Improved Particle Swarm Optimization Based Hyper Beamforming of Linear Antenna Arrays

Gopi Ram [1], Durbadal Mandal [1], Rajib kar [1], and Sakti Prasad Ghoshal [2]
[1]National Institute of Technology, Department of ECE, Durgapur, India
[2]National Institute of Technology, Department of EE, Durgapur, India
Email: {gopi203hardel, durbadal.bittu, rajibkarece, spghoshalnitdgp}@gmail.com

***Abstract*—In this paper optimized hyper beamforming method is presented based on hyper beam exponent parameter for linear antenna arrays. Hyper beam is derived from sum and difference beam patterns of the array. As compared to conventional hyper beamforming of linear antenna array, real coded genetic algorithm (RGA), particle swarm optimization (PSO), and improved particle swarm optimization (IPSO) applied to the hyper beam of the same array can achieve much greater reduction in SLL and much more improved first null beam width (FNBW), keeping the same value of hyper beam exponent. The optimized hyper beam is achieved by optimization of current excitation weights and uniform inter-element spacing. The approach is illustrated through 10-, 14-, and 20-element linear antenna arrays. Various results are presented to show the advantage of this approach considering maximum SLL reduction and much more improved FNBW.**

***Index Terms*—hyper beam, linear antenna arrays, RGA, PSO, IPSO, SLL, FNBW**

I. INTRODUCTION

Beamforming is a signal processing technique used to control the directionality of the transmission and reception of the radio signals. This is achieved by distributing the elements of the array in such a way that signals at particular angle experience constructive interference while others experience destructive interference. Beamforming can be used at both transmitting and receiving ends in order to achieve spatial selectivity. Hyper beamforming refers to spatial processing algorithm used to focus an array of spatially distributed elements (called sensors) to increase the signal to interference plus noise ratio (SINR) at the receiver. This beamforming processing improves significantly the gain of the wireless link over a conventional technology, thereby increasing range, rate, and penetration. It has found numerous applications in radar, sonar, seismology, wireless communication, radio astronomy, acoustics and biomedicine [1]-[11]. It is generally classified as either conventional (switched and fixed) beamforming or adaptive beamforming. Switched beam forming system [12] is a system that can choose one pattern from many predefined patterns in order to enhance the received signals. Fixed beamforming uses fixed set of weights and time delays (or phasing) to combine the signals received from the sensors in the array, primarily using only information about the locations of the sensors in space and the wave direction of interest [13]. Adaptive beamforming or phased array is based on the desired signal maximization mode and interference signal minimization mode. It is able to place the desired signal at the maximum of main lobe. A new optimized hyper beamforming technique is presented in this paper, RGA [14]-[17], PSO [18]-[20], and IPSO [21]-[25] algorithm approach is applied to obtain optimal hyper beam patterns [14]-[18]. The hyper beamforming/any other beamforming [13] offers high detection performance like beam width, the target bearing estimation and reduces false alarm, side lobe suppression.

Manuscript received July 19, 2013; revised November 19, 2013

II. DESIGN EQUATIONS

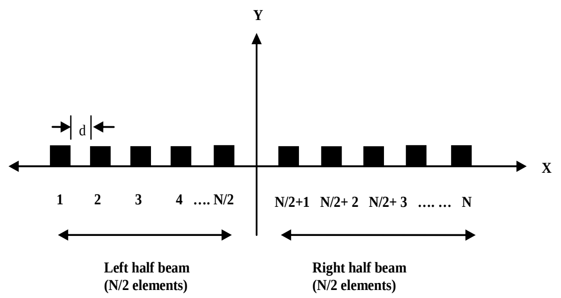

Figure 1. Geometry of an N-element linear array along the x-axis.

Hyper beam technique generates a narrow beam as compared to conventional beam with improved performance of SLL and FNBW that depend on the variation of exponent parameter value. For hyper beamforming for linear antenna array the inter-element spacing in either direction is $\lambda/2$ in order to steer the beam in that particular direction. The sum beam can be created by summation of the absolute values of complex left and right half beams. The difference beam is the absolute magnitude of the difference of complex right beam half beam and left half beam signal. Furthermore the difference beam has a minimum in the direction of the sum beam at zero degree. The resulting hyper beam is obtained by subtraction of sum and difference beams, each raised to the power of the exponent u. Consider a broadside linear array of N equally spaced isotropic

doi: 10.12720/ijsps.1.2.152-158

elements as shown in Fig. 1. The array is symmetric in both geometry and excitation with respect to the array center [13].

