

One and Two Dimensions Unequally Array Pattern Synthesis with the use of a Modified Particle Swarm Optimization Algorithm

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Abstract: - A computationally efficient global optimization method, the adaptive particle swarm optimization (APSO), is proposed for the synthesis of uniform and Gaussian amplitude arrays of two cases, i.e., the prior constraint in the synthesis of the element positions for both the cases is $d_{\min} = 0.5 \lambda$, where d_{\min} is the minimum distance between two adjacent elements. The upper limit in the distance between the elements, d_{\max} is varied from 0.5λ to 0.6λ for the first case and from 0.5λ to λ for the second case. The proposed iterative method aims at linear and planar array and the optimization of phases- positions by minimizing the side-lobes level and respecting a beam pattern shape. Selected examples are included, which demonstrate the effectiveness and the design flexibility of the proposed method in the framework of the electromagnetic synthesis of linear and planar antennas arrays.

Key-Words: - Adaptive particle swarm optimization, unequally spaced linear and planar arrays antennas.

1 Introduction

In the area of the antenna array pattern synthesis, a non-uniformly spaced array can successfully achieve the design specifications by optimally adjusting the positions of the elements with predefined excitations [1]. An antenna array with certain radiation characteristics is often asked to be designed. Necessarily, the nulls have to be in a certain direction [2], or the main lobe has to be directed in a certain direction; also other requirements for the direction and the level of the side lobes [3] might be stated.

The global synthesis of antenna arrays that generate a desired radiation pattern is a highly nonlinear optimization problem. Many analytical methods have been proposed for its solution. Examples of analytical techniques include the well-known Taylor method and the Chebyshev method [4]. In many applications, the synthesis problem of an antenna array consist of finding an appropriate set of amplitude and phase weights that will yield the desired far-field pattern with an equally spaced linear array [5]. However, it is well known that the antenna performance related to the beam width and side lobes levels can be improved by choosing both the best position and the best set of the amplitude and phase for each element of an unequally spaced

array [6]. The paper is aimed to present a modular method, based on a modified particle swarm optimizer (APSO) algorithm, which is able to simultaneously optimize the excitation coefficients (amplitude and phase) and the best position, according to different constraints, such as side lobes peak minimization, and beam pattern (BP) shape modeling. The APSO is characteristic by finding good near-optimal solutions early in the optimization run. The APSO does not use derivatives, and is also independent on the complexity of the objective function under consideration. Six examples are used to demonstrate the effectiveness of the proposed algorithm-based procedure for the antenna array optimization. The APSO simulated results are also compared with those obtained by modified differential algorithm in [7].

2 Problem Formulation

The far field factor of a linear array with an even number of uniformly spaced isotropic elements ($2N$) can be written in the form:

$$F(\theta) = 2 \sum_{k=1}^N a_k \cos\left(\frac{2\pi}{\lambda} d_k \sin(\theta) + \delta_k\right) \quad (1)$$

Where λ is the wavelength, θ denotes the angular direction, a_k is the excitation amplitude, δ_k is the excitation phase and d_k is the x coordinate, normalised to wavelength, of the n^{th} array element. The set $v = (\delta_1, \dots, \delta_N, d_1, \dots, d_N)$ is the vector of variable parameters used to synthesize a desired pattern. The position d_k can be computed from the inter-element spacing, according to the following formula:

$$d_i = \sum_{k=1}^N \Delta d_k - \frac{\Delta d_1}{2} \quad (2)$$

The array factor in dB is given by

$$P(\theta) = 20 \log(F(\theta)_{normalised}) \quad (3)$$

The mathematical statement of the optimization process is:

$$Find \max f(v) \rightarrow v_{opt} \quad (4)$$

Where $f(v)$ is the objective function of parameter variables v .

$$f = Max - \int_0^{\pi} |F_d(\theta) - F(\theta)| d\theta \quad (5)$$

The fitness can be seen as the difference area between desired pattern and obtained pattern. The greater value of the fitness function, the better match between the obtained pattern and the desired one. Equation (5) is used for evaluating the fitness value during the optimization process.

3 Adaptive Particle Swarm algorithm

Modern heuristic algorithms are considered as practical tools for nonlinear optimization problems, which do not require that the objective function to be differentiable or be continuous. The particle swarm optimization (PSO) algorithm as discussed by Xiao [8] is an evolutionary computation technique, which is inspired by social behaviour of swarms. PSO is similar to the other evolutionary algorithms in that the system is initialized with a population of random solutions. Each potential solution, call particles, flies in the D-dimensional problem space with a velocity which is dynamically adjusted according to the flying experiences of its own and its colleagues. The location of the i^{th} particle is represented as $X_i = (x_{i1}, \dots, x_{id}, \dots, x_{iD})$. The

best previous position (which giving the best fitness value) of the i^{th} particle is recorded and represented as $P_i = (p_{i1}, \dots, p_{id}, \dots, p_{iD})$, which is also called *pbest*. The index of the best *pbest* among all the particles is represented by the symbol g . the location P_g is also called *gbest*. The velocity for the i^{th} particle is represented as $V_i = (v_{i1}, \dots, v_{id}, \dots, v_{iD})$. The particle swarm optimization consists of, at each time step, changing the velocity and location of each particle toward its *pbest* and *gbest* locations according to the equations (6) and (7) respectively:

$$v_{id} = w * v_{id} + c_1 * rand() * (p_{id} - x_{id}) + c_2 * rand() * (p_{gd} - x_{id}) \quad (6)$$

$$x_{id} = x_{id} + v_{id} \quad (7)$$

Where w is inertia weight, c_1 and c_2 are acceleration constants as discussed by Eberhart [9], and $rand()$ is a random function in the range [0 1]. For equation (6), the first part represents the inertia of previous velocity; the second part is the cognition part, which represents the private thinking by itself; the third part is the social part, which represents the cooperation among the particle as discussed by Kennedy [10]. V_i is clamped to a maximum velocity $V_{max} = (v_{max,1}, \dots, v_{max,d}, \dots, v_{max,D})$. V_{max} determines the resolution with which regions between the present and the target position are searched as discussed by Eberhart [9]. The process for implementation PSO is as follows:

