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Thinned-Nonuniformly Spaced Arrays

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Abstract

This paper presents how to optimally minimize the relative sidelobe levels of linear and planar arrays by simple method. Genetic algorithm (GA) is used to optimize the arrays, by thinning and changing the relative spacing of the arrays at the same time. In this technique, the gene of each element has two parts one for the spacing and the other for excitation. Also, Simulation results for linear and planar arrays are depicted.

GA is used to determine which elements are turned off in a periodic array to yield the lowest relative sidelobe level (rsll), and also to determine the optimum spacing between the elements.

1. Introduction

Nature abounds with examples of plants and animals adapting to their environments. An animal changes color to hide. A plant develops extensively deep roots because of strong winds or little moisture. Engineers can use nature's philosophy in order to design better products. GA [1-11] is used to determine the optimum thinning and spacings between the elements in antenna arrays to get the minimum relative sidelobe level (RSLL). The spacing between elements is physically limited by the size of the antenna elements and mutual coupling.

2. Genetic Algorithm (GA)

GA optimizers are robust stochastic search methods modeled on the principles and concepts of natural selection and evolution [2]. As an optimizer, the powerful heuristic of the GA is effective at solving complex combinatorial and related problems. In general, a GA optimizer must be able to perform six basic tasks: 1) Encode the solution parameters as genes, 2) Create a string of the genes to form a chromosome, 3) Initialize a starting population, 4) Evaluate and assign fitness values to individuals in the population, 5) Perform reproduction through the fitness-weighted selection of individuals from the population, and 6) Perform recombination and mutation to produce members of the next generation. Figure (1) shows a block diagram of a simple GA.

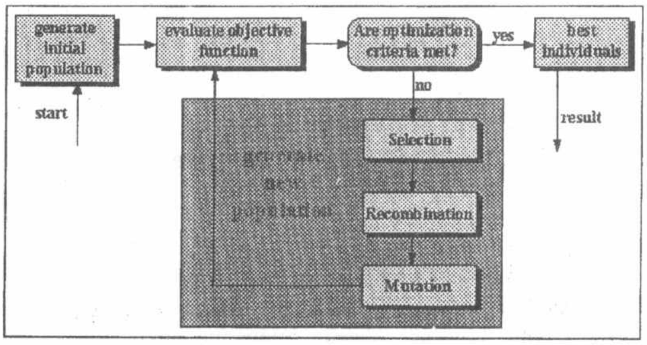

Fig.(1) A block diagram of a simple Genetic-Algorithm optimizer.

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3.Thinning and Nonuniform Spacing of Linear Arrays

Thinning of arrays means turning off some elements of the array to create a desired amplitude density across the aperture. An element connected to the feed network is "on", and an element connected to a matched or dummy load is "off". An element is represented by one bit for excitation (thinning), and three bits for the spacing, so four bits represent every element of the antenna. Figure (2) shows the linear array configuration with nonuniform spacing between the elements, the spacing between element number one and two may not equal to the spacing between element number two and three, and so on. Also there are constraints on the spacing to avoid overlapping, and mutual coupling between elements.

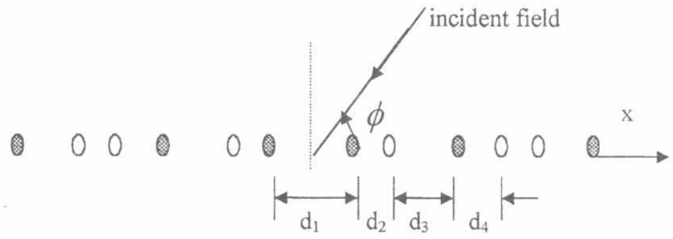

Fig.(2) Diagram of a thinning and nonuniform spacing of linear array.

The fitness function is the antenna array factor for nonuniform spacing, which is represented by:

$$AF(\phi) = 2\sum_{n=1}^{Nel} a_n \cos\left[k\left(\sum_{m=1}^{n} d_m - \frac{d_1}{2}\right)\cos\phi\right], \qquad (1)$$

where

a_n : represents the excitation of the element number n, $= \begin{cases} 0 & \text{off} \\ 1 & \text{on} \end{cases}$

$d_1/2$: the distance of element 1 from the physical center of the array,

d_m : the spacing between element m-1 and element m,

$2N_{el}$: total number of antenna elements.

k : wave number.

