Decimal genetics Algorithms for Null steering and Sidelobe Cancellation in switch beam smart antenna system

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Abstract

Sidelobes cancellation is challenging task in beamforming and beam steering in smart antenna systems. The high level of sidelobes can significantly degrade the system performance as well as antenna power efficiency. In this paper, we present the new decimal genetic algorithm to reduce the sidelobe and at the same time create the nulls toward interferers and jammers. This technique takes advantage of Chebyshev coefficients window as an initial weight vector to speed up the optimization process. The simulation results have shown that this technique is able to find the most suitable weights vector to reduce the sidelobe power and at the same time create the nulls toward interferers. Verification has been done for Uniform Linear Array (ULA) structure. However, this technique can be used for non regular geometrical antenna array structure with variety of beam pattern requirements

Keywords: *Genetic algorithm; Smart antenna; Null steering; Sidelobe cancellation*

1. INTRODUCTION

The principle objective of switch beam antenna array is to steer the main beam to desired location. The uniform linear array (ULA), which is an array of uniformly spaced antenna, can produce the sufficient narrow beam. However, the first sidelobe of a ULA radiation pattern is only about 13.2 dB down from the main lobe level. This is undesirable phenomenon for directive applications, such as radar and direction finding. The sidelobes can be reduced to any desired level by tapering the amplitude of the elements excitation. In tapering process the main task is to calculate an appropriate weights vector which can produce the narrow beam with minimum level of sidelobe. One drawback of amplitude tapering is beamwidth expanding. It means to gain lower amount of sidelobe we must accept the wider value of beamwidth.

Various analytical and numerical techniques have been developed to provide the finest trade-off between sidelobe level and beamwidth value. Examples of analytical techniques include the well-known Taylor and Chebyshev method [1]. In recent years, numerical approaches have become more popular as they are applicable not only to regular arrays such as linear arrays and circular arrays but also to arrays with complicated geometry layout and radiation pattern requirement. Examples of numerical techniques include the linear or nonlinear optimization methods [2], [3] and adaptive methods [4], [5]. Another interesting technique to reduce the sidelobe level is non-uniform spacing or space perturbation. In this technique, the sidelobes can be reduced in height to approximately 2/N times the main lobe level, where N is the number of elements [6] while the beamwidth remains essentially the same as for the uniform array. However, space perturbation is far away to apply for real time application since it depending on servo motor functional speed. Recently, the genetic algorithm has found more popularity to optimize the antenna radiation pattern. In conventional genetic algorithms usually the binary coding and decoding is used for crossover mating. In [7] the decimal GA algorithm has been proposed. This technique is applicable for real as well as complex decimal numbers. However, this technique needs the initial weights calculated using other techniques like MMSE, therefore it makes the technique computationally intensive.

This paper presents the new decimal GA technique to taper the amplitude of array excitation which avoids priory MMSE calculation. Instead, the initial weights vector can be adapted from simple look-up table calculated using conventional array weighting such as Chebyshev window function. This technique can use either real or complex weights vector without binary coding and decoding for crossover process. The remaining material of the paper is organized in four sections, section two describe the proposed GA algorithms, the evaluation or fitness function is described at section three, the results are presented in section four and the paper concludes at section five.

2. THE GENETIC ALGORITHM

The proposed decimal GA algorithm is similar to decimal GA proposed in [7]. However, there are some differences which make this technique faster to apply for sidelobe cancellation and null steering. The flow of this technique is briefly explained herein.

2.1 CONSTRUCTION OF CHROMOSOMES

Unlike the binary GA which chromosomes are represented by the string of binary number, in this technique the chromosome are represented by either complex or real decimal numbers. To fit this technique to smart antenna structure, the chromosomes are corresponded to weights of antenna elements. In the other words each chromosome is consist of M number of genes where M is the number of antenna elements. As an example chromosome one $\bar{w}_1$ can be represented by equation 1.

$$\bar{w}_1 = \left[w_{11} \; w_{12} \cdots \; w_{1M} \right] \qquad (1)$$

Here, $w_{11}\; w_{12} \cdots \; w_{1M}$ are the antenna elements weights or genes. Each of this weight has boundaries with up and down limit. The random set of chromosome can be easily constructed using following relation represented by equation 2.

$$\overline{w}_n = (u_1 - u_2)\times\overline{r} + u_2 \qquad u_2 < \overline{w}_n \le u_1 \qquad (2)$$

Where, u1 and u_2 are the maximum and minimum limit value of the weights and $\overline{\mathrm{r}}$ is real random vector between zero and one. For instance, when real amplitude weighing is considered for the problem, the value of u_1 and u_2 are one and zero respectively, and $\overline{\mathrm{r}}$ is the vector whose elements can be any real number between zero and one.

