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Particle Swarm Optimization을 이용한 비균일 급전, 비균등 간격의 선형 어레이 설계

(Design of a Randomly Excited and Randomly Spaced Linear Array Using the Particle Swarm Optimization)

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요 약

본 논문에서는 particle swarm optimization (PSO)을 사용하여 가장 낮은 SLL값을 갖거나 가장 좁은 빔폭을 가지는 비균일 급전, 비균등 간격의 선형 어레이를 설계하였다. 어레이 소자의 급전 크기와 급전 소자간의 간격을 조절하기 위해 변수로 지정하였다. 두 가지 변수를 동시에 무작위로 조절하여 빔패턴을 최적화하였다. 빔패턴의 널 포인트를 기준으로 나누어 각각의 사이드로브에 가중치를 부여함으로써 적합도 함수의 성능을 향상시켰고, 이를 이용하여 최적의 빔패턴을 얻을 수 있었다. 이 때, 가중치 값과 빔패턴을 나누는 각은 여러 번의 시도를 통해 얻을 수 있었다. SLL 뿐만 아니라 빔폭까지 고려하기 위해 fitness function에 추가적인 항목 $\beta\times BW$ 을 첨가하였다. 이로써, 가장 낮은 SLL값을 갖거나 가장 좁은 빔폭을 갖는 빔패턴을 갖는 어레이를 설계하였다. 10개의 어레이 소자를 이용하여 최적화 하였을 때, 전자는 -43dB의 SLL값과 32.2°의 빔폭을 가졌고, 후자는 -26dB의 SLL값과 24.2°의 빔폭을 가졌다.

Abstract

In this paper, we use particle swarm optimization (PSO) to design a randomly excited and randomly spaced linear array with either the lowest side lobe level (SLL) or the narrowest beamwidth. The positions and the excitation amplitudes of the array elements are considered as variables to be controlled. The beam pattern is optimized by controlling the two variables simultaneously and randomly. The best beam patterns are obtained using PSO in the fitness function where performance is improved by the random assignment of weight coefficients to each angular sector of the beam pattern. The weight coefficients and angles are obtained through several trial runs. Also, an extra term, $\beta * BW$, is added to the fitness function to account for the beamwidth as well as the SLL. Is produces the best result for the beam pattern with either the lowest SLL or the narrowest beamwidth. In the former case, the SLL and beamwidth are about -43dB and 32.2°, respectively, with only 10 elements. In the latter case, the SLL and beamwidth are about -26dB and 24.2°, respectively.

Keywords : Antenna Arrays, random excitation and space, particle swarm optimization (PSO)

I. Introduction

Low side lobe level (SLL) and narrow beamwidth are important parameters in antenna arrays used in high-performance communications, including smart antenna systems, radar, remote sensing, and satellite communication. Suppressing the SLL while preserving the gain and maintaining a narrow beamwidth are desirable in the design of antenna arrays. The desired array pattern can be obtained by controlling parameters such as the geometrical configuration of the overall array, the relative

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displacement between the elements, the number of array elements, the excitation amplitudes and phases.

The binomial and the Dolph-Tschebyscheff array techniques[1] are well-known methods for reducing the SLL in conventional designs. There are also many other methods of suppressing the SLL including cosine, raised cosine, Hamming, Blackman-Harris, and Kaiser weighting[2]. These methods control the excited amplitudes of the array elements with uniform spaces, and impose particular rules on the design of arrays. Thus, they are limited in their ability to produce the low SLL and narrow beamwidth simultaneously.

To overcome this limitation, the optimization algorithms, such as dynamic programming[3~4], simulated annealing (SA)[5~6] and genetic algorithms (GA)[7~9] had been used to obtaining a desired array pattern with low SLL. Among these optimization methods, the GA method is usually faster than the SA method because of the GA's parallel search potential. However, the GA algorithm is more complex than a PSO algorithm. Also, the numerical parameters of the GA, population size, crossover and mutation, are more difficult to change than the PSO's parameters, population size, inertial weight, c_1 and c_2. In addition to them, the PSO's ability to control convergence is better than GA's[17]. Due to these advantages of the PSO algorithm, it is used in this paper.

