An Adaptive K-nearest-neighbor Interference Alignment Algorithm Based on Minimizing Projection in Cellular System

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Abstract. For the disadvantages that the high computational complexity and the heavy overheads of the system when interference alignment is applied to the cellular system for co-channel interference cancellation, this paper proposed an adaptive K-nearest-neighbor interference alignment algorithm based on minimizing projection. This algorithm adaptively prechooses interference according to the threshold of signal-to-interference ratio(SIR) and uses the optimal method to minimize the projection of the interference casting to signal subspace, which can obtain the precoding vector only at the transmitter and align the prechosen interference to the interference subspace, thus the computational complexity of interference alignment could be greatly decreased. Simulation results show that, at the threshold of SIR of 15dB, the proposed algorithm can get a performance as well as the existing methods when the number of antennas can meet the demands, and the performance can be much better than the existing ones when the number of antennas couldn't meet the demands.

Introduction

In modern wireless communication networks, with the sharp increase of mobile users, the resource of frequency spectrum becomes nervous. Factor-one frequency reuse deployment of cellular networks could efficiently release the tension of frequency resource, but it would introduce much more co-channel interference, which becomes a major obstacle to the improvement of communication quality. Interference alignment (IA)[1][2][3] is a new method of interference cancellation, which could align the interference in a low dimensional subspace of the receiver and remain the none-interference subspace for the useful signal by uniting the transmitters to design the precoding vectors. The unique advantages of high system capacity and system degree make IA been the focus of researchers in the field of interference cancellation.

To improve the practical application of IA and solve the contradiction of system capacity and the shortage of frequency spectrum, lots of researches have been done by researchers around the world. Reference [4] provides an interference alignment technique for a downlink cellular system which can decrease the feedback of the system, but it's too complex to achieve. Reference [5] and [6] try to combine the interference alignment technique to the large MIMO-OFDM system, and show that IA could improve the system throughput, but there exists the problems of high computational complexity and system overheads. To decrease the complexity when IA applied to large cellular network, a clustered IA technique is proposed in reference [7] and [8], and further researches on clustering technique are done in reference [9], but the technique doesn't work well when there is too many cells in a cluster. Reference [10] proposes an IA technique in multi-cell cooperative systems based on Poisson point process, and shows that there exists a optimal number of cooperative stations to get the maximum system capacity, but doesn't know the exact value. To obtain the precoding vector, most methods are based on the iterative algorithms[12], such as minimum interference leakage (Min-IL) and maximum SINR (Max-SINR), but the channel should be reciprocal. So, it is of significant to find a method to decrease the high computational complexity and system overheads.

Aimed at the problems mentioned above, based on the existing clustered model, this paper proposed an adaptive K-nearest-neighbor IA algorithm (AK-IA) based on minimizing projection. By setting the threshold of SIR and minimizing the projection the interference casted to the signal subspace, the algorithm could adaptively choose K strongest interference and obtain the precoding vector at the transmitter only. As the number of interference to be aligned is decreased, the proposed algorithm could decline the computational complexity and the system overheads, and it can also be used in the situation when the number of antennas can't meet the demands.

System Model

Our research is based on the clustered model as shown in Fig. 1. In the model, each cluster consists of N cells. Factor-one frequency reuse is deployed in each cell. Thus the entire cluster can be equivalent to the interference channel model consists of N transmitter and receiver pairs.
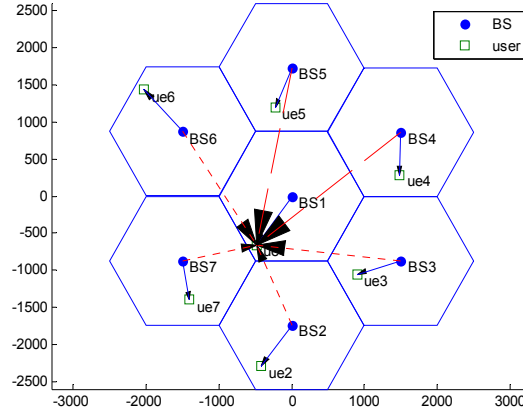

