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Optimizing Multiple Interference Cancellations of Linear Phase Array Based on Particle Swarm Optimization

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Abstract. *In this paper, a novel optimization method based on the particle swarm optimization (PSO) algorithm for the multiple interference cancellation design of a linear phase array is proposed. A linear phase array is a linear array antenna with phase-only perturbations. Adaptive array antenna is able to suppress the interferences in the interfering directions by using optimization techniques so that it can increase the Signal to Interference Ratio (SIR). The particle swarm optimization can solve combinatorial optimization problems. The particle swarm optimization is applied to*
nd the weighting vector, which makes the pattern nulling optimization of the proposed adaptive antenna. This PersonNametechnique is also able to do the cancellation of multiple interferences for different incident directions in practical wireless communication systems. One example is provided to manifest demonstrate the proposed phase-only perturbations approach based on particle swarm optimization. Simulation example demonstrates the effectiveness of the proposed method in this paper.
Keywords: Particle swarm optimizations, linear phase array, phase-only perturbations, multiple interference cancellations

1. **Introduction.** Modern communication asks for high quality and efficiency in a wireless communication system, Radiation pattern nulling optimization techniques are very important to suppress undesired interfering signals. Adaptive beamforming techniques are used to obtain the desired antenna radiation pattern by adjusting the antenna parameters such as position, phase and amplitude weights of the linear antenna array. The methods of nulling mentioned in literatures [1-3] have their relative merits. But, the most efficient choice is the control of phase shift weight of each array element. Adaptive pattern nulling technique minimizes the power of an interfering signal coming from any direction by putting a null in its direction [4-5].

Due to the fast development of computer, modern numerical optimization techniques are used to radiation pattern design becoming possible. There are several traditional kinds of numerical optimization methods such as least mean square algorithm, minimum noise variance algorithm, conjugant gradient method, etc. Each of these has its merits and demerits. Least mean square algorithm is a gradient-based algorithm, which does not require the knowledge of the direction of arrival of the input signal but needs a reference signal. Minimum noise variance algorithm is a generalized gradient-based technique, which requires the direction of arrival of the desired signal. Conjugant gradient method is a gradient-based method. The gradient-based methods are fast and effective, but may easily get stuck locally.

The concept of PSO algorithm was first established by Kennedy and Eberhart in 1995 [6-8], based on the mechanism of the movement nature of swarms and inspired by social behavior of bird flocking. PSO algorithm adopts to imitate creatures wisdom to solve all sorts of problems. It is like a kind of possessing community intelligence method to consider each member of graylag group as a particle in three dimension space. To take advantage of possessing exploration and development characteristics in particle group, the best solution can be globally searched in problem space. Every particle stands for the solution at problem. Each takes charge of the best solution search in its own area. By means of memory share of race group, particle will take obligation of race group. Eventually, the optimization problem search will be

nished. PSO algorithm is used for solving the optimization problem [9]. A perturbation method consists of small perturbations in the element phases to obtain the desired nulling pattern, which has got much attention. In this article, nulling techniques for a linear antenna array are investigated. The technique features are phase-only perturbations. A search procedure based on PSO algorithm is used to obtain the required perturbations for the designed patterns with null steering.

In this paper, the optimization of radiation pattern, which shows that the array can suppress interferences by placing nulls, has been achieved. In order to reach this goal, the particle swarm optimization (PSO) algorithm is used to make the search of optimal weighting vector. As known, compared with gradient-based search methods [10], the PSO algorithm can carry out a global search. In this article, we focus on suppressing the multiple different interfering sources.

In this paper, the proposed numerical method can be used in a real time signal processing and the mobile communication. The structure of this paper is as follows: In Section 2, the developing of pattern formula is described. In Section 3, the particle swarm optimization approach for pattern nulling in detail is presented. In Section 4, Computer simulations and results are presented. Finally, concludes are given in Section 5.

2. **Developing of Pattern Formula.** For a linear array of $2N$ equispaced sensor elements as Figure 1, an interfering signal with wavelength λ impinges on any adjacent two sensor elements n and $n+1$ separated by a distance d and from a direction θ with respect to array normal as shown in Figure 2.