The PSO algorithm was introduced by Kennedy and Everhart in 1995[10]. This stochastic evolutionary computation technique is based on the movement and intelligence of swarms, and is being applied increasingly as an efficient alternative to GA and SA in solving optimization design problems involving antenna arrays. Therefore, it had been used for the design of phased arrays[11~13] and antenna array geometry synthesis with minimal SLL and null control[14~16]. Khodier and Christos[14] optimized the excited amplitudes of the array elements to suppress the SLL and control the null points. Mikki and Kishk[15] controlled the null points of the array patterns by optimizing the amplitudes. Then, Jin and Rahmat-Samii[16] discussed the design of aperiodic (i.e., non-uniform and thinned) antenna arrays. In all of these studies, the amplitudes and positions of the array elements were optimized separately. Furthermore, they did not control each side lobe efficiently. That is, they evaluated all side lobes together without priority. In addition, with the exception of the study by Jin and Rahmat-Samii[16], they did not consider the beamwidth of the pattern.

In this paper, the positions and the excited amplitudes of the fixed array elements are considered variables to be optimized simultaneously by using the PSO algorithm to produce the best array pattern with either the lowest SLL or the narrowest beamwidth. The best array patterns can be obtained by using the PSO's fitness function which the performance is improved by assigning different weight coefficients to each angular sector in the array pattern. The weight coefficients and divided angles are obtained through several trial runs. In addition, an extra term, $\beta \times BW$, is included in the fitness function to account for the beamwidth as well as the SLL. The optimized array patterns have much lower SLL or significantly narrower beamwidth then Dolph-Tschebyscheff array with the SLL of -26 dB. The details of our implementation are described in section III.

II. PSO Algorithm

The optimization procedure resembles the social behavior of a swarm of bees searching a field for the location with the most flowers. It is based on a population of particles that fly in the solution space with a velocity that is adjusted dynamically according to its own flying experience, *pbest*, and the flying experience of the best among the swarm, *gbest*.

The terminology used to describe PSO is as follows[17]:

1) Particle: one single individual in the swarm.

2) Location: a particle's N-dimensional coordinate, which represents a solution to the problem.

3) Swarm: the entire collection of particles.

4) Fitness: a function to calculate how well the problem is solved.

5) $pbest$: the location in the parameter space of the best fitness value returned for a specific particle.

6) $gbest$: the location in the parameter space of the best fitness value returned for the entire swarm.

The PSO algorithm process is iterative and the main steps are shown in Fig. 1. Once the fitness function and population size are defined, the PSO algorithm is started by random initialization of the locations and velocity vectors for each particle. The location of each particle is evaluated to determine how well it solves the problem, and then $pbest$ and $gbest$ are initialized. Next, each particle's velocity is updated using the following equation:

$$v_n^{t+1} = \omega * v_n^t + c_1 rand(\ ) * \left(pbest_n^t - x_n^t\right) + c_2 rand(\ ) * \left(gbest_n^t - x_n^t\right) \quad (1)$$

where v_n is the velocity of the particle in the nth dimension, t is the iteration, ω is an old velocity scale factor known as the inertial weight, x_n is the particle's position in the n^{th} dimension, and c_1, and c_2 are scaling factors that determine the relative "pull" of $pbest$ and $gbest$. The random number function $rand(\ )$ produces a value between 0.0 and 1.0.

