# Genetic Algorithm based Antenna Selection for MIMO System

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***Abstract*—Multiple-Input Multiple-Output （MIMO) system with flat fading channels has a capacity increasing with a larger number of antennas. However, increasing the size of antennas brings more considerable energy costs. Antenna selection is used to reduce the cost while meeting specific system performance. This paper proposes a novel Genetic Algorithm based Antenna selection method for the Multiple-Input Multiple-Output system. By using a novel fitness function and a simple chromosome structure in Genetic Algorithm, a fixed number of antennas is selected from the receive antennas of MIMO system, which makes the capacity of system reach a suboptimal maximum value. Simulation results show that this Genetic Algorithm based Antenna Selection method can reach a capacity performance close to optimal brute force method and lower the computational complexity.**

***Index Terms*—Antenna selection, Genetic Algorithm, Multiple-Input Multiple-Output system, channel capacity**

## I. Introduction

Multiple-Input Multiple-Output (MIMO) is a complex system having multiply transmit and receive antennas. MIMO system has a more reliable network, increased capacity as well as higher spectrum efficiency [1]. The capacity of the MIMO system has linear relationship with the minimum number of antennas for transmission and antennas for reception. However, a large number of antennas and radio frequency chains in MIMO bring large power consumption, mainly in encoding and decoding in channels. The power consumption of antennas and radio frequency chain cannot be neglected compared with transmitting power consumption. When antennas set is already large, the further increasing antennas makes energy efficiency saturated. To guarantee the energy efficiency of MIMO, the numbers of antennas should be constrained.

Antenna selection (AS), which selects a small optimal antenna set in a more extensive size antenna set, is proposed to maximize the capacity of system and reduce the energy consumption. Antennas selection dynamically change the antennas access into the system by switching off unsuitable ratio channel. Work [2] shows that the MIMO system with antenna selection has higher performance than the MIMO system having the same number of antennas and having no antenna selection.

The optimal brute force antenna selection method can achieve maximum capacity but has huge computational complexity. The computational complexity of optimal brute force antenna selection is exponential to the size of full antennas set, which is not affordable to a large MIMO system.

To reduce the computational complexity, mathematical techniques are used to treat antenna selection as an optimization problem. Norm based antenna selection (NBS) [2] is implemented based on the rows correlation in the channel matrix. This method has low computational complexity but much smaller subset capacity, especially when channel matrix has linear dependent rows. Gorokhov [3] gets the suboptimal antenna set by removing the antenna which contributes least to the capacity of the system. Fast antenna selection [4] selects the antenna subset by adding the antenna having the most considerable capacity contribution. Fast antenna selection [4] is faster than Gorokhov. Both algorithms have a capacity near-optimal antenna selection. However, the computational complexity of Gorokhov and Fast antenna selection is not linear to the size of antennas set. When the size of MIMO system is significant, Gorokhov and Fast antenna selection still have low efficient.

Work [5] points that antenna selection problem can be considered a classification problem, and Support Vector Machine, which evaluates feedback overhead, can achieve the best performance compared to K-Nearest Neighbor. However, this machine learning based algorithm has a high requirement of computational resources, which is uneasy to satisfied.

Holland [6] proposed Genetic Algorithm (GA), an optimization technique that emulates genetic inheritance based on chromosomes. GA has been widely applied on signal process, wireless communication, and automatic programming problem. GA is used in antenna selection in paper [7,8,9], which has good performance and low computational complexity.

We proposed a GA based antenna selection method with a novel fitness function and a simple chromosome structure that controls the selected receive antennas at a fixed number. Our Algorithm has the capacity performance close to the optimal brute method and a lower computational complexity at the meantime. The paper is organized in six sections. In section II, we review the related work of Genetic Algorithm based antenna selection. In section III, we give the signal model of MIMO system. In section IV, our novel Genetic Algorithm based antenna selection is presented, and computational complexity of this Algorithm is discussed. In section V, we simulate our

Algorithm, and the result of the simulation is discussed. In section VI, we give a conclusion to our wok.

## II. Related Work

MIMO system uses spatial diversity and angel diversity to avoid multipath fading [10]. For traditional phased array radar, spatial resolution needs to be improved due to related hardware and additional antennas. Each antenna in a MIMO system can transmit mutually orthogonal signals, which can be extracted by a set of matched filters (MF) at receive antennas. The critical merit of MIMO is the property of substituting the spatial dimension for the bandwidth resource. To be specific, even narrow-band systems can operate like traditional wide-band systems.

