Synthesis of Multibeam Antennas Arrays with a Modified Particle Swarm Optimization Algorithm

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Abstract: *In this paper, we intend to study the synthesis of the multibeam arrays. The synthesis implementation's method for this type of arrays permits to approach the appropriated radiance's diagram. An adaptive particle swarm optimization algorithm (APSO) is proposed to synthesis multibeam antenna arrays. The problem is formulated and solved by means of the proposed algorithm. The examples are simulated to demonstrate the effectiveness and the design flexibility of adaptive PSO in the framework of electromagnetic synthesis of linear arrays.*

Keywords: *Multibeam, optimization, adaptive particle swarm optimization, synthesis, linear antenna arrays.*

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1. Introduction

In the domain of antenna arrays, several methods of synthesis exist such as stochastic and determinist method [4, 2]. Considering the diversity of aims searched for by users, we don't find a general method of synthesis which is applicable synthesis to all cases, but rather an important number of methods to every type of problem. This diversity of solutions can be exploited to constitute a useful tool for a general approach of synthesis of a multibeam array. Recently, evolutionary algorithms have been successfully applied to antenna array synthesis problems like null steering in phased arrays by positional perturbations [1], reconfigurable phase differentiated array design [5, 9], the corrugated horn antenna design [10]. Recently, adaptive particle swarm optimization algorithm is proposed for solving global numerical optimization problem. The result shows that the APSO can find a high quality solution even for a very high dimensional problem.

In this paper, we are interest to present the adaptive swarm optimization method that will be applied to the synthesis of multibeam arrays. A big flexibility between features of the antennas array: amplitude and phase of feeding, ondulation domain, and secondary lobe level∞ is introduced.

2. Problem Formulation

An array can form multiple narrow beams towards different directions. For example, suppose it is desired to form two or three beams towards the steering angles 1, 2, and 3. The design of a linear array antenna is based on finding both magnitudes and phases excitation that can generate the desired patterns.

We consider a linear array of 2N isotropic antenna elements, which are assumed, uncoupled, symmetrically and equally spaced with half wavelength. Its array pattern can be described as follows [10]:

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

where N =element number, λ =wavelength, δ_k =phases of the elements (-180°≤θ≤+180°), a_k =amplitude of the elements, d_k =distance between position of i^{th} element and the array center, and θ =scanning angle. In order to generate a beam pattern fulfilling some constraints, SLL lower than a fixed threshold or reproducing a desired shape, an array configuration must be synthesized. First of all, it is necessary to define the objective function that measures the difference between desired and synthesized beam pattern. Let us define a function called fitness function as follows:

$$Fitness = Max - \int_0^{\pi} \left| f_d(\theta) - f(\theta) \right| d\theta \tag{2}$$

The fitness function defined in equation 2 represents the general form for antenna pattern synthesis, and the desired mask shape can be defined as follow and plotted in Figure 1:

- Of three principal lobes, we define all the angular zones T1 to T15.
- Of two principal lobes, we have T1 = T2 = T3 = T4 = T5 = T6.

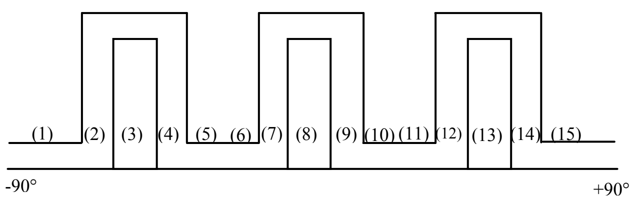

Figure 1. The shaped multi beam mask.