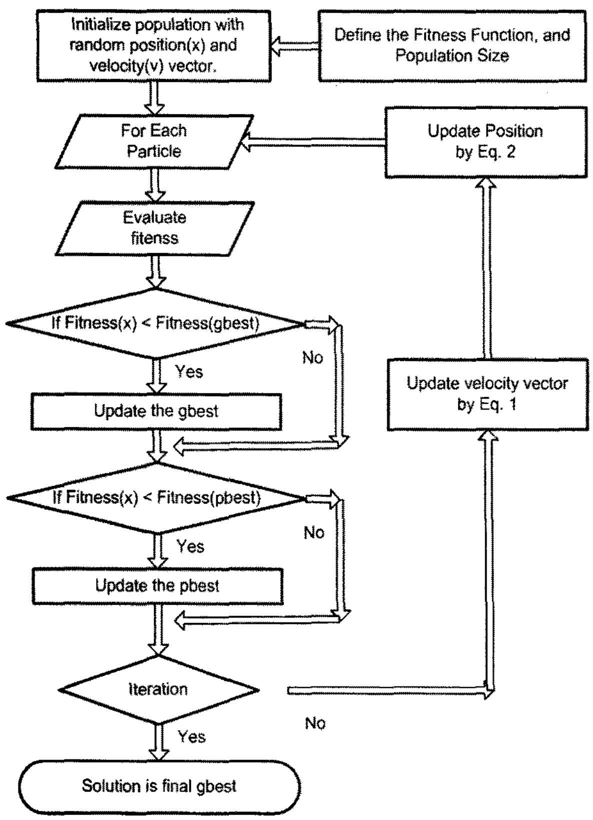


그림 1. PSO 알고리즘 순서도

Fig. 1. Flowchart of the PSO algorithm.

Next, the position of each particle is updated using the following equation

$$x_n^{t+1} = x_n^t + \Delta t * v_n^t \quad (2)$$

where Δt is the time index of the current and previous iterations. Particles find the best position by repeating this process. It is similar to the activity of a bee flying through the problem space to find the best position.

III. Array Design

In this paper, we are interested in designing the geometry of the array with the lowest SLL and the narrowest beamwidth. Initially, the array geometry is as shown in Fig. 2. First of all, the mutual couplings in a real array are not considered. If we have 2N isotropic radiators placed symmetrically along the x-axis, the array factor could be written as

$$AF(\theta) = 2\sum_{n=1}^{N} I_n \cos\left[kx_n \cos(\theta) + \alpha_n\right] \quad (3)$$

where, k is the wave number, and I_n, x_n and α_n are the excitation amplitude, position, and phase, respectively, of the n^{th} element. If we assume a uniform excitation phase, $\alpha_n = 0$ the array factor can

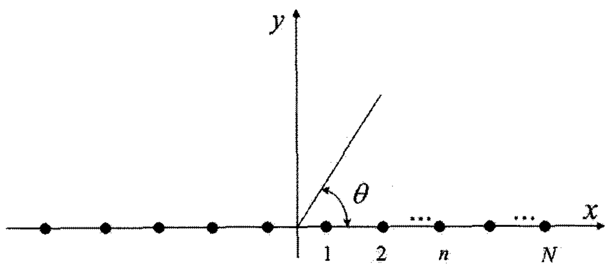


그림 2. 2N개의 소자가 대칭적인 선형 어레이 구조

Fig. 2. Geometry of the 2N-element symmetric linear array.

be written as

$$AF(\theta)=2\sum_{n=1}^{N} I_n \cos\left[kx_n \cos(\theta)\right] \quad (4)$$

The PSO algorithm is used to optimize the positions, x_n, and the excitation amplitudes, I_n, of the N elements. First, we optimize the two parameters separately for comparison. Then, we optimize them simultaneously to obtain the array pattern with the lowest SLL or the narrowest beamwidth.

1. Search the optimized positions and amplitudes separately

In this section, the 10 element array with the low SLL is designed by optimizing the positions and amplitudes separately using the PSO. To demonstrate the superior performance of the PSO, the optimized array patterns are compared with the uniform and the Dolph-Tschebyscheff array patterns.

For the first example, the positions of the uniform array were optimized randomly using the PSO[14]. To speed up the PSO algorithm, we uniformly initialized the particle positions at a distance of $\lambda/2$ between neighboring elements in stead of distributing them randomly. In the all PSO processes in this paper, the scaling factors c_1 and c_2 are both set to 2[18] and the inertial weight ω varied linearly from 0.9 to 0.4 over the iterations[19]. We selected an arbitrary population size of 20 for this example.

