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Optimization of Linear Arrays using Modified Social Group Optimization Algorithm

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In this paper, optimization of the linear array (LA) antenna is performed using modified social group optimization algorithm (SGOA). First step of the work involves in transforming the electromagnetic engineering problem to an optimization problem which is completely described in terms of objectives. Linear array synthesis is inherently considered as a multi-attribute problem. The pattern synthesis of LA is carried out with several objectives involving sidelobe level (SLL), beam-width (BW) and desired nulls. The SLL suppression with BW constraint is considered as first objective of this work and the results are compared with several evolutionary computing algorithms like ant lion (ALO), grey wolf (GWO) and root-runner (RRA). Following this, the MSGOA is further used to synthesise null patterns in which the pattern is completely described in terms of nulls with SLL and BW as constraints. The entire simulation-based experimentation is performed using Matlab® on i5 computing system.

Keywords: Linear arrays, MSGOA, Optimization, Patterns, Sidelobe levels

Introduction

Antenna array (AA) refers to the arrangement of antennas in a specific geometrical shape. These AA are well suited for wireless communication applications because of its higher directive features. It is possible to achieve high directivity as the elements in the array collectively operate as a single element antenna. [1]Hence, each element has a significant contribution to the overall radiation of the array. Directivity plays a major role in wireless systems for long distance communications. Hence, the antenna arrays are best candidates for radiating the signal in wireless systems.

The antenna array can be of several geometrical shapes in one, two and three dimensions. Mostly, they exist in linear and planar geometry. Among these, linear arrays are popular and simple to design and establish. In LA, all the elements are arranged on a straight line separated by inter-element spacing measured in wavelengths. Each element is provided with individual current excitation and accordingly, the array will have specific current distribution which can uniform and non-uniform. Usually, the uniform current distribution is treated as simple as all the elements are excited uniformly without any bias. However, the corresponding SLL and BW are not significantly suitable for communication purpose. For better communication, it is desired have the SLL as low as possible along with narrow BW.[2] It is possible to achieve this by manipulating the current distribution and providing non-uniform distribution. However, the challenge is to determine the non-uniform distribution which can satisfy the above objectives. Several numerical techniques are proposed in the literature which are complex with typical computational steps. In the recent days, evolutionary computing tools are extensively used, as they are simple and do not have any complex mathematics involved. To the list we have some significant literature in which the linear array antenna synthesis with several objectives has been addressed using flower pollination algorithm[3,4], social group optimization[5–7], ALO[8], GWO[9] and RRA.[10] The problem statement considered of the work reported in this paper involve in determining the set of design parameters which can produce the desired patterns in line with the objective. The design parameters are excitation amplitudes while the remaining parameters are uniformly distributed.

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In this paper, MSGOA[11–13] is used as an intelligent technique for LA synthesis. Similarly, null pattern synthesis is also addressed with single and multiple nulls.

Problem Formulation

The formulations of the array factor of LA and fitness function based on different objectives considered in this work are discussed in this Section as follows.

Linear Array

The distributions of antenna elements in the LA are as shown in Fig.1. The current distribution is symmetric around centre element and hence the number of elements is referred as 2N. Accordingly, the current excitations are to be determined only for N elements in a 2N element LA. The array factor (AF) of such LA in which d refers to the inter-element spacing (measured in λ), β is the propagation constant and
θ denoting the look angle is given as[1]

$$AF(\theta)=2\sum_{i=1}^{N} I_i \cos(\beta d_i \cos\theta) \qquad \ldots (1)$$

Fitness Formulation

The formulation of the fitness function is essential as it takes a significant part in the optimization process. In this work, single and multiple null positions are recovered in terms of the corresponding E values at those locations. In the unconstrained case, there is no involvement of the SLL or BW while in the constrained case, both the SLL and the BW are included in the objective function. Accordingly, the formulation of the fitness function is framed as follows.

$$\left.\begin{aligned} f_1 &= SLL_{desired} - SLL_{obtained} && if\ f_1 > 0 \\ &= 0 && if\ f_1 < 0 \end{aligned}\right\} \qquad \ldots (2)$$

