Antenna Array Pattern Synthesis for 5G Wireless Communications

[1]Nancy Ghattas, [1]Atef M.Ghuniem, [1]Abdelazeem A.Abdelsalam and [1]Ahmed Magdy

[1]Electrical Engineering Department, Suez Canal University, Ismailia, Egypt

Abstract. One of the potential 5G communication techniques that could enable the explosive growth of wireless communication services is beamforming, which helps make effective use of the existing frequency band and maintain signal quality. The beamforming technique aims to shape the radiation pattern to be targeted at the desired user and effectively suppress noise and interference. In this paper, beamforming optimization using the Hybrid Particle Swarm Optimization algorithm and Gravitational Search Algorithm technique (PSOGSA) using Linear Antenna Array (LAA) by suppressing the Sidelobe Level (SLL) of LAA is presented. The optimization process is introduced to find the optimum elements amplitude excitation, and positions in the array. PSOGSA optimization result is illustrated in comparison with other existing algorithms. Simulation results demonstrate the effectiveness of using PSOGSA, which has achieved the most suppressed SLL. The recommended approach can be applied to different antenna array designs and is successful in resolving beamforming optimization problems.

Keywords: Antenna arrays, Beamforming, Hybrid algorithms, Optimization, Sidelobe level, Signal processing.

1 Introduction

In order to effectively use the available frequency band while providing signal coverage and raising signal data rates, it is important to keep up with the progress of wireless communication developments and the growing number of users. An emerging technology in 5G wireless communication systems is smart antennas. It offers strong wireless network solutions that enhance communication services, regulate power, signal coverage, and multipath fading. Adaptive Beamforming (ABF), which improves reception and transmission while minimizing a number of millimeter wave band flaws like increased propagation losses and the vulnerability to obstruction blocking, is one of the most important and well-known parts of the development of recent technologies of antennas [1, 2]. The effectiveness of the conventional beamforming methods has been established. However, addressing the electromagnetic issue might lead to discontinuous and non-differentiable zones. It is therefore of utmost importance to implement an appropriate optimization method that can protect computing resources and generate a global optimum. However, due to the increasing needs for wireless communication, smart antennas must place a higher emphasis on the usage of beamforming optimizations [3, 4].

A wide variety of algorithms such as Runnge Kuta Optimizer (RUN) [5], Slim Mold Algorithm (SMA) [6]. Also Particle Swarm Optimization (PSO) that is widely used in optimization problems [7-11]. Harris Hauk Optimization (HHO) [12], Gravitational Search Algorithm (GSA) [13-15], and numerous initiatives have been launched in the area of research to improve antenna arrays using various methods [16]. There are numerous studies that use beamforming for linear antenna arrays (LAA). For example, antenna arrays pattern synthesis using Taguchi's optimization (Tag.) is presented in [17]. Cuckoo Search (CS) algorithm is used previously in the beamforming of different antenna arrays [18]. Genetic Algorithm (GA) is used in various optimization fields [19]. Differential Evolution (DE) [20], Biogeography-Based Optimization (BBO) [21], and Particle Swarm Optimization that is hybridized with Gravitational Search Algorithm (Hybrid PSOGSA) [22-23] are employed in many optimization problems.

This work investigates PSOGSA-based LAA beamforming optimization. To identify the amplitude excitations and ideal placement of array elements, PSOGSA is employed. Compared to other methods, the optimization has used PSOGSA to produce suppressed Sidelobe Level (SLL) using a less number of antennas.

This paper is arranged as follows: The introduction is in section 1. Section 2 illustrates the problem formulation, the design of LAA and the array factor, and the objective function. The PSOGSA method is illustrated in Section 3. Simulation results for the comparison of different algorithms is found in Section 4. The study's final conclusions are presented in Section 5.

2 Problem formulation

For antenna array design optimization, different array parameters can be controlled. Fig. 1 show the antenna array based on LAA topology using 2N array elements along the x-axis.