3. Adaptive Particle Swarm Optimisation

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 [11] 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 ith particle is represented as $X_i=(x_{i1},...,x_{id},...x_{iD})$. The best previous position (which giving the best fitness value) of the ith particle is recorded and represented as $P_i=(p_{i1},...,p_{id},...,p_{iD})$, 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 ith particle is represented as $V_i=(v_{i1},...,v_{id},...,v_{iD})$. 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 3 and 4, respectively:

$$v_{id}=w*v_{id}+c_1*rand()*(p_{id}-x_{id})+c_2*rand()*(p_{gd}-x_{id}) \quad (3)$$

$$x_{id} = x_{id} + v_{id} \quad (4)$$

where w is inertia weight, c_1 and c_2 are acceleration constants [9], and *rand()* is a random function in the range [0 1]. For equation 3, 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 [5]. V_i is clamped to a maximum velocity $V_{max}=(v_{max,1},...,v_{max,d},...,v_{max,D})$. V_{max} determines the resolution with which regions between the present and the target position are searched [8]. The process for implementation PSO is as follows:

- Set current iteration generation $G_c=1$. Initialize a population which including m particles, for the ith particle, it has random location X_i in specified space and for the dth dimension of V_i, $v_{id}=rand_2()*v_{max,d}$, where $rand_2()$ is a random value in the range of [-1 1].
- Evaluate the fitness for each particle.
- 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.
- Change the velocity and location of the particle according to the equations 1 and 2, respectively.
- $G_C=G_C+1$, 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 [8], 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 3 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 de 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 Figure 2. F_i is the fitness of the ith 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 ith 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 ith 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.

```
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 i^th particle );
   ELSE execute( step d ) in standard PSO
}
```

Figure 2. Inserted pseudo code of adaptive PSO.

For APSO, ΔF_i is set as a relative error function, which is $(F_i-F_{gbest})/Min(abs(F_i),abs(F_{gbest}))$, where $abs(X)$ gets the absolute value of X, $Min(X_1,X_2)$ gets the minimum value between X_1 and X_2.The critical constant ε is set as 1e-4, and the count constant Tc is set as 3.

4. Results and Discussion

In this section, we consider an array of 10 isotropic elements spaced 0.5 λ apart in order to generate two beams towards the steering angles -20°, 40° with amplitude-phase synthesis. Because of symmetry, here only five phases and five amplitudes are to be optimized. Acceptable Side Lobe Level (SLL) should be equal to or less than the desired value - 25dB. Figures 3 and 4 show the normalized absolute power pattern in dB, the maximum side lobes level reach - 25.87 dB, there is a very good agreement between desired and obtained results. The optimized excitation magnitudes and phases (degree) elements is shown in the Figure 6, and values are presented in the Table 1. For design specifications of amplitude-phase synthesis, APSO is run for 500 generations as indicated in Figure 5.

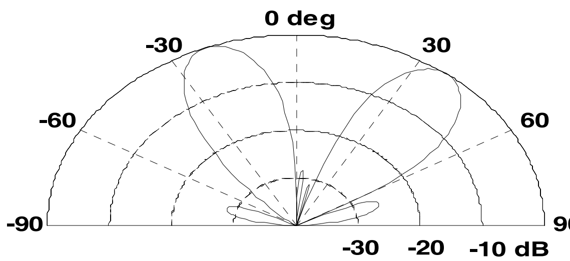

Figure 3. Multi-beam arrays with maximum sidelobes level equal to – 25.87 dB in polar coordinates.

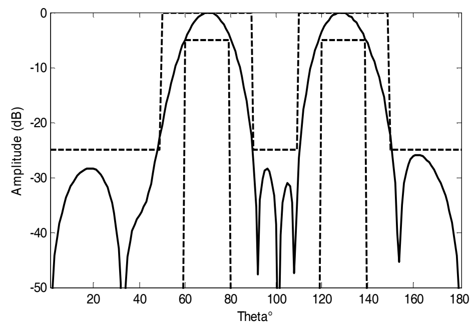

Figure 4. Multi-beam arrays with maximum sidelobes level equal to – 25.87 dB.

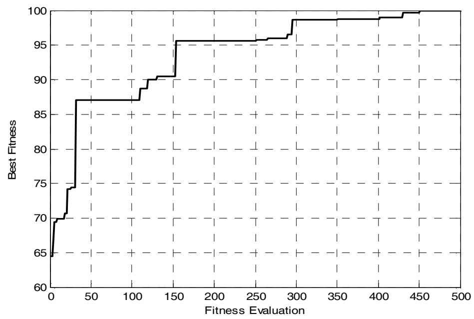

Figure 5. Convergence of the algorithm versus the number of iterations.