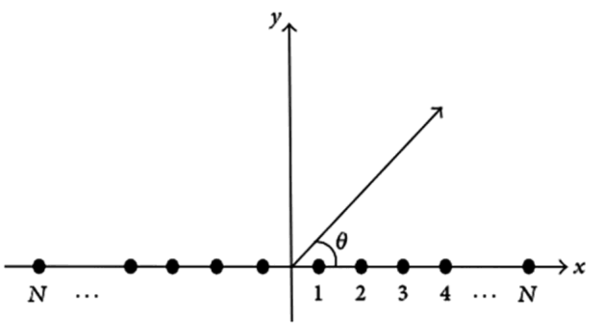

Fig. 1 — Geometry of linear array antenna

$$f_2 = \left| BW_{uniform} - BW_{obtained} \right| \qquad \ldots (3)$$

$$f_3 = \sum_{n=1}^{3} \left| 60 - AF[\theta_n] \right| \qquad \ldots (4)$$

$$where\ \theta_1 = 23.6^o, \theta_2 = 53.2^o$$

$$\left.\begin{aligned} fitness &= f_1 \quad (SLL\ optimization) \\ fitness &= f_3 \quad (Nulls-unconstrained\ case) \\ fitness &= f_1 + f_2 + f_3 \quad (Nulls-constrained\ case) \end{aligned}\right\} \qquad \ldots (5)$$

Here f_1, f_2 and f_3 are the fitness evaluations for nulls, SLL and BW. However, the final fitness is evaluated as given in Eq. (4) for unconstrained and constrained cases separately. Incorporating the obtained SLL and the uniform SLL which are used to compute the difference between them is given as f_2. The observed SLL from the radiation pattern is the maximum value of the AF(θ) between the first null and the end of the radiation pattern.

Modified SGOA

Modified SGOA[11] algorithm is another variant of the SGOA.[8] The creators of the SGOA are involved in developing the MSGOA. The conventional SGOA updates each individual through two phases namely the improvement phase and acquisition phase. The modified SGOA keeps the initial phase of improvement without any modifications while the phase of acquiring observes updating the individual with respect to a determinant known as social awareness probability (SAP).

An individual is a potential solution represented by $I_{i,j}$. Here 'i' refers to the index of the individual in the population while the 'j' refers to the index of the dimension. A population of N individuals, each with dimension of D is generated randomly as an initial step which is further mitigated in every generation according to a set of formulae according to the structure of the algorithm.
In the improvement phase, the individual is updated in the following manner

$$I_{i,j}(t+1) = c * I_{i,j} + r * (G_j - I_{i,j}) \qquad \ldots (6)$$

Here, c is self-introspection parameter which is lies in the range (0,1).

Similarly, in the later phase of acquiring all individuals are accessed sequentially from the population and compared with the randomly chosen other individual. If the fitness of the individual is inferior to the fitness of the random individual then the individual is updated according to the determinant factor SAP. A fixed value is assigned to SAP which preferably lies in the range (0.7, 0.9) and compared with a random number r. If the random number r is less than SAP, then the new individual is expressed as

$$I_{i,j}(t+1) = I_{i,j} + r_1 * (I_{i,j} - I_{r,j}) + r_2 * (B_j - I_{r,j}) \quad \ldots (7)$$

If not, then the individual transformation takes place using the following method.

$$I_{i,j}(t+1) = lb + r * (ub - lb) \quad \ldots (8)$$

Further, if the individual taken sequentially from the population is superior to the randomly chosen individual then the selected individual is updated as follows.

$$I_{i,:}(t+1) = I_{i,:} + r_1 * (I_{r,:} - I_{i,:}) + r_2 * (B_j - I_{i,j}) \quad \ldots (9)$$

Here, each individual is a solution referred as antenna array current distribution and the number of elements in the array is the number of design variables.

Results and Discussion

Broadly, two different objectives are considered in the simulation-based experimentation. The first objective deals with LA synthesis in terms of optimization of SLL with BW constraint, while the second objective is to secure nulls in the desired directions with constraint on BW as well as SLL. Accordingly, the simulation results are presented as examples and comparative study is also drawn wherever it is necessary. However, in all the examples, for a unified study, the length of the LA is taken common as 2*N=10. The results pertaining to each example are presented in the following sub-sections.

Example-1: SLL Optimization with Uniform BW Constraint

The uniform LA has a SLL of −12.92dB (SLL_{uni}), while the corresponding BW is 23.2° (BW_{uni}). In this example, the amplitude distribution is made non-uniform and is determined using MSGOA with the objectives of suppressing the SLL further below SLL_{uni} with the respective BW fixed at BW_{uni}. According to the objective, the corresponding fitness referred as f_1 is considered. As a result, the SLL is minimized to −14.92 dB which has clear reduction of 2 dB. The corresponding radiation pattern compared with uniform pattern is given Fig. 2. The non-uniform amplitude distribution corresponding to this example is given in Table 1.