- a). Set current iteration generation $G_c = 1$. Initialize a population which including m particles, for the i^{th} particle, it has random location X_i in specified space and for the d^{th} dimension of V_i , $v_{id} = rand_2() * v_{max,d}$, where $rand_2()$ is a random value in the range of [-1 1];
 - b). Evaluate the fitness for each particle;
 - c). Compare the evaluated fitness value of each particle with its *pbest*. if the current value is better than *pbest*, and then set the current location as the *pbest* location. Furthermore, if current value is better than *gbest*, then reset *gbest* to the current index in particle array;
 - d). change the velocity and location of the particle according to the equations (6) and (7), respectively;
 - e). $G_c = G_c + 1$, loop to step b) until a stop criterion is met, usually a sufficiently good fitness value or G_c is achieve a predefined maximum generation G_{max} .
- The parameters of PSO includes: number of particles m , inertia weight w , acceleration constants c_1 and c_2 , maximum velocity V_{max} . As evolution goes on, the swarm might undergo an undesired process of diversity loss. Some particles becomes

inactively while lost both the global and local search capability in the next generations. For a particle, the loss of global search capability means that it will be only flying within a quite small space, which will be occurs when its location and $pbest$ is close to $gbest$ (if the $gbest$ has not significant change) and its velocity is close to zero for all dimensions; the loss of local search capability means that the possible flying cannot lead perceptible effect on its fitness. From the theory of self-organization as discussed by Nicolis [11], if the system is going to be in equilibrium, the evolution process will be stagnated. If $gbest$ is located in a local optimum, then the swarm becomes premature convergence as all the particles become inactively. To stimulate the swarm with sustainable development, the inactive particle should be replaced by a fresh one adaptively so as to keeping the non-linear relations of feedback in equation (6) efficiently by maintaining the social diversity of swarm.

However it is hard to identify the inactive particles, since the local search capability of a particle is highly depended on the specific location in the complex fitness landscape for different problems. Fortunately, the precision requirement for fitness value is more easily to be decided for specified problem. The adaptive PSO is executed by substituting the step d) of standard PSO process, as the pseudo code of adaptive PSO that is shown in Fig.1.

```

int[ ]similar Count = new int[m]; // at initialization stage
// Next code is employed to replace step d)
// in standard PSO process
For (i = 0; i < m; i++) { // for each particle
    IF (i ≠ g & & |ΔFi| < ε)
        THEN similar Count[i]++; // add1
    ELSE similar Count[i] = 0; // reset
    IF (similar Count[i] > Tc) // predefined count
        THEN replace (the ith particle);
    ELSE execute (step d) in standard PSO
}

```

Fig.1 Inserted pseudo code of adaptive PSO

F_i is the fitness of the i^{th} particle, F_{gbest} is the fitness of $gbest$. $\Delta F_i = f(F_i, F_{gbest})$, where $f(x)$ is an error function. The ε is a predefined critical constant according to the precision requirement. T_c is the count constant. The replace () function is employed to replace the i^{th} particle, where the X_i and V_i is reinitialized by following the process in step a) of

standard PSO, and its $pbest$ is equal to X_i . The array *similar Count*[i] is employed to store the counts which are satisfying the condition $|\Delta F_i| < \varepsilon$ in successively for the i^{th} particle which is not $gbest$. The inactive particle is natural to satisfy the replace condition; however, if the particle is not inactively, it has less chance to be replaced as T_c increases.

For APSO, ΔF_i is set as a relative error function, which is $(F_i - F_{gbest}) / \text{Min}(\text{abs}(F_i), \text{abs}(F_{gbest}))$, where $\text{abs}(x)$ gets the absolute value of x , $\text{Min}(x_1, x_2)$ gets the minimum value between x_1 and x_2 . The critical constant ε is set as 0.0001, and the count constant T_c is set as 3. For the problem at hand, the number of dimensions is equal to twice the number of antenna elements because both the phase and position of each parameter must be specified by the PSO. Also, a swarm of 60 particles was used. The algorithm parameters c_1 and c_2 specify the relative weight that the global best position has versus the particle's personal best. Empirical testing has found 2.0 to be a reasonable value for both c_1 and c_2 . Linear velocity damping was applied with the upper limit 0.9. Velocity damping improves the convergence behaviour of the particle swarm by gradually increasing the relative emphasis of the global and personal best positions on a particle's velocity. The upper limit of the inertia weight is 0.9 and the lower limit 0.4.

4 Numerical Results

4.1 Synthesis of linear array

The position-phase synthesis of a symmetric unequally spaced linear array was carried out based on APSO for different d_{max} , the upper limit in the distances between the elements. The number of array elements considered for the APSO based synthesis is 20; hence the number of parameters to be optimized is 40.

In order to illustrate the capabilities of the APSO for the shaped beam pattern synthesis of a linear array, four examples are considered. APSO is proposed for the synthesis of uniform and Gaussian amplitude arrays of two cases, i.e., the prior constraint in the synthesis of the element positions for both the cases is $d_{\text{min}} = 0.5 \lambda$, where d_{min} is the minimum distance between two adjacent elements. The upper limit in the distance between the elements, d_{max} is varied from 0.5λ to 0.6λ for the first case and from 0.5λ to λ for the second case.

The maximum side-lobe level of uniform amplitude, unequally spaced 20 elements array with the upper limit in the element spacing $d_{max} = 0.6\lambda$ is -20,53 dB. As shown in Fig.2.

