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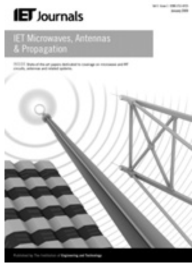

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Array pattern synthesis approach using a genetic algorithm

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Abstract: In this study, a new array pattern synthesis approach using a genetic algorithm (GA) is proposed. The proposed approach has a unique set of objectives to be achieved by exploiting the GA optimisation capabilities. These objectives are: (i) steering the pattern main lobe in the direction of the signal of interest, (ii) minimising the side lobes level, (iii) steering pattern nulls in the directions of jammers and interferers, (iv) forcing the pattern nulls to have prespecified values in order to insure sufficient elimination of jammers and interferers and (v) the whole pattern synthesis will be done by changing the amplitudes and phases of the array elements' complex weights without any physical changes in the array; thus the method will be suitable for adaptive processing applications in which the array pattern will be dynamically adapted to the environments. Numerical examples will be used to demonstrate the effectiveness of the proposed array pattern synthesis approach using a uniform linear array of isotropic elements. Finally, the effect of changing the array number of elements and the weighting factor will be investigated using numerical examples.

1 Introduction

Five controls in an antenna array can be used to shape the array pattern properly: the geometrical configuration (linear, circular, rectangular, spherical etc.) of the overall array, the spacing between the elements, the excitation amplitude of the individual elements, the excitation phase of the individual elements and the relative pattern of the individual elements [1].

The increasing amount of electromagnetic pollution has prompted the study of array pattern nulling techniques. These techniques are important in radar, sonar and communication systems to minimise degradation of the signal-to-noise ratio because of undesired interference [2]. Most of the current research on antenna arrays is focused on using robust and easily adapted optimisation techniques to improve the nulling performance [3]. Classical gradient-based optimisation methods are not suitable for improving the nulling performance of linear antenna arrays for several reasons, including the following:

- The methods are highly sensitive to the starting points when the number of variables, and hence the size of the solution space, increases.
- They frequently converge to local suboptimum solutions.
- They require a continuous and differentiable objective function.
- They require piecewise linear cost approximation (for linear programming).
- They have problems with convergence and algorithm complexity (for non-linear programming).

During the last two decades, genetic algorithms (GAs) have been used for array pattern synthesis; a brief literature review will be introduced as follows: in [4], array pattern nulling by element position perturbations using a GA is presented. The proposed method has provided superior accuracy in nulls' locations to the analytic method and has maintained the required null depth. A binary coded GA is used in [5] to reduce the side lobes level of a linear array by excitation coefficient tapering. The study shows good side lobes performance (approximately −33 dB) for a 30 element array. The radiation pattern of linear arrays with large number of elements (20–100) is improved using a GA in [6]. The side lobes for 20 and 100 element arrays are reduced to −20 and −30 dB, respectively. A decimal GA technique to taper the amplitude of the array excitation to achieve reduced side lobes level and null steering in single or multiple beam antenna arrays is proposed in [7] and the maximum side lobes level reduced to −20 dB approximately. In [8], a low-profile phased antenna array with low side lobes was designed and fabricated using a GA. The side lobes level was suppressed by only 6.5 dB after optimisation. An approach for side lobes reduction in a linear antenna array using a GA is proposed in [9, 10]. In [10], the side lobes for symmetric linear antenna arrays are reduced without significantly sacrificing the first null beam width. An approach to determine an optimum set of weights for antenna elements to reduce the maximum side lobes level in a concentric circular antenna array with the constraint of a fixed beam width is proposed in [3]. In [11], a method of adaptive beam forming is described for a phased antenna array using a GA. The algorithm can determine the values of phase excitation for each antenna to steer the main beam in specific directions. In [12], a low side lobes pattern synthesis for a conformal array on a curved surface with quadratic function using GA is presented.

In our earlier work in [13], the obtained side lobes level by using a least-squares-based beam forming approach to space-time adaptive processing applications have values in order of +18 dB. Hence it could be verified that the GA-based array pattern synthesis methods are superior to the gradient-based methods.

