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Flower Pollination Algorithm for Adaptive Beamforming of Phased Array Antennas

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Abstract— This paper introduces the flower pollination algorithm (FPA) as an optimization technique suitable for adaptive beamforming of phased array antennas. The FPA is a new nature-inspired evolutionary computation algorithm that is based on pollinating behaviour of flowering plants. Unlike the other nature-inspired algorithms, the FPA has fewer tuning parameters to fit into different optimization problems. The FPA is used to compute the complex beamforming weights of the phased array antenna. In order to exhibit the robustness of the new technique, the FPA has been applied to a uniform linear array antenna with different array sizes. The results reveal that the FPA leads to the optimum Wiener weights in each array size with less number of iterations compared with two other evolutionary optimization algorithms namely, particle swarm optimization and cuckoo search.

Keywords—Adaptive beamforming; Cuckoo search (CS); Evolutionary optimization; Flower pollination algorithm (FPA); Particle swarm optimization (PSO); Phased array antennas.

I. Introduction

Adaptive beamforming of phased array antennas has been used extensively in modern radar and communication systems. By computing the excitation weights through a real-time optimization process, the adaptive beamforming technique has the ability to: 1) steer the main beam towards the desired signal or signal-of-interest (SOI) and 2) put nulls towards the direction of the interferers or signals-not-of-interest (SNOIs).

The nature-inspired evolutionary optimization algorithms such as genetic algorithm (GA), particle swarm optimization (PSO), and cuckoo search (CS) are capable of performing better and more flexible solutions than the classical optimization methods. In particular, the PSO algorithm has been applied to a variety of electromagnetic problems including beamforming [1] and antenna array synthesis [2]. It was shown in [3] that the PSO algorithm can outperform GA and other conventional algorithms for many optimization problems.

The CS algorithm which is based on the lifestyle of cuckoos was developed by Yang and Deb [4]; it is based on the obligate blood parasitic behaviour of some cuckoo species in combination with the Lévy flight behaviour of some birds. The CS algorithm has been applied to the optimization of antenna arrays [5] and antenna array synthesis [6]. In [4], simulations were carried out to compare the performance of the CS algorithm with the PSO and GA on various benchmark test functions, and it was found that the CS is more efficient in finding the global optima with higher success rate than both the PSO and the GA.

On the other hand, the flower pollination algorithm (proposed by Yang in 2012) [7] is a new population-based intelligent optimization algorithm simulating the flower pollination behaviour. By using a set of benchmark functions, FPA has proved to outperform

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both the GA and the PSO in obtaining better results and fast convergence rate [7].

In this paper, we show that the optimum Wiener weights of the phased-array antenna can be obtained by using the FPA. In particular, by minimizing a cost function representing the mean square error (MSE) between the weighted array output and a reference signal which is similar to the desired signal or highly correlated with it. In order to validate the performance of the FPA as an adaptive beamformer, it is applied on a uniform linear array (ULA) antenna with variable number of elements. Simulation results show that, unlike PSO, the FPA and CS converge to the exact Wiener weights in all configurations of The ULA. Moreover, the FPA has a faster convergence rate than both the PSO and CS.

II. Flower Pollination Algorithm (FPA)

FPA is the latest nature-inspired algorithm proposed by Yang in 2012 [7] inspired by the fertilization (pollination) process of flowers. The main purpose of a flower is ultimately reproduction via pollination. Flower pollination is typically associated with the transfer of pollen, and such transfer is often linked with pollinators such as insects, birds, bats, and other animals.

Pollination can be achieved by self-pollination or cross-pollination. Cross-pollination, or allogamy, means pollination can occur from pollen of a flower of different plant, while self-pollination is the fertilization of one flower, such as peach flowers, from pollen of the same flower or different flowers of the same plant, which often occurs when there is no reliable pollinator available.

Biotic, cross-pollination may occur at long distance, and the pollinators such as bees, bats, birds, and flies can fly a long distance, thus they can considered as the global pollination. In addition, bees and birds may behave as Lévy flight behaviour [8], with jump or fly distance steps obey a Lévy distribution. Furthermore, flower constancy can be used an increment step using the similarity or difference of two flowers.

In [7], the above characteristics of pollination process, flower constancy, and pollinator behaviour are idealized in the following four rules:

1) Biotic and cross-pollination are considered as global pollination process with pollen-carrying pollinators performing Lévy flights.
2) Abiotic and self-pollination are considered as local pollination.
3) Flower constancy can be considered as the reproduction probability is proportional to the similarity of two flowers involved.
4) Local pollination and global pollination are controlled by a switch probability $p \in [0, 1]$.

