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A CLONAL SELECTION ALGORITHM FOR ARRAY PATTERN NULLING BY CONTROLLING THE POSITIONS OF SELECTED ELEMENTS

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Abstract—In this paper, a method based on clonal selection algorithm (CLONALG) is proposed for null steering of linear antenna arrays by controlling only the positions of selected elements. The CLONALG is a relatively novel population-based evolutionary algorithm inspired by the clonal selection principle of the human immune system. In order to illustrate the accuracy and flexibility of the proposed algorithm, several numerical examples of Chebyshev pattern with the single and double nulls imposed at the directions of interference are given.

1. INTRODUCTION

Antenna array pattern synthesis with the prescribed nulls in radiation pattern to reject unwanted interference sources while receiving the desired signal from a chosen direction has received considerable attention in the past and still of great interest [1, 2]. A number of null steering techniques based on classical optimization methods and analytical approaches have been presented and used in the literature [1, 2]. In general, the null steering techniques are based on the variations of array parameters such as the element excitations

(amplitude and/or phase) and positions of array elements. These null steering techniques have been used with their own benefits and limitations in the antenna array pattern nulling.

It is well known that the classical optimization techniques are likely to be stuck in local minima if the initial guesses are not reasonably close to the final solution. The most of the classical optimization techniques and analytical approaches also suffer from the lack of producing flexible solutions for a given antenna pattern synthesis problem. The disadvantages of the classical and analytical techniques and rapid development of computer technologies in recent years have encouraged the researcher to use the evolutionary optimization algorithms based on computational intelligence methodologies. It was shown that the evolutionary optimization techniques such as the genetic algorithm [3], ant colony optimization [4], particle swarm optimization [5] and differential evolution [6] are capable of performing the better and more flexible solutions than the classical optimization techniques and the conventional analytical approaches.

The position only methods require a mechanical driving system such as servomotors to move every element in the array. When the number of elements in the array increases, the computational time to find the new position perturbations will also increase along with the number of mobilized elements in the array. To reduce the number of mobilized elements in the array and to effectively increase the array robustness, the method of controlling only the positions of selected elements is preferred [7].

In this paper, a method based on CLONALG [8] is presented to steer single and double nulls to the directions of interference by controlling only the positions of selected antenna array elements. The CLONALG is a simple population-based evolutionary algorithm inspired by the clonal selection principle [9] of the human immune system. The CLONALG has some distinguished features. It operates on a population of points in search space simultaneously, not on just one point, does not use the derivatives or any other information, and employs probabilistic transition rules instead of deterministic ones. It also has the ability of getting out local minima. As a relatively novel optimization algorithm, the CLONALG has been successfully applied to solve various engineering problems [8, 10–15].

2. PROBLEM FORMULATION

Consider an equally spaced linear array with an even number of isotropic elements ($2N$). If the array elements are symmetrically

situated and excited around the center of the linear array, the far field array factor of such an array is real, and it can be written as

$$F(\theta) = 2\sum_{k=1}^{N} a_k \cos\left(\frac{2\pi}{\lambda} d_k \sin\theta\right) \tag{1}$$

where λ is the wavelength, θ is the scanning angle from broadside, a_k is the amplitude of the kth element, and d_k is the distance between position of the kth element and the array center. The contribution of each element position of the array to the null locations is calculated by replacing d_k given in Eq. (1) by $d_k + \delta_k$ where δ_k is the position perturbation of the kth element. In order to find an optimal set of element position values that achieves the desired nulling performance, the following cost function will be minimized by using the CLONALG

$$C = \sum_{\theta=-90^\circ}^{90^\circ} \left[W(\theta)\left|F_o(\theta) - F_d(\theta)\right| + ESL(\theta)\right] \tag{2}$$

where $F_o(\theta)$ and $F_d(\theta)$ are, respectively, the pattern obtained by using CLONALG and the desired pattern. $W(\theta)$ and $ESL(\theta)$ are included in the cost function to control the null depth level and maximum sidelobe level, respectively.

