A Proposed Method for Synthesizing the Radiation Pattern of Linear Antenna Arrays

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Abstract – The design of antenna arrays is one of the most challenging optimization problems in recent research interests. In this research work a new method of optimization proposed. This method called "Characteristics Evolution Optimization" is based on parallel processing of streams of binary digits, and hence it can perform well in parallel processing digital systems. In this article, a 16 - element linear antenna array has been taken into consideration, and the performance of the proposed technique for synthesizing the radiation pattern of the array has been investigated and compared with other existing techniques, such as DE (Differential Evolution), IWO (Invasive Weed Optimization), and PSO (Particle Swarm Optimization). Various variants of Invasive Weed Optimization have been investigated as well. It has been observed that the proposed method (Characteristics Evolution optimization) outperforms the other optimization techniques significantly in different aspects.

Keywords: Pattern Synthesis, Linear Array, Antenna Arrays Characteristics Evolution Optimization, Radiation patterns
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1. Introduction

Antenna Arrays play an important role in detecting and processing signals arriving from different directions. The role of antenna array synthesis is to determine the physical layout of the array, and the amplitude and phase excitation that produces a radiation pattern that is closest to the desired radiation pattern. The shape of the desired pattern can vary widely depending upon the application. Some applications require a low sidelobe level, while other applications require an interference reduction using null control. However, the global synthesis of antenna arrays that generate a desired radiation pattern are a highly non-linear optimization problem, and hence analytical methods are not applicable anymore. For this purpose, several optimization techniques have been developed to suite non-linear optimization problems. Many methods are bio-inspired. These methods have proven to be highly successful. Some of these are Genetic Algorithm (GA), and Particle Swarm Optimization (PSO). In GA, a sample of possible solutions is assumed, then mutation, crossover, and selection are employed based on the concept of survival of the fittest solution. Particle swarm optimization (PSO) is a computational method in which optimization is done by trying to improve a candidate solution problem at each iteration with respect to a given measure of quality.

It is a population-based method. Here the population of candidate solutions are known as particles. The position and velocity of each particle are updated by a fitness function. The objective of PSO is to find a solution for a constrained minimization problem based on a particular cost function.

In this research work a new method of optimizing the synthesis of antenna array radiation/sensitivity patterns is introduced. This method/algorithm is called "Characteristics Evolution Optimization". Firstly, the linear array design synthesis problem is explained, and hence, the new method is introduced with the solution of the optimization problem, and compared to other optimization methods such as Invasive Weed Optimization (IWO), Particle Swarm Optimization (PSO), and Differential Evolution Algorithm (DE).

2. Formulation Of the Design Problem

To synthesize the radiation pattern of the linear antenna array, the overall gain of the array as a function of θ is required, i.e., $a(\theta)$. However, the class of this function is large, as it includes large number of sum and difference pattern components.

2. 1 Sum and Difference Patterns

Many applications of linear arrays involve the need to produce sum and difference patterns such that the main beam of the sum pattern points at θ, the twin main beams of the difference pattern straddle θ, and both patterns should exhibit a symmetrical sidelobe structure.

Figure 1 illustrates a linear antenna array with *2N* equally spaced elements, where the distance between the elements can be adjusted to get the overall desired radiation/sensitivity pattern of the array. Thus, the array factor can be written as

$$a_a(\theta) = \sum_{n=-N}^{-1} \frac{I_n}{I_1}.\exp(j\left[\frac{2n+1}{2}\right]kd(cos\theta - cos\theta_o) + \sum_{n=1}^{N} \frac{I_n}{I_1}.\exp(j\left[\frac{2n-1}{2}\right]kd(cos\theta - cos\theta_o) \quad (1)$$

For the sum pattern where $I_n = I_{-n}$, the above equation can be expressed as

$$S(\theta) = 2\sum_{n=1}^{N}\frac{I_n}{I_1}.\cos\left[(2n-1)(\frac{\pi d}{\lambda})(cos\theta - cos\theta_o)\right] \quad (2)$$

