Multi Objective Linear Array Synthesis Using Differential Evolution and Modified Invasive Weed Optimization Techniques

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Abstract. A radiation pattern synthesis methods based on the ecological inspired equations is proposed for linear antenna arrays. The amplitude weights of the elements are optimized by heuristic evolutionary tools like Differential Evolution (DE) and Invasive weed optimization to maintain a multi objective specified pattern. The characteristics of the two algorithms are explored by experimenting on a multi task fitness function .The simulation study claims that the DE is arguably a powerful tool in terms of computational time. This paper provides a comprehensive coverage and comparative study of the two above said algorithms, focusing on the pattern synthesis.

Keywords: Pattern synthesis, Antenna arrays, Differential Evolution, Multi-Objective fitness function, Invasive weed optimization.

1 Introduction

The synthesis of equispaced linear array patterns with a shaped beam has been considered by some authors in the specialized literature [1]. There are many applications where the antenna pattern is required to be shaped to achieve a desired effect. In this paper a technique for the synthesis of shaped beam antenna pattern of a linear array is described .The fields radiated from a linear array are a superposition of the fields radiated by each element in the presence of other elements. Each element has an excitation parameter and this can be individually adjusted so that the excitation can be as desired. The excitation of each element will be complex, with amplitude and phase. Antenna array synthesis essentially involves determination of the amplitude and phase of the elements that will produce a desired radiation pattern. The synthesis of an antenna array with a specific radiation pattern, limited by several constraints is a nonlinear optimization problem. Evolutionary search method provides an efficient way to choose the design parameters. Although this method has been successfully applied in many areas such as Digital communication [2], signal processing [3], it is not well known to the electromagnetic community. It is the goal of this paper to introduce Evolutionary techniques to the electromagnetic community and demonstrate its great potential in electromagnetic optimizations.

V.V. Das and P.M. El-Kafrawy (Eds.): SPIT 2012, LNICST 117, pp. 131–136, 2014.

Antenna array optimization has received a great attention in the electromagnetic community. Unlike deterministic algorithms, one does not need expert knowledge of antenna's physics to achieve optimal result. In Section 2 proposed algorithms DE and IWO for training the Linear antenna array is described. Section 3 is dedicated for discussion and experimental results.

2 Overview of DE and IWO

IWO is a population-based algorithm that replicates the colonizing behaviour of weeds. The algorithm for IWO may be summarized as follows:

- A finite number of weeds are initialized randomly spread over the entire D-dimensional search space. This initial population of each generation will be termed as $X = \{x_1, x_2, x_3 \ldots x_m\}$
- Each member of the population X is allowed to produce seeds within a specified region centered at its own position. The number of seeds produced by X_i, $i \in \{1,2\ldots\ldots,m\}$ depends on its relative fitness in the population with respect to the best and worst fitness. The number of seeds produced by any weed varies linearly from $seed_{min}$ to $seed_{max}$ with $seed_{min}$ for the worst member and $seed_{max}$ for the best member in the population.
- The generated seeds are being randomly distributed over the D- dimensional search space by normally distributed random numbers with mean equal to zero; but varying variance. This step ensures that the produced seeds will be generated around the parent weed, leading to a local search around each plant. However, the standard deviation (SD) of the random function is made to decrease over the iterations. If $sd_{\max}$ and $sd_{\min}$ be the maximum and minimum standard deviation and if *pow* be a real no. , then the standard deviation for a particular iteration may be given as in equation

$$sd_{ITER} = \left(\frac{iter_{max} - iter}{iter_{max}}\right)^{pow} (sd_{max} - sd_{min}) + sd_{min} \quad (1)$$

- Some modifications are incorporated in the classical IWO algorithm to enhance the performance. IWO with the suggested modifications performs much better than the classical IWO; the modified standard deviation for a particular iteration may be given as in equation

$$sd_{ITER} = \left(\frac{iter_{max} - iter}{iter_{max}}\right)^{pow} |cos(iter)| \; (sd_{max} - sd_{min}) + sd_{min} \quad (2)$$

- Fig.1 illustrates the decrement of sd with iterations for classical IWO and the modified IWO.
- The **|cos(iter)|** term adds an enveloped as well as periodical variation in sd, which helps in exploring the better solutions quickly and prevents the new solutions from discarding an optimal solution when the sd is relatively large. This facilitates quicker detection of optimal solutions and better results as compared to the classical IWO.