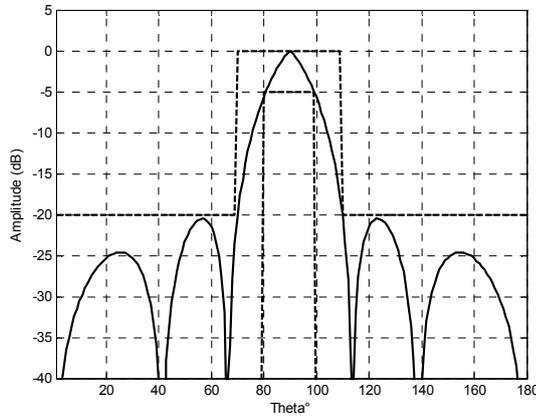


Fig.2 The mask of desired pattern (dashed line) and the radiation pattern obtained by the APSO (solid line)

The total number of function evaluations is 118 iterations for this kind of excitation.

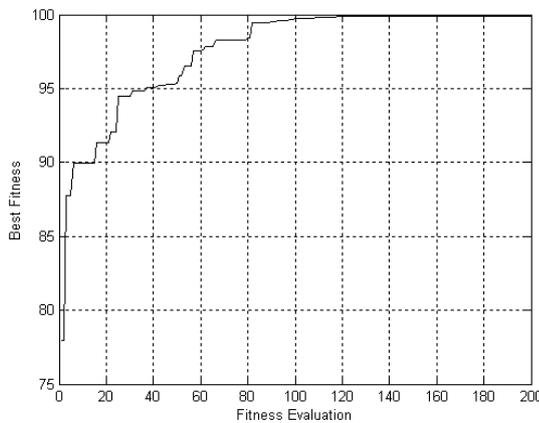


Fig.3 Convergence of the algorithm versus the number of iterations.

The adaptive particle swarm optimization synthesis results of phases and positions for the case of uniform excitation are traced in Fig.4 and Fig.5 respectively and are given in Table 1.

The synthesized element parameters for this case are shown in Table 1.

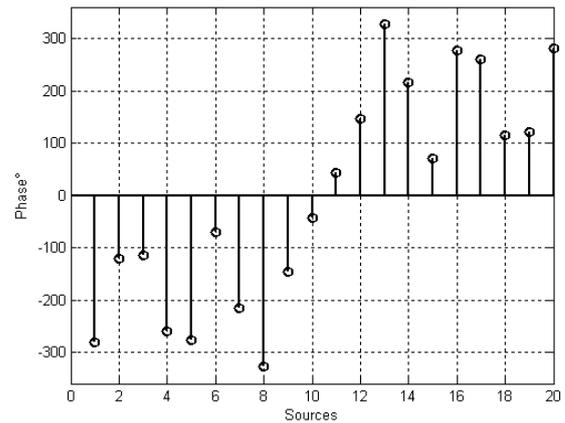


Fig.4 The phase distribution.

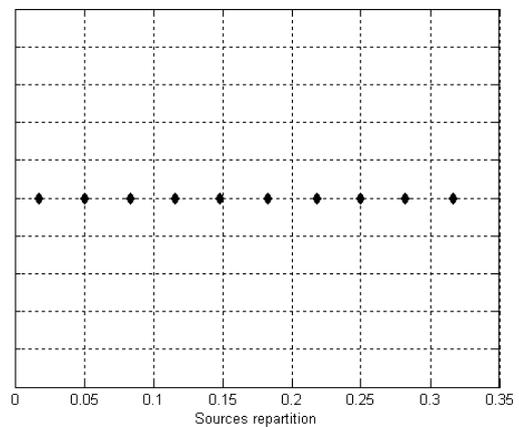


Fig.5 The position of sources

The array pattern synthesis for the gaussian amplitude is shown in Fig.6. From this figure we can see that the maximum sidelobe level is -23,24 dB, which is about 2,71dB lower than for the uniform excitation.

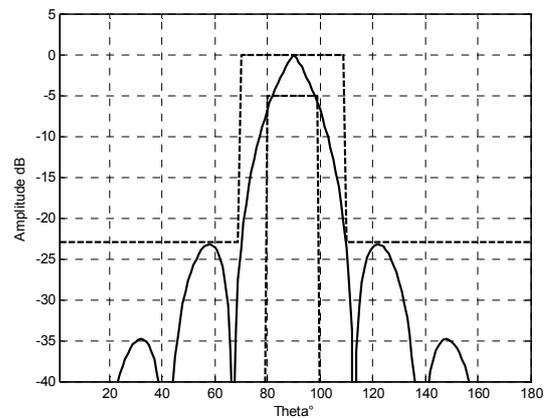


Fig.6 The mask of desired pattern (dashed line) and the radiation pattern (solid line).

For the design specification of phase-position synthesis APSO is run for 157 generations.

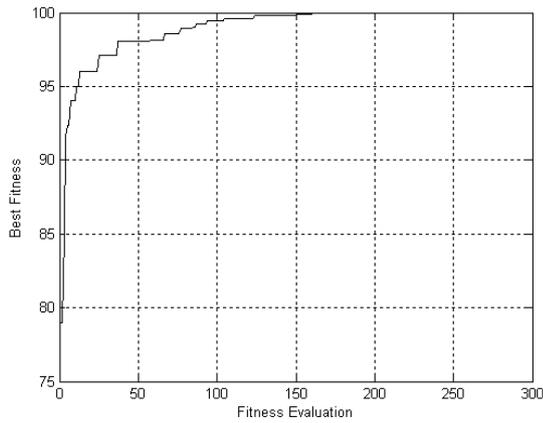


Fig.7 Convergence of the algorithm versus the number of iterations.

The elements phases and positions required to achieve this desired pattern are presented in Fig.8 and Fig.9 respectively, and the simulated results are shown in Table1.

