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Particle Swarm Optimization for Antenna Selection in MIMO System

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Abstract This paper investigates the receive antenna selection problem to maximize capacity in wireless MIMO communication system, which can be formulated as an integer programming optimization problem and can not be directly solved because of its non-convex characteristics caused by the discrete binary antenna selection factor. To deal with this challenge, a computationally efficient approach, particle swarm optimization(PSO) algorithm is introduced, in which the particle is defined as the discrete binary antenna selection factor and the objective function is associated with the capacity corresponding to the specified antenna subsection represented by the particle. Furthermore, in order to meet the condition that the number of selected antennas should keep fixed, the particle elements are relaxed to change between [0 1] and the position of the higher elements are taken as the index of the antenna subsection to be activated. Then the best antenna subset can be found by seeking the global optimal particle in PSO. Numerical results reveal that PSO algorithm exhibits a promising performance when applied to both the classical benchmark function and our antenna selection scenario.

Keywords MIMO · Antenna selection · Channel capacity · Particle swarm optimization

1 Introduction

Multiple-input multiple-output (MIMO) communication is widely acknowledged as a key technology in bandwidth-constrained wireless systems because it can achieve a drastic

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increase in capacity by taking the full advantage of multiple antennas without extra spectrum. However, a major critical factor in the deployment of MIMO systems is the cost of multiple analog chains (such as low noise amplifiers, mixers, and analog-to-digital converters at the receiver terminal) and the increase of signal processing complexity; Furthermore, with increasing number of antennas, the probability that at least some antennas are experiencing deep fading increases. To deal with such challenges, a promising technique referring to antenna subset selection has been proposed [1]. The core idea of antenna selection is to use a limited number of analog chains that are adaptively switched to a subset of the available antennas, which can effectively reduce the number of radio frequency chains required, yet preserving the selection diversity gains. Therefore, the antenna selection technique has attracted considerable interests of researchers.

Previous work of comprehensive tutorial papers on antenna selection can be found in [2,3]. The criteria for antenna selection can be mainly divided into two kinds, aiming at minimizing the error probability [4,5] or maximizing the capacity performance [6,7]. These antenna selection techniques can be implemented either at the single transmit (receive) side [1,8] or at the both transmit and receive sides [6,9]. At the transmit side, antenna selection reduces complexity and increases capacity if a minimal amount of feedback is allowed when compared with an open loop MIMO system [2]. At the receive side, antenna selection can reduce the complexity. For spatial multiplexing systems, [10] provides several antenna selection algorithms where linear receivers are employed. Space time code system combined with antenna selection have been considered in [11–13]. To the best of the authors' knowledge, the simplest antenna selection methods are the norm-based selection algorithm (NBS) [2] as well as the correlation-based selection method (CBS) [14]. Concretely speaking, NBS seeks antennas with the largest channel gains and CBS chooses antennas with the lowest correlation between them. However, NBS performs well only at low signal to noise ratio (SNR) regime and CBS can develop its advantage when applied in correlated channel. Generally, the optimal antenna selection algorithm requires an exhaustive search (ES) over all possible candidates, which is computationally prohibitive particularly for large array systems. Therefore, recently great effort has been attached to find suboptimal algorithms that can obtain better capacity performance but with much lower computational complexity [15–17], for example, Dua et.al. in [15] attempts to address the receive antenna selection problem by using convex optimization to achieve the better trade-offs between performance and complexity. But the original antenna selection problem is reformulated by relaxing or approximating in order to be solved by convex optimization, which may be counterproductive and compromise the capacity performance. In [16], an adaptive markov-chain monte-carlo(AMCMC) optimization method is employed to address the antenna selection problem to obtain the near optimal capacity performance. In order to improve the convergence and efficiency of AMCMC, a Kullback-Leibler divergence between is defined in the algorithm. Also, a priority generic algorithm (GA)-based antenna selection algorithm has been proposed in [17], which aims at achieving close performance to the optimum algorithm but with lower computational complexity. However, the genetic manipulation such as crossover and mutation may still take much computational time.

In this paper, different from the previous work, we propose a low complexity approach for antenna selection based on particle swarm optimization (PSO). PSO is a powerful and promising optimization method and characterized as a simple but computationally efficient concept. PSO can solve complex multidimensional problems without solution domain restrictions or problem reformulations, and it does not have mathematical limitations such as the convexity requirement on the problem formulation. Therefore, it can perfectly deal with the optimization of a non-convex function. Compared with other evolutional optimization algorithms, PSO has the advantages of cooperation between particles and good flexibility in controlling the balance between local and global exploration of the problem space. Besides, PSO is easy to implement and there are few parameters to adjust. Therefore, this optimization method has been successfully applied to various facets of signal processing [18].

Our major contributions in this paper are described as follows:

(1) The receive antenna selection problem for MIMO system is formulated as a combinatorial optimization problem and a low complexity PSO-based receive-antenna-selection algorithm is proposed.

(2) The implementation that how to apply PSO in antenna selection problem to maximize the ergodic capacity is provided and preliminary experiments on testifying the performance of PSO by benchmark functions compared with genetic algorithm (GA) have been carried out to show the efficiency of PSO algorithm. Results reveal that PSO has promising search ability.

(3) Both the capacity performance as well as the complexity evaluation of PSO in addressing antenna selection problem are presented to show its efficiency when compared with other algorithms. Numerical results reveal that PSO offers near optimal capacity performance at a lower complexity. Since the capacity performance can be flexibly controlled by adjusting the parameters of PSO, it can provide a viable approach by striking a better tradeoff between performance and computational complexity.

The rest of this paper is organized as follows. In Sect. 2 The system model is introduced and the receive antenna selection problem is formulated. Section 3 presents the basic concept of PSO and the detailed the PSO-based antenna selection procedure. In Sect. 4, preliminary numerical experiments are carried out to testify the efficiency of PSO by benchmark functions. Then Monte Carlo simulations are presented in Sect. 5. Finally, Sect. 6 concludes the paper.