During beamforming, the amplitude excitation and position for array element can be defined to minimize the SLL at certain directions. The following represents the antenna array factor:

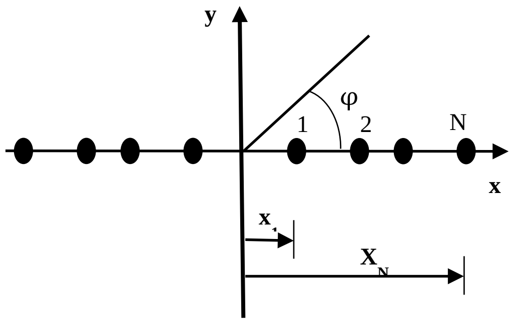

Fig. 1. 2N-elements LAA.

$$\textbf{Array Factor}\ (\varphi) = 2\sum_{n=1}^{N} I_n \cos(kx_n \cos\varphi + \alpha_n), \quad (1)$$

where I_n represents amplitude excitation; N is the array elements number; x_n is the location of array elements, α_n is the phase excitation of the array elements; and φ represents the azimuth angle. The wave number is k.

In this study, PSOGSA algorithm is employed to search the optimum antenna array parameters for achieving the most minimized SLL. The following equation must be used to minimize the SLL. For SLL suppression, the normalized fitness function is formulated as:

$$\textbf{Fitness function} = \min(\max\{20\log\left|\frac{\text{Array Factor}(\varphi_{SL})}{\text{Array Factor}(\varphi_0)}\right|\}), \quad (2)$$

where φ_{SL} represent the sidelobe limited area to be minimized and Array Factor(φ_0) describe the maximum array factor (0 dB) obtained at $\varphi_0 = 90^0$.

3 Particle Swarm Optimization and Gravitational Search Algorithm (PSOGSA)

Several heuristic optimization algorithms were introduced using hybridization methods where different algorithms are hybridized in different levels. PSOGSA is presented by Mirjalili in [22], which is a hybrid algorithm that is a merge of (GSA) and (PSO). PSOGSA were used to a CAA, demonstrating the possibility of antenna pattern synthesis [23]. In the following, we present a study and explanation of conventional PSO and GSA.

A. Particle Swarm Optimization

Through order to discover the optimum solution, PSO, an evolutionary computational technique that mimics the bird groups social behavior, uses a number of particles as candidate solutions that fly through the search space. The particles in PSO are considered the location at time t, velocity, and the best solution to update its location. PSO is described as below:

$$\boldsymbol{Vel_i(t+1) = d \times Vel_i(t) + C_1 \times rand \times ax_i(t)}$$

$$\boldsymbol{+C_2 \times rand \times \left(gbest - y_i(t)\right)} \quad (3)$$

$$\boldsymbol{y_i(t+1) = y_i(t) + Vel_i(t+1).} \quad (4)$$

The equation variables are defined as follows:
Vel_i is the particles velocity, y_i represents particle i current location, d is a constant, $rand$ is a random number within [0,1], and $gbest$ is the best solution of the agents.
The PSO initial step is to locate the particles randomly. Then, the particles velocities are calculated in (3). Then, the position of particles is calculated as (4). This process will continue until find the end solution.

B. Gravitational Search Algorithm

GSA draws its inspiration from Newton's law for gravity. The masses of agents in GSA are proportional to their value of objective function. The gravitational forces between all masses draw them towards one another. According to how far apart they are, the heavier masses pull the other masses. The GSA was mathematically described by the following. Suppose a system with N agents. All of the agents are initially placed around the search area. The gravitational forces exerted by agent j on agent i at a certain time t are found as below for all times:

$$\boldsymbol{F(t) = G_r \frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t)+\varepsilon}\left(x_j^d(t) - x_j^d(t)\right)}, \quad (5)$$

Where M_{aj} is the gravitational mass for j, M_{pi} is the gravitational for i, gravitational constant is represented by G_r is at t, and ε is a constant. The Euclidian distance between i and j is defined by R_{ij}. G_r is calculated as below:

$$G_r = G_0 \times exp(-\alpha \times \frac{iter}{max}) \quad (6)$$

Where α is the descending factor, G_0 describes the initial factor, $iter$and max represent the current iteration and the maximum iteration, respectively.
ac_i is the acceleration of i at t iteration, and is calculated as follows:

$$ac_i(t) = \frac{F_r(t)}{M_{ii}(t)}, \quad (7)$$

where M_{ii} is the gravitational mass. $\boldsymbol{F_r}$ is the force that implied to agent i is described by:

$$\boldsymbol{F_r}(t) = \sum_{j=1, j\neq i}^{N} rand_j\, F(t), \quad (8)$$

Where $rand_j$ random range is [0,1]. F is the gravitational forces.