Fig. 1 Adaptive K-nearest-neighbor Model

To be easy, taking cell 1 as an example, the user ue1 in the cell 1 can receive the useful signal (the solid line in Fig. 1) of its own cell BS (Base Station) BS1 and the interference signals (the dot line and broken line in Fig. 1) of other cell BSs simultaneously. Assuming that all the BS equipped with N_t transmitting antennas, transmits d data streams with the power of P, the user terminal equipped with N_r receive antennas. Thus, the receive signal of a user in cell i can be expressed as

$$
\begin{aligned}
\boldsymbol{y}_i &= \sum_{j=1}^{N} \sqrt{\gamma_{ij}} \boldsymbol{H}_{ij} \boldsymbol{V}_j \boldsymbol{x}_j + \boldsymbol{n}_i \\
&= \sqrt{\gamma_{ii}} \boldsymbol{H}_{ii} \boldsymbol{V}_i \boldsymbol{x}_i + \sum_{j=1, j \neq i}^{N} \sqrt{\gamma_{ij}} \boldsymbol{H}_{ij} \boldsymbol{V}_j \boldsymbol{x}_j + \boldsymbol{n}_i
\end{aligned}
\tag{1}
$$

where, the first part of the Eq. represents the useful signal, and the second part represents the interference signals. is the $d \times 1$ signal vector transmitted by BS j, $\boldsymbol{V}_j$ is the $N_t \times d$ pre-coding vector at BS j, γ_{ij} is the pass loss from BS j to user i, $\boldsymbol{H}_{ij}$ is the $N_r \times N_t$ channel coefficients between BS j and user i, its elements obey the zero mean unit variance complex Gaussian ($CN(0,1)$), $\boldsymbol{n}_i$ is the additive white Gaussian noise (AWGN) at user i.

However, based on the clustered model, with the increase of the number of the cells in the cluster, the number of interference signals need to be aligned will increase greatly, which would lead to high computational complexity and system overheads. In practical communication systems, the transmitted signals arrive at a certain user usually have quite different power levels due to distance-dependent path-loss. Note that the achievable rate is affected mainly by the strong interference and is quite insensitive to the weak interference[9]. Thus, an appropriate judging criterion should be introduced to select strong interference while ignoring the weaker ones, which may decrease the computational complexity and system overheads.

In this paper, we use the criterion based on the threshold of SIR to select the interference for IA and call the selected interference valid interference (the dot line in Fig. 1) and the remaining interference invalid interference (the broken line in Fig. 1). Assuming that the threshold of SIR is T_{th},

united by dB, the receiving signal power level transmitted by BS j at user i is P_{ij}, united by dBm, α_{ij} represents the interference from BS j to user i is valid or not, then

$$\alpha_{ij} = \begin{cases} 1 & P_{ii} - P_{ij} \leq T_{th} \\ 0 & else \end{cases}, j \neq i \tag{2}$$

As each BS has the same transmitting power and $P_{ij} = P - L_{ij}$, the Eq. (2) can be equivalent as

$$\alpha_{ij} = \begin{cases} 1 & L_{ij} - L_{ii} \leq T_{th} \\ 0 & else \end{cases}, j \neq i \tag{3}$$

where, $L_{ij} = -10\lg(\gamma_{ij})$ represents the pass-loss from BS j to user i, the cells of which the interference is valid to user i form a set Ω_i, and the number of cells in Ω_i is K_i. As K_i is different in each cell and could adaptively change adjust to the threshold of SIR, we call this model adaptive K-nearest-neighbor model. Based on this model, the signal at user i can be expressed as

$$
\begin{aligned}
y_i &= \sum_{j=1}^{N} \alpha_{ij} \sqrt{\gamma_{ij}} H_{ij} V_j x_j + n_i \\
&= \alpha_{ii} \sqrt{\gamma_{ii}} H_{ii} V_i x_i + \sum_{j=1, j \neq i}^{N} \alpha_{ij} \sqrt{\gamma_{ij}} H_{ij} V_j x_j + n_i
\end{aligned}
\tag{4}
$$

