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Design of Array Antenna for Symmetrical Sum Patterns to Reduce Close-in Sidelobes using Particle Swarm Optimization

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Abstract

In this paper, Synthesis of sum patterns to generate narrow beams with individual heights of sidelobes which can be adjusted to any arbitrary specification using particle swarm optimization (PSO) is presented. The array design is first formulated as an optimization problem with the goal of reducing first two sidelobes to -50dB and by reducing the remaining sidelobes to -40dB. The objective of the PSO algorithm is to determine the optimized set of amplitude excitation coefficients to obtain the desired pattern. Using these optimized amplitude distributions, pattern are numerically computed for small and large arrays and are presented in θ domain.

Key words

Array Antennas, Radiation Pattern, Particle Swarm Optimization, Fitness Function

1. Introduction

Antenna arrays are being widely used in wireless, satellite, mobile and radar communication systems. They help in improving the system performance by enhancing the directivity, improving the signal quality and increasing the spectral efficiency. In many applications it becomes necessary to sacrifice gain and beamwidth in order to achieve lower side lobe level. With the increasing Electromagnetic pollution, it is necessary to generate Nulls in the desired direction [1].

R S Elliott [2-3] presented a design method to achieve sum and difference patterns with side lobes of individually arbitrary heights using continuous line source. Hans Steyskal [4] extended the least means square pattern synthesis methods for the generation of pattern nulls in a given set of angles. Several traditional Numerical techniques like Schelkunoff, Woodward lawson, Taylor's, Tchebyscheff [5, 6] produced good results in array synthesis problems, but suffer several drawbacks like heavy computational complexity and time.

To solve such problems with less computations and efficient capabilities, several computational intelligent techniques are chosen as an alternative to traditional numerical techniques. These techniques are simply classified as evolutionary and heuristic. They mimic the evolutionary phenomenon and natural behavior, and transform them into a series of steps to depict an algorithmic representation. Such algorithms have shown good convergence and fast computation than traditional techniques.

Among such algorithms Genetic Algorithm, Particle Swarm Optimization, Simulated Annealing , Ant Colony Optimization, Artificial Bee Colony, Fire Fly etc.. [6-12] are effectively integrated for multi-objective optimization problem solving in antenna array synthesis. Stochastic approach to optimize fixed number of elements is implemented in [13]. Another such technique verified for application in array synthesis is Tabu Search. Tabu Search is used for side lobe level reduction with fixed beam width constraint. GA by now has come to a stage to be called as a benchmark algorithm for its application in electromagnetics. Any newly proposed algorithm has to compete with the GA in its efficiency towards multi-objective antenna design problems. Many flavours of GA are proposed since its origin. Binary GA (BGA) and Real Coded GA (RGA) are two major variants of GA basing on the number system used to represent the gene of a population. Due to this feature they have immediately drawn the attention of the electromagnetic engineers. The RGA was proposed and executed for solving symmetrical array optimization problems in [14]. Also BGA has successfully achieved array thinning [15, 16] which involves in decreasing the number of elements without compromising with the array pattern. Similarly many more variety of array synthesis is efficiently solved as reported in [17-21]. Among evolutionary, heuristic and stochastic techniques listed above, PSO is much popular because of its ease to implement with minimum number of mathematical processing [22].

The PSO is adopted for linear array synthesis and could witness good results than GA [23]. In this paper PSO is used to achieve the required objective. Generating weights for the amplitudes of current distribution of the elements in the linear array, that could produce the radiation pattern in which the close in side lobes to the main lobe are suppressed to a very low value keeping the farther side lobes at another level higher than the close in SLL, is briefly the objective of the problem considered in this paper. Such radiation patterns have a typical application where an exact cross section of the target is to be known suppressing the interference caused by the close in SLL. The most synthesis method intends to suppress the sidelobe level while preserving the gain of the main lobe [24]. Other aim is to place the null in a specified direction by reducing the effects of interference and jamming. Therefore, in the present work an attempt is made to suppress the side lobe level by optimizing the amplitude excitation coefficient of the individual elements while preserving the gain of the main beam and controlling the nulls near the main beam.

The paper is organized as follows. In Section 2, the array factor formulation and problem design is discussed. The formulation of the fitness function is discussed in the section 3. Section 4 deals with concept of particle swarm optimization algorithm. Defining amplitudes of current excitation of the elements of the symmetric array antenna in order to achieve the desired close in SLL is the objective of the proposed work. The coefficients of the current distribution are obtained as the solution set to the described formulation in the fitness function section. The implementation of the PSO to the problem specified is described in section 5 deals. The synthesized radiation patterns with reduced sidelobes are presented in section 6. Finally, conclusions are drawn in section 7.

