Application of Chaos Mind Evolutionary Algorithm in Antenna Arrays Synthesis

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Abstract—**Mind evolutionary algorithm (MEA) uses 'similartaxis' operation and 'dissimilation' operation to imitate the human mind evolution to processes optimization, overcoming the prematurity and improving searching efficiency. But it has several defects: the generation of the initial population is blind, random and redundant; the addition of naturally washed out temporary subpopulations is monotonous; existing searching modes easily to fall into local convergence. This paper proposed Chaos Mind Evolutionary Algorithm. Two chaotic sequences produced in different ways bring adequate diversity to the population. As a result, the searching area is widened. Chaotic Mind Evolutionary Algorithm is used in antenna array synthesis in this paper. Computer simulations show that Chaos Mind Evolutionary Algorithm can be applied in optimization problems of uniformly-spaced linear array and the optimization result is better than that obtained from Genetic Algorithm.**

Index Terms—**mind evolutionary algorithm, chaotic optimization, similartaxis operation, dissimilation operation, pattern synthesis**

I. Introduction

With the rapid development of the telecommunications industry, the electromagnetic environment of space is increasingly deteriorating, electromagnetic interference is enhancing and the quality of communication is declining. To solve these problems, smart antenna which has the ability of low side-lobes, strong directional and anti-interference has been a great deal of concern. The antenna pattern synthesis problem becomes a hot research. Antenna array synthesis means in a given antenna radiation pattern or antenna performance, design antenna array element number, element spacing, elements' current amplitude and phase distribution. For some antenna arrays with given element number and element spacing, this problem is to find every elements' excitation current amplitude and phase distribution.

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Because the objective function or constrains of antenna optimization problems are multi-parameter, nonlinear, non-differentiable and even discontinuous, so the traditional numerical optimization methods which based on gradient optimization technology can not effectively achieve the satisfactory results of the project. Intelligent algorithm has become a powerful tool for optimal design because of its strong global search and the search is not dependent on the specific problems' gradient information and searching space's information. In recent years, Intelligent Algorithm gets access to a wide range of applications and the development in microwave technology and antenna design.

Genetic algorithm (GA) is a kind of intelligent algorithm which often applied to study synthesis of antenna arrays in recent years. GA was applied in synthesis of antenna arrays in 1994 first by J. M. Johnson and Y. R. Samii[1]. But GA is easy to be trapped in part optimum value, and convergence speed reduces obviously in later searching stage.

Mind evolutionary algorithm (MEA) is brought forward based on thinking of human mind development [2]. MEA simulated the similartaxis and dissimilation phenomenon in human society and resolved the problem of prematurity and low convergence speed of traditional Intelligent Algorithm to a certain extent. In this paper, chaos is incorporated into MEA to construct a Chaotic MEA (CMEA), where the parallel population-based evolutionary searching ability of MEA and chaotic searching behavior are reasonably combined. The algorithm not only has good searching guide but also make the best of chaos's ergodicity, so that the algorithm has higher convergence rate and better searching ability. CMEA is applied in optimization problems of uniformly-spaced linear array. Simulation results and comparisons demonstrate the effectiveness and efficiency of CMEA in antenna synthesis.

II. Mind Evolutionary Algorithm

Many real optimization problems can be formulated as the following functional optimization problem.

$$\min f(x)$$

$$a_i \le x_i \le b_i, i = 1,2,3\cdots,n \qquad x = (x_1, x_2, \cdots x_n) \quad (1)$$

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where f is the objective function, a_i and b_i are lower and upper bounds for the variable x_i , and n is the dimensions of the variable vector x .

The aggregation of all individuals in every generation in MEA is called a population; a population is divided into some subpopulations. There are two kinds in subpopulations: superior subpopulations and temporary subpopulations. Superior subpopulations record the winners' information in global competition; temporary subpopulations record the middle process in global competition. The billboard provides the chance for the communication of the individuals and the subpopulations. There are three basic kinds of information in billboard: the sequence number, action and score of the individual or the subpopulation. The score is the valuation that the environment evaluates to the action of the individual or subpopulation. The individuals in subpopulations paste their information on local billboard. And the global billboard is used to paste the subpopulations' information.