One widespread criterion of performance evaluation of MIMO system is capacity. Work [2] consider select $L$ receive antennas among $M$ to achieve the maximum capacity bound. The basic formula is as follows:

$$C_{full} = \log_2\left[\det\left(I_M + \frac{\bar{\Gamma}}{M} HH^+\right)\right] \quad (1)$$

$$C_S = \max\left\{\log_2\left[\det\left(I_M + \frac{\bar{\Gamma}}{N} \breve{H}\breve{H}\right)\right]\right\} \quad (2)$$

Where $H$ is the $N \times M$ matrix, and the $h_{ij}$ is the identically distributed symmetric complex Gaussian random variables with zero means and unit variance. $\bar{\Gamma}$ denotes the standard of SNR per receiver, and $H^+$ means the Hermitian transpose of matrix $H$. Work [2] aims to maximize the capacity as shown in (1), when the best antenna set with size $L$ is selected. $\breve{H}$ is generated by remove $N$-$L$ rows from $H$. It is difficult to analysis (2) directly. At starting point, it assumes each receive antenna owns a transmit antennas set of size $N$. In this way; we can get the data stream carried by each transmitter set and then obtain the maximum SNR, which indicates the maximum capacity. Therefore, the capacity bound with antenna selection can be represented by:

$$C_{bound} = \sum_{i=1}^{L} \log_2\left(1 + \frac{\bar{\Gamma}}{N} \mathrm{y}_i\right) \quad (3)$$

where $y_i$ is ordered chi-square-distributed variables with $2M$ degrees of freedom. After deriving analytical capacity bounds, work [2] tests each selection set and verity them with Monte Carlo simulations.

The optimal antenna selection computes all the possible antenna subsets in the full antenna set, which brings a high computational complexity. We denote the number of receiving antennas, the number of transmitting antennas, the number of selected receiving antennas and the number of transmits antennas by $N_r$ , $N_s$ $L_r$ $L_S$ and. To select the optimal receive antenna subset of maximum capacity, the capacity computation of the fixed antenna set needs to be done $\binom{N_r}{L_r}$.To choose the optimal transmit antenna subset with maximum capacity, the capacity computation of selected antennas set needs to be done $\binom{N_S}{L_S}$. The computational complexity is exponential to the size of antennas, which is not affordable for a big size MIMO system.

Antenna Selection can be regarded as a mathematical optimization problem. Work [2] has proposed a correlation-based or norm-based antenna selection algorithm (NBS) to minimize the number of antennas as well as maximize the capacity. This paper has set the upper bound capacity of full-complexity system as the sum of the logarithms of ordered chi-square distributed variables. It selects the rows with the largest Euclidean norm in the channel matrix. When $L_r = 1$ this method is optimal. When $L_r > 1$ this Algorithm is suboptimal. The evaluation by Monte Carlo simulations shows that the proposed AS Algorithm has the almost capacity compared with the capacity of the full-complexity system. The computation complexity of this Algorithm is $O(N_s N_r)$ . Because of its simplicity, this Algorithm is widely used in antenna selection. However, the maximum capacity of this Algorithm is much lower than the optimal method when there exist some linear dependent rows in the channel matrix.

Paper [11] proposed a suboptimal transmit antenna selection for the rank-deficient channel matrix to maximize the MIMO system's capacity. This method is further improved in paper[12] by fast realization of this method.

Gorokhov [3] maximum the capacity of MIMO system by selecting a near-optimal subset of antennas. This Algorithm begins with a full antenna set. In each step, the antenna, which has the least contribution to the capacity of the system, is removed. Then, the original channel matrix is replaced by the new channel matrix with the removed antennas so that the capacity of the MIMO system is updated. The removing process continues until the number of subsets in satisfied. The computation complexity of this Algorithm is $O(N_S^2 N_\mathrm{r}^2)$ .

Fast Antenna selection [4] is enlightened by Gorokhov. This Algorithm begins with an empty antenna set. In each step, the antenna that can contribute most to the MIMO system's capacity is added to the antenna subset. Then, the channel matrix and the capacity is updated. The choosing process continue until the numbers antennas in the subset meet the given number. Fast antenna selection can achieve capacity close to the optimal method and Gorokhov. The computation complexity of this Algorithm is $O(N_S^2 N_r L_\mathrm{r})$ , which is lower than Gorokhov.

