

## Particle Swarm Optimization Algorithm for Smart Antenna System

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**Abstract:** This study presents a particle swarm optimization algorithm to optimize the performance of the smart antenna system. All particles of the population are assessed to cost function chosen to be equal to the mean square error between the array output signal and a reference signal considered to be similar to the desired signal. The results obtained show that particle swarm optimization algorithm has a small mean square error and improved output signal resolution than those of two well known adaptive algorithms namely, Recursive Least Square (RLS) and Sample Matrix Inversion (SMI) algorithms.

**Keywords:** Smart antenna, adaptive algorithm, particle swarm optimization, mean square error, inverse, RLS

### INTRODUCTION

Smart antenna is an antenna array that can emphasize the signal of interest and minimize the interfering signals by adjusting or adapting its own beam pattern. Smart antennas have several benefits in the field of wireless communication such as: improving system capacity, reducing sensitivity of non ideal behaviours, providing robustness to system perturbation as well as separate the received signals spatially with aid of Spatial Division Multiple Access (SDMA) concept (Liberti and Rappaport, 1999). Smart antennas have recently large number of applications such as: mobile communications (Liberti and Rappaport, 1999), software radio (Reed, 2002), Wireless Local Area Network (WLAN) and Metropolitan Area Network (WMAN) (Stallings, 2000), radar systems (Skolnik, 2001), satellite communication (Jeng and Lin, 1999) as well as wide band Code Division Multiple Access (CDMA) (Ahn and Kim, 2009). Particle Swarm Optimization (PSO) algorithm is formulated by Edward and Kennedy.

They had borrowed the social behaviour of animals to solve the optimization searching problems (Haupt and Haupt, 2004). PSO algorithm is approximately similar to Genetic Algorithm (GA) but it is much simpler. Due to its simplicity, many problems that solved by GA are modified to solved by PSO algorithm. In the last few years, there were many attempts to use this technique in electromagnetic applications.

Robinson *et al.* (2002) have proved that PSO is able to accomplish the same results of GA to design profile corrugated horn antenna. Gies and Rahmat-Samii (2004) have used PSO algorithm to solve difficult reflector antenna synthesis problems. Jin and Rahmat-Samii (2005) have optimized the geometric parameters of multiband and

wide band patch antenna using PSO algorithm to achieve a desired performance. Papadopoulos *et al.* (2006) have used PSO algorithm to find spatial and feeding configuration of array elements of switch beam planer antenna array. Pantoja *et al.* (2007) have optimized the design of log-periodic dipole array with aid of PSO algorithm. Li *et al.* (2008) used PSO to optimize the antenna array pattern. Gangopadhyaya *et al.* (2009) have determined accurately the resonant frequency of rectangular aperture-coupled microstrip antenna using PSO algorithm. Chamaani *et al.* (2010) have obtained using PSO, optimum trade off between side lobe level and beam width in time domain for ultra-wide band antenna array.

In this study, a particle swarm optimization algorithm is used to adapt the weights of the adaptive smart antenna system. The optimal weights resulted at each sample of time (iteration) are used to orient the main beam of the smart antenna radiation pattern in the direction of the desired signal and cancel the interfering signals by pointing nulls in their directions. As a matter of comparison, the simulation results of PSO algorithm are compared with that of Sample Matrix Inversion (SMI) algorithm and Recursive Least Square (RLS) algorithm. In this study, the necessary equations used to realize and identify adaptive smart antenna are given. The basic theory of PSO algorithm is also presented.

### SMART ANTENNA SYSTEM

In an M-elements adaptive array antenna as shown in Fig.1, output signal  $y(n)$  is given by (Godara, 2004):

$$y(n) = \mathbf{w}^H(n) \mathbf{x}(n) \quad (1)$$

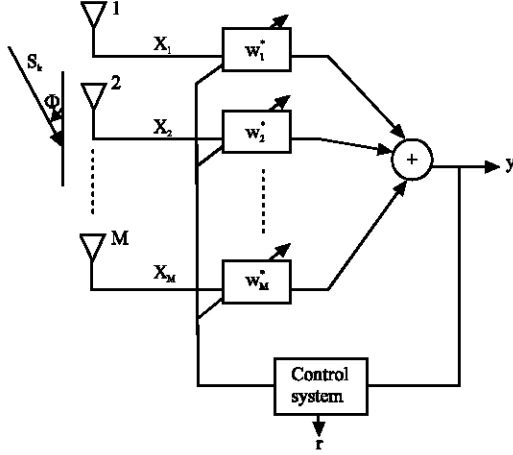


Fig. 1: Simple smart antenna

where,  $w(n)$  and  $x(n)$  represent the weights vector and input signals vector, respectively. The symbol  $H$  denotes the complex conjugate transpose of the vector. It is shown in Fig. 1 that the signals coming from all elements at a time instant ( $n$ ) are multiplied by the complex weights and summed to form the array output at that instant of time. A reference signal ( $r$ ) identical to the desired signal ( $s_o$ ) is used to control the weights of array elements. If the antenna receives a desired signal  $s_o(n)$  and  $K$  interfering signals  $s_k(n)$  with the presence of random noise  $N$  then:

$$x(n) = s_o(n)a_o + \sum_{k=1}^K s_k(n)a_k + N \quad (2)$$

Where:

$N = (M \times 1)$  matrix

$a_k$  = Steering vector of the  $k$ th signal given by (Godara, 2004):

$$a_k = \begin{bmatrix} 1 \\ e^{j\beta d \cos \Phi_k} \\ e^{j2\beta d \cos \Phi_k} \\ \vdots \\ e^{j(M-1)\beta d \cos \Phi_k} \end{bmatrix} \quad (3)$$

Where:

$(\beta = 2\pi/\lambda)$  = Wave number

$\lambda$  = Wavelength of the desired signal

$d$  = Distance between every two adjacent elements

$\Phi_k$  = Azimuth angle of the  $k$ th signal

### PARTICLE SWARM OPTIMIZATION ALGORITHM IN SMART ANTENNA SYSTEM

PSO algorithm retains the conceptual simplicity of GA whereas, it is much easier to implement and apply to design problems with both discrete and continuous design parameters (Papadopoulos *et al.*, 2006). This

technique can be used to optimize the array output by making it approximately similar to the desired signal. When the desired signal direction is known the phase of weights can be deduced from the steering vector of the desired signal  $a_o$  as:

$$w = \begin{bmatrix} |w_1| \\ |w_2| e^{j\beta d \cos \Phi_o} \\ |w_3| e^{j2\beta d \cos \Phi_o} \\ \vdots \\ |w_M| e^{j(M-1)\beta d \cos \Phi_o} \end{bmatrix} \quad (4)$$

such that the main beam can be oriented in the direction of the desired signal. By optimizing the magnitudes of the weights, nulls can be pointed in the direction of interfering signals. In this case, the particle (par) of the PSO algorithm can be expressed as (Haupt and Haupt, 2004):

$$\text{par} = |w_1| \quad |w_2| \quad \dots \quad |w_M| \quad (5)$$

The cost function (cost) can be selected to be the Mean Square Error (MSE) between the array output signal and the reference signal which is assumed to be similar to the desired signal such that:

$$\text{cost} = |r(n) - w^H(n)x(n)|^2 \quad (6)$$

PSO algorithm is usually started by assuming the population size to be equal to  $P$  where,  $P$  represents the number of particles in the population. Consequently, the initial population (pop) can be expressed by  $(P \times M)$  random matrix.

Each element in each particle moves about the cost surface with a certain velocity. Therefore, the initial velocity matrix (vel) can also be expressed by  $(P \times M)$  random matrix. Each particle is then assessed to the cost function. The minimum cost and the particle which carries index equal to the minimum cost index can be considered to be the initial global cost (gcost) and initial global particle (gpar), respectively.

While the local best cost vector (lcost) and the best local population matrix (lpop) are initialized by equalizing them with the cost vector and the population matrix respectively. When the initialization process is over, the updating process starts. At first, the velocity is updated according to the following equation (Haupt and Haupt, 2004):

$$\text{vel}_{i+1}(m,n) = \text{vel}_i(m,n) + c_1 \times r_1 (\text{lpop}_i(m,n) - \text{pop}_i(m,n)) + c_2 \times r_2 (\text{gpar}(n) - \text{pop}_i(m,n)) \quad (7)$$

where,  $c_1$  and  $c_2$  represents a learning factors,  $r_1$  and  $r_2$  denotes independent uniform random numbers,  $i$  denotes the current iteration,  $m = 1, 2, \dots, P$  and  $n = 1, 2, \dots, M$ . The particle position can be updated using the following expression (Jin and Rahmat-Samii, 2005):

$$\text{pop}_{i,a} = \text{pop}_i + \text{vel}_{i,a} \Delta t \quad (8)$$

where,  $\Delta t$  denotes the time interval between two consecutive iterations which assumed to be unity. The new population is assessed to the cost function. The new best local cost vector can be updated from the following equation:

$$l \cos t_{i+1}(m) = \text{minimum}(l \cos t_i(m), l \cos t_{i+1}(m)) \quad (9)$$