2 System Model and Problem Formulation

2.1 System Model

Consider a narrow band MIMO system with transmitter equipped N_t antennas and receiver equipped N_r elements. Suppose that antenna selection is implemented at the receiver, where L out of N_r receive antennas will be activated for transmission. Denote the original $N_r \times N_t$ channel matrix as $\mathbf{H}$, following the correlated channel model provided in [19], the channel matrix can be written as:

$$\mathbf{H} = \mathbf{R}_{rx}^{1/2}\mathbf{H}_c\mathbf{R}_{tx}^{1/2} \tag{1}$$

where $\mathbf{R}_{tx}^{1/2}$ is the $N_t \times N_t$ transmit-side normalized correlation matrix, $\mathbf{R}_{rx}^{1/2}$ is the $N_r \times N_r$ receive-side normalized correlation matrix, and $\mathbf{H}_c$ is an spatially white zero-mean unit variance complex i.i.d. Gaussian matrix.Then the received complex signal vector can be written as:

$$\mathbf{r} = \mathbf{Hs} + \mathbf{n} \tag{2}$$

where $\mathbf{s} \in C^{N_t \times 1}$ represents the transmitted data vector and $\mathbf{n} \in C^{N_r \times 1}$ is a complex Gaussian noise vector with zero-mean and covariance matrix $\sigma^2\mathbf{I}$. As such, the capacity of the MIMO system is given by:

$$C = log_2 \det(\mathbf{I}_{N_t} + \gamma \cdot \mathbf{\Sigma}_s\mathbf{H}^H\mathbf{H}) \tag{3}$$

where γ denotes the average SNR and $\mathbf{\Sigma}_s = E\left\{\mathbf{ss}^H\right\}$ is the covariance matrix of the transmitted signals. $\mathbf{I}_{N_t}$ denotes the $N_t \times N_t$ identity matrix and $\det(\cdot)$ denotes the determinant manipulation.

Assuming that perfect channel state information (CSI) is available at the receiver, and L out of N_r receive antennas are activated. Denote the indices of the selected antennas as $\mathbf{s} = [s_1 \ldots s_L]$ and the $L \times N_t$ channel matrix after antenna selection as $\mathbf{H}_s$, which coincides with $\mathbf{H}$ for those rows corresponding to these indices. Choose the covariance matrix of the transmitted signals as $\mathbf{\Sigma}_s = \mathbf{I}_{N_t} \big/ N_t$, then, the capacity of the MIMO channel with antenna selection is given by:

$$C = log_2 \det(\mathbf{I}_{N_t} + \gamma \big/ N_t \cdot \mathbf{H}_s^H \mathbf{H}_s) \tag{4}$$

It can be seen that the capacity in (4) becomes a function of the antennas chosen in $\mathbf{H}_s$. Our goal is to find the best antenna subset to maximize the capacity.

2.2 Problem Formulation

For convenience, we first define the antenna selection operator as follows:

$$\mathbf{\Delta} = [\, \Delta_1 \ \ldots \ \Delta_{N_r} \,] \tag{5}$$

where

$$\Delta_i = \begin{cases} 1, & \text{if the } i\text{th antenna is selected} \\ 0, & \text{otherwise} \end{cases} \quad i = 1 \ldots N_r \tag{6}$$

Then the capacity after antenna selection can be expressed as:

$$C = log_2 \det(\mathrm{I}_{N_t} + \gamma \big/ N_t \cdot \mathbf{H}_s^H \mathbf{H}_s) \tag{7}$$

$$= log_2 \det\left(\mathbf{I}_{N_t} + \gamma \big/ N_t \cdot \left[\mathbf{H}_s^H \ \mathbf{0}_{N_t \times (N_r - L)}\right] \begin{bmatrix} \mathbf{H}_s \\ \mathbf{0}_{(N_r - L) \times N_t} \end{bmatrix}\right) \tag{8}$$

Denote

$$\bar{\mathbf{H}}_s = \begin{bmatrix} \mathbf{H}_s \\ \mathbf{0}_{(N_r - L) \times N_t} \end{bmatrix}_{N_r \times N_t} \tag{9}$$

Then the relationship between $\mathbf{H}$ and $\mathbf{H}_s$ can be expressed as:

$$\bar{\mathbf{H}}_s = \mathbf{P}_r \cdot diag(\mathbf{\Delta}) \cdot \mathbf{H} \tag{10}$$

where $\mathbf{P}_r$ is a row permutation matrix satisfying $\mathbf{P}_r^H \mathbf{P}_r = \mathbf{I}_{N_r}$ and $diag(\mathbf{\Delta})$ is an $N_r \times N_r$ diagonal matrix with Δ_i is its diagonal entry. This gives $\bar{\mathbf{H}}_s^H \bar{\mathbf{H}}_s = \mathbf{H}^H \cdot diag(\mathbf{\Delta}) \cdot \mathbf{P}_r^H \cdot \mathbf{P}_r \cdot diag(\mathbf{\Delta}) \cdot \mathbf{H} = \mathbf{H}^H \cdot diag(\mathbf{\Delta}) \cdot \mathbf{H} = \mathbf{H}_s^H \mathbf{H}_s$. With this equation, the capacity with antenna selection can be rewritten as:

$$C = log_2 \det(\mathbf{I}_{N_t} + \gamma \big/ N_t \cdot \mathbf{H}_s^H \mathbf{H}_s) \tag{11}$$

$$= log_2 \det(\mathbf{I}_{N_t} + \gamma \big/ N_t \cdot \bar{\mathbf{H}}_s^H \bar{\mathbf{H}}_s) \tag{12}$$

$$= log_2 \det(\mathbf{I}_{N_t} + \gamma \big/ N_t \cdot \mathbf{H}^H \cdot diag(\mathbf{\Delta}) \cdot \mathbf{P}_r^H \cdot \mathbf{P}_r \cdot diag(\mathbf{\Delta}) \cdot \mathbf{H}_t) \tag{13}$$

$$= log_2 \det(\mathbf{I}_{N_t} + \gamma \big/ N_t \cdot \mathbf{H}^H \cdot diag(\mathbf{\Delta}) \cdot \mathbf{H}) \tag{14}$$

$$= log_2 \det(\mathbf{I}_{N_r} + \gamma \big/ N_t \cdot diag(\mathbf{\Delta}) \cdot \mathbf{H}\mathbf{H}^H) \tag{15}$$