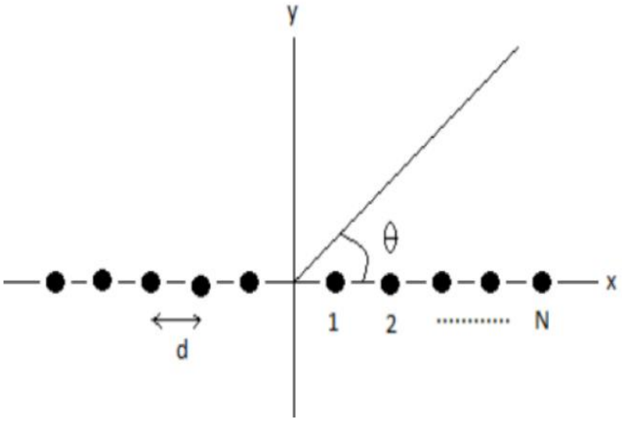

Figure 1. Linear Antenna Array with equally spaced *2N* elements.

For the difference pattern where $I_n = -I_{-n}$, the array factor can be expressed as

$$D(\theta) = j2\sum_{n=1}^{N}\frac{I_n}{I_1}.\sin\left[(2n-1)(\frac{\pi d}{\lambda})(cos\theta - cos\theta_o)\right] \quad (3)$$

An array with $2N+1$ elements is not suitable for the generation of a difference pattern, due to the presence of the central element. However, it can be used to produce a sum pattern, and hence the pattern can be expressed as

$$S(\theta) = 1 + 2\sum_{n=1}^{N}\frac{I_n}{I_1}.\cos\left[2n(\frac{\pi d}{\lambda})(cos\theta - cos\theta_o)\right] \quad (4)$$

3. Description Of the Proposed Method

The algorithm called "Characteristics Evolution Optimization CEO" is used to synthesize the radiation pattern of the array as binary representations of the array gains in various directions.

The main concept of this algorithm is based on the tendency of less evolved organisms to adopt the most significant characteristics of the more highly evolved organisms, and simultaneously, modify their characteristics accordingly. This process of adoption and modification leads to continuous evolution, and hence several diverse groups are formed with significant differences amongst them.

In Characteristics Evolution Optimization algorithm CEO, several groups with significant differences, specifications, and characteristics are formed. These groups are left to evolve independently for a specified period of time. As a result, when one of the groups is found to be more successful than other groups, the remaining groups start merging with the successful group. Eventually, the merged group evolves to obtain a higher success. The proposed algorithm (CEO) tries to adopt this procedure to obtain the optimum solution.

The step wise explanation of the algorithm is yet to be explained.

3.1 Initialization

The radiation pattern of a linear array with *2N* elements shown in Figure 1 is considered. To initialize the pattern synthesis, a population size of *NP* is considered, with each particle being initialized in a *N*-dimensional space. The particles are initialized with numbers ranging from 0 to R, where R is the predefined range.

Each particle consists of *N* numbers to be converted into their binary forms called "parts". The bit length used to represent the numbers can be defined by the user, where larger bit lengths provide better accuracy. Decimal numbers can be represented in binary forms by shifting the decimal point to the right to appropriate steps, so that the number on the left of the decimal point can be represented in the allocated bit length. For example, to represent 2.765 in binary system using five bits would become 11011. Once the particles are finalized, their fitness function is calculated according to the optimization function at hand. The particles are then arranged according to their fitness values.

3.2 Segregation into Groups

The entire population is equally segregated into groups, then the particles are arranged according to their fitness values within their respective groups.

3.3 Adoption of Characteristics

In every group, the group members try to adopt the characteristics of their corresponding leader, i.e. the member with the best fitness value. In binary representation, each bit is considered as a characteristic. The importance of the characteristics increases from right to left and the importance of the characteristics decreases from left to right as shown in Figure 2.