The second part in Eq. (4) is the valid interference. Using $\bar{H}_{ij} = \alpha_{ij} H_{ij}$ as the equivalent channel coefficients, then Eq. (4) can be rewritten as

$$
\begin{aligned}
y_i &= \sum_{j=1}^{N} \sqrt{\gamma_{ij}} \bar{H}_{ij} V_j x_j + n_i \\
&= \sqrt{\gamma_{ii}} \bar{H}_{ii} V_i x_i + \sum_{j=1, j \neq i}^{N} \sqrt{\gamma_{ij}} \bar{H}_{ij} V_j x_j + n_i
\end{aligned}
\tag{5}
$$

Adaptive K-nearest-neighbor IA Algorithm

Building the United IA Equation

As for IA, all the interference signals should be aligned in a very small subspace at the receiver, thus enough subspace could be remained for the useful signal. Therefore, for user i,

$$\text{span}(H_{i1}V_1) = \cdots = \text{span}(H_{ij}V_j) = \cdots = \text{span}(H_{iN}V_N), \forall i, j = 1, 2 \cdots N, j \neq i \tag{6}$$

where, $\text{span}(x)$ represents the subspace spanned by vector x. To achieve IA, the number of antennas at the transmitter and receiver need to meet the following equation,

$$N_r + N_t \geq d(N+1) \tag{7}$$

Meanwhile, to guarantee that the interference after IA doesn't interfere the useful signal, the subspace of interference need to be orthogonal to the subspace of the useful signal, that is

$$\text{span}(H_{ii}V_i) \perp \text{span}(H_{ij}V_j), \forall i, j = 1, 2 \cdots N, j \neq i \tag{8}$$

Eq. (8) can be rewritten as

$$(H_{ii}V_i, H_{ij}V_j) = 0, \forall i, j = 1, 2 \cdots N, j \neq i \tag{9}$$

(α, β) represents the inner product of vector α and β. Then, all the interference is aligned to the orthogonal subspace of the useful signal, which keep the useful signal from interfering.

Taking cell 1 for example, the Eq. (9) can be rewritten as the following format

$$\begin{cases} (H_{11}V_1, H_{1j}V_j) = 0, & \forall j = 2, 3 \cdots N \\ (H_{i1}V_1, H_{ii}V_i) = 0, & \forall i = 2, 3 \cdots N \end{cases} \tag{10}$$

In Eq. (10), the first equation is the condition that all the interference is aligned the orthogonal subspace of the useful signal in cell 1; the second equation is the condition that the interference from cell 1 is aligned to the orthogonal subspace of useful signal in cell i. Therefore, it guarantee that each cell's useful signal will not be interfered by other cell's signal and also not interfere others.

According to the adaptive K-nearest-neighbor model established above, for any user i, to make all the valid interference aligned to the orthogonal subspace of useful signal, the IA condition is

$$(\bar{H}_{ii}V_i, \bar{H}_{ij}V_j) = 0, \quad \forall j \in \Omega_i \tag{11}$$

The Eq. (10) can be expressed as

$$(\bar{H}_{ii}V_i)^{\mathrm{H}}(\bar{H}_{ij}V_j) = 0, \quad \forall j \in \Omega_i \tag{12}$$

Assume I_i represents the IA matrix consisting of all the interference in user i, that is $I_i = \begin{bmatrix} \bar{H}_{i1}V_1 & \bar{H}_{i2}V_2 & \cdots & \bar{H}_{iN}V_N \end{bmatrix}$, then Eq. (12) can be rewritten as

$$(\bar{H}_{ii}V_i)^{\mathrm{H}} I_i = \mathbf{0} \tag{13}$$

Uniting all the cells, the united IA equation of the whole cluster can be gotten as follows

$$SI = \mathbf{0} \tag{14}$$

Where,

$$S = \mathrm{diag}(\bar{H}_{11}V_1, \bar{H}_{12}V_2, \cdots, \bar{H}_{1N}V_N) \tag{15}$$

$$I = [I_1^{\mathrm{T}}, I_2^{\mathrm{T}}, \cdots, I_N^{\mathrm{T}}]^{\mathrm{T}} \tag{16}$$

S represents the block diagonal matrix composed of all the useful signal, I represents the united interference matrix composed of all the interference signal.