Note that the equation in (14) follows the theorem that $\det(\mathbf{I}_M + \mathbf{UV}) = \det(\mathbf{I}_N + \mathbf{VU})$. It can be seen now the channel capacity with antenna selection is a function of $\mathbf{\Delta}$. The receive antenna selection problem in MIMO system to maximize capacity can be characterized as:

$$\begin{aligned} &\text{Maxmize: } log_2 \det(\mathbf{I}_{N_r} + \gamma \big/ N_t \cdot diag(\mathbf{\Delta}) \cdot \mathbf{HH}^H) \\ &\text{Subject to: } sum(\mathbf{\Delta}) = L \\ &\qquad \Delta_i \in \{0, 1\} \end{aligned} \tag{16}$$

For the optimization problem characterized by (16), the variables are binary valued (0 or 1) integer variables rendering the selection problem NP-hard. To deal with this problem, a direct way is an exhaustive search over all possible candidates to find the antenna subset to maximize the capacity. However, this task is computationally prohibitive for a large antenna size. Owing to this fact, PSO is introduced for receive antenna selection to improve the computational efficiency.

3 The PSO-Based Antenna Selection Algorithm

In this section, basic concept of PSO algorithm is first introduced. After that, the details of PSO applied in antenna selection problem are presented.

3.1 Basic Concepts of PSO

PSO, first developed by Kennedy and Eberhart in 1995, is a kind of evolutionary computational technology based on the intelligent behavior of organisms, which is put forward by learning from the behaviors of bird flock seeking food [20]. In PSO algorithm, a group of random particles imitating bird flock are initialized in the searching space, all the particles have fitness values which are evaluated by the objective function to be optimized, and their velocities which direct their "flying" direction contribute an important part in PSO. The particles are "flown" through the problem space by following the current optimum particles. PSO searches for optimal fitness value and the corresponding particle by updating generations of the particle $\mathbf{x_i}(\tau)$ and its velocity $\mathbf{v_i}(\tau)$ according to:

$$\begin{aligned} \mathbf{v}_i(\tau + 1) &= u\mathbf{v}_i(\tau) + c_1 r_1 (\mathbf{p}_i(\tau) - \mathbf{x}_i(\tau)) + c_2 r_2 \left(\mathbf{p_g}(\tau) - \mathbf{x}_i(\tau)\right) \\ \mathbf{x}_i(\tau + 1) &= \mathbf{x}_i(\tau) + \mathbf{v}_i(\tau + 1) \end{aligned} \tag{17}$$

where $\mathbf{p}_i(\tau)$ is the local best particle that particle i has achieved so far and $\mathbf{p}_g(\tau)$ is the global best particle that all particles have achieved so far. c_1 and c_2 are acceleration constants and r_1 and r_2 are uniformly distributed random numbers in [0,1]. The term $\mathbf{v}_i(\tau)$ is limited to its bounds. w is the inertia weight factor and in general, it is set according to:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{T} \cdot \tau \tag{18}$$

where $w_{\max}$ and $w_{\min}$ are maximum and minimum values of the weighting factor respectively. T is the maximum number of iterations and τ is the current iteration number. The velocity updating equation of each particle in (17) consists of three parts: the first part represents the degree of momentum of the particle, the second part is the "cognition" part, which represents the independent behavior of the particle itself, the last part is the "social" part, which denotes cooperation among particles. This iterative process will stop until the maximal iteration number is reached or a sufficient good solution is found.

3.2 PSO-Based Antenna Selection Method

From (17), we know that PSO is an iterative algorithm and continually exploits new and better solutions by updating generations. In order to apply PSO in solving the antenna selection problem, the two key parameters, i.e. the particle and its velocity, have to be determined first. Since the velocity term $\mathbf{v_i}$ of particle i is correlated with the current individual best particle $\mathbf{p}_i$ and the global particle $\mathbf{p}_g$, which can be obtained by evaluating this particle according to the fitness (objective) function. Then the key point becomes how to define the particle and the fitness (objective) function. Once these two issues have been solved, PSO-based antenna selection can be implemented by updating the iterative generation.

3.2.1 The Definition of the Particle

From the evolutionary process of PSO, we know that each particle in PSO should be defined closely related to the antenna subset. Denote the particles in PSO as $\mathbf{x}_i = \left[x_{i1} \ldots x_{iD} \right]$, $i = 1 \ldots Q$, where D is the dimension of a particle and Q is the size of a randomly distributed initial population, then one direct approach is that the particle is defined as the antenna selection operator, i.e. $\mathbf{x}_i = \mathbf{\Delta}$, $D = N_r$. However, this brings about the problem that the total number of selected antennas may be different in the searching process and may not meet the fixed numbers of L. To deal with this challenge, we relax the condition by $x_{ij} \in [0, 1]$, as in Eq. (19). And in each particle the L larger values out of the N_r elements are picked out, which means the L antennas with higher weight will be activated. By this way, a direct relationship between each particle and the L selected antennas can be successfully established.

$$\mathbf{x}_i \stackrel{\Delta}{=} \mathbf{\Delta}, 0 < x_{ij} < 1, \quad i = 1 \ldots Q, \quad j = 1 \ldots N_r \tag{19}$$

3.2.2 The Definition of the Fitness Function

In PSO, each particle is evaluated by the fitness function to reflect its quality. According to the particle definition, the fitness function in the antenna selection scenario can be defined as the capacity value corresponding to the specified antenna subsection, i.e.,

$$F(\mathbf{x}_i) = log_2 \det(\mathbf{I}_{N_r} + \gamma / N_t \cdot diag(\mathbf{x}_i) \cdot \mathbf{H}\mathbf{H}^H) \tag{20}$$

It can be seen that this fitness function can readily reflect the capacity achieved by the specified antenna subset.The larger the fitness value, the better the corresponding particles is. With the definition of the particle as well as the fitness function above, the detailed PSO-based antenna selection method can be summarized as follows:

Step 1-Initialization. Randomly generate a total number of Q particles $\mathbf{x}_i, i = 1 \ldots Q$ as well as their corresponding velocities $\mathbf{v}_i$.