MEA has two important operations 'similartaxis' operation and 'dissimilation'. In all subpopulations, the process that the individuals compete for the winners is called similartaxis. In the whole solution space, the process of each subpopulation competing for the global winner and ceaselessly prospecting for new point in the solution space is called dissimilation. Similartaxis exploits the part information that system gets from the environment, quickly search for the local optimum. However, the dissimilation operation searches in the whole solution space and choose better individuals as centers to create new temporary subpopulations. If a subpopulation can't produce new point in the similartaxis process, the subpopulation has been mature.

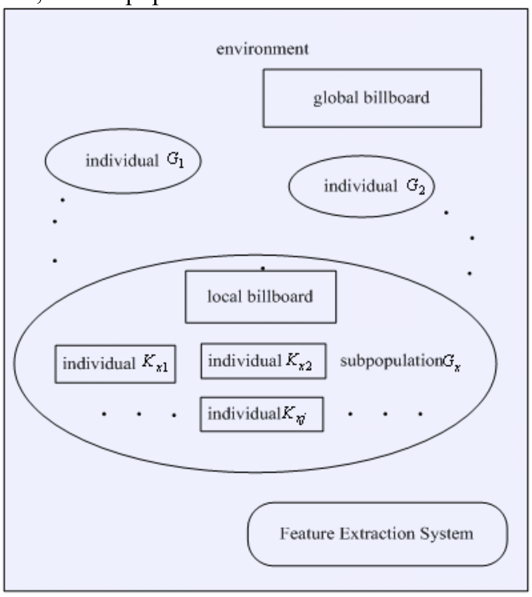

Figure 1. Framework of MEA

The simple MEA is described as following:

Step1 Set evolutionary parameters: population size, subpopulation size and conditions for end.

Step2 Initialization: scatter individuals composing initial population in whole solution space.

Step3 Similartax: individuals are produced by normal distribution with variance around each winner and the individual with highest score is the new winner replacing the old one in following steps.

Step4 Dissimilation: realize global optimization, some with lower score are washed out and replaced by new ones scattered at random in solution space.

Step5 Conditions for end: if the end conditions are filled, turn to step6; else repeat step3 and step 4.

Step6 Output evolutionary result, algorithm ends.

III. CHAOS OPTIMIZATION ALGORITHM

The phenomenon of chaos is the common phenomenon in the nonlinear dynamic systems. The chaos's behaviors are complex and similar to the random process, but have the inherent property of regularity. The chaos optimization algorithm is sensitively to the initial value, easily to jump out the local minimum, and quickly to search out the global optimization. The computation precision of chaos optimization algorithm is high. It has the property of global asymptotical convergence [4-6].

A. The Chaostis Characteristic of Logistic Mapping

Logistic mapping is the most typical model of Chaos Dynamics. It can be expressed as follow:

$$x_{k+1} = \mu \cdot x_k \cdot (1 - x_k)\ ,\ n = 0,1,...,N \quad x_0 \in (0,1) \qquad (2)$$

where μ is the control parameter. Regard the finite difference eq. (2) as a dynamic system and it exhibits chaotic dynamics when $\mu = 4$ and $x_0 \notin \{0, 0.25, 0.5, 0.75, 1\}$. That is, when the control parameter $\mu = 4$, the system which doesn't have the stable solution at the completely chaotic state, and the chaos variable x_n ergodic in the scope (0,1). It also exhibits the sensitive dependence on initial conditions, which is the basic characteristic of chaos. A minute difference in the initial value of the chaotic variable would result in a considerable difference in its long time behavior. The track of chaotic variable can travel ergodically over the whole search space.

