Proceedings of ISAP2007, Niigata, Japan

Polarization Diversity Smart Antenna with Triple-COLD Array Using Genetic Algorithm

#Yerram Ravinder [1], V.M. Pandharipande [2]
Centre for Excellence in Microwave Engineering,
ECE Department, University College of Engineering
Osmania University, Hyderabad-7, India
[1]yerramravi@yahoo.com, [2]vijaympande@yahoo.com

1. Introduction

In current times, the demand fir the capacity enhancement is ever increasing in wireless communications. Capacity enhancement is primarily achieved by implementation of space division multiple access (SDMA) using smart antennas. Conventional space diversity reception fails when two or more user signals arrive from the same direction or are very close to each other. SDMA works efficiently only when the spatial separation expressed in terms of the angles of arrival between the desired user and the interfering users is below a certain threshold [1]-[2]. In this case any adaptive array would not distinguish between the desired and undesired signals. Therefore, the capacity of the SDMA is limited under such conditions. Polarization diversity is the solution for such a scenario. Capacity of the system can be doubled using these dual polarization diversity schemes [2]-[4].

In this paper it is demonstrated that the triple-COLD array (TCA) can be used as a dual diversity smart antenna. This antenna adapts to arbitrary polarization and angle of arrival. It works as spatial diversity antenna when there is sufficient spatial separation, in terms of angles of arrival, between the signals. And, it works as polarization diversity antenna when users arrive from very close or the same to the desired user direction. Polarization diversity is achieved by assigning different sets of polarization angles (ellipticity and orientation) to different users when these users arrive from very close or the same direction. This polarization sensitive TCA combined with adaptive minimum bit error rate (AMBER) algorithm [6] provides significant performance gain in terms of smaller BER for the desired user under such scenario with different polarizations. BER can be directly minimized by using the AMBER approach using gradient based algorithms such as simplified conjugate gradient (CG) algorithm proposed as in [6]. But in this approach, the choice of the appropriate algorithmic parameters may turnout to be challenging. To overcome these challenges, we propose to use genetic algorithm for direct minimization of BER.

In this contribution, we investigated the BER performance of TCA for BPSK signals. BER is directly minimized using genetic algorithm alternate to gradient methods. The performance is compared with standard MMSE approach.

2. Triple-COLD Array

TCA is an array of three COLD elements orthogonal to each other as shown in Fig. 1. Where as the COLD (Co centered Loop and Dipole) is an array of co centered short dipole and a small loop. The loops and dipoles are sensitive to the polarizations of incident plane waves. The dipoles are sensitive to the incident electric field components and the loops to magnetic field components of the incident wave. An arbitrary plane wave coming into the array can be characterized by its arrival angles, elevation angle θ_i , azimuth angle ϕ_i and its polarization ellipticity angle α_i, orientation angle β_i, and its amplitude A_i. The steering vector is given by [5]

$$s_i = [U_i \;\; U_i \exp(j\frac{2\pi d}{\lambda}\sin\theta_i \sin\phi_i) \ldots\ldots \; U_i \exp\{j(l-1)\frac{2\pi d}{\lambda}\sin\theta_i \sin\phi_i\}]^T \tag{1}$$

ISBN: 978-4-88552-223-9 C3055©IEICE

where

$$U_i = \begin{bmatrix} \sin\gamma_i \cos\theta_i \cos\phi_i e^{j\eta_i} - \cos\gamma_i \sin\phi_i \\ \sin\gamma_i \cos\theta_i \sin\phi_i e^{j\eta_i} + \cos\gamma_i \cos\phi_i \\ -\sin\theta_i \sin\gamma_i e^{j\eta_i} \\ -\cos\gamma_i \cos\theta_i \cos\phi_i - \sin\gamma_i \sin\phi_i e^{j\eta_i} \\ -\cos\gamma_i \cos\theta_i \sin\phi_i + \sin\gamma_i \cos\phi_i e^{j\eta_i} \\ \cos\gamma_i \sin\theta_i \end{bmatrix}^T \tag{2}$$

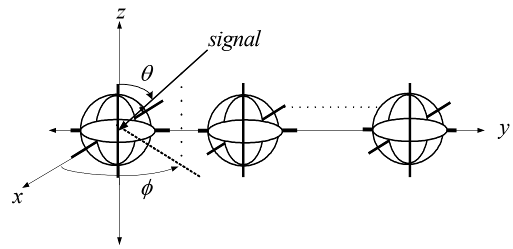

Fig. 2 Triple-COLD Array

γ,η are given by $cos2\gamma=cos2\alpha cos2\beta$ and $tan\eta=tan2\alpha csc2\beta$. This triple-COLD array is completely modeled by (1) and (2). These are used as the elements of the smart antenna. This array is made adaptive by adjusting the weights either by MMSE [5] or Adaptive Minimum Bit Error Rate approach (AMBER). The probability of error function for BPSK modulation scheme using the array is given by

$$p(y_R; w) = \frac{1}{K} \frac{1}{\sqrt{2\pi w^H w \rho_n}} \sum_{k=1}^{K} \exp\left(-\frac{\left(y_R - y_R(k; w)\right)^2}{2\pi\rho_n^2 w^H w} \right) \tag{3}$$

where w is the weight vector, y_R is the out put of the receiver, ρ_n is the kernel width and K is the length of the training sequence as given in [6]. This is the objective function for minimization of bit error rate. Weights are calculated for MBER using GA. As this array is polarization sensitive, it adapts to the desired signal polarization (α, β) and its angle of arrival (AoA) (θ, ϕ). This is demonstrated by numerical simulation of BER in this paper.