The spacing between elements can be represented by binary or decimal values. There are an infinite number of continuous element-spacing combinations. A binary encoding of the spacing between elements brings the number of possible combinations to a large, but finite value. The element spacing is represented by:

$$d_m = d_0 + \sum_{n=1}^{N_{pbit}} b[n]\, d\, (0.5)^{n-1} \quad , \qquad (2)$$

where

- d_0 : the minimum allowable element spacing > 0;
- N_{pbit} : the number of bits representing the spacing;
- $b[n]$: the vector containing the binary code (Genes);
- d : the largest quantization level.

For example if we want the minimum allowable spacing between the elements equals λ/4 and the maximum allowable spacing between the elements equals 0.6875λ, then $d_0 = \lambda/4$ and $d = \lambda/4$. If b[n] = [111] then $d_m = 0.6875\lambda$, if b[n]= [000] then $d_m = \lambda/4$, if b[n] = [010] then $d_m = 0.375\ \lambda$, and so on.

For a 48-elements, each chromosome consists of 96 bits, the symmetry around the origin is assumed (4 bits * 24-element= 96 bits). Figure (3) shows the normalized far field pattern of 48-elements with isotropic patterns after using the genetic-algorithm optimizer. The maximum rsll achieved in this case equals – 24.6 dB, the optimum thinned-excitations, are appeared at the center of the figure, the first left bit "1" represents the excitation of the first right element from the center of the antenna, and the last right bit "0" represents the excitation of the last right element of the antenna. The antenna beamwidth is 3.2°. Figure (4) shows the thinning of the elements according to the achieved results by using GA.

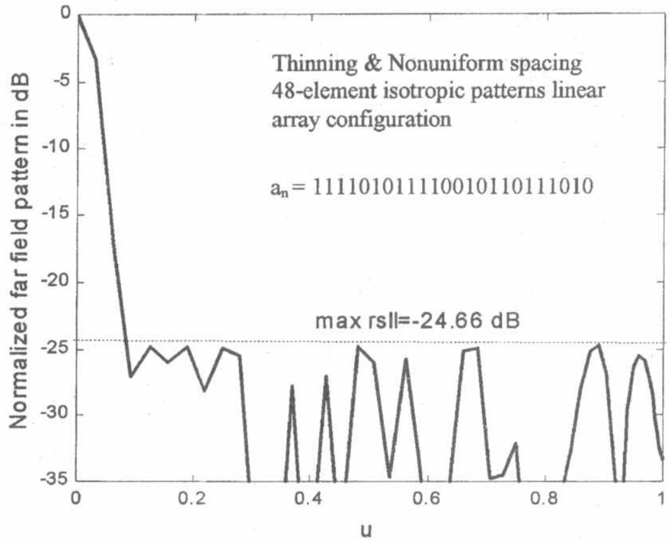

Fig.(3) The far-field pattern of a thinned linear with nonuniform spacing array of 48-elements with isotropic-element patterns (max. spacing = 0.5 λ).

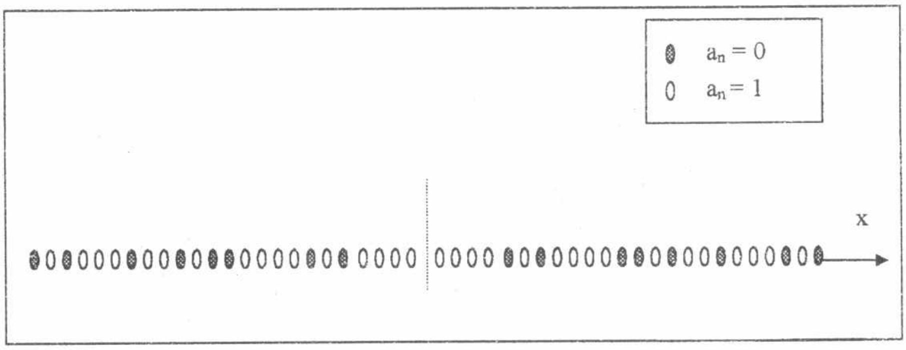

Fig.(4) Diagram of an 48-elements linear array configuration after thinning.