While the new best local population matrix includes the particles corresponding to the minimum cost that results from Eq. 8. In other words, the new best local population can be formulated as:

$$l \text{pop}_{i+1}(m,:) = \begin{cases} \text{pop}_{i+1}(m,:) & \text{cost}_{i+1}(m) \leq l \cos t_i(m) \\ l \text{pop}_i(m,:) & \text{otherwise} \end{cases} \quad (10)$$

Subsequently, the minimum value of the best local cost is compared with the global cost. If the global cost is less than the minimum best local cost then the global cost and the global particle vector remain as they are otherwise the global cost and the global particle vector take the values of the minimum best local cost and the best local particle corresponding to it, respectively. The previous process continues until an acceptable global cost value is achieved. When the aforesaid scenario is over the optimum particle will be the global particle.

## RESULTS AND DISCUSSION

A smart antenna system with six omni-directional antenna elements ( $M = 6$ ) and half wavelength inter-elements spacing is considered here to implement the proposed algorithm. The desired signal is assumed to arrive at  $\Phi_0 = 50^\circ$ . It is also assumed that one interfering signal is received at  $\Phi_1 = 120^\circ$  with the presence of white noise. If the sampling frequency  $f_s$  is taken to be equal to  $(100 f)$  where,  $f$  denotes the frequency of the desired signal, the instantaneous value of the desired signal can be written as:

$$s_o(n) = \cos\left(2\pi n \frac{f}{f_s}\right) = \cos\left(\frac{2\pi n}{100}\right) \quad (11)$$

while the interfering plus noise signal at each iteration  $I(n)$  for 100 iteration is given by  $I(n) = \text{randn}(1,100)$

where,  $\text{randn}$  denotes a Matlab function that generates random numbers of normal distribution. The instantaneous value of the signal vector is then given by:

$$x(n) = s_o(n)a_o + I(n)a_i \quad (12)$$

The instantaneous value of the weight vector can easily be found from Eq. 4. If the population size  $P = 10$  then the initial population matrix is set to be  $(\text{pop} = \text{rand}(P, M))$  where,  $\text{rand}$  denotes another Matlab function generates uniform random numbers and the initial velocity matrix  $(\text{vel} = \text{rand}(P, M))$ . These random particles are assessed to the cost function expressed in Eq. 6. Now, the best local cost ( $l \cos t$ ) vector and the best local population matrix ( $l \text{pop}$ ) take the values ( $\text{cost}$ ) and ( $\text{pop}$ ), respectively. The best global cost can be given by  $(g \text{ cost} = \min(l \cos t))$  where,  $\min$  is a Matlab function denotes the minimum value. The best global particle is the particle corresponding to the minimum cost. Before starting, let the values of  $c_1 = 1$  and  $c_2 = 3$ . The updating process is begins by updating the velocity matrix using Eq. 7 with  $r_1 = \text{rand}(1)$  and  $r_2 = \text{rand}(1)$ . The population matrix is updated using Eq. 8 with  $\Delta t = 1$ . With aid of the Matlab function  $\min$ , Eq. 9 is applied to update the best local cost. As a result, the best local population is updated using Eq. 10. The minimum local cost is compared with the global cost then set the global cost to be equal to the lowest value and the global particle to be equal to the particle corresponding to the selected cost. The updating process continues until the global cost become less than or equal to certain cost margin (which assumed to be  $10^{-3}$ ). After that the optimum weights vector of the  $n$ th sample of time can be found from Eq. 4 where the magnitudes of the weights are taken from the global particle. The same scenario is repeated for  $(n+1)$ th sample of time. The desired signal and the array output signal are shown in Fig. 2. Figure 2 shows the two signals are similar for all samples of time.

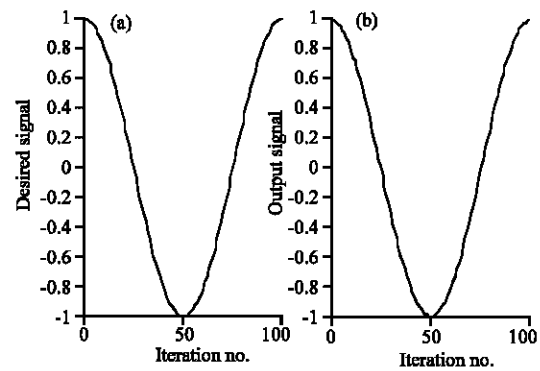


Fig. 2: The waveform of; a) the desired signal and b) the array output signal using PSO algorithm

