Linear Antenna Array Synthesis and Null Control for Wi-Max Applications for MIMO Channels using a Cognition based Improved Particle Swarm Optimization

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Abstract: *In this paper, a novel algorithm for Adaptive (Smart)linear Antenna Array synthesis(directional antennas) with less number of co-channel interferers and for dynamic noise environments for Wi-Max base stations is proposed known as GA inspired Improved PSO (GA-IPSO).This novel Algorithm is able to accomplish the optimization task in a faster and effective way. We have applied this algorithm for antenna array synthesis and null control for superior performance by optimizing the elements positions (position only synthesis).Results quickly reveals that the proposed novel algorithm is superior in performance than any other optimization variants such as Genetic Algorithm and Differential Evolution(faster convergence of IPSO compared to GA and DE). Two design examples are considered and the results are illustrated. Results show a very good agreement between the desired and the synthesized specifications. Also the results of optimization are compared with the uniform array case and show better side lobe level reduction and advanced nullcontrol.My problem is modeled as a minimization problem ie. Minimizing the near in side lobe level.*

Keywords: Position only,beam width, IPSO, uniform array, Side lobe level, null control

I. Introduction

Antenna designers are constantly challenged with the temptation to search for optimum solutions for complex Electromagnetic device designs. The ever increasing advances in computational power have fuelled this temptation. Thewell-known brute force design methodologies are systematically being replaced by the state- of-the-art optimization techniques [1].The ability of using numerical methods to accurately and efficiently characterize the relative quality of a particular design has excited the EM engineers to apply stochastic global Evolutionary optimizers (EO).The EO techniques have been applied with growing applications to the design of Electromagnetic systems of increasing complexity. The recent popularity experienced by EO methods is not unique to the field of Electromagnetics. Among various EO techniques, the improved particle swarm optimization (IPSO) has attracted considerable attention. These schemes are finding popularity within Electromagnetic community as design tools and problem solvers because of their versatility and ability to optimize in complex multimodal search spaces applied to non-differentiable cost functions.

The overall radiation pattern of the antenna array can be shaped by the structure of the array, distance between the elements and its amplitude and phase excitations [2].Synthesis of linear arrays have been extensively studied from the past decades. Applied to linear antenna array optimization to optimize the excitation weights and element positions for better side lobe level reduction and advanced null control have been studied. So in this paper the IPSO has been used to non-uniformly optimize the element positions to produce a minimum side lobe level with no back lobes pattern of the linear antenna array. The design of linear array for applications in Wi-Max (Worldwide Interoperability for Microwave access) base stations for improved signal to interference ratio,lowercost,resistance to multipath and fading,improved co-channel Interference,enhanced frequency reuse,improved spectral efficiency and space-time diversity for MIMO channels in Wireless communications is discussed further in section 2.

Relying on the social behavior of swarm of bees, fish and other animals, the concept of IPSO [3, 4], new to the EM community, has been developed. The IPSO is a robust stochastic evolutionary computation technique based on the movement and intelligence of swarms looking for the most fertile feeding location.IPSO's foundation is based on the principle that each solution can be represented as a particle (agent) in a swarm. The process is further discussed in section 3.

II. Linear Antenna Array

The geometry of 2N element periodically spaced Linear Antenna Array and placed symmetrically along x- axis is considered as shown in figure1.

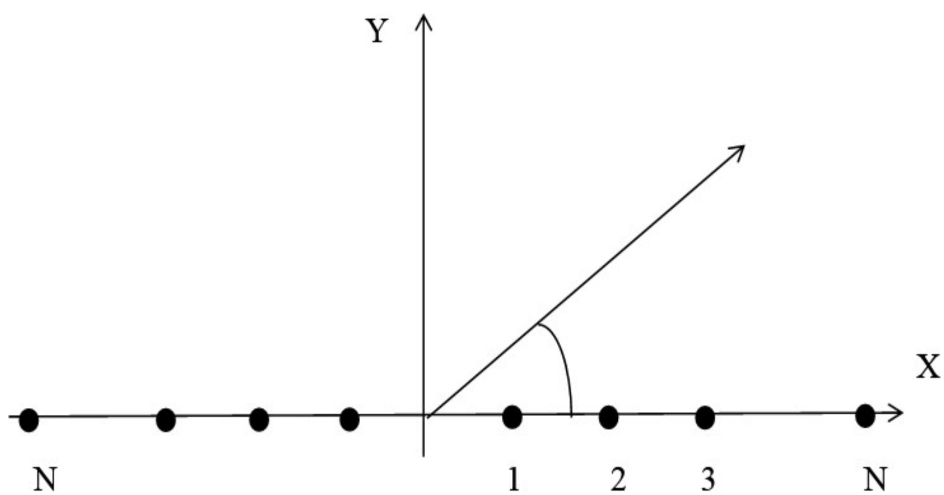

Figure1. Geometry of 2N element array placed along x-axis

The Array factor in the azimuth plane [6] is

$$\mathbf{AF}\ (\theta) = \sum_{n=1}^{2N} \boldsymbol{Incos[kxncos(\theta) + \varphi n]} \tag{1}$$

Where k is the wave number is the azimuth angle, I_n,n,x_n are the excitation amplitudes, phases and position of element n respectively.