The results achieved give thinning to a 33% from the total number of elements. The allowable maximum and minimum spacing between the elements are restricted to 0.5 λ and 0.25 λ, the spacings between elements are:
0.25, 0.357, 0.357, 0.285, 0.285, 0.250, 0.285, 0.464, 0.357, 0.428, 0.5, 0.357, 0.357, 0.25, 0.321, 0.357, 0.393, 0.285, 0.321, 0.321, 0.428, 0.393, 0.393 0.321λ.
Referring to figure (2), the first value (0.25 λ) represents the distance from the first right element and the physical center of the antenna, $d_1/2$, the second spacing represents the relative distance between the first and the second element of the antenna, d_2, and so on. Figure (5) shows the improvement of the fitness function versus the iteration number. The population size is 200 chromosomes, the selection strategy is the population decimation technique, and the probability of mutation is 0.1.

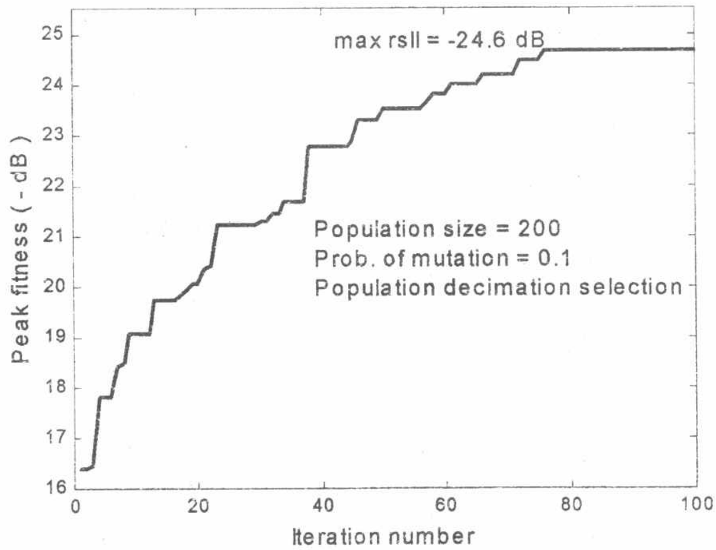

Fig. (5) A plot of the best costs of a thinned array of 48-elements with nonuniform spacing with isotropic element patterns over 100 iterations (max. spacing = 0.5 λ)

If the maximum allowable spacing between the elements is permitted to become 0.7 λ instead of 0.5 λ, the maximum rsll becomes -26 dB instead of - 24.6 dB, and the antenna beamwidth is reduced to 1.2°. Figure (6) shows the normalized far field pattern of a 48-element with isotropic element patterns, the maximum allowable spacing between the elements equals 0.7 λ,

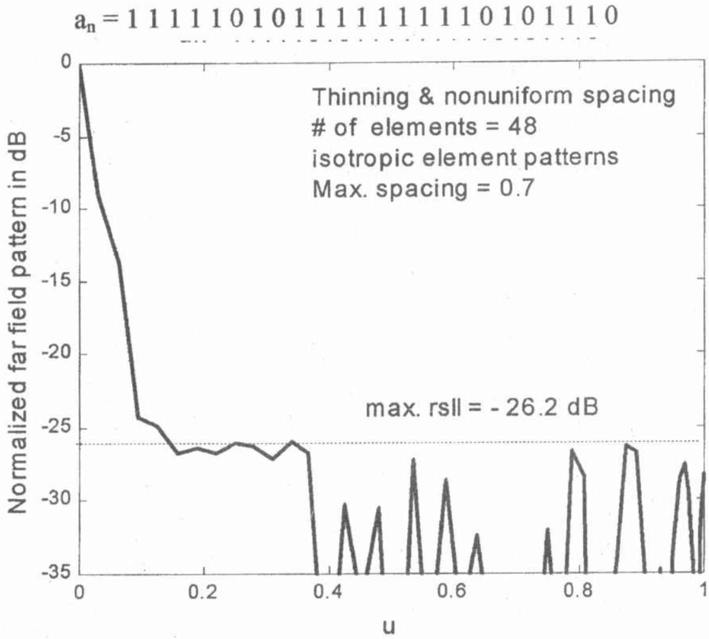

Fig. (6) The far-field pattern of a thinned linear array with nonuniform spacing array of a 48-element with isotropic-element patterns. The max spacing is 0.7 λ.