The goal of this paper is to introduce an array pattern synthesis approach which uses a single GA-based processing scheme to achieve a unique set of objectives:

- Steering the main lobe in the direction of the signal of interest (SOI).
- Minimising the side lobes level. The fulfillment of this objective will result in reducing the energy which will leak from the array through these side lobes and also it may result in reducing the noise at the receiver because of reducing the amount of the received low signals' energy which is in order of the thermal noise. Also, the side lobes reduction in this paper depends on minimising the pattern average value; so the side lobes level will be reduced in all directions not only in the direction of maximum side lobe.
- Steering pattern nulls in the directions of jammers and interferers.
- Forcing the pattern nulls to have prespecified values in order to insure sufficient elimination of jammers and interferers.
- The whole pattern synthesis will be done by changing the amplitudes and phases of the array elements' complex weights without any physical changes in the array; thus the method will be suitable for adaptive processing applications in which the array pattern will be dynamically adapted to the environments.

In Section 2, a brief introduction to GAs will be presented. In Section 3, the proposed new array pattern synthesis technique will be introduced in two modes of operation: mode 1 is the unconstrained side lobes and nulls' levels mode in which the GA will be used to determine the array elements' complex weights in order to only place nulls in the directions of interferers and maintain the pattern value in the direction of the SOI while neither the side lobes nor the nulls levels will be controlled, this will result in array pattern characterised by its high side lobes level. Mode 2 is the constrained side lobes and nulls' levels mode in which side lobes level will be minimised and the nulls level will have prespecified values. Mode 1 is introduced only to demonstrate the advantages of the new proposed method when the side lobes and nulls' levels is constrained. Two numerical examples will be presented to demonstrate these two modes of operation.

Section 4 investigates the effects of changing the number of array elements and the weighting factor on the performance of the proposed pattern synthesis approach using numerical examples.

2 Genetic algorithms

GA is a powerful search and optimisation technique based on the concept of natural selection and natural genetics [14]. The GA repeatedly modifies a population of individual solutions. At each step the GA selects individuals at random from the current population to be parents and uses them to produce the children of the next population. Over successive generations, the population 'evolves' towards an optimal solution which is considered to be the solution which gives

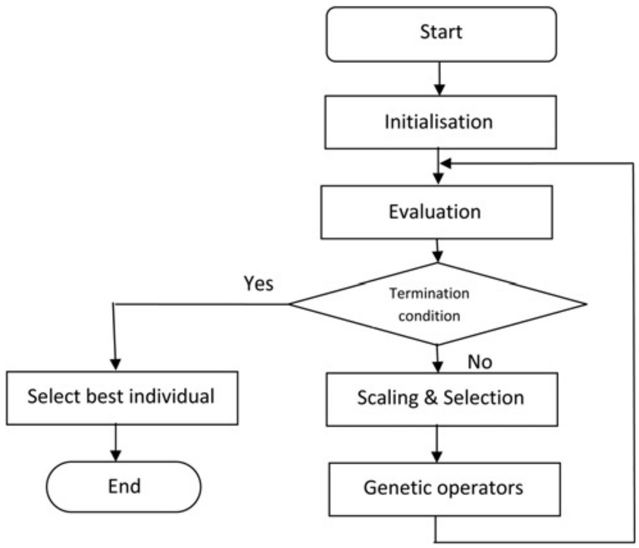

Fig. 1 *GA basic components*

the minimum of the objective function or also called the fitness function [14–17]. It is worth mentioning that the GAs in this paper are implemented based on the built in GA of R2013a MATLAB software package.

The basic GA components are shown in Fig. 1 and will be reviewed briefly as follows [14]:

- Genetic representation of solution: in GAs, the term chromosome typically refers to a candidate solution to a problem. In this paper, real number encoding is used to represent individual solutions or chromosomes.
- Population initialisation: after choosing a representation, the next step in implementing GA is to initialise a population of solutions and choose its size. In this paper, uniform random initialisation is used and the population size is selected to be ten times the number of the antenna array elements taking into consideration that two chromosomes will be used to represent each array element complex weight one for the real part and the other for the imaginary part [15].
- Evaluation of the fitness function: the fitness function is the function to be optimised and it is a problem dependant. The GA should find the global minimum of the fitness function which is considered to be the best solution.
- Fitness scaling: fitness scaling converts the raw fitness scores that are returned by the fitness function to values in a range that is suitable for the selection of parents for reproduction. In this paper, the ranking method in which the scaling of raw scores is based on the rank of each individual instead of its score is used [15].
- Selection methods: after scaling the raw fitness scores, the coming decision to implement a GA is how the population will reproduce. Reproduction is the process of selecting individuals for mating to produce offspring in the next generation, and the number of offspring each will create. The selection of individuals is done, generally, in a way that most fit individuals have more chance to contribute to one or more offspring, and hence keep their genes in the next generation with the hope that the offspring will have better fitness than their parents [14]. In this paper, the stochastic uniform selection method is used. Stochastic uniform selection method lays out a line in which each parent corresponds to a section of the line of length proportional to its scaled value. The algorithm moves along

the line in steps of equal size. At each step, the algorithm allocates a parent from the section it lands on. The first step is a uniform random number less than the step size. Also, Elitism is an addition to reproduction methods that forces the GA to retain some number of the best individuals at each generation. Such individuals may be lost if they are not selected to reproduce or may be destroyed by genetic operators such as crossover or mutation [14, 15]. In this paper, the most fit two chromosomes will survive directly to the next generation as elite chromosomes.

- Genetic operators: after selecting the individuals for mating the next step in implementing a GA uses genetic operators to produce new individuals. This decision in fact is related to the first decision of choosing the representation because the methods for implementing genetic operators are different for different representations [15]. Crossover and mutation are the most frequently used genetic operators and will be described as follows:

1. The crossover operator, like in biological genetic, is the exchange of genes between parent's chromosomes to produce offspring. In GA, the crossover could be done by selecting vector entries, or genes, from a pair of individuals in the current generation and combines them to form a child. Crossover could be implemented by several methods in this paper the scattered crossover method is used. In this method, crossover is done by creating a random binary vector and selecting the genes where the vector's elements are ones from the first parent, and the genes where the vector's elements are zeros from the second parent, and combines the genes to form the child [14, 15]. The fraction of each population, other than elite children, that are made up of crossover children is set to 0.8. The remaining chromosomes will be mutation children.
2. Mutation children are created by applying random changes to a single individual in the current generation to create a child. In this paper, mutation is done by the addition of a random number, or mutation, which is chosen from a Gaussian distribution to each entry of the parent vector. Typically, the amount of mutation, which is proportional to the standard deviation of the distribution, decreases at each new generation. Mutation prevents premature convergence to suboptimal solution by providing a source of diversity to the population when it has converged [14].

- Termination condition: there are several criteria that could be used as a termination condition. However, in this paper, a maximum number of 500 generations will be used to terminate the algorithm. This maximum number of generations could be reduced to comply with the time constraints of a specific application at the expense of the algorithm performance quality.

3 Array pattern synthesis approach using a GA

In this section, the proposed array pattern synthesis approach using a GA will be presented, given the directions of the SOI and interferers which could be obtained using any direction of arrival estimation methods [18–20].

The algorithm should find the weights complex values as each array element is associated to one complex weight. The weight complex values should be selected in order to fulfill the algorithm objectives.

In the next two sections, the two modes of operation of the proposed pattern synthesis approach will be introduced and then two numerical examples will be presented in Section 3.

3.1 Mode 1: unconstrained side lobes and nulls' levels

The most important component of the proposed pattern synthesis approach is the fitness function which must be formed in order to fulfill the algorithm objectives which are placing deep nulls at the directions of interferers and maintain the pattern value in the SOI direction at a prespecified value. So the fitness function which is used to determine the complex weights in this mode could be written as

$$\text{Fitness} = \sum_{i=1}^{i=J} \left|P_i\right| + \left|P_s - C\right| \tag{1}$$

where J is the number of interferers (jammer) signals, P_i is the array beam pattern complex value in the direction of the ith jammer, P_s is the array beam pattern complex value in the direction of the SOI, C is the complex value at which the pattern value in the SOI direction should be maintained and $|\,|$ denotes the absolute (magnitude) of the complex quantities.