2.2 INITIAL POPULATION

The initial population number is double of good population number. The top fifty percent of initial population is chosen as a good population after evaluation of each chromosome in initial population by the fitness function.
Some literature use term evaluation function instead of fitness function, however these two terms are equivalent. To speed up the convergence of GA iteration, the initial population can include approximate of the best chromosome which in sidelobe cancellation issue this approximation can be achieved from conventional array weighting [8] such as Kaiser or Taylor weighting.

2.3 REPRODUCTION

When the initial population is created, the top fifty percent of this population having better fitness value are chosen. Now it is the time for parent selection process. To do so, among different available techniques such as tournament, genitor, roulette wheel and ranking [9], roulette wheel can suit the application. This technique randomly chooses the chromosomes with higher fitness value as parents for next generation. It means the higher the value of the fitness function the more chance chromosome has to be selected as a parent. The top 50 percent of the population is chosen as the parent for next generation and the remained 50 percent are discarded at this stage. Next step is reproduction; the reproduction process consists of three basic genetic operations: crossover mating, mutation and Elite principle. Crossover mating is common term in binary coding and decoding GA algorithm however, for decimal GA the operation is slightly different, for the GA here we proposed the crossover as a linear summation and subtraction operation. Since, these operations can carry the good feature of parent to the next generation. Unlike the other technique, four children are created from two parents who can be represented by following equations:

$$\overline{c}_n = \frac{1}{4}\left(3\overline{w}_n + \overline{w}_{n+1}\right) \qquad (3)$$

$$\overline{c}_{n+1} = \frac{1}{2}\left(\overline{w}_n + \overline{w}_{n+1}\right) \qquad (4)$$

$$\overline{c}_{n+2} = \frac{1}{2}\left(2\overline{w}_n - \overline{w}_{n+1}\right) \qquad (5)$$

$$\overline{c}_{n+3} = \frac{1}{2}\left(2\overline{w}_{n+1} - \overline{w}_n\right) \qquad (6)$$

In this process, four children will be results of crossover mating. It means if the parent population is $\mathrm{p_p}$ the children population $\mathrm{p_c}$ would be equal to $2\mathrm{p_p}$. Now, the whole population of offspring and parent is $3P_P$. this population is evaluated using fitness function. In the next process, before mutation operation, the elite children who have the best fitness function in the population directly go to the next generation; this mechanism is called Elite principle. Therefore the mutation process will not affect the best chromosome or individual, and it keeps the trend of GA iteration always rising trend, therefore the value of the fitness in each iteration never get worse from the previous iteration in the algorithm. In proposed GA two chromosomes with the best fitness value after crossover mating are picked of as Elite members. Then the next process which is mutation is done. Different numbers of simulation have shown that the mutation with the probability of 1/M has always better results than the other probability value. Where M is the number of antenna arrays.

The mating process can be simply applied to the whole population, if we create a matrix of population. For instance, If the number of population after crossover process is $3P_p$, the mutation matrix has a dimension of $(3Pp\text{-}2)\times M$ genes. Then number of genes with the rate of 1/M will be changed base on equation 7.

$$w_{nk} = (u_1 - u_2)\times r + u_2 \qquad u_2 < w_{nk} \le u_1 \quad (7)$$

Where, r is the random number between zero and one. After mutation process, the population is ranked again, and 33 percent with worse fitness value are directly discarded before roulette wheel parent selection. The best chromosome after the crossover mating is evaluated and if the criteria are met the algorithm will be stopped otherwise this procedure is continuously repeated to achieve the desirable results.