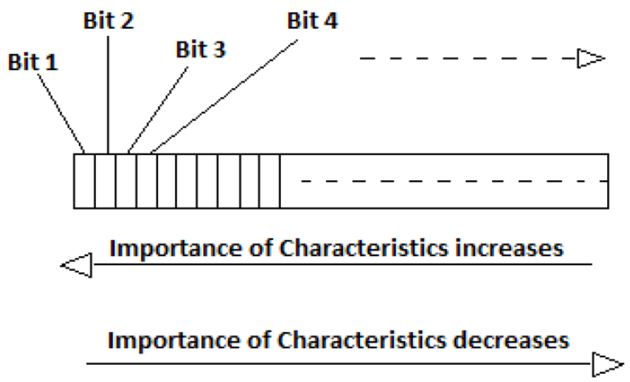

Figure 2. A particle contains *N* parts. Each part consists of several bits or characteristics.

Every particle has *N* parts, and each part has "Bit Length" number to represent the number of characteristics, as shown in Figure 3.

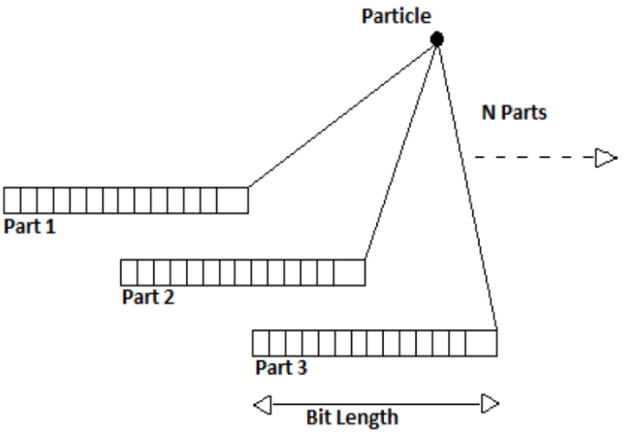

Figure 3. Particle representation. Every particle has *N* parts, each part has "Bit Length" characteristics, with values of 1 or 0.

The adoption process is illustrated in Figure 4. During this process, every characteristic in any part is assigned a particular adoption probability number that determines the probability that a particular characteristic will be adopted. During the adoption process in a group, every particle adopts the characteristics of the best particle of that group, according to the assigned adoption probability number. Thus, there can be "Bit Length" number of adoption probability numbers. For example, if the third characteristic of the second part of the best particle in a particular group is 1, then the chance of this 1 getting transmitted to the third characteristic of second part of some other particle of that same group is given by third adoption probability number.

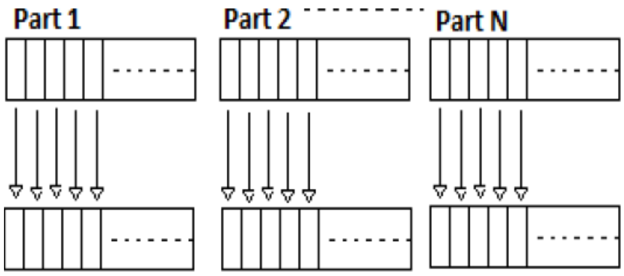

Figure 4. Adoption process. Every characteristic in every part tries to adopt the characteristics from the corresponding characteristic position and part of other particle.

The adoption probability number is assigned to the groups in a descending order from left to right, i.e., from the most important characteristic to the least important characteristic. The most important characteristics are assigned the highest adoption probability numbers to make sure that the other particles move closer to the best particle.

On the other hand, the less important characteristics are assigned less adoption numbers, since we do not want other particles to rapidly come at exactly the same position as that of the best particle in the *N*-dimensional space. It is required that other particles search wider space. Thus, as the particles try to imitate the main characteristics of the best particle of that group, they have the freedom to span the nearby space using the less important characteristics.

3.4 Evolution of Characteristics

As the particles try to adopt the characteristics of the best particle, they themselves try to evolve and search the entire space by changing their own characteristics. Every characteristic is given an evolution probability number which determines the probability of the characteristics to get altered, i.e., from 1 to 0 or from 0 to 1.

The evolution probability number is assigned to the groups in an ascending order from left to right, i.e., from the most important characteristics to the least important characteristics. This is done to avoid extreme deviation from their positions while preserving their rights to explore the region around them. Thus, each particle evolves itself individually, according to its evolution probability number.

3.5 Competitive Selection

For a particular group, there are now three sets of particle positions that have been formed. The first set consists of the original positions, the second set is formed after particles adopt the characteristics of the best particle of the group, and the third set is formed after the particles evolve their own characteristics.

