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Efficient Detection of Signal in MIMO System Using Modified Memetic Algorithm with Higher Order QAM Constellations

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Abstract: Multiple Input Multiple Output (MIMO) is a technology to meet high data rate necessity for next generation communication system. It can well use the spectrum to enhance the communication throughput. Design a low-complex, high performance detection algorithm for the MIMO system has been a vital issue. The efficient detection of MIMO signal using Modified Memetic Algorithm (MMA) with Quadrature Amplitude Modulation (QAM) varying constellation size is proposed in this paper. The performance of the proposed work is at far with the optimum Maximum Likelihood Detector (MLD) in terms of Bit Error Rate (BER) and computational complexity. Three stages are there in proposed work. In the first stage, using partial ML detections certain bits are detected. The undetected bits in the first stage are calculated in the second stage using soft values generation method. Using MMA algorithm the undetected bits is detected in the last stage. The soft values obtained from second stage and the partial ML bits from the first stage are combined and used as the input for the last stage. In this stage, the best individuals are obtained. MMA uses hill climbing local search technique to obtain the high quality individuals as starting point. The simulation results demonstrate that MMA based MIMO detectors outperformed the state of art detectors for different antenna configurations. Also it gives reduced complexity as compared to the existing detectors. For a 4×4, 16-QAM MIMO system, the proposed work gives BER of 10^{-4} for 8dB SNR with the complexity value of 51.4.

Keywords: MIMO systems, QAM, ML Detection, Genetic Algorithm, Memetic Algorithm.

1 Introduction

MIMO system is one of the most talented technologies that can provide enormous data rates with consistent link quality for wireless communication [1–8]. The MIMO systems have been adopted in the wireless standards like IEEE 802.11n, IEEE 802.16e, LTE and also 5th generation (5G) communication networks. To receive high performance symbol in MIMO system, the receiver wants an well defined detection algorithm. In MIMO system, design of low complexity and high performance receiver is the main challenge [2, 3].

Consider n_t transmitting and n_r receiving antennas of MIMO system. The transmitted signals are represented in both time and space using QAM modulation. MIMO systems are described by two models, namely real equivalent model and complex equivalent model. The proposed algorithm is adopted in both models. The complex baseband equivalent model of MIMO system is represented in Eq. (1),

$$Y = HX + n \tag{1}$$

where H is an $(n_t \times n_r)$ AWGN (Additive White Gaussian Noise) channel matrix. X is a complex transmitted signal vector of length n_t and all the elements are separately drawn from a constellation of M-QAM scheme [2]. From all the digital modulation techniques QAM have high spectral efficiency thus it gives low BER as compare to other modulation techniques. To find best symbol $\hat{A}$ for received signal Y is the main goal of the MIMO detection and it is represented by the Eq. (2) as,

$$\hat{A} = \underset{A\in O_{n_t}}{\arg\min} |Y - HX|^2 \tag{2}$$

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1.1 State of Art

The optimum detection method of MIMO system is Maximum-Likelihood (ML) detection because it has reduced BER but as we increase the number of transmitting antennas its complexity increases exponentially. Linear detectors such as Zero Forcing (ZF), Successive Interference Cancellation (SIC) or Minimum Mean-Square Error (MMSE) based detection [1, 2] have reduced complexity than ML but it has poor performance. The non linear detectors such as depth first and the breadth first search algorithms are also used to detect the MIMO signals. One of the depth first strategy is the Sphere Decoder (SD) [3–5], which guarantees the best performance but the changeable throughput results in additional overhead in the hardware. The most familiar approach of breadth first search methods is the K Best algorithm. It gives constant throughput with the performance close to ML [6]. But K values are increased means the complexity also increases.

To overcome the above issues, optimization techniques are introduced. One of the efficient optimization algorithms are used to solve hard problems is Genetic Algorithm (GA) [9, 10]. The main innovation of GA founds the best cost signal but it is not well suitable for line tuning structures. To resolve the above problem introduce new algorithm called Modified Memetic algorithm (MMA) in MIMO system. It produces better results compared to GA and other equivalent MIMO detectors.