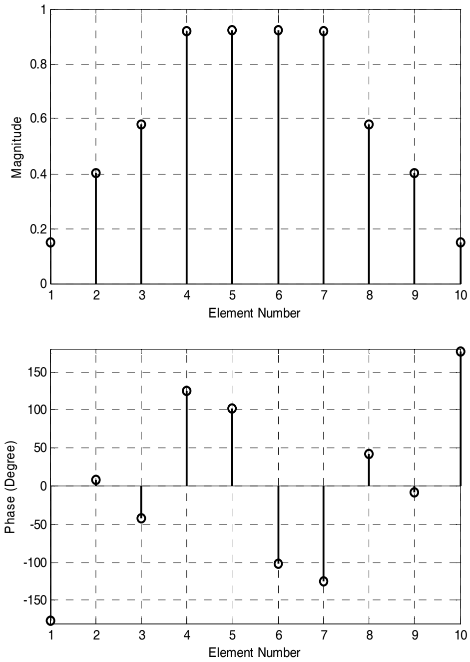

Figure 6. The element excitation required to achieve the desired pattern.

In order to illustrate the capabilities of APSO for solving the array configuration for desired pattern synthesis by varying the amplitude and phase of the elements feed, we introduce the case of an array with 20 equispaced isotropic elements with λ/2 interelement spacing, which is supposed to generate three beam steered towards the three angles θ_1=-30°, θ_2 = 0°and θ_3=20°, Figures 7 and 8 show the output pattern, the relative amplitudes of the three beams were equal to unity, after 409 iterations maximum side lobes level of

-22.29dB was achieved and the optimization process ended due to meeting the design goal as plotted in Figure 9. Amplitude and phase distributions in degree are shown in Figure 10, and presented in the Table 2.

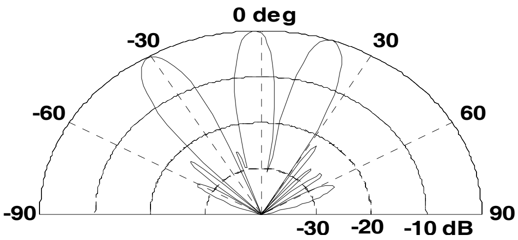

Figure 7. Multi-beam arrays with maximum sidelobes level equal to – 22.29 dB in polar coordinates.

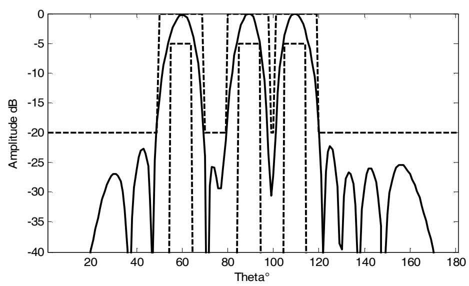

Figure 8. Multi-beam arrays with maximum sidelobes level equal to -22.29dB.

