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Antenna selection based on large-scale fading for distributed MIMO systems①

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Abstract

An antenna selection algorithm based on large-scale fading between the transmitter and receiver is proposed for the uplink receive antenna selection in distributed multiple-input multiple-output (D-MIMO) systems. By utilizing the radio access units (RAU) selection based on large-scale fading, the proposed algorithm decreases enormously the computational complexity. Based on the characteristics of distributed systems, an improved particle swarm optimization (PSO) has been proposed for the antenna selection after the RAU selection. In order to apply the improved PSO algorithm better in antenna selection, a general form of channel capacity was transformed into a binary expression by analyzing the formula of channel capacity. The proposed algorithm can make full use of the advantages of D-MIMO systems, and achieve near-optimal performance in terms of channel capacity with low computational complexity.

Key words: distributed MIMO systems, antenna selection, particle swarm optimization, large-scale fading

0 Introduction

Multi-input multi-output (MIMO) technique can improve the reliability of transmission and channel capacity exponentially without extra bandwidth[1]. For traditional centralized antenna systems, due to the inter-cell interference, the spectral and energy efficiencies remain low, especially at the cell edges. Recently, a distributed antenna system (DAS) as a promising candidate for future wireless communications has got wide attention for the reason that it can provide power saving, extend coverage and increase system capacity[2]. Distributed MIMO (D-MIMO) systems, which combine the advantages of MIMO systems and DAS, can obtain better performance than traditional co-located MIMO (C-MIMO) systems[3,4]. In a typical D-MIMO system, radio access units (RAUs) equipped with a number of antennas are deployed on the distributed system over a large area and connected to a central unit (CU). Relying on its distributed construction, D-MIMO systems can not only inherit the advantages of DAS which decreases path loss and overcomes shadow effect, but also improve capacity performance remarkably.

Generally, MIMO systems should have the same number of radio frequency chains as the number of antennas at both transmitter and receiver, which dramatically increases additional hardware costs and system complexity. In order to solve this problem, antenna selection technologies have been proposed at the right moment, which only use a subset of transmit and/or receive antennas with the best channel condition to communicate and it achieves excellent performance with fewer radio frequency chains and decreases the complexity and hardware cost of MIMO systems. In recent years, a number of studies have been done on antenna selection techniques and several antenna selection algorithms have been proposed[5-10]. The optimal antenna selection algorithm, namely exhaustive search algorithm (ESA), is an exhaustive search of all possible combinations for locating the best antenna subset[5]. However, the required computational complexity grows exponentially with the number of antennas, which is unaffordable for antenna selection problem in practical scenarios. In view of this, several suboptimal antenna selection algorithms are proposed, such as the norm-based selection algorithm (NBS)[6], norm and

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correlation based algorithm (NCBA)[10]. These algorithms used in traditional C-MIMO systems can be applied directly into D-MIMO systems. However, in the C-MIMO systems, the antenna distance between the user terminal (UT) and the base station (BS) are equal so that path losses in the large-scale fading are not considered. On the contrary, the antenna distance between the UT and the RAUs are unequal in the D-MIMO systems so that path loss becomes an important factor to be considered.

In order to make use of the full advantages of D-MIMO systems, a near-optimal antenna selection algorithm is proposed in this paper based on large-scale fading for D-MIMO systems, which combines improved particle swarm optimization (PSO) algorithm with large-scale fading based RAU selection. Taking account of the large-scale fading, the proposed algorithm shows remarkable capacity performance and low computational complexity. Simulation results confirm that its capacity performance approaches that of the exhaustive search algorithm and is better than the previous algorithms.

The rest of paper is organized as follows. In Section 1, the D-MIMO system model is illustrated. In Section 2, a binary expression of channel capacity is introduced and a near-optimal antenna selection algorithm based on large-scale fading is presented to optimize the binary expression of channel capacity. Simulation results are presented in Section 3 and final conclusions are given in Section 4.

Notation. Throughout this paper, for matrix $\boldsymbol{A}$, $\boldsymbol{A}^{\mathrm{T}}$, $\boldsymbol{A}^{\mathrm{H}}$, and $\det(\boldsymbol{A})$ denote the transpose, complex conjugate transpose, and the determinant of $\boldsymbol{A}$, respectively. The terms $\mathbb{C}^{a\times b}$ represent the $(a\times b)$-dimensional space with complex valued elements.

1 Distributed MIMO system models

It is considered that a (M, N, L) D-MIMO system where a central unit (CU) connects to $N = 5$ RAUs via high-speed, less-delay and error-free channels such as optical fiber links. Each RAU is equipped with L antennas that serve UT with M antennas, shown in Fig. 1. The signal information is transmitted between CU and RAUs. Assume all processes are perfectly synchronized.