Due to the physical proximity and other factors such as wind, local pollination can have a significant fraction p in the overall pollination activities. In the global pollination step, flower pollens are carried by pollinators such as insects, and pollens can travel over a long distance. This ensures the pollination and reproduction of the most fittest, and thus we represent the most fittest as $\mathbf{g}^*$. The first rule can then be formulated as:

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + L(\mathbf{g}^* - \boldsymbol{x}_i^t) \quad (1)$$

where $\boldsymbol{x}_i^t$ is the solution vector (pollen) i at iteration t, $\mathbf{g}^*$ is the current best solution, and L is the strength of the pollination which is a step size randomly drawn from Lévy distribution. We draw $L > 0$ from a Lévy distribution:

$$L \sim \frac{\beta \Gamma(\beta) \sin(\frac{\pi\beta}{2})}{\pi} \frac{1}{s^{1+\beta}}, \quad (s \gg s_0 > 0) \quad (2)$$

where $\Gamma(\beta)$ is the standard gamma function, and this distribution is valid for large steps $s > 0$. In most cases, $\beta = 1.5$.

The local pollination (Rule 2) can be represented as:

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + \gamma(\boldsymbol{x}_j^t - \boldsymbol{x}_k^t) \quad (3)$$

where $\boldsymbol{x}_j^t$ and $\boldsymbol{x}_k^t$ are pollens from different flowers of the same plant species. The parameter γ is drawn from uniform distribution in the range from 0 to 1.

The FPA optimization algorithm is summarized by the pseudo code of Figure 1.

III. Wiener Solution

Assume an M-element ULA that receives a SOI, $s(k)$, arriving from angle θ_0 and N SNOIs, $i_n(k)$, arriving from angles θ_n ,(n = 1, …, N) (see Figure 2). The parameter k denotes the k^{th} time sample, each element is considered to be an isotropic source, while all the arriving signals are monochromatic with $N + 1 \leq M$. The received signal, $x_m(k)$, at the input of every m^{th} element (m = 1, …, M) includes additive, zero mean, white Gaussian noise, $n_m(k)$, with variance σ^2. Thus, the input vector is:

$$\mathbf{x}(k) = \mathbf{a}_0 s(k) + [\mathbf{a}_1\ \mathbf{a}_2 \dots \mathbf{a}_N][i_1(k)\ i_2(k) \dots i_N(k)]^T + \mathbf{n}(k) \quad (4)$$

where $\mathbf{a}_n = [1\ \ e^{j\frac{2\pi}{\lambda}q \sin\theta_n} \dots\ e^{j(M-1)\frac{2\pi}{\lambda}q \sin\theta_n}]^T$ $(n = 0,1, \dots, N)$ is the array steering vector of θ_n, $\mathbf{n}(k)$ is the vector of the M uncorrelated noise signals, $n_m(k)$, λ is the wavelength, and q is the spacing between adjacent elements of the ULA. Finally, the superscript T denotes the transpose operation. The array output is given by

$$\mathbf{y}(k) = \mathbf{w}^H \mathbf{x}(k) \quad (5)$$

where $\mathbf{w} = [w_1\ w_2 \dots w_M]^T$ is the vector of beamformer weights and the superscript H denotes the Hermitian transpose operation. Referring to Figure 2, the signal $d(k)$ is the reference signal and $\varepsilon(k)$ is an error signal such that $\varepsilon(k) = d(k) - \mathbf{w}^H \mathbf{x}(k)$. For the sake of simplification, we will suppress the time dependence notation k. Squaring the error, we get

$$|\varepsilon|^2 = |d|^2 - 2d\mathbf{w}^H\mathbf{x} + \mathbf{w}^H\mathbf{x}\mathbf{x}^H\mathbf{w} \quad (6)$$

Objective min or max $f(\mathbf{w})$, $\mathbf{w} = (w_1, w_2, \ldots, w_D)$
Initialize a population of n flowers/pollens with random solutions
Find the best solution $\mathbf{g}^*$ in the initial population
Define a switch probability $p \in [0, 1]$
while ($t < MaxGeneration$)
    for $i = 1 : n$ (all n flowers in the population)
        if rand < p,
            Draw a (D-dimensional) step vector L which obeys a Lévy distribution
            Global pollination via $\mathbf{w}_i^{t+1} = \mathbf{w}_i^t + L(\mathbf{g}^* - \mathbf{w}_i^t)$
        else
            Draw γ from a uniform distribution in [0, 1]
            Randomly choose j and k among all solutions
            Do local pollination via $\mathbf{w}_i^{t+1} = \mathbf{w}_i^t + \gamma(\mathbf{w}_j^t - \mathbf{w}_k^t)$
        end if
        Evaluate new solutions
        If new solutions are better, update them in the population
    end for
    Find the current best solution $\mathbf{g}^*$
end while
Output the best solution found

Figure 1. FPA pseudo code.