For broadside beams, the array factor is given in (1) [12].

$$AF(\theta)=\sum_{n=1}^{N} I_n e^{j(n-1)Kd[\sin\theta\cos\phi-\sin\theta_0\cos\phi_0]} \quad (1)$$

where;

$\theta =$ angle of radiation of electromagnetic plane

$d =$ spacing between elements;

$K =$ propagation constant;

$N =$ total number of elements in the array;

$I_n =$ excitation amplitude of n th element.

The equations for the creation of sum, difference and simple hyper beam pattern in terms of two half beams are as follows (2) [13]:

Sum pattern, $Sum(\theta)=|R_L|+|R_R|$ (2)

Difference pattern, $Diff(\theta)=|R_L-R_R|$ (3)

where

$$R_L=\sum_{n=1}^{N/2} I_n e^{j(n-1)Kd[\sin\theta\cos\phi-\sin\theta_0\cos\phi_0]}$$

$$R_R=\sum_{n=N/2+1}^{N} I_n e^{j(n-1)Kd[\sin\theta\cos\phi-\sin\theta_0\sin\phi_0]}$$

Hyper beam is obtained by subtraction of sum and difference beams, each raised to the power of the exponent u; the general equation of hyper beam is a function of hyper beam exponent u as follows:

$$AF_{Hyper}(\theta)=\left\{\left(|R_L|+|R_R|\right)^u-\left(|R_L-R_R|\right)^u\right\}^{1/u} \quad (4)$$

where u ranges from 0.2 to 1. If u ranges below 0.2, hyper beam pattern will contain a large depth spike at the peak of the main beam without changing in the hyper beam pattern. If u ranges increases more than 1, side lobes of hyper beam will increases than convention radiation pattern.

All the antenna elements are assumed isotropic. Only amplitude excitations and inter-element spacing are used to change the antenna radiation pattern. The cost function (CF) for improving the SLL of radiation pattern of hyper beam linear antenna arrays is given below

$$\begin{aligned} CF = \; & Max\left|AF_{Hyper}(\theta_{msl1},I_n)\right|/\left|AF_{Hyper}(\theta_0,I_n)\right| \\ & + Max\left|AF_{Hyper}(\theta_{msl2},I_n)\right|/\left|AF_{Hyper}(\theta_0,I_n)\right| \end{aligned} \quad (5)$$

where θ_0 is the angle where the highest maximum of central angle is attained in $\theta\in[-\pi/2,\pi/2]$. θ_{msl1} is the angle where maximum side lobe $AF_{Hyper}(\theta_{msl1},I_n)$ is attained in the lower band of hyper beam pattern. θ_{msl2} is the angle where the maximum side lobe $AF_{Hyper}(\theta_{msl2},I_n)$ is attained in the upper side band of hyper beam pattern. In cost function, both numerator and denominator are in absolute magnitude. Minimization of CF means maximum reduction of SLL. RGA, PSO, and IPSO is employed for minimization of CF by optimizing current excitation weights of elements and inter-element spacing. Results of the minimization of CF and SLL are described in section IV.

III. Evolutionary Technique Employed

A. *Real Coded Genetic Algorithm (RGA)*

GA is mainly a probabilistic search technique, based on the principles of natural selection and evolution. At each generation it maintains a population of individuals where each individual is a coded form of a possible solution of the problem at hand and called chromosome. Chromosomes are constructed over some particular alphabet, e.g., the binary alphabet {0, 1}, so that chromosomes' values are uniquely mapped onto the decision variable domain. Each chromosome is evaluated by a function known as fitness function, which is usually the objective function of the corresponding optimization problem.

Steps of RGA as implemented for optimization of non-uniform current excitation weights and inter-element spacing are [14]-[17]:

- Initialization of real chromosome strings of n_p population, each consisting of a set of current excitation weights (M) and uniform inter-element (01). Size of the set is M+1.in a particular M-element array design.
- Decoding of strings and evaluation of CF of each string.
- Selection of elite strings in order of increasing CF values from the minimum value.
- Copying of the elite strings over the non-selected strings.
- Crossover and mutation to generate off-springs.
- Genetic cycle updating.
- The iteration stops when the maximum number of cycles is reached. The grand minimum CF and its corresponding chromosome string or the desired optimal solution of M number of current excitation weights and one number of uniform inter-element spacing are finally obtained.