It is assumed that the communication band is narrow enough to have a flat response across the frequency band, and signal model is linear time-invariant. The received signal parameterized by the distance vector $\boldsymbol{d}$ is given as Ref. [2]

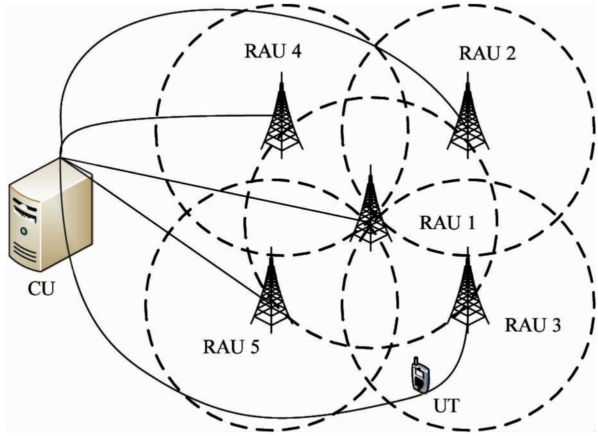

Fig. 1 Distributed MIMO system model

$$\boldsymbol{r}(t,\boldsymbol{d}) = \boldsymbol{H}(\boldsymbol{d})\cdot\boldsymbol{s}(t) + \boldsymbol{z}(t) \tag{1}$$

where $\boldsymbol{s}(t)\in\mathbb{C}^{M}$ and $\boldsymbol{z}(t)\in\mathbb{C}^{NL}$, for the uplink, denote the transmit signal from the UT and noise vector at the time t respectively, $\boldsymbol{z}(t)$ is independent and identically distributed, and complex zero mean Gaussian noise with unit variance. D-MIMO channel matrix $\boldsymbol{H}(\boldsymbol{d})\in\mathbb{C}^{NL\times M}$ is parameterized by the distance vector $\boldsymbol{d} = [d_1\ d_2\cdots d_N]^{\mathrm{T}}$, where $d_n\,(n = 1, 2, \cdots, N)$ is the distance between the UT and the nth RAU.

$$\boldsymbol{H}(\boldsymbol{d}) = \begin{bmatrix} \boldsymbol{H}_1(d_1) \\ \vdots \\ \boldsymbol{H}_N(d_N) \end{bmatrix} \tag{2}$$

where $\boldsymbol{H}_n(d_n)\in\mathbb{C}^{M\times L}$ is the channel matrix from the UT to nth RAU, and can be expressed as

$$\boldsymbol{H}_n(d_n) = \begin{bmatrix} h_{11}^{n}(d_n) & \cdots & h_{1L}^{n}(d_n) \\ \cdots & \cdots & \cdots \\ h_{M1}^{n}(d_n) & \cdots & h_{ML}^{n}(d_n) \end{bmatrix}_{M\times L} \tag{3}$$

where $h_{ml}^{n}(d_n)$ is the composite fading channel coefficient from the m-th antenna at UT to the l-th antenna at the n-th RAU and it includes small-scale fading and large-scale fading (shadow fading and path loss), which can be written as Ref. [3]

$$h_{ml}^{n}(d_n) = h_{ml}^{n} d_n^{\frac{-\alpha}{2}} 10^{\frac{\xi}{20}} \tag{4}$$

where $h_{ml}^{n}\sim CN(0,1)$ is fast fading, α is path loss exponent and $\alpha = 4$ is adopted, $\xi\sim N(0,\sigma_{sh}^{2})$ is the logarithm of shadow fading, $\sigma_{sh}\in\{8, 10\}$.

2 Antenna selection algorithm

2.1 Binary expression of channel capacity

In order to apply the improved PSO algorithm better in antenna selection, the general form of channel capacity is transformed into a binary expression by rederiving the formula of channel capacity.

Assume that the perfect channel state information (CSI) is only available at the receiver, and the total power is uniformly allocated among the transmit antennas. On account of the antenna optimal selection problem, K optimal antennas are selected from the NL available ones to serve the UT and the channel matrix is $\widetilde{\boldsymbol{H}} \in \mathbb{C}^{K\times M}$. Then the channel capacity in D-MIMO systems can be expressed as,

$$\begin{aligned} C &= \log_2 \det(\boldsymbol{I}_M + \frac{SNR}{M}\widetilde{\boldsymbol{H}}^H\widetilde{\boldsymbol{H}}) \\ &= \log_2 \det(\boldsymbol{I}_M + \frac{SNR}{M}[\widetilde{\boldsymbol{H}}^H \quad \mathbf{0}_{M\times(NL-K)}] \begin{bmatrix} \widetilde{\boldsymbol{H}} \\ \mathbf{0}_{(NL-K)\times M} \end{bmatrix}) \\ &= \log_2 \det(\boldsymbol{I}_M + \frac{SNR}{M}\hat{\boldsymbol{H}}^H\hat{\boldsymbol{H}}) \end{aligned} \quad (5)$$

where $\boldsymbol{I}_M$ is a $M\times M$ identity matrix, $(\cdot)^{\mathrm{H}}$ represents the conjugate transpose. $\mathbf{0}_{(NL-K)\times M}$ and $\mathbf{0}_{M\times(NL-K)}$ are zero matrix, $\hat{\boldsymbol{H}}$ is defined as $\hat{\boldsymbol{H}} = \begin{bmatrix} \widetilde{\boldsymbol{H}} \\ \mathbf{0}_{(NL-K)\times M} \end{bmatrix}$.

