Use of Multi-Objective Genetic Algorithms to Optimise the Excitation and Subarray Division of Multifunction Radar Antennas.

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Abstract:
In this paper, a method of applying multi-objective genetic algorithms (MOGAs) to optimise the excitation and subarray division of an active array antenna is presented. This enables beampatterns with multiple desired characteristics such as low sidelobes, maximum power efficiency and nulls in particular locations to be generated. The division of the array elements into subarrays is also optimised simultaneously by the MOGA.

Keywords: Multi-objective genetic algorithm, active array, subarray, antenna optimisation.

1. Introduction to GAs and MOGAs

Active electronically scanned array antennas are becoming commonplace in designs of radar systems. Arrays of several thousand radiating elements achieve power levels comparable with earlier single feed mechanically scanned systems. In order to steer the array and produce radiation patterns with desired characteristics, careful control of the array excitation is needed, particularly if the array is to be used in a multifunction manner where quite different beam patterns are required from the same array. This presents a complex non-linear optimisation problem.

The division of the array into a number of subarrays can simplify arrays and feed networks but raises the question of the optimum subarray divisions to make. The use of subarrays can also improve the signal to noise ratio and promote formation of sum and difference patterns [1,2].

There are many techniques for optimising the array excitations needed such as hill-climbing, and least squares methods[3] but they can be prone to convergence on local minima or maxima. They also require a good starting point in order to find the global optimum. They generally converge to a single point hence providing a single solution to the problem. If these techniques were applied to the subarray division optimisation problem, a single result would not permit any trade-off analysis to be performed after a single run of the algorithm.

The development of global search techniques such as simulated annealing and other evolution-based methods can improve the problem of local convergence because they conduct global searches of the design space.

One such method is the genetic algorithm (GA). The GA is based on Darwin's Theory of Evolution where ‘populations’ of solutions are evolved over a number of ‘generations’.

The GA samples the search space stochastically and is far less likely to converge on non-global optima. For background material the interested reader is referred to [4] which contains several papers on introductory GA use.

The applications for GAs are widening as they become accepted as useful optimisation techniques. This is particularly true in the field of electromagnetics and antenna design.

The GA itself is generic and relies on a distinct ‘fitness function’ to calculate a measure of success of a solution during the optimisation process. For example, the fitness function may be monitoring radiation pattern sidelobe levels when the GA is optimising the excitation of elements in an active array. The fitness function is usually the most computationally expensive part of the algorithm. This is especially true in complex antenna optimisation code.

Simple GAs converge to a single solution. In problems where there are several, often conflicting objectives (true of many engineering problems), a multi-objective genetic algorithm (MOGA) can be used which evolves a set of solutions (the population) towards the Pareto-optimal front where trade-off analysis can be performed to select a suitable solution.

2. Literature

There are relatively few papers published in the literature concerning optimisation of subarrays using GA techniques. Wang et.al[6], proposed a method for the optimisation of seismic array subarray configuration. In their paper, the SNR performance of a 20 element array with inter-element spacing of 2.5km was optimised using a simple GA. The algorithm formed subarrays by switching off certain elements in the array. The technique was not used to generate optimum weights or amplitude tapers for each of the subarrays but still obtained a 26% improvement in SNR using simple on/off excitations. Other authors have applied the GA to 'pre-formed' subarrays and found optimum excitation tapers to apply to the subarrays with encouraging results[1,2].

3. Aims & Test Case

There have been many papers written on the application of genetic algorithms to antenna array optimisation and also on generic multi-objective genetic algorithms. This paper attempts to bring the techniques together and apply MOGAs to simultaneously optimise the array excitations and the subarray division of a planar array antenna.

The algorithm is to be capable of optimising the subarray divisions, the number of subarrays and the excitations to apply to the subarrays.

4. Chromosome Encoding

The first step was to determine a suitable chromosome encoding scheme. The chromosome encoding scheme used to represent the subarrays and excitations has to be resistant to the genetic operators of crossovers and mutation, that is, it must produce valid chromosomes after these operations have occurred.

A suitable encoding scheme was implemented by using five different binary chromosomes. The five chromosomes are independent of each other and subject to separate crossover and mutation operations.

For each solution, each chromosome contains enough information to generate up to 50 subarrays (early runs of the algorithm showed that the maximum number of subarrays likely to be generated was 46). This allows the chromosome to be of fixed length and avoids the added complication of dealing with variable length chromosomes. The chromosomes contain a certain amount of redundant information, but this does not appear to slow down or degrade the optimisation process.

The information stored in the chromosomes is used to 'grow' a subarray from an initial start-point in the array. Therefore the chromosomes actually contain a series of choices as to which of the elements surrounding a chosen start point are to be included in the subarray.

When decoding the chromosomes, the subarrays are formed, one at a time, and a status flag updated to indicate which of the 400 array elements have been chosen as subarray members. The genes in the first chromosome, chromosome 1, provide the start-point information and when decoded, point to a position along a vector containing all remaining valid start-points.

Chromosomes 2 to 4 indicate which of the 48 elements surrounding the start point are potential members of the same subarray. Specifically, chromosome 2 indicates which of the 8 elements surrounding the start point are also potentially in the array. Chromosome 3 contains 16-bit genes relating to the elements which surround those selected by chromosome 2. Finally, chromosome 4 contains 24-bit genes that relate to the 24 elements around those selected by chromosome 3. Figure 1 illustrates the decoding of chromosome 2 into the elements surrounding the start point.

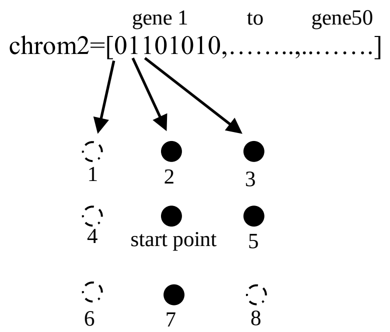

Figure 1 Chromosome Decoding Example.