B. *Particle Swarm Optimization* (*PSO*)

PSO is a flexible, robust population-based stochastic search/optimization technique with implicit parallelism, which can easily handle with non-differential objective functions, unlike traditional optimization methods. PSO is less susceptible to getting trapped on local optima unlike GA, Simulated Annealing, etc. PSO is developed through simulation of bird flocking in multidimensional space. Bird flocking optimizes a certain objective function. Each particle knows its best value so far (pbest). This information corresponds to personal experiences of each particle. Moreover, each particle knows the best value so far in the group (gbest) among pbests. Namely, each particle tries to modify its position using the following information:

- The distance between the current position and pbest.
- The distance between the current position and gbest.

Mathematically, velocities of the particles are modified according to the following equation [18-20]:

$$V_i^{(k+1)} = w * V_i^k + C_1 * rand_1 * \left(pbest_i - S_i^k \right) + C_2 * rand_2 * \left(gbest - S_i^k \right) \tag{6}$$

where V_i^k is the velocity of i[th] particle at k[th] iteration; w is the weighting function; C_j is the weighting factor; $rand_i$ is the random number between 0 and 1; S_i^k is the current position of particle i at iteration k; $pbest_i$ is the personal best of particle *i*; *gbest* is the group best among all pbests for the group. The searching point in the solution space can be modified by the following equation:

$$S_i^{(k+1)} = S_i^k + V_i^{(k+1)} \tag{7}$$

The first term of (6) is the previous velocity of the particle. The second and third terms are used to change the velocity of the particle. Without the second and third terms, the particle will keep on ''flying'' in the same direction until it hits the boundary. Namely, it corresponds to a kind of inertia and tries to explore new areas. The values of w, C_1 and C_2 are given in the next section.

C. *Improved Particle Swarm Optimization* (*IPSO*)

The global search ability of traditional PSO is very much enhanced with the help of the following modifications. This modified PSO is termed as IPSO [21]-[25].

i) The two random parameters $rand_1$ and $rand_2$ of (6) are independent. If both are large, both the personal and social experiences are over used and the particle is driven too far away from the local optimum. If both are small, both the personal and social experiences are not used fully and the convergence speed of the technique is reduced. So, instead of taking independent $rand_1$ and $rand_2$, one single random number r_1 is chosen so that when r_1 is large, $(1-r_1)$ is small and vice versa. Moreover, to control the balance of global and local searches, another random parameter r_2 is introduced. For birds flocking for food, there could be some rare cases that after the position of the particle is changed according to (7), a bird may not, due to inertia, fly toward a region at which it thinks is the most promising for food. Instead, it may be leading toward a region which is in the opposite direction of what it should fly in order to reach the expected promising regions. So, in the step that follows, the direction of the bird's velocity should be reversed in order for it to fly back into the promising region. $sign(r_3)$ is introduced for this purpose. Both cognitive and social parts are modified accordingly.

Finally, the modified velocity of j^{th} component of i[th] particle is expressed as follows:

$$V_i^{(k+1)} = r_2 * sign(r_3) * V_i^k + (1-r_2) * C_1 * r_1 * \left\{ pbest_i^k - S_i^k \right\} + (1-r_2) * C_2 * (1-r_1) * \left\{ gbest^k - S_i^k \right\} \tag{8}$$

where r_1, r_2 and r_3 are the random numbers between 0 and 1; S_i^k is the current position of particle i at iteration k; $pbest_i^k$ is the personal best of i^{th} particle at k^{th} iteration; $gbest^k$ is the group best among all *pbests* for the group at k^{th} iteration. The searching point in the solution space can be modified by the following equation (9) $sign(r_3)$ is a function defined as:

$$sign(r_3) = -1 \text{ when } r_3 \le 0.05, \quad = 1 \text{ when } r_3 > 0.05 \tag{9}$$

IV. Numerical Results

In order to demonstrate the effectiveness of the proposed optimal design method for hyper beam pattern of linear antenna, using RGA, PSO, and IPSO algorithms.