Solving the IA Precoding Vector

When getting the precoding vector, the existing solutions, such as the distributed iterative algorithm and the Eigen-matrix method, need to iterate between the transmitter and the receiver and based on the reciprocal channel, which can be hardly used in time-varying, frequency-varying or frequency-selective channel. When the number of cells is large, the computational complexity and system overheads are too high. Although the clustered method in reference [7] and [8] can decrease the implementation complexity, it still couldn't be applied to the condition when the number of cells in a cluster is large. Based on the adaptive K-nearest-neighbor model established above, the precoding vector can be gotten at the transmitter without the reciprocal channel.

In order to make all the interference signal aligned to a small interference subspace, and approach the minimum interference of the interference signal to the useful signal, we use minimizing the whole leakage interference power method to get the least square solution of Eq. (14). When the interference couldn't be aligned exactly, it will cast a projection on the useful signal. Assume b_{ij} is the projection that the interference from BS j to user i casted to useful signal, it can be expressed as

$$b_{ij} = \frac{(\bar{H}_{ii}V_i)^{\mathrm{H}}(\bar{H}_{ij}V_j)}{\|\bar{H}_{ii}V_i\|}, \quad \forall j \in \Omega_i \tag{17}$$

In the Eq.17, $\|x\|$ represents the mode of the vector x. This projection is the leakage of the interference from BS j to user i when IA technique is used. The vector $V^* = [V_1^{*\mathrm{T}}, V_2^{*\mathrm{T}}, \cdots, V_N^{*\mathrm{T}}]^{\mathrm{T}}$ which makes the whole leakage interference power minimum is the least square solution of Eq. (14), that is

$$V^* = \arg\min_V \sum_{i=1}^N \sum_{j \in \Omega_i} \|b_{ij}\|^2 \tag{18}$$

Putting the Eq. (13) and Eq. (17) into Eq. (18), then

$$V^* = \arg\min_V \sum_{i=1}^N \left\| \frac{(\bar{H}_{ii}V_i)^{\mathrm{H}} I_i}{\|\bar{H}_{ii}V_i\|} \right\|^2$$

$$\arg\min_V \sum_{i=1}^N \frac{\left((\bar{H}_{ii}V_i)^{\mathrm{H}} I_i\right)\left((\bar{H}_{ii}V_i)^{\mathrm{H}} I_i\right)^{\mathrm{H}}}{(\bar{H}_{ii}V_i)^{\mathrm{H}}(\bar{H}_{ii}V_i)} \tag{19}$$

Therefore, the problem of getting the solution of Eq. (14) is equivalent to the optimization problem of minimizing the whole leakage interference power, as the following equation

$$\min \quad \sum_{i=1}^N \frac{\left((\bar{H}_{ii}V_i)^{\mathrm{H}} I_i\right)\left((\bar{H}_{ii}V_i)^{\mathrm{H}} I_i\right)^{\mathrm{H}}}{(\bar{H}_{ii}V_i)^{\mathrm{H}}(\bar{H}_{ii}V_i)} \tag{20}$$

$$s.t. \quad \|V_i\| = 1, i = 1, 2 \cdots N$$

In the Eq.(20), the constraint is to ensure the invariance of the transmitting power. As we can see, the Eq.(20) is a constrained optimization problem containing nonlinear equality constraint, the penalty function method can be used to solve this problem.Changing the constraints into some kind of penalty function and adding to the objective function, the constrained optimization problem can be changed into an unconstrained optimization problem, as follows

$$\psi(V,\sigma) = \sum_{i=1}^{N} \frac{\left((\bar{H}_{ii}V_i)^{\mathrm{H}} I_i\right)\left((\bar{H}_{ii}V_i)^{\mathrm{H}} I_i\right)^{\mathrm{H}}}{(\bar{H}_{ii}V_i)^{\mathrm{H}}(\bar{H}_{ii}V_i)} + \frac{\sigma}{2}\sum_{i=1}^{N}\left(V_i^{\mathrm{H}}V_i - 1\right)^2 \tag{21}$$