3. THE LINEAR ARRAY AND RADIATION PATTERN SYNTHESIS

The array structure considered for this research is linear. However, the technique can be applied to any type of array with unknown geometrical shape. The equispaced array factor with different excitation amplitude can be written as equation (8).

$$AF = \sum_{k=1}^{M} w(k).e^{j(k-1).\frac{2\pi}{\lambda}.d(\sin(\theta)-\sin(\theta_0)).\cos\phi} \quad (8)$$

Where, d is the distance between array with the value of half a wavelength and θ, ϕ and λ are the azimuth angle, elevation angle and wavelength of carrier signal respectively, θ_o is the pointed angle of main beam in the azimuth. Herein, we assume that the elevation angle ϕ is zero for more simplicity. M Is the number of antenna and W is the weight vector for the antenna array.

3.1 THE EVALUATION OR FITNESS FUNCTION

The evaluation function can be written as the main beam power ratio to sidelobe power ratio. So it can be written as equation 9.

$$E1 = \frac{P_M}{\sum P_S} \quad (9)$$

Where, P_M and P_S are the main beam power and sidelobe power respectively, however the GA performance is directly depend on the evaluation function equation. If minimum amount of sidelobe for all direction is required then the evaluation function changes to following relation.

$$E2 = \frac{P_M}{\min\limits_{sidelobe}(P_S)} \qquad (10)$$

It means that the algorithm, in each iteration will find the maximum amount of sidelobe and try to find the best weight to reduce this sidelobe to lower level. So all of sidelobe by this technique can be found and suppressed into minimum level. In the case when the null steering is required for the system, the evaluation function can have a relation represented in equations 11,12,13,14.

$$E3 = E2 + \alpha_1.E2 + \alpha_2.E2 \cdots \alpha_n.E2 \qquad (11)$$

$$P_{null1} = \alpha_1.E2 \qquad (12)$$

$$P_{null2} = \alpha_2.E2 \qquad (13)$$

$$\vdots$$

$$P_{null_n} = \alpha_n.E2 \qquad (14)$$

In this relation $\alpha_1, \alpha_2 \ldots \alpha_n$ are the real numbers which show the depth of the null in compare with the minimum sidelobe level in the pattern. Therefore the depth of each sidelobe can be defined by these coefficients.

4. NUMERICAL RESULTS

The simulations parameters are list down in table 1. The results have shown in figure 1, 2, 3 and 4.

Desire beam pattern / Simulation parameters	One main beam and 3nulls	Two main beam and 2nulls
array type	16 elements ULA	16 elements ULA
Main beam angle	θ_0 =30 degree	θ_0 =0 and ---45 degree
Null direction	β=[-30,0,60] degree	B=[-20,60] degree
Chromosome type	Decimal Real & complex numbers	Decimal Real & complex numbers
Cross-over technique	Decimal Sum &subtraction	Decimal Sum& subtraction

Mutation probability	0.10	0.10
Population number	32 and 64	32 and 64
#of independent run	10	10
#of iteration	50	50

Table 1: Simulation parameters

The GA is repeated for ten independent run, each consist of 50 iterations. Note that even the number of independent run is ten; the close optimized values usually can be achieved after 2 independent run equivalents to one hundred iterations. The population number for figure 1 and 2 is 32 while for figure 3 and 4 is 64