The probability density function of logistic mapping is

$$\rho(x) = \begin{cases} \dfrac{1}{\pi\sqrt{x(1-x)}}, 0 < x < 1 \\ 0, x \le 0, x \ge 1 \end{cases} \qquad (3)$$

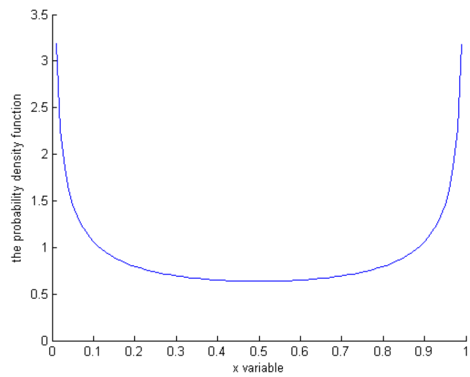

Figure 2. Logistic's probability density function

The curve shows that the probability is higher in [0,0.05] and [0.95,1]. As a result, the distribution of Logistic is non-uniform. If the points produced by chaotic mapping is the range of [0.05, 0.95], the searching time will be longer.

B. The Chaostis Characteristic of Tent Mapping

Tent map has uniform probability density, power spectral density and ideal related characteristics. Its formulate is

$$x_{k+1} = \begin{cases} 2x_k, 0 \le x_k \le 0.5 \\ 2(1-x_k), 0.5 < x_k < 1 \end{cases} \quad (4)$$

Its probability density function is

$$\rho(x) = 1 \quad (5)$$

Tent mapping has simple structure and good ergodic uniformity, more suitable for a large number of data processing sequences. It iterates faster than Logistic mapping. But there are small iterative cycle and unstable periodic point in tent mapping. It will make the iteration to the fixed point 0. In order to avoid iterates to fixed point, this paper uses the following method to improve tent mapping:

$$x(k+1) = \begin{cases} x(k)/0.4 & x(k) \le 0.4 \\ (1-x(k))/0.6 & x(k) > 0.4 \end{cases} \quad (6)$$

We can see that from Fig.3 the points generated by improved tent mapping are scattered uniformly in [0.1]. It overcomes its own lacks, such as small cycle and instability cycle points.

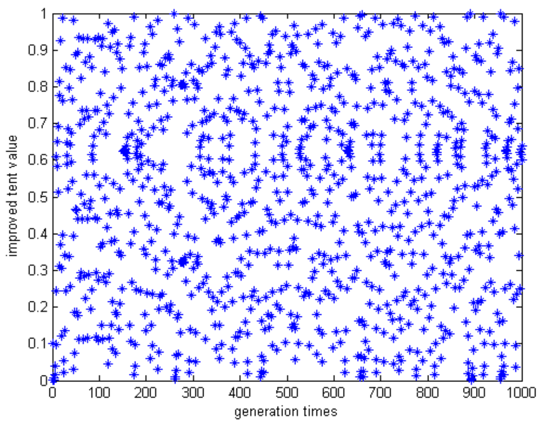

Figure 3. The chaos state of improved tent mapping

IV. CHAOTIC MIND EVOLUTIONARY ALGORITHM

Based on the proposed SMEA and the chaotic local search(CLS), a two-phased iterative strategy named Chaotic MEA (CMEA) is proposed, in which SMEA is applied to perform global exploration and CLS is employed to perform locally oriented search (exploitation) for the solutions resulted by MEA.

The method of improving the algorithm is: use improved tent chaotic sequence to generate initial population. And use logistic chaotic sequence to add washed out temporary subpopulations.

The randomness, ergodicity and the initial data's sensitivity of chaotic sequence ensure that the values will be uniformly distributed in the solution space. So it may be able to overcome data redundancy of the random sequence. On the other side, it increases the diversity of the population and expands the searching scope of the algorithm by using different chaotic sequence to add washed out temporary subpopulations.

To assess the performance of CEMA, this paper selects three typical functions that commonly used to test optimization algorithm to experiment, which has multi-peaks, non-raised and so on. The objective function is

$$F_1 = 100({x_1}^2 - x_2)^2 + (1-x_1)^2$$
$$-2.048 \le x_1, x_2 \le 2.048$$
$$F_2 = \left(4 - 2.1x_1^2 + x_1^4/3\right)x_1^2 + x_1x_2 + \left(-4 + 4x_2^2\right)x_2^2$$
$$-10 \le x_1, x_2 \le 10$$
$$F_3 = \frac{\sin^2\sqrt{\left(x_1^2 + x_2^2\right)} - 0.5}{\left[1.0 + 0.001\left(x_1^2 + x_2^2\right)\right]^2} - 0.5$$
$$-10 \le x_1, x_2 \le 10$$