Let an $NL\times NL$ diagonal matrix $\boldsymbol{\Delta}$ be used for antenna selection at N RAUs, which is represented as

$$\boldsymbol{\Delta} = \begin{bmatrix} \Delta_1 & & & \\ & \Delta_2 & & \\ & & \ddots & \\ & & & \Delta_{NL} \end{bmatrix}_{NL\times NL} \quad (6)$$

where $\Delta_i (i=1, \cdots, NL)$ is defined as the antenna selection variable for each available antenna. If the i-th antenna is picked out, $\Delta_i = 1$, otherwise, $\Delta_i = 0$. The total number of candidate Δ_i is K whose value equals 1 in $\boldsymbol{\Delta}$. According to the relationship between $\hat{\boldsymbol{H}}$ and $\boldsymbol{H}(\boldsymbol{d})$, it can be represented as $\hat{\boldsymbol{H}} = \boldsymbol{P\Delta H}(\boldsymbol{d})$, where $\boldsymbol{P}$ is a permutation matrix satisfying condition as $\boldsymbol{P}^H\boldsymbol{P} = \boldsymbol{I}$. Accordingly, $\hat{\boldsymbol{H}}^H\hat{\boldsymbol{H}}$ can be represented as $\hat{\boldsymbol{H}}^H\hat{\boldsymbol{H}} = \boldsymbol{H}^H\boldsymbol{\Delta H}(\boldsymbol{d})$. Using $\det(\boldsymbol{I}_M + \boldsymbol{UV}) = \det(\boldsymbol{I}_N + \boldsymbol{VU})$, the channel capacity in Eq. (5) can be transformed as,

$$\begin{aligned} C &= \log_2 \det(\boldsymbol{I}_M + \frac{SNR}{M}\hat{\boldsymbol{H}}^H\hat{\boldsymbol{H}}) \\ &= \log_2 \det(\boldsymbol{I}_M + \frac{SNR}{M}\boldsymbol{H}(\boldsymbol{d})^H \cdot \boldsymbol{\Delta} \cdot \boldsymbol{H}(\boldsymbol{d})) \\ &= \log_2\left(\det\left(\boldsymbol{I}_{NL} + \frac{SNR}{M}\boldsymbol{\Delta H}(\boldsymbol{d})\boldsymbol{H}(\boldsymbol{d})^H\right)\right) \end{aligned} \quad (7)$$

As a result, the antenna selection problem becomes a combinatorial optimization problem on obtaining appropriate $\boldsymbol{\Delta}$ and maximizing the channel capacity (Eq. (7)).

2.2 RAU selection based on large-scale fading

So far, a few schemes have discussed on the RAU selection problem in D-MIMO systems. The scheme in Ref. [11] computes the Euclidean norms of channel matrix, and selects all antennas from the RAU which contains the maximal Euclidean norm as the optimal transmission antennas. This scheme ignores the possibility that some antennas in other RAUs have better performance than those in RAU with the maximal Euclidean norm.

In this paper, a more effective RAU selection scheme has been proposed for the characteristic of distribution in D-MIMO systems. In this scheme, P optimal RAUs are selected from the N available ones to reduce the number of selectable antennas greatly so as to decrease the computational complexity of selection. Since N available RAUs with a number of antennas have been distributed into the small cells, the total antennas in all RAUs can be decreased by the large-scale fading between different RAUs and UT. So the following antenna selection will be performed with only $P\times L$ candidate antennas.

The RAU selection is a norm-based approach, which compares the norm of all antennas and picks out the K maximal values one by one, where K denotes the number of the required optimal antennas. Then, P optimal RAUs is found out that these K antennas are involved in N available RAUs to build a new candidate set and the channel matrix $\boldsymbol{H}(\boldsymbol{d}) \in \mathbb{C}^{NL\times M}$ can be transformed as $\boldsymbol{H}_p \in \mathbb{C}^{PL\times M}$. Generally, since the large-scale fading has a significant effect on the composite fading channel coefficient $h_{ml}^n(d_n)$ in Eq. (4) under different d_n, the antennas will obtain better CSI with a better large-scale fading coefficient, and vice versa. So these K antennas will hardly be involved in every RAU at the same time, i. e., $P < N$. However, with an extremely low probability that the K antennas are uniformly distributed in all RAUs, i. e., $P = N$, and all RAUs should be considered in order to achieve the optimal scheme.

Therefore, the antenna selection problem of selecting K optimal antennas from the NL selectable antennas in D-MIMO systems can be simplified as a problem of selecting K optimal antennas from the PL selectable antennas, i. e., the size of all potential solutions will be simplified from C_{NL}^K to C_{PL}^K. Thus, by utilizing the RAU selection based on large-scale fading, the computational complexity will be decreased enormously with the decrease of the number of selectable antennas, which is impossible for antenna selection in traditional C-MIMO systems because it does not consider the large-scale fading. The main steps of RAU selection are summarized in Table 1 with the right column showing the complexity corresponding to each part of the algorithm.