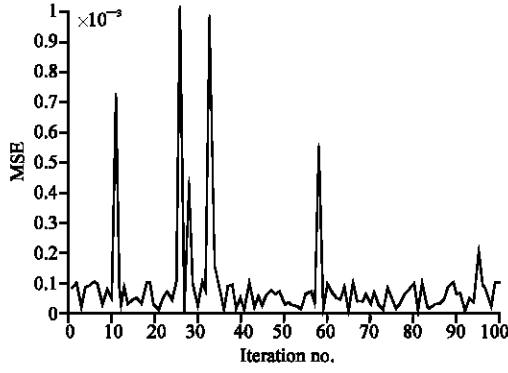


Fig. 3: Mean square error at each iteration using the PSO algorithm

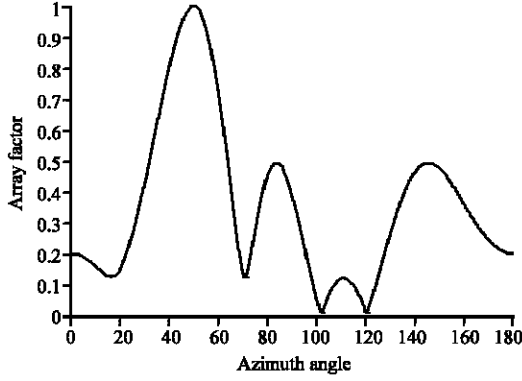


Fig. 4: The resulted normalized array factor

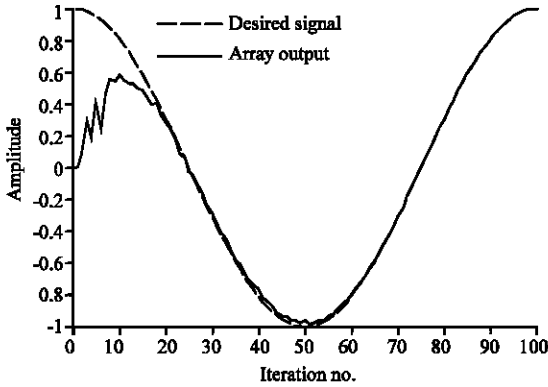


Fig. 5: The desired and array output signal of RLS adaptive algorithm

Figure 3 shows the Mean Square Error (MSE) at each sample of time and it is found to be  $\leq 10^{-3}$  for all samples making the array output signal similar to the desired signal. Figure 4 shows the resulted normalized array factor of the last sample of time. To highlight the merit of PSO algorithm, it is compared with two well known adaptive

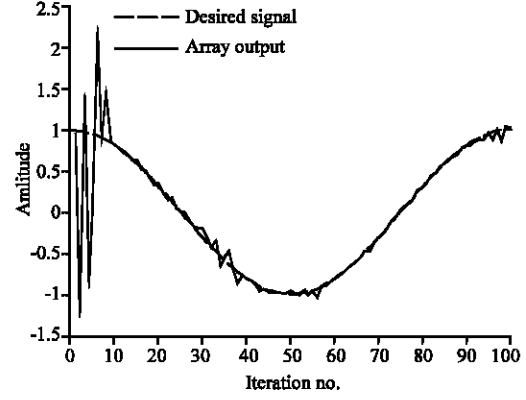


Fig. 6: The desired and array output signals of SMI adaptive algorithm

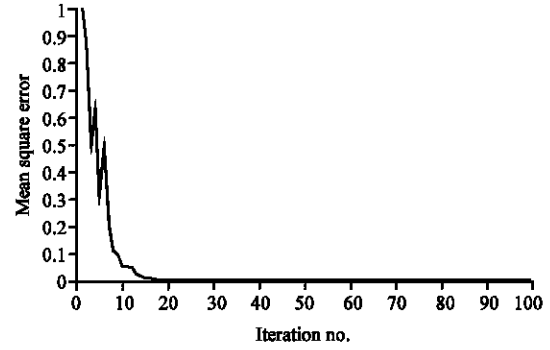


Fig. 7: The mean square error of RLS adaptive algorithm

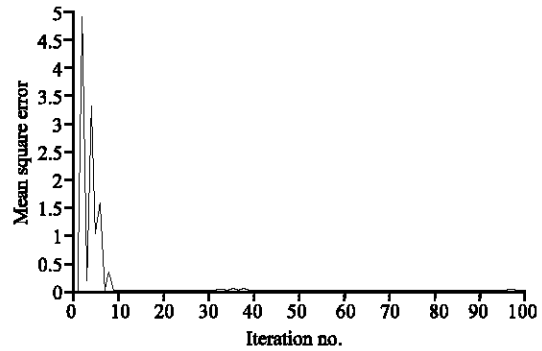


Fig. 8: The mean square error of SMI adaptive algorithm

algorithms namely; Recursive Least Square (RLS) and Sample Matrix Inversion (SMI) algorithms (Godara, 2004). It is shown in Fig. 5 and 6, the above two adaptive algorithms have bad resolution compared with that of the PSO algorithm.