1.2 Contribution

Low complexity with reduced BER detection of MIMO system using QAM symbol alphabet A is proposed in this paper. It represented by three stages and operates at the bit level in Fig. 1. In the first stage, using iterative algorithm [11], [12], partial ML bits $\hat{b}_{ML}(y)$ will be detected. In the second stage, soft values S_k are determined by using undetected bits values. In the third stage, from the partial ML bits and soft values S_k detect the best individuals b_k by use of MMA algorithm. This algorithm is work based on greedy optimization algorithm described in [14]. The first two stages are used to improve the initialization and the last stage includes local search procedure that improves the individuals even for small population size [15, 17].

This algorithm well suited to MIMO systems because it works with even small population sizes result in a low complexity. To obtain improved soft values [11], the outputs in the last stage are fed back to the previous stage.

The remaining of this paper is as follows: On Section 2 describes the detection of partial ML bits and generates the soft values. Section 3 explains the proposed MMA. Complexity analysis is done on Section 4, Simulation analysis of the proposed work is done on Section 5 and finally drew a conclusion on Section 6.

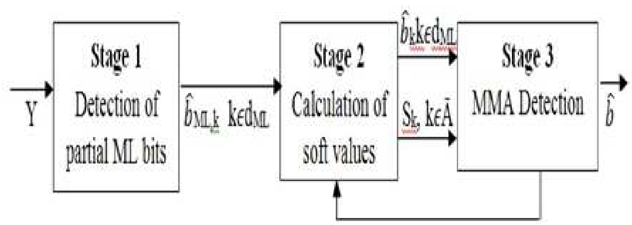


Fig. 1: Block diagram of the proposed MIMO detector.

2 Detection of ML Bits and Soft Values Generation

Consider a QAM symbol with $|A| = 2^M$ with $M = \log_2 |A|$, and a unique vector can be written as $v = (v_1, \ldots, v_B)^T \in C^B$ then,

$$a = \sum_{s=1}^{M} v_s b_s(s) = v^T b(s) \tag{3}$$

for every symbol $a \in A$ with a bit vector $b(s) \in \{-1,1\}^B$. From the literature [11], based on the value of $|A|$, the complex vector v is represented: e.g., $|A| = 16$ for $v = \left(1\ 2\ j\ 2j\right)^{\mathrm{T}}$ and $|A| = 64$ for $v = \left(4\ 2j\ 1\ 2j\ 4\ j\right)^{\mathrm{T}}$. Let $a_p = (a)_p$ denote the pth element of a. The MIMO symbols are obtained from a QAM symbol in terms of binary and it is represented by the Eq. (4) as

$$y = Ab + n. \tag{4}$$

The equivalent channel matrix, $A \triangleq H \otimes v^T \in C_r^n \times Mn_t$ ($\otimes$ denotes the Kronecker product) and the binary value of the transmit symbol vector a as, $b = b(s) \triangleq b^T(s_1) \cdots b^T(s_{nt})^T \in \{-1,1\}Mn_t$. At the bit level the ML detection rule (2) can be modified as

$$\hat{b}_{ML}(y) = \underset{b \in \{-1,1\}}{\arg\min} = \|y - Ab\|^2 \tag{5}$$

2.1 Detection of Partial ML bits

Computes a few elements $\hat{b}_{ML,k}$ from the partial ML detection $\hat{b}_{ML}(y)$ is the first stage for the proposed MIMO detection. The iterative algorithm is used to compute the partial ML bits [12, 13], which follows as, let $z \triangleq A^H y$, $G \triangleq A^H A$ and $I \triangleq \{1, \ldots, M_{nt}\}$ and $b = (b^T(s_1) \cdots b^T(s_{nt}))^T = (b_1 \cdots b_{Mnt})^T$ are the set of elements and b_k, z_k, and $G_{k,l}$ are the elements of b, z, and G respectively, with $k,\ l \in I$. For a bit b_k expand the ML metric $\|y - Ab\|^2$ with $k \in I$.