Combining the Lagrange function and the penalty function to structure the augmented Lagrange function as the subproblem at each step of iteration of the penalty function method,that is

$$\psi(V,\mu,\sigma) = \sum_{i=1}^{N} \frac{\left((\bar{H}_{ii}V_i)^{\mathrm{H}} I_i\right)\left((\bar{H}_{ii}V_i)^{\mathrm{H}} I_i\right)^{\mathrm{H}}}{(\bar{H}_{ii}V_i)^{\mathrm{H}}(\bar{H}_{ii}V_i)} - \sum_{i=1}^{N}\mu_i\left(V_i^{\mathrm{H}}V_i - 1\right) + \frac{\sigma}{2}\sum_{i=1}^{N}\left(V_i^{\mathrm{H}}V_i - 1\right)^2 \tag{22}$$

In the Eq.(22), $\mu = (\mu_1,\cdots,\mu_i,\cdots,\mu_N)^{\mathrm{T}}$ is the Lagrange multiplier, σ is the penalty factor. Updating the Lagrange multiplier and the penalty factor at each step and putting them to the Eq. (22) to obtain it's minimum value until the termination condition is satisfied, the final solution obtained is the optimal IA pre-coding vector $V^* = [V_1^{*\mathrm{T}}, V_2^{*\mathrm{T}}, \cdots, V_N^{*\mathrm{T}}]^{\mathrm{T}}$.

Steps of the Algorithm

In summary, the steps of this algorithm are as follows:

Step1 Clustering cellular network. For the criterion of minimizing the inter-cluster interference, use the existing clustering methods to cluster the cellular network to achieve the independence of inter-cluster interference.

Step2 Establishing the set of valid interference Ω_i. Set the threshold of SIR T_{th} according to the type and characteristics of network services, and establish the set of valid interference of each cell in the cluster referring to the Eq. (2) or (3) in this paper.

Step3 Building the united interference matrix I. Using the set of valid interference, build the interference matrix of each cell referring to Eq. (14), and then unite them to get the united interference matrix referring to Eq. (17).

Step4 Initializing the parameters. Setting the initial value of V, μ and σ.

Step5 Solving the sub-problem. Obtaining the minimum value point of $\min\psi(V,\mu,\sigma)$ according to the Eq. (22).

Step6 Checking the termination condition. If the termination condition is satisfied, out put the V as the final optimal IA pre-coding vector; else, update the Lagrange multiplier and the penalty factor, and skip to **step5**.

Analysis of the Algorithm Complexity

The complexity of the algorithm proposed in this paper is in the calculation of the leakage interference power in Eq. (22). Assume the total number of valid interference in the cluster is K, that is $K = \sum K_i$, then the united interference matrix I is a $NN_r \times (N-1)$ thin matrix. As I contains KN_r none zero elements and S contains NN_r none zero elements. Ignoring the low order term, the complexity of multiplication can be separately expressed as

$$W_{mult} = O((K+N)N_r^2 N_t) \tag{23}$$

We compare the calculation complexity of each step of the proposed algorithm with the Max-SINR IA[12] and the Min_IL IA[12], the comparison is shown as follows:

TABLE 1 Calculation Complexity Comparison

algorithm	Proposed IA
Max-SINR IA	$O(N^2 N_r^5 N_t)$
Min-IL IA	$O(N^2 N_r^3 N_t)$
Proposed IA	$O((K+N)N_r^2 N_t)$

As we can see, the complexity of the proposed algorithm is proportional to K. As the number of valid interference is usually much smaller than the total interference number, that is $K < N(N-1)$, and there is no need to get the eigenvalue of the matrix at each step, the proposed algorithm can decrease the complexity greatly.