GA is an optimization technique that emulates the inherence of chromosome [6]. GA has been applied in various domains, including signal processing, wireless network, automatic programming, and optimization. GA works well in solving nonlinear programming problems and performs better when the initial search range is big. Work [8] proposed a variant of GA to treat the joint problem of antenna selection and precoding. Work [9] applies GA based antenna selection to get maximum throughput in a large but finite MIMO system. This method has lower computational complexity compared with the exhaustive search optimal method.

Work [7] applies GA to selects antenna subset in receive antennas and transmit antennas using the instantaneous capacity of MIMO system as a selection criterion. The selected number of antennas is a fixed wireless channel number, which joints the antenna selection of receive antennas and transmits antenna together. The selected antenna subset is initialed with a random sample. In each evolutionary step, the individual chromosome in the current population is decoding to the system's different capacity. According to these capacity results, individuals are chosen to do crossover operation and create the next generation population. This GA based Algorithm can spend less time compared with the optimal method using exhaustive search technique and can achieve capacity close to the optimal method.

However, previous works do not provide an insight into the change of $N_L$ . We proposed a novel GA base antenna selection method with a fitness function which can get fixed numbers of selected antennas $N_L$ and change the $N_L$ to get the dynamic situation. Also, our chromosome is designed to be simple so that it can realize it on resources constrained sensors.

## III. MIMO System Model

Our MIMO system model has a number of $M$ receive antennas and a number of $N$ transmit antennas. At the transmit end, the data is done space time encoding and outputted to $N$ transmit antennas. At the receiving end, the signal is received by $M$ antennas and done space time decoding. We assume the signal channel of the model is flat Rayleigh fading channel and is quasi-static [2]. Under this assumption, the channel's coherence time is long enough so that when we encode the data with the rate near the Shannon limit, a large data stream can be transmitted within one coherence time. Therefore, the capacity of each channel can be regarded as an independent random variable. The $M \times N$ matrix of channel is:

$$H = \begin{pmatrix} h_{11} & h_{12} & \cdots & h_{1N} \\ h_{21} & h_{22} & \cdots & h_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ h_{M1} & h_{M2} & \cdots & h_{MN} \end{pmatrix} \tag{4}$$

where $h_{ij}$ channel is a complex Gaussian variable with zero mean and unit variance, especially, the real and imaginary part have 0.5 variance each.

We assume the energy of every transmit signal is equal under the energy-limited MIMO system. After the white Gaussian noise is added to the environment, the received signal is:

$$y = \sqrt{E_S} Hs + n \tag{5}$$

where $E_s$ is the average signal energy, $H$ denotes the channel matrix, $s$ represents for the transmit signal vector, and $n$ is the Gaussian noise vector.

We assume the channel matrix is known at the receive end and completely unknown at the transmit end. Therefore, we use an identity transmit signal matrix in the capacity calculation [2]. The capacity of MIMO system is:

$$C(H) = \log_2 \det(I_M + (E_S / N_0) HH^H) \tag{6}$$

where $\det(\cdot)$ is the determination, $I_M$ is $M \times M$ the identity matrix, $N_0$ is the energy of white Gaussian noise, and $(\cdot)^H$ is the Hermitian transpose.

## IV. GA based Antenna Selection

We assume there are a number of $M$ receive antennas and a number of $N$ transmit antennas. Our object is to choose $L$ antennas from $M$ receive antennas and keep all $N$ transmit antennas to make the selected antenna system have a maximum capacity. The capacity equation is given by (6). To reduce the computational complexity and perform close to optimal selection at the meantime, we proposed a GA based antenna selection, which chooses $L$ antennas at receive antenna set and fix the $N$ transmit antennas. Our GA-based antenna selection has a novel fitness function that can fix the number of selected antennas and a simple chromosome structure, making its application in the real world has a huge potential.

To create the GA for antenna selection, we design a chromosome for each antenna selection. The length of the chromosome is the size of receive antennas $M$. Every bit in our chromosome is a binary number, which is corresponding to a receive antenna. When the bit is one means that the corresponding receive antenna has been selected. Otherwise, when the bit is zero means that the corresponding receive antenna has been not selected.