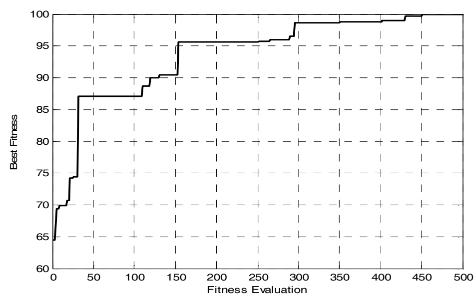

Figure 9. Convergence curve

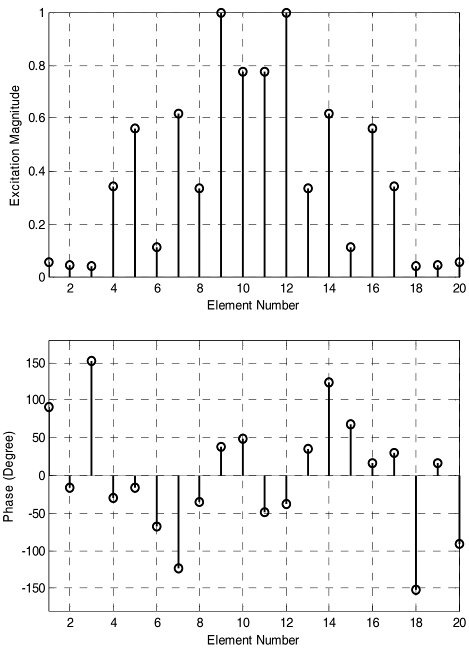

Figure 10. The element excitation required to achieve the desired pattern.

With the same array as the second case, and the same type of synthesis, we present synthesis results of multibeam array as indicated in the Figures 11, 12 and 14. Figures 11 and 12 show normalized absolute power pattern in dB for multibeam array by amplitude-phase synthesis. For design specifications of amplitude-phase synthesis, APSO is run for 1000 generations as shown in the Figure 13; the elements excitation required to achieve the desired pattern are shown in Figure 14. Side lobes level obtained for desired pattern is -20dB. Simulated results are shown in Table 2.

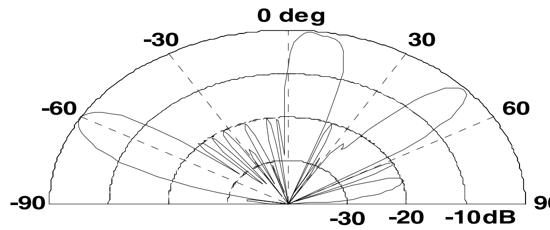

Figure 11. Multi-beam arrays with maximum sidelobes level equal to – 20 dB sidelobes in polar coordinates.

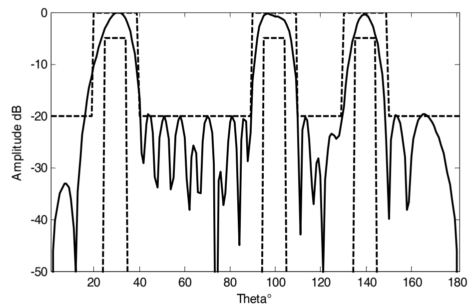

Figure 12. Multi-beam arrays with maximum sidelobes level equal to – 20 dB sidelobes.

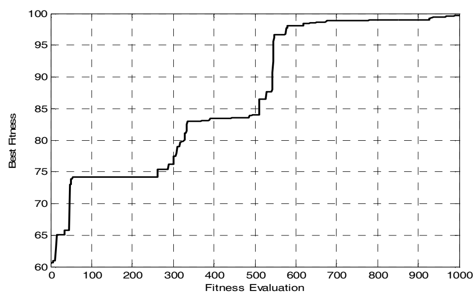

Figure 13. Convergence curve of the fitness value of 20 element array.

In order to evaluate the performance of the proposed algorithm, we compare the numerical results calculated by the adaptive particle swarm optimiser, and the Taylor-Kaiser [4]. We show the comparison of the gains of two 20-element three-beam arrays with half wavelength spacing, and steered towards the three angles of -30°, 0° and 150° among the APSO results as indicated in Figure 15, and the Taylor-Kaiser simulated results in [4]. The adaptive particle swarm optimizer side lobe level is -20, 68 dB and the relative amplitudes of the three beams were equal to unity, this result remain comparable to the Taylor-Kaiser, and an improvement in the side lobe level is obtained. For the simulation package we use the Matlab software.

