

Low-Computational Complexity Detection and BER Bit Error Rate Minimization for Large Wireless MIMO Receiver Using Genetic Algorithm

G. Ranjitham¹ and K. R. Shakar Kumar²

*¹Department of Electrical and Electronics Engineering
Sri Ramakrishna Engineering College, Coimbatore-22 –T. N., India.*

*²Département of Electronics and Communication Engineering,
Ranganathan Engineering College, Coimbatore –T. N., India.*

ABSTRACT

MIMO system where large number of transmitters and receivers are used for transmission of data simultaneously, the complexity of detection process is more as the channel matrix is more complex. This Paper deals simulation study of about reducing the computational complexity in Multiple Input Multiple Output (MIMO) receiver using partial ML detection along with Genetic algorithm. Maximum Likelihood Detection is considered as a path finding problem and partial ML detection along with Genetic Programming is used to solve it. This study uses Matlab communication tool box version 7. 1 and also aims in proving that MIMO receiver using partial ML detection along with GA, gives less Bit Error Rate (BER) and reduced computation complexity compared to Vertical-Bell Laboratories Layered Space Time (V-BLAST), Maximum Likelihood detection (MLD), Ant Colony Optimization (ACO), Modified Ant Colony Optimisation (MACO). Simulation analysis 1 deals with comparison of various algorithms like Modified Ant Colony optimization, Ant colony Optimization, Maximum Likelihood Detection and V-BLAST detection. Simulation analysis 2 deals with varying the receiver antenna configuration. Simulation analysis 3 involves the study of the computational complexity. From the above study it is inferred that, as the number of receiver increase, keeping number of transmitter antenna constant in QAM, BER decrease. V-BLAST has a better Bit Error Rate Performance than ML. ACO has a better Bit Error Rate Performance than V-BLAST. MACO has a better Bit Error Rate Performance than ACO. Partial ML with GA has a better Bit Error Rate Performance than MACO. Preparation complexity of partial ML along with Soft Input Genetic Algorithm decreases with increase in number of antenna configurations.

Keywords: MIMO, BER, VBLAST, MACO, ACO, QAM, ML detection.

Introduction to MIMO

Multiple Input Multiple Output (MIMO) communication refers to a technology in which the system uses an array of antennas (i. e. multiple antennas) at either the transmitter or the receiver. By employing multiple antennas at both ends of the link, the performance of the transmission is enhanced, in higher data rates without extra frequency and power resources. Wireless communication has the potential to provide high-speed high-quality information exchange between portable devices located in any distance apart.. There are many potential applications that uses this technology such as multimedia internet-enabled cell phones, smart homes and appliances, autonomous sensor networks, video teleconferencing and distance learning, and automated highway systems. There are two significant challenges in these applications: first, is the phenomenon of fading, and the second, signal interference between them. The challenges are mostly due to limited availability of radio frequency spectrum and a complex time-varying wireless environment (fading and multipath), bit error rate minimization and computational complexity. Nowadays, wireless communication is to increase data rate and improve transmission reliability. In other words, because of the increasing demand for higher data rates, better quality of service, fewer dropped calls, higher network capacity and signal clarity are some of key goals.

GA based MIMO

Genetic algorithm (GA) is a search heuristic that relates the process of natural evolution. This heuristic is routinely used to generate solutions to optimization and search problems. Genetic algorithms belong to the larger class of Evolutionary Algorithms (EA), which generate solutions to many optimization problems using properties likes mutation, cross over, selection and inheritance. GA is much applicable for physically realizable, real-time applications, where low complexity and fast convergence is of a major requirements.

The method adapted is that a population of candidate solutions are chosen in a common pool to an optimization problem is evolved first. Each possible candidate solution has a set of properties are mutated and altered. Though the performance of GA is near to the ML detection performance, finding the optimal solution to complex high dimensional, multimodal problems often requires very expensive fitness function values and evaluation and when the number of elements which are exposed to mutation is large there is often an exponential increase in search space size. So it is essential to apply for Partial ML detection along with Genetic programming or Genetic Algorithm.