Step 2-Evaluation. Evaluate the fitness value of each particle by using the fitness function in (20). Set the local best particle $\mathbf{p}_i = \mathbf{x}_i$ and select the particle $\mathbf{x}_g$ with the highest fitness value as the global best particle $\mathbf{p}_g = \mathbf{x}_g$.

Step 3-Evolution. Using $\mathbf{p}_i(\tau)$ and $\mathbf{p}_g(\tau)$, each particle and its velocity is evolved according to (17) for the next iteration.

Step 4-Updating. Calculate the fitness values of all the particles. Then choose the current local best particle $\mathbf{p}_i(\tau)$ of particle i as the better one between $\mathbf{x}_i(\tau)$ and $\mathbf{p}_i(\tau - 1)$ and determine the current global best particle $\mathbf{p}_g(\tau)$ by comparing the best of $\mathbf{p}_i(\tau)$ at current iteration with the global best particle at previous iteration $\mathbf{p}_g(\tau - 1)$.

Step 5-Termination. Repeat the above Step 2 to Step 4 until a stopping criterion, such as a sufficiently good solution being discovered or a maximum number of generations being completed is satisfied. The global best one among all the particles is taken as the final answer.

4 Preliminary Numerical Experiments

In this section, in order to show the performance of the PSO algorithm more clearly, several typical benchmark functions are presented. Besides, the GA algorithms is also simulated for comparison. For PSO and GA, choose population size $Q = 20$ and the maximum number of iterations $T = 100$; The probability of selecting the best individual in GA is 0.1. Crossover probability in GA is 0.8. Mutation probability in GA is 0.05. Acceleration constant in PSO are chosen as $c1 = c2 = 2.0$. The inertia weight factor in PSO are chosen as $w_{\max} = 0.9$, $w_{\min} = 0.4$. For convenience, the benchmark functions are defined in Table 1 and the dimensions of those benchmark functions in the experiment is chosen as $D = 10$ (Figs. 1, 2, 3, 4).

The first Schaffer function has a global minimum of 0 at $(0, \ldots, 0)$ and it is very close to the local ones. The second Spherical function is a high dimensional unimodal function with its global minimum at $(0, \ldots, 0)$, which is always employed as a measure to evaluate the local optimal searching ability. The third Rosenbrock function is a non-convex function, the global optimum of which is inside a long, narrow, parabolic shaped flat valley and the gradients generally do not point towards the optimum. Since it is difficult to converge to the global optimum, this problem has been extensively employed in evaluating the performance of optimization algorithms. The fourth Ackley function is a tough multimodal optimization problem, because the global minimum is surrounded by a large number of local minima, this makes the algorithm reach the global peak without being stuck at one of these local minima extremely difficult. The performance of the PSO method in comparison with GA tested by those benchmark functions are show in Figs. 5, 6, 7 and 8 respectively. It can be clearly seen that PSO achieves a much lower fitness value than that of GA as iteration proceeds. However,

Table 1 Benchmark functions used in the experiments

Function	Formulation	Range	Min. value
Schaffer	$f_1(\mathbf{x}) = 0.5 + \left(\sin^2\sqrt{\sum_{i=1}^{D} x_i^2} - 0.5\right) \Big/ \left[1.0 + 0.001\left(\sum_{i=1}^{D} x_i^2\right)^2\right]^2$	$x_i \in [-10,10]$	$f_1(\mathbf{0}) = 0$
Spherical	$f_2(\mathbf{x}) = \sum_{i=1}^{D} x_i^2$	$x_i \in [-100, 100]$	$f_2(\mathbf{0}) = 0$
Rosenbrock	$f_3(\mathbf{x}) = \sum_{i=1}^{D-1}\left[100\left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2\right]$	$x_i \in [-6, 6]$	$f_3(1) = 0$
Ackley	$f_4(\mathbf{x}) = -20 \times \exp\left(-0.2 \times \sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right) + 20 + \exp(1)$	$x_i \in [-32, 32]$	$f_4(\mathbf{0}) = 0$