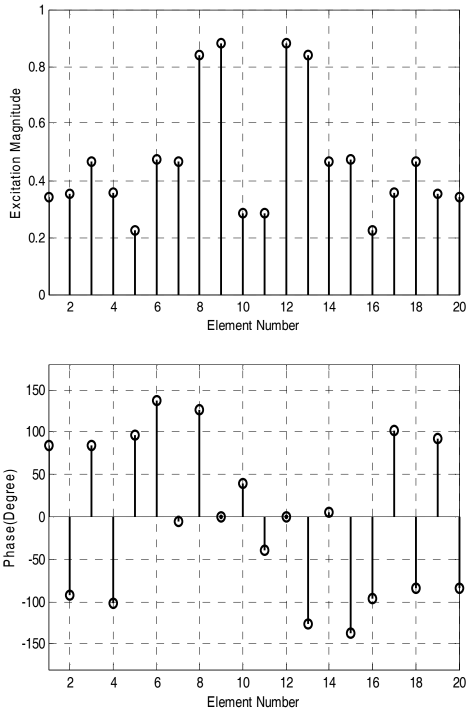

Figure 14. The element excitation required to achieve the desired pattern.

Table 1. Amplitude and phase distributions.

Element N°	Amplitude (Volt)	Phase (Degree)
1	0.1500	176.7861
2	0.4014	-8.3079
3	0.5782	42.5650
4	0.9181	-124.4579
5	0.9218	-101.5167
6	0.9218	101.5167
7	0.9181	124.4579
8	0.5782	-42.5650
9	0.4014	8.3079
10	0.1500	-176.7861

Table 2. Amplitude and phase distributions.

Element N°	Figure 8		Figure 11		Figure 15	
	Amp (Volt)	Phase (Degree)	Amp (Volt)	Phase (Degree)	Amp (Volt)	Phase (Degree)
1	0.0532	-91.1633	0.1881	-51.6006	0.3406	-84.855
2	0.0448	16.3637	0.2491	125.3746	0.3520	92.6129
3	0.0394	-152.641	0.3566	-56.528	0.4656	-84.6717
4	0.3419	29.6334	0.2929	86.7229	0.3548	101.5339
5	0.5595	15.7105	0.2906	-142.563	0.2236	-96.1824
6	0.1119	68.3023	0.8176	41.9520	0.4751	-136.742
7	0.6166	124.1886	0.2069	-53.4742	0.4677	5.0306
8	0.3347	35.3515	0.6379	-33.2029	0.8388	-125.982
9	0.9973	-38.2793	0.6679	108.2260	0.8829	-0.4011
10	0.7740	-48.374	0.8517	-3.5294	0.2832	-39.6487
11	0.7740	48.3748	0.8517	3.5294	0.2832	39.6487
12	0.9973	38.2793	0.6679	-108.226	0.8829	0.4011
13	0.3347	-35.3515	0.6379	33.2029	0.8388	125.982
14	0.6166	-124.188	0.2069	53.4742	0.4677	-5.0306
15	0.1119	-68.3023	0.8176	-41.9520	0.4751	136.7421
16	0.5595	-15.7105	0.2906	142.5634	0.2236	96.1824
17	0.3419	-29.6334	0.2929	-86.7229	0.3548	-101.533
18	0.0394	152.6417	0.3566	56.528	0.4656	84.6717
19	0.0448	-16.3637	0.2491	-125.374	0.3520	-92.6129
20	0.0532	91.1633	0.1881	51.6006	0.3406	84.855

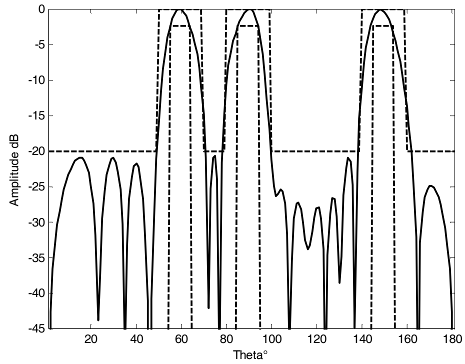

Figure 15. Multi-beam arrays with maximum sidelobes level equal to – 20, 68 dB.

5. Conclusions

In this paper, we only developed a technique of synthesis of multibeam arrays. We are interested to the multibeam arrays, particularly to their optimization by adaptive particle swarm algorithm. Results show that there is an agreement between the desired specifications and the synthesized one. This demonstrates the effectiveness of the proposed procedure.

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