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# Application of Genetic Algorithm for Large-Scale Multiuser MIMO Detection with Non-Gaussian Noise

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## Abstract

Based on experimental measurements conducted on many different practical wireless communication systems, ambient noise has been shown to be decidedly non-Gaussian owing to impulsive phenomena. However, most multiuser detection techniques proposed thus far have considered Gaussian noise only. They may therefore suffer from a considerable performance loss in the presence of impulsive ambient noise. In this paper, we consider a large-scale multiuser multiple-input multiple-output system in the presence of non-Gaussian noise and propose a genetic algorithm (GA) based detector for large-dimensional multiuser signal detection. The proposed algorithm is more robust than linear multi-user detectors for non-Gaussian noise because it uses a multi-directional search to manipulate and maintain a population of potential solutions. Meanwhile, the proposed GA-based algorithm has a comparable complexity because it does not require any complicated computations (e.g., a matrix inverse or derivation). The simulation results show that the GA offers a performance gain over the linear minimum mean square error algorithm for both non-Gaussian and Gaussian noise.

**Index Terms**: MIMO Systems, Genetic Algorithm, Multiuser Detection, Non-Gaussian Noise

## I. INTRODUCTION

Using tens to hundreds of antennas for transmitters and receivers, a large-scale multiuser multiple-input multiple-output (MIMO) system offers a much higher spectral efficiency than conventional MIMO systems [1, 2]. It has therefore attracted considerable attention and is regarded as one of the key technologies for 5G wireless communication. However, it also poses a big challenge for detecting signals with large dimensions.

The current existing optimal detectors (e.g., maximum likelihood or maximum a posterior (MAP)) and nonlinear detectors (e.g., sphere decoding) are impractical for implementation because of the prohibitive complexity caused by the extremely large signal dimension. By contrast, although linear detectors (e.g., zero forcing (ZF) and MMSE) are simple to implement, the performance achievable is usually far from optimal. Other detectors, such as sparse-aware detectors [3, 4], have been proposed to achieve a better trade-off between complexity and performance. Most current detectors are largely dominated by the widespread use of additive Gaussian noise assumptions. However, it is well known that in many practical communication channels, such as indoor and urban radio channels, ambient noise is largely impulsive in nature, which can adversely affect the performance of conventional receivers optimized for Gaussian noise [5, 6]. Conventional linear and nonlinear multiuser detectors, which are derived according to the Gaussian noise assumption, may suffer considerable performance losses in the presence of non-Gaussian noise. It is therefore necessary to design a robust multiuser detector that can combat the effects of random impulses introduced through non-Gaussian noise. Therefore,

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in this study, we propose a genetic algorithm (GA) based multiuser detector. The main contributions of this study are summarized as follows:

1. The GA is a heuristic search algorithm inspired by the genetic mechanisms of species evolution [7]. The algorithm works well even for nonlinear programming problems and has been successfully applied to signal processing [8]. To the best of our knowledge, few studies have been conducted on the implementation of the GA in large-scale MIMO systems for multiuser detection. This is the first study applying the GA technique to multiuser detection in a large-scale MIMO system in the presence of non-Gaussian noise.
2. On the one hand, the GA-based detector follows a multiple-directional search approach in which many peaks are searched in parallel, thereby reducing the possibility of local minimum trapping. Consequently, the GA-based detector may perform better than other conventional signal detectors in the presence of non-Gaussian noises. On the other hand, the GA only needs to evaluate the objective function (or fitness function) to guide its search, which means there is no requirement for a matrix inverse or derivation, among other factors. Therefore, the complexity of GA-based multi-user detection is comparable to that of conventional linear detectors.
3. An imperfect channel is also considered in this study. We observed that the GA-based detector works efficiently under practical scenarios.

The remainder of this paper is organized as follows. The system model is introduced in Section II. In Section III, we present a GA-based multi-user detector for large-scale MIMO systems. The numerical results are presented in Section IV. Finally, we provide some concluding remarks in Section V.