2. Array factor formulation and problem design

A linear array is the simplest array geometry in which all the elements of the array are arranged along the straight line. The representation of such geometry is as shown in the Fig.1. The array factor of an antenna array is the product of element factor and spacing factor. The formulation of such array factor for any antenna array geometry plays a vital role in determining its radiation characteristics and several other electromagnetic properties of it. Elements of the linear array considered are isotropic in nature with element wise uniform radiation pattern for all azimuthal and elevation angles. But exhibit a variety of patterns when packed as an array.

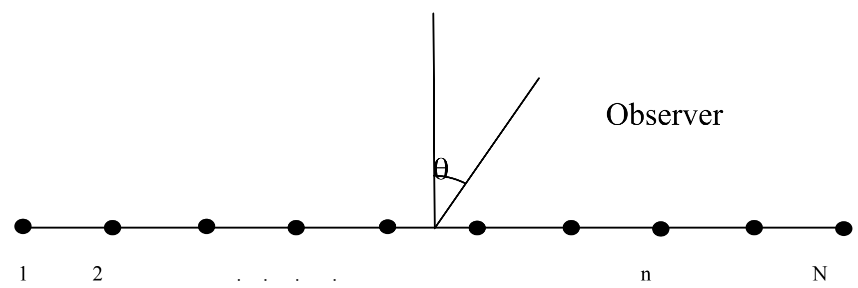

Fig.1. Linear Array Geometry

The elements are excited around the center of the linear array. For even numbered linear array the array factor with the above consideration can be written as

$$E(\theta) = 2\sum_{n=1}^{N} A_n \cos\,[\pi(n-0.5)\sin\theta] \qquad -(1)$$

$$E(\theta)_{\text{norm}} = \frac{|E(\theta)|}{|E(\theta)_{\max}|}$$

the normalised form of the eq(1) is given as

$$E(\theta)_{\text{dB}} = 20 * \log_{10}(E(\theta)_{\text{norm}}) \qquad -(2)$$

Here,

θ =angle between the line of observer and broadside

A_n =excitation of current for the nth element on either side of the array.

N= Number of Elements

Amplitude of excitation, phase and spacing between the elements are the steering parameters of the radiation pattern in the linear array. Proper amplitude distribution would give the desired shaped radiation pattern. Considering this the design of the array involves in determining the amplitudes of excitation which could reproduce the pattern corresponding to desired criterion.

3. Fitness Function

The Fitness function for observing varying SLL with respect to first two SLLs immediate to main beam called as close in SLLs and SLLs away from the main beam is given as

$$ff1_{\max} = \max(\text{SLL}_1, \text{SLL}_2)$$

and

$$ff2_{\max} = \max[\text{AF}(-\theta(\text{SLL}_2) > AF(\theta) > AF(\theta(\text{SLL}_2))]$$

$$where \quad -90 < \theta < 90$$

$$\left.\begin{aligned} f1 &= ff1_{\max} + \text{SLL}_c && if\ \ ff1_{\max} > -\text{SLL}_c \\ &= 0 && otherwise \end{aligned}\right\} -(3)$$

$$\left.\begin{aligned} f2 &= ff2_{\max} + \text{SLL}_f && if\ \ ff2_{\max} > -\text{SLL}_f \\ &= 0 && otherwise \end{aligned}\right\} -(4)$$

and the final fitness is given as

$$FF = f1 + f2 \qquad -(5)$$

Here,

$ff1_{max}$ refers to maximum value of the close in SLLs

$ff2_{max}$ refers to maximum of remaining SLLs.

SLL_1, SLL_2 are side lobe levels of 1st and 2nd side lobes immediate to main lobe.

$-SLL_c$ refers to desired close in SLL which is -50dB in this case

$-SLL_f$ refers to desired other side lobes level which is -40dB in this case

Equation (1) is the reason for minimising close in side lobe levels and Equation (2) takes the role of maintaining other SLLs at -40dB. A cost enhancement factor which is simply a numerical value can be added to ff1 to compete with the ff2. This is the obvious case of increasing the cost of close in side lobe levels anticipating fast convergence to the desired level.