The excitations of the elements are shown at the top of Figure (6), while the calculated spacings between the elements are:
0.312, 0.625, 0.5, 0.562, 0.562, 0.25, 0.375, 0.312, 0.312, 0.687, 0.625, 0.562, 0.562, 0.62, 0.562, 0.437, 0.625, 0.312, 0.437, 0.25, 0.437, 0.625, 0.687, 0.375 λ.

For 48-element array, with $\sin\phi$ element patterns, the fitness function is described by equation (3). The maximum rsll equals -29 dB, and the maximum allowable spacing 0.5 λ. The antenna beamwidth equals 3.48°. Figure (7) shows the normalized far field pattern in dB, while the excitation coefficients of the elements are shown at the top of this Figure.

$$AF(\phi) = 2\sin\phi \sum_{n=1}^{Nel} a_n \cos\left[k\left(\sum_{m=1}^{n} d_m - \frac{d_1}{2}\right)\cos\phi\right], \qquad (3)$$

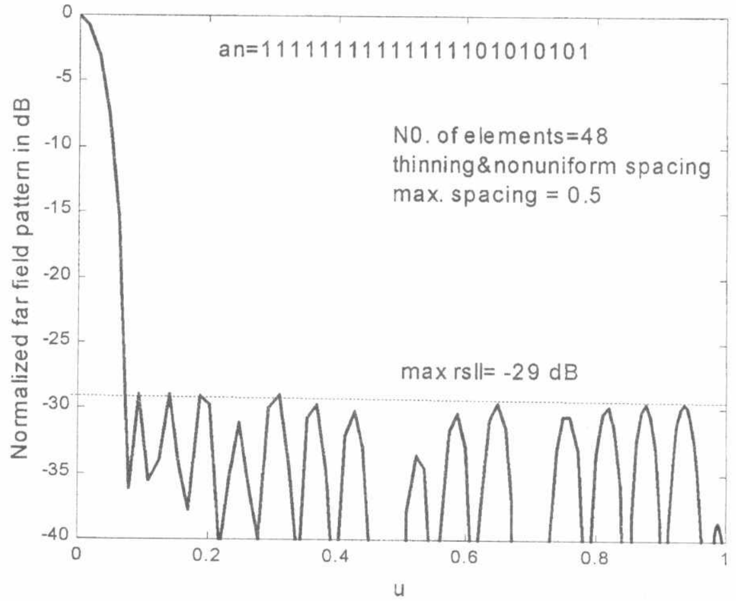

Fig.(7) The far-field pattern of a thinned linear array with nonuniform spacing (max. spacing=0.5 λ) of 48-element array with $\sin\phi$ element patterns

The calculated spacings between elements are:
0.25, 0.357, 0.28, 0.321, 0.28, 0.393, 0.25, 0.393, 0.321, 0.393, 0.357, 0.393, 0.464, 0.5, 0.464, 0.321, 0.25, 0.428, 0.28, 0.357, 0.5, 0.25, 0.393, 0.321 λ.

Considering the case of 48-element array, with $\sin\phi$ element patterns, with restricted maximum allowable spacing 0.7 λ, the maximum rsll reduces to – 30.3 dB while the antenna beamwidth diminishes to 0.87^{o}. figure (8) shows the normalized far field pattern in dB while the excitation coefficients of the elements are shown at the top of figure (8), and the calculated spacings between the elements are:
0.321, 0.625, 0.562, 0.625, 0.625, 0.625, 0.625, 0.312, 0.312, 0.562, 0.625, 0.625, 0.562, 0.562, 0.562, 0.562, 0.25, 0.312, 0.5, 0.625, 0.625, 0.687, 0.375, 0.5 λ.

The convergence of the fitness function (maximum rsll) with the number of iterations is shown in figure (9). One hundred iterations is expected to be sufficient.

From the above results, one deduces that with no restrictions on the maximum allowable spacing, we expect to get better maximum rsll values but on the other hand we should be aware from grating lobe appearance and the problems associated with.