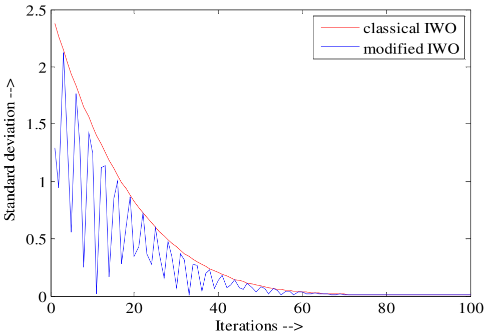

Fig. 1. Comparison of the variations of standard deviation (sd) with iterations for the classical and modified IWO

A differential evolution algorithm (DEA) is an evolutionary computation method that was originally introduced by Storn and Price in 1995. DE uses a population *P* of size *Np*, composed of floating point encoded individuals that evolve over G generations to reach an optimal solution. Each individual *Xi* is a vector that contains as many parameters as the problem decision variables *D*.

$$P^{(G)} = [X_i^{(G)}, \ldots\ldots\ldots\ldots X_{N_p}^{(G)}]$$

$$X_i^{(G)} = [X_{1,i}^{(G)}, \ldots\ldots\ldots\ldots X_{D,i}^{(G)}]^T,\ i = 1, \ldots, N_p \tag{3}$$

The optimization process in differential evolution is carried out with three basic operations viz, mutation, crossover and selection. This algorithm starts by creating an initial population of $N\ p$ vectors. Random values are assigned to each decision parameter in every vector according to

$$X_{j,i}^{(0)} = X_j^{\min} + \eta_j * (X_j^{\max} - X_j^{\min}) \tag{4}$$

Where $j = 1, \ldots\ldots\ldots\ldots, D$; $X_j^{\min}$ and $X_j^{\max}$ are the lower and upper bounds of the j^{th} decision parameter and η_j is a uniformly distributed random number with in [0, 1]. The mutation operator creates mutant vectors $(X_i^{'})$ by perturbing a randomly selected vector (X_a) with the difference of two other randomly selected vectors (X_b and X_c),

$$X_i^{'(G)} = X_a^{(G)} + F * (X_b^{(G)} - X_c^{(G)}),\ i = 1, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots, N_p \tag{5}$$

Where X_a, X_b and X_c are randomly chosen vectors $\in$ $\{1, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots, N_p\}$ and $a \neq b \neq c \neq i$. The scaling constant (F) is an algorithm control parameter used to control the perturbation size in the mutation operator and improve algorithm convergence. The crossover operation generates trial vectors $(X_i^{''})$ by mixing the parameters of the mutant vectors with the target vectors (X_i) according to a selected probability distribution. Crossover constant C_R is an algorithm parameter that controls the diversity of the population and aids the algorithm to escape from local optima.

3 Simulation and Discussion

A linear array of an even number of identical isotropic elements (such as vertical monopoles), is positioned symmetrically along the x-axis, as shown in Fig.1. The separation between the elements is "d" and "M" is the number of elements placed at each side of the y-axis. If mutual coupling between antenna elements is neglected, and assuming that the amplitude of excitations is symmetrical about the y-axis, the radiation pattern (AF) for the described structure can be written as

$$\boldsymbol{AF} = \sum_{n=1}^{N} e^{j(n-1)(kd\cos\theta+\beta)} \tag{6}$$

This can be written as $\boldsymbol{AF} = \sum_{n=1}^{N} e^{j(n-1)\psi}$ where $\boldsymbol{\psi = kd\cos\theta + \beta}$, I= [I_1, I2,….,I_M], I_n's are the excitation coefficients of the array elements, k=2π/λ is the phase constant, and $\boldsymbol{\theta}$ the angle of incidence of a plane wave. The objective function is formulated as an optimization task that takes care of the side lobe level, desired pattern, and null width. The objective function is designed to have the of the weighted summation of different constraints given by

$$f_{SL} = \alpha * |MLL|_{mean} + \beta * |MSLL - DSLL|_{mean} +$$
$$\gamma * |MNL - DNL|_{mean} + \eta * |AF_0(\theta) - AF_d(\theta)|_{mean}$$