Let $I_k \triangleq \{1, \ldots, k-1, k+1, \ldots, Mn_t\}$ and $b_k \triangleq (b_1 \cdots b_{k-1} b_{k+1} \cdots b_{Mnt})^T$.

$$\text{Here, } \|y - Ab\|^2 = \|y\|^2 - x(b) \tag{6}$$

$$x(b) \triangleq 2\Re\{z^H b\} - b^T G b$$

$$
\begin{aligned}
&= 2b_k R\{z_k\} - G_{k,k} b_k^2 - \sum_{l \in I_k} b_k G_{k,l} b_l \\
&\quad - \sum_{k' \in I_k} b_{k'} G_{k',l} b_k + 2 \sum_{k' \in I_k} b_{k'} R\{z_{k'}\}_l \\
&\quad - \sum_{k' \in I_k} \sum_{l \in I_k} b_{k'} G_{k',l} b_l
\end{aligned}
$$

Then ML detection rule (4) rewritten as

$$\hat{b}_{ML}(y) = \arg\min_{b \in \{-1,1\}} Mnt = x(b) \tag{7}$$

$\hat{b}_{ML,k}$ is unknown it can be determined by bounding values. It follows,

$$l_k(D) \leq \hat{b}_{ML,k} \leq u_k(D) \tag{8}$$

$$l_k(D) \triangleq 2(\Re\{z_k\} - \sum_{l \in D_k} |\Re\{G_{k,l}\}| - \sum_{l \in D_k} |\Re\{G_{k,l}\}\hat{b}_{ML,l}) \tag{9}$$

$$u_k(D) \triangleq 2(\Re\{z_k\} + \sum_{l \in D_k} |\Re\{G_{k,l}\}| - \sum_{l \in D_k} |\Re\{G_{k,l}\}\hat{b}_{ML,}) \tag{10}$$

Here, D denotes the set of already detected bits and D or d denote the set of undetected bits.

In each iteration, if $l_k(D) \geq 0$ thus $\hat{b}_{ML,k} = 1$ update the detected set D i.e, $D^{(new)} = D \cup \{k\}$ and $u_k(D) \leq 0$ thus $\hat{b}_{ML,k} = -1$ update the respective D set elements.

The lower and upper bounds $l_k(D_{ML})$ and $u_k(D_{ML})$ satisfy below condition:

$$l_k(D_{ML}) < 0 \;\text{ and }\; u_k(D_{ML}) > 0, \text{ for all } k \in D_{ML} \tag{11}$$

Otherwise a bit would have been detected.

If no new bits are detected the iterative procedure is terminated. After termination D_{ML} is the set of the detected ML bits, i.e., $\hat{b}_{ML,k}$ bits are detected bits in the partial ML detection stage.

2.2 Soft Values Generation

Generate the soft value S_k from the expected value of $\hat{b}_{ML,k}$, i.e.,

$$S_k \triangleq E\{\hat{b}_{ML,k}\}, k \in D_{ML}$$

From the bounds $l_k(D_{ML})$ and $u_k(D_{ML})$, the soft values S_k can be easily calculated.

$$S_k = \frac{l_k(D_{ML}) + u_k(D_{ML})}{u_k(D_{ML}) - l_k(D_{ML})}, \; k \in D_{ML} \tag{12}$$

Here, $-1 < S_k < 1$. If more bits are detected then the quality of the soft values improved [11].

3 Proposed Algorithm

3.1 A. Principle

The main work of stage 3 is to determine best individual bits b_k, $k \in D_{ML}$. This is done by the proposed algorithm called MMA with high performance in MIMO system. Incorporating GA with local search technique is known as Memetic algorithm (MA) [15]. In MMA initialize the population at random or heuristic [20]. Then, each individual are use the local search technique to develop its fitness value. Once two parents are selected, their chromosomes are joined by using crossover operation and generate the new individuals. Again use local search technique quality of individuals is enhanced [21, 22]. The task of hill climbing technique in MMA is to find high quality individuals efficiently than the GA.