Table 1 Antenna RAU selection algorithm. The complexity corresponding to each part of the algorithm is shown in the right column

Step	Manipulation	Complexity
1	RAUSelection(M, N, L, K, $\boldsymbol{h}_1$, $\boldsymbol{h}_2$, $\cdots$, $\boldsymbol{h}_{NL}$)	
2	$\boldsymbol{\Omega}: = \{1, 2, \cdots, NL\}$	
3	$\boldsymbol{\chi} := \{1, 2, \cdots, N\}$	
4	$\boldsymbol{H} := [\boldsymbol{h}_1, \boldsymbol{h}_2, \cdots, \boldsymbol{h}_{NL}]^{\mathrm{H}}$	
5	$\boldsymbol{S}: = \boldsymbol{\Omega}$	
6	for $j := 1$ to NL	
7	$\alpha_j: = \boldsymbol{h}_j^H \boldsymbol{h}_j$	$O(MNL)$
8	end	
9	for $n: =1$ to K	
10	$J: = \arg\max\limits_{j \in \Omega} \alpha_j$	$O(MNK)$
11	$Q: = \lfloor \frac{J}{L} \rfloor$	
12	if $Q \in \chi$	
13	$\chi: = \chi - \{Q\}$	
14	end	
15	$\boldsymbol{\Omega} : = \boldsymbol{\Omega} - \{J\}$	
16	end	
17	for $i: =1$ to length$[\boldsymbol{\chi}]$	
18	$r: =\boldsymbol{\chi}[i]$	
19	$\boldsymbol{S}: = \boldsymbol{S} - \{r, r+1, \cdots, r+L\}$	
20	end	
21	return $\boldsymbol{S}$	

2.3 Particle swarm optimization algorithm based on large-scale fading

In this section, an antenna selection scheme that utilizes particle swarm optimization (PSO) has been presented. PSO is a collaborative computational technique derived from the social behavior of bird flocking and fish schooling[12]. PSO is found that it has a huge advantage in solving global optimization problems, thus it can be applied to solve the antenna selection problem[13].

PSO algorithm in the antenna selection can be characterized by parameters and notations ($\boldsymbol{I}_s$, F, Q, G, D, $\boldsymbol{X}_k^l$, $\boldsymbol{P}_k^l$, $\boldsymbol{G}_{\text{best}}$, $\boldsymbol{V}$), where $\boldsymbol{I}_s$ is the space of all potential solutions, F denotes a fitness function, i. e. the channel capacity, Q is the size of population, i. e. the number of particles, G is the maximum number of iteration and D is the dimension of the particle position, i. e. the number of the $P \times L$ selectable antennas. $\boldsymbol{X}_k^l$ denotes the position of the k-th particle at the l-th iteration. $\boldsymbol{P}_k^l$ denotes the best position at which particle k has been up to the l-th iteration. $\boldsymbol{G}_{\text{best}}^l$ denotes the globally best position ever visited by any particle up to the l-th iteration in terms of fitness function F. $\boldsymbol{V}_k^l$ denotes the velocity of the k-th particle at the l-th iteration.

There are some improvements to the conventional PSO. Firstly, a priority-based mechanism is addressed to initialize the population. In this modification, the initial population is constructed by Q particles and the position of each particle $\boldsymbol{X}_k^0 = (x_{k,1}^0, x_{k,2}^0, \cdots, x_{k,D}^0)$ is a random permutation of $\{1, 2, \cdots, D\}$, where $x_{k,i}^0$ denotes the priority of the i-th antenna for the k-th particle, the larger the value of $x_{k,i}^0$, the higher probability the i-th antenna is selected.

In conventional PSO, the initial population is generated randomly. A different method of optimizing the initial populations is proposeed, which reduces the average convergence time (the number of iterations until reaching an acceptable solution). The basic idea is to use the large-scale fading (path loss and shadow fading) to optimize the value of $x_{k,i}^0$. If the i-th antenna has a good CSI with a good large-scale fading, but the value of $x_{k,i}^0$ is very low, the i-th antenna will have a low priority probability to be selected, which means that it should take a lot of iterations to increase the priority for the i-th antenna before it is chosen. In order to solve this problem, $x_{k,i}^0$ is multiplied by the large-scale fading coefficient of the i-th antenna to increase the priority probability of the i-th antenna with a good large-scale fading coefficient, while decreasing priority probability of those antennas having the bad CSI but with a higher weight $x_{k,j(j\neq i)}^0$. As a result, the initial population will be optimized by large-scale fading coefficient and a sufficiently good solution is found quickly. The optimized position of each particle in the initial population can be represented as

$$\widetilde{\boldsymbol{X}}_k^0 = \boldsymbol{X}_k^0 \cdot \boldsymbol{W} \tag{8}$$

where $\boldsymbol{W}$ is a $D \times D$ diagonal matrix of large-scale fading,

$$\boldsymbol{W} = \begin{bmatrix} w_1 & & & \\ & w_2 & & \\ & & \ddots & \\ & & & w_D \end{bmatrix}_{D\times D} \tag{9}$$

where $w_i \in (0,1)$, $i = 1,2,\cdots,D$, w_i denotes the large-scale fading on the i-th antenna, which is normalized by the maximum of large-scale fading coefficient.

