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Optimization of Radiation Patterns of Circular Antenna Arrays using Genetic Algorithm for Wireless Communications

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Abstract

The circular arrays are extremely useful in direction finding, wide bandwidth HF communication systems, wrap - around shipborne communications, navigational aids, space craft communications, null steering systems for mobile communication applications, and wide bandwidth microwave direction finders. The presence of high side lobes causes electromagnetic interference in radar receivers due to nearby objects. Sometimes this interference is so high that it blocks the required echoes completely. Moreover, with the presence of high side lobes the radar systems are susceptible for jamming. In the present paper, an attempt is made to design circular antenna array with optimum low side lobe level and narrow beamwidth. Genetic algorithm is used in the present paper to optimize the radiation patterns of circular antenna array.

Keywords- Circular array, Genetic Algorithm, Narrow beam width.

Introduction:

Linear arrays [1-2] with narrow main beamwidth are used for point to point communications and high angular resolution radars. However, in the applications where angular symmetry in direction finding and 360 degrees scanning is required, they are not suitable. In view of these facts, efforts are made to design the circular arrays.

Circular array antenna [3-7] is an assembly of similar radiating elements electrically and geometrically in the form of a circle. The radiation pattern of circular antenna array with isotropic elements depends on the main parameters like the excitation current, excitation phase, and the spacing between the elements. In the array design process excitation currents, excitation phases, and inter element spacing are the three parameters that can be controlled to achieve the required objective.

Geometry of Circular antenna array (CAA) and Design equations:

The geometry of CAA is as shown in Fig.1

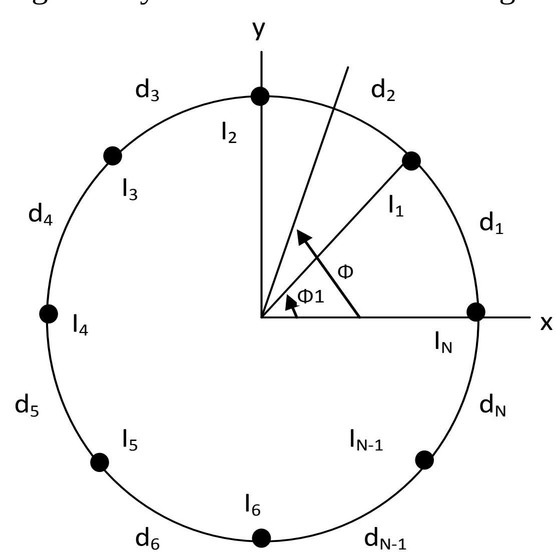

Fig 1. Circular Antenna Array

The array factor of this CAA is calculated as follows

Normalised field can be written as

$$E(r,\theta,\phi) = \sum_{n=1}^{N} \alpha_n \frac{e^{-jk R_n}}{R_n} \qquad (1)$$

Where

$$R_{n=}\sqrt{r^2 + a^2 - 2arcos\psi_n} \qquad (2)$$

For the far field the array field reduces to

$$E(r,\theta,\phi) = \frac{e^{-jk R_n}}{R_n} \sum_{n=1}^{N} \alpha_n e^{jkasin\theta \cos(\phi-\phi_n)}$$

(3)

Where α_n is the complex excitation coefficient both amplitude and phase

$$\alpha = -I_n e^{j\varphi n} \qquad (4)$$

ϕ_n is angular position of the nth element

$$ka = \sum_{i=1}^{N} di \qquad (5)$$

$$\phi n = 2\pi \sum_{i=1}^{n} di/ka \qquad (6)$$

I_n is excitation currents,
φ_n is excitation phases,
d is inter element spacing,
k is the wave number,
N is no of elements and
ϕ is the angle of incidence.

Finally the array factor of CAA can be reduced and is given as

$$AF(\phi,\alpha,d) = \sum_{n=1}^{N} \alpha_n e^{j(kacos(\phi-\phi n))} \qquad (7)$$

Genetic Algorithm:

Genetic algorithm (GA) [8-12] is a global optimization technique which works on the mechanics of natural selection and genetics. It can be used to optimize the solution of any problem. GA is best suited if the objective function is discontinuous, highly non linear, high dimension, stochastic and has unreliable or undefined derivatives. It does not use any gradient information. It is most widely used technique in business, science and engineering areas.