The envelope of the desired pattern is given in the Fig.2

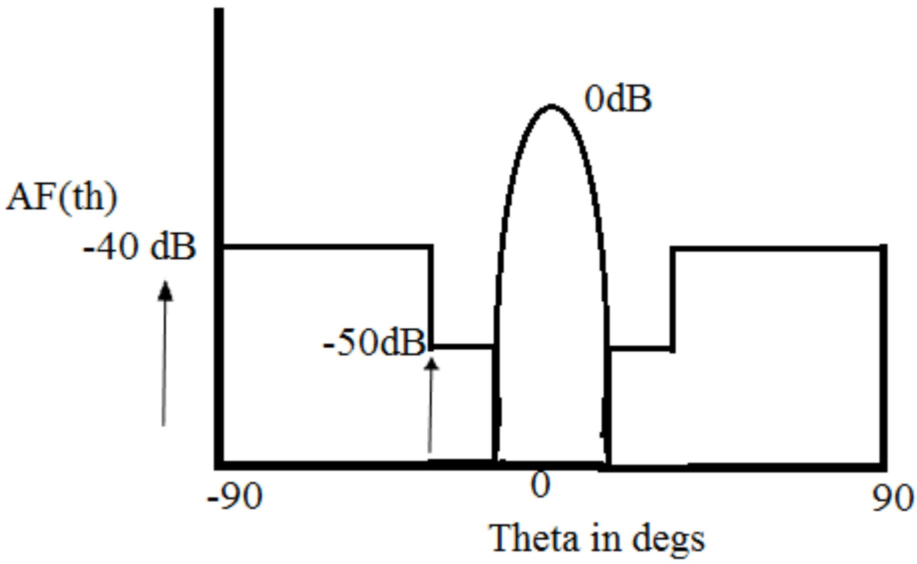

Fig.2 Envelope of the desired pattern

4. Particle Swarm Optimization

Particle swarm optimization is an intelligent optimization technique which mimics the social behaviour of birds. Kennedy and Eberhart [23] formulated the mutual and individual coordination among the birds in the flock while moving towards the target (food). This algorithm has proved its consistency in speed with many multimodal applications over many heuristic and evolutionary approaches. This is due to the nature of the algorithm in updating the design variable in two stages namely position and velocity for every generation.

While realizing the algorithm for the current problem discussed in the preceding section, each bird is considered as a collection of elements (antennas) which forms an array. The number of elements in the proposed geometry of array for the desired pattern reflects the dimension of the problem. In a multidimentional search space each bird corresponds to a potential solution. A bird updating its position and velocity is similar to the corresponding solution sliding towards global optimum.

There are over ten variants of PSO. Each variant has its own formulation and steps slightly varying from the standard PSO (SPSO) as proposed by Kennedy and Eberhart. All the variants deviate from the SPSO by the way the updating process is carried. The type of PSO employed in this work is called as Accelerated PSO (APSO) [25].

SPSO generally uses

a) Global Best (gbest) b) Personal Best (pbest)

and the velocity update is given by the following equation

$$v_i(t+1) = v_i(t) + a\,\varepsilon_1[\text{gbest} - x_i(t)] + b\varepsilon_2[\text{pbest} - x_i(t)] \qquad \text{-(6)}$$

where ε_1 and ε_2 are random vectors between 0 and 1, a and b are learning parameters approximately equal to 2.

The position update takes place according to the following formulation

$$x_i(t+1) = x_i(t) + v_i(t+1) \qquad \text{-(7)}$$

Here as in APSO uses only the gbest is considered in updating the velocity. This is given as

$$v_i(t+1) = v_i(t) + a\,\varepsilon_n + b[\text{gbest} - x_i(t)] \qquad \text{-(8)}$$

ε_n is drawn from (0,1)

The position update usually follows the same formula as presented in SPSO.

The elimination of the pbest in the update process has not only decreased the computational time involved in calculating the pbest but also reduced the memory consumption

5. Implementation of PSO to array synthesis

The effective implementation of the algorithm for the current problem of close in SLL starts with population initialization and later velocity and position are evaluated and updated in each generation. Generation of population and assuming them as amplitudes of current excitation. Initially a set of solutions are generated randomly as positions. This is explained as follows.

$$Position = \begin{bmatrix} x_{11}, x_{12}, \dots\dots\dots, x_{1n} \\ x_{21}, x_{22}, \dots\dots\dots, x_{2n} \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ x_{m1}, x_{m2}, \dots\dots\dots, x_{mn} \end{bmatrix} \quad -(9)$$

The population matrix is of size m X n where 'm' denotes the number of birds and each bird denotes an array of '2n' elements. The elements of the position matrix are normalised value within the range of 0-1. The amplitude matrix is directly taken from the position. The velocity and the position matrices should be of same dimensions. This is mentioned as follows.

$$Velocity = \begin{bmatrix} v_{11}, v_{12}, \dots\dots\dots, v_{1n} \\ v_{21}, v_{22}, \dots\dots\dots, v_{2n} \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ v_{m1}, v_{m2}, \dots\dots\dots, v_{mn} \end{bmatrix} \quad -(10)$$

The corresponding personal best is an array of length 'm'. Each member of this array corresponds to the personal best of the respective number row ie; individual (bird).