Example-2: SLL Optimization for a Desired BW

In this example, the desired BW is considered from the literature. It is reported in the available literature that the SLL can be suppressed to −26.52 dB, when the BW is relaxed to 33.1° using RRA. Similarly, ant lion optimization (ALO) and grey wolf optimization (GWO) algorithms have reported an SLL of –26.05 dB and −26.08 dB. In this work, the non-uniform amplitude distribution of LA is determined using MSGOA algorithm and could successfully surpass the above, producing patterns with SLL as low as 27.5 dB which is approximately 1dB lower than the RRA. The radiation patterns corresponding to this objective are given in Fig. 3. The MSGOA determined amplitude distribution corresponding to this example is given in Table 1.

Example-3: Patterns with Single Null

In this example, the objective is to generate radiation pattern using non-uniform amplitude distribution as determined by MSGOA algorithm which has a null at 23.6°, which is similar to the null position of the uniform pattern. However, initially no constraint

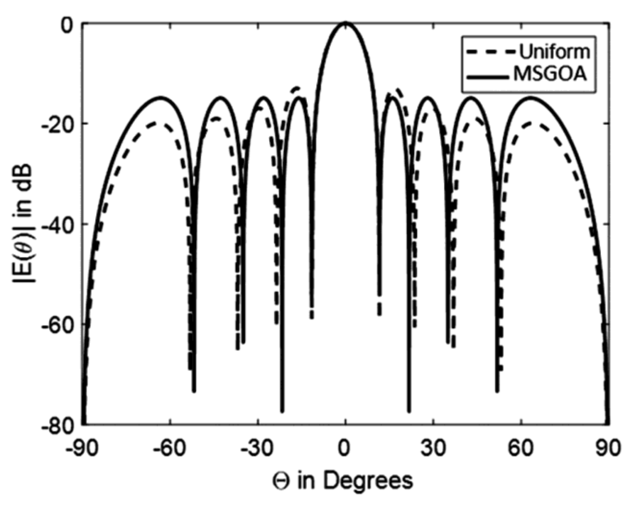

Fig. 2 — SLL optimised pattern with uniform BW constraint

Table 1 — Non-uniform amplitude distribution

Objective	Non-uniform amplitude distribution	SLL	BW
Example-1	0.805, 0.759, 0.675, 0.56, 0.916	−14.91 dB	23.2°
Example-2	0.696, 0.619, 0.485, 0.327, 0.22532	−27.5dB	33.1°
Example-3 (unconstrained)	0.829, 0.448, 0.721, 0.687, 0.492	−14.25dB	24.6°
Example-3 (constrained)	0.435, 0.57, 0.552, 0.317, 0.584	−13.72dB	23.2°
Example-4 (unconstrained)	0.282, 0.786, 0.62, 0.465, 0.959	−9.33 dB	20.3°
Example-4 (constrained)	0.445, 0.633, 0.514, 0.4, 0.581	−13.54dB	23.2°

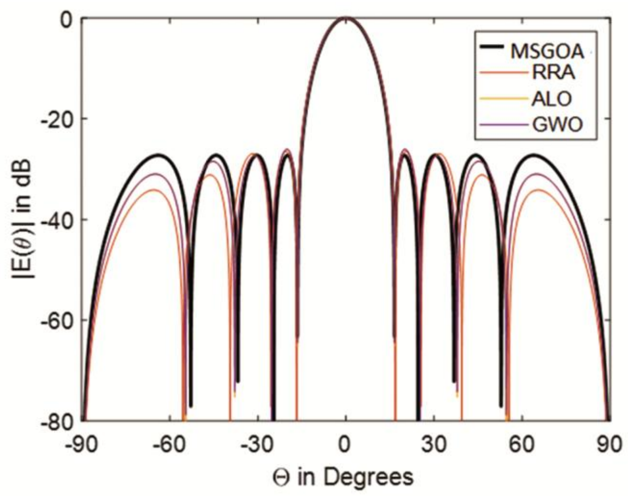

Fig.3 — SLL optimised patterns of example-2

on SLL and BW are imposed. This is referred as unconstrained case. Similarly, the same experiment is repeated with constraints on SLL and BW. The corresponding radiation patterns along with convergence plots are presented in Fig. 4 and Fig. 5 respectively. The non-uniform amplitude distribution corresponding to this example is given in Table 1.