F_1 is Rosenbrock function which has a global minimum. The global minimum position is (1, 1) and the value is 0. It is used to test the premature convergence of the algorithm. F_2 is Camel function which has six local minimums. The two global minimums are -1.031628, and their positions are (-0.0898, 0.7126) and (0.0898, -0.7126). F_3 is Schaffer function which has infinite local maximum . The only one global is maximum 1 and its position is (0, 0). The parameters of the experiment are: MEA and CMEA have the same large initial populations, the population size is 30, the subpopulation size is 18, the temporary subpopulation is 12, and termination time is 100.

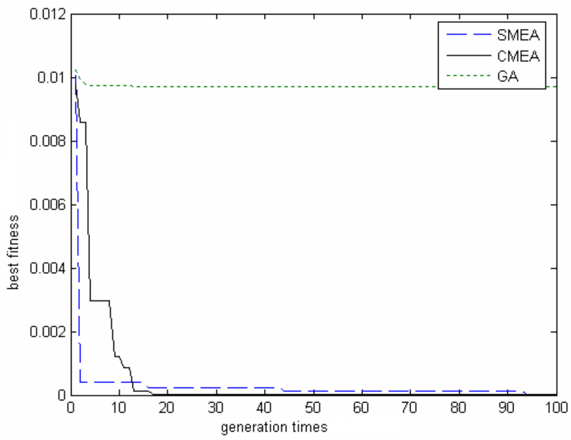

Figure 4. The convergence curve of Rosenbrock

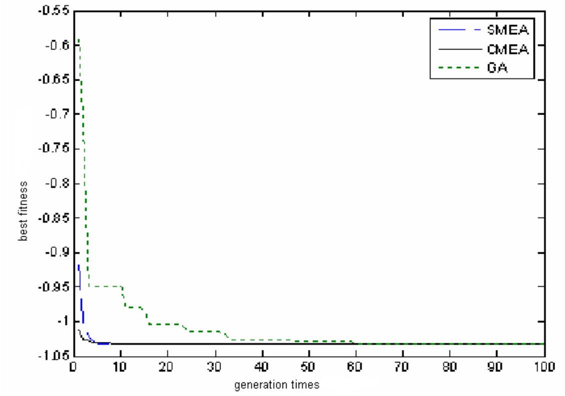

Figure 5. The convergence curve of Camel

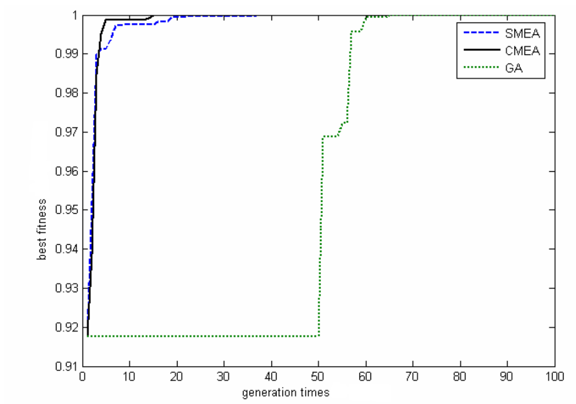

Figure 6. The convergence curve of Schaffer

TABLE I.
COMPARISON OF THREE FUNCTIONS' OPTIMIZATION RESULTS

function	algorithm	X_1	X_2	solution
Rosenbrock	MEA	0.9947	0.9990	1.8231e-6
	CMEA	0.9996	0.9992	8.0936e-7
	GA	0.9091	0.8309	3.0325e-3
Camel	MEA	0.0899	-0.7122	-1.031625035
	CMEA	-0.0898	0.7126	-1.031628033
	GA	-0.0876	0.7106	-1.031600471
Shaffer	MEA	0.0066	-0.0030	0.9975
	CMEA	0.0014	-0.0001	0.9981
	GA	0.0098	0.0098	0.9975

From Fig.4-6 and Table 1, it can be seen in the three kinds of functions optimization, MEA and CMEA are effective. They are both able to find the optimal solution. From the solutions' accuracy, the optimal values' accuracy gained by CMEA is higher than those gained by MEA and the solutions' positions are more accurately. This is because in different stages of the optimization process adopting different chaotic sequences to generate subpopulations. It's not only to ensure the uniform distribution of the subpopulations and also improves the quality of the individuals. Thereby enhance the convergence of the algorithm and the accuracy of the optimal value.