C. The hybrid PSOGSA algorithm

PSOGSA combines the features of GSA and PSO into a single hybrid algorithm. In order to optimize beamforming, the hybridization of these techniques is as below [22]:

$$Vel_i'(t+1) = w \times Vel_i'(t) + c_1' \times \text{rand} \times ac_i(t) + c_2' \times \text{rand} \times \left(\text{gbest} - y_i'(t)\right), \qquad (9)$$

where Vel_i' is the velocity of the agent, w, c_1' and c_2' are constants, the best solution is $gbest$, $rand$ is a random number between 0 and 1; y_i' represents particle i current location where are updated by:

$$y_i'(t+1) = y_i'(t) + Vel_i'(t+1). \qquad (10)$$

PSOGSA algorithm is shown in Fig. 2. The initialization of each agent is random. GSA parameters are determined. Every iteration should update the best solution. Finally, the positions of agents are updated through (9) and (10). When reaching the end criteria after updating the velocities and positions of particle, the function will stop.

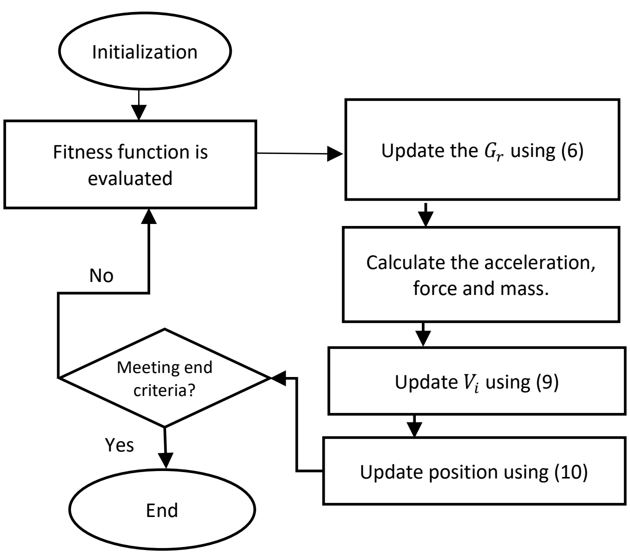

Fig 2. PSOGSA algorithm flow chart.

4 Simulation results

LAA array pattern synthesis is done using PSOGSA to obtain the most suppressed SLL. The PSOGSA parameters used are as follows: number of iterations equal to 400, and search agents equal to 25. The simulation results are illustrated in comparing with other algorithms: PSO [9], GSA [14], CS [18], and BBO [21].

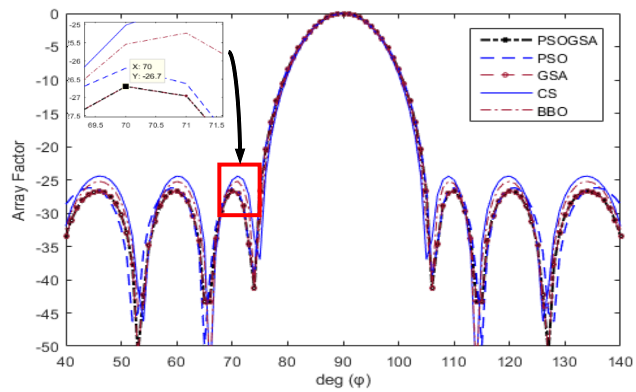

Fig. 3. Amplitude optimization array factors of LAA (N=10)

Table 1 Amplitude optimization SLL, FNBW, and optimum values of amplitude excitation of LAA (N=10)