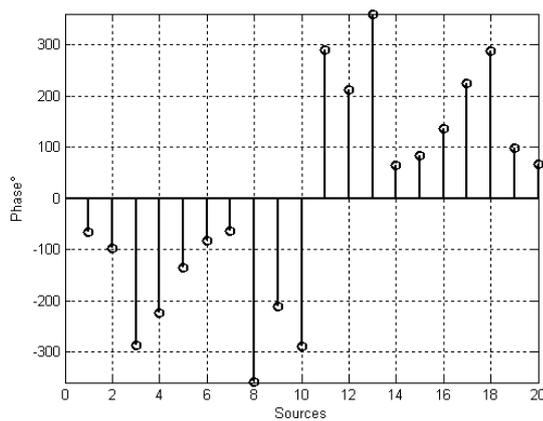


Fig.8 The phase distribution.

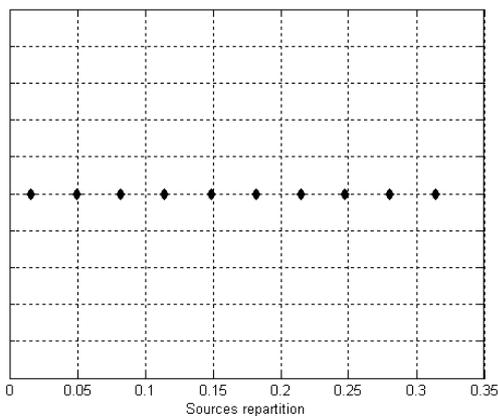


Fig.9 The position of sources

In this section we study the APSO based phase-amplitude synthesis for low side lobe with the upper limit in the distances between the elements equal to λ .

The Fig.10 shows the normalized absolute power pattern in dB for the uniform excitation, the maximum side lobe level reach - 25 dB. Acceptable side lobe level should be equal to or less than the desired value - 25 dB, we note that there is a very good agreement between desired and obtained results.

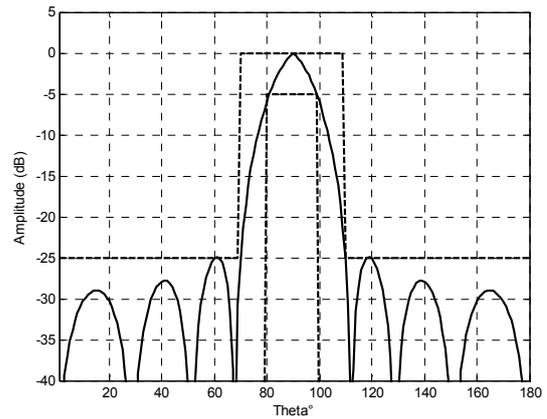


Fig.10 The mask of desired pattern (dashed line) and the radiation pattern (solid line).

After 294 iterations, the fitness value reach to it maximum and the optimization process ended due to meeting the design goal. The convergence curve of fitness is presented in Fig.11.

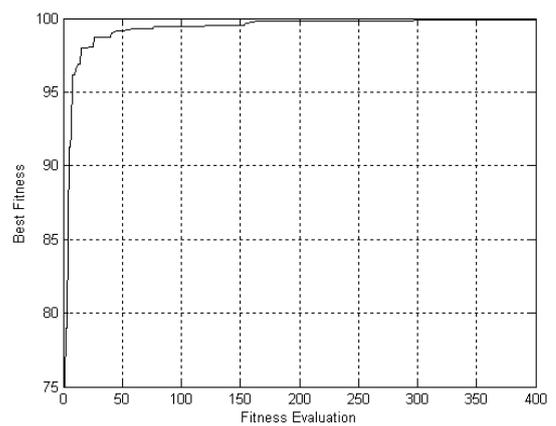


Fig.11 Convergence of the algorithm versus the number of iterations

The optimized excitation magnitudes and phases elements are shown in Fig.12 and Fig.13 respectively, and the values are presented in Table1.

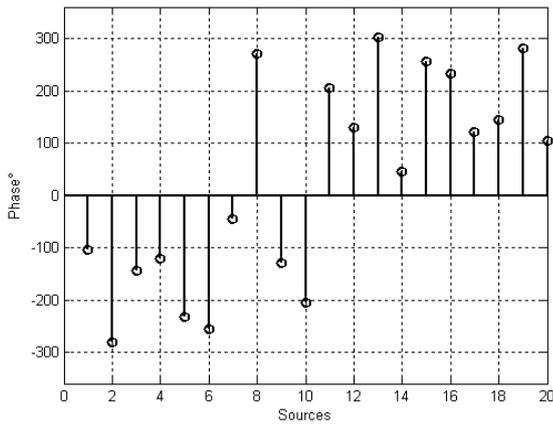


Fig.12 The phase distribution.

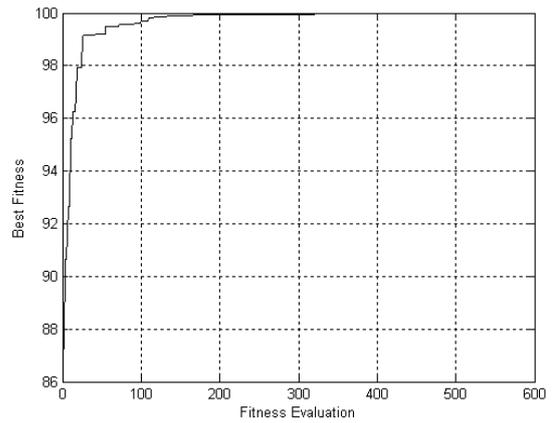


Fig.15 Convergence of the algorithm versus the number of iterations.

The element excitation and position required to achieve the desired pattern are traced in Fig.16 and Fig.17 respectively and shown in Table 1.