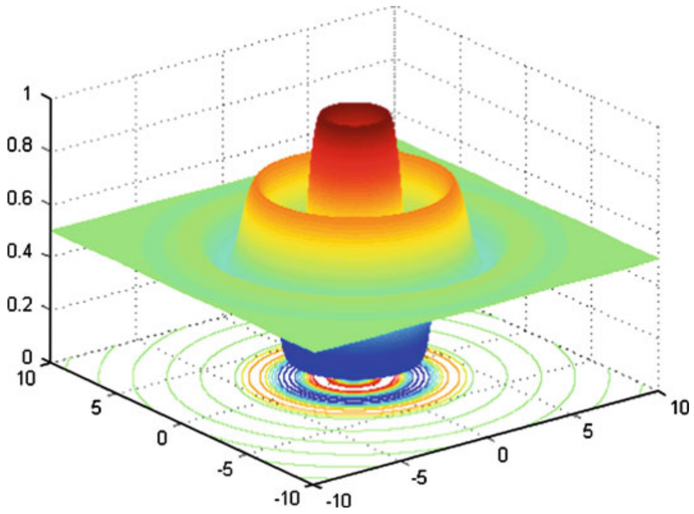

Fig. 1 Graph of Schaffer function with $D = 2$

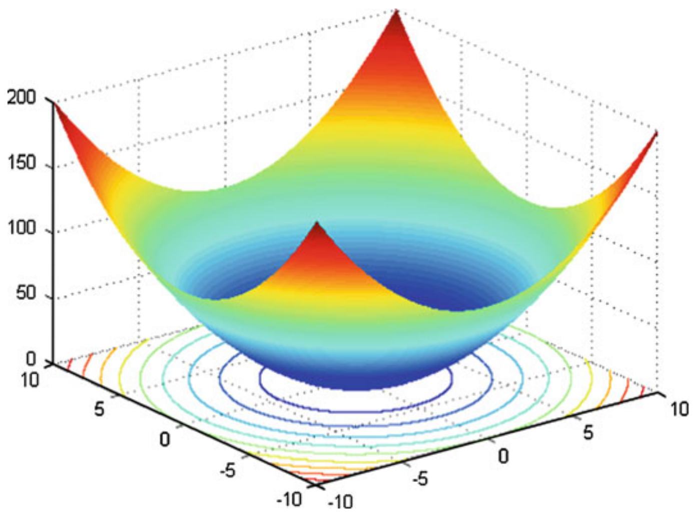

Fig. 2 Graph of spherical function with $D = 2$

it should be noted that, in Figs. 7 and 8, sometimes GA performs better than PSO in terms of fitness values, this is because different types of bench functions may adapt to different evolutionary mechanisms. Nevertheless, PSO provides better final results as iteration goes on, which indicates that it has a more efficient exploitative behavior.

5 Simulation Results

In this section, simulations are provided to validate the PSO antenna selection method derived previously. To demonstrate the performance of the PSO method, simulation results of the

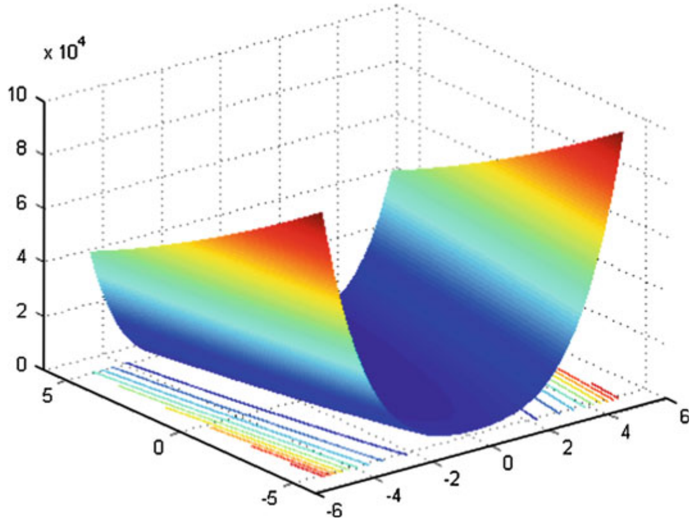

Fig. 3 Graph of Rosenbrock function with $D = 2$

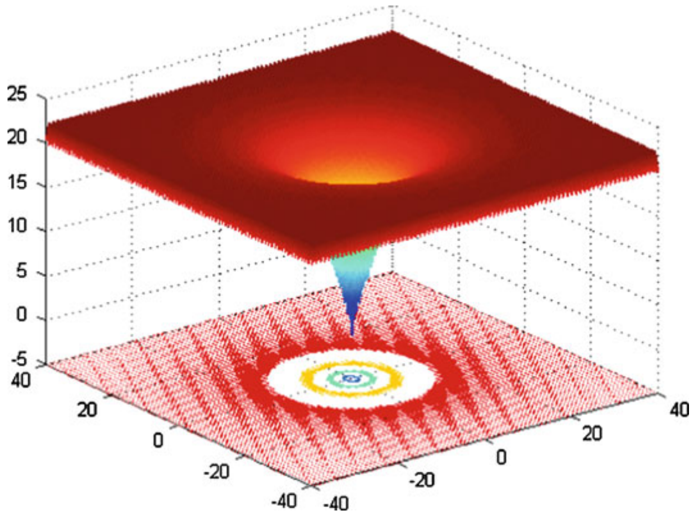

Fig. 4 Graph of Ackley function with $D = 2$

optimal exhaustive search algorithm (ESA), the GA-based antenna selection method the NBS scheme and the random selection algorithm (RSA) are also provided for comparison. Performance is evaluated in terms of capacity averaged over 2,000 independent realizations of the channel matrix. A single user MIMO system is considered and the correlated channel model described in section 2 is adopted. For simplicity, assuming that the number of transmit antenna keeps $N_t = 4$ unchanged, where L out of N_r receive antennas are selected to be activated. Several scenarios, $(N_r, L) = (8, 4), (12, 4), (16, 4), (20, 4)$ are investigated. For fair comparison, the population size and the maximum number of iterations in GA are chosen the same as PSO. For GA, choose the crossover probability 0.8, mutation probability 0.05

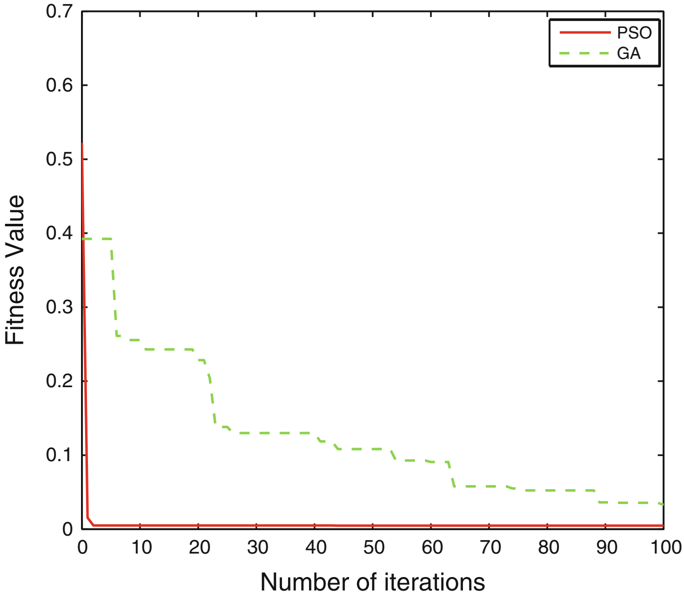

Fig. 5 Comparison of the best value of Schaffer function in 100 runs for PSO and GA