V. THE THEORY OF ANTENNA ARRAY SYNTHESIS

A. Traditional Methods of Antenna Array Synthesis

The antenna array synthesis is that given the radiation pattern of antenna array or given the antenna array's performance parameters, designing the elements' number, the space between elements, the amplitudes and phases of all the elements. For an antenna array with given elements' number and the space between elements, it is to optimize the amplitudes and phases of the array elements.

Generally speaking, antenna pattern synthesis can be classified into three categories. One group requires that the patterns exhibit a desired distribution in the entire visible region. This is referred to as beam-forming, and it can be accomplished using the Fourier transform and the Woodward-Lawson method. Another category requires that the antenna patterns possess nulls in desired directions. The method introduced by Schelkunoff can be used to accomplish this. A third group includes techniques that produce patterns with narrow beams and low side lobes.

There have been many classic methods in antenna array synthesis, such as Woodward method, Chebyshev polynomial method, Taylor synthesis method, Schelkunoff polynomial method and so on. Woodward method is that for a required radiation pattern, through sampling in different discrete location to achieve the expected pattern. But if the number of antenna array element is too large, the antenna radiation pattern gained by Woodward method is more ups and down, as it shows in Fig.7. Chebyshev polynomial method is that if the side-lobes' level is given, we can gain the narrowest main-lobe; if the width of the main-lobe is given, we can gain the lowest side-lobes' level. However it restricts all of the side-lobe on the same level, as it shows in Fig.8. It is not good for the whole antenna design. And if the element space is smaller than $\lambda/4$, Chebyshev polynomial method is not suitable for this kind of problem.

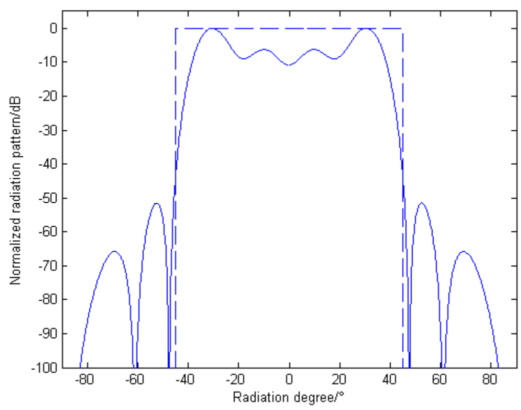

Figure 7. The antenna pattern gained by Woodwrd

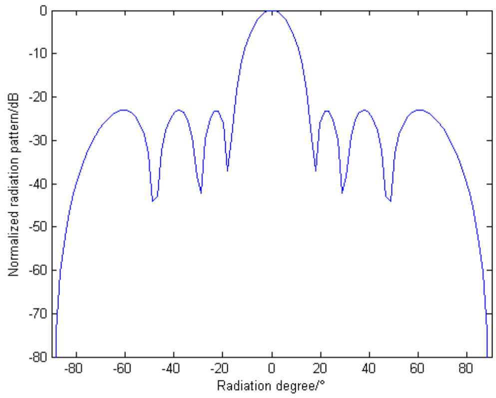

Figure 8. The antenna pattern gained by Chebyshev

This shows that classic methods of antenna array synthesis often have following characteristics:

- They are generally based on gradient search optimization.
- Most of these methods are pointed at special problems and their application scopes are small.
- Two problems can not be avoided. Firstly it must choose good initial data to ensure the achievement of the optimization objective. Finally in the solution space, there are special requirements for the continuity and differentiability of the objective function, such as requiring the objective function is continuous and differentiable in the solution space. However, the object functions for synthesis of array antennas usually have the characteristics of multi-parameters, non-differentiable even discontinuities.

Therefore classic gradient-based optimization methods are difficult to achieve satisfactory results.