There are a number of possible fitness functions that produce the best results. For this paper, we obtained the fitness function through trial and error, and it can be expressed as

$$Fitness=\frac{1}{\phi_{d4}}\left[p_1\int_0^{\phi_{d1}}|AF(\theta)|^2 d\theta + p_2\int_{\phi_{d1}}^{\phi_{d2}}|AF(\theta)|^2 d\theta + p_3\int_{\phi_{d2}}^{\phi_{d3}}|AF(\theta)|^2 d\theta + p_4\int_{\phi_{d3}}^{\phi_{d4}}|AF(\theta)|^2 d\theta\right] \quad (5)$$

where, p_1 ,p_2, p_3 and p_4 are the weights for evaluating the array pattern, and ϕ_{d1}, ϕ_{d2}, ϕ_{d3} and ϕ_{d4} are the divided angles to weigh. Generally, the side lobes near the main beam tend to have higher SLL values than the others and so are given a higher weight coefficient. This permits efficient array pattern synthesis. In this example, the weights (p_1 ,p_2, p_3 and p_4) were determined to be 1.0, 1.1, 1.3, and 1.55, respectively, through several trials in our optimization processes. The divided angles (ϕ_{d1}, ϕ_{d2}, ϕ_{d3} and ϕ_{d4}) were set to 37°, 54°, 66°, and 88°, based on the null positions, respectively.

The array pattern optimized using the PSO and the uniform array pattern are shown in Fig. 3. The PSO array exhibits lower SLL (-17.2dB vs. -12.97dB) and narrower beamwidth (22° vs. 23.2°) than the uniform array. However, there are more side lobes, and the array size is somewhat larger. The positions of the 10 elements for the uniform array and PSO array are shown in Table 1.

The convergence curve of the fitness value as a function of the number of iterations for the 10-element array is shown in Fig. 4. The fitness value starts at about 50 and quickly drops to a constant value of about 34 in about 200 iterations. Fig. 5 shows the convergence curves of the velocity and position vectors of particle #1. After about 200 iterations, the velocity and distance vectors were converged to a constant value. The zero velocity in Fig. 5 (a) means the particle no longer moves to find the best position because it has already succeeded in

표 1. 균일급전 선형 어레이와 균일급전 PSO 어레이의 10개 소자의 간격. 표의 숫자는 $\lambda/2$로 표본화 하였다

Table 1. The positions of the 10 elements for the uniform array and PSO array. The positions are normalized with respect to $\lambda/2$.

Element No.	±1	±2	±3	±4	±5
Uniform	±0.5	±1.5	±2.5	±3.5	±4.5
PSO	±0.479	±1.509	±2.504	±3.842	±5.202

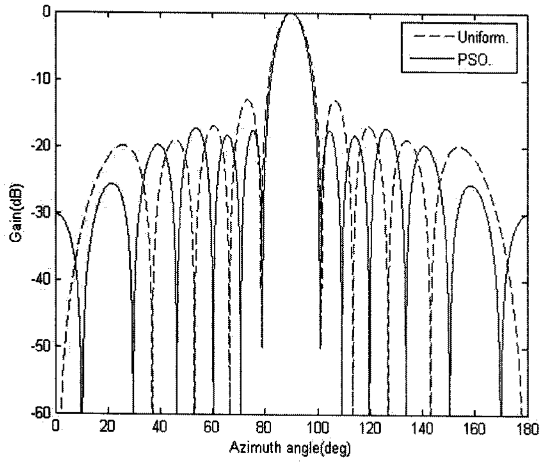


그림 3. 어레이 소자의 간격을 조절하여 최적화된 어레이 패턴

Fig. 3. Array patterns optimized by controlling the positions of the array elements.

