A Heuristic Approach to Antenna Array Topology Optimization in MIMO Systems

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***Resumo*— Este artigo discute o projeto de sistemas de múltiplas entradas e múltiplas saídas (MIMO) de antenas e propõe um algoritmo genético para obter a posição e orientação de cada antena do arranjo MIMO que maximiza a capacidade ergódica para um dado cenário de propagação. Nossos resultados mostram que o efeito do acoplamento eletromagnético pode ser explorado pelo otimizador para diminuir a correlação do sinal aumentando a capacidade. Também é feita uma comparação entre arranjos lineares uniformes (ULA), arranjos circulares uniformes (UCA) e o arranjo otimizado pelo algoritmo genético.**

***Palavras-Chave*— MIMO, otimização de arranjo, algoritmo genético, capacidade**

***Abstract*— This paper discusses the design of multiple input multiple output (MIMO) antenna systems and proposes a genetic algorithm to obtain the position and orientation of each MIMO array antenna that maximizes the ergodic capacity for a given propagation scenario. Our results show that the electromagnetic coupling effect can be exploited by the optimizer in order to decrease signal correlation and increase MIMO capacity. A comparison among uniform linear array (ULA), uniform circular array (UCA) and the GA-optimized array is also carried out.**

***Keywords*— MIMO, array optimization, genetic algorithm, capacity.**

I. INTRODUCTION

MIMO systems have been an important research topic due to their capability of providing a significant increase in channel capacity proportional to the number of transmit and/or receive antennas. This is generally achieved by exploiting spatial diversity at the transmit and receive branches [1], [2]. When considering realistic antenna models, the channel capacity will depend on three main variables: The transmit antenna array configuration, the receive antenna array configuration and the environment configuration, namely, the distribution of the channel scatterers [3].

Multiplexing and diversity gains in MIMO systems can be obtained, for instance, by resorting to not only spatial divesity but also to polarization diversity. While spatial diversity can be achieved by ensuring enough antenna separation, polarization diversity can be achieved by exploiting different antenna orientations in the array configuration [4]. In cellular systems, a reasonable degree of spatial diversity can be obtained at the base-station. However, at the mobile terminal, this situation is completely different, since a good separation of the antennas ensuring spatial diversity is not always possible. Moreover, electromagnetic coupling between terminal antennas is a practical problem that affects system performance. Therefore, under these constraints, optimizing the antenna placement at the mobile terminal to yield a satisfactory performance is a challenging problem [5], [6].

Genetic algorithm (GA) based optimization has been used with success in various engineering problems. In [7], a genetic algorithm is used to optimize antenna arrays used for channel characterization, i.e. determination of multipaths directions of arrival (DOA). In [8], the authors resort to GA-based optimization to find the channel parameters such as multipath attenuations and delays. Recently, GA has been used to find good antenna element positions in sparse MIMO radar arrays [9] by minimizing the side-lobes of the radar pattern. Another recent work [10] uses GA to find the optimal distribution of a 3 $\times$ 3 MIMO system for an indoor propagation channel. An interesting aspect of that work is the inclusion of electromagnetic coupling in the model. However, the work does not show either which distributions were found or how the distributions change according to different multipath channel parameters.

The work of [11] defends the idea of using nature inspired methods for MIMO antenna design, but the works mentioned in there deal with the problem of antenna geometry definition and not antenna array topology for different propagation environments. In [12] a method of moments is proposed to optimize MIMO antenna position and orientation. The optimization is done by minimizing the antenna cross correlation, by considering an i.i.d propagation scenario. Although antenna cross correlation degrades capacity, we cannot say that the configuration that minimizes antenna correlation is the same that maximizes MIMO capacity in non i.i.d. propagation scenarios.

In this work, we address the antenna array capacity optimization problem by resorting to a genetic algorithm method. The goal is to find an optimal or suboptimal configuration for antenna position and orientation that maximizes the ergodic channel capacity. Assuming array of dipoles and a channel model that interfaces the propagation environment with the antenna array response pattern, the genetic algorithm manages to find, for each antenna, the best position and orientation subject to a space constraint. Due to the nature of genetic algorithms, the proposed method is very general. It can incorporate different types of antenna models, and it can also be used in different propagation channel models. Our simulations take into account different sets of antennas and constraints in terms of available space, and also consider electromagnetic

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coupling effects. We also compare the capacity provided by the optimized MIMO array with that of standard linear and circular arrays.