Partial ML along with Genetic programming

The BER performance of ML detector is better than any other modulation technique, but the computational complexity of ML detector is very large. In order to get the near ML performance but with reduced complexity we move in for partial ML detection

along with Genetic programming. The basic block diagram for the proposed work is shown in figure 1. 1

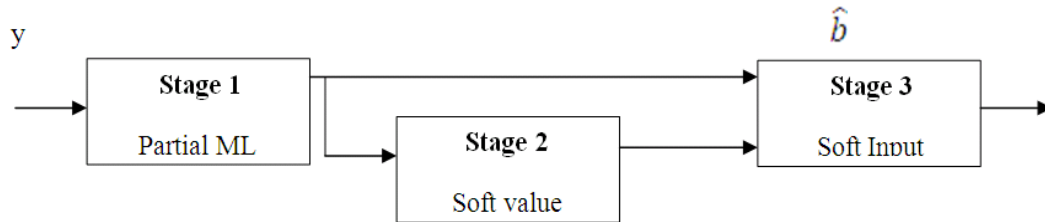


Figure. 1. 1 Block diagram of the GA MIMO detector

The detector operates at the bit level and consists of three stages. The first stage in **Figure1. 1** is responsible for, partial ML detection, calculates some bits of the ML solution by means of the iterative algorithm. In the second stage, soft values for the undetected bits are generated. In the third stage, the undetected bits are detected by means of a soft-input genetic algorithm, which is a novel soft-input version of a genetic algorithm used for solving large binary quadratic programming problems.

Stage 1-Partial ML along with Genetic programming

The modulation scheme taken into account is Auadarture amplitude modulation and BPSK schemes. Every symbol *s* in the QAM constellation is given as

$$s = v^T \tilde{b} \quad (1. 1)$$

where *v* is a vector such that $v \in C^B$. The mathematical representation of MIMO using QAM constellation is modified as

$$y = Ab + n \quad (1. 2)$$

where $A \cong H \otimes v^T$ (\otimes denotes the Kronecker product)

For BPSK constellation the mathematical representation remains as

$$Y = Hs + n \quad (1. 3)$$

The ML detector is formulated as

$$\hat{b}_{ML}(y) = \arg \min_{b \in \{1, -1\}} \sum_t |y_t - Ab_t|^2 \quad (1. 4)$$

In partial ML detection some elements $\hat{b}_{ML, k}$ of \hat{b}_{ML} is detected. The partial ML detector is derived by expanding, with respect to a single bit b_k , the metric $\|y - Ab\|^2$ minimized by the ML detector. The index set which has all the elements of *b* is taken excluding the *k*th bit. So the ML detection can be modified as

$$\hat{b}_{ML}(y) = \arg \min_{b \in \{1, -1\}} \sum_t \{b_k \Psi_k(b_{-k}) + \rho_k(b_{-k})\} \quad (1. 5)$$

where

$$\Psi_k (b_{\sim k}) \cong 2 (R\{Z_k\} - \sum_{i \in I-K} R\{G_{k, i}\} b_i) \text{ and } \rho_k (b_{\sim k}) \cong 2 \sum_{k' \in I-K} R\{Z_{k'}\} b_{k'} - \sum_{k' \in I-K} \sum_{l \in I-K} b_{k'} G_{k', l} b_l$$

When $\Psi_k (\hat{b}_{ML, \sim k}) \neq 0$ and $\hat{b}_k = \hat{b}_{ML, \sim k}$ if and only if $\hat{b}_k = \text{sgn} (\Psi_k (\hat{b}_{ML, \sim k}))$ is assumed then ML solution \hat{b}_{ML} satisfies

$$\hat{b}_{ML, k} = \text{sgn} (\Psi_k (\hat{b}_{ML, \sim k})) \quad (1.6)$$

The above value should lie between $L_k (D)$ and $U_k (D)$ where $L_k (D) \cong 2 (R\{Z_k\} - \sum_{l \in \bar{D}-k} |R\{G_{k, l}\}| - \sum_{l \in D-k} R\{G_{k, l}\} \hat{b}_{ML, l})$ and $U_k (D) \cong 2 (R\{Z_k\} - \sum_{l \in \bar{D}-k} |R\{G_{k, l}\}| - \sum_{l \in D-k} R\{G_{k, l}\} \hat{b}_{ML, l})$

Here D = detected bits and \bar{D} = undetected bits.

