14}$$

Similarly, to satisfying MMSE criterion, the partial derivative of the mean square error with respect to $\mathbf{A}^{(2)}$ is zero.

$$\frac{\partial \mathrm{E}\left\{\| A\overline{\boldsymbol{Y}}_j^{(2)} - \boldsymbol{S}_j \|_F^2\right\}}{\partial \mathbf{A}^{(2)}} = 0$$

With the independence characteristic of the transmitted data, $\mathbf{A}^{(2)}$ could be derived to the vector as Eq. (9):

$$\mathbf{A}^{(2)} = E\left[(\boldsymbol{S}_j\boldsymbol{S}_j^H + \boldsymbol{S}_j P_2^H)(\boldsymbol{S}_j\boldsymbol{S}_j^H + \boldsymbol{S}_j P_2^H + P_2\boldsymbol{S}_j^H + P_2P_2^H)^{-1}\right] = \frac{1}{1+\sum_{l=1,l\neq j}^{L}(\frac{\beta_l}{\beta_j})^4} \tag{15}$$

$$\hat{\boldsymbol{S}}_j^{(2)} = A^{(2)}\overline{\boldsymbol{Y}}_j^{(2)} = \frac{1}{1+\sum_{l=1,l\neq j}^{L}(\frac{\beta_l}{\beta_j})^4}\frac{\boldsymbol{Y}_j^{(2)}}{\sqrt{p_r}M\beta_j} \tag{16}$$

$$\widetilde{\boldsymbol{H}}_{jj}^{(2)} = \frac{\boldsymbol{y}_j(\hat{\boldsymbol{S}}_j^{(2)})^H}{\left\|\boldsymbol{y}_j(\hat{\boldsymbol{S}}_j^{(2)})^H\right\|} \overset{a.s.}{=} \boldsymbol{H}_{jj} + \sum_{l=1,l\neq j}^{L}(\frac{\beta_l}{\beta_j})^2\boldsymbol{H}_{jl} \tag{17}$$

Observing the above expression, we can notice that the value of the interference term in the second iteration is the square of β_l/β_j that is much less than the interference term β_l/β_j in the first iteration. Note that even in the severe pilot contamination the large-scale fading rate β_l/β_j is less than 1, otherwise this user will trigger the handover to the interfering cell. Above all, we find that the interference term is the square of β_l/β_j whose power index is same with the cycle index.

Repeat the above steps Eq. (4) - (12) , it follows the same law at the n-th iteration:

$$\hat{\boldsymbol{S}}_j^{(n)} = A^{(n)}\overline{\boldsymbol{Y}}_j^{(n)} = \frac{1}{1+\sum_{l=1,l\neq j}^{L}(\frac{\beta_l}{\beta_j})^{2n}}\frac{\boldsymbol{Y}_j^{(n)}}{\sqrt{p_r}M\beta_j} \tag{18}$$

$$\widetilde{\boldsymbol{H}}_{jj}^{(n)} \overset{a.s.}{=} \boldsymbol{H}_{jj} + \sum_{l=1,l\neq j}^{L} (\frac{\beta_l}{\beta_j})^n \boldsymbol{H}_{jl}\ , \quad \text{as} \quad M->\infty \tag{19}$$

In Eq.(19), the interference term is the n-th power of β_l / β_j whose power index is same with the cycle index. With the iterative number n constantly increasing, the pollution term in Eq. (18) and Eq. (19) is effectively decreased and the effect of the pilot contamination almost vanishes. When the difference of the updated channel estimation $\widetilde{\boldsymbol{H}}_{jj}^{(n)}$ and the previous channel estimation $\widetilde{\boldsymbol{H}}_{jj}^{(n\text{-}1)}$ is less than the predefined small value ε, the loop is ended and the updated channel estimation $\widetilde{\boldsymbol{H}}_{jj}^{(n)}$ is applied for downlink precoding. Through multiple iterations of the data detection and channel estimation, it can be proved that even in the scenario of the severe pilot contamination the pollution term of the data detection and the channel estimation could be successfully suppressed eventually.

4. Numerical Results

To demonstrate the conclusion of above analysis, we run several simulations in a basic multi-cell Massive MIMO system. The simulation parameters are shown in Table 1. To show the impact of the pilot contamination, three cells are configured the same uplink pilots with one cell as the target cell and the other cell as the interfering cell causing the pilot contamination. The severity of the pilot contamination is controlled by the large-scale fading coefficient of the target cell and the interfering cell, respectively. The structure of the data and pilots is shown as in Figure 2. The length of data and pilots will be explained in each simulation. The quality of the channel estimation is measured by the mean square error (MSE) of channel estimation.