Pbest=[Pb1 Pb2……….Pbm] -(11)

6. Results and Discussions

In the present work, Particle Swam Optimization is applied to determine the amplitude excitation coefficients to obtain the optimized radiation pattern with first two maximum close-in sidelobe level less than -50dB and the remaining sidelobes at -40dB. Here, an equally placed linear array with one-half-wavelength-spaced isotropic elements is considered. The weights are obtained following the algorithm steps and the objective function formulation mentioned in the previous sections for number of array elements equal to 20 to 100 insteps of 20. The optimized weights are then substituted in the array factor formulation to obtain the desired radiation pattern. The optimized Amplitude distributions computed using PSO and their respective radiation patterns are presented in Figures 3 – 12.

The algorithm is tuned to a population equal to 20, a and b equal to 2 and ε_1 and ε_2 randomly chosen for each iteration between a range of (0, 1). The linear array formulated has its main beam positioned at θ=0 to depict the broadside characteristics. It typically has the amplitude distribution with maximum amplitude at the center element and decreasing as we move towards the array end elements [26,27]. The same is evident from the following amplitude distribution plots. Also as the number of elements N is increased the position of the close in sidelobes shifted close to the main beam leading to a narrow main beam. This increase in N also increased the number of the density of sidelobes in the pattern which is evident from the following radiation pattern plots.

Number of elements in the array are considered to be 20 to produce the simulation results pertaining to the amplitude distribution and corresponding radiation pattern as shown in the Fig.3 and Fig.4 respectively. The amplitudes obtained for the first 10 are copied to the remaining 10 elements in reverse to maintain the desired symmetry. From the radiation pattern plot (Fig.4) it is evident that the first two SLL are maintained perfectly under -50dB keeping the remaining SLL below -40dB.