GA is Initially developed by John Holland, University of Michigan (1970's) , Based on the mechanics of biological evolution to understand processes in natural systems and to design artificial systems retaining the robustness and adaptation properties of natural systems.

GA conceptually follows steps inspired by the biological process of evolution. It follow the idea of survival of the fittest better and better solutions evolve from previous generations until a near optimal solutions is obtained.

Terms related to GA:

Gene – a single encoding of part of the solution space, i.e. either single bits or short blocks of adjacent bits that encode an element of the candidate solution

Chromosome – a string of genes that represents a solution

Population – the number of chromosomes available to test

Selection – A proportion of the existing population is selected to bread a new bread of generation. Parents with better fitness have better chances to produce offspring. There are three types of selection are there which are popular rank, tournament and roulette wheel.

Crossover - a genetic operator that combines (mates) two individuals (parents) to produce two new individuals (Childs). The idea behind crossover is that the new chromosome may be better than both of the parents if it takes the best characteristics from each of the parents. There are 4 types of crossover single point, two point, uniform and real value.

Mutation - a genetic operator used to maintain genetic diversity from one generation of a population of chromosomes to the next. It is analogous to biological mutation. Mutation Probability determines how often the parts of a chromosome will be mutated. Types of mutation are bit reversal and polynomial.

Fitness Function - A fitness function quantifies the optimality of a solution (chromosome) so that that particular solution may be ranked against all the other solutions.

It depicts the closeness of a given 'solution' to the desired result. Most functions are stochastic and designed so that a small proportion of less fit solutions are selected. This helps keep the diversity of the population large, preventing premature convergence on poor solutions.

The fitness function for the optimization is given as

Fitness=min(max(20*log AF)/AF)

Termination – Termination of the algorithm can be done if a solution is found that satisfies minimum criteria or Fixed number of generations found or Allocated budget (computation, time/money) reached or the highest ranking solution's fitness has reached

GA parameters selected here are

Max number of iterations : 100

Population size : 50
Mutation rate : 0.15

The process of GA is indicated as flow chart in the Fig.2.

Results

Radiation patterns for circular antenna array of 20, 30, 40 and 60 elements are numerically evaluated using the equations 1 to 7 with uniform excitation. The Genetic algorithm is applied to optimize the excitation currents, excitation phases and inter element spacing of circular antenna array. For 20 elements CAA the radiation patterns are numerically evaluated and they are presented in Fig 3. From the results it is observed that the sidelobe level is -7.9dB with uniform excitation and -10.16dB with optimization which is reduced drastically. The beam width is 13.04^o with uniform excitation and 12.8^o with optimization. The results are tabulated in Table 1 for 20 elements CAA.

Figures [4 – 6] shows that the radiation patterns of 30, 40 and 60 elements CAA with uniform excitation and GA method. The corresponding sidelobe level and beam width comparison values are presented in tables 2 – 4.

Tables 5 and 6 indicate the optimized values of excitation currents, excitation phases and inter element spacing of the CAA with 20 elements and 30 elements by using GA method respectively.

