Optimization of a Constrained Feed Network for an Antenna Array Using Simple and Competent Genetic Algorithm Techniques

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This paper, which describes the optimization of a novel, constrained feed network for a space-based antenna array, is a joint effort between the Air Force Research Laboratory (AFRL) Antenna Technology Branch at Hanscom AFB and the Illinois Genetic Algorithms Laboratory (IlliGAL) at the University of Illinois at Urbana-Champaign. Recently, under the guidance and direction of the Air Force Office of Scientific Research (AFOSR), the two laboratories have formed a collaboration, the common goal of which is to apply simple, competent, and hybrid GA techniques to challenging antenna problems. As shown below, this particular optimization problem demonstrates the utility of using advanced GA techniques to obtain acceptable/enhanced solution quality.

Figure 1 shows a single section of the antenna system, which consists of a front-end array and a constrained feed network[1]. An incoming plane wave impinges the N-element linear array, and the resulting element excitations are propagated through an N by M Rotman lens, the outputs of which are weighted and fed into an M by M Butler Matrix. The center $M/2$ Butler outputs from each of P sections are time-delayed, weighted (*e.g.*, fixed weights, like a Taylor distribution, *etc.*), and combined to compute the final radiation pattern of the system. The overall goal is to produce a far-field pattern having at least -30-dB sidelobes over a 20% bandwidth by optimizing weights, w_i (as shown in the figure), for P sections of the system.

We applied both a simple genetic algorithm (SGA)[2] and the hierarchical Bayesian optimization algorithm (hBOA)[3] to a simulated model of the system in which the Rotman lens transfer functions (one for each of P sections) were

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[1] Mailloux, R.J. (2001). A low-sidelobe partially overlapped constrained feed network for time-delayed subarrays. IEEE Transactions on Antennas and Propagation, *49*(2), pp. 280–291.

[2] Goldberg, D.E. (1989). Genetic algorithms in search, optimization, and machine learning. Reading, MA: Addison-Wesley.

[3] Pelikan, M., & Goldberg, D.E. (2000). Hierarchical problem solving by the Bayesian optimization algorithm. Genetic and Evolutionary Computation Conference (GECCO-2000), pp. 267–274.

constructed using experimental data. For this model, $N = 64$, $M = 8$, and $P = 3$; thus, this problem involves the optimization of 24 complex weights (*i.e.*, $M \times P$).

We compared the performance of the SGA and hBOA using three different objective functions. Figure 2(a) shows the objective function for Case 1. The pink curve is a typical far-field radiation pattern produced by the system. The x-axis represents u-space (*i.e.*, $\sin\theta$), and the y-axis measures the normalized amplitude of the pattern in decibels. The black "mask" represents the objective function. For this case, we perform a point-by-point subtraction of the mask from the pattern. For a given frequency and set of complex weights, an error value is computed by calculating the sum of the squared differences between the pattern and mask (*i.e.*, $error(w, f) = \Sigma_i[pattern_i - mask_i]$); no penalty is administered, however, when the pattern lies below the mask in the sidelobe region (*i.e.*, if the difference between the pattern and mask is negative, it is not used in the computation). In essence, we are trying to force the pattern to conform to the mask in the main-beam region while forcing the pattern to lie below the mask in the sidelobe regions. The overall fitness value for a given set of complex weights is the average of the error across the entire frequency band.

Figure 2(b) shows the general objective function for both Cases 2 and 3. Here, for a given frequency and set of complex weights, the error is computed by calculating the squared difference between the peak of the pattern (in the mainlobe region) and the highest sidelobe (in the sidelobe regions). Thus, Case 2 involves a single subtraction, rather than a point-by-point comparison of the pattern to the mask. Similar to Case 1, however, the overall fitness value for a given set of complex weights is the average of the error across the entire frequency band. Case 3 is identical to Case 2, except the overall fitness value is equal to the *maximum* error across frequency. In other words, Cases 1 and 2 are aimed at minimizing the *mean* error across frequency, whereas Case 3 minimizes the *maximum* error across frequency. Of the three objective functions, Case 3 is the most relevant to this particular problem, since we are ultimately trying to minimize the maximum sidelobe level across frequency.