TABLE I. Chosen Parameters Used for Different Optimization Algorithms

Parameters	GA	PSO	IPSO
Population size	120	120	120
Iteration cycles	100	100	100
C_1	-	1.5	1.5
C_2	-	1.5	1.5
$v_i^{\min}$	-	0.01	0.01
$v_i^{\max}$	-	1.0	1.0

A. *Analysis of Radiation Patterns of Hyper Beams for u= 0.5 and 1 with Different Algorithms*

The following observations are made from Table II and Fig. 2, Fig. 3, Fig. 4, in which the exponent value u=0.5. The algorithms yield SLL values of -100.6 dB(RGA), -117.2 dB(PSO), and -165.2 dB (IPSO) for the 10-element array, then, -96.21 dB(RGA), -113 dB(PSO), and -133.5 dB (IPSO) for the 14-element array and finally, -83.69 dB(RGA), -88.71 dB(PSO), and -103.7 dB (IPSO)for the 20-element array of respective optimized hyper beam patterns against SLL of -32.78 dB, -33.02 dB and -33.20 dB, of respective non-optimized hyper beam patterns. Regarding FNBW values for the same respective arrays, the algorithms yield 41.04 degrees (RGA), 39.60 degrees (PSO), and 34.56 degrees (IPSO) then, 25.92 degrees (RGA), 25.20 degrees (PSO), and 24.48 degrees (IPSO) and finally, 19.44 degrees (RGA), 18.72 degrees (PSO), and 18 degrees (IPSO), of respective optimized hyper beam patterns against FNBW of 33.12 degrees, 23.04 degrees and 16.56 degrees of respective non-optimized hyper beam patterns. Thus, Figures as well as Tables clearly show much improvement of both SLL and FNBW by IPSO based optimization, as compared to the other algorithms.

From Table III and Figs. 5, 6, 7, in which the exponent value u=1.0, the same nature of observations can be made with regard to SLL and FNBW values for the algorithms. In this case, also, IPSO proves its superiority in yielding better SLL and FNBW as compared to the other algorithms. IPSO efficiently computes N number of near global optimal current excitation weights and one number optimal uniform inter-element separation for each hyper beam linear antenna array to have maximum SLL reduction and much improved FNBW.

TABLE II. SLL, FNBW, OPTIMAL CURRENT EXCITATION WEIGHTS AND OPTIMAL INTER-ELEMENT SPACING FOR HYPER BEAM PATTERN OF LINEAR ARRAY WITH HYPER BEAM EXPONENT(U=0.5), RGA, PSO, AND IPSO FOR DIFFERENT SETS OF ARRAYS

N	Algorithms	Optimized current excitation weights and $[I_1, I_2, I_3, I_4 .... I_N]$	Optimal inter-element spacing in (λ)	SLL of hyper beam with optimization (dB)	FNBW of hyper beam with optimization (deg)
10	GA	0.2844 0.5240 0.8813 0.9032 0.4231 0.8425 0.4564 0.6402 0.3414 0.3853	0.5441	-100.6	41.04
	PSO	0.2398 0.6414 0.9123 0.9722 0.4312 0.9502 0.4327 0.6582 0.3571 0.3982	0.5717	-117.2	39.60
	IPSO	0.1238 0.2641 0.5838 0.5730 0.5457 0.7945 0.5427 0.1974 0.3336 0.1641	0.8185	-165.2	34.56
14	GA	0.3631 0.2555 0.4905 0.0043 0.6114 0.5778 0.8634 0.5042 0.5782 0.5913 0.7502 0.5545 0.2878 0.3431	0.5878	-96.21	25.92
	PSO	0.2319 0.1857 0.6027 0.5089 0.7906 0.4163 0.6275 0.7212 0.9097 0.2907 0.2525 0.2755 0.5506 0.3615	0.6036	-113	25.20
	IPSO	0.1312 0.2095 0.5971 0.6664 0.9859 0.7928 0.8959 1.0000 0.9793 0.5137 0.5286 0.3526 0.3526 0.2272	0.7823	-133.5	24.48
20	GA	0.2505 0.3933 0.4881 0.4829 0.3027 0.6697 0.3436 0.9551 0.5974 0.8952 0.5252 0.9773 0.4056 0.6612 1.0000 0.1577 0.8144 0.3284 0 0.5558	0.5361	-83.69	19.44
	PSO	0.1675 0.2453 0.2113 0.5168 0.6011 0.5661 0.7962 0.2148 0.8279 0.2476 0.9888 0.3429 0.8064 0.1836 0.2281 0.1792 0.4317 0.6579 0.2244 0.3467	0.5353	-88.71	18.72
	IPSO	0.3617 0.2056 0.5012 0.1511 0.5013 0.3303 0.5574 0.1488 0.7185 1.0000 0.3869 0.5352 0.6220 0.6664 0.5299 0.5658 0.3381 0.3749 0.1919 0.1004	0.5982	-103.7	18

