ABSTRACT. In this paper, based on phase-only perturbation method, an innovative uplink Multiple-Input Multiple-Output Spatial Division Multiple Access (MIMO-SDMA) optimization technique of smart antennas by is proposed. Particle swarm optimization (PSO) algorithm is used to search the optimal weighting vector of the phase shift perturbations for array factor. The deduced radiation pattern formulas available for searching optimal solutions are used to search the optimal weighting vector of the array factor of a smart antenna. The design for an optimal radiation pattern of a smart antenna can not only adjustably suppress interferers by placing nulls at the directions of the interfering sources but also provide maximum main lobes in the directions of the desired signals at the same time, i.e., to maximize the Signal to Interference Ratio (SIR). In order to achieve this goal, a new convergent method referred as the two-way convergent method for particle swarm optimization is proposed. The optimal radiation pattern design of smart antennas is studied by phase-only perturbation method to achieve uplink MIMO-SDMA optimization.

Keywords: Multiple-Input Multiple-Output, Spatial Division Multiple Access, Smart Antennas, linear phase array, Particle swarm optimization

1. Introduction. The advent of fast and low-cost digital signal processors has made smart antennas practical for cellular land or satellite mobile communication system systems. Therefore, the study of smart antenna systems is becoming the interest of engineers and researchers in the communication field. The goal is to improve the system performance by increasing channel capacity and spectrum efficiency, extend range coverage, steer multiple beams to track more mobiles, suppress multipath and co-channel interferences for signal propagations [1].

PSO algorithm combines the advantages of efficient heuristics incorporating domain knowledge and population-based search approaches to solve the optimization problems. In PSO algorithm, each single solution is a "bird" in the search space. It is called "particle". All of particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by the current optimum particles. Particle swarm optimizations are used to search the optimal weighting vector of the phase-only perturbations of array factor [2]. Compared with nulling or main lobe designs, the optimal radiation pattern design brings different convergent criteria for optimization problems [3-6]. It must not only suppress the interferences in their
directions but also enhance the main lobe towards the desired signal’s direction. The simulation results show the effectiveness of the particle swarm optimization for this kind of optimization problem. The optimization design of a smart antenna has been limited to adjust the main lobe of radiation pattern towards the users. But, it is not good enough for the practical mobile communication system.

In the modern wireless communication, it asks for high quality and good efficiency. Base station antennas use omnidirectional or sectored pattern, which could cause the power waste in unexpected direction and interference for the others. A single antenna cannot change the beam pattern without mechanism. The beam pattern can be changed if the communication system has two or more antennas combined together. In order to have high quality and good efficiency, the practical mobile communication system must not only adjustably maximize the main lobe towards the direction of the desired signals, but also suppress interferences by placing nulls in the directions of interfering signals in the smart antenna radiation pattern. Thus, Multiple-Input Multiple-Output Spatial Division Multiple Access (MIMO-SDMA) can be really come true. In a smart antenna system, there will be several signals use a co-channel at the same time. Therefore, these signals will interfere with one another [7-8]. The uplink SDMA technique can offer the allocations of multiple mobile users to a common communication channel with its spatial separation ability and can avoid making interferences one another. Thereby, the system capacity can be increased. The optimal radiation pattern method can make uplink MIMO-SDMA optimization come true and is able to be satisfied with the practical mobile communication system. In order to achieve this goal, a new convergent method referred as the two-way convergent method for particle swarm optimizations is proposed. The system can be is optimized via putting pattern nulls in interfering directions and maximizing the main lobes power toward users so that the signal to interference ratio (SIR) is maximized. So, the uplink smart antenna system possesses the optimal SIR and achieves Spatial Division Multiple Access (SDMA) optimization [9-10].

2. Deduction of Radiation Pattern Array Factor Formula. Uplink system diagram of a smart antenna is designed by phase perturbations in a linear array using particle swarm optimization (PSO) as shown in Figure 1. For a linear array of \(2N\) equispaced sensor elements, a signal of wavelength \(\lambda\) from direction \(\theta\) with respect to the array normal impinges on any two adjacent element \(n\) and element \(n+1\) by the distance \(d\) as shown in Figure 2. Obviously, the signal will reach element \(n\) first, then element \(n+1\). The time difference \(\tau\) can be expressed as follows [11]:

The \(\nu\) is the propagation speed of radio wave. Then, there is a time delay \(\tau\) as follows:

\[
\tau = \frac{d \sin \theta}{\nu} \tag{1}
\]