Let us assume uniform phase excitation for all the elements i.e.$\boldsymbol{\varphi}$=0.

$$\mathbf{AF}\ (\theta) = \sum_{n=1}^{2N} \boldsymbol{Incos[kxncos(\theta)]} \tag{2}$$

The goal of optimization is to minimize the side lobe levels and controlling of nulls by employing non- uniform excitations an\d element positions to individual elements of the antenna array, i.e by varying $I_n$and x_n.Therefore the fitness function [7] is given by

$$\textbf{Fitness}=\sum \frac{1}{} \int^{\theta ui} \boldsymbol{AF(\theta)^{\wedge 2}d\theta} + \sum\ \boldsymbol{AF(\theta k)^{\wedge}2} \tag{3}$$

$i\ \overline{\Delta\theta i}\ \ \theta li$ k

Where θ_{li} and θ_{ui} are the special regions in which side lobe level is minimized,θ_k's are the direction of nulls and $\Delta\theta i= \theta_{ui}-\theta_{li}$.The first term of the equation minimizes the side lobe level and the second term is for controlling the nulls.

III. Improved Particle Swarm Optimization

In the standard PSO algorithm, the convergence speed of particles is fast, but the adjustments of cognition component and social component make particles search around Pgd and Pid . According to velocity and position renewal formula, once the best individual in the swarm is trapped into a local optimum, the information sharing mechanism in PSO will attract other particles to approach this local optimum gradually, and in the end the whole swarm will be converged at this position. But according to velocity and position renewal formula (1), once the whole swarm is trapped into a local optimum, its cognition component and social component will become zero in the end; still, because $0 < \omega < 1$ and with the number of iteration increase, the velocity of particles will become zero in the end, thus the whole swarm is hard to jump out of the local optimum and has no way to achieve the global optimum. Here a fatal weakness may result from this characteristic. With constant increase of iterations, the velocity of particles will gradually diminish and reach zero in the end. At this time, the whole swarm will be converged at one point in the solution space, if gbest particles haven't found gbest, the whole swarm will be trapped into a local optimum; and the capacity of swarm jump out of a local optimum is rather weak. In order to get through this disadvantage, in this paper we presents a new algorithm based on PSO. In order to avoid being trapped into a local optimum, the new PSO adopts a new information sharing mechanism. We all know that when a particle is searching in the solution space, it doesn't know the exact position of the optimum solution. But we can not only record the best positions an individual particle and the whole swarm have experienced, we can also record the worst positions an individual particle and the whole swarm have experienced, thus we may make individual particles move in the direction of evading the worst positions an individual particle and the whole flock have experienced,this will surely enlarge the global searching space of particles and enable them to avoid being trapped into a local optimum too early, in the same time, it will improve the possibility of finding gbest in the searching space. In the new strategy, the particle velocity and position renewal formula are as follows:

$$\mathbf{V_t = \omega V_{t-1} + c_1 r_1(P_{t-1}-X_{t-1}) + c_2 r_2(G_{t-1}-X_{t-1})} \qquad \mathbf{(4)}$$

$$\mathbf{Xt = X_{t-1} + V_t} \qquad \mathbf{(5)}$$

In standard PSO algorithm, the next flying direction of each particle is nearly determined; it can fly to the best individual and the best individuals for the whole swarm. From the above conclusion we may easily to know it will be the danger for being trapped into a local optimum. In order to decrease the possibility of being trapped into the local optimum, the new PSO introduces genetic selection strategy: To set particle number in the swarm as m, father population and son population add up to 2m. To select randomly q pairs from m; as to each individual particle i, if the fitness value of i is smaller than its opponents, i will win out and then add one to its mark, and finally select those particles which have the maximum mark value into the next generation. The experiments conducted show that this strategy greatly reduces the possibility of being trapped into a local optimum when solving certain functions. The flow of the IPSO is as follows:

Step 1: to initialize randomly the velocity and position of particles;

Step 2: to evaluate the fitness value of each particle;

Step 3: as to each particle, if its fitness value is smaller than the best fitness value Pidb , renew the best position P_{idb} of particle id ; or else if its fitness value is bigger than the worst fitness value P_{idw}, renew P_{idw} ;

Step 4: as to each particle, if its fitness value is smaller than the best whole swarm fitness value Pgdb , renew the best fitness value P_{gdb} of particle id ; or else if bigger than the worst whole swarm fitness value P_{gdw} , renew P_{gdw} ;

Step 5: as to each particle, 1) To produce new particle t, To produce new particle t ‘, To make a comparison between t and t ‘, then select the better one into the next generation;

Step 6: to produce next generation particles according to the above genetic selection strategy;

Step 7: if all the above steps satisfy suspension needs, suspend it; or turn to Step 3.