Thus, for every particle, there are three positions available in *N*-dimensional space, which enables competitive selection of the best position for each particle in the space.

However, there is another way of competitive selection, that is: to arrange all the particle positions of a particular group in accordance to their fitness values, and then to select the best 1/3rd of the available positions. But this method faces the problem of premature convergence, which rises due to the fact that all the particles close to the current best position would be given a preference.

3.6 Merging of the Groups

All groups continue to evolve independently for a specified period of time. For the purpose of merging the groups, a point of confidence is defined, and the best fitness values of all the groups are recorded. Whenever any group crosses the point of confidence, all the groups are merged together into one single group. This directs all the resources to search the space around the position of the leading group, and all particles search their surrounding spaces according to the previously mentioned rules.

4. Simulation Results

The proposed method (CEO) is used to synthesize the radiation pattern of the linear antenna, and the results are compared to other methods, such as Differential Evolution algorithm (DE), Invasive Weed Optimization (IWO), variants of IWO, and Particle Swarm Optimization (PSO). The parametric setup used of the proposed algorithm is as follows: “Bit Length” ranges from 40 to 50, initial range of spread of the particles ranges from 0 to 10, and the number of groups is set to 4, and each group is assumed to have 50 particles. The population size after recombination of the group is assumed to be 75, and the point of confidence is set to 5. Hence, the four groups merge together when the error goes below 5. The adoption probability number of the characteristics is assumed to vary from 40% for the leftmost, i.e., most important characteristics to 20% for the rightmost characteristics. The evolution probability numbers of the characteristics starting from leftmost bit have values: 1%, 2%, 3%, 4%, 10% for the next 4 bits or characteristic, 20% for the next 6 characteristics, and 40% for the remaining bits or characteristics. For the purpose of competitive selection, all the particle positions of a particular group are arranged according to their fitness values, and the best population size *NP* is selected. The flow chart of Characteristics Evolution Optimization algorithm is depicted in Figure 5.

The design problem statement is to synthesize the radiation pattern of a linear array with 16 elements. The maximum sidelobe level (desired_min_SL) is required to be at -30dB. The function used to determine the error value is abs(max_SL-desired_max_SL), where abs is the absolute value function, and the desired maximum sidelobe level (desired_max_SL) is -30dB. The angle scanned for the sidelobes ranges from 0^o to 77^o and from 103^o to 180^o. Figure 6 illustrates the synthesized radiation pattern of 16-elements linear array with -30dB sidelobe level.

The parametric setup used for PSO, DE, IWO [9] and its variants is as follows: For the Differential Evolution algorithm (DE), the crossover constant is set to 0.5, and the mutation factor is set to 0.2. The Number of populations is assumed to be 400. For Particle Swarm Optimization (PSO), w_max and w_min parameters are considered as 0.9 and 0.4, respectively, and $V_{max} = 0.5\pi$ For the Invasive Weed Optimization (IWO), the number of agents is assumed to be 10 times the dimension. S_initial = 1, S_final=0.00000001, the Maximum number of seeds is set to have a value of 5, and the maximum number of populations is assumed to be 20 times the dimension.

The variants of the IWO used in this example are briefly described as follows: Modified IWO [1] uses a |cos(iter)| term in calculating the standard deviation, to allow for the fast convergence of the weeds present in location of the global optimum solution without having to wait for the standard deviation to decrease with iterations. MIWO [2] uses a modified formula for calculating the standard deviation, which is based not only on the iteration but also on the fitness value of corresponding weed. So, the standard deviation is different for every weed. This gives opportunity to the far away weeds to get closer to the global optimum solution, and prevent the close weeds to get trapped. DIWO [2] merges the MIWO with the differential evolution. It adopts the concept of mutation and crossover from DE algorithm and applies it to MIWO [2].