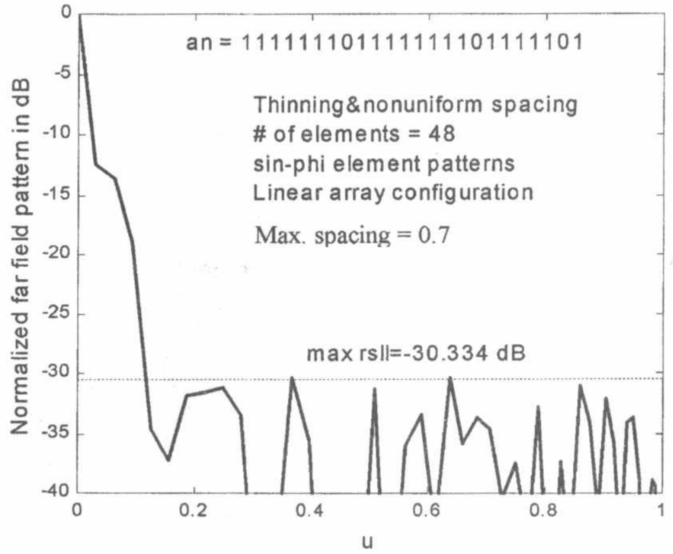

Fig. (8) The far-field pattern of a thinned linear array with nonuniform spacing (max. spacing = 0.7 λ) of a 48-elements with sin ϕ element patterns

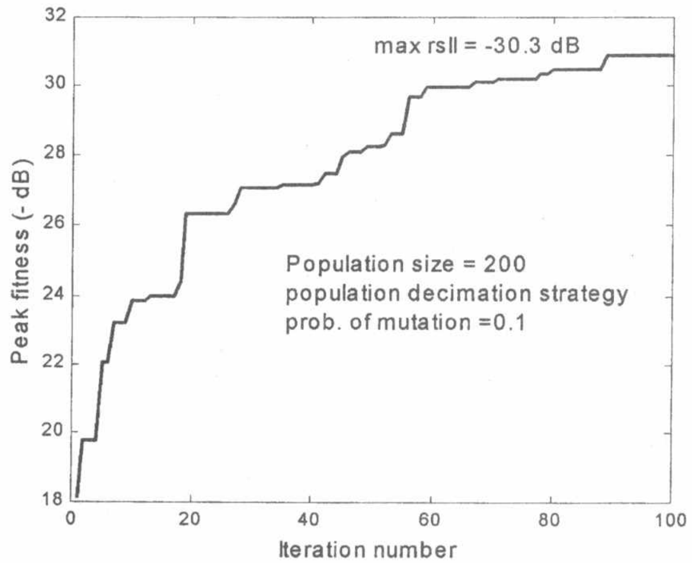

Fig. (9) A plot of the best costs of a thinned array of 48-element with nonuniform spacing with sin ϕ elements patterns over 100 iterations (maximum. spacing = 0.7 λ)

4.Thinning and Nonuniform Spacing of Planar Arrays

In planar arrays, the chromosome has many genes, genes for the spacing between the elements in the x-direction, genes for the spacing between the elements in the y-direction, and genes for the excitation coefficients. So, the chromosomes are very complicated to deal with .The coefficients of excitation and spacings are represented in planar-array chromosomes (2-D matrix). Three bits represent the spacing between any two successive elements, and one bit represents the excitation coefficient of each element (thinning). Crossover and mutation are carried out at the planar-array chromosomes (2-D matrix).
Figure (13) shows the crossover method of the planar-array chromosomes.

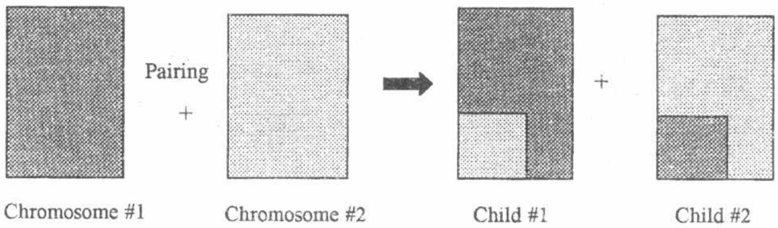

Fig. (13) The crossover area in the case of planar array

Now, considering an 20 x 20 elements of planar array placed in the x-y plane, as shown in figure 14; the fitness function; which is the array factor of the planar array; is given by equation 4.