B. The Mathematical Model of Antenna Array Synthesis

For a linear antenna array (shown as Figure9) with given elements and spacing arranged in axis as it shows in Fig.9, its pattern formula is

$$F(\theta)=\sum_{n=1}^{N} I_n \exp\left[j(n-1)kd\cos\theta+\varphi_n\right]$$

where I_n is the n element's amplitude; φ_n is the phase difference between adjacent elements; θ is the angle between the array axis and the ray; d is the space between the elements; $k=2\pi/\lambda$ is wave number.

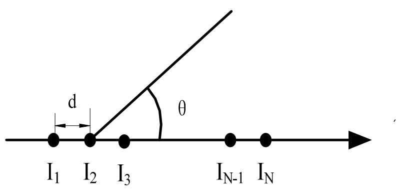

Figure 9. The model of uniform linear antenna

Let the antenna array's main-lobe point at θ_0 , then $\varphi_n=-(n-1)kd\cos\theta_0$, eq. (7) can be written as following

$$F(\theta)=\sum_{n=1}^{N} I_n \exp\left[j(n-1)kd(\cos\theta-\cos\theta_0)\right] \quad (8)$$

Let the pattern's imaginary part be zero, equation (8) can be written as following

$$F(\theta)=\sum_{n=1}^{N} I_n \cos\left[(n-1)kd(\cos\theta-\cos\theta_0)\right] \quad (9)$$

If N is even and the current's amplitudes is symmetrical, then the equation is

$$F(\theta)=\sum_{n=1}^{N/2} 2I_n \cos\left[\frac{2n-1}{2}kd(\cos\theta-\cos\theta_0)\right] \quad (10)$$

In antenna array, the symmetric array is usually used to cut down the parameters' number, then reducing the computing amount.

C. The General Objective Function of Antenna Array Synthesis

Antenna array synthesis is a multi-objective, multi-parameters and non-linear optimization problem. In engineering application, it is impossible to set null in every interference location to restrict interference. We can only choose some strong interference to generate null. At the same time, adopt design of low side-lobes level to restrict other interference from other direction. Considering the main-lobe position, the main-lobe width, side-lobes' level, null position and null depth, we can choose a general objective function [7]:

$$\begin{aligned} fitness &= w_1\cdot\frac{|\theta_0-\theta_{des}|}{180^0} \\ &+ w_2\sum_{i=1}^{N} a_i\cdot\left|SLL_{\max}-SLL_{des}\right| \\ &+ w_3\cdot\frac{\theta_{BWFN}-\theta_{BWFN\_des}}{180^0} \\ &+ w_4\sum_{i=1}^{M} b_i\cdot\left|NULL_{\theta_i}-NULL_{\theta_i\_des}\right| \end{aligned} \quad (11)$$

where θ_0 is the main-lobe's position in experiment and θ_{des} is the required main-lobe's position; $SLL_{\max}$ is the highest side-lobes' level in experiment and SLL_{des} is the required side-lobes' level; θ_{BWFN} is the main-lobe's width in experiment and θ_{BWFN_des} is the required main-lobe's width; $NULL_{\theta_i}$ is the null depth at θ_i in experiment and $NULL_{\theta_i\_des}$ is the required null depth at θ_i. w_i is every objective's weight coefficient. Weight coefficients are very important for the whole design. They are directly related to the objectives' convergence trend and convergence rate. So we must analyze every objective's value and choose appropriate weight coefficients to balance the optimization rate of every optimization objective and obtain a best global optimal solution. Through analysis and computer simulation, we obtain the weight factors' general range: $w_1\in[0.3,0.5]$, $w_2\in[0.9,1.4]$, $w_3\in[0.5,0.8]$, $w_4\in[0.1,0.3]$.

VI. SIMULATION RESULTS

Different methods, GA and CMEA, were investigated and compared with simulation solutions in order to assess the effectiveness and the flexibility of the proposed method. The experiment parameters of GA are: p_c=0.6, p_m=0.1. The experiment parameters of CMEA are: the subpopulation size is 18, the temporary subpopulation is 12. In two algorithms, the evolutionary generation is 100 and the population size is 30.