In Section II, we present the channel model that is exploited by the proposed algorithm. In Section III, we present the genetic algorithm used for the optimizations and also detail how the population is represented, how reproduction occurs, and how we used the ergodic channel capacity as the fitness function of the genetic algorithm. Section IV presents the simulation results and results discussion. Finally, in Section V we draw the conclusions.

II. Channel Model

In Figure 1 the channel geometric model used to generate the plane waves and to interface it to the antenna arrays is illustrated. We assume that the distance between antenna arrays and the scattering clusters is much higher than the distance between the array elements. In this case we can assume that the DOA and direction of departure (DOD) of a given plane wave are the same for all the antenna elements of the array. Each cluster is modeled by a finite set of plane waves, and has a main direction of arrival/departure, both in azimuth and elevation. Angle spread and polarization spread within a cluster follow a gaussian distribution.

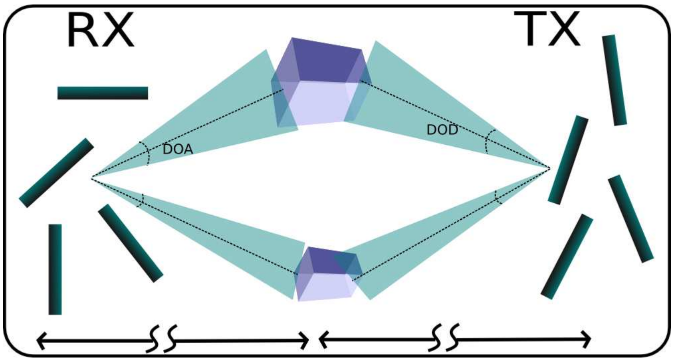

Fig. 1. Geometric Channel model used in simulations.

The channel double-directional impulse response, associated with the DOA pair (ϕ_{Rx}, θ_{Rx}) and DOD pair (ϕ_{Tx}, θ_{Tx}) is given by the contribution of a finite number of dominant multipaths components [13]:

$$\mathbf{A}(\phi_{Rx}, \theta_{Rx}, \phi_{Tx}, \theta_{Tx}) = \sum_{l=1}^{L} \mathbf{A}_l(\phi_{Rx,l}, \theta_{Rx,l}, \phi_{Tx,l}, \theta_{Tx,l}), \quad (1)$$

where L is the number of arriving paths, and ϕ and θ denote, respectively, azimuth and elevation angles. The contribution of each path A_l can be expanded as fallows:

$$\begin{aligned} \mathbf{A}_l(\phi_{Rx}, \theta_{Rx}, \phi_{Tx}, \theta_{Tx}) &= \mathbf{W}_l e^{j\phi_l} \\ &\times \delta(\phi_{Rx} - \phi_{Rx,l})\delta(\theta_{Rx} - \theta_{Rx,l}) \\ &\times \delta(\phi_{Tx} - \phi_{Tx,l})\delta(\theta_{Tx} - \theta_{Tx,l}), \end{aligned} \quad (2)$$

where $\phi_l = j2\pi f_c$, and $\mathbf{W}_l$ is the polarimetric transmission matrix defined as:

$$\mathbf{W}_l = \begin{bmatrix} \gamma_{HH} & \gamma_{VH} \\ \gamma_{HV} & \gamma_{VV} \end{bmatrix} \quad (3)$$

The $(m,n)^{th}$ entry $h_{m,n}$ of the MIMO channel matrix $\mathbf{H}$ $(M \times N)$ can be expressed in terms of the directional channel impulse response according to the following expression [13]:

$$\begin{aligned} h_{mn} = \sum_{l=1}^{L} & \mathbf{g}^T{}_{Tx}(\phi_{Tx,n,l}, \theta_{Tx,n,l}, \mathbf{r}_{Tx,n}) \\ & \times \mathbf{A}_l(\phi_{Rx,l}, \theta_{Rx,l}, \phi_{Tx,l}, \theta_{Tx,l}) \\ & \times \mathbf{g}_{Rx}(\phi_{Rx,m,l}, \theta_{Rx,m,l}, \mathbf{r}_{Rx,m}) \\ & \times exp(j[\mathbf{k}(\phi_{Rx,l}, \theta_{Rx,l}) \cdot \mathbf{x}_{Rx,m}]) \\ & \times exp(j[\mathbf{k}(\phi_{Tx,l}, \theta_{Tx,l}) \cdot \mathbf{x}_{Tx,n}]), \end{aligned} \quad (4)$$

where $\mathbf{g}_{Rx}$ is the antenna pattern response to the direction $(\phi_{Rx,m,l}, \theta_{Rx,m,l})$ while $\mathbf{g}_{Tx}$ is the antenna pattern response to the direction $(\phi_{Tx,m,l}, \theta_{Tx,m,l})$ at the transmitter. The response of the antenna considers the impact of mutual electromagnetic coupling of nearby antennas. We calculate this effect integrating the numerical electromagnetics code (NEC) in our simulation. The (2×1) vector $\mathbf{g}_{Rx}$ is the product of the complex scalar gain g_{Rx} (phase am amplitude) of the receiver antenna, and the unitary (2×1) polarization vector $\mathbf{p}_{Rx}$ composed by the vertical and horizontal responses:

$$\mathbf{g}_{Rx}(\phi_{Rx,n,l}, \theta_{Rx,n,l}, \mathbf{r}_{Rx,n}) = g_{Rx}(\phi_{Rx,n,l}, \theta_{Rx,n,l}, \mathbf{r}_{Rx,n})\mathbf{p}_{Rx} \quad (5)$$

Similarly, for the transmitter antenna pattern response $\mathbf{g}_{Tx}$ we have:

$$\mathbf{g}_{Tx}(\phi_{Tx,n,l}, \theta_{Tx,n,l}, \mathbf{r}_{Tx,n}) = g_{Tx}(\phi_{Tx,n,l}, \theta_{Tx,n,l}, \mathbf{r}_{Tx,n})\mathbf{p}_{Tx} \quad (6)$$

The vector $\mathbf{r}_{Rx,m}$ defines the antenna orientation, $\mathbf{k}$ is the wave vector, $\mathbf{x_{Rx}}$ is the relative position of the m^{th} receiver antenna and $\mathbf{x}_{Tx}$ is the relative position of the n^{th} transmitting antenna. The inner product of the vector wave $\mathbf{k}$ (arriving or departuring wave) with an antenna position (transmitter or receiver), is defined by:

$$\mathbf{k}(\phi, \theta) \cdot \mathbf{x} = \frac{2\pi}{\lambda}(xcos\theta cos\phi + ycos\theta sin\phi + zsin\theta sin\phi) \quad (7)$$

The electromagnetic coupling has a strong effect when the antennas are separated by small distances (typically less the $\lambda/2$). With hand-held telecommunication devices this is often, if not always, the case. Instead of implementing an electromagnetic code from ground-up, we chose in this work to use an available and well established code, integrated to our channel model. We use the NEC, which is a public domain software. The version we chose to work with is NEC2C, a C language implementation of the NEC2 Fortran original code. The NEC code uses the method of moments (MOM) to solve the electromagnetic field problem. One of its main qualities is the low computational cost of the solutions, since MOM codes are much faster than e.g. finite element method based codes.

III. Genetic Algorithm Optimization

GA works by analogy to genetic inheritance and differentiation that occurs in biology that permits a specie to fit itself to the environment in an adaptation process. The genetic code is a digital code that represents the individual characteristics that can be inherited from previous generations and be passed by to the next generations. Our individual is the antenna array, our genetic code is the channel array model stored in the computer memory. A population, or generation, is a collection of antenna arrays. The genes that define an array are the antenna type, antenna position and antenna orientation. We start with a random generation, where each antenna has a position and orientation assigned to it by a random variable with uniform distribution, within the limits of the desired volume space for the antennas. The number of individuals in the generation is increased by crossing and mutation. The crossing operation is the reproduction of new individuals that inherit part of the characteristics from one individual and other part from other individual, the parents. Which characteristic will come from each parent is decided by an aleatory factor. The mutation operation is an aleatory small change in the genes.