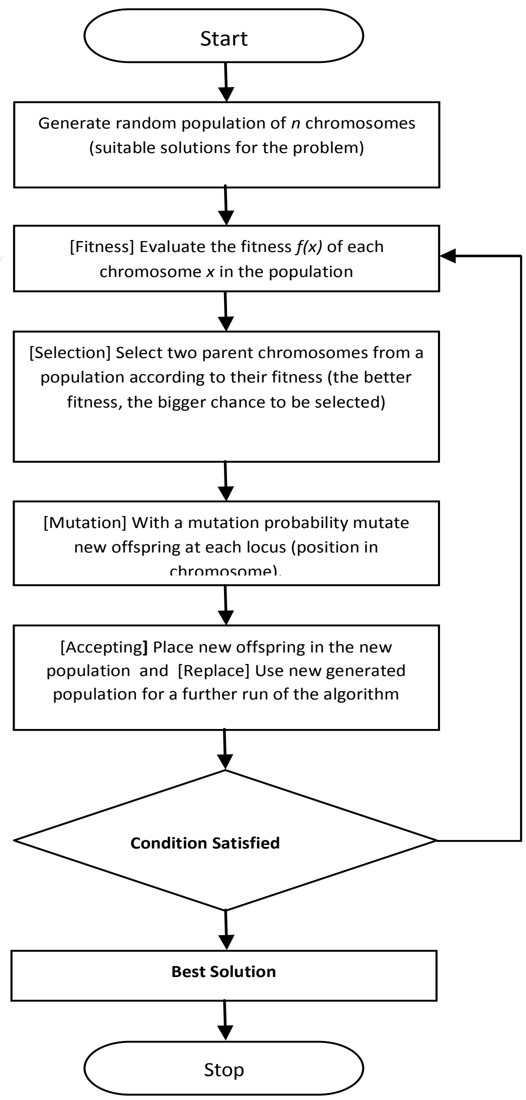

Fig 2. Flow chart of Genetic Algorithm

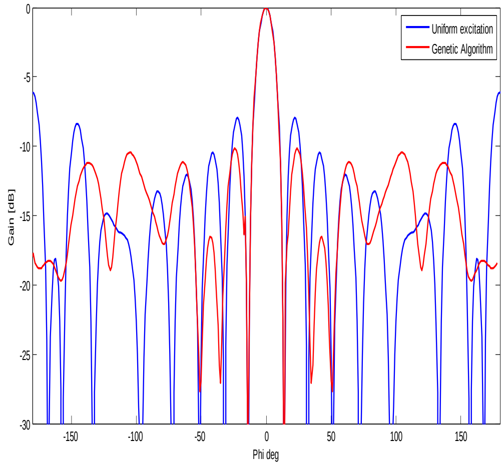

Fig 3. Radiation pattern of CAA for N=20

20 Elements				
	1st SLL	2nd SLL	Max SLL	B.W
Uniform	-7.9	-10.45	-6.43	13.0^o
GA	-10.16	-16.6	-10.5	12.8^o

Table 1. Comparison values for 20 elements CAA

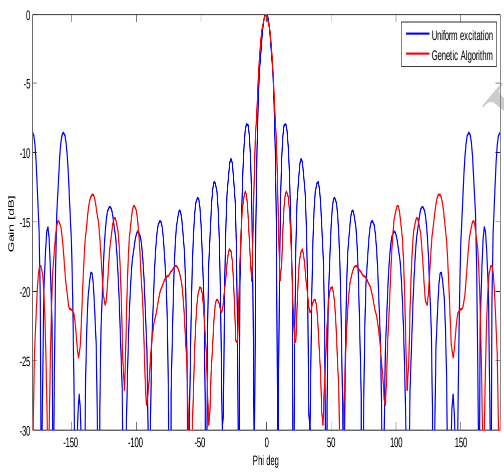

Fig 4. Radiation pattern of CAA for N=30

30 Elements				
	1st SLL	2nd SLL	Max SLL	B.W
Uniform	-7.9	-10.77	-7.9	9.8^o
GA	-12.79	-17.01	-12.79	8.4^o

Table 2. Comparison values for 30 elements CAA

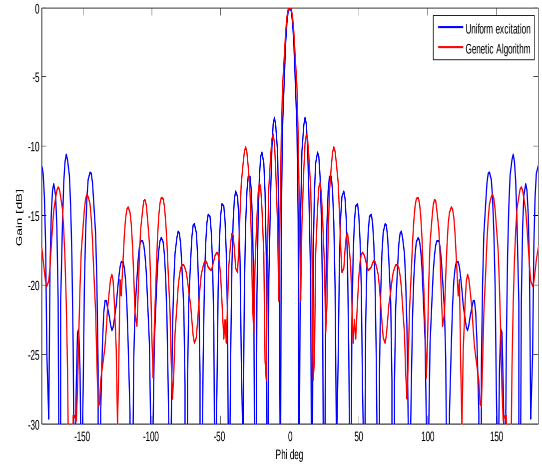

Fig 5. Radiation pattern of CAA for N=40

40 Elements				
	1st SLL	2nd SLL	Max SLL	B.W
Uniform	-7.9	-10.4	-7.9	7.2^o
GA	-9.12	-12.6	-9.12	6.4^o

Table 5. Comparison values for 40 elements CAA

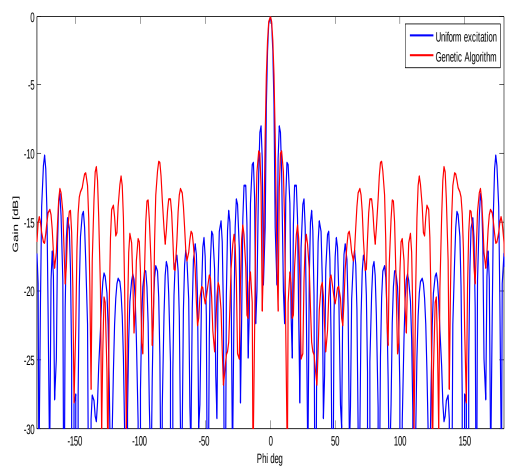

Fig 6. Radiation pattern of CAA for N=60

60 Elements				
	1st SLL	2nd SLL	Max SLL	B.W
Uniform	-8.02	-10.6	-8.02	4.8^o
GA	-9.994	-18.6	-9.994	4.2^o

Table 4. Comparison values for 60 elements CAA

Excitation currents	Spacing	Excitation angle
0.7427	0.3349	-60.1147
0.9875	0.5075	-50.6781
0.9906	0.6518	-36.1766
0.7082	0.7490	-30.6017
0.9467	0.7208	-4.3831
0.9467	0.2973	-0.4698
0.8180	0.4102	-1.4553
0.9498	0.6235	-10.8977
0.9467	0.3255	-10.9550
0.8243	0.5890	-0.6474
0.9875	0.3600	2.7445
0.6894	0.3035	10.2789
0.8275	0.2816	17.1028
0.9780	0.7302	8.2391
0.8808	0.4290	25.0440
0.7992	0.2910	25.6972
0.8463	0.6675	38.6174
0.8996	0.2439	6.3197