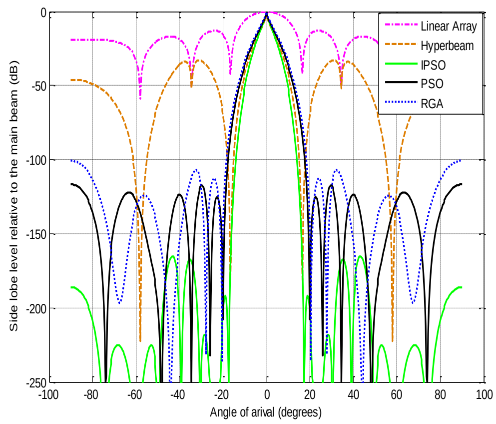

Figure 2. Best pattern found by IPSO for the 10-element array with improved SLL and FNBW at u=0.5.

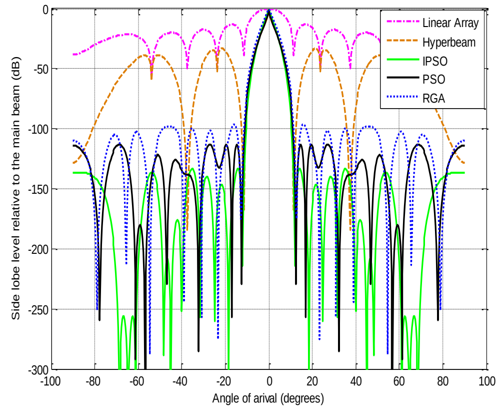

Figure 3. Best pattern found by IPSO for the 14-element array with improved SLL and FNBW at u=0.5.

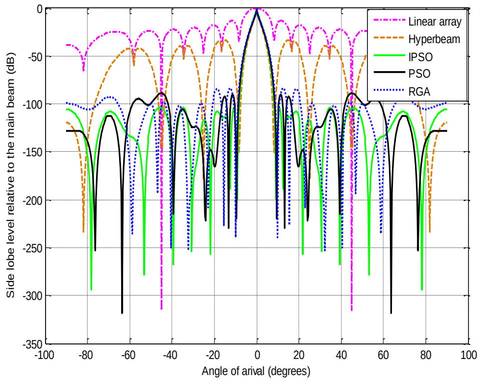

Figure 4. Best pattern found by IPSO for the 20-element array with improved SLL and FNBW at u=0.5.

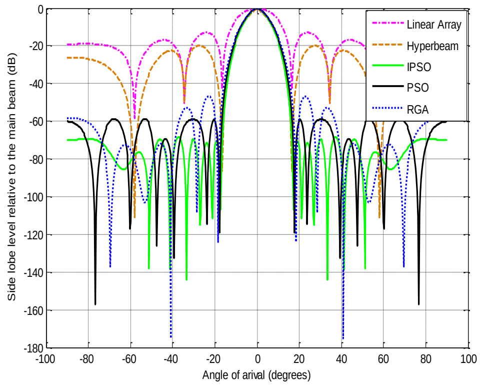

Figure 5. Best array pattern found by IPSO for the 10-element array at u =1 with improved SLL.

TABLE III. SLL, FNBW, OPTIMAL CURRENT EXCITATION WEIGHTS AND OPTIMAL INTER-ELEMENT SPACING FOR HYPER BEAM PATTERN OF LINEAR ARRAY WITH HYPER BEAM EXPONENT(U=1), RGA, PSO, AND IPSO FOR DIFFERENT SETS OF ARRAYS