3.2 Algorithm

Function $MA(P, i, n, k, i_a, i_b, i_c)$
Step 1 Initialize P # Population size $(P) = 50$
for $i := 1$ to P **do**
$P[i] := RS(n)$ # Random Solution
$P[i] := LS(P[i])$ # Local Search
Step 2: Hill-Climbing (problem) return state node:
present, neighbor;
present: = Make-Node(Initial-state
(problem));
Loop **do**
neighbor: = highest-value-successor
(present)
if (Value(neighbor) $<$ Value(present)) **then**
return State(present)
else current: = neighbor
end loop
end for
Step3: for i = 1 to M # Crossovers **do**
select two parent i_a, $i_b\backslash$ in randomly
$i_c :=$ crossover (i_a, i_b)
$i_c := LS(i_c)$
add i_c to M
end for
Step 4: for $i := 1$ to M # Mutations **do**
select an i of M randomly;
$i\{k\} :=$ mutate (i)
$i\{k\} :=$ LS $(i\{k\})$
add $i\{k\}$ to P
end for
Step 5 $N :=$ select(N)
if N converged **then**
for each i of best populations do
individual: = LS(mutate(i));
end if
return best solution found
end function

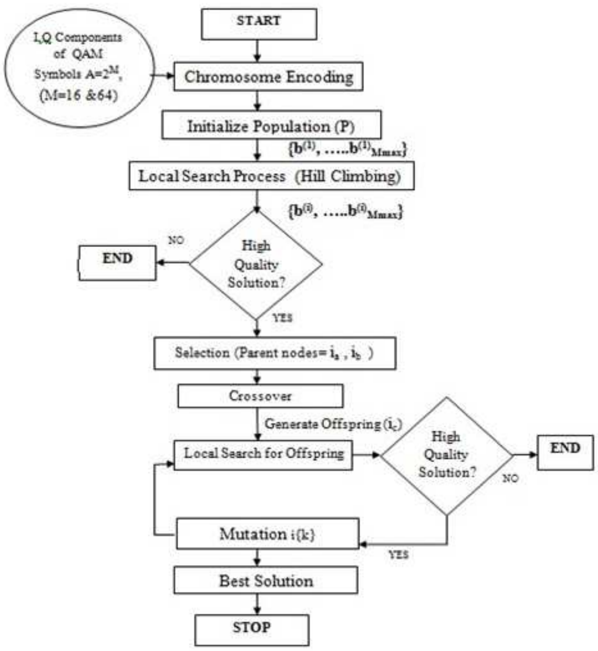


Fig. 2: Flowchart of MMA for MIMO detection.

3.3 Modified Memetic Algorithm (MMA) Functions

Fig. 2 shows the flowchart of MMA for MIMO detection. The functions of the MMA will be described as follows:

Individuals:
In MIMO detection based on MMA, the individuals are represented by the set of QAM symbol alphabet A, where $|A| = 2^M$ with $M = \log_2 |A|$ transmitted by the transmit antennas [13]. Consider the symbols $A = 2^M$, $M = 16$ and 64. The initial set $\{b^{(1)}, \ldots, b^{(1)}_{Mmax}\}$ are generated at first. Then find individuals with best fitness by the use of a local search technique.

Local Search (Hill Climbing):
Among numbers of local search techniques available in the literature, Hill Climbing (HC) is a common strategy. By the use of hill climbing method convert the preliminary initial start set from the second stage $\{b^{(1)}, \ldots, b^{(1)}_{Mmax}\}$ into $\{b^{(i)}, \ldots, b^{(i)}_{Mmax}\}$ which is the optimized initial start set and this is consider as the input to the MMA. The same procedure is executed for every individual in the crossover and mutation operations to obtain high quality solutions.

Hill-climbing starts with randomly generated solutions and repeatedly produce its the neighbors until a better solution is found. This new solution is better than old solution it becomes the current solution and the algorithm producing its neighbors until find the better solution. If there are no improving solutions in the current neighborhood, the method will be stopped.

Crossover:
According to the *uniform crossover* algorithm, pairs of individuals are organized randomly from the current individual set $\{b^{(i)}_1, \ldots, b^{(i)}_m\}$ of size $m^{(i)}$. One of the individuals appears in two pairs if $m^{(i)}$ is odd. Each individual pair (i_a, i_b) produces an *offspring individual* (i_c), whose bits are equal in the parent individuals bits, then randomly choose the remaining bits. The current individual set is then considered as extended set of offspring individuals. $m^{(i)}_{extension} = \lceil(3/2)m^{(i)}\rceil$ is the size of the extended set, where $\lceil m^{(i)}\rceil$ denotes the least integer value not lesser than $m^{(i)}$ [11].