3. CLONAL SELECTION ALGORITHM

3.1. Human Immune System (IS)

One aim of the human immune system (IS) is to protect the human body against attacks from antigens (such as viruses, bacteria, fungi, and other parasites) and eliminate the infected cells [9]. The cells called lymphocytes are the fundamental components of the human IS. There are two main types of lymphocytes: B lymphocytes (B-cells) and T lymphocytes (T-cells). Both B-cells and T-cells are able to recognize the antigens in different but complementary ways. We have only focused on the B-cells process to provide a very simplified way to explain the immune response. B-cells are covered with antibody receptors. The antibodies are molecules capable of recognizing and binding to antigens. Each antibody will respond optimally to a specific antigen rather like a key which fits into a keyhole. The degree of binding refers to affinity. The higher the affinity, the stronger the binding and thus the better the immune recognition. After successful recognition, the IS initiates a response to deactivate antigen.

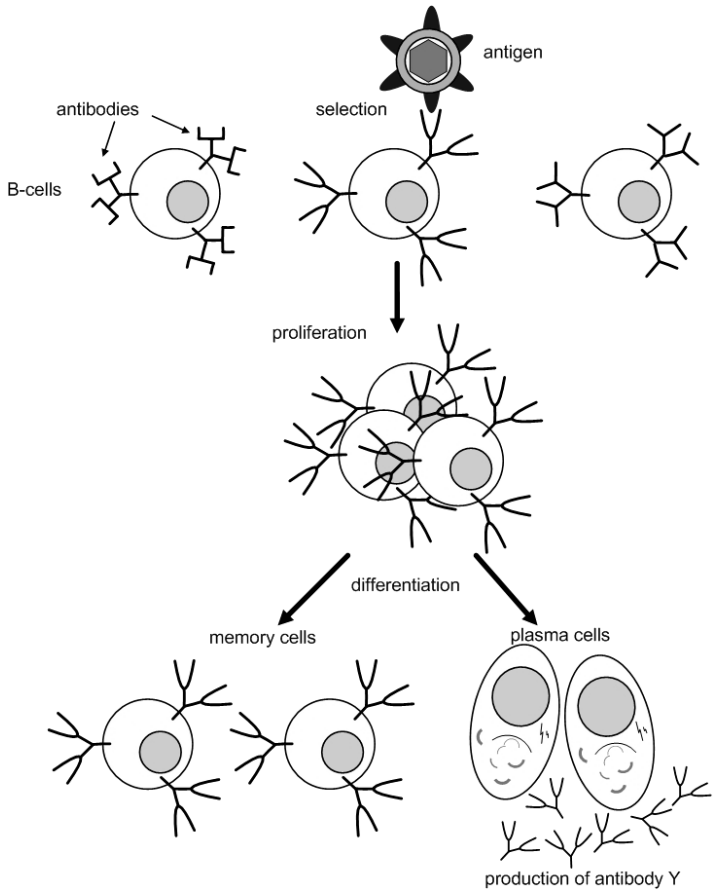

Figure 1. The clonal selection principle.

3.2. Clonal Selection Principle

The whole process of antigen recognition, cell proliferation, and differentiation is called the clonal selection principle [9]. As it is shown in Fig. 1, after an antigen is recognized by a B-cell receptor with certain affinity, then the B-cell is stimulated and will start to proliferate by cloning. Cloning is a mitotic process which produces exact copies of the parent cells. The cloning rate is proportional to the antigenic affinity. Some of new cloned cells will be differentiated into plasma cells, which are the most active antibodies secretors. The new cloned cells can undergo somatic hypermutation, creating offspring B-cells with mutated receptors. This hypermutation process enables the

new cells to match the antigen more closely. The B-cells with high affinities are selected to differentiate into memory cells which do not secret antibodies but instead remember the antigenic pattern. The B-cells that are not stimulated as they do not match any antigens in the human body will eventually die.

Once the body has successfully defended against an antigen, memory cells remain and circulate in the blood, lymph, and tissues for very long periods of time. When the same or similar antigen is encountered in the future, memory cells are stimulated and more abundant production of antibodies is observed.

