Antenna Selection in MIMO Systems using Evolutionary Algorithms

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***Abstract*—In this paper, our main goal is to fulfill the antenna selection (AS) criterion for a multiple–input multiple-output (MIMO) system, which, in our case, is the maximization of the channel capacity. In order to accomplish this, we display the performance of biogeography-based optimization (BBO) algorithm on the channel capacity function and compare it with the genetic algorithm (GA), the real-value genetic algorithm (RVGA) as well as the ant colony optimization (ACO). The results, which are presented in this paper, are based exclusively on simulated channels and highlight the superiority of BBO over the aforementioned optimization algorithms.**

***Index Terms*— Multiple–input multiple-output (MIMO) systems, antenna selection (AS), biogeography-based optimization (BBO), genetic algorithm (GA), real-value genetic algorithm (RVGA), ant colony optimization (ACO), exhaustive search (ES).**

I. Introduction

Nowadays, due to the increasing demand of faster data transmission speed, multiple–input multiple-output (MIMO) systems have played a major role on antenna array communications. With their contribution we have achieved higher data rates and improved reliability. Although, the use of multiple antennas, at both sides of a communication link, implies hardware complexity, which leads to increasing cost demands. This becomes clear enough, if we take into consideration that the number of the analogue RF chains (i.e. amplifiers, A/D converters etc.) increase linearly with the number of antennas used, and consequently, so does the cost. Owing to this fact, it is more preferable to have a smaller number of RF chains than the number of antennas in each link end.

In order to mitigate the complexity of the MIMO system, antenna selection method has been introduced [1, 2]. The principle of this method is to use the best L_R out of N_R antennas located at the receiver side and the best L_T out of N_T antennas located at the transmitter side. Thus, the question arises is, which antenna sub-set will be chosen from each link end, in order to provide us with the maximum channel capacity.

However, reducing the number of antennas will inevitably lead to performance degradation. For this reason, it is of the essence to find an antenna optimal algorithm that will give us the best results. One way to find the appropriate sub-set is to search over all possible combinations of antennas in each side, which implies unaffordable computational complexity (exhaustive search – ES). Hence, the only way to counterbalance this high computational complexity is to find sub-optimal algorithms with performance as close as possible to the one provided by the ES.

In this paper, we evaluate the BBO [3] performance and compare it with three other evolutionary algorithms. The simulation results show that the performance of BBO enhance the maximum capacity result in comparison with the others EAs.

II. MIMO System Model and AS Problem Definition

A. MIMO capacity model

We consider a spatial multiplexing MIMO system with N_T transmits antennas and N_R receive antennas, in a frequency non-selective fading wireless channel. Then, the complex N_R x 1 signal vector $\mathbf{y}$ can be written with the following form:

$$\mathbf{y} = \sqrt{\frac{E_x}{N_T}}\mathbf{H}\mathbf{x} + \mathbf{z}, \tag{1}$$

where $\mathbf{x} = [x_1, x_2, \ldots, x_{N_T}]^T$ is the complex N_T x 1 transmitted symbol vector. E_x is the constant signal energy of each transmitted signal x_i, which is derived from the ith transmit antenna. $\mathbf{H}$ denotes the N_R x N_T channel matrix, its element h_{ij} stands for the channel gain between the ith transmit antenna and the jth receive antenna with a zero-mean and unit variance independent and identically distributed (i,i,d) complex Gaussian random variable. $\mathbf{z} = [z_1, z_2, \ldots, z_{N_R}]^T$ represents the N_R x 1 white complex Gaussian noise vector with zero-mean and covariance matrix $N_0\mathbf{I}_{N_R}$, where $\mathbf{I}_{N_R}$ is a N_R x N_R identity matrix.

Suppose that the channel state information (CSI) is available at the receive side only and the transmitted complex vector $\mathbf{x}$ is statistically independent, i.e., $E\{\mathbf{x}\mathbf{x}^H\} = \mathbf{I}_{N_T}$, where E{} is the expected value operator, thus the capacity of the deterministic MIMO channel can be represented by [2, 9]:

$$C = log_2 \det\left(\mathbf{I}_{N_T} + \frac{E_x}{N_T N_0}\mathbf{H}^H\mathbf{H}\right), \tag{2}$$

The above equation for the capacity is applicable when $N_R \geq N_T$ [10]. det(.) and $(.)^H$ are the determinant and the Hermitian operation, respectively.

B. The AS Problem

Suppose that there are L_T and L_R RF chains at transmit and receive sides respectively, $L_T \leq N_T$ and $L_R \leq N_R$. The main purpose of the AS problem is to select the proper antenna subset, i.e., L_T out of N_T antennas at the transmitter side and L_R out of N_R antennas at the receiver side, so as to maximize the capacity given by:

$$\bar{C} = log_2 \det\left(\mathbf{I}_{L_T} + \frac{E_x}{L_T N_0}\bar{\mathbf{H}}^H\bar{\mathbf{H}}\right), \quad (3)$$

Where $\bar{\mathbf{H}}$ is a L_R x L_T sub-block matrix of **H**. Taking into consideration that, for a MIMO wireless system with (N_R, N_T) antennas there will be N_{select} different possibilities of selection of (L_R, L_T) active antennas given by:

$$N_{select} = \frac{N_T!}{L_T!(N_T - L_T)!} * \frac{N_R!}{L_R!(N_R - L_R)!}, \quad (4)$$

the optimal ES AS will be a complex task to implement.