Method	Amplitude excitation (I_n)	Max SLL (dB)	FNBW
PSOGSA	0.9923, 0.8853, 0.6982, 0.4755, 0.3374	-26.7	32°
GSA	0.8994, 0.8024, 0.6328, 0.4309, 0.3058	-26.7	32°
PSO	1.0, 0.9010, 0.7255, 0.5120, 0.4088	-24.62	32°
CS [14]	1.0, 0.9019, 0.7273, 0.5153, 0.4157	-24.44	30°
BBO [13]	1.0, 0.8988, 0.7189, 0.5025, 0.3862	-25.21	31.4°

4.1 Optimization of Amplitude excitation(I_n):

SLL suppression will be presented in this section for LAA by optimizing amplitude excitations (I_n) and phase is fixed to be ($\alpha_n = 0$) and elements spacing is constant ($\lambda/2$) as mentioned in (2). Array factor in [18] will be as below:

$$\text{Array Factor } (\varphi) = 2\sum_{n=1}^{N} I_n \cos((n-0.5)\pi\cos\varphi). \quad (11)$$

The following cases are performed for $\varphi_{SL} = [0°, 76°]$ to suppress the SLL. The optimization lower and upper limits for amplitude excitation is within the range [0,1]. The comparison with other algorithms; BBO, CS, PSO, and GSA is presented in this section.

Example 1 illustrates the design of LAA with 10 antenna elements. Table 1 and Fig. 3 presents the simulation results. PSOGSA provides SLL of -26.7dB, which is equal to SLL and FNBW for GSA. SLL for PSO is equal to -24.62dB, for CS is –24.44dB, and for BBO is -25.21dB.

Example 2 illustrates the design of LAA with 24 antenna elements. The following cases are performed for $\varphi_{SL} = [0°, 83°]$ to suppress the SLL. Table 2 and Fig. 4 presents

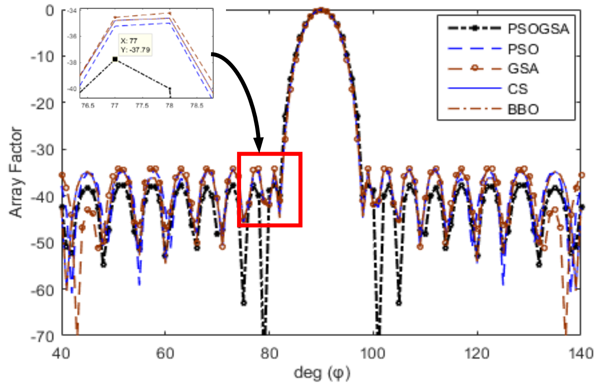

Fig. 4. Amplitude optimization array factors of LAA (N=24)

Table 2 Amplitude optimization SLL, FNBW, and optimum values of amplitude excitation of LAA (N=24)

Method	Amplitude excitation (I_n)	Max SLL (dB)	FNBW
PSOGSA	0.9839, 0.9834, 0.9088, 0.8315, 0.7694, 0.6289, 0.5559, 0.4254, 0.3240, 0.2453, 0.1763, 0.1198	-37.79	16°
GSA	0.8264, 0.8240, 0.7915, 0.7096, 0.6555, 0.6074, 0.4992, 0.4099, 0.3420, 0.2716, 0.1991, 0.2073	-34.02	16°
PSO	1.0, 0.9712, 0.9226, 0.8591, 0.7812, 0.6807, 0.5751, 0.4768, 0.3793, 0.2878, 0.2020, 0.2167	-34.46	15.6°
CS [14]	1.0, 0.9773,0.9281, 0.8573, 0.7753, 0.6854, 0.5767, 0.4684, 0.3836, 0.2749, 0.2227, 0.20	-34.5	14.8°
BBO [13]	1.0, 0.9796, 0.9011, 0.8581,0.7375, 0.6103, 0.5205, 0.4463, 0.3016, 0.2236, 0.1495, 0.0957	-37.14	17.2°

the simulation results. PSOGSA provides SLL of -37.79dB, which is equal to SLL and FNBW for GSA. SLL for PSO is equal to -34.46dB, for CS is –34.5dB, and for BBO is -37.14dB.