IV. Examples

Two Examples were selected to illustrate the method of IPSO to optimize the amplitude excitations and element positions for reduced side lobe level and null controlling. The element spacing for amplitude only method is λ/2(for reduced mutual coupling between the elements), where the frequency of operation is 300MHz.The mutual coupling among the antenna elements is ignored in this analysis. For the optimizing of element positions the excitations were taken uniform to be 1.This algorithm is implemented using **MATLAB R2013a**.The no. of generations =1000,c1=2,c2=2,w=0.9-0.4 linearly,no. of particles=100(more to better control the genetic mutation operator in IPSO),search space=[-5 5].The above algorithmic parameters were obtained using Meta-Heuristics which took few minutes for low dimensional but one whole day for higher dimensional problem hyperspace (above 8 dimensions) over a 1GHz Quad Core **INTEL** processor(Lenovo Desktop).

IV.I ***Example1:***

The first example corresponds to the synthesis of 10 element array with minimum side lobe in the region [2º 76º] & [106º 180º].The proposed IPSO algorithm parameters are given in table1.Table 2 shows the results for non-uniform spacing of symmetric Linear arrays and the corresponding fitness value plots at each generation in figure 3 respectively.
It is seen from figure 2. That there is an improvement in the side lobe level using IPSO as compared to uniform case. There is a reduction in side lobe from -15.22dB to -25dB, a reduction of 10dB. .Also the FNBW has increased from4.59º to 5.73º.

IV.II ***Example2:***

The second example illustrates the synthesis of 28 element array for minimum side lobe level in the region [2º 82º] & [100º 180º].with desired nulls at 61º, 121º.The array pattern and fitness value plot for the optimized array are shown in figures 4,5,6,7. It is seen from figure6.that the IPSO algorithm offers grand improvement in first side lobe level around 9dB for N=22 case compared to the uniform case. In addition broad nulls around are achieved in the desired directions.

TABLE1. Optimized Element Positions for 10 element Array Normalized with respect to λ/2

10 element array	(+/-) X_1,X_2,X_3,X_4,X_5
	0.2996λ,1.056λ,1.8395λ,2.9243λ,4.0031λ

TABLE 2. Optimized Element Positions for 28 element Array Normalized with respect to λ/2

	(+/-) $X_1,X_2,X_3,X_4,X_5,X_6,X_7,X_8,X_9,X_{10},X_{11},X_{12},X_{13},X_{14}$
28 element array	0.1569λ,0.6852λ,0.9084λ,1.4109λ,1.7682λ,2.3286λ,2.8372λ,3.5021λ,4.0629λ,4.5366λ,5.1796λ, 5.8766λ,6.3834λ,6.8737λ.

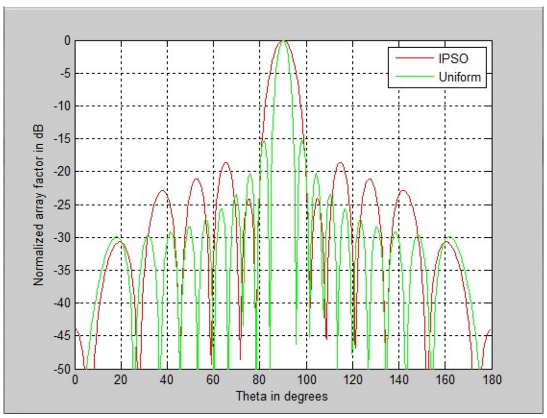

Figure2. Normalized Array factor of 10 element Linear array.

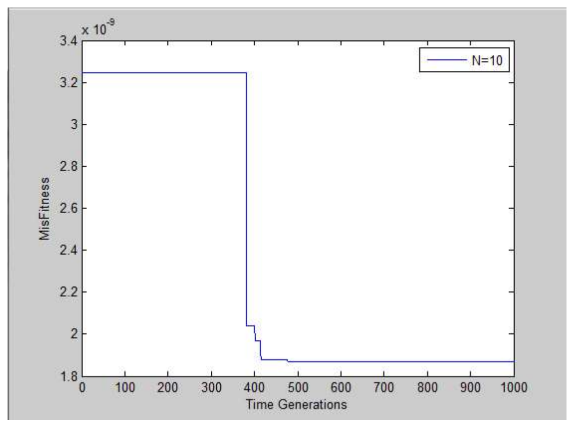

Figure3 . Global Best Fitness values vs # of time generations of 10 linear array.