The steps in our GA based antenna selection is showed as follows:

Step 0 Initialization: First, we generate the channel matrix $H$ for $M$ receive antennas, and $N$ transmit antennas. Each channel in this matrix is a gaussian random complex variable with independently identically distribution. Then, we construct an initial population of size $P$, with $P$ parent chromosomes in it. In each chromosome, it has $M$ random genes, which is either one or zero. The $i$ th position gene is corresponding to the $i$ th receive antennas. When $i$ th position gene is 1 means that the $i$ th receive antennas is selected in channel matrix $H$. We fixed the transmit antennas, which means the full transmit antennas is always selected. Therefore, when we choose the $i$ th receive antenna, there will be $N$ channel selected. The selected channel is the one that is between $i$ th receiving antenna and $N$ transmitting antennas.

Step 1 Evaluation: The fitness function of each generation is the capacity of selected antennas. The chromosome is encoding to corresponding selected receive antennas. Then, the channel between the selected receive antennas and $N$ transmit antennas is used to calculate the capacity of MIMO system. The capacity is calculated by (6), in which $H$ is the selected channel matrix in this generation and $Es/No$ is the SNR we defined. Generally, GA would choose a random number of receiver antennas. To control the number of selected, we add a constrain in our fitness function. To be specific, when a scheme with exactly $L$ antennas generated, we would set its initial fitness to 100. After getting the averaged capacity after $G$ generations, it should be subtracted by 100 to get its real value.

Step 2 Selection: After generating $P$ chromosomes, we pick a random number of individuals from the population and sort them by their fitness. After that, the member with maximum fitness would be selected into the next generation. We repeat this selection operation until the size of the new population reaches $P$ again.

Step 3 Crossover: To create the new chromosome, the crossover is taken on the two selected chromosomes with a given probability. The crossover operation in our scheme is showed in Fig.1. we randomly take a crossover position for parent A and parent B. Then, the two parts of parent A and parent B are exchanged. Then, we get the two new chromosomes.

Step 4 Mutation: We randomly take a position in chromosome and change its value with a mutation probability. If the value of this position is 1, our Algorithm changes it to 0. If the value of this position is 0, our Algorithm changes it to 1. One example of the mutation is showed in Fig.1.

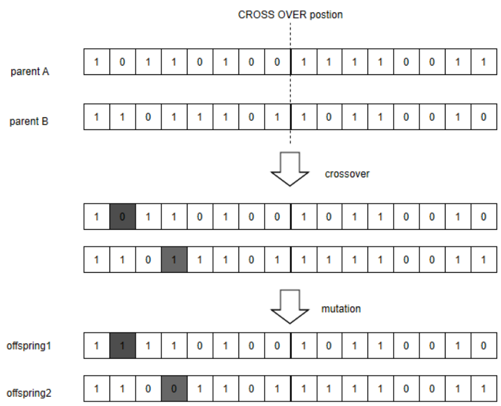


Fig. 1. Crossover and mutation operation in our GA based antenna selection

Step 5 Repeat or End: We repeat the above 1 to 4 steps until the generation reaches our defined $G$. Finally, the chromosome which can make fitness function maximum is chosen. The chromosome of the maximum fitness function has the channel matrix of the maximum capacity. The maximum capacity of the MIMO system and the corresponding selected $L$ receive antennas is obtained.

Computation complexity of our proposed GA based antenna selection is calculated in terms of the capacity calculation times of selected antenna subset. The capacity calculation time is the product of the population size and the number of generations, which is $O(PG)$ .

## V. Simulation

We simulate our proposed GA based antenna selection with MIMO system we describe in section III. The number of transmit antennas is $M$ and are always selected. The number of receive antenna is $N$ and $L$ of them are selected. Rayleigh fading channel is taken so that we generate the full $M \times N$ channel matrix by Gaussian random function. Then we use our GA to emulate the process of gene inherence to get the suboptimal antennas subset with the maximum channel capacity. The parameters of our GA are showed in Table I. We compared our GA based antenna selection with random antenna selection, optimal brute force antenna selection, Fast Antenna selection and NBS.

TABLE I
Parameters of our GA

| Parameter | Value |
|---|---|
| Size of Population set, p | 500 |
| Total generations, G | 50 |
| Crossover rate | 0.5 |
| Mutation rate | 0.2 |

First, we simulate the GA based antenna selection with the size of receive antennas set $M$=64, size of transmit antennas set $N$=8, and selected receive antennas $L$=44. The convergence behavior of our proposed Algorithm with SNR=30dB is shown in Fig.2. The capacity is increased with the number of generations, G, growing. Besides, the rate of convergence of our GA is large. Our Algorithm reaches the maximum capacity before G=10. The capacity remains the same after G=10. We can observe that our GA based antenna selection has a good performance in a big search area.