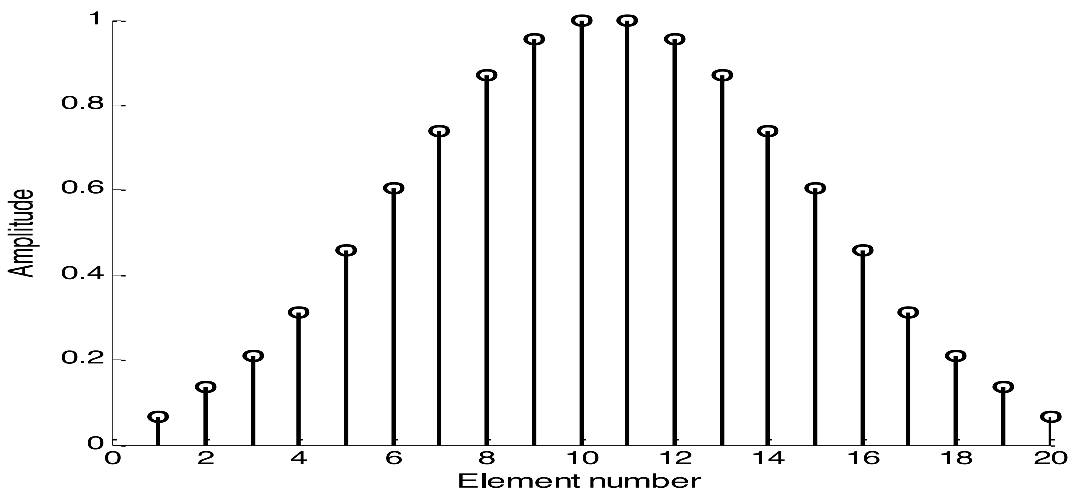

Fig 3: Amplitude Distribution for N=20

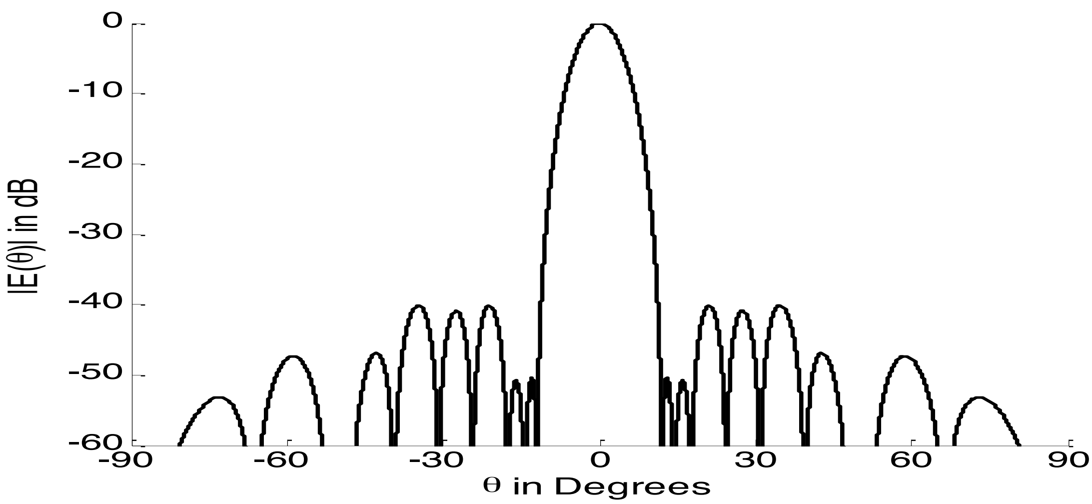

Fig. 4: Radiation pattern for N=20 with reduced close-in side lobes to -50dB

The simulation is repeated, this time the number of elements being 40. The corresponding amplitude distribution and the radiation pattern plots are given in Fig.5 and Fig.6 respectively. It can be read from Fig.5 that amplitude distribution follows the trend of having large magnitudes for the centre elements and decreasing gradually as they progress towards the end elements to preserve the broadband characteristics.