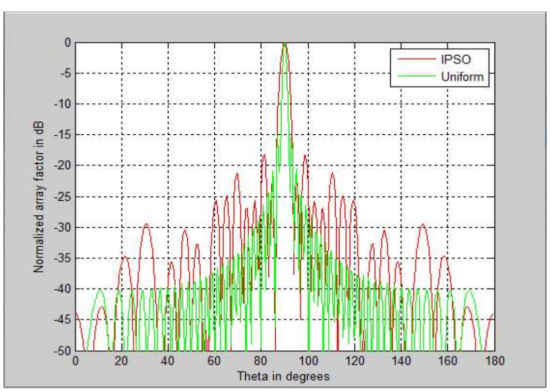

Figure4. Normalized Array factor of 28 element Linear Array

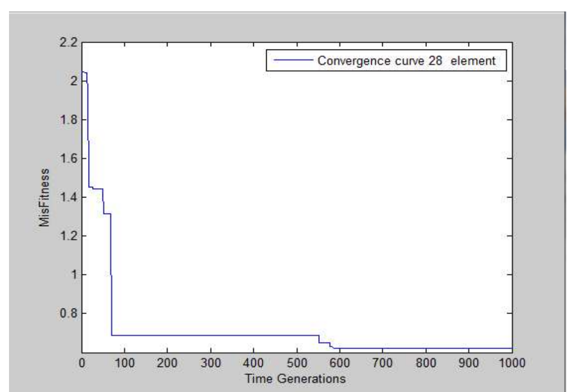

Figure5. Global Best Fitness Values vs. time generations Of 28 element array.

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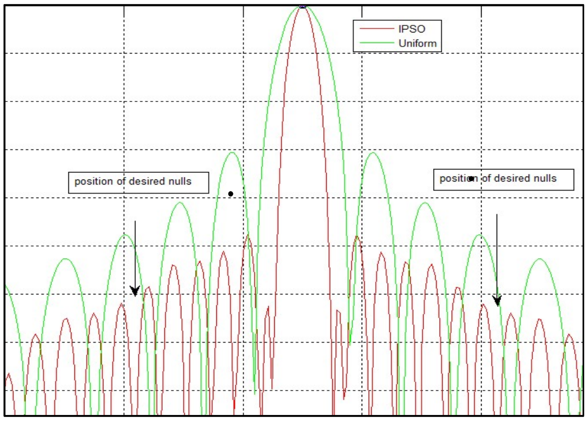

Figure6 . Normalized Array factor of 22 element Linear Array With nulls in desired directions.

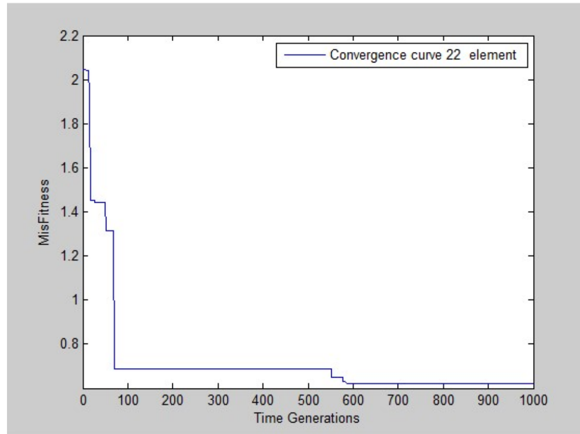

Figure7 . Global Best Fitness Values vs. time generations of 22 element array

TABLE3. Optimized Element Positions for 22 element Array Normalized with respect to λ/2 after 50 runs.

22 element array	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
	0.3005	1.177	1.855	2.685	3.524	4.428	5.468	6.580	7.953	9.552	11.00
	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{17}	X_{18}	X_{19}	X_{20}	X_{21}	X_{22}
	-0.3005	-1.177	-1.855	-2.685	-3.524	-4.428	-5.468	-6.580	-7.953	-9.552	-11.00

V. Conclusions

An optimization method for the synthesis of linear array pattern functions has been proposed and assessed. Results clearly show a very good agreement between desired and synthesized specification for the above cases. The optimization routine is a widely known powerful tool and in this case we have used it successfully to antenna array optimization.

At present we are working on conformal arrays for curved aircrafts and missile surfaces to reduce aerodynamic drag.. This work is being used to improve the directivity and efficient reduction in side lobe level.

VI. References

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