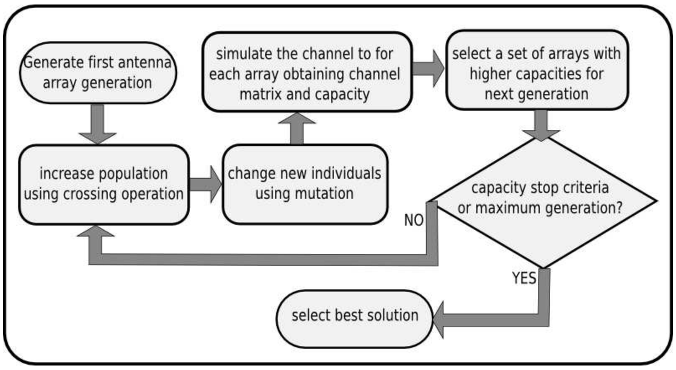

Fig. 2. Fluxogram of the employed genetic algorithm.

The next step is to select the individuals better suited to the environment, using the fitness function, and then repeat the reproduction step with this selected group. The reproduction and selection steps are repeated until an optimization criteria is met, or a certain number of generations is met. Our fitness function is defined by the channel ergodic capacity as will be detailed later. Figure 2 shows a general diagram of the genetic algorithm optimization method, applied to our problem.

A. Population and Reproduction

The antenna is represented in the system by the tuple $(kind, position, orientation)$. The kind is an integer token that identifies the antenna far-field pattern. In this work we consider ideal half-wave dipoles, although more than one kind of antenna could be used. The position vector $\mathbf{x} = [x, y, z]^T$ and orientation vector $\mathbf{r} = [\alpha, \beta, \gamma]^T$ (yaw, pitch, roll). A collection of antennas $[a_1, a_2, ...a_M]$ defines an array. An array is one individual in the population. The genetic algorithm needs a finite set to search into, so position and orientation need to be both limited an quantized. The degrees of freedom of the position are limited by a limited volume defined prior to simulation. The available volume is generally a practical constraint of the antenna array design in small terminals. The quantization is naturally imposed by the computer quantization of the floating point numbers.

The genetic code of each individual in the collection is formed by the antennas' tuples. The reproduction is done by combining portions of DNA from two parents. A new array is derived by choosing antennas from two ancestor arrays. A pseudo-random function is used to choose from which parent each antenna will be copied for the new individual in the population. After the reproduction, a small pseudo-random change is made in each antenna parameter. Such a change defines the mutation procedure. It is worth noting that the amount and extent of the mutation have a strong impact on the algorithm performance. Small changes can make the algorithm converge faster but it is more prone to get stuck in a local maximum, while stronger changes make it leave local maximum for better maxima but makes the system less stable. Therefore, a tradeoff between convergence speed and stability exists, as usual in numerical optimization methods.

Another parameter to take into account is the size of the offspring in each generation. A small offspring provides faster computation and less memory usage, at the expense of more iterations necessary to solve the problem.

B. Fitness Function

In order to select the individuals for the next generation, it is necessary to use a fitness function, which is always problem-related. The interface between the fitness function and the genetic algorithm makes it possible to choose any kind of fitness function, as long as the function respects the intputs and outputs of the interface. The input for the fitness function has to be the current generation of individuals, in our case, the various array configurations obtained by the crossing and mutation operations. The output of the function has to be some value attached to each individual making it possible to classify it. In our case, that value corresponds to the ergodic channel capacity, in bits per channel use, which is given by [14]:

$$C = \frac{1}{N_q} \sum_{q=1}^{N_q} log_2 det \left[I_{Nr} + \frac{SNR}{Nt} \mathbf{H}_q \mathbf{H}_q^H \right]. \qquad (8)$$

where N_q is the number of realizations to compute the expectation statistics and $\mathbf{H}_q$ represents the q^{th} channel realization. Note that, according to (4), each entry h_{mn} of $\mathbf{H}_q$ $(M \times N)$ depends on relative antenna positions $\mathbf{x}_{Rx,1..M}$ and antenna far field patterns according to their orientations $\mathbf{r}_{Rx,1..M}$ at a given channel realization. Recall that only the receive antennas are the object of the present investigation. The antennas at the transmitter (i.e. the base station for the downlink) are supposed to have less placement constraints and are not optimized here. Therefore, the objective function of the genetic algorithm is to solve the following problem:

$$\underset{\mathbf{x}_{Rx,1..M}, \mathbf{r}_{Rx,1..M}}{\arg\max} \quad C(\mathbf{x}_{Rx,1..M}, \mathbf{r}_{Rx,1..M}) \qquad (9)$$