## II. SYSTEM MODEL

Consider an uplink multiuser MIMO system consisting of one base station equipped with M antennas and $K$ users (UEs) with a single antenna. Let $\mathbf{x} = [x_1, x_2, x_K]^T$ denote the symbol vector sent by $K$ UEs, where each entry is chosen from a finite alphabet determined based on the implemented modulation scheme, e.g., BPSK. At the BS, the aggregated signal vector, denoted as $\boldsymbol{y} = [y_1, y_2, \cdots, y_M]^T$, is given by

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}, \tag{1}$$

where, $\mathbf{H} \in \mathbb{C}^{M\times K} \in$ is a channel matrix with independent identically distributed (*i.i.d.*) zero-mean, unit-variance complex Gaussian elements, and $\boldsymbol{n} = [n_1, n_2, \cdots, n_M]^T$ is a noise vector. We adopted the same two-term Gaussian mixture model for additive non-Gaussian noise, as given in [9]. The probability density function of this noise has the following form:

$$p = (1-\epsilon)\mathcal{N}(0,\sigma^2) + \epsilon\mathcal{N}(0,\kappa\sigma^2), \tag{2}$$

where $0 \le \epsilon \le 1$ and $\kappa \ge 1$. Note that the larger the non-Gaussian parameter $\epsilon$ is, the more non-Gaussian the noise that is distributed.

Given system model (1), the MAP detector is the optimal detector used for detecting the transmitted symbol vector $\mathbf{x}$, and is expressed as

$$\hat{\mathbf{x}} = \arg\max_{x\in \mathrm{A}^K} P_r(\mathbf{x}\mid\mathbf{y}) = \arg\max_{x\in \mathrm{A}^K} P_r(\mathbf{y}\mid\mathbf{x})P_r(\mathbf{x}). \tag{3}$$

With Gaussian noise and the equal prior probability of $\mathbf{x}$ assumptions, the MAP detector (3) can be equivalently expressed as

$$\hat{\mathbf{x}} = \arg\min_{x\in \mathrm{A}^K} \frac{1}{2}\left\|\mathbf{y}-\mathbf{H}\mathbf{x}\right\|_2^2. \tag{4}$$

The least squares detector, where $\|\mathbf{x}\|^2$ is the $l_2$ norm of a vector $\mathbf{x}$. This detector can guarantee optimal performance; however, it has prohibitive complexity when the constellation size or a number of antennas is large. Therefore, linear detectors, such as ZF and MMSE, were derived based on (4) by relaxing the constraint of finite alphabets.

However, for most practical wireless channels, such as urban, indoor radio, and underwater acoustic channels, the ambient noise is known through experimental measurements to be non-Gaussian owing to the impulsive nature of man-made electromagnetic interference and a large amount of natural noise. In single-user wireless systems, it is widely known that non-Gaussian noise can be detrimental to the performance of conventional systems based on the Gaussian

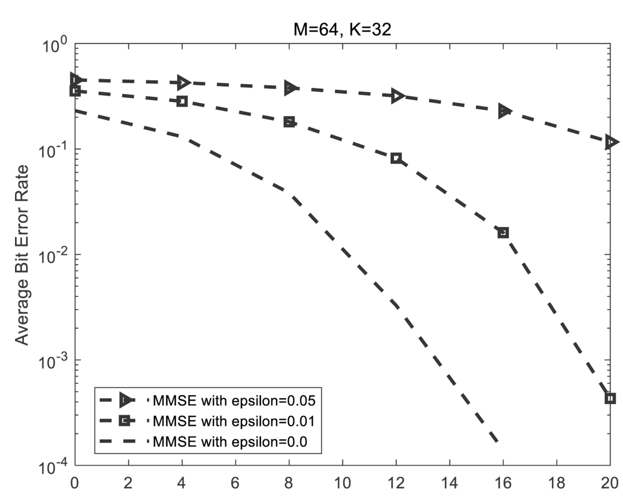


**Fig. 1.** BER performance comparison for MMSE with Gaussian and non-Gaussian noises for a 64 × 32 MIMO system.

noise assumption. It is therefore unsurprising that linear and non-linear multiuser detectors lack robustness to many types of non-Gaussian statistical behaviors. An early study on the bit error rates (BERs) in non-Gaussian direct-sequence code-division multiple-access (CDMA) channels showed that the performance of conventional multiuser detectors depends heavily on the distribution of ambient noise [10-12]. From the results illustrated in Fig. 1, we observe that the performance of the MMSE detector is degraded by non-Gaussian noise. The larger the non-Gaussian noise parameter $\epsilon$ is, the greater the degradation in performance. Therefore, a robust multiuser detector is required to combat non-Gaussian noise.

## III. GENETIC DETECTOR FOR LARGE-SCALE MIMO SYSTEMS

In this study, we consider the GA technique, which is a heuristic and stochastic optimization approach, and offers more promising alternatives. Compared with other conventional detectors, the GA may be the most robust in several respects. First, the GA is a multi-directional search method that seeks many peaks in parallel and can reduce the possibility of local minimum trapping. Second, instead of the optimization function, the GA evaluates the fitness of each signal vector to guide its search. In other words, the GA does not require any advanced computations such as a matrix inverse (which is required by ZF and MMSE detectors). Finally, the GA explores the search space in which the probability of finding the best solution is high. Although the GA requires extremely intensive computations, the development of supercomputing resources makes it a good candidate for most optimization problems. The standard GA allows us to make modifications to suit the design requirements for a given environment. In this paper, considering large-scale MIMO systems, some specific modifications to the chromosome representation, initialization, fitness function, GA parameters, and termination conditions are introduced.

