Journal of Engineering and Applied Sciences 5 (4): 332-336, 2010
ISSN: 1816-949X

A Modified Continuous Genetic Algorithm for Smart Antenna System

Abdulkareem S. Abdallah and Falih M. Mousa
Department of Electrical Engineering, College of Engineering, University of Basrah, Basrah, Iraq

Abstract: This study presents a modified continuous genetic algorithm to optimize the performance of the smart antenna system. The chromosomes of this modified algorithm are assessed to double crossovers and blending. Moreover, the first chromosome is excluded from the mutation process in order to increase the algorithm speed. The performance of the proposed algorithm is compared with that of two well-known adaptive algorithms, namely; the Recursive Least Square (RLS) and Sample Matrix Inversion (SMI). The simulation results demonstrate that the proposed system has better output signal resolution and smaller mean square error.

Key words: Smart antenna, adaptive algorithm, genetic algorithm, mean square error, MoM, Iraq

INTRODUCTION

The term smart antenna is referred to any antenna array that can adjust or adapt its own beam pattern in order to emphasize signals of interest and to minimize interfering signals. Smart antennas have numerous important benefits in wireless applications such as: providing robustness to system perturbation, reducing sensitivity to non ideal behaviours, improving system capacity, as well as separating the received signals spatially with aid of Space Division Multiple Access (SDMA) concept (Liberti and Rappaport, 1999).

Smart antennas have wide range of applications include but not limited to mobile wireless communications (Liberti and Rappaport, 1999), software radio (Reed, 2002), Wireless Local Area Network (WLAN) and wireless metropolitan area network (Stallings, 2000), radar systems (Skolnik, 1980), satellite communications (Jeng and Lin, 1999) as well as wideband code division multiple access systems (Ahn and Kim, 2009).

Genetic Algorithms (GAs) have recently found extensive applications in solving global optimization searching problems. They have several advantages over the traditional numerical optimization approaches such as: optimize with continuous or discrete parameters do not require derivative information study with a large number of variables and provide a list of optimum parameters, not just a single solution (Haupt and Werner, 2007). In the last few years, there were many attempts to use this technique in electromagnetic applications.

Altshuler and Linden (1997) have designed wire antennas using GA by synthesizing the wire configuration in order to obtain the desired electromagnetic properties. Edwards *et al.* (1999) have described efficient Method of Moment (MoM) algorithm to model printed eccentric spiral antennas which is then run under a GA optimization routine to design antennas with specific performance attributes. In Choo *et al.* (2000) have optimized the shape of broadband microstrip antennas using GA without increasing the overall volume or manufacturing cost of antenna.

Avila *et al.* (2004) have used GA to optimize the offset reflector antenna to obtain a uniform radiation pattern on Brazilian territory. Zainud-Deen *et al.* (2005) have calculated the complex excitations of the adaptive array with aid of MoM and GA to maximize the output power of the desired signal and minimize the total output power. Sedaghat-Pisheh *et al.* (2006) have presented GA optimization of a broadband coplanar waveguide fed on chip slot antenna.

Celik and Iskander (2008) have introduced a GA solution to adjust optimally the beam pattern of the array elements to minimize the output power fluctuation in a given scan range for 60 GHz hybrid smart antenna system. In this study, a special type of GAs named continuous genetic algorithm is used to adapt the weights of the adaptive smart antenna. The optimal weights resulted at each sample of time (iteration) are then used to orient the main beam of the smart antenna radiation pattern in the direction of the desired signal and cancel the interfering signals. As a matter of comparison, the simulation results of the modified continuous GA 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 the continuous GA is also presented. The performance improvement of the proposed system is shown by simulation results.