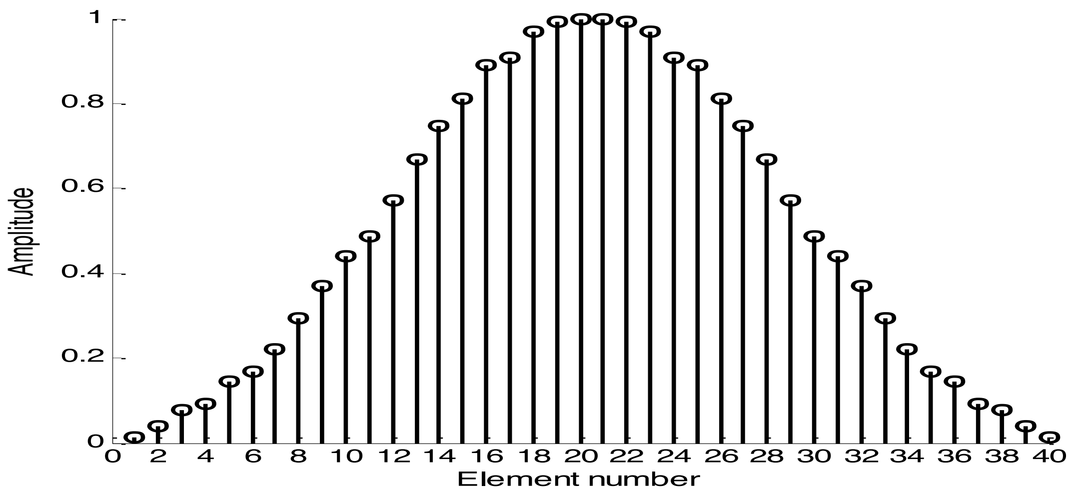

Fig 5: Amplitude Distribution for N=40

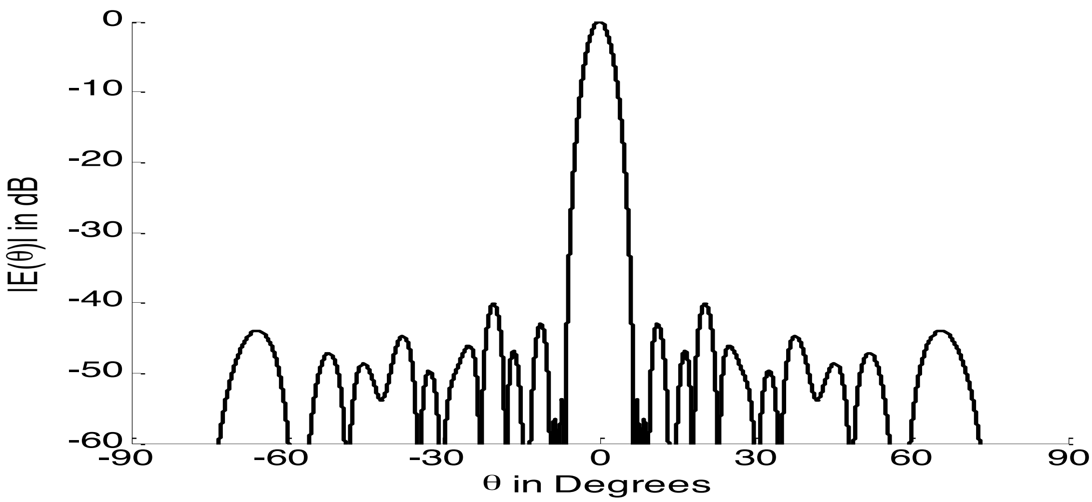

Fig. 6: Radiation pattern for N=40 with reduced close-in side lobes to -50dB

Changing the number of elements causes the PSO to get different optimum weights for the elements. This is observable throughout this work. As a next step of simulation, the radiation pattern and the corresponding amplitude distribution are obtained for 60 elements as shown in Fig.7 and Fig.8 respectively. The simulation is repeated for 80 element and 100 element linear symmetric array and the resulting optimum weights (Fig.9 & Fig.11 respectively) and the desired radiation patterns (Fig.10 & Fig.12 respectively) are obtained. It can be observed that a set of centre elements maintain same amplitudes with not much variation. It is intuitive that the SLL of

-40dB is maintained uniformly by all the remaining side lobes (other than the close in) with increase in number of elements from 20 to 100.