It can be concluded from examples 1 and 2 that there is no noticeable difference in SLL for PSOGSA compared with other methods in the case of 10 element array, while in the case of increasing the array element numbers to 24, compared to other techniques, PSOGSA yields better improvements.

4.2 Optimization of elements positions(x_n):

SLL suppression will be presented in this section for LAA by optimizing array element position(x_n), and phase is fixed to be $(\alpha_n = 0)$ and using uniform amplitude $(I_n = 1)$ as mentioned in (2). Array factor in [18] will be as below:

$$\text{Array Factor}(\varphi) = 2\sum_{n=1}^{N} \cos(kx_n \cos\varphi). \qquad (12)$$

We have examined the two cases of using 10, and 24 array elements. In a linear array, antenna location is crucial because mutual coupling effects can result from placing antennas too close together, whereas grating lobes can result from placing antennas too far apart. The element spacing can changed through [0.5 λ, 1.5 λ].

In example 3, the optimization is applied to LAA with 10 antenna elements. Table 3 and Fig. 5 illustrate the optimization results. The following cases are performed for $\varphi_{SL} = [0°, 78°]$ to suppress the SLL. PSOGSA provides SLL of -20.93dB. SLL for PSO is equal to -18.9dB, for GSA is –18.9dB.

Example 4 illustrates the design of LAA with 10 antenna elements. Table 4 and Fig. 6 presents the simulation results. The following cases are performed for $\varphi_{SL} = [0°, 78°]$ to

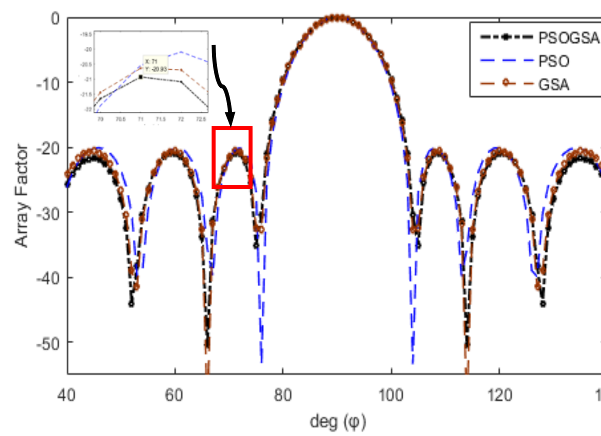

Fig. 5. Position optimization array factors of LAA (N=10)

Table 3. Position optimization SLL, FNBW, and optimum values of element positions of LAA (N=10)

Method	Element position (x_n)	PSLL (dB)	FNBW
PSOGSA	0.4491, 1.4427, 2.4511, 3.7226, 5.1891	-20.93	22°
GSA	0.4855, 1.0220, 1.9858, 2.8838, 4.1815	-18..9	22°
PSO	0.2146, 0.5999, 1.0611, 1.5870, 2.25	-18.70	22°

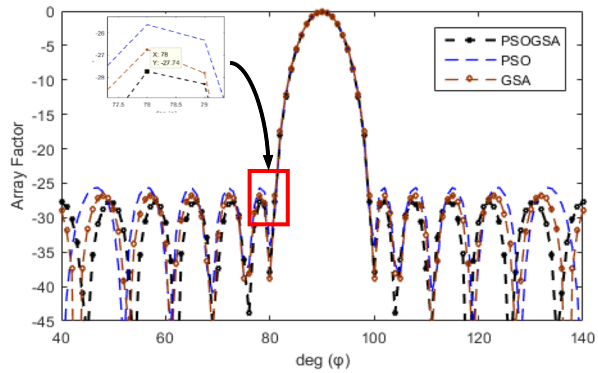

Fig. 6. Position optimization array factors of LAA (N=24)

Table 4. Position optimization SLL, FNBW, and optimum values of element positions of LAA (N=24)

Method	Element position (x_n)	PSLL (dB)	FNBW
PSOGSA	0.4393, 0.5142,1.4782, 1.3629, 2.2165,2.9571, 2.9155,4.1375,4.3447, 5.4059,6.3278, 7.6418	-27.74	20°
GSA	0.3997,0.6369, 1.4249, 1.9090, 2.3104, 3.3377, 3.4260, 4.4633, 5.1102, 6.0487, 7.1850, 8.5956	-26.7	20°
PSO	0.3577, 1.1489, 1.9750, 2.7863, 3.5446, 4.3750, 5.3146, 6.2584, 7.1933, 8.4507, 9.8986, 11.4673	-24.55	20°

suppress the SLL. PSOGSA provides SLL of -27.74dB. SLL for PSO is equal to -24.55dB, for GSA is –26.7dB.