Mutation:
In this stage, the individuals which are having the minimum Hamming distance $\mathrm{d}(b^{(i)}_j, b^{(i)}_{j'})$ is larger than 3 are considered as the offspring individuals. Also, in each mutation step choose the number of bits flipped value is greater than 1. Proper selection of mutation parameters in MMA it gives better results as compared to GA.

Then, all new individuals are generated by the crossover and mutation stages are again optimized by use of hill climbing local search stage [21].

Selection:
Finally, the extended set $m^{(i)}_{extension} = \lceil(3/2)m^{(i)}\rceil$ individuals attained from the local search stage is reduced in the selection stage [11]. The identical individuals are eliminated first. Let $\{b'_1, \ldots, b'_n\}$ for $n \le m^{(i)}_{extension}$ represent the resulting individual set. If $n > m_{\max}$, the start set for the next iteration is select as the $m_{\max}$ individuals b'_j with high $f(b'_j)$ values (i.e, $m^{(i+1)} = m_{\max}$). If $n \le m_{\max}$, for the next iteration $\{b^{(i+1)}_1, \ldots, b^{(i+1)}_{m(i+1)}\}$ is the start set. (i.e, $m^{(i+1)} = n$). Thus, $m^{(i+1)} = n$ if $n \le m_{\max}$ and $m^{(i+1)} = m_{\max}$ if $n > m_{\max}$, thus $m^{(i+1)} \le m_{\max}$ is satisfied. After the predetermined number of J iterations, i.e., $b^{(J+1)}_1$ is the best individual in the corresponding individual set $\{b^{(J+1)}_1, \ldots, b^{(J+1)}_{m(J+1)}\}$. This is considering being final result of MMA.

4 Complexity Analysis

The complexity of the MIMO system defined as number of floating point operations such as additions, multiplications etc., are required to compute the transmitted vector x [23, 24]. Table 1 shows the complexity analysis of the MLD, ZF, MMSE, GA and MMA approaches, in terms of number of transmitting and receiving antennas are used to detect the signal.

Table 1 estimates the complexity of various detectors in MIMO system with dimensions of $N_t = N_r = \{4, 8, 16\}$ for 16 QAM and 64 QAM. This shows that proposed work gives reduced complexity as compared to GA. The normalized value of complexity equation are calculated for the state of art detectors with $N_t = N_r = 4$ and 16

Table 1: Complexity Analysis of Various MIMO Detectors.

Algorithms	Complexity Equation (C in flops)	Complexity value for $n_t = n_r = 4$, 16QAM
ZF	$2(n_r^2 n_t) + n_r^3 + n_t n_t$	1
MMSE	$2(n_r^2 n_t) + n_r^3 + n_r^2 + n_t n_t$	1.07
MLD	$M^{nt}(n_r^2 + n_r n_t + 2n_r + \log M^{nt})$, $M = 16$ or 64	14120
GA	$(g+1)[p(n_r n_t + n_r) + p \log p]$, $g = 10, p = 50$	57.4
MMA	$g n_t^5 + n_r^4 + n_r \log n_r + p(n_t)$	51.4

Table 2: Various Parameters used in Proposed MIMO Detector.

Parameters	Values		
Antenna Size	4×4	8×8	16×16
Channel	AWGN	AWGN	AWGN
Modulation	16, 64-QAM	16, 64-QAM	16, 64-QAM
Population Size	50	50	50
Generations	10	10	10
Crossover rate	0.65	0.71	0.79

QAM. For GA and MMA consider the population size $P = 50$ and the generation $G = 10$. This table shows that the MLD algorithm is 14120 times more complex than the ZF algorithm.

5 Simulation Results

5.1 Simulation Setup

In MIMO system the performance of the proposed MMA approach was evaluated by means of simulations with different antenna configurations and various QAM constellation sizes. The detector parameters are summarized in Table 2. The channel used in proposed detector is AWGN channel because it gives reduced BER as compared to Rayleigh channel [23].