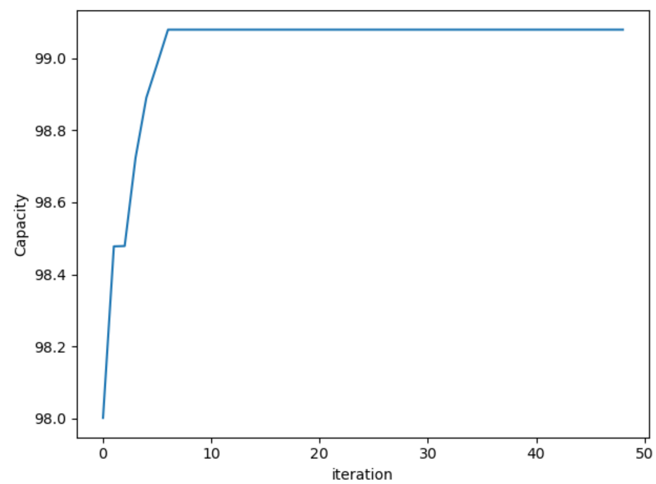


Fig. 2. Convergence behavior of our proposed Algorithm

Next, we compare our GA based antenna selection with random antenna selection, optimal brute force antenna selection, NBS, and Fast Antenna selection. The Fig.3 demonstrates the performance of 5 algorithms, including GA under different SNR from 1dB to 20dB. We can observe that optimal brute force antenna selection always has a maximum capacity, and random antenna selection always has the worst capacity. When SNR increases, our GA based antenna selection has a small advantage over other suboptimal methods. NBS method has a lower capacity than our GA-based antenna selection, Fast Antenna selection, and NBS.

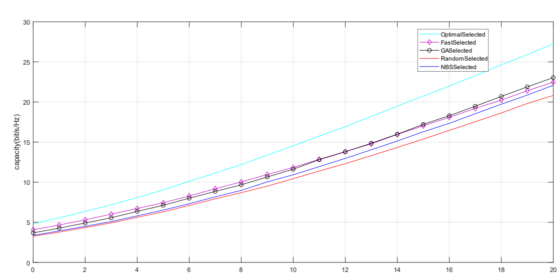

Fig. 4. Algorithms' performances under different SNR

Then, we simulate the dynamic change of the numbers of selected receive antennas in antenna selection when the SNR is 30dB with 16 receive antennas and 4 transmit antennas, Fig.4 compares the performance of each Algorithm with the selected number varying from 1 to 16. Traditional GA always get an optimal solution. Our GA based antenna selection fix the upper bound numbers of selected antennas in each simulation. System capacity virus numbers of selected receive antennas is shown in Fig.5. When the number of selected antennas increases, the system channel capacity of all antenna selection schemes increases. Except for the optimal brute force method, which always has a maximum capacity when the number of selected antennas change, our GA based antenna selection always has a higher capacity compared with another algorithms simulated regardless of the change in selected number.

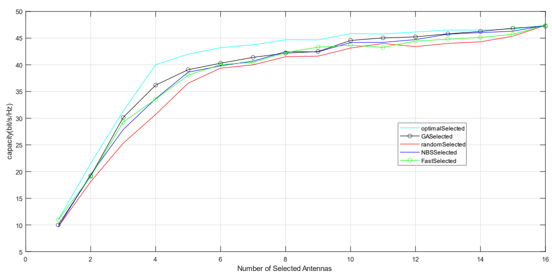


Fig. 5. Algorithms' performances with different selected number

Finally, the computation complexity of GA based antenna selection is calculated using the capacity calculation times. Using P=500 and G=50, the capacity calculation times is 50000, which is a fixed number in our simulation. Our computation complexity is much lower than the optimal brute force method, which is exponential to the size of receive antennas.

## VI. Conclusion

In this paper, we proposed a GA based antenna selection, which has a capacity performance close to the optimal method and has a fixed low computation complexity. Also, the simplicity of the implementation of this Algorithm makes a further application, which is implemented on limited resource sensors, has huge potential.

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