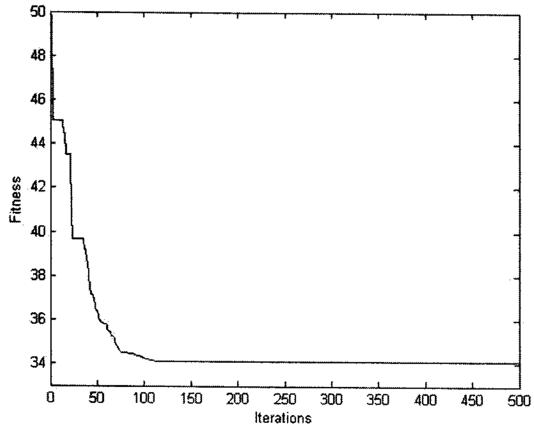
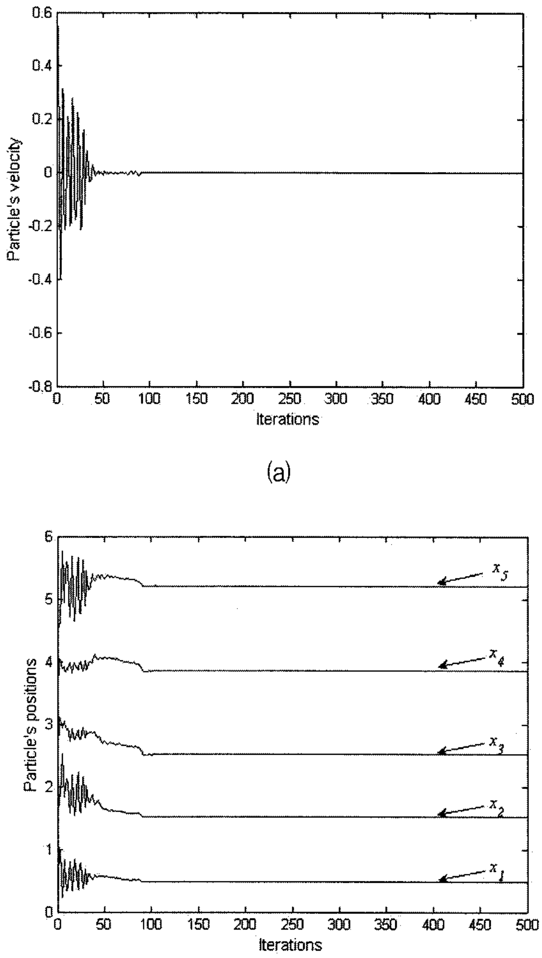


그림 4. 그림 3의 적합도 함수의 수렴곡선

Fig. 4. Convergence curve of the fitness value of the Fig. 3.

finding it.

For the second example, we started with the non-uniform Dolph-Tschebyscheff array distribution for 10 elements spaced at $\lambda/2$ with an SLL of -26dB, and optimized it to suppress the SLL using the PSO. The population size was the same as in the first example. However, the weights (p_1 ,p_2, p_3 and p_4) were determined to be 0.6, 1.2, 1.8, and 5.0, respectively, through several trials. The divided angles (ϕ_{d1}, ϕ_{d2}, ϕ_{d3} and ϕ_{d4}) were set to 35°, 50°, 62°, and 78°, respectively. The resulting optimized array pattern with the SLL of -28.4 dB and beamwidth of 34.6° is shown in Fig. 6. It presents



(b)

그림 5. 입자 #1의 (a)속도와 (b) 간격의 수렴곡선

Fig. 5. Convergence curves for (a) velocity and (b) position of particle #1.

표 2. Dolph-Tschebyscheff 배열과 PSO 어레이의 10 개 소자의 급전크기.

Table 2. The excitation amplitudes of the 10 elements for the Dolph-Tschebyscheff array and PSO array.

Element No.	±1	±2	±3	±4	±5
Dolph	1	1.357	1.974	2.493	2.798
PSO	±0.7829	±1.3007	±1.9742	±2.5431	±2.8964

that the 2.4dB decrease in SLL has the side effect of a 2.2° increase in beamwidth.

The convergence curve of the fitness values as a function of the number of iterations for the 10-element array is shown in Fig. 7. The fitness value converged to a constant after about 100

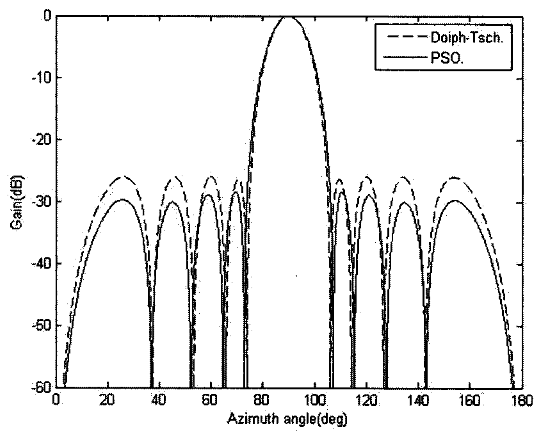


그림 6. 어레이 소자의 급전 크기를 조절하여 최적화된 어레이 패턴

Fig. 6. Array patterns optimized by controlling the excitation amplitudes of the array elements.