N	Algorithms	Optimized current excitation weights and $[I_1,I_2,I_3,I_4.......I_N]$	Optimal inter-element spacing in (λ)	SLL of hyper beam with optimization (dB)	FNBW of hyper beam with optimization (deg)
10	GA	0.1339 0.1010 0.4353 0.3657 0.6166 0.5295 0.6264 0.4194 0.3935 0.2296	0.6503	-46.76	36.72
	PSO	0.3889 0.4254 0.2096 0.7456 0.7961 0.4382 0.3525 0.5002 0.1764 0.1603	0.6436	-58.88	35.28
	IPSO	0.3694 0.1708 0.4351 0.2054 0.8947 0.5693 0.8845 0.7954 0.5723 0.2177	0.6662	-68.41	34.56
14	GA	0 0.4146 0.6005 0.7859 0.7903 0.7755 0.4159 0.9358 0.2159 0.3125 0.4533 0 0.6501 0.1934	0.5824	-46.76	25.20
	PSO	0.1011 0.2588 0.3020 0.5343 0.6365 0.6937 0.5245 0.8198 0.3813 0.4761 0.3815 0.4803 0.1301 0.3374	0.6698	-51.4	24.48
	IPSO	0.1502 0.2040 0.5449 0.6115 0.9731 0.7120 0.6551 0.9843 0.7383 0.1339 0.5322 0.3944 0.1799 0.1548	0.7829	-68.02	23.76
20	GA	0.2739 0.0772 0.4652 0.3369 0.4341 0.6162 0.5613 0.8008 0.4211 0.7082 0.6840 0.8283 0.3579 0.4822 0.3872 0.7091 0.3145 0.3415 0.1838 0.4675	0.5587	-42.85	18.72
	PSO	0.5918 0.0903 0.4110 0.0131 0.6447 0.1519 0.7800 0 0.8548 0.8593 0.6530 0.7593 0.9763 0.9991 0.7571 0.8972 0.5175 0.7424 0.2818 0.2433	0.5961	-52.97	18
	IPSO	0.0211 0.1184 0.0003 0.2518 0.6632 0.8141 0.6432 0.7758 1.0000 0.8710 0.9334 0.7521 0.9012 0.7768 0.4344 0.4526 0.5307 0.5098 0.3481 0.3303	0.7384	-64.7	17.28

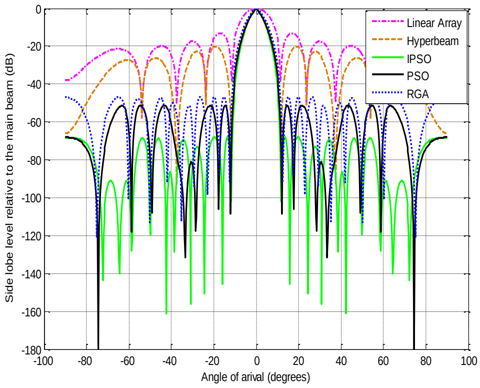

Figure 6. Best array pattern found by IPSO for the 14 -element array at u =1 with improved SLL.

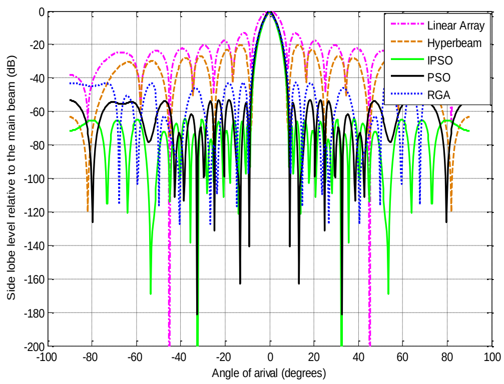

Figure 7. Best array pattern found by IPSO for the 20 -element array at u =1 with improved SLL.

V. Comparative Effectiveness and Convergence Profiles of RGA, PSO, and IPSO

The minimum *CF* values against number of iteration cycles are recorded to get the convergence profile for each array set. Fig. 8 and Fig. 9 portray the convergence profiles of minimum CF for 10-element array sets, respectively. The simulation programming was done in MATLAB language using MATLAB 7.5 on dual core(TM) processor, 2.88 GHz with 2 GB RAM.

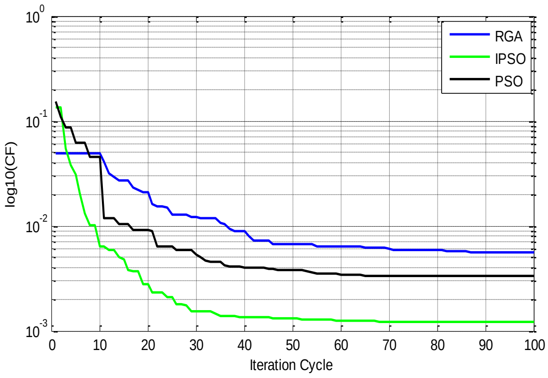

Figure 8. Convergence profile of IPSO in case of 10-element linear antenna array at u=0.5.

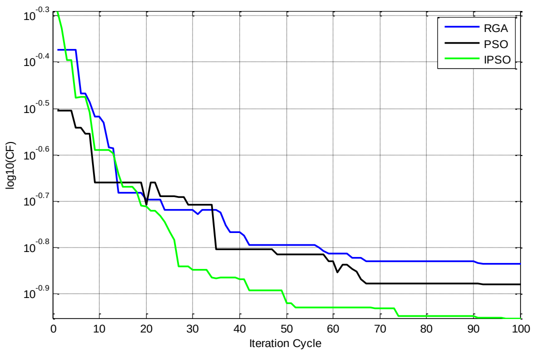

Figure 9. Convergence profile of IPSO in case of 10-element linear antenna array at u=1.