The \(\tau\) corresponds to a phase shift of \(\frac{2\pi}{\lambda}d \sin \theta\).

\[
\psi = \frac{2\pi}{\lambda}d \sin \theta = kd \sin \theta \tag{2}
\]
FIGURE 1. Uplink smart antenna system designed by phase-shift perturbations using a particle swarm optimization

FIGURE 2. The incident signal reaching any two adjacent elements

Then, for far field, the array factor of the adaptive linear array for receiver $m$ of a smart antenna can be written as

$$AF_m(\theta) = \frac{1}{M} \sum_{n=1}^{2N} w_{mn} e^{j(n-1)\phi}, \quad m = 1, 2, 3, \ldots, M$$

(3)

where $M$ is the number of users.

$w_{mn}$ is the complex array weight at element $n$ of receiver $m$. It can be expressed as:

$$w_{mn} = \alpha \ e^{j\beta_{mn}}$$

(4)
where $\alpha$: amplitude weight at element $n$ for receiver $m$

$\beta_{mn}$: phase shift weight at element $n$ for receiver $m$

If the reference point is set at the physical center of the array, the array factor can be rewritten as:

$$AF_m(\theta) = \frac{1}{M} \sum_{n=1}^{2N} w_{mn} e^{j(n-N-0.5)\theta} = \frac{1}{M} \sum_{n=1}^{2N} \alpha e^{j(n-N-0.5)\theta + \beta_{mn}}, \quad m = 1, 2, 3, \ldots, M$$

(5)

Furthermore, assumed, amplitude weights are constant and phase shift weights are in odd symmetry, equation (5) can be simplified to

$$AF_m(\theta) = 2 \cdot \frac{1}{M} \sum_{n=1}^{N} \alpha \cos((n - 0.5)\theta + \beta_{mn}), \quad m = 1, 2, 3, \ldots, M$$

(6)

The array factor, given by (6), describes the model of the radiation pattern and is suitable for optimal solution search. As only the real part is left, it is available for searching the optimal solutions using optimization technique. For using the optimization technique, the fitness function cannot include the imaginary part.

### 3. Particle Swarm Optimization for Optimal Pattern Design.

In PSO algorithm, each particle (individual) adjusts its "flying" according to its own flying experience and its flying experience of companions. Each particle is treated as a point in a D-dimensional space. The ith particle is represented as $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$. The best previous position (the position giving the best fitness value) of the ith particle is recorded and represented as $P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$. The index of the best particle among all the particles in the population is represented by the symbol g. The rate of the position change (velocity) for particle $i$ is represented as $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$. The particles are manipulated according to the following equations:

$$v_{id} = \omega \cdot v_{id} + c_1 \cdot \text{Rand}() \cdot (p_{id} - x_{id}) + c_2 \cdot \text{Rand}() \cdot (p_{gd} - x_{id})$$

(7)

$$x_{id} = x_{id} + v_{id}$$

(8)

where $c_1$ and $c_2$ are two positive constants, $c_1$ and $c_2$ are usually $c_1 = c_2 = 2$, $\text{Rand}()$ is two random functions in the range $[0, 1]$, and $\omega$ is the inertia weight.

Equation (7) is used to calculate the particle's new velocity according to its previous velocity and the distances of its current position from its own best experience (position) and the group's best experience. Then the particle flies toward a new position according to equation (8). The performance of each particle is measured according to a pre-defined fitness function, which is related to the problem to be solved. The inertia weight $\omega$ is employed to control the impact of the previous history of velocities on the current velocity, thus to influence the trade-off between global (wide-ranging) and local (nearby) exploration abilities of the "flying points". A larger inertia weight 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 can provide a balance between global and local exploration abilities and thus require less iteration on average to find the optimum. In this paper, an analysis of the impact of this inertia weight together with the maximum velocity allowed on the performance of particle swarm optimization is given, followed by experiments that illustrate the analysis and provide some insights into optimal selection of the inertia weight and maximum velocity allowed. The utility of a particle swarm optimization is shown for global
A particle swarm optimization is used to adjust the phase shift weights based on the power of the array in the interfering directions. The goals are to minimize the total output power of the interfering signals and maximize output power of the desired signals to the receiver. During the process of PSO algorithm iteration, the weighting vector kept for the next step iteration should make the output power of the desired signal to be increased and the output power of the interfering signal to be decreased monotonically. So, the PSO algorithm is applied to find the optimal radiation pattern of the proposed smart antenna by using the two-way convergent method. Obviously, this technique can increase the signal to interference ratio (SIR). Then, the MIMO-SDMA optimization of smart antennas can be achieved.