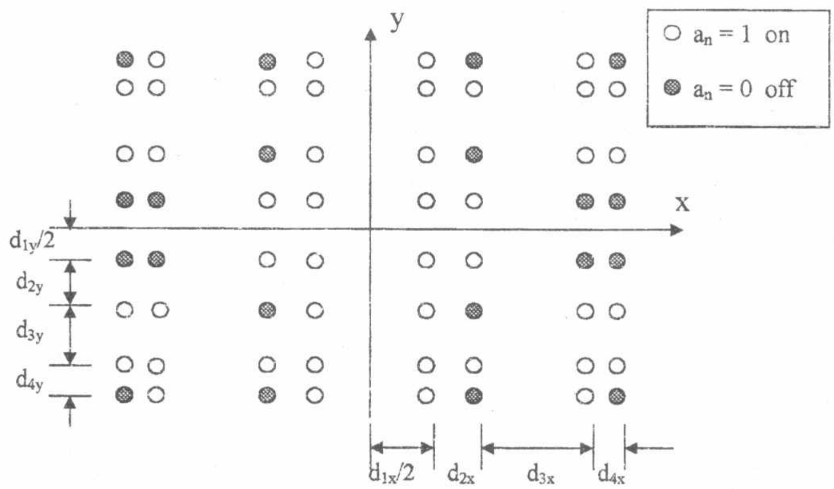

Fig. 14 Diagram of the thinned and nonuniform spacing planar array

$$AF(\theta,\phi) = 4\sum_{n=1}^{N_{el}}\sum_{m=1}^{M_{el}} a_{nm} \cos\left[k\left(\sum_{k=1}^{n} d_{kx} - \frac{d_{1x}}{2}\right)\sin\theta\cos\phi\right]$$

$$\times \cos\left[k\left(\sum_{p=1}^{m} d_{px} - \frac{d_{1y}}{2}\right)\sin\theta\sin\phi\right] \qquad (4)$$

Figure (15) shows, the normalized far field E - plane - pattern of a planar array after applying the GA optimizer. The maximum achieved rsll equals –34.88 dB, in the plan ϕ = 90° plane. The antenna beamwidth is 7.9°. Figure (17) shows the excitations of the elements (zero or one) in one quarter of the array, the number of the filled elements is 72% of the antenna elements. The symmetry around the x and y-axis is valid. The spacings between the elements in the x-direction are:

0.25, 0.464, 0.464, 0.428, 0.464, 0.285, 0.357, 0.428, 0.428, 0.428 λ.

The first distance (0.25 λ) represents the spacing from the physical center of the array and the first element in the x-direction ($d_{1x}/2$), the second distance (0.464 λ) represents the distance between the first and the second element in the x-direction (d_{2x}) and so on.

Similarly spacings between the elements in the y-direction are:

0.25, 0.357, 0.25, 0.25, 0.5, 0.25, 0.321, 0.393, 0.428, 0.393 λ.

The effect of iterations is studied; Figure (16) shows the improvement in the peak fitness value over 120 iterations. after 100 iterations the solution is almost converged. The population size is 200 chromosomes, the probability of mutation is 0.1, and the selection strategy is the population decimation (Discarding of 50% of the old population, generating a new offspring; and mixing them with the old generation (parents) and ranking them according to their fitness (steady-state GA).)

As a note, the calculation time of the genetic algorithm with the planar array configuration take a lot of time compared with the linear array configuration. Figure (18) shows the diagram of the planar array after thinning, by applying the genetic-algorithm optimizer.