4.3 Optimization of elements positions (x_n) and amplitude excitations$(\mathbf{I_n})$:

SLL suppression will be presented in this section for LAA by optimizing array both element position(x_n) amplitude excitations $(\mathrm{I_n})$ on the same time while the phase is fixed to be$(\alpha_n = 0)$. Array factor in [18] will be as below:

$$\text{Array Factor}(\varphi) = 2\sum_{n=1}^{N} \mathrm{I_n} \cos(kx_n\cos\varphi). \qquad (12)$$

We have examined the optimization in example 5 using 10 array elements. Table 5 and Fig. 7 illustrate the optimization results. The following cases are performed for $\varphi_{SL} = [0°, 81°]$ to suppress the SLL. PSOGSA provides SLL of -33.64dB. SLL for PSO is equal to -32.21dB, for GSA is –29.55dB.

4.4 Results discussion:

From the above analysis, it can be concluded that PSOGSA results the most minimized SLL over the other employed

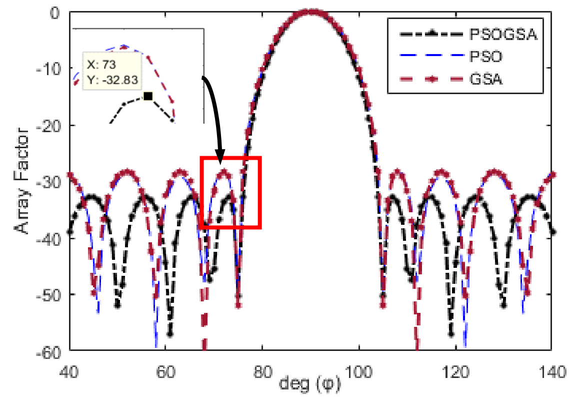

Fig. 7. Position and amplitude optimization array factors of LAA (N=10)

Table 5. Position and amplitude optimization SLL, FNBW, and optimum values of element positions of LAA (N=10)

Method		Amplitude $(\mathbf{I_n})$/ Position (x_n)	SLL (dB)	FNBW
PSOGSA	A	1.0000, 0.6012, 0.5839, 0.4772, 0.2265/	-32.83	30°
	D	0.4948, 1.4561, 2.7155, 4.2045, 5.7045		
GSA	A	0.6287, 0.8757, 0.8873, 0.6858, 0.3690/	-29.55	30°
	D	0.3161, 0.9510, 2.1160, 3.4895, 4.9367		
PSO	A	0.1610, 0.3138, 0.8892, 0.8750, 0.5472/	-32.21	`30°
	D	0.5913, 1.8039, 3.0780, 4.4035, 5.7563		

techniques in the case of amplitude excitation optimization and also in element position optimization in the case of 10 and 24 element array. Additionally, it should be observed that all techniques minimize FNBW and minimize SLL when the number of array items is increased. From example 5, the optimization of both amplitude and position of elements results SLL minimization while FNBW is more wide than in single element optimization. It can be concluded that is very effective to optimize more than one parameter in the antenna array.

5 Conclusion

This paper demonstrated beamforming optimization of antenna arrays by employing the hybrid optimization algorithm. The optimization process was done for LAA optimal pattern synthesis by targeting the optimum amplitude excitations and spacing between array elements to suppress the SLL to the most minimized level to reduce signal interference. Other current algorithms are used to compare the results of the beamforming optimization. The simulation results demonstrate that PSOGSA beamforming of LAA is better to other approaches because it significantly reduces SLL. This demonstrates emphatically how effective PSOGSA is and how it may be used to address various beamforming optimization issues. Other antenna array shapes for beamforming applications can also be synthesized using it.

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