2.1 MBER with Genetic Algorithm

Even though the array gradient-based optimization is capable of minimization of BER, the convergence of the algorithm is sensitive to the choice of the algorithm's parameters. For example, the choice of the initial weight vector is critical in order for the solution to converge to the minimum of the BER surface. Another parameter that affects the performance of the MBER solution is the step size μ used for updating the array weights in the direction opposite to the BER gradient. The choice of this step size must be based on a compromise, since a step size that is too high might not allow convergence to the minimum BER point; where as the opposite scenario will require a high number of iterations for attaining convergence to the MBER solution.

An attractive method that might be able to assist the MBER in circumventing the above – mentioned problems is constituted by the family of Genetic algorithms (GA) [7]. Although GAs have been used in numerous applications, such as machine learning and modelling adaptive processes, by far the largest application of GAs is in the domain of function optimization. GAs are different from traditional algorithms, because they do not attempt to optimize the desired decision variable. Instead they encode the decision variables such as weight vectors into finite length strings or GA individuals, which are then optimized. In case of adaptive array considered here, both the real and imaginary part of complex-valued weights have to be represented by a single GA string to create an individual. A GA does not commence its optimization process from a single point in the search space, but rather from an entire set of individuals, which form the initial population. In other words, GAs may be invoked in robust global search and optimization procedures that do not require the knowledge of the function's derivatives or any gradient related information concerning the search space. Hence, non differentiable functions as well as functions with multiple local minima, like BER surface of the communication system considered here, represent classes of problems, where GAs can be efficiently applied. The complexity of the CG is proportional to the number of iterations used for finding the MBER solution, where as the complexity of the GA based solutions, is proportional to the product of the population size and the number of generations.

3. Simulation Results

The performance of the antenna array is investigated through simulation for five users arriving from different directions with arbitrary polarizations assuming they are all of equal power. Because large number of parameters required for specifying both the desired and undesired signals, many types of curves can be plotted. However, we plotted few of them to demonstrate how efficiently this array can be used for polarization and spatial diversity. Inter element spacing is taken as $\lambda/2$ and the number of elements to be 2. It is assumed that the first user is to be desired and the rest four are the interfering users. Weight vector is calculated using AMBER approach by using the GA which directly minimizes the BER. Firstly the probability of error equation (3) is used as the objective function to be solved by the GA. Each individual in a population represents either the real or imaginary part of the weight values. At the beginning of the GA process the individuals are initialized randomly. These individuals are then evaluated for the sake of finding the best array weights in the sense of the MBER related objective function. This GA operation is followed by the selection, crossover and mutation processes, before the individuals are re-evaluated again. The process will continue, until the specific termination criteria advocated is satisfied.

Table 1 Parameters for GA simulation

Population size	30	Crossover type	Scattered
Number of Generations	150	Crossover probability	0.8
Selection	Stochastic Uniform	Encoding and Decoding	Binary
Mutation	Uniform	Elite count	2
Mutation probability	0.01	Fitness scaling	Rank

The parameters, used for simulation in our GA set up, are outlined in the Table 1. To evaluate the BER performance of the TCA, AOA of users ϕ_i = [15^o 15^0 15^o 20^o 25^o] and elevation angles θ are assumed to be 90^0 for all the users. In this case the first three users are arriving from the same direction and other two are from very close to the first (desired) user. Fig. 2 shows the BER performance of the array, versus SNR, with $\beta = 30^o$ for all the users and with different polarization angles α_i =[0 30 45 –45 -15]. Fig. 3 shows the BER performance of the array, versus SNR, with $\beta = 60^o$ for all the users and with different α_i =[0 30 45 –45 -15]. It can be seen from these figures, that a better BER can be achieved by choosing the different polarization angles for each user.

It is shown in Fig. 2 and Fig. 3 that there is an improvement in BER of nearly 10^{-7}-10^{-15} by using GA assisted MBER (GA-MBER) and 10^{-2}-10^{-3} using MMSE approach of TCA compared to that of basic array at SNR 20dB. The performance of the array is again evaluated for another set of polarization angles by choosing β_i =[30 60 90 -30 -90] for $\alpha = 15^o$ and $\alpha = -15^o$, for all the users. These results plotted in Fig. 4 and Fig. 5 confirm the performance of the array that there is an improvement in BER of 10^{-3}-10^{-4} by using GA-MBER and 10^{-2}-10^{-3} using MMSE approach of TCA compared to that of basic array at SNR 20dB. Here the BER performance by MMSE approach serves as bench marker for comparison. The performance is largely improved in terms of the lower BER over the basic array with the help of polarization diversity with the better convergence for any set of polarization angles. The BER performance can be improved by choosing arbitrary sets of polarizations for different users.