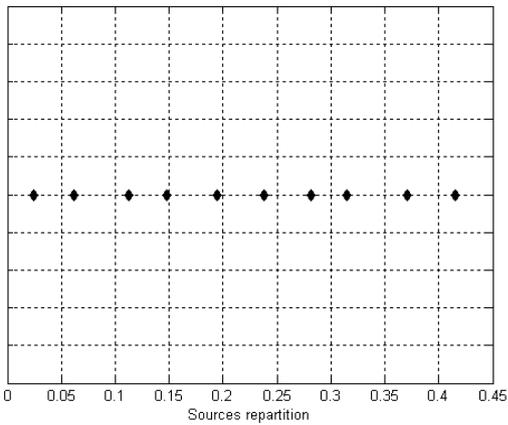


Fig.13 The position of sources

The array pattern for $d_{max} = \lambda$ for the Gaussian law excitation is shown in Fig.14. From this figure we can see that the maximum side lobe level is -26.86 dB.

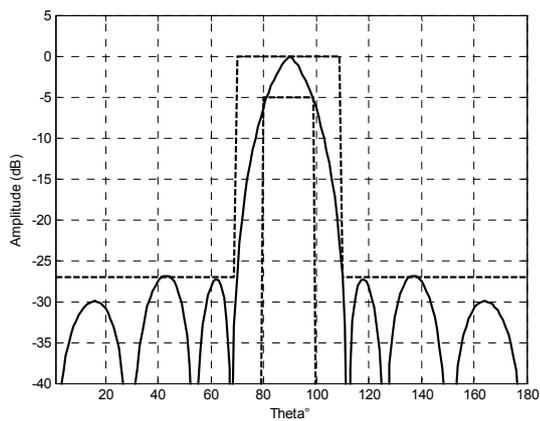


Fig.14 The mask of desired pattern (dashed line) and the radiation pattern (solid line).

The corresponding number of iterations is 311 iterations as shown in Fig.15.

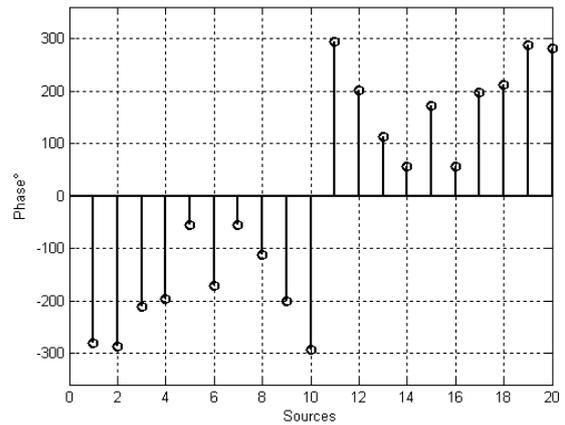


Fig.16 The phase distribution.

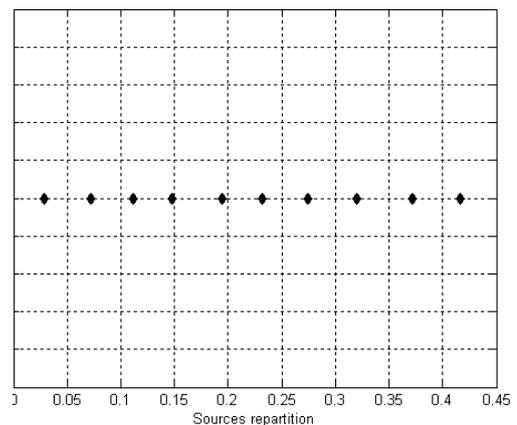


Fig.17 The position of the sources

Therefore from Fig. 2, 6, 10 and 14 we can conclude that, when the upper limit in the maximum distance between the adjacent elements, d_{max} is increased, the maximum sidelobe level decreases for both the cases. When we use the Gaussian excitation, there is a significant reduction in the maximum sidelobe level compared to the uniform one for both cases of synthesis. From the obtained results, we show the effect in lowering the sidelobe level of unequally spaced array for different values of d_{max} , and two kind of excitations laws, uniform and Gaussian respectively. An improvement of about 4.47 dB and 3.62 dB in the side lobe level of the uniform and gaussian law is obtained for $d_{max} = 0.6 \lambda$ and λ respectively. We show the comparison of the far-field patterns among the adaptive particle swarm simulation results, and the MDE algorithm simulated results in [7]. These results remain comparable to the modified differential algorithm.

4.2 Synthesis of planar array

This section presents a design method for planar arrays that permits control of the SLL and the beam width in the two principal planes corresponding to E plane ($\phi = 0^\circ$) and H plane ($\phi = 90^\circ$) respectively.

As an illustrative example, we consider the example problem that applied the adaptive particle swarm is the optimization of a 100 element planar array. Excited by uniform and gaussian amplitude respectively, the objects that should be optimized are the relative excitations phase and distance between elements.

From Fig.18 we can see that, for $d_{max} = \lambda$, position phase synthesis gave a maximum sidelobe level of -21.5 dB and -21.90 dB In the two plans E and H respectively, which is the maximum sidelobe level of uniformly excited array.

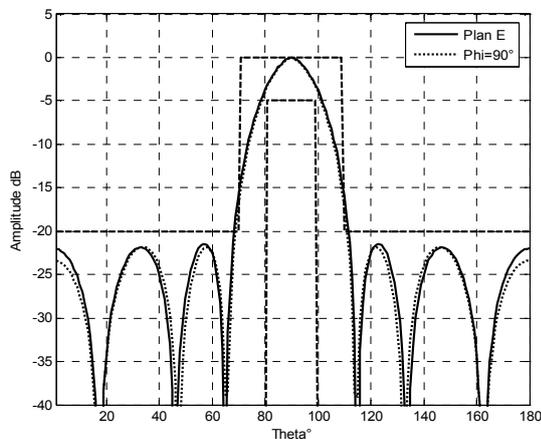


Fig.18 Radiation pattern (both E and H plane).

The best fitness value returned versus the number of calls to the fitness evaluator was achieved after 395.