The ν is the propagation speed of radio wave. Then, there is a time delay τ as follows [11]:

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

The τ corresponds to a phase shift of $\frac{2\pi}{\lambda} d \sin\theta$.

$$\psi = \frac{2\pi}{\lambda} d \sin\theta = kd\sin\theta \tag{2}$$

The array factor for far field is given by

$$AF(\theta) = \sum_{n=1}^{2N} w_n e^{j(n-1)\psi} \tag{3}$$

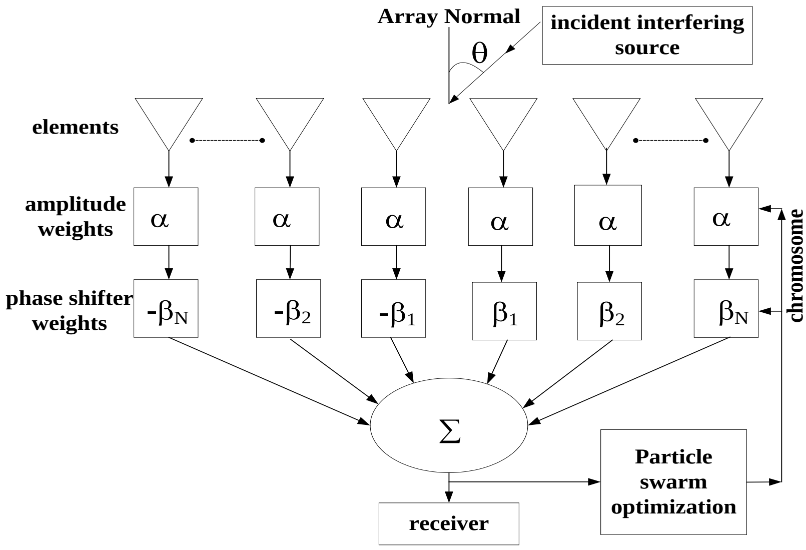

Figure 1. Diagram of an adaptive linear array designed by phase shift perturbations using a particle swarm optimization algorithm

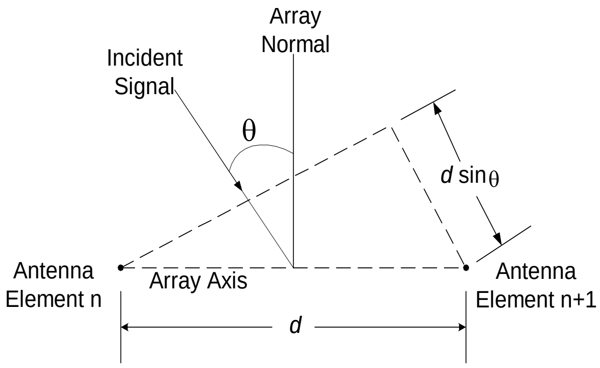

Figure 2. The incident signal reaching any two adjacent elements

If the reference point is at the physical center of the array, the array factor becomes

$$AF(\theta) = \sum_{n=1}^{2N} w_n e^{j(n-N-0.5)\psi} = \sum_{n=1}^{2N} \alpha_n e^{j[(n-N-0.5)\psi+\beta_n]} \tag{4}$$

where
$2N$ = number of elements
$w_n = \alpha e^{j\beta_n}$ complex array weights at element n
$\alpha=$ constant amplitude weight at any element
$\beta_n=$ phase shift weight at element n
$\psi = kd\sin\theta$
θ =an incidence angle of interfering signal or desired signal

If amplitude weights are constant and phase shifter weights are odd symmetry, then equation (4) can be simplified to

$$AF(\theta) = 2\sum_{n=1}^{N} \alpha \cos[(n-0.5)\psi + \beta_n] \tag{5}$$

The equation (5)) is written in normalized form as follows:

$$AF_n(\theta) = \frac{1}{N}\sum_{n=1}^{N} \alpha \cos[(n-0.5)\psi + \beta_n] \tag{6}$$

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 Approach for Pattern Nulling.** PSO algorithm learned from the scenario and used it to solve the optimization problems. In PSO, 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.

In PSO algorithm, instead of using genetic operators, 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 equation:

$$v_{id} = w * v_{id} + c_1 * Rand() * (p_{id} - x_{id}) + c_2 * Rand() * (p_{gd} - x_{id}) \tag{7}$$

$$x_{id} = x_{id} + v_{id} \tag{8}$$

where c_1 and c_2 are two positive constants, c_1 and c_2 are usually $c_1 = c_2 = 2$, $Rand()$ is two random functions in the range [0, 1], and w 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 w 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 [12].