Simulation Results and Analysis

To verify the performance of the proposed algorithm, this paper builds the cellular network environment, and use the leakage interference ratio(LIR) and system capacity of the user at the cell edge as the objective function of the simulation. The setting of the simulation parameters values are referred to the international standards and the related references[10][13], as shown in Table 2.

TABLE 2 System Simulation Parameters

Parameter	Description	Value
R	Cell radius(m)	1000
P	Transmitting power(dBm)	46
σ_n^2	Noise power(dBm)	-97.6
f_c	Carrier frequency(GHz)	2
L	Path loss(dB)	15.3+37.6lg(d), d:(m)
σ	Shadow fading(dB)	4
H	channel	Rayleigh fading channel
h	Channel coefficients	
D	Edge region(m)	666-1000
--	Antenna mode	Omni antenna

Feasibility Analysis

To verify the proposed algorithm, 50 Monte Carlo experiments are done separately for each case that the cell number is 3,7 or 19, the results shown in Fig. 2 and Fig. 3.
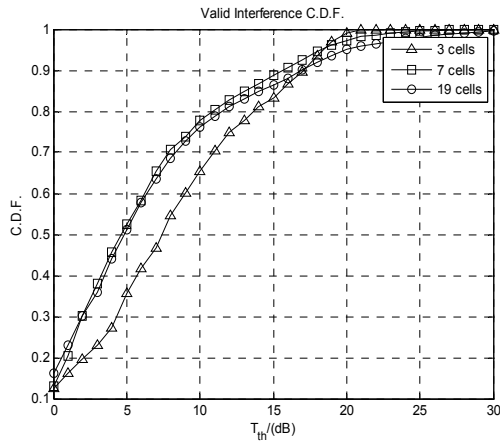

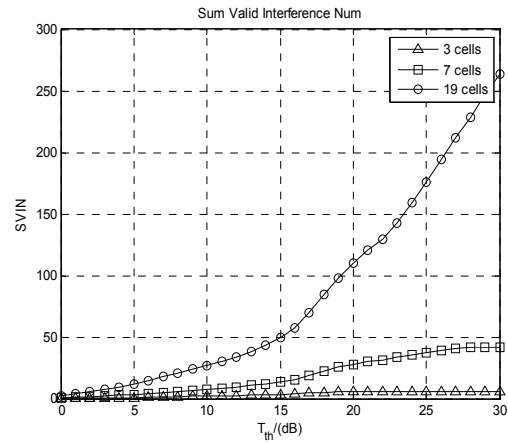Fig. 2 Valid Interference Energy Ratio

Fig. 3 Valid Interference Number

TABLE 3 Valid Interference Statistics at $T_{th} = 15dB$

Cell number	3	7	19
Total interference	6	42	342
Valid interference	3	14	50
Valid interference number ratio(%)	50	33.3	14.6
Valid interference energy ratio(%)	83.3	88.8	86.5

From the interference energy cumulative distribution function (C.D.F.) shown in Fig 2, most of the interference energy is distributed under $T_{th} = 15dB$. From Fig. 3, the number of valid interference increases rapidly when $T_{th} > 15dB$. The distribution statistics of the valid interference when $T_{th} = 15dB$ is shown in Table 3. From Table 3, when $T_{th} = 15dB$, by using the adaptive K-nearest-neighbor method, the chosen valid interference can contain most of the interference energy, and compared to

the existing method, the number of the required interference for IA is declined by more than 50%, which could reduce the computational complexity and system overheads greatly.