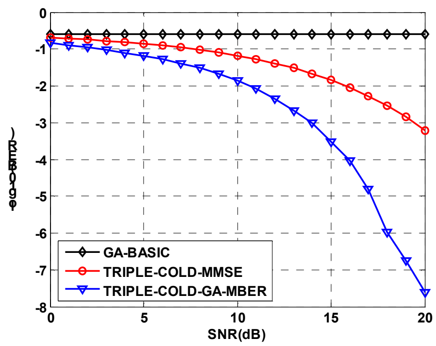

Fig. 2 BER performance of Triple-COLD
α_i = [0 30 45 –45 -15] and β =30 for all users

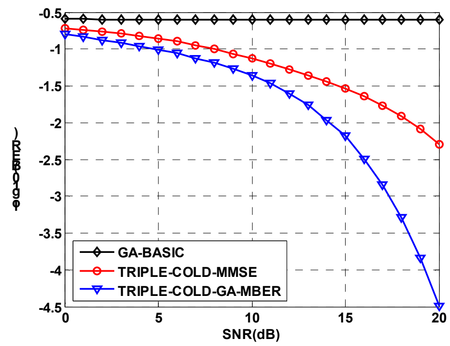

Fig. 4 BER performance of Triple-COLD
β_i = [30 60 90 -30 -90] and α =0 for all users

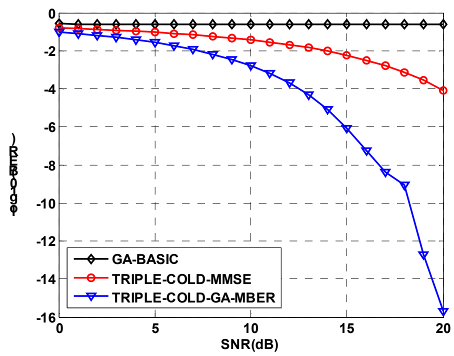

Fig. 3 BER performance of Triple-COLD
α_i = [0 30 45 –45 -15] and β =60 for all users

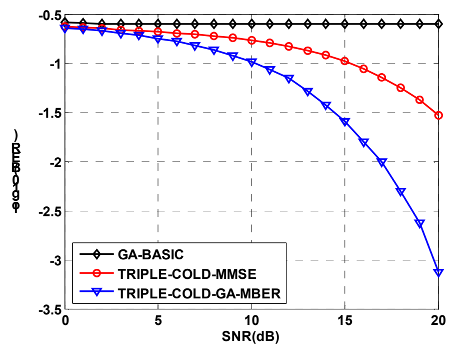

Fig. 5 BER performance of Triple-COLD
β_i = [0 30 45 –45 -15] and α =30 for all users

4. Conclusion

The performance of the polarization diversity smart antenna with TCA has been investigated. It has been demonstrated that the TCA with GA assisted MBER approach utilizes the polarization diversity better and BER performance is better as compared to that of TCA with MMSE even when the users arrive from very close direction or same direction. GA is capable of approaching the MBER solution at a lower complexity than CG algorithm. If this TCA is used in smart antenna for wireless communication systems, implementing the use of polarization diversity along with spatial diversity, will lead to increase in capacity.

References

[1] Joseph C. Liberti, Jr., Theodore S. Rapp port, Smart Antennas for wireless Communications:IS-95 and Third Generation CDMA Applications (Prentice Hall PTR, 2000)

[2] William C.Y, Yu S Yeh, Polarization Diversity System for Mobile Radio, *IEEE Trans. on Communications,* Vol.COM-20, Oct. 1972, pp.912-923.

[3] Roddey G.V, Polarization diversity in Mobile Communications, *IEEE Trans. in Vehicular Technology,* Vol.39, Aug. 1990, pp.177-186,.

[4] R. U. Nabar, V. Erceg, H. Bolskei, D. Gesbert, and A. J. Paulraj, Performance of Multi antenna signaling techniques in the Presence of Polarization Diversity, *IEEE Trans. on Signal Processing,* Vol.50, pp. 2553-2562, Oct. 2002.

[5] R.T. Compton Jr., *Adaptive Arrays – Concepts and Performance* (Englewood Cliffs,NJ: Prentice – Hall, 1998).

[6] S.Chen, N.N. Ahmad and L.Hanzo, Adaptive minimum bit error rate beam forming, *IEEE Trans. on Wireless Commun.,* Vol.4, pp. 341-348, March 2005.

[7] David E. Goldberg, *Genetic Algorithms* (Reading, Massachusetts: Addison-Wesley, 1989)