Corresponding Author: Abdulkareem S. Abdallah, Department of Electrical Engineering, College of Engineering, University of Basrah, Basrah, Iraq

MATERIALS AND METHODS

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

$$y(n) = w^H(n)\, x(n) \tag{1}$$

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 obvious from 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:

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

Where, N is an (Mx1) matrix and a_k denotes the steering vector of the kth signal given by Godara (2004):

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

Where:

$(\beta = 2\pi/\lambda)$	= Represents the wave number
λ	= Represents the wavelength of the desired signal
d	= The distance between every two adjacent elements
Φ_k	= Denotes the azimuth angle of the kth signal

Continuous genetic algorithm in smart antenna systems: Continuous GA represents its variables by floating-point numbers over whatever range deemed appropriate (Haupt and Haupt, 2004). This technique can be used to optimize the array output signal by making it approximately the same as the desired signal. When the direction of the desired signal is known, the phase of weights can be deduced from the steering vector of the desired signal a_o as:

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

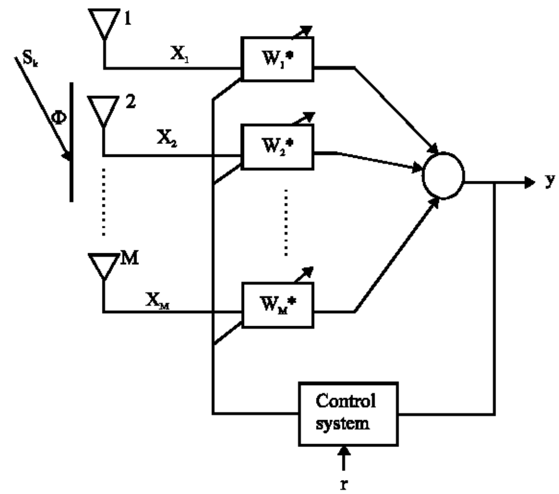

Fig. 1: Simple smart antenna

such that the main beam can be oriented in the direction of the desired signal. By optimizing the magnitude of the weights, nulls can be positioned in the direction of interfering signals and in this case, the chromosomes (chrom) of the continuous GA can be expressed as Haupt and Haupt (2004):

$$\text{Chrom} = \left[\, |w_1| \quad |w_2| \quad \ldots \quad |w_M| \,\right] \tag{5}$$

The Mean Square Error (MSE) can be used as a cost function such that:

$$\text{Cost} = \left| r(n) - w^H(n)\, x(n) \right|^2 \tag{6}$$

The conventional GA optimization technique is usually started by assuming the population size to be equal to P where P represents the number of chromosomes in the population. Therefore, the initial population can be expressed by a (P x M) random matrix and each chromosome is assessed by the cost function. The P chromosomes are then ranked from lowest cost to highest cost.

Only the top chromosomes are kept for mating and the rest are discarded to make room for the new offspring. By choosing the even kept chromosomes as fathers and the odds as mothers then combine every two parents, a new offspring will generated.

A crossover between every two parents occurs by interchanging weights at randomly selected point while the blending occurs by choosing another randomly point (say m) and changing the weight as (Haupt and Haupt, 2004):

$$|w_m|_{new1} = |w_m|_1 - \rho(|w_m|_1 - |w_m|_2) \tag{7}$$

$$|w_m|_{new1} = |w_m|_2 + \rho(|w_m|_1 - |w_m|_2) \quad (8)$$

Where, p is a random value between 0 and 1. Each mating produces two new offspring differ from their parents and after these steps the new population should be rearranged also from the lowest cost to the highest.

In continuous GA, mutation is usually done by replacing random weights belong to random chromosomes with another new random values (Haupt and Haupt, 2004). However in this study, a modified continuous GA is proposed by excluding the first chromosome in order to give the best performance. Therefore, the chromosomes are ranked again from lowest to highest cost and the number of mutations is given by:

$$\text{No. of mutation} = [\text{mutation rate . P. M}] \quad (9)$$

The above process continues until an acceptable cost value is achieved. When the above scenario is over, the optimum chromosome will be the chromosome of index 1.