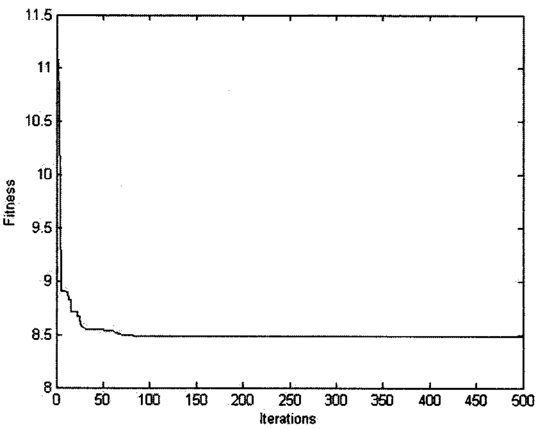


그림 7. 그림 6의 적합도 함수의 수렴곡선

Fig. 7. Convergence curve of the fitness value of the Fig. 6.

iterations. Table 2 shows the excitation amplitudes of the 10-element Dolph-Tschebyscheff array with an SLL of -26dB and the PSO array.

2. Search the optimized positions and amplitudes simultaneously

As shown in Fig. 3 and 6, there is a limit to suppressing the SLL by optimizing only one parameter, either the positions or the excitation amplitudes. The best array pattern with the lowest SLL or the narrowest beamwidth can be obtained by optimizing the two parameters simultaneously. This is illustrated in the next two examples, which start with the positions and the excitation amplitudes from

표 3. SLL이 -26dB와 -43dB인 어레이 패턴과 최적의 SLL값을 갖는 PSO 어레이 패턴의 급전크기와 소자간격. 간격의 숫자는 $\lambda/2$로 표본화 하였다

Table 3. Geometries of the 10 elements array of Dolph-Tschebyscheff array with SLL of -26dB, -43dB and the PSO array with the lowest SLL. The position are normalized with respect to $\lambda/2$.

Element No.	±1	±2	±3	±4	±5
	Positions				
Dolph (-26dB)	±0.5	±1.5	±2.5	±3.5	±4.5
Dolph (-43dB)	±0.5	±1.5	±2.5	±3.5	±4.5
PSO	±0.581	±1.884	±3.342	±4.859	±6.396
	Amplitudes				
Dolph (-26dB)	1	1.357	1.974	2.496	2.798
Dolph (-43dB)	1	2.783	5.364	7.971	9.623
PSO	0.427	1.320	2.513	3.407	3.389

the Dolph-Tschebyscheff array distribution with 10 elements spaced at $\lambda/2$ with the SLL of -26dB. The Dolph-Tschebyscheff array with the SLL of -26dB has the beamwidth of 32.4°.

For the third example, the array pattern with the lowest SLL can be obtained using the fitness function modified as follows:

$$Fitness = \frac{1}{\phi_{d4}}\left[p_1\int_0^{\phi_{d1}}|AF(\theta)|^2 d\theta + p_2\int_{\phi_{d1}}^{\phi_{d2}}|AF(\theta)|^2 d\theta + p_3\int_{\phi_{d2}}^{\phi_{d3}}|AF(\theta)|^2 d\theta + p_4\int_{\phi_{d3}}^{\phi_{d4}}|AF(\theta)|^2 d\theta + p_5\int_{\phi_{d4}}^{\phi_{d5}}|AF(\theta)|^2 d\theta + p_6\int_{\phi_{d5}}^{\phi_{d6}}|AF(\theta)|^2 d\theta + p_7\int_{\phi_{d6}}^{\phi_{d7}}|AF(\theta)|^2 d\theta\right] \quad (6)$$

In (6), the weights, p_i (i= 1 to 7), were set to 1.1, 1.3, 1.8, 2.2, 3.4, 5.0, and 10, respectively, based on the results of several trials. The divided angles, p_i (i= 1 to 7), were set to 9°, 24°, 36°, 46°, 55°, 63°, and 76° because of the increase in null points resulting from the lower SLL and narrower beamwidth. We chose a population size of 100 to increase the probability of finding the best result.