### *A. Chromosome Representation*

A chromosome encoding scheme may vary according to the nature of the problem, and because it can severely limit the search space observed by the system, it has a major impact on the performance. In the GA-based multiuser detector, the detected symbol $x_i$, $i \in \{1, 2, \cdots, K\}$ and cut-off parameter $c$ are available. Each chromosome is represented by a $(K + 1)$-dimensional vector $\mathbf{c} = [c_1, c_2, \cdots, c_{K+1}]$, where the first $K$ entries correspond to the transmitted signal vector $\mathbf{x}$ and the final entry is reserved for the estimation cut-off parameter $c$.

### *B. Initialization*

In general, the population of chromosomes $\boldsymbol{c}^l = [c_1^l, c_2^l, \cdots, c_{K+1}^l]$ is randomly initialized, where $l = 1, \cdots, L$, with $L$ being the population size. A random generation is used to distribute the initial trial solutions to a highly diversified search space. The lower and upper bounds for the first K entries in each chromosome are determined based on the finite alphabet letter $A$. For example, when BPSK is implemented for MIMO systems, −1 and +1 can be used as the lower and upper bounds, respectively. The $(K+1)$th entry is usually set to greater than zero.

### *C. Fitness Function*

Because it evaluates the fitness of each chromosome, and to achieve a good performance, should guarantee that only the high-quality chromosomes are passed through to the next generation, the fitness function plays a critical role in the GA-based detector. By convention, a fitness function should have a positive value. In this study, in the presence of non-Gaussian noise, detecting the transmitted signal should minimize the difference between the original received signal and the transmitted signal multiplied by the channel coefficients, as given in (5), where $\rho(x)$ represents a specific penalty function that is generally convex, $y_j$ is the $j$th entry of the received signal vector $\mathbf{y}$, $h_{jk}$ is the entry at the $j$th row and the $k$th column of the channel matrix $\mathbf{H}$, and $x_k$ is the $k$th entry of the transmit signal vector $\mathbf{x}$. Owing to its robustness in a minimax sense, in this study, we use the Huber penalty function from [13] and described in (6), where $\tau > 0$ is a problem-dependent parameter for tuning the robustness of the detector.

### *D. Termination Condition*

Termination is the criterion by which the GA decides whether to continue or stop a search. With the proposed GA-based detector, the number of iterations required to reach a predefined penalty function is not known in advance, and we adopt the strategy of reaching the maximum generations to avoid an excessively high complexity and detection delay.

### *E. Genetic Operators*

The main procedure used for the GA-based detector is shown in Fig. 2. The GA-based detector simulates the evolutionary process by generating an initial population of candidates $\boldsymbol{c}^l$ and iteratively applying genetic operators, i.e., a selection, crossover, and mutation, in each loop. A selection determines the chromosomes chosen for mating. If the selection of only the best chromosome is employed, the population quickly converges. The crossover is defined such that

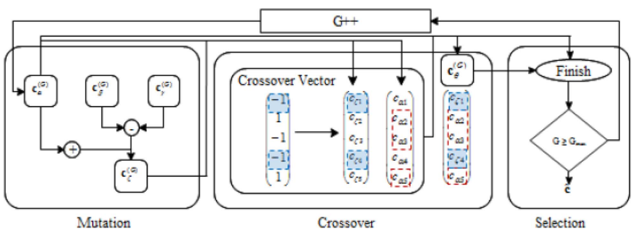


**Fig. 2.** Main procedures of GA-based detector.

two candidates combine to produce two new candidates. The main purpose of a crossover is to obtain good genetic material from the previous to the following generations. The mutation operator introduces a certain amount of randomness into the search.

$$\hat{\boldsymbol{x}} = arg \min_{x \in A^K} \sum_{j=1}^{M} \rho\left(y_j - \sum_{k=1}^{K} h_{j,k} x_k\right), \tag{5}$$

where, $$\rho(d_j) = \begin{cases} \frac{1}{2}\left|d_j\right|^2, \text{for } \left|d_j\right| \le \tau \\ \tau\left|d_j\right| - \frac{1}{2}\tau^2, \text{for } \left|d_j\right| > \tau \end{cases}. \tag{6}$$