VI. Conclusions

In this paper, a novel improved particle swarm optimization (IPSO) used for finding optimal sets of non-uniformly excited hyper beamforming of linear antenna arrays, each with optimal uniform inter-element spacing. Experimental results reveal that IPSO based optimal designs offer considerable reduction in SLL and improved first null beam width (FNBW) as compared to corresponding conventional uniformly excited linear antenna arrays with inter-element spacing of $\lambda/2$, non-optimized hyper beam uniformly excited linear antenna arrays with inter-element spacing of $\lambda/2$ and also optimized hyper beams achieved by RGA, and PSO algorithms. It is found that the proposed IPSO based technique is quite efficient and taking the least execution times for finding optimal hyper beamforming designs of linear antenna arrays where the rest algorithms are entrapped to sub-optimal solutions and corresponding sub-optimal designs in higher execution times.

References

[1] T. Isernia, F. J. A. Pena, O. M. Bucci, M. D'Urso, J. F. Gomez, and J. A. Rodriguez, "A hybrid approach for the optimal synthesis of pencil beams through array antennas," *IEEE Trans. Antennas Propag.*, vol. 52, no. 11, pp. 2912–2918, Nov. 2004.

[2] S. P. Applebaum and D. J. Chapman, "Adaptive arrays with main beam constraints," *IEEE Trans. Antennas Propagat.*, vol. AI-24, pp. 650-662, Sept.1976.

[3] J. D. Krous, *Antenna*, Mc GRAW-HILL, NewYork, 1950.

[4] H. Schilter, "Sonar detection improvement by hyper beam technique."

[5] H. Schlieter and H. Eigenbrod, "Method for the formation of radiated beams in direction finder systems," *Patent US 6021096 A*, Feb. 1, 2000.

[6] R. S. Walkar, "Bearing accuracy and resolution bound of high-resolution beam formers," in *Proc. IEEE ICASSP '85*, Tampa.

[7] K. Takao and K. Komiyama, "An adaptive antenna array under directional constraint," *IEEE Trans. Antennas Propagat.*, vol. AI-24, pp. 662-669, Sept. 1976.

[8] R. J. Mailloux, "Phased array architecture for millimetric active arrays," *IEEE Antennas and Propagation Society Newsletter*, Feb 1986.

[9] J. K. Hsiao, "Normalized relationship among errors and side lobe levels," *Radio Sci.*, vol. 19, pp. 292-302, Jan. 1984.

[10] R. H. MacPhie, "Thinned coincident arrays for the direct measurement of the principal solution in radio astronomy," *IEEE Trans. Antennas Propag.*, vol. AP-51, pp. 788–793, Apr. 2003.

[11] H. Steyskal, R. A. Shore, and R. L. Haupt, "Methods for null control and their effects on the radiation pattern," *IEEE Trans. Antennas Propagat.*, vol. 34, no. 3, pp. 404-409, Mar. 1986.

[12] C. A. Balanis, *Antenna Theory Analysis and Design*, John Wiley & Sons, New York 1997.

[13] V. Anita, S. S. J. Lakshmi, I. Sreedevi, H. Khan, K. S. Kumar, and P. Ramakrishna, "An adaptive processing of linear array for target detection improve," *International Journal of Computer Application(0975-8887)*, vol. 42, no. 4, Mar. 2012.

[14] R. L. Haupt, "Phase-only adaptive nulling with a genetic algorithm," *IEEE Trans. Antennas Propagat.*, vol. 45, no. 6, pp. 1009-1015, June 1997.

[15] R. L. Haupt and D. H. Werner, *Genetic Algorithms in Electromagnetics*, IEEE Press Wiley-Interscience, 2007.

[16] Y. C. Chung and R. L. Haupt, "Adaptive nulling with spherical arrays using a genetic algorithm," in *Proc. IEEE AP-S Int. Symp. Dig.*, vol. 3, 1993, pp. 2000-2003.

[17] G. R. Hardel, N. T. Yalapragada, D. Mandal, and A. K. Bhattacharjee, "Introducing dipper nulls in time modulated linear symmetric antenna array using real coded genetic algorithm," in *Proc. IEEE Symposiumon Computers and Informatics*, March 2011, pp. 249-254.