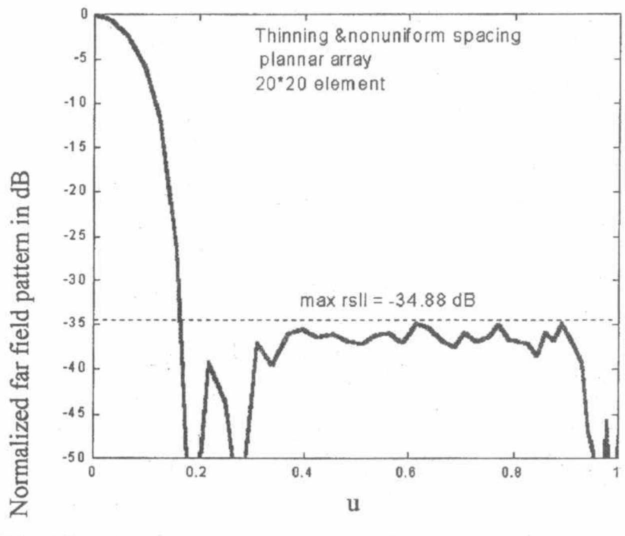

Fig. 15 The far-field pattern of a thinned planar array with nonuniform spacing of a 20 x 20 elements with isotropic-element patterns

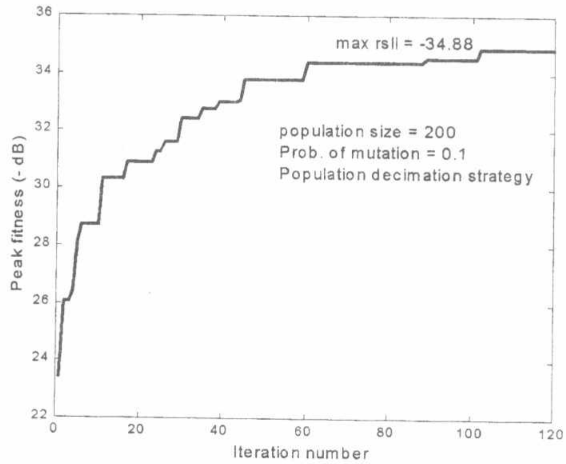

Fig. 16 A plot of the best costs of a thinned planar array of 20 x 20 elements with nonuniform spacing with isotropic element patterns over 120 iterations

y

0	1	1	1	1	1	0	1	0	0
0	1	0	1	0	1	1	1	0	1
0	1	1	0	1	0	0	1	1	0
0	1	1	1	1	1	1	1	1	0
0	1	1	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0	0	1
1	1	1	1	1	1	1	1	0	1
0	1	1	1	1	1	1	1	0	0
1	1	1	1	1	1	0	0	1	1
1	1	1	1	1	0	0	1	1	1

x

Fig. 17 The excitations of the thinned planar array in one quarter of the array.

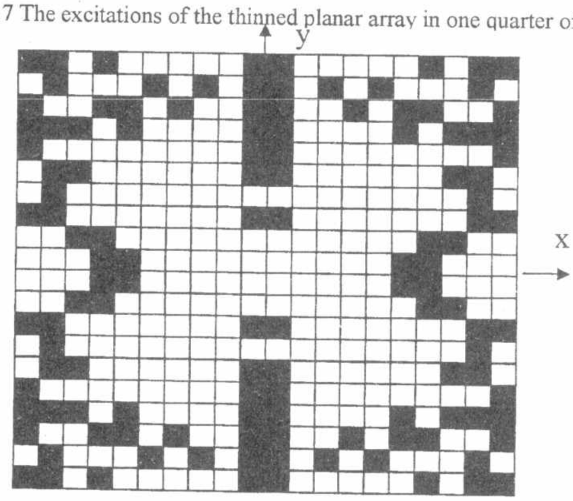

Fig. 18 Diagram of an optimized thinned 20 x 20 elements planar array. The white blocks indicate elements that are turned on, and the black are elements that are turned off.(the spacing between elements is not depicted in this diagram)

5. Conclusion

GA is used to optimally minimize the sidelobe levels of arrays by two simple methods; the first one, is thinning of arrays, and the second is changing the relative spacing between the elements. The beauty of the GA is that, it can optimize a large number of discrete parameters. Previous methods of array thinning used statistical methods of representing an amplitude taper and fail to produce an optimum thinning. The GA intelligently searches for the best thinning that produces low sidelobes.

To find the element spacings, of a nonuniformly spaced array, there are an infinite number of continuos element-spacing combinations. A binary encoding of the spacing between elements brings the number of possible combinations to a large but finite, values. Quantization noise must be considered when optimizing continuous parameters. GA is slow and not useful for real-time pattern control such as adaptive nulling. On the other hand, the algorithms are quite useful for optimizing array designs.

6. References

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