Table 1. Simulation Parameters

Simulation parameters	Values
Multicell Massive MIMO system	Three cells with same uplink pilots
Number of antenna	Base Station: 100 antenna (the antenna spacing:0.5λ, the uniform planar array with 10 rows and 10 columns); User Equipment: single antenna
Large-scale fading coefficient	Ideal scenario without the pilot contamination: $\beta_j = 1, \beta_i = 1$ Light pilot contamination scenario: $\beta_j = 0.8, \beta_j = 0.1$ Severe pilot contamination scenario: $\beta_j = 0.6$, $\beta_j = 0.2$
Channel model	Complex Gaussian channel with independent identical distribution (i.i.d.) and $CN(0,1)$, dimensioned 100×1.
Transmission power	Uplink transmitting power $p_r = 0dB$
Modulation and coding scheme	QPSK, 1/2 Convolutional Codes
Channel estimation	LS channel estimation or the proposed algorithm
Simulation Frames	10000 Frames

Figure 4 describes the large scale fading coefficients of target cell and interfering cell are 0.8 and 0.1, respectively, the Bit Error Rate(BER) curve are evaluated with the different numbers of iterative times. Where, the range of SNR is -11dB to -1dB, the number of iterations is 1, 2 and 3 times, the length of the pilot and data are 10 and 200, respectively. From the Figure 4, we found that when the base station executes once iteration, the BER decreases with the increasing of SNR and is reduced to zero as the SNR greater than -4dB; when the base station execute twice iteration, we notice that the BER decreases significantly and reduced to zero when SNR is greater than - 6dB; when the base station execute the thrice iterations, the BER continues to decline and is close to zero when the SNR greater than -7dB. Therefore, the proposed iterative algorithm can effectively improve the detection performance and quickly acquire the detection data with the desired performance.

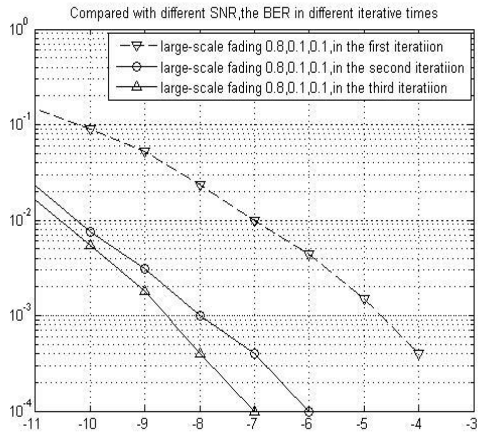

Figure 4. SNR versus BER with Different Iteration Number

In Figure 5, BER VS SNR curve is evaluated with different large-scale fading coefficients. Where, the range of SNR is -11dB to -1dB, and the iterative number are three times. The large-scale fading coefficients of the target cell and inter-cells are set with 1 and 0, 0.8 and 0.1, 0.6 and 0.2, and the length of the pilot and data are 10 and 200, respectively. From the Figure 5, we found that when the large-scale fading coefficient of the target cell is greater than the interfering cell, then the lower BER in data detection. Wherein, when the large-scale fading coefficients between the target cell and interfering cells are 0.6 and 0.2, then at -5dB or more the desired data is detected completely correct, at this time, the signal is mainly affected by noise pollution and the pilot pollution; when the large-scale fading coefficients between the target cell and interfering cells are 0.8 and 0.1, then at -7dB or more the desired data is detected completely correct, at this time, the signal is mainly affected by noise pollution and the pilot pollution; when the large-scale fading coefficients between the target cell and interfering cells are 1 and 0, then at -8dB or more the desired data is detected completely correct, at this time, the signal is mainly affected by noise pollution