For $k \in \bar{D}$ the value of $\hat{b}_{ML, \sim k}$ is updated as When $L_k (D) > 0$, set $\hat{b}_{ML, k} = 1$; When $U_k (D) < 0$, set $\hat{b}_{ML, k} = -1$; For other cases $\hat{b}_{ML, k}$ is left undetected. After assigning values to $\hat{b}_{ML, k}$ the value of D and \bar{D} is updated

Stage 2-Generation of Soft Values

For the undetected bits the soft value \check{b}_k is calculated and this is used in the genetic algorithm developed in the third stage. The value of \check{b}_k is defined as

$$\begin{aligned} \check{b}_k &\cong E\{\hat{b}_{ML, k}\} = E\{\text{sgn}(x_k)\} \\ &= (1) P_r\{x_k > 0\} + (-1) P_r\{x_k < 0\} \\ &= \{L_k (D_{ML}) + U_k (D_{ML})\} / \{L_k (D_{ML}) - U_k (D_{ML})\} \end{aligned} \quad (1.7)$$

The value of \check{b}_k lies between -1 and 1.

Stage 3-The soft input Genetic Algorithm

The Soft input Genetic Algorithm (SGA) is a soft-input version of the genetic algorithm that is used for solving large binary quadratic programming problems. The SGA is different from genetic algorithms previously proposed for MIMO detection in that (i) it uses the soft values provided by Stage 2 and the partial ML detection results provided by Stage 1 for an improved initialization, and (ii) it includes a local search procedure, which makes the search for improved CSs more effective. Therefore, the SGA performs well even for very small population sizes. These reduced population sizes result in a low complexity and make the SGA suited to large MIMO systems with large number of antennas. **Figure. 1. 2** shows the BER performance of 4x128 MIMO system using QAM modulation scheme under PML+SGA, MACO, ACO, SD, VBLAST. It is observed that partial ML along with Genetic Algorithm has a better BER performance when compared with other detection techniques. **Table 1** shows Numerical comparison of BER performance of 4x128 MIMO under QAM Modulation. It is inferred that combination of PML and SGA gives a minimum Bit Error Rate than V-BLAST, ACO, MACO, ML. From the discussions and table 1 it is inferred that

- BER decreases as the number of receiver increases (i. e) when the MIMO system configuration is 4x128 the BER is $10^{-2.5}$ which is very much less than

the $10^{-1.25}$

- BER performance of PML+SGA using QAM ($10^{-2.5}$ for 4x128) is better than MACO (10^{-2} for 4x128), ACO ($10^{-1.6}$ for 4x128), ML ($10^{-0.9}$ for 4x128), V-BLAST ($10^{-1.4}$ for 4x128) detection techniques using QAM.

Simulation Analysis 2 explains the preparation complexity of partial ML along with Soft Input Genetic Algorithm (i. e) the number of mathematical calculations involved in detection technique. **Figure 1. 3** shows that as the number of transmitter and receiver increases, the preparation complexity of partial ML along with Soft Input Genetic Algorithm decreases. Thus Partial ML along with Soft Input Genetic Algorithm is suitable for large MIMO system.