Example 1

For a antenna array with $d = \lambda/2$, $N = 12$, we request main lobe point at 0° , the shaped range is [-45°,45°], the normalized antenna pattern is $F(\theta) = 1$ in the shaped range. The simulation results are as Fig.10:

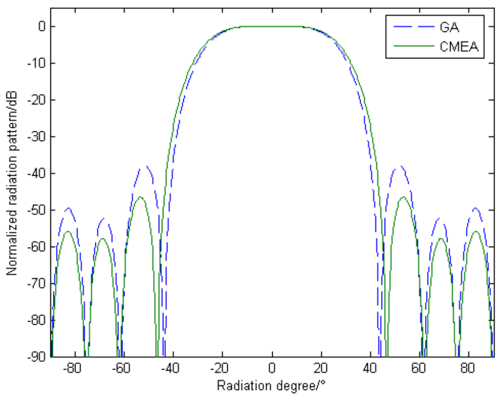

Figure 10. Radiation pattern of shaped beam

TABLE II.
COMPARISON OF OPTIMIZED RESULTS OF NORMALIZED AMPLITUDES

Number	GA	MEA
1	0.0098	0.0021
2	0.0325	0.0046
3	0.6636	0.4575
4	0.8344	0.6863
5	1.0000	0.9150
6	0.9955	1.0000
7	0.9955	1.0000
8	1.0000	0.9150
9	0.8344	0.6863
10	0.6636	0.4575
11	0.0325	0.0046
12	0.0098	0.0021

From Fig.10 and Fig.2, we can see that the antenna pattern gained by Woodward-Lawson, fluctuating about 10 dB in shaped range. But the optimization patterns gained by GA and CMEA are similar and satisfy the requirement. It is interesting to observe that the CMEA can make the better main-lobe, the less null level, as well as the side-lobe peak value is lower than GA.

Example 2

For a antenna array with $d = \lambda/2$, $N = 9$, we request the antenna pattern is $F(\theta) = \csc^2 \theta$ in shaped range [9°,30°] , the side-lobes must be lower as possible as they can. Simulation results are as Fig.11:

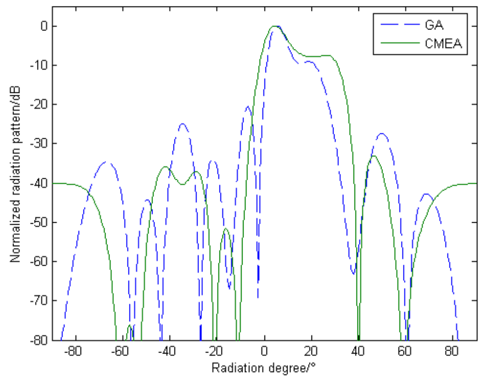

Figure 11. Radiation pattern of shaped beam

TABLE III.
COMPARISON OF OPTIMIZED RESULTS OF NORMALIZED AMPLITUDES AND PAHSES DIFFERENCE

N	GA		CMEA	
	amplitude	phase	amplitude	phase
1	0.9798	-47°	0.7869	-18°
2	1.0000	-55°	1.0000	-36°
3	0.9073	-87°	0.7183	-83°
4	0.6855	-84°	0.1439	-72°
5	0.2460	-75°	0.4034	-3°
6	0.0968	-67°	0.2303	-77°
7	0.6331	-90°	0.0001	-80°
8	0.1532	-47°	0.0001	-54°
9	0.1452	-70°	0.0883	-68°

From the antenna pattern, it can be seen that the pattern optimized by CMEA is good agreement with the desired radiation patterns while its side-lobes reduce greatly. The comparative side-lobe is 15dB lower than GA's. From their convergence curves, we can know that CMEA has faster convergence rate and better fitness function than GA. From Table 3 we can see that the optimized amplitudes and phases are very different because the optimization problem of array antenna is a multi-value problem which has the similar pattern with different amplitudes and phases of elements.