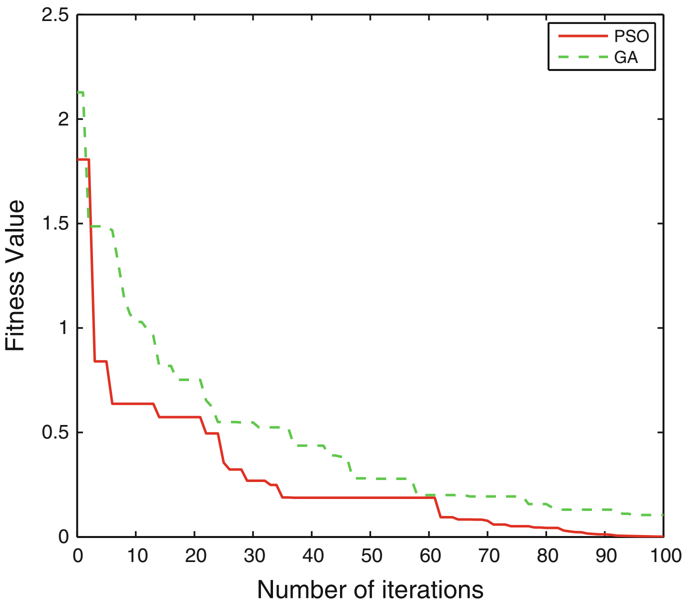

Fig. 6 Comparison of the best value of spherical function in 100 runs for PSO and GA

and the probability of selecting the best individual 0.1. Parameters of PSO in the simulation are defined in Table 2 for easy reference.

Figure 9 shows the capacity curves versus SNR for different algorithms with $N_r = 8$ and $L = 4$. It can be discovered that, the ESA shows the best achievable capacity.

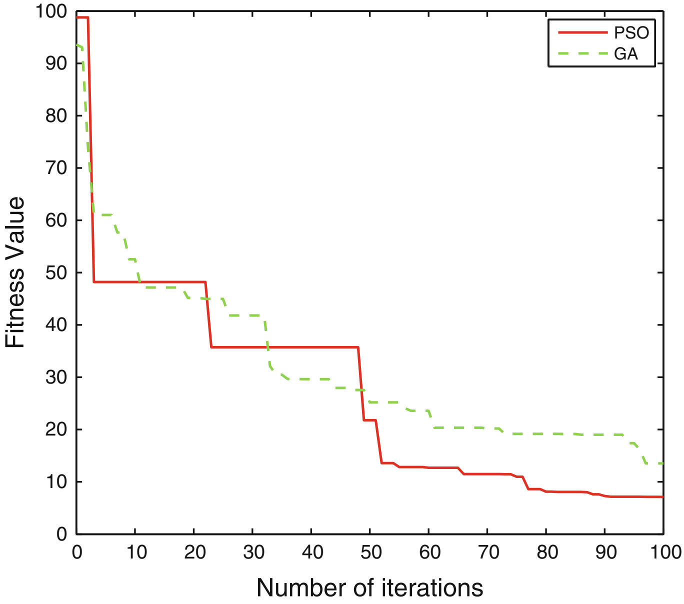

Fig. 7 Comparison of the best value of Rosenbrock function in 100 runs for PSO and GA

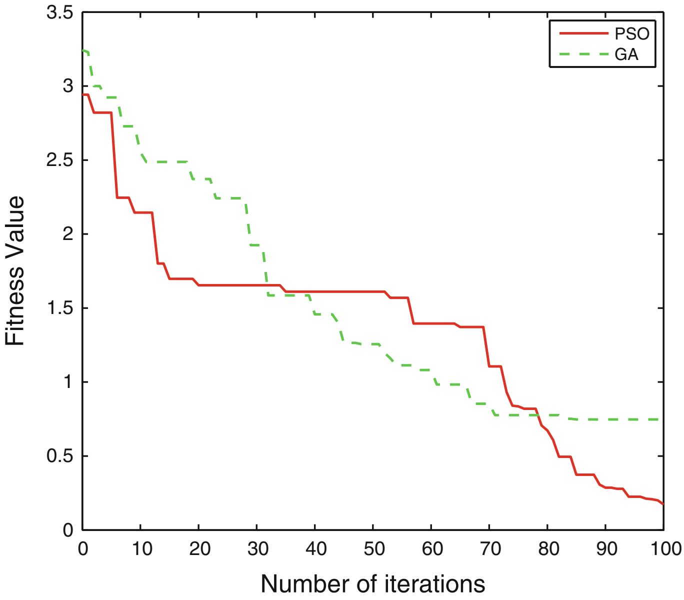

Fig. 8 Comparison of the best value of Ackley function in 100 runs for PSO and GA

The PSO achieves nearly the same performance as the ESA and the gap between them can be neglected. PSO outperforms GA and NBS while GA performs better than NBS in terms of capacity. The RSA shows the worst capacity performance among all these schemes.