Example-4: Patterns with Multiple Null

In this example, in order to study the efficiency and the robustness of the algorithm, an additional null (53.2°) is introduced in the objective. As a result, the objective is re-coined to produce radiation pattern with both the nulls. Similar to the previous example, both the unconstrained and constrained cases are considered in the simulation-based experimentation. Accordingly, the patterns are presented in Fig. 6 and Fig. 7 along with the

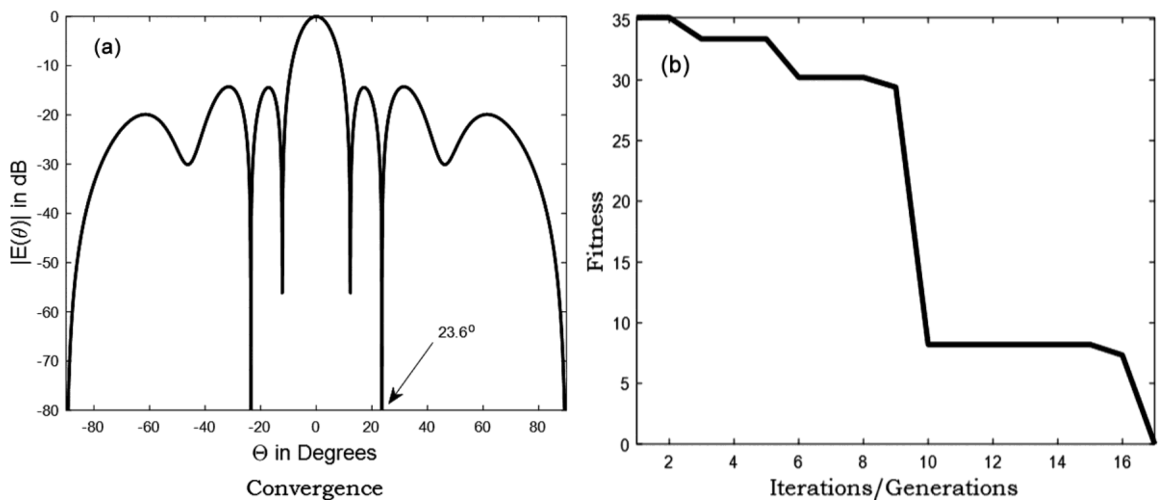

Fig. 4 — (a) Single null at 23.6° with no constraint, (b) convergence plot

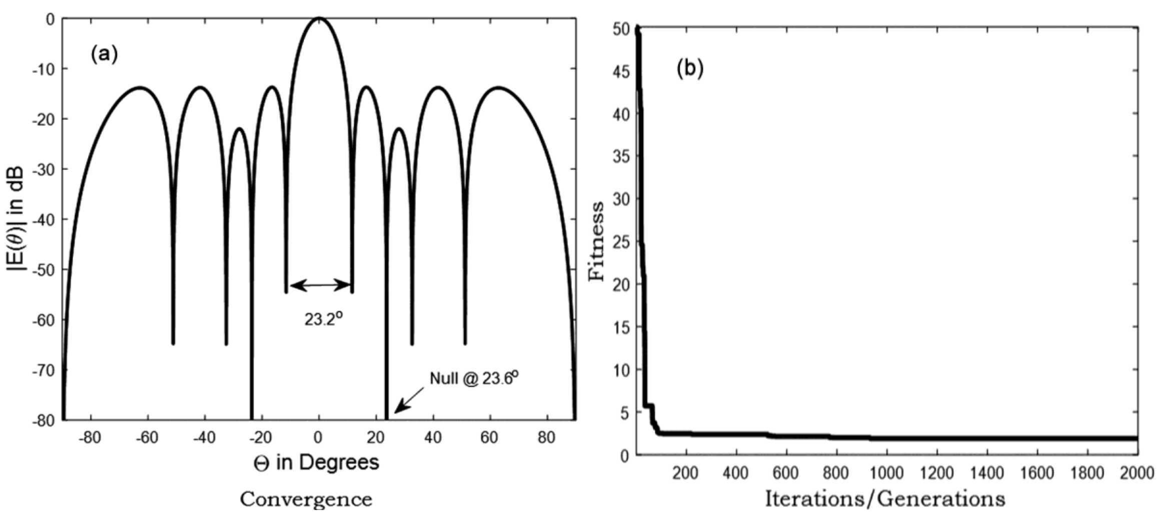

Fig. 5 — (a) SLL and BW Constrained null pattern @ 23.6°, (b) Convergence plot

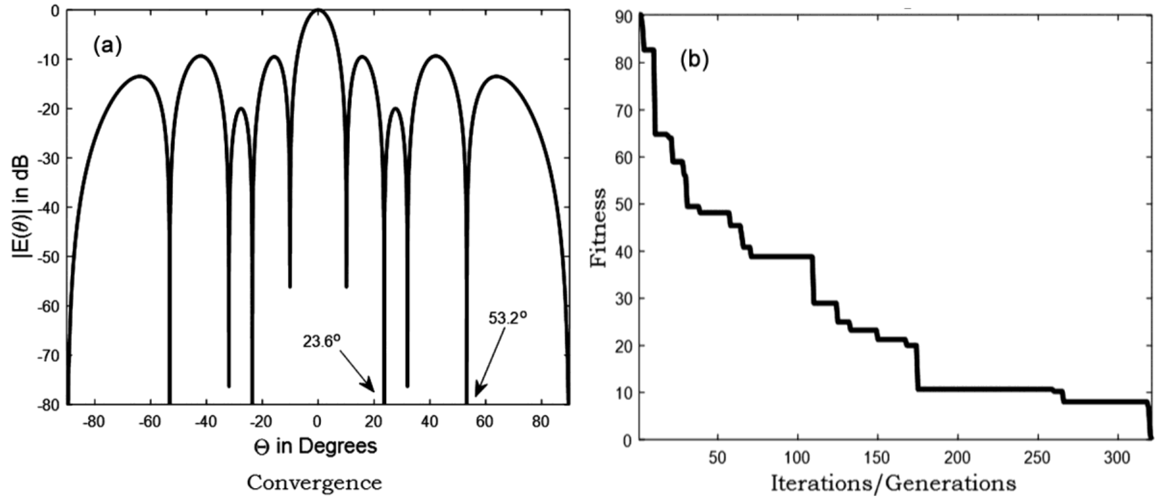

Fig.6 — (a) Radiation pattern with nulls at 23.6°& 53.2° with no constraint, (b) convergence plot

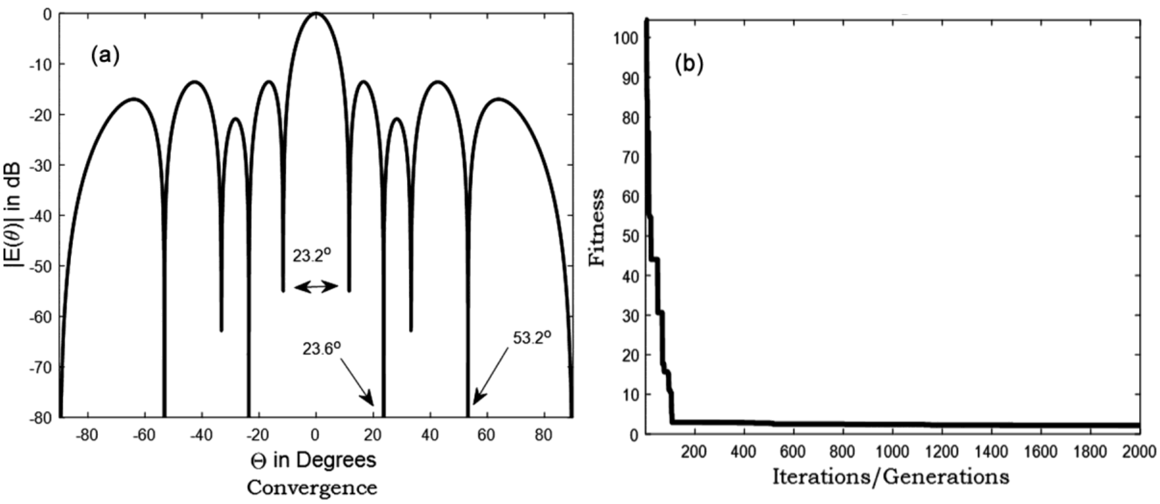

Fig. 7 — (a) SLL and BW Constrained null pattern @ 23.6° & 53.2°, (b) convergence plot

convergence plots. The corresponding amplitudes of current distribution are mentioned in Table 1.

Conclusions

The problem of linear antenna array synthesis is investigated using MSGOA algorithm which is new variant of SGOA and termed to be much efficient than traditional SGOA. Employing the amplitude only technique, the non-uniform amplitude distribution is determined to produce patterns with SLL optimization and null patterns. In SLL optimization case, two types of patterns are drawn. In the first case, the resultant patterns are compared with uniform patterns and the corresponding SLL is 2 dB better than uniform pattern. In the second case, the patterns are compared with those obtained using ALO, GWO and RRA and reported 1dB betterment in terms of SLL. In null pattern optimization, the radiation pattern is described entirely by nulls at 23.6° and 53.2°. Null pattern synthesis could firmly produce patterns with nulls at the above two locations individually as well as at the same instance under no constraint and with constraint. In this work, isotropic elements are considered and hence replacing the isotropic element practical antenna elements like dipoles would be a good scope of future work.

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