IV. SIMULATION RESULTS

In this section, a set of computer simulation results are presented. We aim at investigating the link between the GA-optimized antennas' positions and orientations to the propagation environment in question. We also evaluate the theoretical channel capacity obtained by optimizing the antenna array configurations using the proposed GA algorithm.

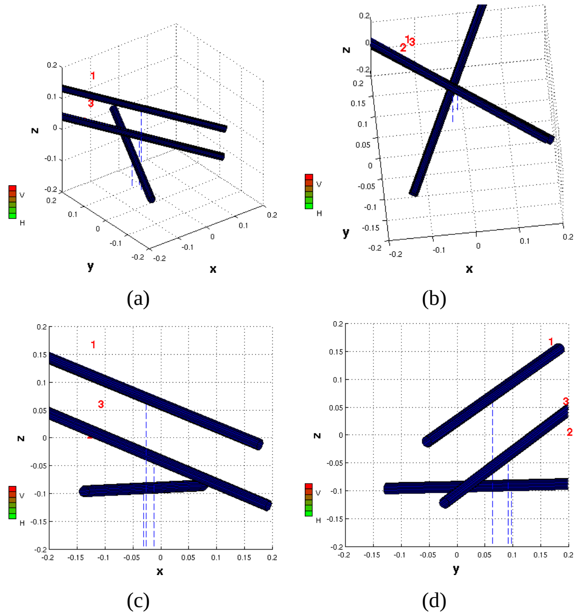

Fig. 3. Evolved 3x3 MIMO configuration, One cluster. Uniform cluster main direction distribution. SNR=20dB. Volume=$(0.2\lambda)^3$.

A. One cluster, 3x3 MIMO

Figure 3 shows the simulation results for a 3×3 MIMO system, with search space limited to $(0.2\lambda)^3$. It considers one cluster and its main direction is not fixed, but uniformly distributed around the space. The cluster has angle spread of 20^o. We made 20 simulations, and all results show a pattern similar to that of Figure 3. Since the available space is too small to achieve signal diversity trough antenna spacing, the optimizer made use of two strategies, orthogonal polarizations and orthogonal patterns. According to Figure 3, antenna 3 is orthogonally polarized to antennas 1 and 2. Antennas 1 and 2 are placed in parallel. The electromagnetic coupling effect makes antennas 1 and 2 to get directional gains in opposite directions. Figure 5 shows how the optimizer made use of polarization and pattern diversity, exploiting the electromagnetic mutual coupling effect, in order to produce MIMO diversity. Figure 4 shows the histogram for all 20 simulations.

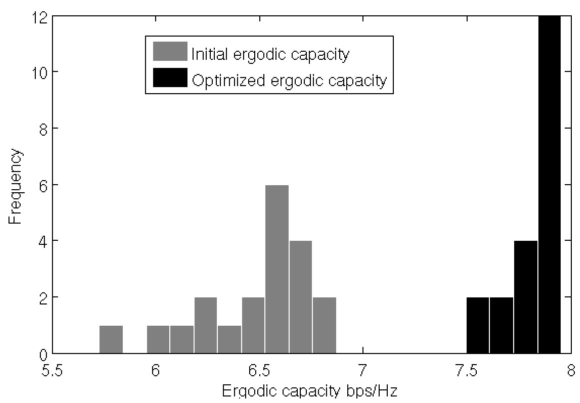

Fig. 4. Histogram for evolved 3x3 MIMO configuration, One cluster. Uniform cluster main direction distribution. SNR=20dB. Volume=$(0.2\lambda)^3$.