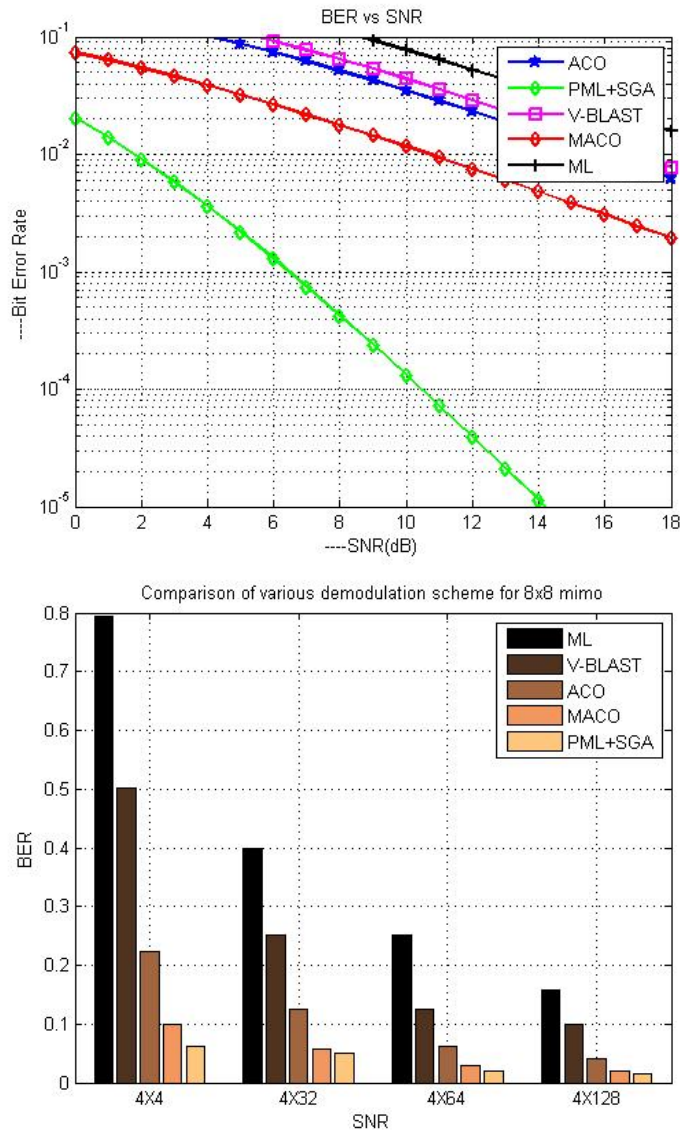
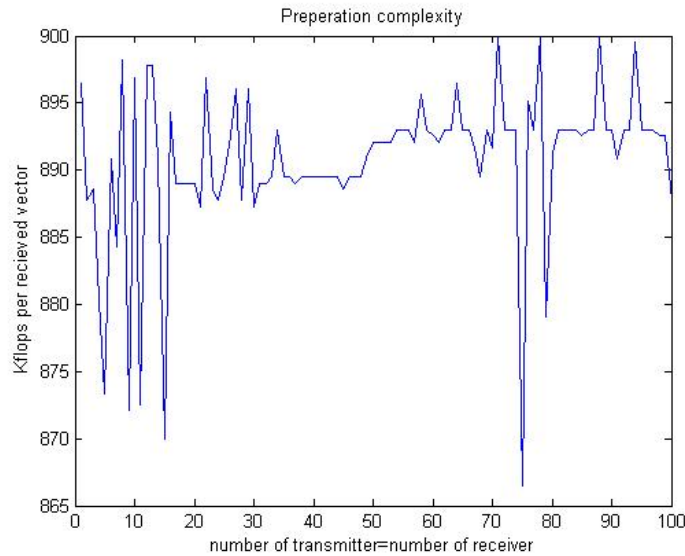


Figure. 1. 2 BER performance of 4x128 MIMO and its Bar chart.

Table 1 Numerical Comparison of BER performance of 4xn MIMO system using different detection technique with QAM modulation

mxn configuration	PML+SGA	MACO	ACO	ML	V-BLAST
4x4	$10^{-1.25}$	10^{-1}	$10^{-0.8}$	$10^{-0.2}$	$10^{-0.4}$
4x32	$10^{-2.0}$	$10^{-1.3}$	$10^{-1.2}$	$10^{-0.6}$	$10^{-0.9}$
4x64	$10^{-2.3}$	$10^{-1.8}$	$10^{-1.4}$	$10^{-0.7}$	$10^{-1.1}$
4x128	$10^{-2.5}$	10^{-2}	$10^{-1.6}$	$10^{-0.9}$	$10^{-1.4}$

**Figure 1. 3** Preparation complexity of PML+SGA

Conclusion

From the simulation and experimental results, it is observed that Partial ML and Soft Input Genetic Algorithm along with Quadrature Amplitude Modulation (QAM) is the best detection technique among all other detection technique such as Vertical-Bell Laboratory Layered Space Time (V-BLAST), Maximum Likelihood Detection (ML), Ant Colony Optimization and Modified Ant Colony Optimization Technique (MACO) with Quadrature Amplitude Modulation (QAM) and can produce performance which is equivalent to Maximum Likelihood detection (MLD)

The following are the conclusion derived from this paper As the number of receivers increases, BER reduces. As the number of receivers increases, SNR increases. V-BLAST has a better Bit Error Rate Performance than ML. ACO has a better Bit Error Rate Performance than V-BLAST. MACO has a better Bit Error Rate Performance than ACO. Partial ML with GA has a better Bit Error Rate Performance than MACO.

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