RESULTS AND DISCUSSION

A smart antenna system with six omni-directional antenna elements (M = 6) and a half wavelength inter-elements spacing is considered here to implement the proposed algorithm. The desired signal is assumed to arrive at $\Phi_0 = 40°$. It is also assumed that one interfering signal is received at $\Phi_1 = 120°$ with the presence of white noise. If the sampling frequency f_s is taken to be equal to (100f) where f denotes the frequency of the desired signal, the instantaneous value of the desired signal can be written as:

$$s_0(n) = \cos(2\pi n \frac{f}{f_s}) = \cos(\frac{2\pi n}{100}) \quad (10)$$

While the interfering plus noise signal at each iteration I(n), for 100 iteration is given by (I(n = randn) where (randn) denotes a MATLAB function that generates random numbers of normal distribution. The instantaneous value of the signal vector is then given by:

$$x(n) = s_0(n)a_0 + I(n)a_1 \quad (11)$$

The instantaneous value of the weight vector can easily be found from Eq. 4. If the population size P equal to 8, then the initial population can be set to population = rand where (rand) denotes another MATLAB function that generates a uniform random numbers. According to the cost function given in Eq. 6, the indices of chromosomes are rearranged from lowest to highest cost and four chromosomes are then discarded and four are kept. The four kept chromosomes are separated into two fathers and two mothers and the mating process starts. In order to increase the speed of the GA, a double crossovers and double blending at random points are made and the new four offspring are put instead of the four discarded parents. By choosing mutation rate to be equal to 20%, the number of mutations is found as 10 by using Eq. 8.

After mutating the chromosome of the new population (except the first chromosome), another re-arranging process is occurred. The cost of the first chromosome which gives minimum cost is compared with a cost margin of 10^{-6}. If this cost is found to be larger than the cost margin, a new discarding, mating and mutation occur.

Otherwise, the first chromosome can be considered to be the optimum one. As a results, the optimum weights vector of the nth iteration can be expressed as in Eq. 4 and the same scenario is repeated for the $(n+1)^{th}$ iteration. The desired signal and the array output signal are shown in Fig. 2. The two signals are approximately identical for all iterations. Figure 3 shows the Mean Square Error (MSE) at each iteration and it found to be less than or equal to

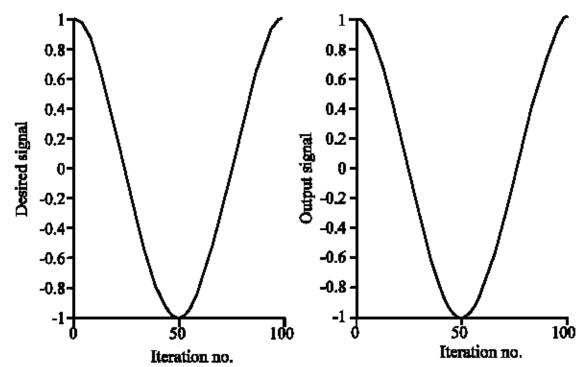

Fig. 2: The waveform of (a) the desired signal (b) the array output signal using the proposed GA