PSO algorithm combines the advantages of efficient heuristics incorporating domain knowledge and population-based search approaches for optimization problems. In this paper, we show the usefulness of a particle swarm optimization for global search. A particle swarm optimization is used to adjust the phase shift weights based on the power of the array in the interfering directions. The goal is to minimize the total output power of the interfering signals to the receiver [13]. So, the fitness function is the square of $AF_n(\theta)$ in equation (6). Obviously, this technique can increase the signal to interference ratio (SIR).

The flow chart of particle swarm optimizations 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 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 runs start, this position becomes each particles 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 location.
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 the termination criteria is satisfied, then stop, or else go to step 3.

4. **Computer Simulations and Results.** To verify the good performance of particle swarm optimization algorithm, The multiple interference cancellation design of a linear phase array with phase-only perturbations is demonstrated. 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 600;
the maximum value of inertia weight w is 0.9; the minimum value of inertia weight w is 0.4. ;
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, the minimum value of inertia weight, the acceleration constants and the maximum speed of particle are specified before the implementation of the algorithm. These parameters affect the optimization process.

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 half of λ. The

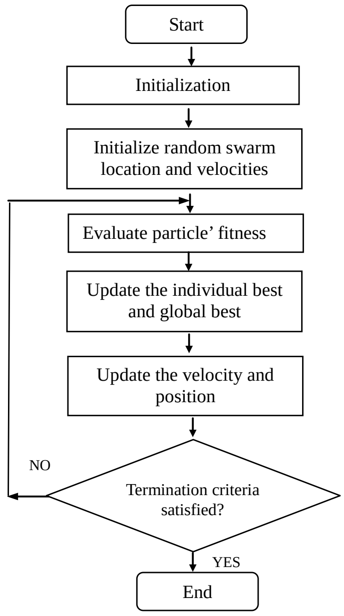

FIGURE 3. The flow chart of particle swarm optimization algorithm

technique features are by phase-only perturbations. Amplitude weights are constant and phase shift weights are in odd symmetry. The value of α is constant set between 0.1 and 1. The value of β_n is set between -π and π. The unit of β_n is rad.

Example

In this case, assumed with respect to array normal, the interfering directions are 500 and -250 respectively. The particle swarm optimization is going to stop at 600 iterations. The results are as Table 1 and Figure 4. The radiation pattern is mapped from 900 to 2700 as shown in Figure 5 and Figure 6 in polar coordinate.

In the particle swarm optimization, the termination criteria are predefined. If the number of the current generation is equal to 600, the particle swarm optimization iteration will stop automatically.

The proposed particle swarm optimization technique is also able to do the cancellation of multiple interferences for different incident directions in the above example. The method based on the particle swarm optimization for the adaptive multiple interference cancellation of linear array antenna on phase-only perturbations is efficiently presented.

TABLE 1. The best set of weights β_n for the radiation pattern optimization

Interfering sources at 50° and -25°
$\beta_1 = -3.132$
$\beta_2 = -3.140$
$\beta_3 = -3.140$
$\beta_4 = -1.685$
$\beta_5 = -2.867$
$\beta_6 = 3.140$
$\beta_7 = 3.127$
$\beta_8 = -3.140$
$\beta_9 = 2.484$
$\beta_{10} = -3.140$