3.3. Clonal Selection Algorithm (CLONALG)

The CLONALG [8] inspired by the clonal selection principle [9] of the human IS is a newly discovered, high-performance evolutionary algorithm capable of solving general N-dimensional, linear and nonlinear optimization problems [8, 10–15]. The concept of the CLONALG is shown in Fig. 2.

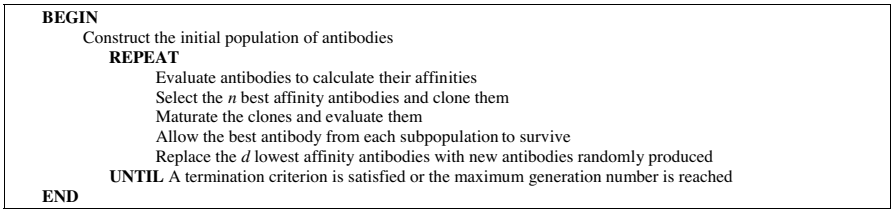

Figure 2. A simple CLONALG.

The CLONALG starts by randomly generating the initial population (N_{pop}) of antibodies in a given bounds for the problem considered. Each antibody which means a candidate solution is represented by a binary string of bits. The bit string length is suitably selected by the user corresponding to the problem for obtaining a reasonable precision. The antibodies are evaluated over an affinity (fitness) function and ranked in decreasing order of affinity. The first n antibodies are selected for cloning operation. The number of clones generated for all these n selected antibodies is given by

$$N_c = \sum_{i=1}^{m} \text{round}\left(\frac{\beta N_{pop}}{i}\right) \tag{3}$$

where β is the multiplying factor and round $(\cdot)$ is the operator that rounds its argument toward the closest integer. After cloning

operation, the clones are subject to a hypermutation process inversely proportional to their affinity; the higher the affinity the smaller the mutation rate. Hence, the mutation rate of a clone is inversely proportional to the fitness of its parent. The antibodies in each subpopulation which consists of the parent and its clones maturated by hypermutation operation are then evaluated in the affinity function, and the best antibody of each subpopulation becomes memory cell and is allowed to survive. The antibodies with d lowest affinities are replaced by the new antibodies generated randomly to maintain the diversity of antibody population so that the new areas of the search space can be potentially explored. The next generation starts with a new antibody population produced as described above. These processes are repeated until a termination criterion is attained or a predetermined generation number is reached. A very clear overview of the clonal selection principle and the CLONALG, from immunology and engineering points of view, can be found in [8].

4. NUMERICAL RESULTS

In order to illustrate the effectiveness and flexibility of the proposed CLONALG, two examples are presented. In the examples, a 30-dB Chebyshev pattern for 20 equispaced elements with an interelement spacing of 0.5λ was used as the initial pattern. The affinity value of the antibodies in CLONALG is calculated by

$$AFF = \frac{1}{1+C} \tag{4}$$

The population size of the antibodies (N_{pop}) and the number of iteration are, respectively, selected as 70 and 150, and each antibody is represented by a string of 16 bits. The typical CLONALG parameter values of n, β, and d are set to 40, 2, and 30, respectively. The simulation results are obtained within 2–3 minutes on a personal computer with a Pentium IV processor running at 2400 MHz. In all of the examples, the cost function parameters given in Eq. (2) are chosen as

$$F_d(\theta) = \begin{cases} 0, & \text{for } \theta = \theta_i \\ \text{Initial Chebyshev pattern}, & \text{elsewhere} \end{cases} \tag{5}$$

$$W(\theta) = \begin{cases} 100, & \text{for } \theta = \theta_i \\ 1, & \text{elsewhere} \end{cases} \tag{6}$$

$$ESL(\theta) = \begin{cases} 5, & \text{if } MSL(\theta) > -28\,\text{dB} \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where *MSL* given in Eq. (7) represents the maximum sidelobe level of achieved pattern in the sidelobe region.