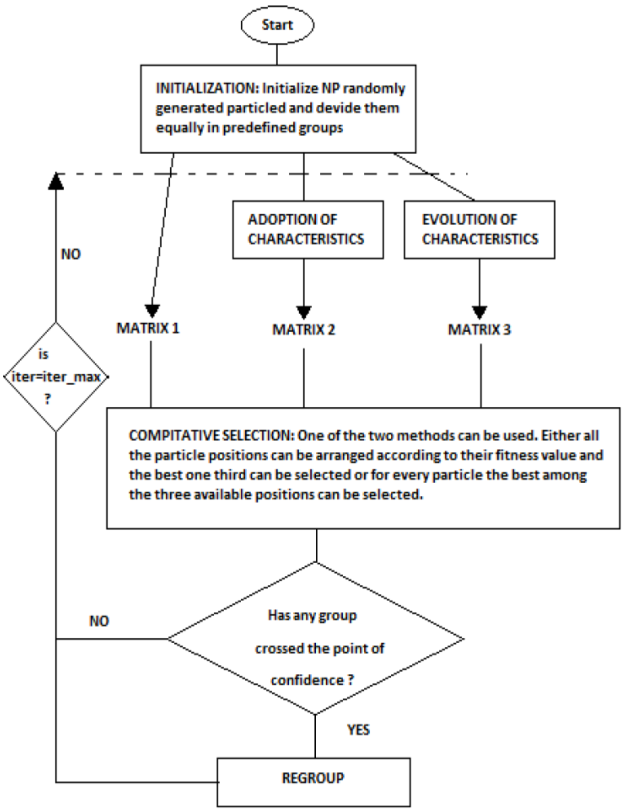

Figure 5. Flow chart of Characteristics Evolution Optimization.

For the purpose of plotting the error graphs and finding the beam widths, every algorithm is run 20 times. The graphs shown in Figure 7 and Figure 8 are the average of the 20 values. The lines in the graphs are artificially smoothened for better presentation.

The performance of the algorithm vastly depends upon the point of confidence, which determines the condition of merging of the groups. The larger the point is, the sooner groups will merge. However, this may cause the particles to get stuck in a local optimum solution. The error plots for different values of point of confidence are illustrated in Figure 7 and Figure 8.

The performance also depends on the available "Bit Length" of a given part. The larger the "Bit Length" is, the better the performance will be.

However, it takes more time for the process to converge, due to the difficulty involved in training a longer sequence of bits. To achieve an acceptable performance, the "Bit Length" is set initially to a small value, to allow faster convergence, and at latter stages the "Bit Length" is increased.

Figure 7 illustrates the error graphs for the radiation pattern synthesis of 16-element linear array using different algorithms. It can be seen that the proposed algorithm exhibits quit better performance compared to other algorithms.

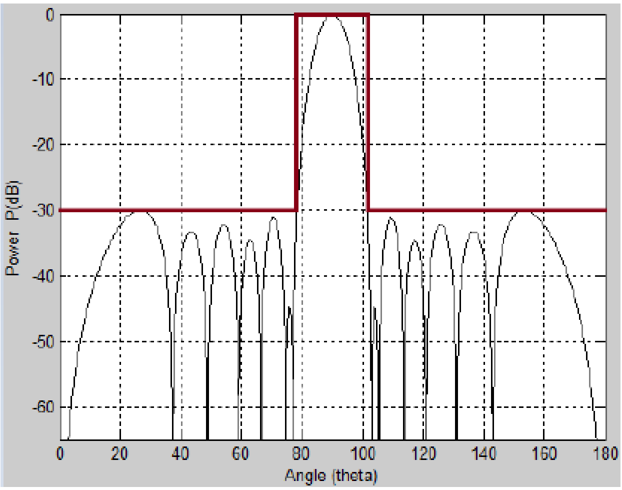

Figure 6. Synthesized radiation pattern of 16-elements linear array with -30dB sidelobe level.