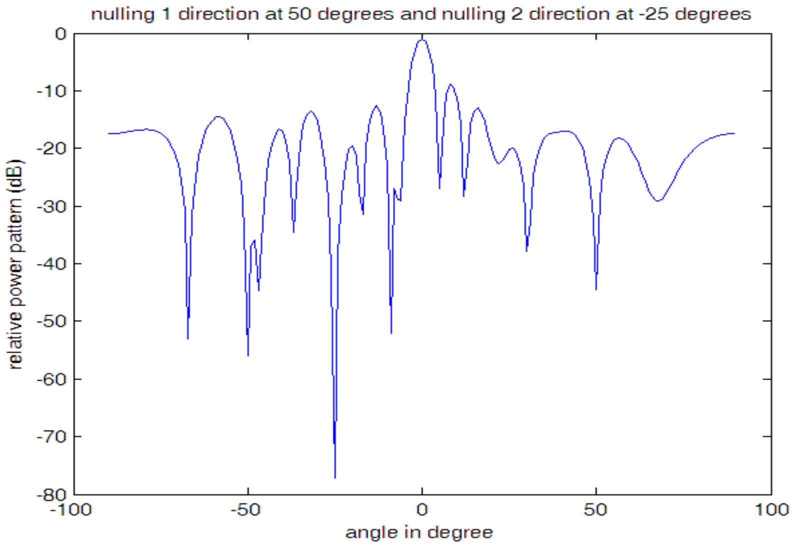

FIGURE 4. Adaptive antenna pattern for interfering sources at angle 50° and -25°

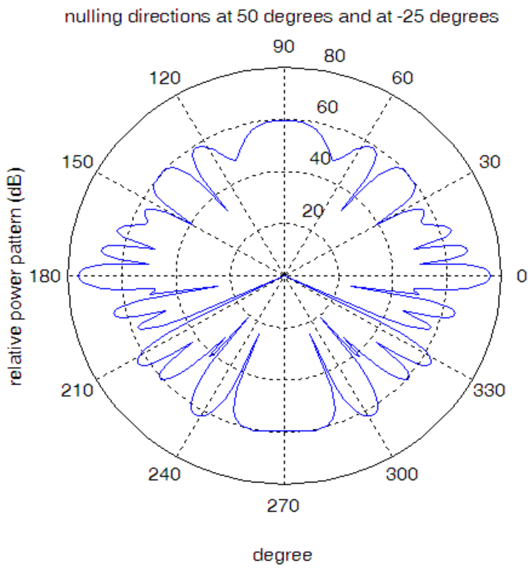

FIGURE 5. Radiation pattern of adaptive antenna in polar coordinate (scaled in dB)

5. **Conclusions.** In this paper, the PSO technique was introduced into the interference cancellations in an adaptive array. By phase-only perturbation method, the nulling design of an adaptive antenna has been studied by the approach of PSO algorithm. The PSO algorithm in an adaptive array can be used to suppress interfering signals.

Adaptive arrays can automatically adjust the element weightings to null out interfering signals in their directions. Pattern nulling design of an adaptive antenna for suppressing interferences via phase-only perturbations using PSO algorithm is proposed and achieved. First of all, the uplink output array factor formula based on phase composed by adaptive antenna array was deduced. In order to be able to adopt the PSO algorithm to search the optimal solution, the formula is reformed through assuming that amplitude weights are constant and phase shift weights are in odd symmetry. A search procedure based on the PSO algorithm was designed and used to obtain the required perturbations for the desired radiation pattern nulling. The excellent interference cancellation of adaptive

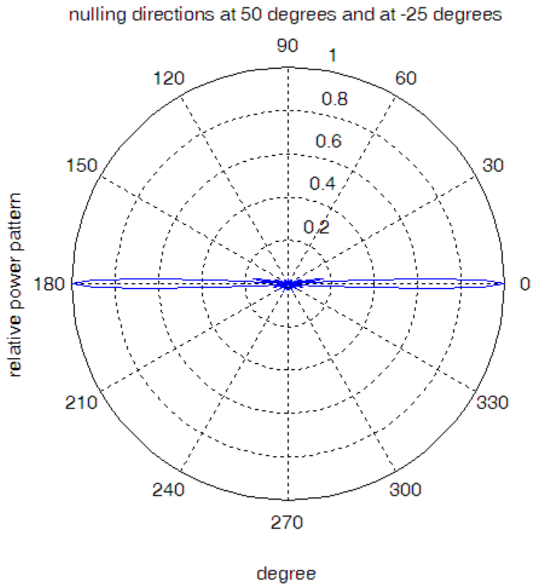

FIGURE 6. Radiation pattern of adaptive antenna in polar coordinate (scaled in decimal)

linear array antenna by phase-only perturbations using particle swarm optimization has been derived, which can make signal to interference ratio (SIR) increase.

The phase-only perturbations are easy to be operated by electricity, so it is suitable to mobile communication in real time signal processing. It has shown that the particle swarm optimization can effectively and successfully be used for this problem. Eventually, it is hopeful that this optimization approach can be helpful for antenna engineers as a simple, useful and reasonable alternative.

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