In the first example, a single null imposed at the direction of the second peak ($\theta_i = 14^\circ$) from the main beam of the Chebyshev pattern is considered. The achieved patterns produced by the CLONALG are illustrated in Figs. 3(a), (b), and (c) when the positions of all elements, the selected 14 and 12 elements of the array are perturbed, respectively. As can be seen from Fig. 3 that all desired nulls are deeper than 115 dB. The position perturbations obtained by the CLONALG to produce the patterns in Fig. 3 are listed in Table 1. The position perturbations given in Table 1 are used to find the significance of each element to the null locations and consequently find the number of controlled elements. The method proposed here freezes the positions of the element that have insignificant contributions to the nulls.

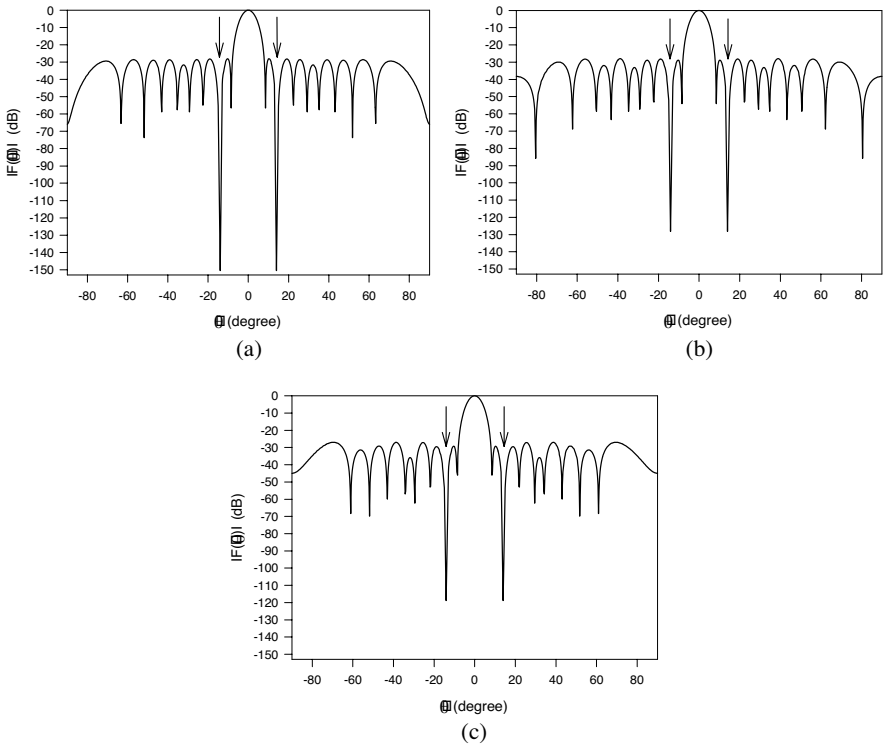

Figure 3. Radiation pattern with single null imposed at 14° obtained by using the position perturbations for (a) 20 elements, (b) 14 elements, and (c) 12 elements.

Table 1. Element position perturbations (δ_k) in λ for Figs. 3 and 4 obtained by using CLONALG.

k	Fig. 3a	Fig. 3b	Fig. 3c	Fig. 4a	Fig. 4b	Fig. 4c	Fig. 4d
±1	0.006640	–	–	0.023986	0.027918	0.028068	0.025000
±2	0.021775	0.017702	–	0.037992	0.038716	0.038199	0.030000
±3	0.029412	0.031789	0.027151	0.014302	–	–	–
±4	0.009665	–	–	–0.018492	–	–	–
±5	–0.019835	–0.019482	–0.034736	–0.027997	–0.023774	–	–
±6	–0.050000	–0.053695	–0.063000	–0.035408	–0.038768	–0.020313	–
±7	–0.050000	–0.055000	–0.066980	–0.048002	–0.043032	–0.024503	–0.028578
±8	–0.050000	–0.041373	–0.064200	–0.072078	–0.070648	–0.037000	–0.040349
±9	0.006501	–	–	–0.069984	–0.067870	–0.050374	–0.059384
±10	0.050000	0.071000	0.073937	0.075443	0.081016	0.081078	0.065446

