Evaluation of the Adaptive Beamforming Capability of an ESPAR Antenna Using the Genetic Algorithm

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***Abstract* — The Electrically Steerable Parasitic Array Radiator (ESPAR) antenna, which is expected to be a key component in wireless ad hoc networking, is a single-output array. Because it is not possible to observe the output signal of each element of the antenna, it is impractical to directly apply most of the algorithms designed for conventional array antennas. Therefore, to evaluate the adaptive beamforming capability of the ESPAR antenna, the Genetic Algorithm (GA) is applied and the results are compared with those obtained by applying the Steepest-Gradient Algorithm (SGA) to the ESPAR antenna. The GA results reveal that the ESPAR antenna possesses the ability to form a beam and null at the same time, even when the angular difference between the desired and interference signal is less than 60 degrees.**

***Index Terms* — Adaptive arrays, genetic algorithm, beamforming.**

I. Introduction

Adaptive arrays, which are able to electronically steer their mainlobe to any desired direction while also automatically placing deep pattern nulls in the specific direction of interference sources, have been attracting a great deal of attention [1-2]. However, in a typical adaptive array in which the beam is electrically steerable, each element of the array is excited with a different phase of the information signal to form radiation beams and nulls. Because of the structure's inherent complexity, conventional adaptive arrays have been excluded from use in mass-produced communication products such as user terminals. To overcome this restriction, electrically steerable or switchable parasitic antenna arrays have been introduced [3-4].

The Electronically Steerable Parasitic Array Radiator (ESPAR) is one such antenna that is being developed for use in wireless ad hoc computer networks [4]. The antenna consists of a single feed element surrounded by a ring of reactively loaded parasitic elements. By electrically controlling the loading reactances, directional beams and nulls can be formed and steered throughout the azimuth. Thus the physical structure of the antenna is simple, and it requires relatively little power to operate when compared to its phased array counterparts. Since wireless ad hoc networks are autonomous networks that do not need infrastructure such as base stations and cable, they present an inexpensive and simple solution compared to existing wired networks.

An ad hoc network using ESPAR antennas as wireless terminals is certainly a smart idea. However, the main problem is how to realize it. Needless to say, an outstanding control algorithm is necessary for completing the network. Because the output signal of each element of the ESPAR antenna cannot be observed, it is impractical to directly apply most of the algorithms designed for conventional array antennas. Nevertheless, the Steepest Gradient Algorithm (SGA) has been applied to the ESPAR antenna [4]. Similar to the traditional case, the SGA method quickly converges to a minimum once an algorithm is close to that minimum. However, it has the disadvantages of becoming stuck in local minima, requiring gradient calculations, working on only continuous parameters, and being limited to optimizing only a few parameters. Random-search methods don't require gradient calculations, but tend to be slow, and are susceptible to becoming stuck in local minima. One more disadvantage of the SGA, when it is used in an ESPAR antenna, is that it is generally difficult to obtain the optimum solution when the angular difference between a desired signal and an interfering one is less than 60 degrees. This is due to the fact that local techniques are highly dependent on the starting point and noise. Therefore, the Genetic Algorithm (GA) [5-6] is proposed for application to the ESPAR antenna. However, while GA works well for designing antennas, it is slow on serial computers, and is not well suited to real-time applications such as adaptive nulling. Accordingly, we use GA in this paper to evaluate the ESPAR antenna's adaptive beamforming capability.

II. Signal Model of the ESPAR Antenna

Figure 1 shows a seven-element ESPAR antenna. We obtained the output signal, $y(t)$, for a general case of $Q+1$ signals and added noise, $n(t)$, with Directions of Arrival (DoA) θ_q ($q=0,1,\ldots,6$):

$$y(t) = i^T s(t) + n(t) = \sum_{q=0}^{Q} i^T a(\theta_q) u_q(t) + n(t)$$

where q is the number of surrounding elements of an ESPAR antenna, and $s(t)=[s_0(t), s_1(t), \ldots, s_6(t)]^T$; $s_i(t)$ is the RF signal impinging on the i-th element, and $\mathbf{i} = [i_0, i_1, \ldots, i_6]^T$ is the RF current vector with the component i_j impinging on the j-th element.