[18] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proc. IEEE Int. Conf. on Neural Network*, vol. 4, 1995, pp. 1942-1948.

[19] D. Mandal, N. T. Yallaparagada, S. P. Ghoshal, and A. K. Bhattacharjee, "Wide null control of linear antenna arrays using particle swarm optimization," *IEEE INDICON*, Kolkata, India, pp. 1–4, Dec. 2010.

[20] R. C. Eberhart and Y. Shi, "Particle swarm optimization: Developments, applications and resources, evolutionary computation," in *Proc. Congress on Evolutionary Computation*, 2001, pp. 81–86.

[21] S. Mondal, D. Mandal, R. Kar, and S. P. Ghoshal, "Non-recursive fir band pass filter optmization by improved particle swarm optimization," in *Proc. INDIA-2012, Advances in Intelligent and Soft Computing*, Springer, vol. 132, 2012 , pp. 405-412.

[22] S. H. Ling, H. H. C. Iu, F. H. F. Leung, and K. Y. Chan, "Improved hybrid particle swarm optimized wavelet neural network for modeling the development of fluid dispensing for electronic packaging," *IEEE Trans. Ind. Electron.*, vol. 55, no. 9, pp. 3447–3460, Sep. 2008.

[23] D. Mandal, D. Sadhu, and S. P. Ghoshal, "Thinned concentric circular array antennas synthesis using improved particle swarm optimization," *ACEEE International Journal on Communication*, vol. 02, no. 02, pp. 21-25, July 2011.

[24] D. Mandal, S. P. Ghoshal, and A. K. Bhattacharjee, "A novel particle swarm optimization based optimal design of three-ring concentric circular antenna array," in *Proc. IEEE International Conference on Advances in Computing, Control, and Telecommunication Technologies*, 2009, pp. 385-389.

[25] D. Mandal, S. P. Ghoshal, and A. K. Bhattacharjee, "Linear antenna array synthesis using improved particle swarm optimization," *Second IEEE International Conference on Emerging Applications of Information Technology*, Kolkata, India, Feb. 19-20, 2011, pp. 365 - 368.

Gopi Ram passed B. E. degree in Electronics and Telecommunication Engineering, from Government Engineering College, Jagdalpur, Chhattisgarh, India in the year 2007. He received the M. Tech degree from National Institute of Technology, Durgapur, West Bengal, India in the year 2011. Presently, he is attached with National Institute of Technology, Durgapur, West Bengal, India, as Institute Ph.D Research Scholar in the Department of Electronics and Communication Engineering. His research interest includes Array Antenna design; via Evolutionary Computing Techniques.

Durbadal Mandal passed B. E. degree in Electronics and Communication Engineering, from Regional Engineering College, Durgapur, West Bengal, India in the year 1996. He received the M. Tech and Ph. D. degrees from National Institute of Technology, Durgapur, West Bengal, India in the year 2008 and 2011 respectively. Presently, he is attached with National Institute of Technology, Durgapur, West Bengal, India, as Assistant Professor in the Department of Electronics and Communication Engineering. His research interest includes Array Antenna design; filter Optimization via Evolutionary Computing Techniques. He has published more than 180 research papers in International Journals and Conferences.

Rajib Kar passed B. E. degree in Electronics and Communication Engineering, from Regional Engineering College, Durgapur, West Bengal, India in the year 2001. He received the M. Tech and Ph. D. degrees from National Institute of Technology, Durgapur, West Bengal, India in the year 2008 and 2011 respectively. Presently, he is attached with National Institute of Technology, Durgapur, West Bengal, India, as Assistant Professor in the Department of Electronics and Communication Engineering. His research interest includes VLSI signal Processing, Filter optimization via Evolutionary Computing Techniques. He has published more than 190 research papers in International Journals and Conferences.

Sakti Prasad Ghoshal passed B. Sc and B. Tech, degrees in 1973 and 1977, respectively, from Calcutta University, West Bengal, India. He received M. Tech degree from I.I.T (Kharagpur) in 1979. He received Ph.D. degree from Jadavpur University, Kolkata, West Bengal, India in 1992. Presently he is acting as Professor of Electrical Engineering Department of N.I.T. Durgapur, West Bengal, India. His research interest areas are: Application of Evolutionary Computing Techniques to Electrical Power systems, Digital Signal Processing, Array antenna optimization and VLSI. He has published more than 225 research papers in International Journals and Conferences