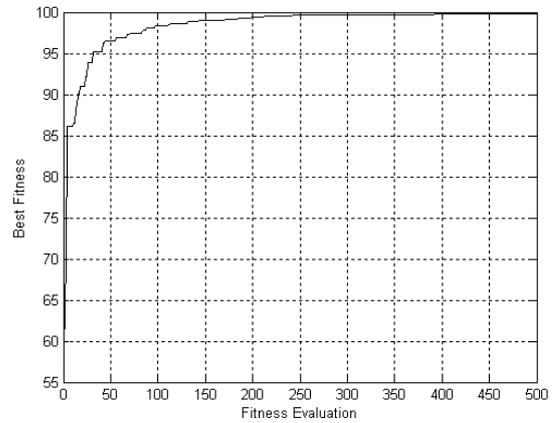


Fig.19 Convergence of the algorithm versus the number of iterations.

The optimized excitations phases and positions according to the two axis are show in Table 2.

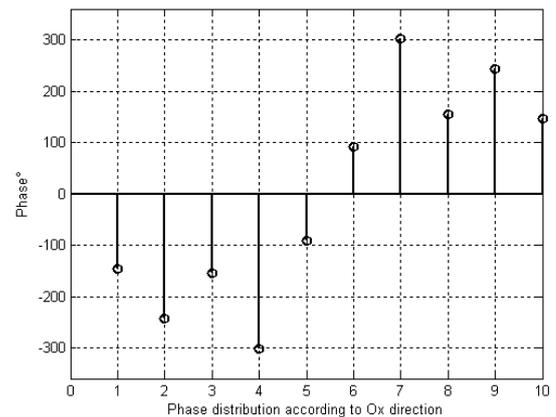


Fig.20 The phase distribution according to Ox.

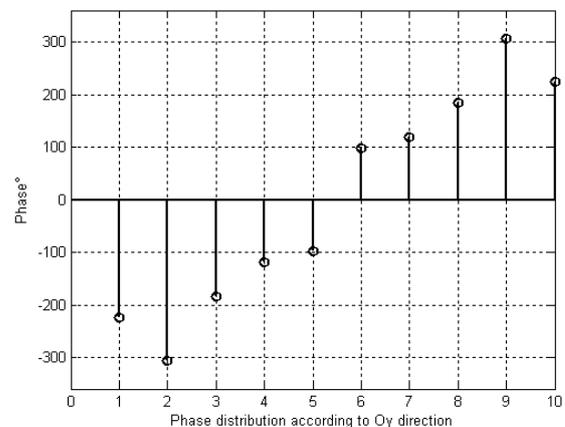


Fig.21 The phase distribution according to Oy.

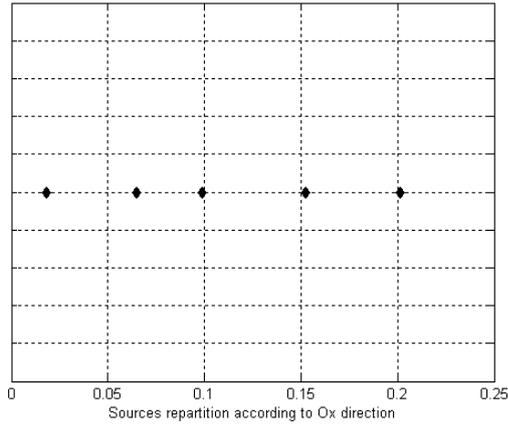


Fig.22 Source repartition according to Ox.

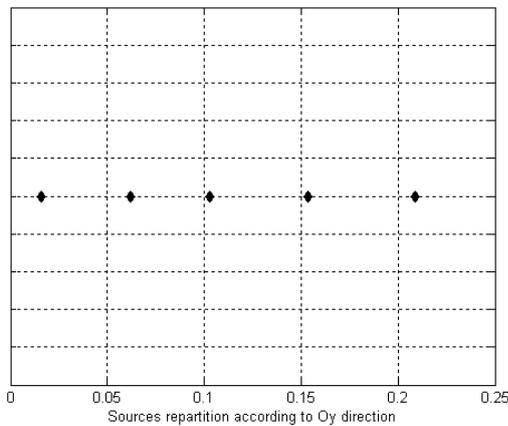


Fig.23 Source repartition according to Oy.

The desired beam width is achieved and the specified SLL is respected. For the next example, we take an array with 100 elements, in position-phase synthesis with prefixed gaussian amplitude; the design of this array is based on finding the position and phase distribution of each element.

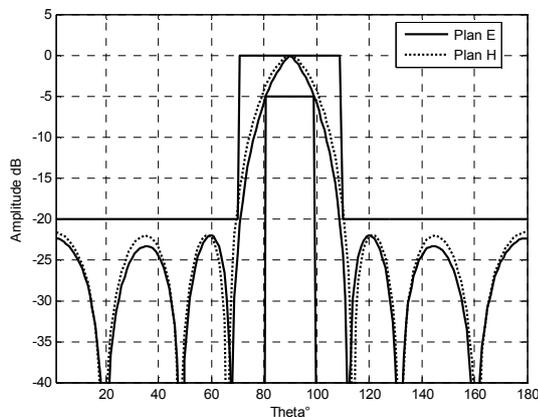


Fig.24 Radiation pattern (both E and H plane).

Fig. 24 shows normalized absolute power pattern in dB, in the plane $\phi = 0^\circ$ the SLL is set to -22.09 dB, and in the plane $\phi = 90^\circ$ the SLL is set to -21.62dB, there is a very good agreement between desired and obtained results.

The algorithm is run for 267 iterations with an initial population of 60 particles.