Taking the expected value of both sides and simplifying the expression, we get the mean square error (MSE) as follows

$$E[|\varepsilon|^2] = E[|d|^2] - 2\mathbf{w}^H\mathbf{r} + \mathbf{w}^H\mathbf{R}_{xx}\mathbf{w} \quad (7)$$

where

$$\mathbf{r} = E[d^*.\mathbf{x}] \quad (8)$$

and $\mathbf{R}_{xx} = E[\mathbf{x}\mathbf{x}^H]$ is the signal correlation matrix. The symbol * denotes the complex conjugate. It should be noted that the cost function Eq. (7) is a quadratic function of $\mathbf{w}$ in the M-dimensional space. We can find the minimum of Eq. (7) by taking the gradient with respect to $\mathbf{w}$ and equating it to zero; thus the Wiener-Hopf equation is given as

$$\nabla_{\mathrm{w}}(E[|\varepsilon|^2]) = 2\mathbf{R}_{xx}\mathbf{w} - 2\mathbf{r} = 0 \quad (9)$$

The optimum Wiener solution, $\mathbf{w}_{Wiener} = \mathbf{R}_{xx}{}^{-1}\mathbf{r}$. If we allow the reference signal d to be equal to the desired signal s, and if s is uncorrelated with all interferers, then we may simplify the correlation $\mathbf{r}$. Using Eqs. (4) and (8), the simplified correlation $\mathbf{r} = E[s^*.\mathbf{x}] = S.\mathbf{a}_0$, where $S = E[|s|^2]$ is the mean power of the SOI. The optimum Wiener weights in this case

$$\mathbf{w}_{Wiener} = S\mathbf{R}_{xx}{}^{-1}\mathbf{a}_0 \quad (10)$$

IV. Numerical Results

The PSO, CS, and the FPA algorithms were applied on a ULA with variable array size $4 \le M \le 32$ elements and a uniform step of four elements. The population size for the three algorithms is fixed at 25, so that the number of cost function evaluations becomes directly proportional to the number of iterations. The switch probability p of FPA in Figure 1 is fixed at 0.8.

The ULA receives a SOI arriving from $\theta_0 = 20°$ and two SNOIs arriving from $\theta_1 = -20°$ and $\theta_2 = 40°$. The signal-to-noise ratio (SNR) is assumed to be 30 dB and $q = 0.5\lambda$.

The three algorithms were used to minimize the same cost function given in Eq. (7). The best obtainable minimum f_{min} for each algorithm is shown in Table 1 along with the number of iterations and the error for each array size M, the error in Table 1 is defined as $\|\mathbf{w}_{Wiener} - \mathbf{w}_{algorithm}\|$, where $\mathbf{w}_{Wiener}$ is the exact

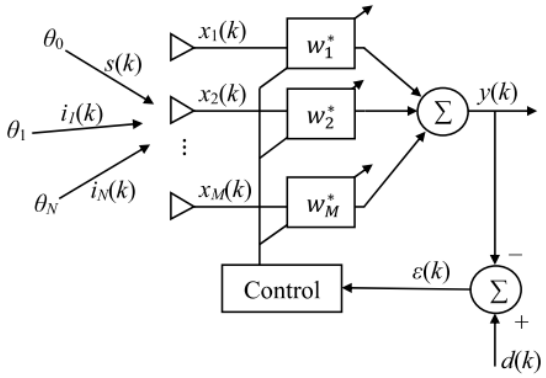

Figure 2. Adaptive beamformer for phased array antenna system.

weight vector in Eq. (10) and $\mathbf{w}_{algorithm}$ is the optimum weight vector generated from each algorithm. From Table 1, we can see that the PSO converges to the exact Wiener weights for M = 4, 8, and 12 elements only, besides it has the slowest convergence among the three algorithms for all cases of M. On the other hand, both the CS and the FPA converge to the exact weights for

Table 1. Simulation Results for The ULA with Variable Array Size

M	f_{min} (best)		Error		Number of iterations		
	PSO	**CS or FPA**	**PSO**	**CS or FPA**	**PSO**	**CS**	**FPA**
4	3.7495e-04	3.7495e-04	0	0	27503	1200	1455
8	1.2978e-04	1.2978e-04	0	0	85000	8000	6704
12	8.4331e-05	8.4331e-05	0	0	374000	431000	59400
16	6.3974e-05	6.3893e-05	0.0090	0	2240000	1638000	158776
20	2.9960e-04	5.0035e-05	0.4995	0	735000	4229000	244840
24	3.3176e-04	4.2008e-05	0.5382	0	394000	10199000	266638
28	3.4147e-04	3.5849e-05	0.5529	0	512000	16923000	320195
32	1.5869e-04	3.1296e-05	0.3569	0	432000	52364000	388051