## IV. Simulations

In this section, the simulation results are presented to verify the robustness of the GA-based detector for large-scale MIMO systems. BPSK is considered a modulation scheme, such as $A$ = {-1, +1}. The population size is $L$ = 60; the maximum generation number is $G_{max} = 5$; the crossover probability $p_c$ and the mutation probability $p_m$ are 0.88 and 0.08, respectively; and the tuning parameter $\tau$ is set to 0.5. A summary of various GA parameters is provided in Table 1. Note that these parameters are given experimentally, and the theoretical support for selecting those parameters that optimize the performance has yet to be determined. For comparison, the MMSE detector was considered a performance baseline, and the noise parameter $\kappa = 100$ for all simulations.

In Fig. 3, we compare the performances of the conventional MMSE and GA-based detectors in the presence of different non-Gaussian noise distributions for a 64 × 32 MIMO system. We observed that the GA-based detector achieves a better performance than the MMSE for different non-Gaussian noise distributions. More specifically, at BER = 0.01, a performance gain of approximately 1 dB can be achieved using the GA-based detector when $\epsilon = 0.05$.

The effects of different MIMO architectures are shown in Fig. 4. From the simulation results, we can observe that the GA-based algorithm always achieves a better performance than the conventional MMSE. Moreover, we observed that the less over-determined the massive MIMO is, the greater the performance gain achievable by the GA. More specifically, at BER = 0.01, the GA increases by approximately 0.3, 0.4, and 0.6 when the massive MIMO size is 64 × 20, 64 × 32, and 64 × 48, respectively. This is reasonable because when the large-scale MIMO system is overdetermined (e.g., 64 × 20), the MMSE approaches the optimal detector, and the performance gain achievable by the GA is limited.

Finally, we verify the behavior of the GA when considering imperfect channel state information (CSI). In this case,

**Table 1.** Summary of GA parameters.

| Parameters | Value |
|---|---|
| Population size $L$ | 60 |
| Generation $Gmax$ | 50 |
| Crossover Probability $p_c$ | 0.88 |
| Mutation probability $p_m$ | 0.08 |
| Turning parameter $\tau$ | 0.5 |

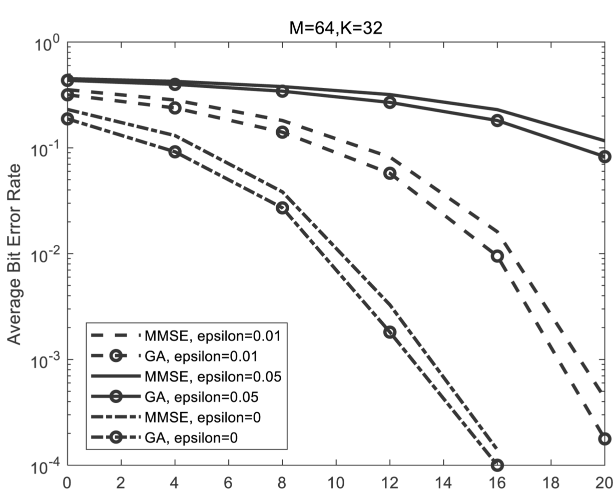


**Fig. 3.** Performance comparison of MMSE and GA with different non-Gaussian noise distributions for a 64 × 32 MIMO system.