Table 2 Parameters definition of PSO

Parameters	Description and value
Population number	$Q = 10$
Maximum iteration number	$T = 5$
Inertia weight factor	$w_{\max} = 0.9$, $w_{\min} = 0.4$
Acceleration constant	$c_1 = c_2 = 2.0$

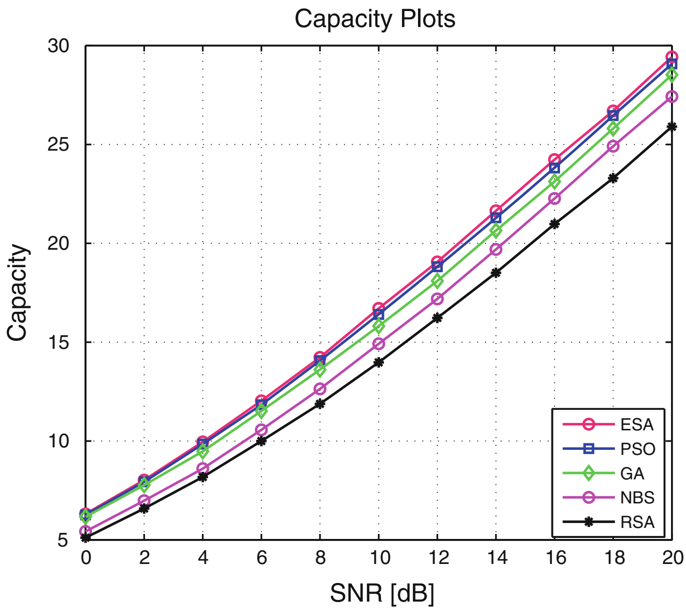

Fig. 9 Capacity *curves* versus SNR for different algorithms with $N_r = 8$, $L = 4$

Figure 10 illustrates the BER versus SNR with various combination of (N_r, L)using PSO. It can be discovered when the number of the receive antennas N_r is fixed, the more the number of the selected antennas, the better the BER performance is. Besides, when the number of the selected antennas L is fixed, the more the number of the receive antennas, the better the BER performance is. This indicates a fact that the the BER performance improved by selection diversity can be achieved either by increasing N_r for fixed L or by increasing L for fixed N_r.

Figure 11 displays the effect of iteration number on capacity with PSO for $N_r = 8$ and $L = 4$. The population number of PSO is fixed at $Q = 10$. As expected, substantial improvement in capacity can be achieved as the iteration number increases. This is because much better antenna subsets may be discovered after sufficient iterations. However, no obvious capacity improvement can be obtained when the iterations reaches certain number. For example, the gap between the two capacity curves corresponding to iteration number 5 and 10 respectively in Fig. 11 is small. That is to say, the capacity obtained under 5 iterations is also a close approximation alternative to that by ESA. This reveals a fact that we may seek a proper maximal iteration number to get a desired capacity performance, depending on the practical requirements.

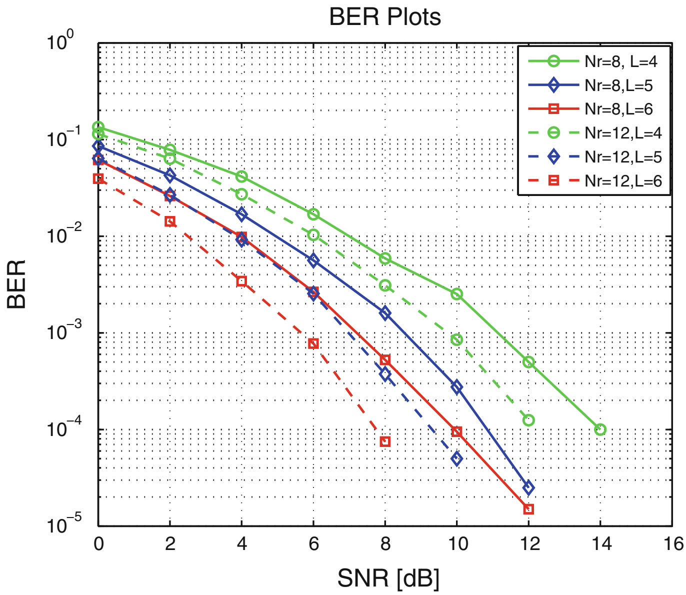

Fig. 10 BER *curves* versus SNR for different combinations of (N_r, L) with PSO, $Q = 10$, $T = 5$

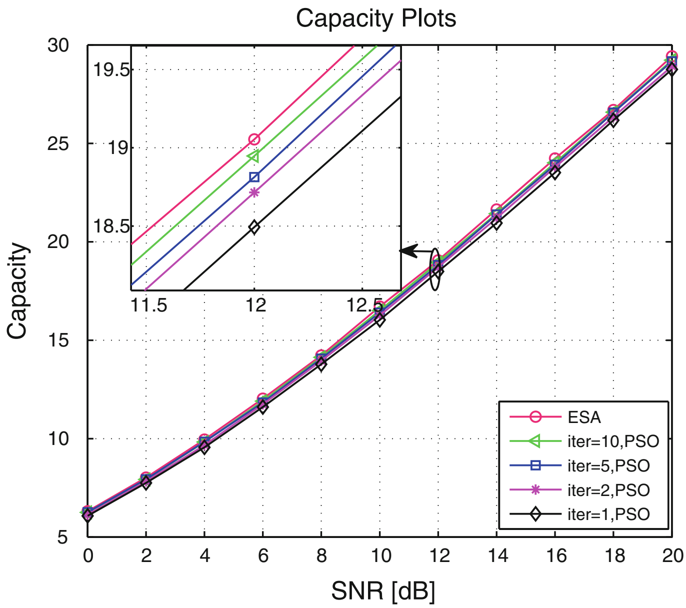

Fig. 11 The effect of different iteration numbers in PSO on capacity with $Q = 10$ and $N_r = 8$, $L = 4$

Figure 12 investigates the capacity convergence ratio versus the number of particles using PSO where the number of the selected antennas is fixed at $L = 4$ and $T = 5$. Capacity convergence ratio can be defined as the capacity obtained by ESA divided by the capacity achieved by PSO. It can be discovered that, the more particles, the higher the capacity