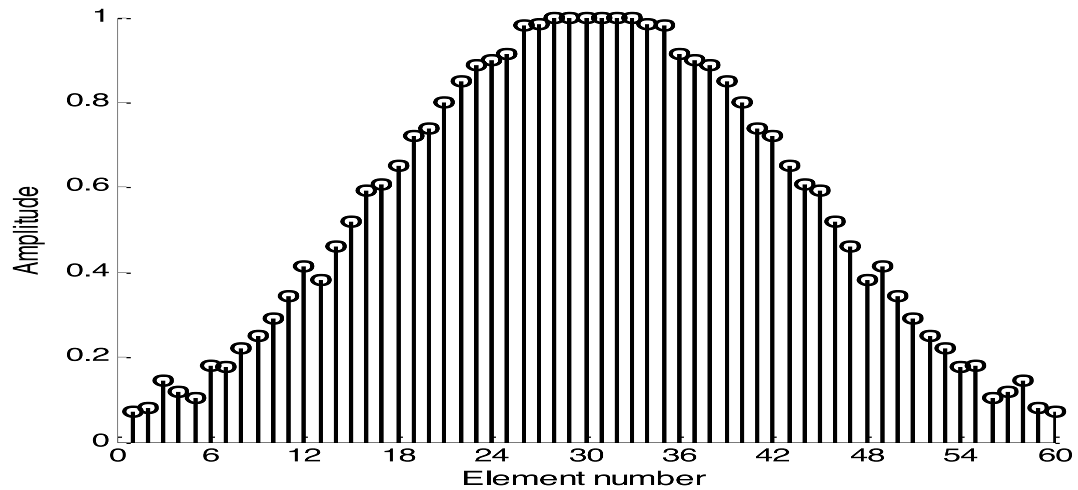

Fig 7: Amplitude Distribution for N=60

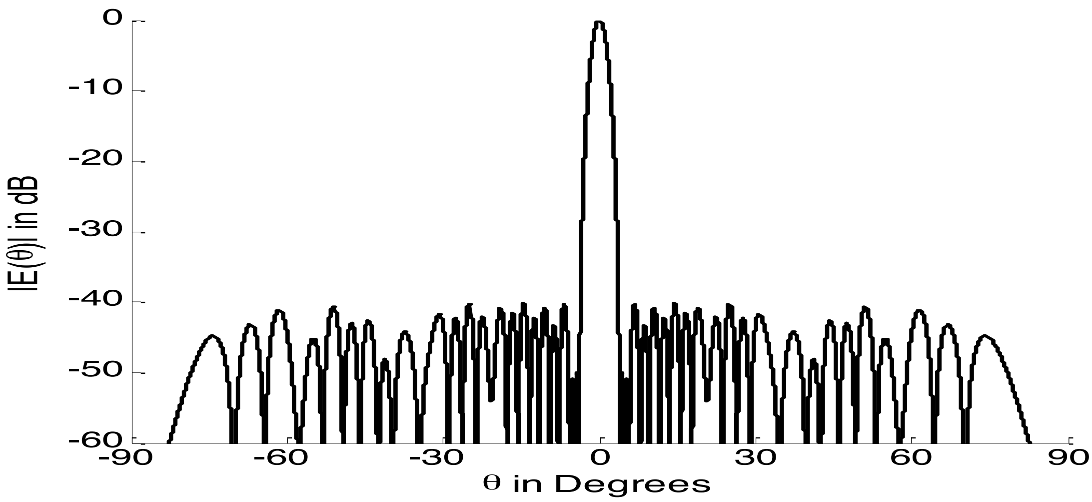

Fig. 8: Radiation pattern for N=60 with reduced close-in side lobes to -50dB

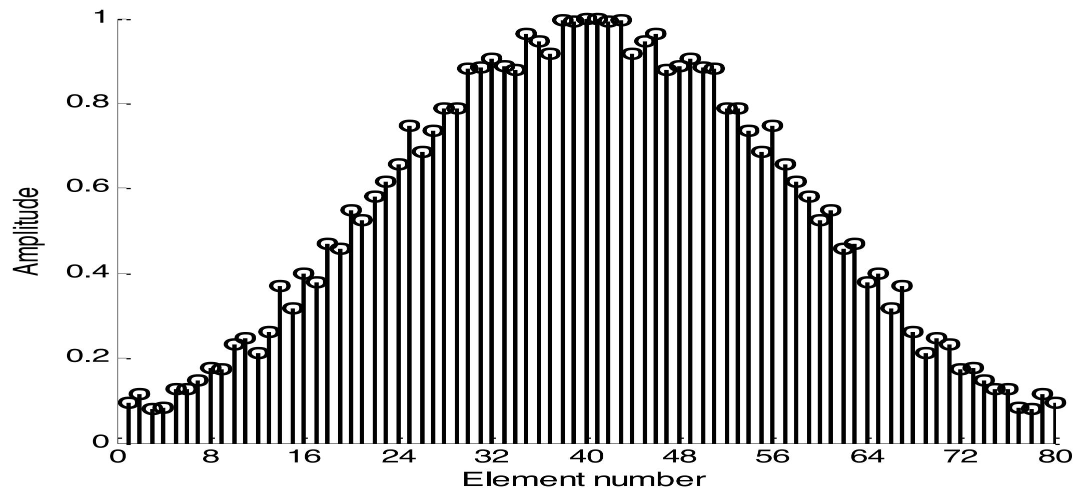

Fig 9: Amplitude Distribution for N=80

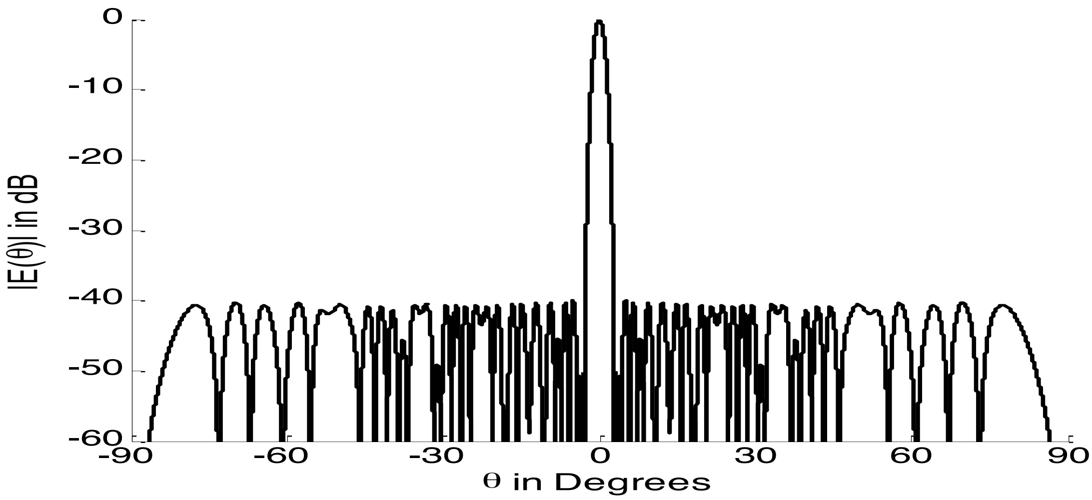

Fig. 10: Radiation pattern for N=80 with reduced close-in side lobes to -50dB

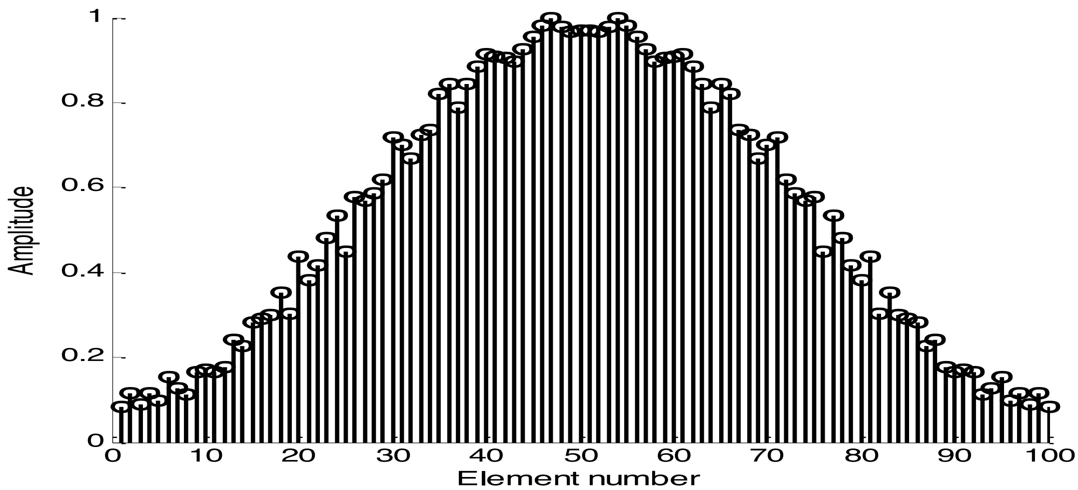

Fig 11: Amplitude Distribution for N=100

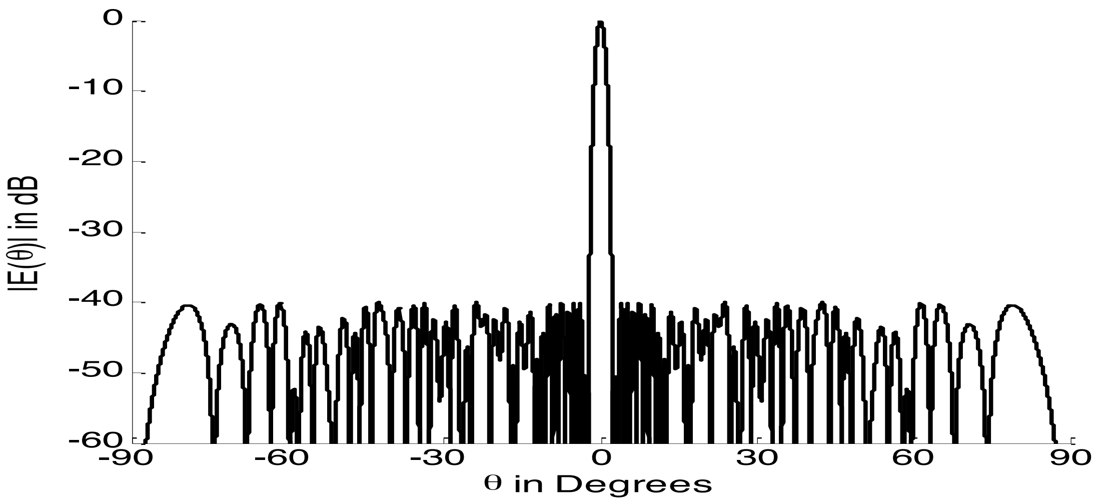

Fig. 12: Radiation pattern for N=100 with reduced close-in side lobes to -50dB

7. Conclusion

It is evident from the literature that as number of elements is increased for a fixed amplitude distribution, the 1^{st} side lobes remains constant with reduction in beam width. However, in the present case, there is a small variation in the side lobe level. The results reveal that PSO algorithm delivers an improved design in terms of significant reduction of side lobe levels while maintaining the strong null in desired directions. The first two close-in side lobes are maintained at -50 dB, maintaining the remaining at a height of -40dB. Thus PSO has good potential as an algorithm for antenna array synthesis and it can be extended to other beam patterns also.

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