0.8463	0.2753	46.2377
0.9341	0.269	59.3069

Table 5 Excitation currents, inter element spacing and excitation angle after optimization for 20 elements

Conclusions:

It is evident from the radiation patterns that application of genetic algorithm is very helpful in reducing the sidelobe levels. The Genetic algorithm is found to be simple, accurate and fast and the patterns are converged after 50 iterations. It is also found from the results that the beam widths are narrowed when compared to the uniform excitation patterns and such beams are very useful in direction finding applications.

Excitation currents	Spacing	Excitation angle
0.9624	0.5482	-2.0161
0.5671	0.2220	-38.2676
0.9969	0.3537	-38.8868
0.9122	0.9341	-1.1220
0.8212	0.8996	-2.2040
0.3600	0.8212	-34.2247
0.3788	0.8714	-18.9556
0.6549	0.9780	-5.7950
0.4573	0.7176	-13.1427
0.8902	0.2471	-11.5858
0.3537	0.2690	-7.8791
0.9404	0.3004	-7.3715
0.7835	0.5263	-10.2108
0.5984	0.2094	-6.9733
0.9310	0.2345	-1.7556
0.9906	0.2282	0.3586
0.9247	0.2125	0.4607
0.8306	0.3224	4.0161
0.5671	0.2533	8.2696
0.4353	0.7678	1.2995
0.3945	0.5608	19.8883
0.8243	0.2314	1.5941
0.2722	0.8620	35.1230
0.7145	0.7741	37.0777
0.8400	0.3224	4.0152
0.8275	0.8463	34.1680
0.3537	0.5733	3.5770
0.9718	0.4792	47.5533
0.9624	0.4322	14.5522
0.8588	0.4792	68.8886

Table 6 Excitation currents, inter element spacing and excitation angle after optimization for 30 elements

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