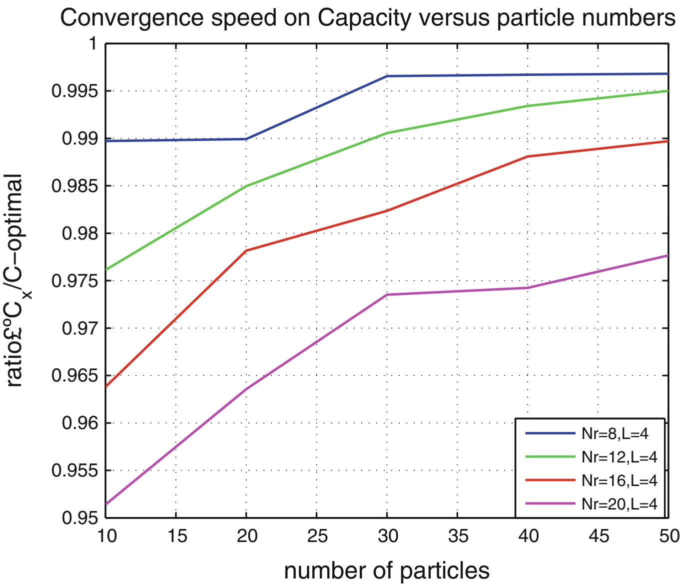

Fig. 12 Capacity convergence ratio versus number of particles in PSO with $T = 5$ and $L = 4$

convergence ratio is, which means the closer between the capacity of the proposed PSO-based antenna selection algorithm and that of the ESA. Besides, as the number of particles increases, the capacity convergence ratio also increases, nevertheless, this increase is getting slow when the particle numbers reach up to some amount. Furthermore, it can be discovered that when $N_r = 8, L = 4$, a 99% of the optimal ESA capacity can be achieved by PSO with $Q = 10$. But when $N_r = 20$, $L = 4$ a 95% of the optimal ESA capacity can be achieved by PSO with $Q = 10$. This reveals a fact that when the number of selected antennas L is fixed but the number of receive antennas has been increased, then more particles and iterations are required if we want to obtain a high capacity convergence ratio. This is because more possible combinations need to be considered with the increasing number of the receive antennas, which directly enlarge the searching space of the antenna selection problem by using PSO.

5.1 Complexity Evaluation

For PSO, the computational effort can be measured as the number of function evaluations, namely, $Q \times T$, where Q is the number of particles and T is the maximal iteration number. This is because comparisons and data duplications can be totally negligible when compared with the function evaluations. Since GA has a same procedure of evaluating the fitness values of individuals as PSO in the iterative course, its computational complexity is also mainly determined by the number of fitness function evaluations compared with the genetic(crossover,mutation) manipulation. Then as for the antenna selection problem mentioned above, the ESA need to testify all the $C_{N_r}^{L}$ combinations of antennas in order to find the best selected antenna subset. Table 3 shows the complexity comparisons in terms of the number of function evaluations for GA, PSO and ESA, under the constraint condition of achieving the required capacity ratio $(C - x/C - ESA)$, which is defined as the capacity obtained by ESA divided

Table 3 Computational complexity comparision for several algorithms

(N_r, L)	PGA	PSO	PSO	ESA
(8,4)	60	50	60	70
(16,4)	300	200	300	1820
(20,4)	550	500	550	4845
$C - x/C - ESA$	>90%	>90%	>95%	100%

by the capacity achieved by specified algorithm. Note that the two PSOs in Table 3 are the same algorithm but with different required capacity ratio.

From Table 3, we can notice that the PSO algorithm has lower complexity and better performance than the GA method. Compared with the GA, the PSO algorithm takes comparable complexity to obtain better results which are with in 95% of the optimal capacity, while the results obtained by GA are within 90% of the optimal capacity. However, if we relax capacity performance requirements from 95 to 90%, the complexity of the PSO algorithm will be reduced. Therefore, the PSO-based antenna selection algorithm has a great advantage in balancing between capacity performance and complexity.

Taking the feasibility of practical application into account, the antenna selection strategies mentioned above are evaluated on the hardware chip by the computational time, which mainly concerns the number of floating-point calculations (FLOPS). A flexible wireless processing equipment implemented by chip GC5322 with the TMS320C67x DSP family integrated as the baseband processor is provided by the TI company [21], which is a highly versatile platform targeted for the TD-SCDMA, WCDMA, HSPA, HSPA+, LTE, WiMAX and CDMA2000 wireless infrastructure market. Advanced features such as MIMO and beamforming can be easily supported without the need for any hardware redesign. Take the advanced DSP chip TMS320C6678 as an example, which has a processing capability of 320000 MMACS (million of multiplications and additions per second). Consider the MIMO antenna selection scenario mentioned above with $N_r = 20$ and $L = 4$. Assumed that the determinants on a matrix of size $M \times N$ may roughly require max (MN^2, NM^2, N^3) FLOPS. On the basis of the complexity evaluation above, the ESA, PSO and GA roughly require 3.876×10^7, 4×10^6, 4.4×10^6 FLOPS respectively; Accordingly, the corresponding computational time spent by these schemes are 121.125, 12.5, 13.75 (:us) respectively. In such scenario, the ESA consumes the longest time, followed by the PSO spending much fewer time. However, if high restrictions on time delay have been attached on the antenna selection algorithm, then probably the ESA scheme with higher computational time may encounter some difficulties. Alternatively, the PSO provides a viable approach by striking a better tradeoff between capacity and computational time.

6 Conclusion

New PSO-based antenna selection strategy is proposed for the MIMO system, which utilizes the particles searching ability to find the best antenna subset to maximize the system capacity. Moreover, the particle has been attached the new definition of the indices of the antenna subset and benchmark functions are employed to testify the performance of PSO. Experiment results show that PSO may strike a much better balance between capacity performance and computational complexity when compared with optimal ES method. As better characteristic can be achieved, the proposed algorithm is expected to be applied to other wireless communication problems.

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