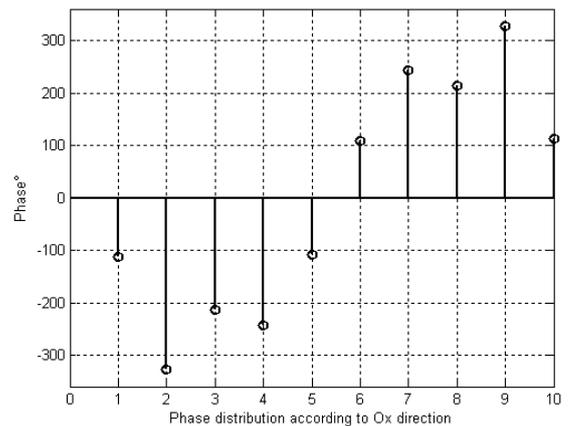
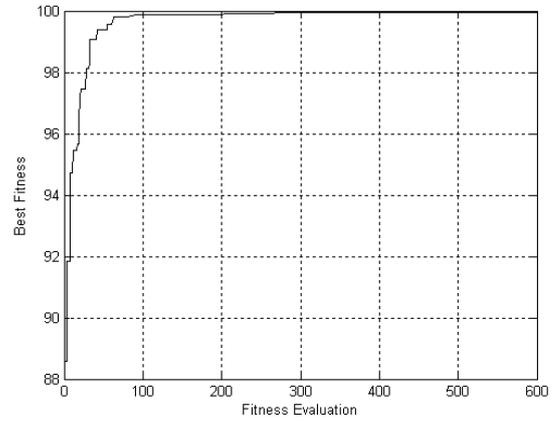


Fig.25 Convergence of the algorithm versus the number of iterations

The optimized excitation phases and positions elements according to the two axis Ox and Oy are traced in Fig.26, Fig.27, Fig.28 and Fig.29 respectively, and shown in Table 2.

Fig.26 The phase distribution according to Ox.

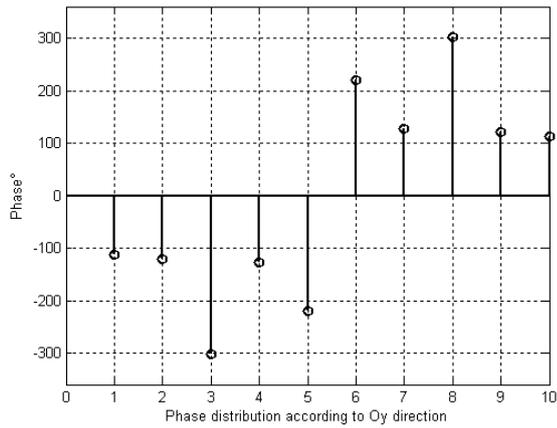


Fig.27 The phase distribution according to Oy .

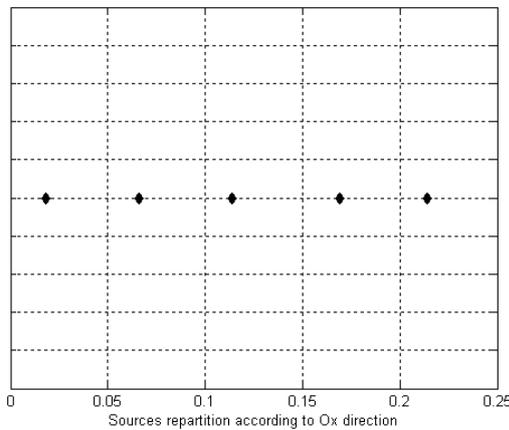


Fig.28 Source repartition according to Ox .

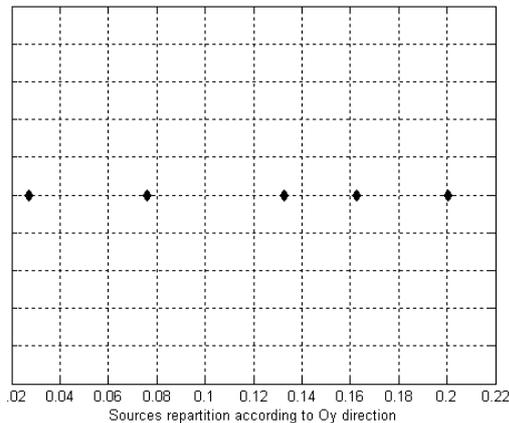


Fig.29 Source repartition according to Oy .

It is clear that in the shaped region, the patterns in the two planes have good performance, and there are no sidelobe that exceeds the specified values. This property of the proposed design enables to choose the size (area) of the region to be covered by the main beam while keeping radiation in the other directions below a desired level.

5 Conclusion

This work shows how algorithms based on adaptive particle swarm optimization can be useful in the array synthesis. Different design goals have been defined, as the side lobe level, nulls in defined directions and desired beam width. In all cases, the Algorithm achieves the desired solution and the convergence is good. The advantages of the presented algorithm are the simplicity in the implementation, the robustness, the flexibility and also the intuitive understanding of it. The application to more complex problems in array synthesis or in the electromagnetism area in general, is straightforward. Particularly, the application can be easily extended to other array synthesis problems with different geometries or including other array parameter besides element position.