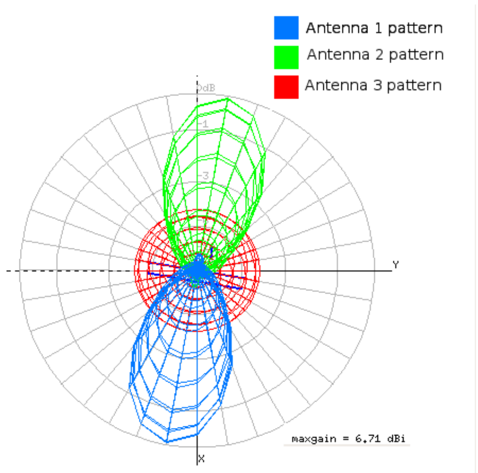

Fig. 5. Resulting antenna pattern for evolved 3x3 MIMO configuration, One cluster. SNR=20dB. Volume=$(0.2\lambda)^3$.

B. Array topology comparison

In work [15], an ULA is compared to a UCA. The work in [16] shows the impact of DOA over correlation for ULA, and the correlation degrades MIMO capacity. The capacity is calculated for one cluster for different DOAs using 4×4 MIMO system. They have concluded that the ULA achieves very high capacities for some DOAs but also very low capacities for other DOAs. The UCA could not achieve the ULA top capacity but had a much more stable behavior, showing the same capacity despite the DOA. In our work we simulate a channel with a cluster having 15^o of angle spread with normal multipath distribution. We also use our genetic algorithm to evolve a 2D topology solution for the problem. For this problem the fitness function was the average ergodic capacity, considering the cluster to be in a different DOA at each statistical realization. The constraint for the evolved array was that the distance between elements should not be greater than $\lambda/2$. The array resulted for the genetic algorithm is shown in Figure 6. As we can see in Figure 7, we found results for ULA e UCA similar to [15], with the UCA being more stable. The ULA had higher peak and average capacity, but had very strong capacity losses for some DOAs, agreeing with [16]. The evolved GA solution was better than both. It had the highest average ergodic capacity while being much more stable than ULA and with all capacities above the UCA solution.

V. Conclusion

The proposed GA based optimization algorithm for antenna array positioning has proved to be successful in finding good MIMO antenna schemes for a given propagation scenario. Some solutions found by the GA optimizer were very subtle, and a human designer would have difficulties trying to identify the best location and orientation for the antennas according to the specified propagation environment. The comparison of ULA, UCA and the array evolved by our method shows that it is a much more efficient engineering method than the intuitive and trial and error approach.

The results so far have shown that pattern and polarization diversities play an important (if not the most important) role

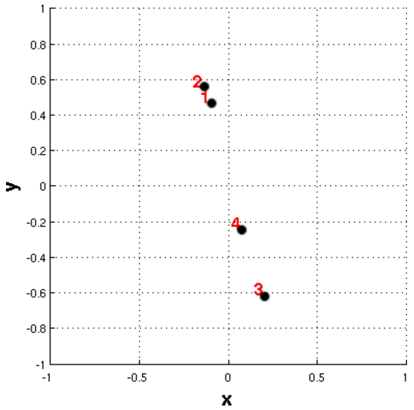

Fig. 6. Array topology resulted from G.A. optimization.

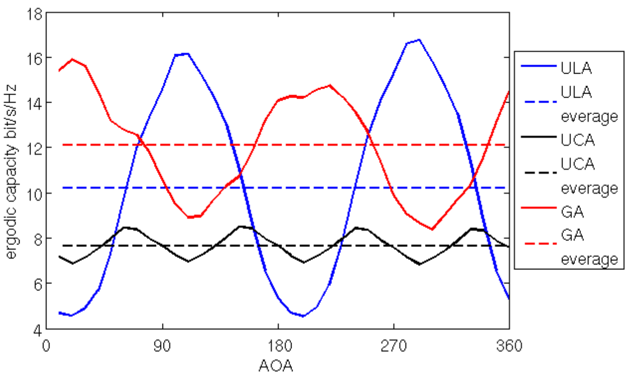

Fig. 7. Performance comparison of ULA, UCA, and G.A. array topologies.

in MIMO capacity when there is little space available for positioning the antennas. One important aspect of the proposed method is its generality, as it can be adapted to be used with different antenna and propagation models.

As a perspective of this work, we should consider the use of different types of antennas, preferably practical mobile terminal antennas.

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