The PSO array pattern and two Dolph-Tschebyscheff array patterns with SLLs of -26 dB and -43 dB are shown in Fig. 8. The PSO array pattern with the SLL of -43dB and 32.2° beamwidth is obtained by optimizing the Dolph-Tschebyscheff array with the SLL of -26 dB and 32.4° beamwidth. If we design the Dolph-Tschebyscheff array with the SLL of -43 dB, the beamwidth should be 46°. It is 8° wider than the PSO's beamwidth. The number of side lobes of the PSO array pattern is a few increased. Table 3 shows the positions and amplitudes for the 10 element arrays of Fig. 8.

For the fourth example, the array pattern with the narrowest beamwidth can be obtained by modifying the fitness function in the PSO algorithm as follows:

$$\begin{aligned} Fitness = \frac{1}{\phi_{d4}} \Bigg[& p_1 \int_0^{\phi_{d1}} |AF(\theta)|^2 d\theta \\ & + p_2 \int_{\phi_{d1}}^{\phi_{d2}} |AF(\theta)|^2 d\theta + p_3 \int_{\phi_{d2}}^{\phi_{d3}} |AF(\theta)|^2 d\theta \\ & + p_4 \int_{\phi_{d3}}^{\phi_{d4}} |AF(\theta)|^2 d\theta + p_5 \int_{\phi_{d4}}^{\phi_{d5}} |AF(\theta)|^2 d\theta \\ & + p_6 \int_{\phi_{d5}}^{\phi_{d6}} |AF(\theta)|^2 d\theta + p_7 \int_{\phi_{d6}}^{\phi_{d7}} |AF(\theta)|^2 d\theta \Bigg] \\ & + \beta \times BW \end{aligned} \tag{7}$$

where, β is the weight of the beamwidth (BW) set to 2.3 based on the results of several trials. On the right-hand side of (7), an extra term, $\beta \times BW$, has been added to account for the beamwidth as well as the SLL. The population size is the same as in the third example. The weights, p_i (i= 1 to 7), were set arbitrarily to 1.2, 1.25, 1.3, 1.8, 2.5, 3.8, and 11.2. The divided angles, ϕ_i (i= 1 to 7), were 12°, 23°, 37°, 48°, 60°, 70°, and 78°. The PSO array pattern and the two Dolph-Tschebyscheff array patterns with beamwidths of 32.4° and 24.2° are shown in Fig. 9. The PSO array pattern with the SLL of -26 dB and 24.2° beamwidth is obtained by optimizing the Dolph-Tschebyscheff array with -26 dB SLL and 32.4° beamwidth. If we design the Dolph-Tschebyscheff array with 24.2° beamwidth, the SLL should be -16 dB. It is 10 dB higher than the PSO's SLL. Table 4 shows the positions and amplitudes of the 10-element arrays of Fig. 9.

In summary, the positions and amplitudes were optimized jointly to overcome the limitation of suppressing the SLL by adjusting only one parameter

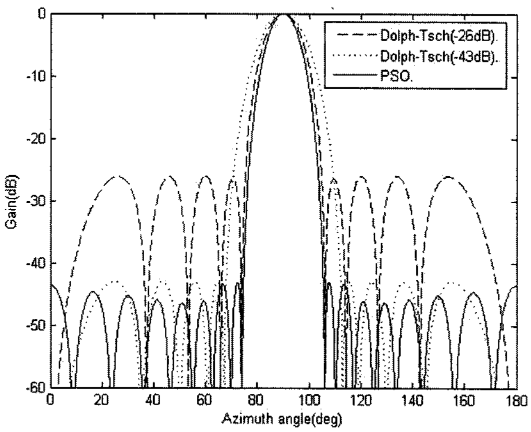


그림 8. SLL이 -26dB와 -43dB인 Dolph-Tschebyscheff 어레이 패턴과 최적의 SLL값을 갖는 PSO 어레이 패턴

Fig. 8. Array patterns for Dolph-Tschebyscheff arrays with SLL of -26dB and -43dB and the PSO array with the lowest SLL.