So, the fitness function is the square of \( AF_m(\theta) \) in equation (6). Obviously, this technique can increase the signal to interference ratio (SIR).

The flow chart of particle swarm optimization is given in Figure 3. Detailed steps of particle swarm optimization approach are as follows:

**Step 1. Initialization:**
The first step toward implementation of the PSO algorithm is to pick the parameters that need to be optimized and give them a reasonable range in which to search for the optimal solution. This requires specification of a minimum value for each dimensional optimization.

**Step 2. Initialize random swarm location and velocities:**
To begin search for the optimal position in the solution space, each particle begins at its own random location with a velocity. They are random both in its direction and magnitude. Since its initial position is the only location encountered by each particle at the run’s start, this position becomes each particle’s respective individual best. The first global best is then selected from among these initial positions.

**Step 3. Evaluate particle’ fitness:**
The fitness function, using the coordinates of the particle in solution space, returns a fitness value to be assigned to the current location. If that value is greater than the value at the respective individual best for that particle, or the global best, then the appropriate locations are replaced with the current location.

**Step 4. Update the individual best and global best:**
As a particle moves through the search space, it compares its fitness value at the current position with the best fitness value which has ever attained at any time up to the current time. The best position that is associated with the best fitness encountered so far is called the individual best. Each particle individual best is evaluated according to the updated position. It is the best position among all of the individual best positions achieved so far. Hence, the global best can be determined.

**Step 5. Update the velocity and position:**
It is the velocity of the moving particles represented by a real-valued vector. The manipulation of a particle’s velocity is the core element of the entire optimization. Careful understanding of the equation used to determine the velocity is the key to understanding the optimization as a whole. The velocity of the particle is changed according to the relative locations of individual best and global best. Based on the updated velocities, it is simple to move the particle to its next...
Step 6. Termination criteria:
This is the condition under which the search process will terminate. In this study, the search will terminate if the following criteria is satisfied: The number of iterations reaches the maximum allowable number. If one of the termination criteria is satisfied, then stop, or else go to step 3.

![Flow chart of particle swarm optimization](image)

FIGURE 3. The flow chart of particle swarm optimization

4. Computer Simulations and Results. In this design, the necessary parameters of the particle swarm optimization are defined as follows:
   - the population size $P$ equals 300;
   - the maximum number of generation equals 500;
   - the maximum value of inertia weight $w$ is 0.8;
   - the minimum value of inertia weight $w$ is 0.3;
   - the acceleration constants $C_1$ and $C_2$ are 2; the maximum speed of particle is 1000.

The population size, maximum number of generation, the maximum value of inertia weight, and the minimum value of inertia weight, the acceleration constants and the maximum speed of particle are specified before the implementation of the algorithm. Their values definitely affect the process of optimal solution search and results.

In this problem, a linear antenna array is composed of 20 isotropic elements. So, $N = 10$. $N$ is variable number. The distance $d$ of two adjacent elements is a half of $\lambda$. The technique features are by phase-only perturbations. Amplitude weights are constant and phase shifter
weights are in odd symmetry. The value of $\alpha$ is constant set between 0.1 and 1. The value of $\beta_n$ is set between $-\pi$ and $\pi$. The unit of $\beta_n$ is rad.

Example: In this uplink smart antenna system, the signals of user 1 and user 2 come from $-40^0$ and $60^0$ respectively. As this example, a two-user system is studied. The user’s number is 2 in this smart antenna system. So, $M$ equals 2. If the number of the current generation is equal to 600, the particle swarm optimization iteration will stop automatically.

Radiation pattern of user 1: For user 1, the signal of user 2 is considered as its interfering signal. After particle swarm optimization implementation, the iterations stop in 500 generations automatically. The weight vector $[\beta_{mn}]$, $m = 1, n = 1, 2, 3, \ldots, N$, for the optimal radiation pattern of user 1 after 500 generations, is derived as listed in Table 1. The optimal radiation pattern is derived as shown in Figure 4. In user 1’s radiation pattern, the null is derived in the $60^0$ interfering direction and the maximum main lobe is derived at $-40^0$. Thus, the optimal radiation pattern of user 1 has been derived. The SIR is 59 dB. So, the interference on user 1 due to user 2 can be ignored.