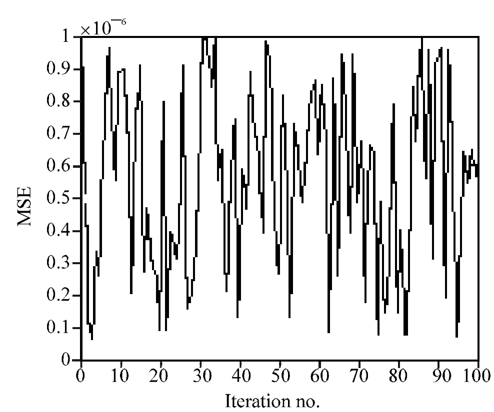

Fig. 3: Mean square error at each iteration using the proposed GA

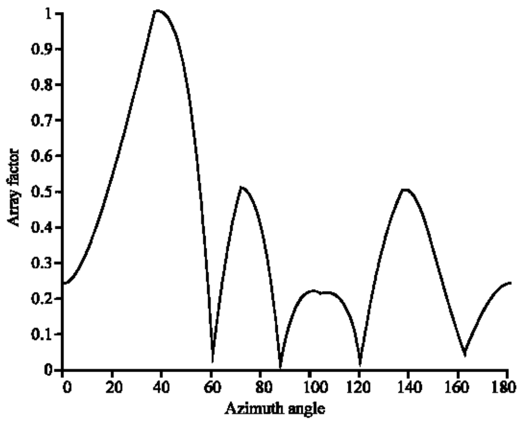

Fig. 4: The resulted normalized array factor

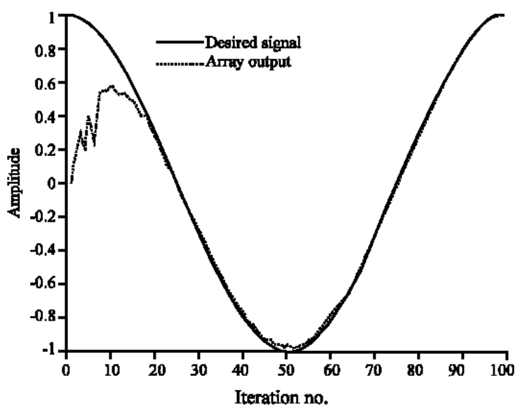

Fig. 5: The desired and array output signals of RLS adaptive algorithm

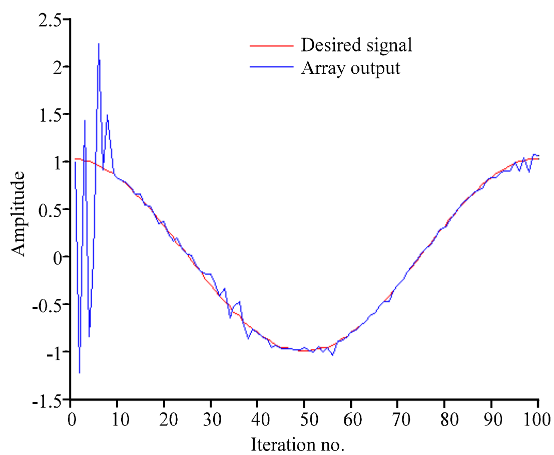

Fig. 6: The desired and array output signals of SMI adaptive algorithm

10^{-6} for all iterations making the array output signal very similar to the desired signal. The resulted normalized array factor of the last iteration is described in Fig. 4. To