Performance Analysis

To analyze the performance of the proposed algorithm, 50 Monte Carlo experiments are done separately for each case that the cell number is 7 or 19. Meanwhile, to reflect the performance of different antenna configurations are simulated and compared with the desired value. The simulation results are shown in Fig. 4 to Fig. 7:
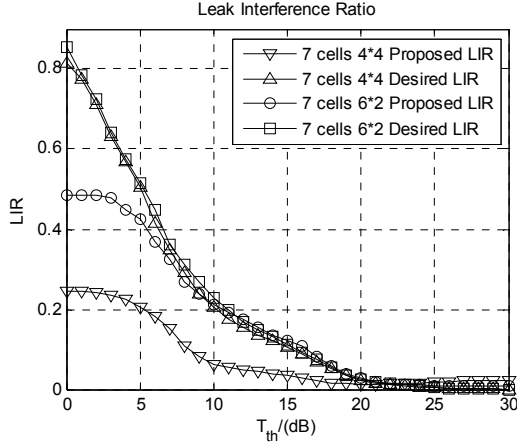
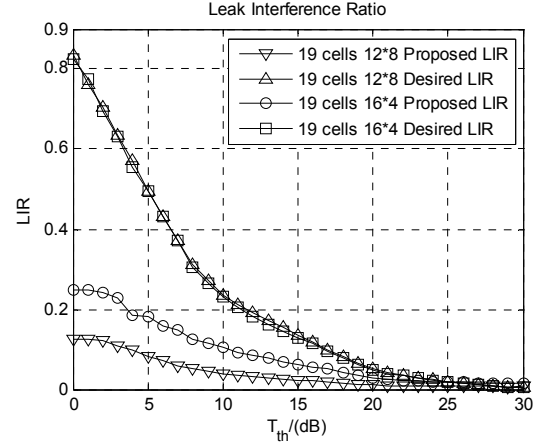Fig. 4 7 cells Leak Interference Ratio
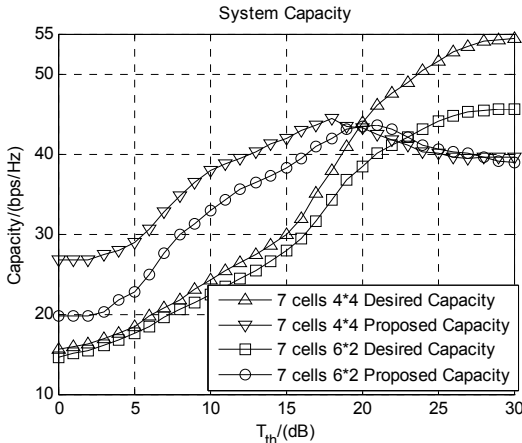
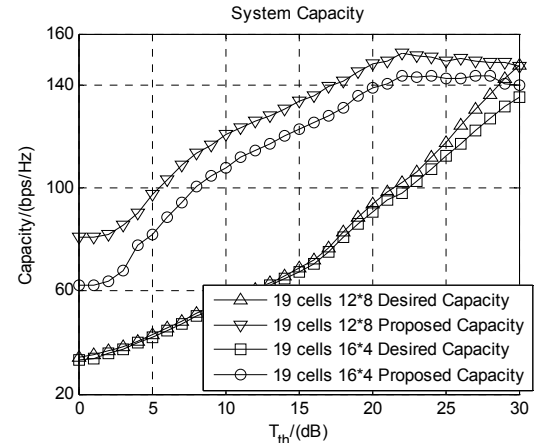Fig. 5 19 cells Leak Interference Ratio

Fig. 6 7 cells System Capacity

Fig. 7 19 cells System Capacity

Fig. 4 and 5 show that with T_{th} going higher the LIR becomes smaller. However with the increase of the threshold of SIR after $T_{th} = 15dB$, the LIR doesn't decreased much lower than that, that is because the majority of the interference energy has been aligned after the prechosen of the valid interference. Fig. 2 and 3 show that the number of the remaining interference is large, but the energy is low, of which the interference is not serious to the useful signal, but will bring a great increase in the computational complexity of the algorithm. This indicates that the proposed AK-IA can achieve a good performance of IA at a low complexity. Fig. 5 indicates that the proposed AK-IA can also be well applied to the cluster with a large number of users.

Fig. 6 and 7 show that the system capacity is increasing with the increase of T_{th}. When $T_{th} = 15dB$, the system capacity can increase more than 30% or even 100% compared to without IA($T_{th} = 0dB$). However, the system capacity doesn't increase much more higher after $T_{th} = 15dB$, that is because the majority of the interference energy has been aligned after the prechosen of the valid interference and though the number of the remaining interference is large, but the energy is low, which contributes little to the system capacity while bringing high computational complexity. Again, it indicates that the proposed AK-IA can achieve a good performance of IA at a low complexity. Fig. 7 also indicates that the proposed AK-IA can be well applied to the cluster with a large number of users.