Figure 7 and 8 expose the problem of high mean square error of the two adaptive algorithms compared with that of PSO algorithm.

## CONCLUSION

Particle swarm optimization algorithm has been proposed to optimize the performance of a smart antenna system. All particles have been assessed to cost function chosen to be equal to the mean square error between the array output signal and a reference signal considered to be the similar to the desired signal. The simulation results show that PSO algorithm is superior to the classical adaptive algorithms such as recursive least square algorithm and sample matrix inversion algorithm due to its low mean square error which is found to be  $\leq 10^{-3}$  and its high output signal resolution.

## REFERENCES

- Ahn, S. and M. Kim, 2009. Performance analysis of smart antenna system using a phase update method in W-CDMA signal environment. International Conference on New Trends in Information and Service Science, June 30-July 2, IEEE Computer Society, Beijing, pp: 740-742.
- Chamaani, S., M.S. Abrishamian and S.A. Mirtaheeri, 2010. Time-domain design of UWB vivaldi antenna array using multiobjective particle swarm optimization. IEEE Antennas Wireless Propagation Lett., 9: 666-669.
- Gangopadhyaya, M., P. Mukherjee and B. Gupta, 2009. The resonant frequency optimization of aperture-coupled microstrip antenna using particle swarm optimization algorithm. Proceedings of the Applied Electromagnetics Conference (AEMC), Dec. 14-16, Kolkata, pp: 1-4.
- Gies, D. and Y. Rahmat-Samii, 2004. Vector evaluated particle swarm optimization (VEPSO): Optimization of a radiometer array antenna. Proceedings of the IEEE Antennas and Propagation Society International Symposium, June 20-25, USA., pp: 2297-2300.
- Godara, L., 2004. Smart Antennas. CRC Press, Boca Raton FL., pp: 3566-3580.
- Haupt, R.L. and S.E. Haupt, 2004. Practical Genetic Algorithms. 2nd Edn., John Wiley and Sons, New Jersey, ISBN: 0471455652.
- Jeng, S.S. and H.P. Lin, 1999. Smart antenna system and its application in low-earth-orbit satellite communication systems. IEE Proc. Microwave Antennas Propagation, 146: 125-130.
- Jin, N. and Y. Rahmat-Samii, 2005. Parallel particle swarm optimization and finite-difference time-domain (PSO/FDTD) algorithm for multiband and wide-band patch antenna designs. IEEE Trans. Antennas Propagation, 53: 3459-3468.
- Li, W.T., S.F. Liu and X.W. Shi, 2008. Application of improved particle swarm optimization in antenna array pattern synthesis. Proceedings of the Global Symposium on Millimeter Waves, April 21-24, USA., pp: 119-122.
- Liberti J. and T.S. Rappaport, 1999. Smart Antennas for Wireless Communications: IS-95 and Third Generation CDMA Applications. Prentice Hall, New York, ISBN-13: 978-0137192878, pp: 528.
- Pantoja, M.F., A.R. Bretones, F.G. Ruiz, S.G. Garcia and R.G. Martin, 2007. Particle-swarm optimization in antenna design: optimization of log-periodic dipole arrays. IEEE Antennas Propagation Mag., 49: 34-47.
- Papadopoulos, K., C. Papagianni, I. Foukarakis, D. Kaklamani and I. Venieris, 2006. Optimal design of switched beam antenna arrays using particle swarm optimization. Proceedings of the 1st European Conference on Antennas and Propagation, Nov. 6-10, Nice, pp: 1-6.
- Reed, J., 2002. Software Radio: A Modern Approach to Radio Engineering. Prentice Hall, New York.
- Robinson, J., S. Sinton and Y. Rahmat-Samii, 2002. Particle swarm, genetic algorithm and their hybrids: Optimization of a profiled corrugated horn antenna. IEEE Antennas Propagation Soc. Int. Symp., 1: 314-317.
- Skolnik, M.I., 2001. Introduction to Radar Systems. 3rd Edn., McGraw-Hill, New York.
- Stallings, W., 2000. Local and Metropolitan Area Networks. 6th Edn., Prentice Hall, ISBN-13: 978-0130129390, New York, pp: 478.