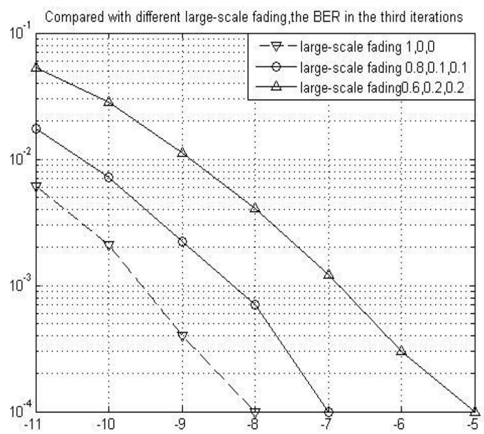

Figure 5. BER versus SNR with Different Large-Scale Fading Coefficient

Figure 6 shows the MSE performance of the proposed algorithm and LS channel estimation as a function of SNR under different values of large-scale fading coefficients. In this simulation, the data length κ is 100bits and the length of pilots τ is 20bits. When $\beta_j = 1$ and $\beta_l = 0$, it is the ideal scenario without the pilot contamination. The proposed approach has better MSE performance than LS channel estimation because the detected data in turn correct the initial channel estimation. When $\beta_j = 0.8$ and $\beta_l = 0.1$, it is the light pilot contamination scenario. LS channel estimation is obviously impacted while MSE of the proposed approach is still close to 0.002. From Figure 6, we can clearly observe in this scenario that the proposed algorithm has better performance gains over LS channel estimation. When $\beta_j = 0.6$ and $\beta_l = 0.2$, it is the scenario with the severe pilot contamination. MSE of LS channel estimation keeps above 0.7, the channel estimation error can't be neglected and shall severely degrade the system performance; MSE of the proposed algorithm is close to 0.006, it means the channel estimation error would not severely degrade the performance gains of Massive MIMO system. Luckily, the number of the data detection and channel estimation loop is only one to achieve the above-mentioned performance in the light pilot contamination scenario. The number of loops needs three times in the severe pilot contamination scenario.

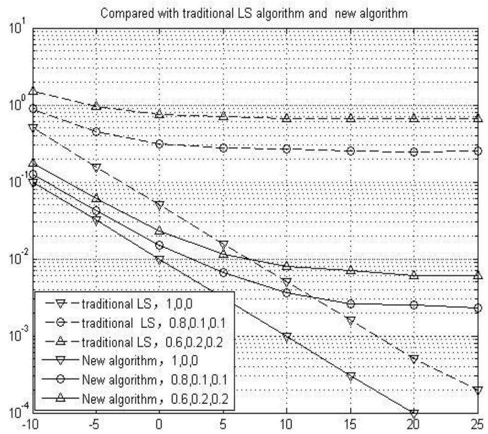

Figure 6. MSE versus SNR with Different Large-Scale Fading Coefficients

Figure 7 shows the MSE performance of our proposed algorithm as a function of SNR under with different data length κ. The length of pilots τ is always 10. In theory, the longer the data is, the more non-coherent the data is and the better the pilot contamination is suppressed by the independence of the longer data. Our simulation results prove the same trends. When the pilot contamination is light, the performance that the data length is 500bits is better 10dB than that the data length is 100bits. When the pilot contamination is severe, the performance that the data length is 500bits has the significant performance gains over that the data length is 100bits.

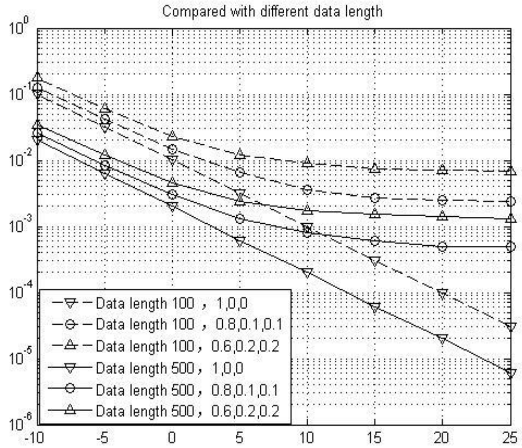

Figure 7. MSE versus SNR with Different Data Length

5. Conclusion

We analyzed the performance of the iterative joint channel estimation and detection algorithm in the multi-cell large-scale antenna system. We showed that the detected signals acquired the large-scale MIMO detection gains through combining Match Filter (MF) precoder and MMSE detection. Because the detected signals attained good detection performance and was less interfered than uplink pilots for the independence characteristic of the data transmitted, it was used as the known signals to update the channel estimation. Both analysis and simulation show that, with the number of the iteration increasing, the pilot contamination was gradually suppressed by the iteration of channel estimation, moreover the detection performance was obviously improved. After only one iteration in light pilot contamination cases and three iteration in severe pilot contamination cases, the proposed algorithm can obtain the detected data and the channel estimation information with the required performance. Thus it reduced the number of iteration and the complexity in contrast with other iterative algorithm.

Future work will consider the iterative joint channel estimation and detection algorithm in coherent large-scale MIMO channel. The new investigation will refresh the derivation of this algorithm and have more extensive application value.

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