Secondly, the selection of antennas is represented by a binary diagonal matrix

$$\boldsymbol{\Delta}(\boldsymbol{X}_k^l) = \begin{bmatrix} \Delta_1 & & & \\ & \Delta_2 & & \\ & & \ddots & \\ & & & \Delta_D \end{bmatrix}, \ \Delta_i \in \{0,1\} \tag{10}$$

where Δ_i is associated with an available antenna. According to the priority of each antenna, K antennas with the highest priority are picked out one by one without replacement, and the corresponding Δ_i is set to 1 while others are set to 0. As a result, by using Eq. (7), the fitness function of the k-th particle is represented as

$$F(\boldsymbol{X}_k^l) = \log_2\left(\det\left(\boldsymbol{I}_D + \frac{SNR}{M}\boldsymbol{\Delta}(\boldsymbol{X}_k^l)\boldsymbol{H}_P\boldsymbol{H}_P^H\right)\right) \tag{11}$$

where $\boldsymbol{I}_D$ is a $D \times D$ identity matrix, $\boldsymbol{H}_P$ is the channel matrix after the RAU selection.

The last modification over the conventional PSO is an improvement in updating velocity. Velocity updating formula in conventional PSO is represented as

$$\boldsymbol{V}_k^l = \omega \cdot \boldsymbol{V}_k^{l-1} + c_1 \cdot U(0,1) \cdot (\boldsymbol{G}_{\text{best}}^{l-1} - \boldsymbol{X}_k^{l-1}) + c_2 \cdot U(0,1) \cdot (\boldsymbol{P}_k^{l-1} - \boldsymbol{X}_k^{l-1}) \tag{12}$$

where $U(0,1)$ is the random variable uniformly distributed in interval $(0,1)$, and $c_1 > 0$ and $c_2 > 0$ are social and cognitive parameters to control the movement of the particle in any specific direction. $\boldsymbol{V}_k^l = (v_{k,1}^l, v_{k,2}^l, \cdots, v_{k,D}^l)$ denotes the velocity of the k-th particle at the l-th iteration, where $v_{k,i}^l$ denotes the magnitude of increasing the priority of the i-th antenna for the k-th particle. Inertia weight ω is employed to control the impact of the previous history of velocities on the current velocity, thereby influencing the trade-off between global (wide-ranging) and local (nearby) exploration abilities of the "flying points." Larger inertia weight ω facilitates global exploration (searching new areas) while a smaller inertia weight tends to facilitate local exploration to fine-tune the current search area. Suitable selection of the inertia weight ω can provide more balance of load between global and local exploration abilities and thus fewer iterations are needed on average to find the optimum[14].

In conventional PSO, $\boldsymbol{V}_k^{l-1}$ just has a fixed impact on $\boldsymbol{V}_k^{l-1}$ with the constant inertia weight ω. It is hard for the conventional PSO to adjust the search capability to achieve the best global solution with a fixed ω. In this paper, adapting the large-scale fading coefficient $\boldsymbol{W}$ (Eq. (9)) as the inertia weight ω in Eq. (12) has a significantly positive effect on the composite fading channel coefficient in $\boldsymbol{H}_p$. Then, velocity formula (Eq. (12)) can be expressed as

$$\boldsymbol{V}_k^l = \boldsymbol{W} \cdot \boldsymbol{V}_k^{l-1} + c_1 \cdot U(0,1) \cdot (\boldsymbol{G}_{\text{best}}^{l-1} - \boldsymbol{X}_k^{l-1}) + c_2 \cdot U(0,1) \cdot (\boldsymbol{P}_k^{l-1} - \boldsymbol{X}_k^{l-1}) \tag{13}$$

Compared with the constant inertia weight ω, large-scale fading $\boldsymbol{W}$ can retains more positive impact on $v_{k,i}^l$ from $v_{k,i}^{l-1}$ with a better large-scale fading coefficient or retains less impact on $v_{k,i}^l$ with a bad large-scale fading. As a result, the particles can adaptively adjust their search capability and their direction of search according to the current environment (large-scale fading) so that they are hard to fall into the local optimum. Based on the large-scale fading coefficients between the UT and RAUs, this scheme provides a macro tendency for all particles to fly towards even better solution so that the average convergence time can be reduced substantially.

The main steps are as follows.

Step 0 Set the iteration counter $l = 0$. Randomly initialize a total number of Q particles $\boldsymbol{X}_k^0$ as well as their corresponding velocities $\boldsymbol{V}_k^0$, $k = 1, 2, \cdots Q$.

Step 1 Evaluate the fitness value of each particle by using the fitness function in Eq. (11). Set the best position of each particle $\boldsymbol{P}_k^0 = \boldsymbol{X}_k^0$ and the global best $\boldsymbol{G}_{\text{best}}^0 = \arg\max_{1 \leqslant k \leqslant Q} F(\boldsymbol{P}_k^0)$.