At this stage, the subarray elements are only potential members of the subarray. The elements chosen by the chromosome only become valid subarray members after satisfying the following criteria:

- they are available (i.e. not members of other subarrays) and
- they are not isolated (i.e. they must be physically located next to other elements in the same subarray).

Once a subarray is formed, the status flag is updated and the procedure repeats until all the elements in the array become members of subarrays.

5. MOGAs and Pareto Ranking.

The solutions produced in each generation of the algorithm were ranked using the Niched Pareto Genetic Algorithm for Multiobjective Optimization proposed by Horn et al[5].

In the Niched Pareto algorithm, the solutions produced by the GA in each generation are ranked according to their dominance amongst the other solutions.

For example, if we consider a two objective problem, for a solution A to dominate solution B it must meet two criteria:

1. Each of the two objective values in A must be at least equal to each of the corresponding objective values in B
2. At least one objective in A must better the corresponding objective in B.

In the subarray problem, the objectives (or fitness values) (f_1, f_2, …f_n) relate to certain characteristics of the radiation pattern. For example, f_1 may measure maximum power output and f_2 maximum sidelobe level.

Niche sharing was used in order to distribute solutions along the Pareto front.

6. Array Synthesis

The array radiation pattern was calculated using the standard method contained within Skolnik[7] where the array factor of an arbitrary two-dimensional array is given by:

$$E_a(\cos\alpha_{xs}, \cos\alpha_{ys}) = \sum_{m=1}^{M} \sum_{n=1}^{N} \left|A_{(n,m)}\right| . e^{j[m.(Tx-Txs)+n.(Ty-Tys)]} \qquad \text{(Eq.1)}$$

where

$$T_{xs} = (\frac{2\pi}{\lambda}) d_x \cos\alpha_{xs} \qquad \text{(Eq.2)} \qquad\qquad T_{ys} = (\frac{2\pi}{\lambda}) d_y \cos\alpha_{ys} \qquad \text{(Eq.3)}$$

$$T_x = (\frac{2\pi}{\lambda}) d_x \cos\alpha_x \qquad \text{(Eq.4)} \qquad\qquad T_y = (\frac{2\pi}{\lambda}) d_y \cos\alpha_y \qquad \text{(Eq.5)}$$

The following equations were used to convert from a Cartesian to spherical coordinate system:

$$\cos\alpha_x = \sin\theta \cos\phi \qquad \text{(Eq.6)} \qquad\qquad \cos\alpha_y = \sin\theta \ \sin\phi \qquad \text{(Eq.7)}$$

$$\cos\alpha_{xs} = \sin\theta_s \cos\phi_s \qquad \text{(Eq.8)} \qquad\qquad \cos\alpha_{ys} = \sin\theta_s \ \sin\phi_s \qquad \text{(Eq.9)}$$

and $A_{(m,n)}$ = amplitude of the *mn*th element.

The test case for this algorithm was a 20 x 20 planar array of isotropic elements. The algorithm was set to produce 32 subarrays.

The algorithm was applied to the test case in order to produce a radiation pattern with low sidelobe levels. Half-wavelength element spacing was used.

7. Results

Early results are encouraging. After a run of just 30 generations with a population size of 30, the algorithm produced numerous solutions with maximum sidelobe levels less than 30dB. In a real problem, this would enable the antenna designer to perform trade-offs amongst these solutions. The design aim of 32 subarrays was successfully achieved. Figure 2 shows a typical antenna pattern selected at random from the 30 solutions in the final population provided by the GA. The multiple objectives measured included the maximum sidelobe level, the number of main beams produced and the total number of subarrays.

Future runs will use larger population sizes and more generations and make more use of the multi-objective capability to optimise beamwidth and power output levels. Figure 3 shows the subarray divisions provided by the algorithm and the normalised excitation values.

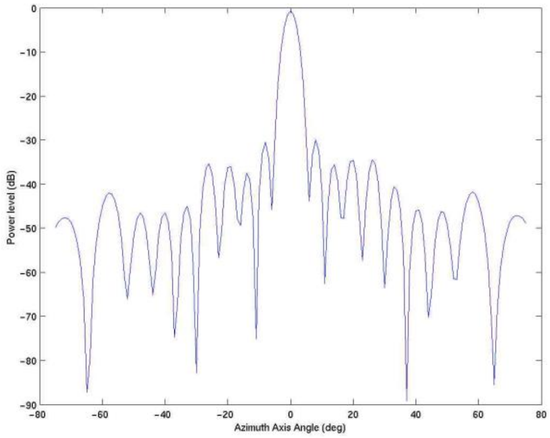

Figure 2. Sample Array Radiation Pattern

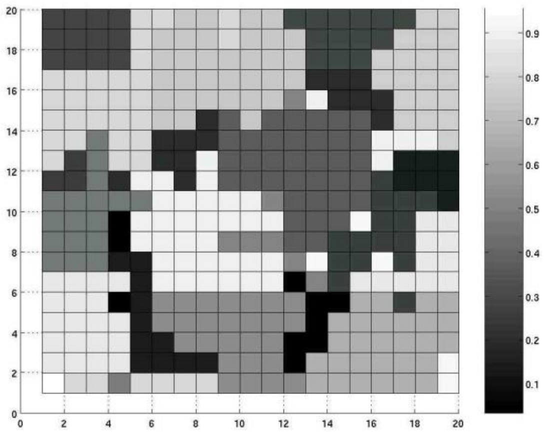

Figure 3. Subarray divisions and Excitation Values.

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