The pattern value at any direction, $P(\theta, \text{Ø})$, could be computed using the following equation

$$P(\theta, \text{Ø}) = [\boldsymbol{W}]^{\mathrm{T}}\left[\boldsymbol{A}(\theta, \text{Ø})\right] \tag{2}$$

where $\boldsymbol{W}$ is the complex weights' vector, T denotes the transpose of the vector and $[\boldsymbol{A}(\theta, \text{Ø})]$ is the steering vector in the direction of $(\theta, \text{Ø})$ which, for the case that all coming signals are in the azimuth plane ($\theta = 90°$), could be expressed as

$$\boldsymbol{A} = \left[1,\ \mathrm{e}^{\mathrm{j}2\pi(d/\lambda)\cos \text{Ø}},\ \mathrm{e}^{\mathrm{j}2\pi(2d/\lambda)\cos \text{Ø}},\ \ldots,\ \mathrm{e}^{\mathrm{j}2\pi(((N-1)d)/\lambda)\cos \text{Ø}}\right]^{\mathrm{T}} \tag{3}$$

where d in the space between array elements, N is the number of array elements and λ is the radar signal wavelength.

3.2 Mode 2: constrained side lobes and nulls' levels

In this mode of operation, the objectives of the GA are:

- Minimising the beam pattern average value in order to minimise the pattern side lobes level.
- Maximising the pattern value in the direction of the SOI (P_s) in order to radiate maximum possible power in this direction.
- Placing deep nulls in the direction of interferers and also the nulls depth values will be prespecified.

The fitness function which is supposed to achieve the above objectives could be written as

$$\text{Fitness} = w \sum_{i=1}^{i=J} \left| \left|\frac{P_i}{P_s}\right| - 10^{N_i/20} \right| + \left|\frac{P_{\mathrm{av}}}{P_s}\right| \tag{4}$$

where N_i is the ith normalised pattern null prespecified value in dB corresponding to the ith jammer and the normalisation is with respect to P_s, w is the weighting factor used to increase the value of the fitness function's first term, subtraction term and hence balance the GA optimisation between the two terms of the fitness function and, P_{av} is the pattern average

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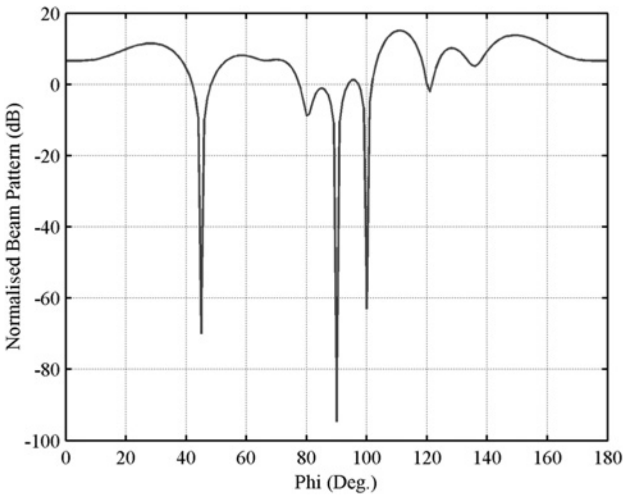

Fig. 2 *Normalised beam pattern, mode 1*

value which could be computed as follows

$$P_{\text{av}} = \frac{\sum_{\theta}\sum_{\text{Ø}}|P(\theta, \text{Ø})|}{N_p} \qquad (5)$$

where N_p is the number of points at which the pattern values are calculated, note also that the term $|P_{\text{av}}/P_{\text{s}}|$ could be considered as the normalised pattern average and hence it could be used as a measure of the side lobes level. It is worth mentioning that, in this paper, all the pattern values will be normalised with respect to the pattern value in the direction of the SOI, P_{s}.