TABLE 1 AMPLITUDES, PASHE AND POSITIONS

| $d_{\min}=0.5\lambda, d_{\max}=\lambda$ | | | | | | | | | | | | |
|---|------------|------------|-------------------|-------------------|------------|------------|------------|------------|-------------------|-------------------|------------|------------|
| Uniforme | | | | | | Gausienne | | | | | | |
| i | Amp.ox (V) | Amp.oy (V) | Phase.ox (radian) | Phase.oy (radian) | Rep.ox (m) | Rep.oy (m) | Amp.ox (V) | Amp.oy (V) | Phase.ox (radian) | Phase.oy (radian) | Rep.ox (m) | Rep.oy (m) |
| 1 | 1 | 1 | 1.6151 | 1.7080 | 0.0182 | 0.0156 | 0.583 | 0.583 | 1.8917 | 3.8498 | 0.0179 | 0.0270 |
| 2 | 1 | 1 | 5.2837 | 2.0861 | 0.0647 | 0.0619 | 0.471 | 0.471 | 4.2286 | 2.2076 | 0.0659 | 0.0759 |
| 3 | 1 | 1 | 2.7155 | 3.2286 | 0.0986 | 0.1027 | 0.367 | 0.367 | 3.7226 | 5.2574 | 0.1139 | 0.1326 |
| 4 | 1 | 1 | 4.2299 | 5.3612 | 0.1524 | 0.1533 | 0.276 | 0.276 | 5.7139 | 2.1291 | 0.1693 | 0.1627 |
| 5 | 1 | 1 | 2.5687 | 3.9000 | 0.2016 | 0.2090 | 0.200 | 0.200 | 1.9587 | 1.9553 | 0.2138 | 0.2005 |

TABLE 2 AMPLITUDES, PASHE AND POSITIONS

| $d_{\min}=0.5\lambda, d_{\max}=0.6\lambda$ | | | | | | $d_{\min}=0.5\lambda, d_{\max}=\lambda$ | | | | | | |
|--|----------------|----------------|--------------|----------------|----------------|---|----------------|----------------|--------------|----------------|----------------|--------------|
| Uniforme | | | Gausienne | | | Uniforme | | | Gausienne | | | |
| i | Amplitu de (V) | Phase (radian) | Position (m) | Amplitu de (V) | Phase (radian) | Position (m) | Amplitu de (V) | Phase (radian) | Position (m) | Amplitu de (V) | Phase (radian) | Position (m) |
| 1 | 1 | 0.7487 | 0.0175 | 0.996 | 5.0682 | 0.0156 | 1 | 3.5685 | 0.0246 | 0.996 | 5.1252 | 0.0284 |
| 2 | 1 | 2.5616 | 0.0504 | 0.961 | 3.7013 | 0.0496 | 1 | 2.2755 | 0.0618 | 0.961 | 3.5272 | 0.0723 |
| 3 | 1 | 5.6969 | 0.0836 | 0.895 | 6.2751 | 0.0815 | 1 | 5.2610 | 0.1125 | 0.895 | 1.9610 | 0.1116 |
| 4 | 1 | 3.7676 | 0.1161 | 0.804 | 1.1059 | 0.1140 | 1 | 0.7969 | 0.1476 | 0.804 | 0.9901 | 0.1477 |
| 5 | 1 | 1.2395 | 0.1478 | 0.697 | 1.4574 | 0.1485 | 1 | 4.4486 | 0.1941 | 0.697 | 3.0022 | 0.1940 |
| 6 | 1 | 4.8314 | 0.1829 | 0.583 | 2.3690 | 0.1822 | 1 | 4.0623 | 0.2378 | 0.583 | 0.9759 | 0.2313 |
| 7 | 1 | 4.5286 | 0.2181 | 0.471 | 3.9140 | 0.2150 | 1 | 2.1007 | 0.2813 | 0.471 | 3.4454 | 0.2739 |
| 8 | 1 | 2.0106 | 0.2492 | 0.367 | 5.0115 | 0.2472 | 1 | 2.5295 | 0.3149 | 0.367 | 3.6759 | 0.3197 |
| 9 | 1 | 2.1267 | 0.2820 | 0.276 | 1.7060 | 0.2804 | 1 | 4.9153 | 0.3708 | 0.276 | 5.0018 | 0.3712 |
| 10 | 1 | 4.8914 | 0.3164 | 0.200 | 1.1641 | 0.3141 | 1 | 1.8258 | 0.4156 | 0.200 | 4.9233 | 0.4159 |

References:

- [1] R.F. Harrington, Sidelobe Reduction by Nonuniform Element Spacing, *IRE Trans. Antennas and Propagation*. Mars 1961, pp.187-192.
- [2] S. Yang, Y. Beng Gan, and A. Qing, Antenna-array pattern nulling using a differential evolution algorithm, *International Journal on RF and Microwave*.2004, vol. CAE 14, p. 57-63.
- [3] W. C. Lue and F. Hsu, Use of B-spline curves and genetic algorithms to reduce the sidelobe level in array-patterns, *Microwave and optical technology letters*, 2003, vol. 38, no. 4, p. 308-311.
- [4] C. Balanis, *Antenna Theory – Analysis and Design*, New York: Wiley, 1982.
- [5] K. Yan, Y. Lu, Sidelobe reduction in array-pattern synthesis using genetic algorithms, *IEEE Transactions on Antennas and Propagation*, 1997, vol. 45, no. 7, p. 1117-1122.
- [6] A. Akdagli and K. Guney, Shaped beam pattern synthesis of equally and unequally spaced linear antenna arrays using modified tabu search algorithm. *Microwave and Optical Technology Letters*, 2003, vol. 36, No. 1, p. 16-20.
- [7] D.K. Kurup, M. Himdi and Rydberg, Synthesis of uniform amplitude unequally spaced antenna arrays using the differential evolution algorithm, *IEEE Transactions on Antennas and Propagation*. Vol. 51, No. 9, Sep. 2003.
- [8] Xiao-Feng Xie, Wen-Jun Zhang and Zhi-Lian Yang, Adaptive Particle Swarm Optimization on Individual Level, *International Conference on Signal Processing (ICSP)*, Beijing, China, 2002: 1215-1218.
- [9] R. Eberhart and Y. Shi, Particle swarm optimization: developments, applications and resources. *IEEE Int. Conf. on Evolutionary Computation*, 2001: 81-86.
- [10] J. Kennedy, The particle swarm: social adaptation of knowledge. *IEEE Int. Conf. on Evolutionary Computation*, 1997: 303-308.
- [11] G. Nicolis, *Prigogine. Self-organization in no equilibrium systems: from dissipative systems to order through fluctuations*. John Wiley, NY, 1977.



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