MSLL=Measured side lobe level; DSLL=Desired side lobe level; MNL=Measured Null level; DNL=Desired Null level; MLL=Main lobe level. The desired pattern is considered to have the following specifications Beam width: 10^0; Null points: [45^0 135^0]; Null Width: 2^0; Side Lobe Level: 20dB Main Beam=90^0 ; Null Side Lobe Level:-40dB.The parametric setup of the two algorithms is given in the Table.1. The weight coefficients of the fitness function given in the Equation are set as [α =*0.55,* β=*0.2,* γ=*0.1,* η=*0.15*].

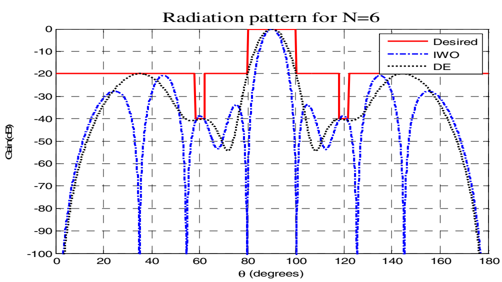

Fig. 2. Normalized radiation pattern of ULA for 6 elements

The pattern in the Fig.2 shows that DE has performed well in detecting the nulls and maintaining the side lobe level -20dB. IWO out performed DE in terms of half power beam width and main lobe level. The experiment is repeated increasing the number of array elements. Graphical and statistical comparisons of the two algorithms are carried out.

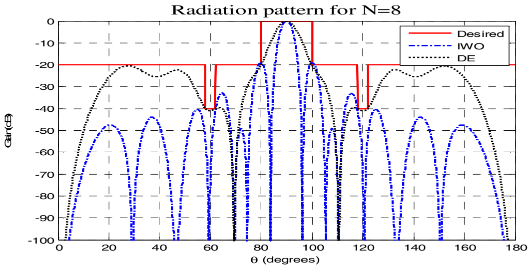

Fig. 3. Normalized radiation pattern for 8 elements

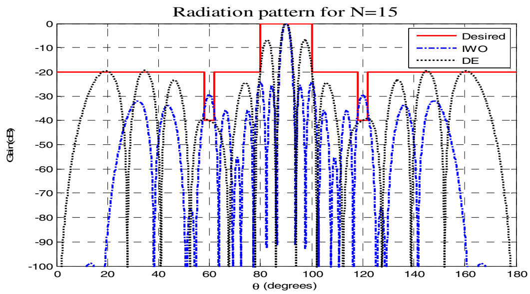

Fig. 4. Normalized radiation pattern for 15 elements

The results reveals that DE performs equally well with respect to IWO. The computational time of DE (2.8 min) is very less when compared to IWO (5.3min). More over IWO requires a huge parametric set up in comparison with DE. The simulated results reveal the fact that IWO can be applicable for a thin beam formation. But DE outperforms IWO in detecting the Null locations and in terms of computation time. As the number of array elements increases IWO suffers more computational burden.

4 Conclusion

In this paper the synthesis of a uniform linear array is done using two evolutionary techniques DE and IWO. The design problem has been recast as an optimization task which amounts for various constraints. As evident from the simulation results DE performs at par with IWO in satisfying the desired objectives at a less computational time. The simulation is done using MATLAB 7.0. The DE can be an attractive tool for different array synthesis. DE Algorithm optimizes the amplitude weights of the

Linear Array to drive down the Side lobe levels and to satisfy the Desired Null levels. Differential Evolution (DE) algorithm is a new heuristic approach mainly having three advantages; finding the true global minimum regardless of the initial parameter values, fast convergence, and using few control parameters. From the simulation results, it was observed that the convergence speed of DE is significantly better than genetic algorithms. Therefore, DE algorithm seems to be a promising approach for engineering optimization problems.

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