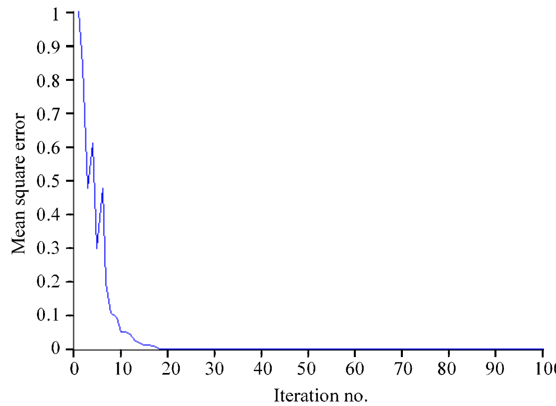

Fig. 7: The mean square error of RLS adaptive algorithm

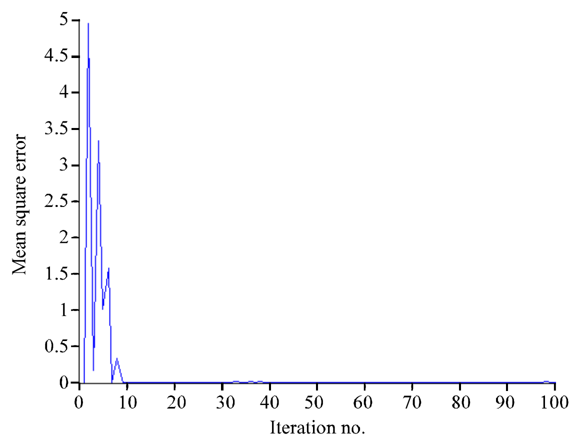

Fig. 8: The mean square error of SMI adaptive algorithm

reveal the merits of the proposed GA, it is compared with two well known adaptive algorithms, namely; the Recursive Least Square (RLS) and Sample Matrix Inversion (SMI) algorithms (Godara, 2004). It is obvious from Fig. 5 and 6 that the earlier two adaptive algorithms have bad output resolution compared with that of the proposed GA. Moreover, these two algorithms have also high mean square errors shown in Fig. 7 and 8 as compared with the proposed GA.

CONCLUSION

A modified continuous genetic algorithm has been proposed to optimize the performance of a smart antenna system by excluding the first chromosome of the population from the mutating process. Also double crossovers and blending at random points have been made to increase the speed of this algorithm. The results show that the proposed algorithm is superior to classical adaptive algorithms such as RLS and SMI algorithms. It has mean square error $<10^{-6}$ and an excellent resolution between the desired and output signals.

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.

Altshuler, E. and D. Linden, 1997. Wire-antenna designs using genetic algorithms. IEEE Antennas Propagation Magazine, 39: 33-43.

Avila, S., Jr. W.P. Carpes and J.A. Vasconcelos, 2004. Optimization of an offset reflector antenna using genetic algorithms. IEEE Trans. Magn., 40: 1256-1259.

Celik, N. and M. Iskander, 2008. Genetic-algorithm-based antenna array design for a 60-GHz hybrid smart antenna system. IEEE Antennas Wireless Propagation Lett., 7: 795-798.

Choo, H., A. Hutani, L. Trintinalia and H. Ling, 2000. Shape optimisation of broadband microstrip antennas using genetic algorithm. Electronics Lett., 36: 2057-2058.

Edwards, R.M., S.K. Khamas and G.G. Cook, 1999. Design of printed eccentric spiral antennas using genetic algorithm optimization. Proceedings of the National Conference on Antennas and Propagation, Mar. 31-Apr. 01, IEEE Internation, New York , UK, pp: 375-379.

Godara, L., 2004. Smart Antennas. CRC Press, Boca Raton FL., pp: 3566-3580.

Haupt, R. and D. Werner, 2007. Genetic Algorithms in Electromagnetics. John Wiley and Sons, Inc., New York.

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.

Liberti J. and T. Rappaport, 1999. Smart Antennas for Wireless Communications: IS-95 and Third Generation CDMA Applications. Prentice Hall, New York.

Reed, J., 2002. Software Radio: A Modern Approach to Radio Engineering. Prentice Hall, New York.

Sedaghat-Pisheh, H., H. Aliakbarian, Z. Safarian, M. Shahabadi and C. Lucas, 2006. Design, simulation and optimization of an on-chip bow-tie slot antenna using genetic algorithm. Proceedings of the International Symposium on Antenna and Propagation Society, (APS'06), IEEE International, pp: 2591-2594.

Skolnik, M.I., 1980. Introduction to Radar Systems. 3rd Edn., McGraw-Hill Book Company, New York, USA., ISBN: 10: 0070579091, pp: 640.

Stallings, W., 2000. Local and Metropolitan Area Network. 6th Edn., Prentice Hall, New York, ISBN-13: 978-0130129390, pp: 478.

Zainud-Deen, S., E. Mady, K. Awadalla and H. ASharshar, 2005. Adaptive arrays of smart antennas-using genetic algorithm. Proceedings of the 22nd National Radio Science Conference, Mar. 15-17, IEEE International, Cairo, Egypt, pp: 1-9.