표 4. 빔폭이 32.4°와 24.2°인 어레이 패턴과 가장 좁은 빔폭을 갖는 PSO 어레이 패턴의 급전크기와 소자간격. 간격의 숫자는 $\lambda/2$로 표본화 하였다

Table 4. Geometries of the 10 elements array of Dolph-Tschebyscheff array with beamwidth of 32.4°, 24.2° and the PSO array with the narrowest beamwidth. The position are normalized with respect to $\lambda/2$.

Element No.	±1	±2	±3	±4	±5
	Positions				
Dolph (32.4°)	±0.5	±1.5	±2.5	±3.5	±4.5
Dolph (24.2°)	±0.5	±1.5	±2.5	±3.5	±4.5
PSO	±0.607	±1.817	±3.125	±4.568	±6.054
	Amplitudes				
Dolph (32.4°)	1	1.357	1.974	2.496	2.798
Dolph (24.2°)	1	0.6748	0.8266	0.9404	1.0014
PSO	1.306	2.247	2.997	3.281	3.549

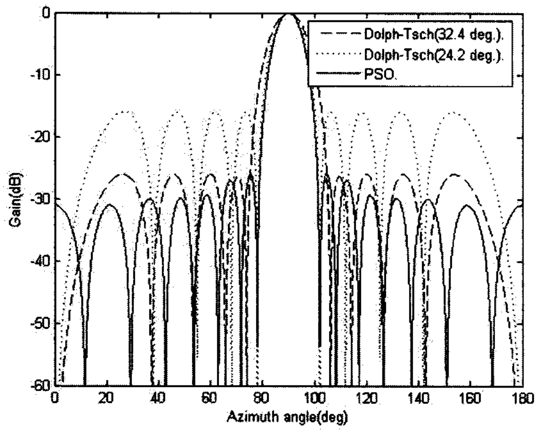


그림 9. 빔폭이 32.4°와 24.2°인 Dolph-Tschebyscheff 어레이 패턴과 가장 좁은 빔폭을 갖는 PSO 어레이 패턴

Fig. 9. Array patterns for Dolph-Tschebyscheff arrays with beamwidth of 32.4° and 24.2° and the PSO array with the narrowest beamwidth.

at a time. In the PSO process, the performance of the fitness function was improved by giving different weights to each angular sector in the pattern. Comparing the PSO arrays in the third and fourth examples with the Dolph-Tschebyscheff array with a -26 dB SLL, the PSO array has an SLL value that is 17 dB lower with the almost same beamwidth of 32.4°, or has an 8° narrower beamwidth with the same -26 dB SLL. However, the array size is slightly larger and the number of side lobes is higher. These results in this paper are useful when someone design the array. He can know how well the array is designed as compared to the best array.

Ⅳ. 결 론

In this paper, we designed a randomly excited and randomly spaced linear array with either the lowest SLL or the narrowest beamwidth. We used the PSO to achieve the best array geometry by simultaneously and randomly optimizing the positions and excitation amplitudes of the fixed elements.

In the PSO processes used here, the fitness function was modified to synthesize the array pattern efficiently by giving a higher weight coefficient to the side lobe near the main beam. The PSO patterns of each particle were divided near the null points and different weight coefficients were given to each angular sector. The divided angles and weights were obtained through several trials. In addition, an extra term, $\beta \times BW$, was added to the fitness function in the last example to account for the beamwidth as well as the SLL.

Our examples showed that when the positions and amplitudes of the 10 element array were simultaneously adjusted by using the PSO, the best array patterns with the lowest SLL or the narrowest beamwidth could be obtained. The PSO arrays have the lowest SLL value, -43dB at a beamwidth of 32.2°, or the narrowest beamwidth of 24.2° at -26 dB SLL.

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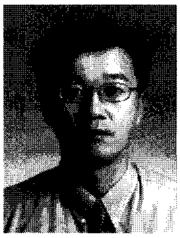

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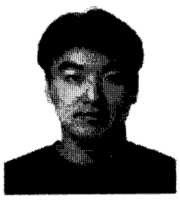

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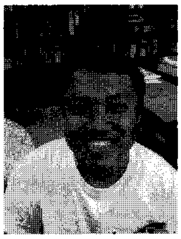

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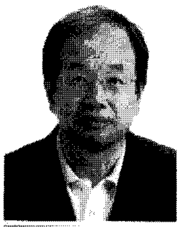

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