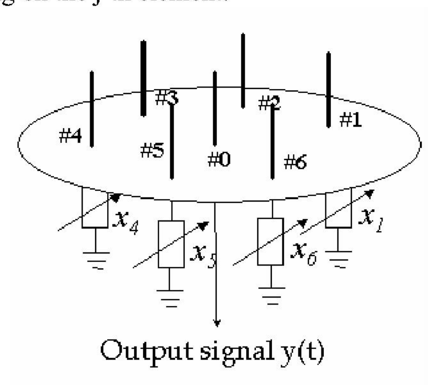

Fig. 1. A seven-element ESPAR antenna

The ESPAR structure makes it necessary to add a spatial delay between each element when a signal comes from a given direction. The steering vector of the ESPAR antenna is defined as:

$$a(\theta) = \begin{bmatrix} 1 & e^{j\frac{\pi}{2}\cos(\theta-\varphi_1)} & e^{j\frac{\pi}{2}\cos(\theta-\varphi_2)} & \cdots & e^{j\frac{\pi}{2}\cos(\theta-\varphi_M)} \end{bmatrix}^T$$

where $\varphi_j = \frac{2\pi}{M}(j-1)$ is the angle of the j-th element, relative to an arbitrary axis.

III. Genetic Algorithm

Genetic algorithms (GAs), as one representative of a host of new global optimization techniques, have become very popular for the solution of electromagnetic design problems [5-8]. This is because GAs are "global" numerical optimization methods, which can handle a large solution space that is not readily handled by other traditional optimization methods [8-9]. GAs are robust to suboptimal solutions due to their inherent stochastic nature. For example, GAs have successfully been employed to design antennas [5] [7] [9-11], synthesize the patterns of antenna arrays [12], design absorbers [8] and estimate the radar cross section of objects [13]. Some other reports about GAs used in electromagnetic problems can be found in [14-17].

GAs encode each parameter into a binary sequence, called a gene, and a set of genes is a chromosome. Each chromosome has an associated cost function, assigning a relative merit to that chromosome. One of the most important aspects is to relate the physical world to the genetic algorithm, and this relation is given by the fitness or cost function. GAs start with a large population of randomly generated chromosomes, which are simulated and ranked based on their "fitness," i.e., how good they are, compared with other solutions in the population. These superior individuals have higher fitness values than their peers, and are therefore given a greater chance of selection during "breeding." In this breeding process, pairs of parent chromosomes are selected based on their fitness, and portions of each are combined to form new offspring chromosomes. The idea is that by exchanging information between two good chromosomes, a better chromosome may be produced. This evolutionary process is carried out for many generations, until a chromosome that meets the requirements of the application is found, or until no progress is observed in the population for several generations. A flow chart of a standard GA optimizer is illustrated in [18]. Much more detail on the actual mathematical process of GAs is also found in [17] [19].

IV. Adaptive Beamforming Using GA

The GA begins by defining a chromosome as an array of genes to be optimized. In this work, direct binary coding is employed to code a bias voltage into a gene and six bias voltages (a set) are used per chromosome. Seven bits code one bias voltage, which means there are 7*6 bits in a bias voltage set or a chromosome for a seven-element ESPAR antenna. This set corresponds to an individual and will have successive modifications to find a good solution. An encoding, selection and cross over procedure is shown in Figs. 2, 3 and 4, respectively. The quantization level of the bias voltage in this procedure is 0.1575V.

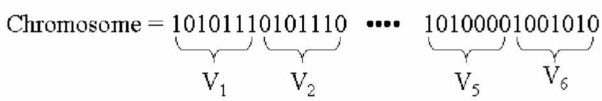

Fig. 2. Encoding procedure.

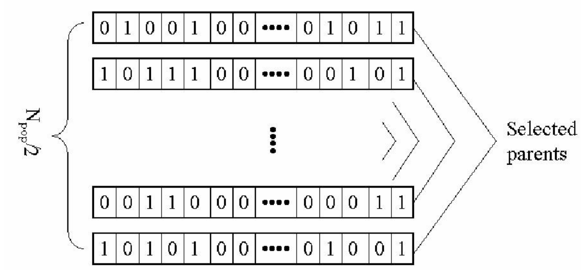

Fig. 3. Selection procedure.