In these figures, the proposed value is better than the desired value. That is because the desired is obtained according to the interference is valid or not, but some invalid interference is naturely in the orthogonal subspace, which leads to the interference is less than the desired. However, when the T_{th} is high, there exists too much valid interference, system needs to sacrifice some aligning performance to align the weak interference, which leads to the decrease of the whole performance. Therefore, it is significant to choose an appropriate threshold of SIR to obtain the optimal performance of IA.

We compare the performance of the proposed algorithm with the Max-SINR IA and the Min-IL IA. Taking 7 cells for example, separately, we use 6×2 and 4×2 antenna configuration and $T_{th} = 15dB$ to simulate the system capacity of the system. The results are shown in Fig. 8 and 9.
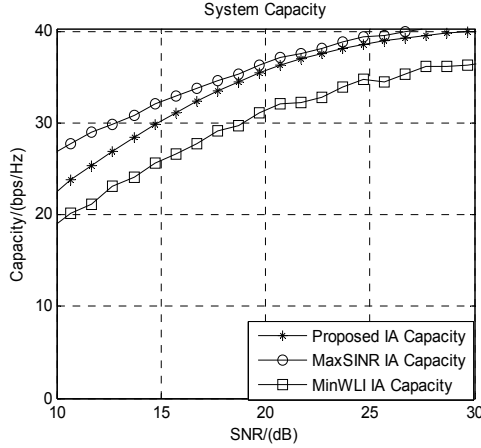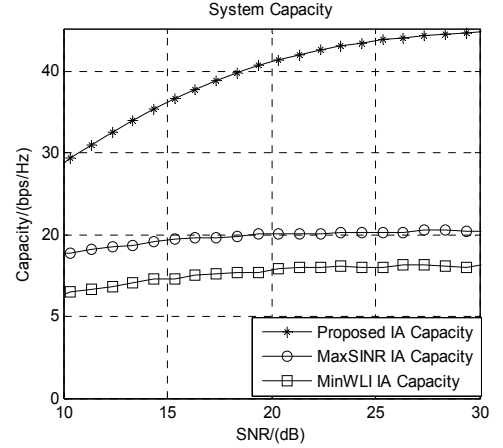

Fig. 8 6×2 Capacity Comparison

Fig. 9 4×2 Capacity Comparison

As shown Fig. 8, When the antenna configuration can meet the Eq. (7), that is $N_r + N_t \geq N + 1$, the proposed IA can obtain almost the same performance of Max-SINR IA. But in Fig. 9, when the antenna configuration can't meet the Eq. (7), that is $N_r + N_t < N + 1$, the performance of the proposed IA is much better than the Max-SINR IA. That's because the proposed IA eliminates the weak interference and mainly aligns the strong interference, which decreases the dimensions of subspace. Meanwhile, the proposed IA doesn't need iteration and the constraint of the reciprocal channel, which decreases the computational complexity. So the proposed IA can be well applied to the networks which have many cells but the number of antenna can't meet the Eq. (7).

Conclusion

Based on the clustered model, this paper proposed an adaptive K-nearest-neighbor interference alignment algorithm based on minimizing the projection. This algorithm could adaptively prechoose the interference according to the threshold of SIR and uses the optimal method to obtain the IA precoding vector at the transmitter, which could decrease the computational complexity. Simulation results show that by choosing an appropriate threshold of SIR, the proposed algorithm could obtain almost the same performance as the exist methods, but the computational complexity and the overheads could be greatly decreased. When the number of antennas can't meet the demands, the proposed performance can still be good and is better than the existing methods. Thus, the proposed algorithm can be applied to the system which has too many cells and the number of antennas can't meet the demands, which improved the applicability of interference alignment algorithm.

Acknowledgement

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