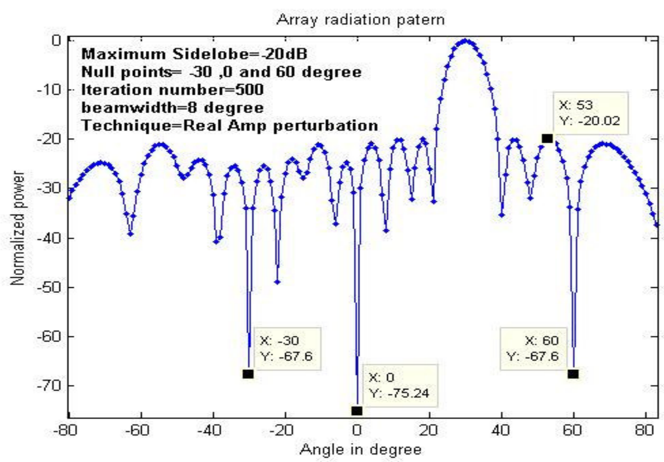

Figure 1: GA with real decimal chromosome type

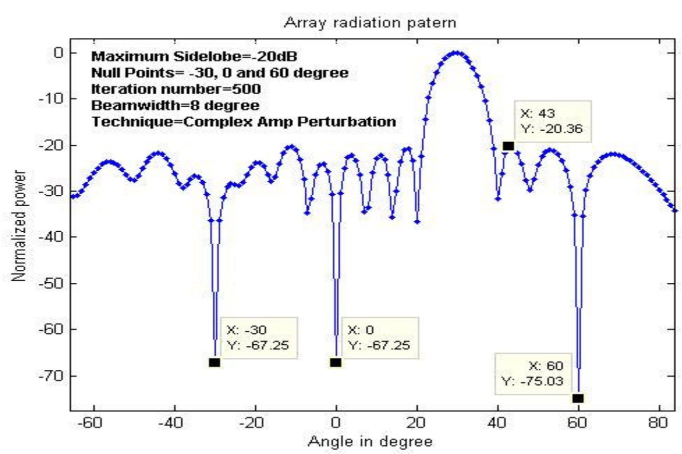

Figure 2: GA with complex decimal chromosome type

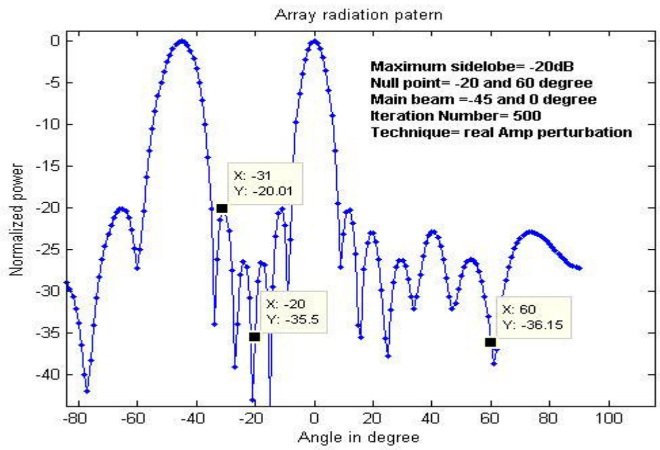

Figure 3: GA with real decimal chromosome type

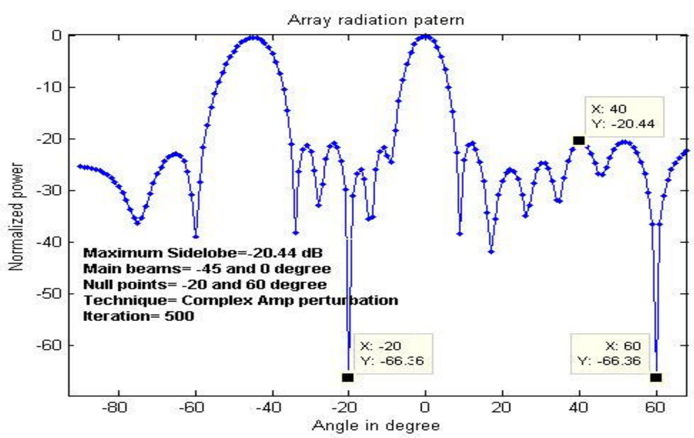

Figure 4: GA with complex decimal chromosome type

The summary of results is organized in table 2.

Beam parameters	Fig 1	Fig 2	Fig 3	Fig 4
Chromosome type	real	complex	real	complex
Main beam	1	1	2	2
Nulls number	3	3	2	2
Maximum sidelobe	-20	-20	-20	-20
Maximum null level(dB)	-67.6	-67.2	-35.5	-66.3

Table 2: summary of the results

Important results is shown in table 2, In the context of antenna and beamforming techniques, when the multiple beam and null steering in different direction is required, the GA with complex weights always outperform than the GA with real chromosomes value. However, the results shown that for sidelobe cancellation and minimization, the GA with real chromosome has a better performance and also has a lower beamwidth penalty. In the other words, the GA with complex chromosome causes to wider the beam more than real chromosome GA algorithms. Therefore, careful choice of chromosome type is needed for different problem of beam pattern optimizations.

4. CONCLUSION

The results have shown the effectiveness of the proposed GA algorithm to find the optimized weights vector. The main advantage of this algorithm over other numerical technique is its flexibility to adopt with different constraint and requirements of the problem. A little modification on the evaluation function is adequate to fit in different assumptions and requirements of different problems. Note that the integration of the GA with conventional numerical technique can speed up the optimization process.

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