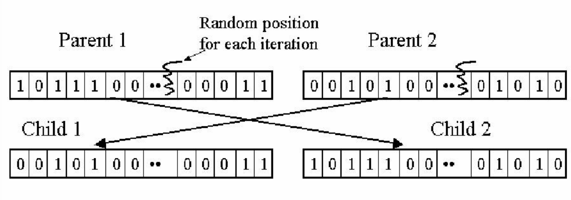

Fig. 4. Crossover procedure.

The fitness function used in this work is the Maximum Cross-Correlation Coefficient (MCCC) [4].

$$\rho_n = \frac{|\, y^H(n) r(n) \,|}{\sqrt{y^H(n) y(n)}\sqrt{r^H(n) r(n)}}$$

where y is the output signal of the antenna and r is the reference signal that we would obtain if there were not any noise or interfering signals. The population initialization gives 40 randomly generated individuals coding a bias voltage set. The decimation strategy is to keep half of the best individuals and to make pairs with the parents from the top and the bottom of the list (Fig. 3). The single-point cross-over is made at a new place of the chromosome for each iteration (Fig. 4), and the mutation probability for one bit is 0.01. To keep the best individual in memory, the elitist strategy is used.

V. Results and Comparison

Figure 5-(a) shows two beam patterns, obtained by the GA (solid line) and SGA (dotted line), for the case when a desired and an interference signal impinge on the ESPAR antenna with a separation angle larger than 60 degrees. Figure 5-(b), in contrast, illustrates the case when a desired and an interference signal impinge on the ESPAR antenna with a separation angle less than 60 degrees. For an angular difference larger than 60 degrees, the two algorithms make no difference; however, for an angular difference less than 60 degrees, the GA gives a much better result than the SGA.

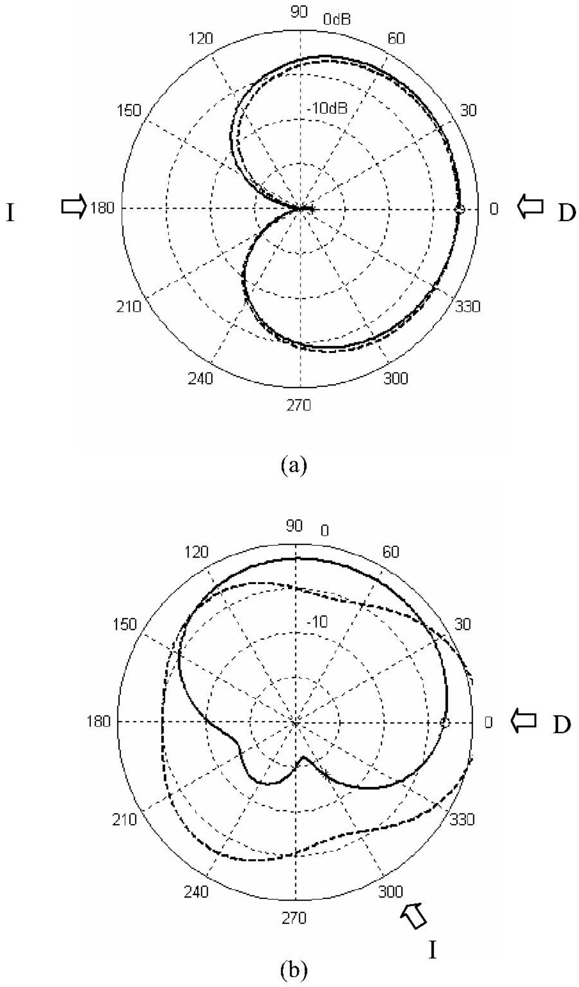

Fig. 5. Comparison of radiation patterns obtained by the GA (solid line) and SGA (dotted line): (a) angular difference is larger than 60 degrees; (b) angular difference is less than 60 degrees.

VI. Conclusion

A GA based on an MCCC criterion was applied to the adaptive beamforming of an ESPAR antenna. The results were compared with those obtained by SGA. The beamforming capability was evaluated by employing the GA, with the results revealing that the ESPAR antenna is an adaptive antenna that possesses the ability to form a beam and null at the same time, even when the angular difference between the desired and interference signal is less than 60 degrees.

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