Example 3

For a antenna array with $d = \lambda/4$, $N = 16$, we request the main-lobe point at $\theta_0 = 0^0$, the width of main-lobe is 20°and the highest side-lobe level is -30dB. The simulation results are as Fig.12:

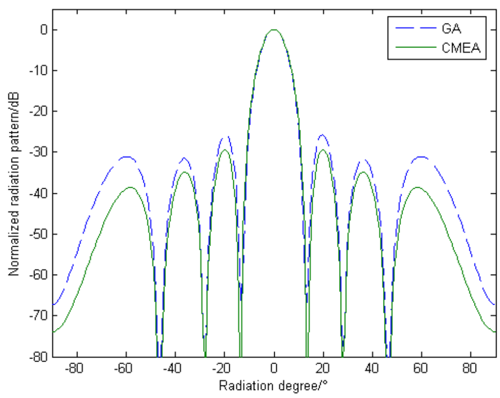

Figure 12. Radiation pattern of least side-lobe in designed range

TABLE IV.
AMPLITUDES OF ARRAY ELEMENTS

N	GA	CMEA
1	0.7497	0.4572
2	0.0000	0.7879
3	1.0000	0.7349
4	0.5484	0.1837
5	0.0971	0.7795
6	0.9537	0.6898
7	0.5596	0.3837
8	0.8846	1.0000
9	0.8846	1.0000
10	0.5596	0.3837
11	0.9537	0.6898
12	0.0971	0.7795
13	0.5484	0.1837
14	1.0000	0.7349
15	0.0000	0.7879
16	0.7497	0.4572

As it can be seen from Fig.12, the two kinds of algorithm can also satisfy the requirement that the main-lobe points at 0°, the width of main-lobe is 20°. However, the highest side-lobe's level of GA is -26dB, and in the results of CMEA every side-lobe's level is lower than that at the same direction in GA. The minimum can be achieved -40dB.

Example 4

For a antenna array with $d=\lambda/2$, $N=12$, we request the main-lobe point at $\theta_0=0^0$, the width of main-lobe is 10°, the highest side-lobe level is -20dB. And at 10, 20, 30, 35, 40, 60 form nulls which below -100dB. The simulation results are as Fig.13:

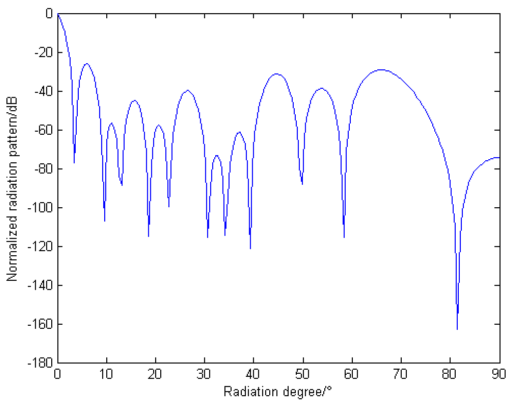

Figure 13. Radiation pattern of nulls in designed positions

TABLE V.
PHASES OF ARRAY ELEMENTS

N	1	2	3	4	5	6
phase	15°	49°	24°	12°	19°	40°
N	7	8	9	10	11	12
phase	25°	8°	54°	6°	59°	46°

In this optimization, we only choose phase as the optimization parameter. This is because the digital phase shifter technology has matured, and in phased antenna array it does not need to pay additional costs. So that in recent years this method is much more attractive. According to the experimental requirements, six locations need to achieve -100dB null depth, at the same time consider the main-lobe's position and the largest side-lobe level. The problem belongs to multi-objective optimization problem. For multi-objective optimization problems, it often not only has one global optimal solution. In this optimization, we adopt weighted method (choose different weights for different objectives) to design the objective. As Fig.13 shows, the antenna pattern gained by CMEA satisfies the multi-objective requirement.

VII. CONCLUSION

Point at the lacks of Mind Evolutionary Algorithm such as the generation of the initial population is blind; the addition of naturally washed out temporary subpopulations is monotonous, we integrated of Mind Evolutionary Algorithm and Chaos Optimization Algorithm with their respective advantages and proposed a new hybrid optimization algorithm. It uses improved tent chaotic sequence to generate initial population. And use logistic chaotic sequence to add washed out temporary subpopulations, increasing the diversity of the population and expanding the searching scope of the algorithm. CMEA is adopted to optimize the amplitude and phase of equal interval linear array. There is good agreement between the desired and calculated radiation patterns. The optimizing result is better than that of GA.

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