3.3 Numerical examples

In this section, two examples will be used to demonstrate the proposed pattern synthesis approach in its two modes of operations. The examples will use 10 isotropic elements array operating at 900 MHz placed along the x-axis and spaced by a distance of $\lambda/2$ and the array vision is limited to the range of $0° \le \text{Ø} \le 180°$ measured starting from the x-axis. We consider that all coming signals are in the azimuth plane ($\theta = 90°$) and these signals are composed of three jammers in the directions of $\text{Ø} = 45°$, $90°$ and $100°$

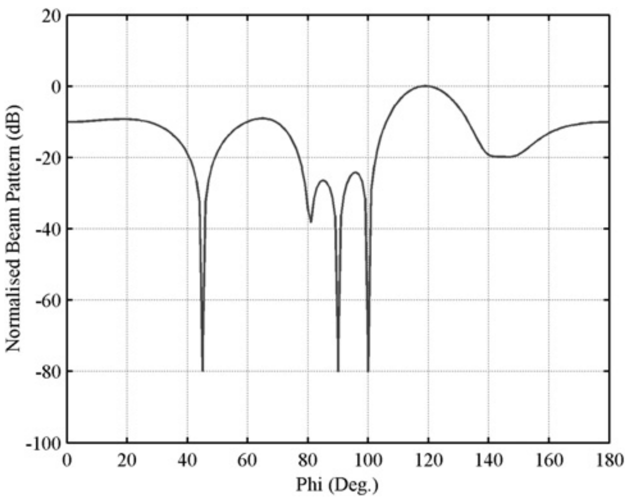

Fig. 3 *Normalised beam pattern, mode 2*

and one SOI arriving at $\text{Ø} = 120°$, also w is set to 100 and C is set to 1.

The normalised beam patterns in dB for modes 1and 2 of operation are shown in Figs. 2 and 3, respectively. For mode 1, the beam pattern is characterised by its high side lobes level, more than 10 dB over the SOI pattern value. Also note that deep nulls are placed correctly in the direction of the jammers in both of Figs. 2 and 3 but in Fig. 2, the variation in their values is obvious. For mode 2, the beam pattern is characterised by its significantly reduced side lobes level and controlled nulls' values as all N_i values are set to −80 dB below the SOI pattern value. The side lobes level improvement could be measured in terms of the normalised, with respect to P_{s}, average pattern values which are equal to 2.48 for mode 1 and 0.28 for mode 2.

4 Effect of changing *n* and *w* on the performance of the proposed pattern synthesis approach

In this section, the effect of changing the number of array elements, N, and the weighting factor, w, will be investigated using two numerical examples based on the same array configuration and parameters used in the previous section, except the investigated parameter, in order to facilitate the comparison. Also only mode 2 of operation will be considered here as it is the basic mode of operation and the other one was introduced for demonstration purposes only.

4.1 Effect of changing the number of elements, N

The number of array elements is directly related to the array degree of freedom (DoF). The DoF is defined as the number of positions' values on the array pattern which could be controlled or specified. For N-element array, the DoF is equal to $N - 1$ positions [21]. So the increasing of the number of array elements will increase the DoF and hence, the algorithm capability to form or control the pattern shape will also be increased. Table 1 shows the normalised pattern average values and the normalised pattern nulls' values for the array patterns corresponding to 10, 25 and 50 element arrays.

It is noticeable that the normalised pattern average value decreases as the number of array elements increases; this result is expected as by increasing the number of elements, the algorithm ability to form the pattern and hence to fulfill the objectives is also increased.

4.2 Effect of changing the weighting factor w

The weighting factor is introduced in (4) in order to balance the GA optimisation between the two fitness function terms. So by decreasing this factor the GA ability to control the

Table 1 Normalised pattern average values and the normalised pattern nulls' values for the array patterns corresponding to 10, 25 and 50 element arrays

N	Normalised nulls' values, dB			Normalized pattern average value
	Ø = 45°	Ø = 90°	Ø = 100°	
10	−80.02	−80.02	−80.03	0.28
25	−80.06	−80.00	−79.70	0.23
50	−80.00	−80.00	−79.99	0.19

Table 2 Normalised pattern average values and the normalised pattern nulls' values for the array patterns corresponding to weighting factor values of 1 and 100

W	Normalised nulls' values, dB			Normalised pattern average value
	Ø = 45°	Ø = 90°	Ø = 100°	
1	−80.17	−81.00	−79.60	0.21
100	−80.02	−80.02	−80.03	0.28

nulls values will decrease and the GA ability to minimise the normalised pattern average value will increase and vice versa. Table 2 shows the normalised pattern average values and the normalised pattern nulls' values for the array patterns corresponding to weighting factors values of 1 and 100.

The results shown in Table 2 verify our previous analysis.

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