Step 2 Update the iteration counter $l = l + 1$. Calculate the velocity of each particle by using improved velocity formula (Eq. (13)). Update the position of the k-th particle as $\boldsymbol{X}_k^l = \boldsymbol{X}_k^{l-1} + \boldsymbol{V}_k^l$.

Step 3 Evaluate the current fitness value of each particle by using the fitness function in (Eq. (11)). Store the position of each particle in temporary vector $\boldsymbol{P}_{best}^{Temp} = [\boldsymbol{P}_1^{Temp}, \boldsymbol{P}_2^{Temp}, \cdots, \boldsymbol{P}_Q^{Temp}]$.

Step 4 If the convergence criteria is satisfied, then terminate. Otherwise go to step 5.

Step 5 If $F(\boldsymbol{P}_k^{Temp}) > F(\boldsymbol{P}_k^{l-1})$, update the best of the k-th particle as $\boldsymbol{P}_k^l = \boldsymbol{P}_k^{Temp}$; otherwise, $\boldsymbol{P}_k^l = \boldsymbol{P}_k^{l-1}$.

Step 6 Update the global best as $\boldsymbol{G}_{best}^l = \arg\max_{1 \leqslant k \leqslant Q} F(\boldsymbol{P}_k^l)$. Go to step 2 and repeat the step 2 to 4.

3 Simulation results and discussion

For performance comparison, simulation results of the proposed PSO antenna selection scheme in D-MIMO systems are presented and all the results are compared with other antenna selection schemes. The channels are assumed to be quasi-static and statistically independent in the MIMO systems. All the simulations are performed using Monte Carlo runs and each result is an average value with 5000 independent simulation runs.

For performance comparison, a D-MIMO system with (M, N, L) set to be $(4, 6, 2)$ is presented, and the number of uplink receive antennas needed to be selected optimally is $K=4$. The population size Q of PSO is 30 and the number of iterations G is 30. The radius of the circular cell is 1000m, and the distances between the UT and 6 antenna RAUs are 1000m, 1500m, 2000m, 500m, 2500m, 700m in the coordinate system respectively. In order to show the performance of the proposed algorithm, it is compared with exhausting search algorithm (ESA)[5], RAU-selection norm-based algorithm (PNBA)[11], norm and correlation based antenna selection algorithm (NCBA)[10] and norm-based antenna selection algorithm (NBS)[6]. Fig. 2 shows that 10% outage capacities achieved by these algorithms increase remarkably as SNR increases, while the achievable capacity of the proposed algorithm approaches that of ESA and better than other algorithms for a wide range SNR.

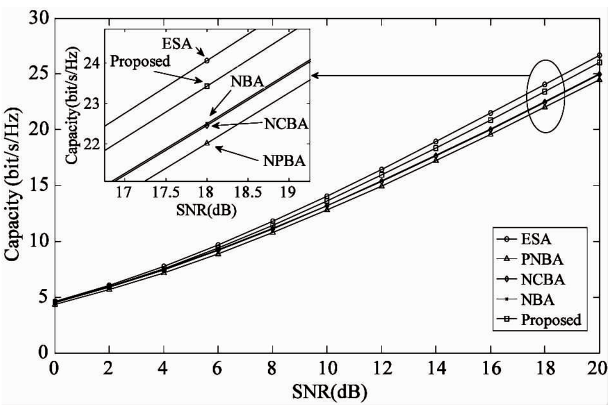

Fig. 2 Capacity versus SNR with $M = 4$, $N = 6$, $L = 2$, $K = 4$, $Q = 30$, $G = 30$

Moreover, another larger D-MIMO system with (M, N, L) set to be $(10, 7, 4)$ is considered, and the number of uplink receive antennas needed to be selected optimally is $K = 10$. The population size Q of PSO is 30 and the number of iterations G is 30. The radius of the circular cell is 1000m, and the distances between the UT and 7 antenna RAUs are 1000m, 1500m, 2000m, 500m, 2500m, 1800m, 700m in the coordinate system respectively. Fig. 3 shows that 10% outage capacities achieved by these algorithms increase remarkably as SNR increases, while the achievable capacity of the proposed algorithm approaches that of ESA and much better than other algorithms for a wide range SNR.

Fig. 4 illustrates the performance of the proposed algorithm with PNBA, NCBA, and NBS for different numbers of selected antennas as a function of selected antennas K for $M=12$, $N=7$, $L=3$, $Q=30$, $G=30$. SNR is set to 25dB. The radius of the circular cell is 1000m, the distances between UT and 7 antenna RAUs