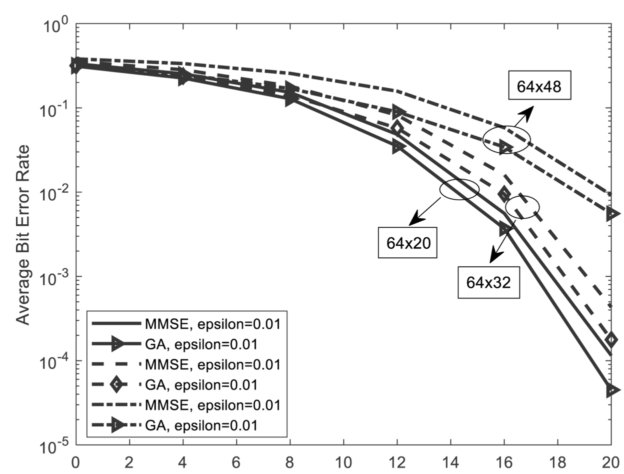


**Fig. 4.** Performance comparison of MMSE and GA for the different MIMO architectures.

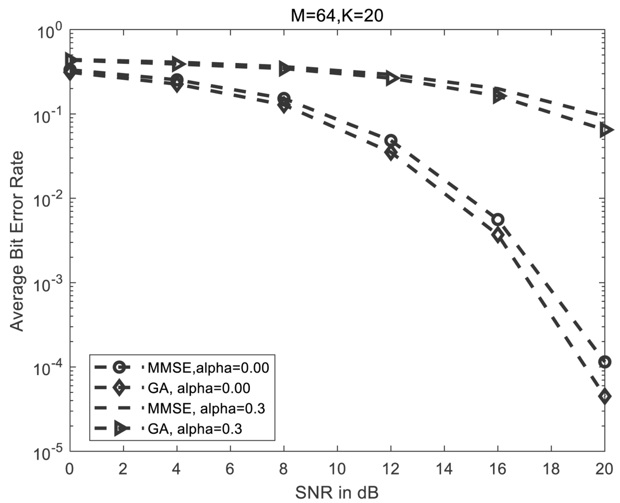


**Fig. 5.** Performance comparison of MMSE and GA with imperfect channel state information for a 64 × 20 MIMO system.

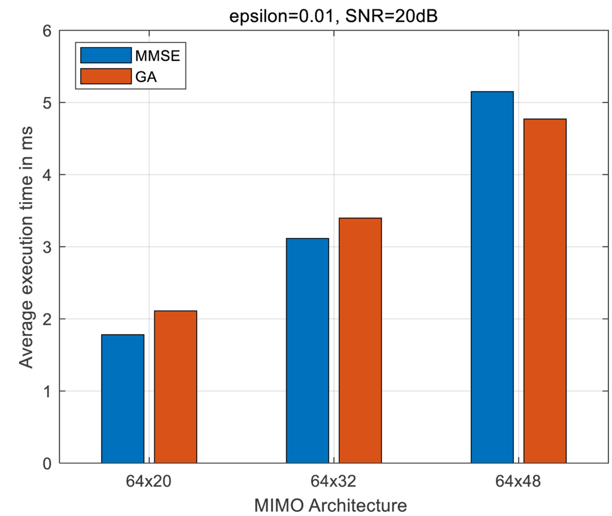


**Fig. 6.** Average execution time comparison of MMSE and GA with different MIMO architectures.

we apply the following imperfect channel model [14, 15]:

$$\bar{\mathbf{H}} = \mathbf{H} + \alpha\mathbf{E}, \tag{7}$$

where, $\mathbf{E}$ is the estimation error uncorrelated with $\mathbf{H}$, the entries of $\mathbf{E}$ are *i.i.d.* zero-mean Gaussian with unit variance, and $\alpha$ is the measured accuracy of the channel estimation. From the simulation results shown in Fig. 5, it is not surprising that both the GA-based detector and the MMSE detector degrade significantly when $\alpha = 0.3$ compared to the case of the perfect CSI (i.e., $\alpha = 0.0$). However, the GA-based detector still slightly outperforms the MMSE, which means that the GA-based detector is still robust, even when the channel information is not fully achievable.

In addition to the better performance achievable by the GA-based detector, as another advantage, it does not require any advanced computations, such as a matrix inverse, which is required by the MMSE, and is usually a significant burden for large-scale MIMO systems. Therefore, the GA-based detector may achieve a complexity comparable to that of the MMSE. In Fig. 6, we can see that for both the 64 × 20 and 64 × 32 MIMO systems, the GA-based detector requires a slightly larger average execution time in comparison to the MMSE. However, for the 64 × 48 MIMO system, the average execution time of the GA was less than that of the MMSE, which is due to the main complexity of the MMSE being derived from a matrix inverse. Therefore, the larger the sizes of the MIMO systems, the higher their complexity. Whereas the GA-based detector only needs to calculate the fitness function without any other complicated computations, the complexity of the GA is dominated by the number of iterations rather than the size of the MIMO system. It is therefore reasonable for the complexity of the GA-based detector to be lower than that of the MIMO system when the number of users is close to the number of antennas at the BS.

## V. CONCLUSIONS

Non-Gaussian noise can significantly degrade the performance of current linear multiuser detectors applied in many practical wireless channels. In this paper, we presented a GA-based multiuser detector for large-scale MIMO systems in the presence of non-Gaussian noise. The simulation results show that the proposed GA-based detector is efficient in combating non-Gaussian noise. In addition, unlike the MMSE, which requires computations of the matrix inverse, the GA-based detector only needs to calculate the simple fitness function and can therefore achieve a comparable complexity. However, because the GA is a heuristic algorithm, the possibility of convergence depends heavily on the initializations and operator parameters. Therefore, in our future research, we might consider applying deep learning to refine the initializations for achieving a faster convergence and further performance improvement.

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