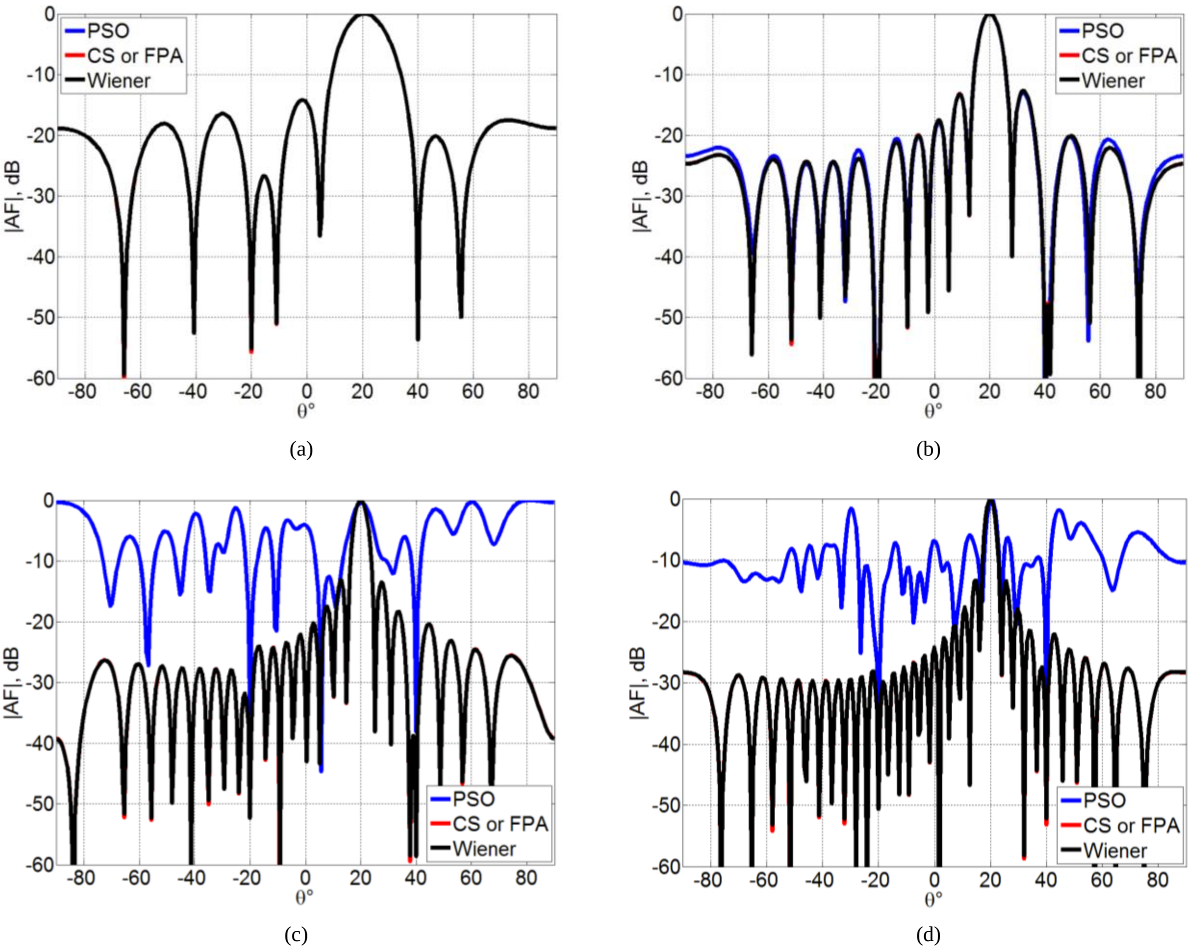

Figure 3. Optimal radiation patterns for SOI at 20° and two SNOIs at −20° and 40°. M equals (a) 8, (b) 16, (c) 24, and (d) 32 elements.

all values of *M* with the FPA has a faster convergence rate than the CS. The radiation patterns for three algorithms are shown in Figure 3 along with the Wiener, ideal, pattern for the three cases of *M* = 8, 16, 24, and 32 elements.

V. Conclusion

A new technique based on the FPA is introduced for phased array antennas Beamforming which steer the main lobe towards the SOI and form nulls towards SNOIs adaptively. The FPA adaptive beamformer leads to the optimum Wiener weights for the ULA with variable array size with faster convergence rate than the PSO and the CS algorithms. By using Graphics Processing Units (GPUs) [9], the computational complexity can be overcome and then the FPA can be used by adaptive beamforming networks in real-time applications. Therefore, the FPA seems to be quite promising in the smart antenna technology. In future work, the FPA will be applied to more complex fitness functions in order not only to control the pattern nulls but also to achieve specific values of sidelobe level.

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