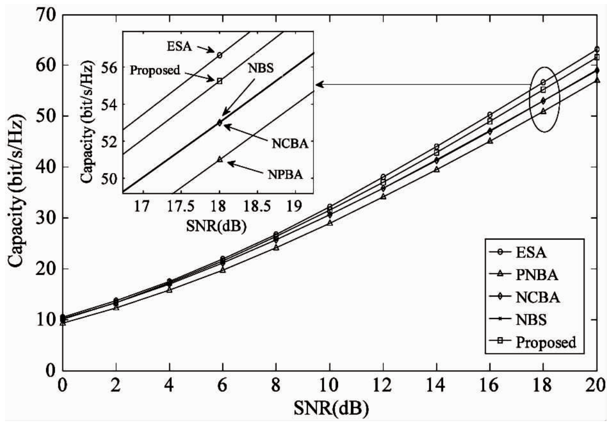

Fig. 3 Capacity versus SNR with $M = 10$, $N = 7$, $L = 4$, $K = 10$, $Q = 30$, $G = 30$

are also 1000m, 1500m, 2000m, 500m, 2500m, 1800m, 700m in the coordinate system respectively. As can be seen from Fig. 4, the outage capacity achieved by each algorithm increases substantially with the number of antennas K. The capacity achieved by the proposed algorithm is better than other algorithms for all values of K. In particular, the advantage of the proposed algorithm will increase continuously with the value of K compared with the other algorithms.

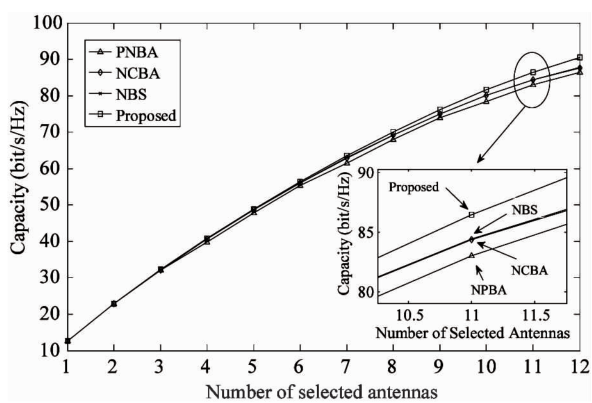

Fig. 4 Capacity versus number of antennas K with $M = 12$, $N=7$, $L=3$, SNR $=25$dB, $Q = 30$, $G = 30$.

Fig. 5 provides some interesting data regarding the performance improvement by applying proposed methods of optimizing population in PSO, with $M=11$, $N=8$, $L=3$, $K=11$, $Q=40$. The SNR is fixed at 20dB. It is assumed that the radius of the circular cell is 1000m, the distances between the UT and 8 antenna RAUs are 1000m, 800m, 1500m, 2000m, 1200m, 500m, 2500m, 1800m in the coordinate system respectively. The conventional PSO with arbitrary population randomly choses initial population, and updates the population with constant inertia weight. The improved PSO not only optimizes the population initialization with large-scale fading coefficient but also improves the updating of population by utilizing inertia weight based on large-scale fading coefficient. It is observed from the simulation results that the conventional PSO finds its global optimum early and this global optimum is obviously worse than the global optimum obtained by improved PSO. Moreover, the channel capacity obtained by the proposed algorithm is larger than that of conventional PSO. It can be seen that the exploration ability of the proposed algorithm is better than that of conventional PSO with the inertia weight W based on large-scale fading. Therefore, it can be concluded that the performance of the proposed algorithm generates a considerable improvement over that of conventional PSO.

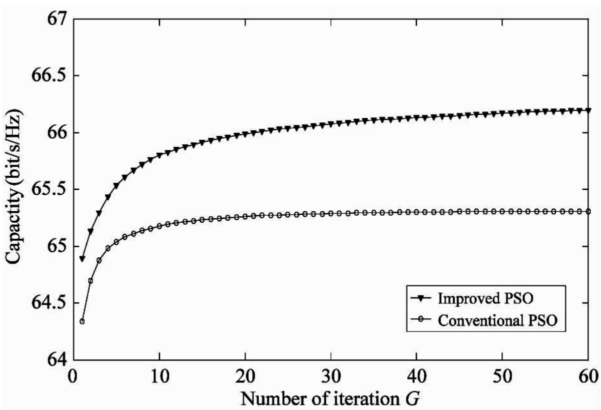

Fig. 5 Capacity versus G with $M = 11$, $N = 8$, $L = 3$, $K = 11$, $Q = 40$, SNR = 20dB

As for computational complexity, it is considered the number of complex multiplications and additions is required. As an example, when $M = 16$, $N = 8$, $L = 4$, $K = 11$, $Q = 30$, and $G = 28$, the proposed algorithm computes $Q \times G = 30 \times 28 = 840$ determinants (or, equivalently, it is assumed that $P = 3$ in this selection, $Q \times G \times (1/3)\min(M, PL)^3 = 483840$ complex multiplications and additions). In contrast, the exhaustive conducts $C_{NL}^{K} = 64512240$ determinants (each determinant requires $(1/3)\min(M, NL)^3 = 1365$ complex multiplications and additions). Gorokhov algorithm[7] requires $M \times N \times L \times K^3 = 681472$ complex multiplications and additions. On the other hand, NBS and NCBA require $M \times N \times L = 512$ and $2M \times N \times L \times K = 11264$ complex multiplications and additions, respectively. Therefore, the proposed algorithm requires higher complexity than NBS and NCBA but lower than other algorithms. The NBS and NCBA, however, suffer a substantial performance loss.