Radiation pattern of user 2: For user 2, the signal of user 1 is considered as its interfering signal. After particle swarm optimization implementation, the iterations stop in 500 generations automatically. The weight vector $[\beta_{mn}]$, $m = 2, n = 1, 2, 3, \ldots, N$, for the optimal radiation pattern of user 2 after 500 generations, is derived as listed in Table 1. The optimal radiation pattern is derived as shown in Figure 5. In user 2’s radiation pattern, the null is derived in the $-40^0$ interfering direction and the maximum main lobe is derived at $60^0$. Thus, the optimal radiation pattern of user 2 has been derived. The SIR is 60 dB. So, the interference on user 2 due to user 1 can be ignored.

For user 1’s radiation pattern, the main lobe is toward the user 1 according to Figure 4. At the same time, the null of the radiation pattern of user 1 is also toward user 2. So, the optimal radiation pattern of user 1 possesses the interference nulling and the desired signal maximizing. Likewise, for user 2, it is the same. The efficiency of particle swarm optimization approach is high, and the interference can be ignored in real time signal processing so that it is suitable for the practical mobile communication. The radiation pattern of the smart antenna in Cartesian coordinate is shown in Figure 6. The radiation patterns of the smart antenna in polar coordinate are shown in Figure 7 and Figure 8.
Table 1  The weight vector $[\beta_{mn}]$ for the optimal radiation pattern of two users

<table>
<thead>
<tr>
<th>Radiation pattern of user 1:</th>
<th>Radiation pattern of user 2:</th>
</tr>
</thead>
<tbody>
<tr>
<td>desired signal direction at $-40^0$ and interfering source at $60^0$</td>
<td>desired signal direction at $60^0$ and interfering source at $-40^0$</td>
</tr>
<tr>
<td>$\beta_{11} = -2.424$</td>
<td>$\beta_{21} = 2.584$</td>
</tr>
<tr>
<td>$\beta_{12} = -0.959$</td>
<td>$\beta_{22} = -0.729$</td>
</tr>
<tr>
<td>$\beta_{13} = 2.169$</td>
<td>$\beta_{23} = 2.877$</td>
</tr>
<tr>
<td>$\beta_{14} = 3.136$</td>
<td>$\beta_{24} = -0.255$</td>
</tr>
<tr>
<td>$\beta_{15} = 0.317$</td>
<td>$\beta_{25} = -3.140$</td>
</tr>
<tr>
<td>$\beta_{16} = 0.928$</td>
<td>$\beta_{26} = 2.990$</td>
</tr>
<tr>
<td>$\beta_{17} = -2.096$</td>
<td>$\beta_{27} = -0.928$</td>
</tr>
<tr>
<td>$\beta_{18} = -1.282$</td>
<td>$\beta_{28} = 1.317$</td>
</tr>
<tr>
<td>$\beta_{19} = 2.001$</td>
<td>$\beta_{29} = -0.436$</td>
</tr>
<tr>
<td>$\beta_{110} = -2.902$</td>
<td>$\beta_{210} = 2.430$</td>
</tr>
</tbody>
</table>

FIGURE 4. Optimal radiation pattern for user 1 at $-40^0$ and interfering source at $60^0$
FIGURE 5. Optimal radiation pattern for user 2 at $60^\circ$ and interfering source at $-40^\circ$.

FIGURE 7. Radiation pattern of two-user uplink smart antenna in polar coordinate (scaled in dB)

FIGURE 8. Radiation pattern of two-user uplink smart antenna in polar coordinate (scaled in decimal)
5. **Conclusion.** The Multiple-Input Multiple-Output Spatial Division Multiple Access (MIMO-SDMA) optimization design of a smart antenna based on phase-only perturbations using the particle swarm optimization is proposed and achieved. In the paper, first, the array factor formula suitable for optimal solution search based on signal phase shift for a smart antenna is deduced. In order to be able to adopt the particle swarm optimization to search the optimal radiation pattern, the formula is reformed through amplitude weights are constant and phase shift weights are in odd symmetry.

Particle swarm optimizations are applied to find the optimal weighting vectors of array factor of the proposed smart antenna. The optimal radiation pattern means that the power of desired signal has to be highest and the power of interfering signals has to be lowest at the same time. So, in this proposed smart antenna, for each user’s optimal radiation pattern, there are one main lobe formed towards one desired user and nulls formed in the directions of other users whose signals are considered as its interfering sources. Thus, this smart antenna system can not only derive maximized main lobes in the directions of all the desired signals but also suppress interferences by placing nulls in its radiation pattern adjustably. In this way, the MIMO-SDMA effect is achieved and optimized. Then, the uplink MIMO-SDMA optimization of a smart antenna has been achieved.

**REFERENCES**