Each case was run three times for both the SGA and hBOA. When we compare the fitness values of the best runs for each case, we see that the two algorithms performed equally well for Case 1, hBOA outperformed the SGA by 20% for Case 2, and hBOA completely annihilated the SGA for Case 3, as illustrated in Figure 3. The blue and orange curves represent solutions obtained using hBOA and the SGA, respectively (at a single frequency). Note that the highest sidelobe of the hBOA solution is only 3 dB away from the target -30 dB, whereas the SGA solution is off by 18 dB. It should also be noted that the standard deviation of the fitness across runs is lower for hBOA than the SGA for all three cases.

These results are not surprising and agree with our fundamental knowledge of genetic algorithms. For a simple problem like Case 1, which involves fitting a function to a mask, *linkage identification* (*i.e.*, the correlation between different building blocks in the chromosome) is not important; therefore, the SGA and hBOA perform comparably. Cases 2 and 3, on the other hand, involve more complicated objective functions (*i.e.*, maximizing the minimum value of a parameter and/or minimizing the maximum value of a parameter). For these more difficult problems where linkage is important, hBOA should outperform the SGA, since hBOA spends much of its computational time identifying the linkage of the problem.

In summary, we have applied both a SGA and hBOA to an antenna optimization problem. From our results, it is clear that the need for competent GA techniques becomes more essential as problem difficulty increases.

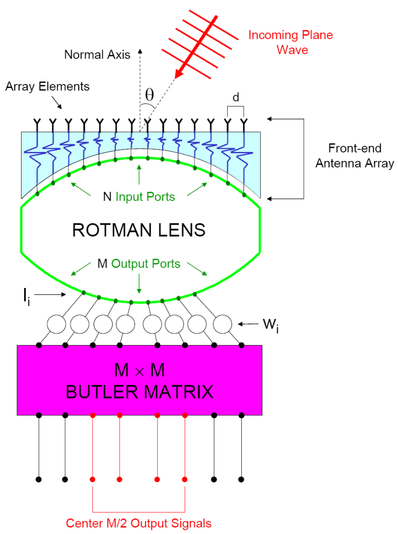

Fig. 1. Single section of antenna system, including front-end array, Rotman lens, and Butler matrix.

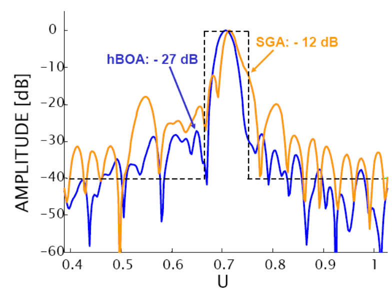

Fig. 3. SGA vs. hBOA results for a single frequency (Case 3).

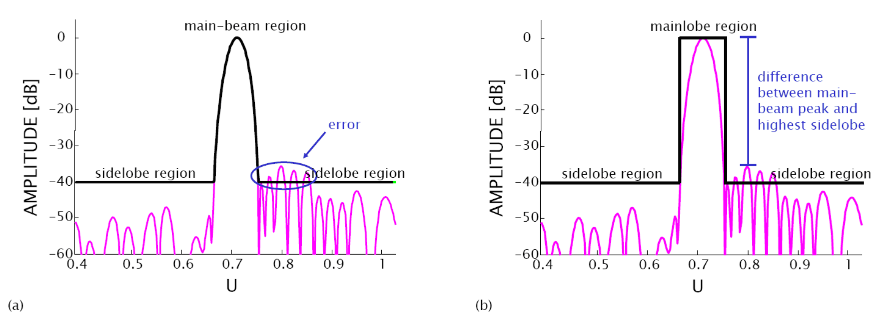

Fig. 2. Objective function illustrations for (a) Case 1, and (b) Case 2.