In order to intuitively compare the computational complexity of the aforementioned five antenna selection schemes, the parameters of their computational time (In Table 2) are evaluated by using practical hardware, say the Texas Instruments digital signal processing (DSP) chip C6711, which possesses computational capability of 500 million of multiplications and additions per second (MMACS)[15]. It is clear from Table 2 that the proposed algorithm is better in terms of computational complexity than ESA and Gorokhov algorithm, especially with the increase of the antennas. NBS and NCBA require less computation than the proposed algorithm, but their performances of the channel capacity are much worse than that of our proposed algorithm. In such a scenario, except for ESA, the aforementioned four schemes are all suitable to the MIMO system in Ref. [15], as the computational time of these antenna selection schemes is all lower than the elapsed time of 80ms between two channel matrix measurements. However, as the time between two channel matrix measurements decreases or other antenna selection scenarios are considered, the aforementioned schemes with higher computational time such as the optimum algorithm may encounter some difficulties. Therefore, the proposed algorithm provides a viable alternative to previous work by striking a better tradeoff between performance and computational complexity.

Table 2 Comparisons of computational complexity with 500 million multiplications and additions per second

Parameters (M, N, L, K, Q, G, P)	ESA (ms)	Gorokhov (ms)	NCBA (μs)	NBS (μs)	The proposed algorithm (ms)
(4,6,4,4,10,25,2)	0.45	0.01	1.53	0.19	0.01
(8,4,4,8,15,25,3)	4.39	0.13	1.28	0.64	0.12
(16,8,4,11,30,28,3)	176000	1.36	22.53	1.02	0.96

4 Conclusions

In this paper, based on large-scale fading, a modified PSO algorithm is presented combined with norm-based RAU selection for antenna selection in D-MIMO system. The proposed algorithm for the antenna selection requires low computational complexity and the performance approaches that of the exhaustive search algorithm, which makes the best use of the large-scale fading in D-MIMO systems to simplify the antenna selection problem by reducing the number of candidate antennas remarkably. This paper indicates that the proposed algorithm is a suitable candidate for solving complex communication problems in D-MIMO system.

References

[1] Paulraj A J, Gore D A, Nabar R U, et al. An overview of MIMO communications: a key to gigabit wireless. *Proceedings of the IEEE*, 2004, 92:198-218

[2] Choi W, Andrews J. Downlink performance and capacity of distributed antenna systems in a multicell environment. *IEEE Transactions on Wireless Communications*, 2007, 6: 69-73

[3] Sawahashi M, Kishiyama Y, Morimoto A, et al. Coordinated multipoint transmission/reception techniques for LTE-advanced [Coordinated and Distributed MIMO]. *IEEE Wireless Communications*, 2010, 17:26-34

[4] Ibernon-Fernandez R, Molina-Garcia-Pardo J M, Juan-Llacer L. Comparison between measurements and simulations of conventional and distributed MIMO system. *IEEE Antennas and Wireless Propagation Letters*, 2008, 7:546-549

[5] Sanayei S, Nosratinia A. Antenna selection in MIMO systems. *IEEE Communications Magazine*, 2004, 42:68-73

[6] Molisch A F, Win M Z, Yang-seok C, et al. Capacity of MIMO systems with antenna selection. *IEEE Transactions on Wireless Communications*, 2005, 4:1759-1772

[7] Gorokhov A, Gore D A, Paulraj A J. Receive antenna selection for mimo spatial multiplexing: theory and algorithms. *IEEE Transactions on Signal Processing*, 2003, 51:2796-2807

[8] Gore D A, Paulraj A J. MIMO antenna subset selection with space-time coding. *IEEE Transactions on Signal Processing*, 2002, 50:2580-2588

[9] Gharavi-Alkhansari M, Gershman A B. Fast antenna subset selection in MIMO systems. *IEEE Transactions on Signal Processing*, 2004, 52:339-347

[10] Liu S, He Z, Wu W, et al. A fast sub-optimal antenna selection algorithm in mimo systems. In: Proceedings of the Wireless Communications and Networking Conference, Las Vegas, USA, 2006. 734-739

[11] Su Y Z, Feng G Z. A novel fast antenna selection algorithm in distributed MIMO systems. In: Proceedings of the 12th IEEE International Conference on Communication Technology, Nanjing, China, 2010. 275-280

[12] Clerc M, Kennedy J. The particle swarm - explosion, stability, and convergence in a multidimensional complex space. *IEEE Transactions on Evolutionary Computation*, 2002, 6: 58-73

[13] Naeem M, Lee D C. Near-optimal joint selection of transmit and receive antennas for MIMO systems. In: Proceedings of the 9th IEEE International Symposium on Communications and Information Technology, Icheon, 2009. 572-577

[14] Porto V W, Saravanan N, Waagen D, et al. Parameter Selection in Particle Swarm Optimization. In: Evolutionary Programming VII, Porto V W, Saravanan N, Waagen D, et al. Springer Berlin Heidelberg, 1998. 591-600

[15] Wallace J W, Jensen M A, Swindlehurst A L, et al. Experimental characterization of the MIMO wireless channel: data acquisition and analysis. *IEEE Transactions on Wireless Communications*, 2003, 2: 335-343

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