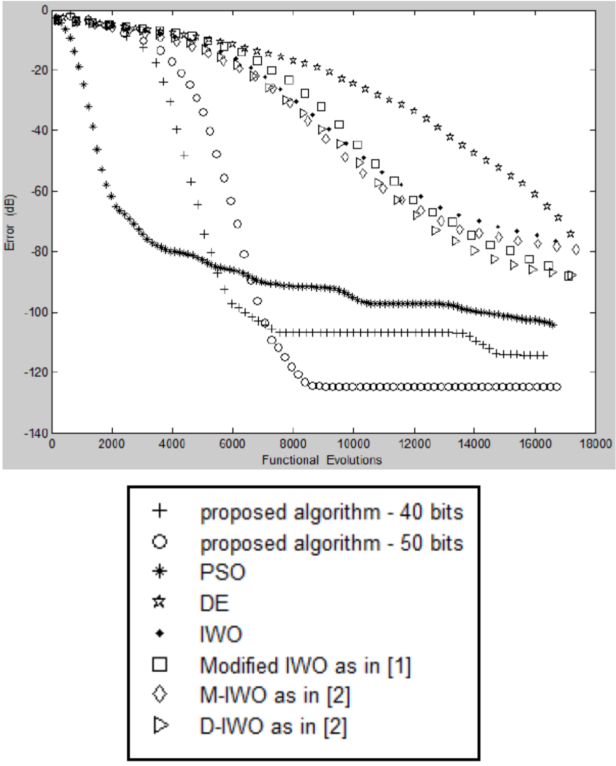

Figure 7. Error plots for pattern synthesis of 16-element array using different algorithms. Error has been expressed in dB with respect to 15.

On the other hand, Figure 8 shows the error graphs for pattern synthesis of the array using the proposed algorithm for different points of confidence. It can be seen that better performance can be achieved by increasing the point of confidence.

Table 1. Listing of the average error and beamwidth obtained by each algorithm after approximately 17000 functional evaluations.

	Average Error (in dB with respect to 15)	Average Beamwidth
Differential Evolution	-74.204	8.61
Particle Swarme optimization	-104.236	9.04
IWO	-76.46	8.928
Modified IWO as in [1]	-88.018	8.682
M-IWO as in [2]	-79.319	8.882
D-IWO	-87.958	8.636
Proposed algorithm for 40 bits	-114.436	8.615
Proposed algorithm for 50 bits	-124.722	8.816

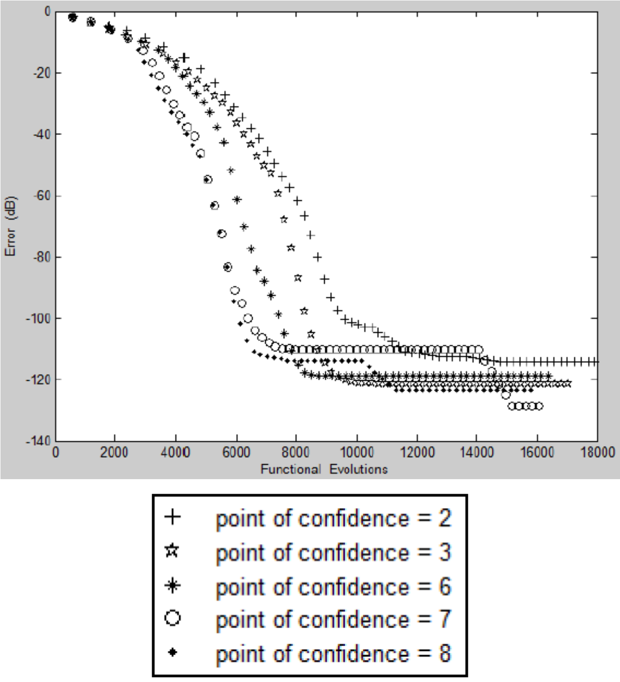

Figure 8. Error plots for pattern synthesis of 16-element array using the proposed algorithm for different points of confidence.

5. Conclusions

In this paper a novel method of optimization (Characteristics Evolution Optimization) is proposed. This method employs the binary representation of numbers to synthesize the radiation pattern of linear array antennas. Since the method works in a parallel fashion, and only with binary numbers, the method can provide significant performance in parallel processing environment. In this research work, the proposed method is used to synthesize the radiation pattern of a 16-element antenna array. The simulation results show that the proposed algorithm exhibits significant performance compared to other algorithms, such as PSO, DE, IWO and variants of IWO.

In its present form, the proposed method encounters some difficulties under certain conditions. However, it is expected that with further research the method can perform very well in most of the optimization problems.

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