II. Simulation Results

In this part, we present the simulation results of the aforementioned evolution algorithms that were used in order to maximize the channel capacity of a wireless MIMO system. We assume that the number of antenna elements at the transmitter and receiver side is N_T = 16 and N_R = 16, respectively. Three scenarios, (L_T, L_R) = (2, 4), (3, 5) and (4, 6) are considered. For ACO, we used the following parameters: initial pheromone value τ_0 = 1E-6, pheromone update constant Q = 20, exploration constant q_0 = 1, global pheromone decay rate ρ_g = 0.9, local pheromone decay rate ρ_l = 0.5, pheromone sensitivity α = 1, and visibility sensitivity β = 5. For RVGA and GA we used the following parameter values: crossover probability p_c = 1, and mutation probability p_m = 0.01. Additionally, for the GA we used roulette wheel selection and single point crossover. Furthermore, for the BBO we had habitat modification probability p_{mod} = 1, step size for numerical integration of probabilities dt = 1, immigration probability bounds per SIV [0, 1], maximum immigration rate for each habitat I = 1, maximum emigration rate for each habitat E = 1, and mutation probability p_m = 0.005. For all the algorithms, the population size is set to 50, the number of generations is also set to 50 and the elitism parameter is set to two.

In general, it is obvious, from Fig.1 that the BBO algorithm performs better among the other evolution algorithms, while they all have the same computational complexity. Moreover, ACO is clearly inferior to all of them. Specifically, we can note that BBO outperforms the other algorithms in the first two scenarios: (L_T, L_R) = (2, 4) and (L_T, L_R) = (3, 5). RVGA comes second in the first scenario: (L_T, L_R) = (2, 4), followed by the GA. Furthermore, in the second scenario: (L_T, L_R) = (3, 5), GA and RVGA have similar results, with the RVGA obtaining better results for higher SNR (Signal to noise Ratio) values, namely 10dB and 20dB. In the last scenario: (L_T, L_R) = (4, 6) GA antagonizes the BBO, resulting in slightly better performance for SNR = 5, 10 and 20dB, yet BBO sustain better overall performance.

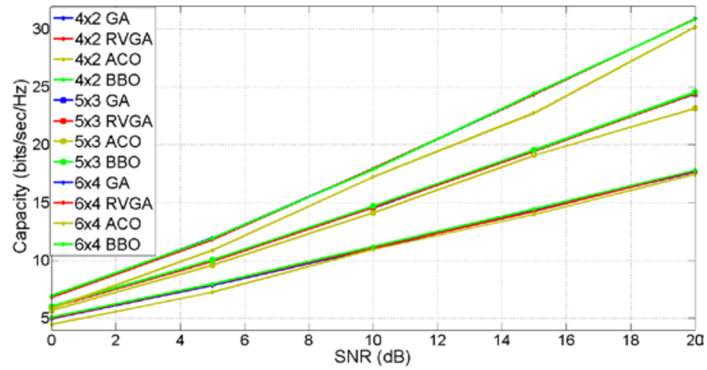

Fig.1.Capacity versus SNR for several (L_T, L_R) combinations.

III. Conclusion

In this paper, we purposed the BBO AS algorithm, in order to examine the problem of joint transmit/receive antenna selection in MIMO wireless systems. We compared the BBO algorithm with other suboptimal algorithms that have the same computational complexity, using the capacity maximization criterion. The simulation results proved that the purposed BBO AS algorithm outperforms the ACO, GA as well as RVGA algorithm in several combinations (L_T, L_R) of transmit and receive antennas, respectively.

References

[1] S. Sanayei and Nostratinia, "Antenna selection in MIMO," IEEE Communications Magazine, vol. 42, no. 10, pp 68.73, Oct. 2004, special issue on Adaptive Antennas and MIMO systems for Wireless Communication.

[2] A. F. Molisch and M. Z. Win, "MIMO systems with antenna selection" IEEE Microwave Magazine, vol. 5, no. 1, pp. 46.56, 2004, March.

[3] D. Simon, "Biogeography-Based Optimization," IEEE Transactions on Evolutionary Computation, vol. 12, pp. 702-713, 2008.

[4] M. Dorigo and T. Stutzle, Ant Colony Optimization. Cambridge, MA: MIT Press, 2004.

[5] C. Blum, "Ant colony optimization: Introduction and recent trends," Phys. Life Reviews, vol. 2, pp. 353–373, 2005.

[6] M. Dorigo, L. Gambardella, M. Middendorf, and T. Stutzle, Eds., "Special section on 'ant colony optimization'," IEEE Trans. Evol. Comput., vol. 6, no. 4, pp. 317–365, Aug. 2002.

[7] D. Goldberg, Genetic Algorithms in Search, Optimization, and Machine Learning. Reading, MA: Addison-Wesley, 1989.

[8] J.-K. Lain, "Joint Transmit/Receive Antenna Selection for MIMO Systems: A Real-Valued Genetic Approach", IEEE Communications Letters, vol.15, pp. 58-60, Jan. 2011.

[9] A. Gorokhov, M. Collados, D. Gore, and A. Paulraj, "Transmit/receive MIMO antenna subset selection," in Proc. IEEE Int. Conf. Acous. Speech Signal Process.(ICASSP '04), pp. 13-16, 2004.

[10] I. Emre Telatar, "Capacity of Multi-antenna Gaussian Channels", AT&T Bell Laboratories, Internal Tech. Memo., June 1995.