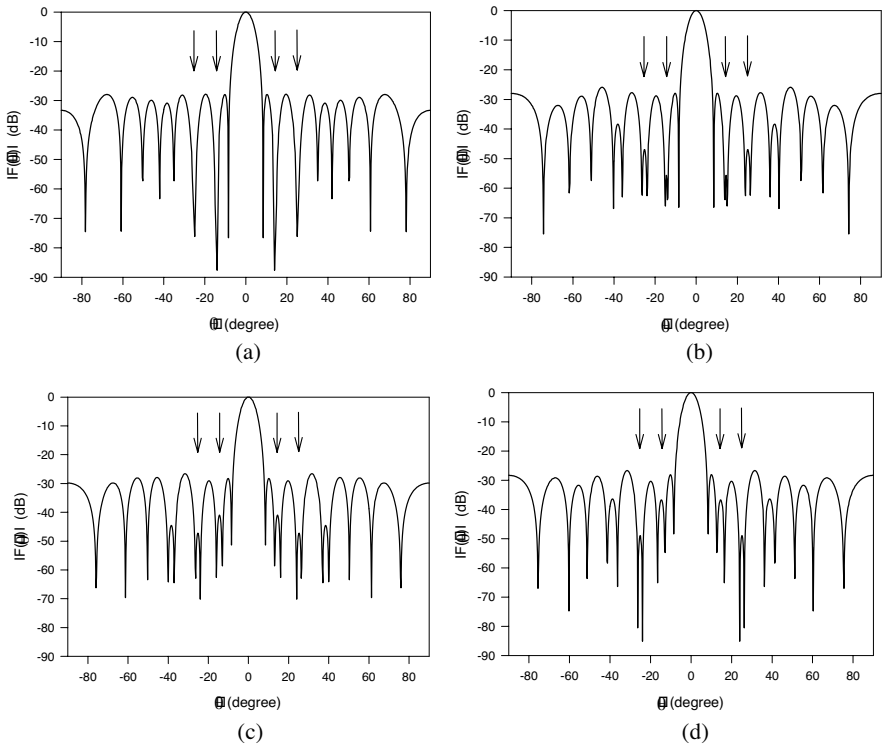

Figure 4. Radiation pattern with double nulls imposed at 14° and 25° obtained by using the position perturbations for (a) 20 elements, (b) 16 elements, (c) 14 elements, and (d) 12 elements.

In the second example, Chebyshev pattern with double nulls imposed at the peaks of the second and the fourth sidelobes ($\theta_{i1} = 14^\circ$

and $\theta_{i2} = 25°$) from the main beam is considered. The resulting patterns obtained by the CLONALG are shown in Figs. 4(a), (b), (c), and (d) when the positions of all elements, the selected 16, 14 and 12 elements of the array are perturbed, respectively. The corresponding position perturbations of the array elements are given in Table 1.

It is apparent from Figs. 3 and 4 that the patterns are symmetric with respect to the main beam. This is because the symmetry property of the element positions around the array center results in a pattern that is symmetric about the main beam. Therefore, when a null imposed at the one side of the main beam, an image null occurs at the other side of the main beam. The results depicted in Figs. 3 and 4 show that the CLONALG proposed in this work can accurately obtain the nulling patterns by controlling only the selected element positions of the linear array. From the null depth and the maximum sidelobe level points of view, the performances of the patterns are also very good. Furthermore, the nulling technique based on CLONALG preserves the characteristics of the initial Chebyshev pattern with little pattern disturbance except for the nulling directions.

5. CONCLUSION

A new technique based on the CLONALG is presented for null steering of linear antenna arrays by controlling only the positions of selected elements. Numerical results show that the algorithm can obtain the patterns with satisfactory null depth and maximum sidelobe level. It is worth noting that even though the CLONALG presented here is used to a particular synthesis of linear array with isotropic elements, it can easily be implemented to nonisotropic-elements antenna arrays with different geometries for the design of various array patterns. We hope that the CLONALG can be very useful to antenna engineers for the pattern synthesis of antenna arrays since it has good accuracy and does not require complicated mathematical functions.

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