5.2 BER Performance of QAM Technique

In this proposed work select the QAM technique because it has high spectral efficiency without extra bandwidth [24, 25]. It gives low BER as compare to other techniques such as QPSK, BPSK and PSK as shown in Fig. 3. To transmit more number of bits per symbol selects higher order constellations of QAM (16 QAM and 64 QAM).

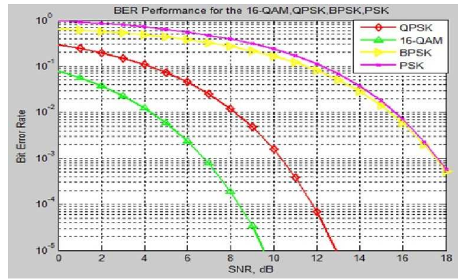


Fig. 3: BER performance of QAM technique.

Table 3: BER comparison of the 8×8 MIMO system with 16 QAM.

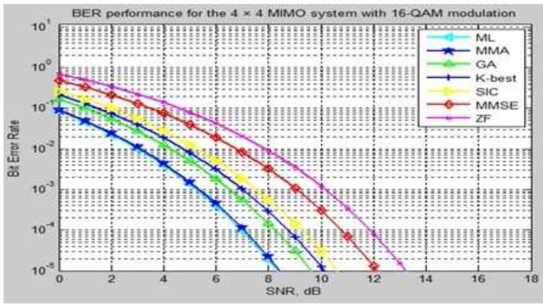
SNR (dB)	Bit Error Rate ML	MMA	GA	K Best	ZF
2	0.015	0.02	0.03	0.09	0.15
4	0.003	0.004	0.009	0.03	0.08
6	0.0003	0.0004	0.001	0.009	0.02
8	0.00001	0.00002	.00007	0.001	0.005
10	0	0	0	.00008	.0005

5.3 BER performance of proposed MIMO systems

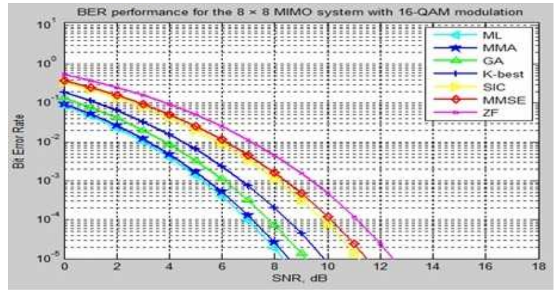
The BER vs SNR performance of the MMA approach was compared to the state of art detectors such as ZF, SIC, MMSE, K-Best, GA and MLD is shown in Fig. 4. Fig. 4(a)–(c) shows results of MIMO system with 16 QAM and dimensions of 4×4, 8×8 and 16×16. This shows that BER value of proposed MMA detector is very close to optimal ML detection and better than GA at low and medium SNR's. Fig. 4(d)–(f) shows results for 64 QAM for same all dimensions, it shows that MMA performs well at medium SNR's as compare to the state of art detectors. The performance advantages of MMA over GA, ZF, MMSE, SIC, K Best and ML increases with growing dimension. Table 3 shows that BER value of 8×8 MIMO system with 16 QAM. It shows that MMA has low BER and close to ML.

6 Conclusion

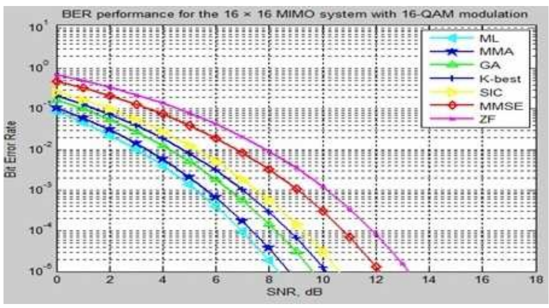
Reduced complexity with low BER signal is detected at the bit level in MIMO system with different QAM constellation is proposed. This detection combine the efficient detection of partial ML bits, soft value generations and a new type of optimum detections based on the principle of MA. Due to their architecture and efficient local search technique such as Hill climbing, the MMA is especially advantageous for MIMO systems. The performances of the MMA are compared with the state of detectors such as ZF, MMSE, K-Best, GA and MLD at low and medium SNRs with different antenna



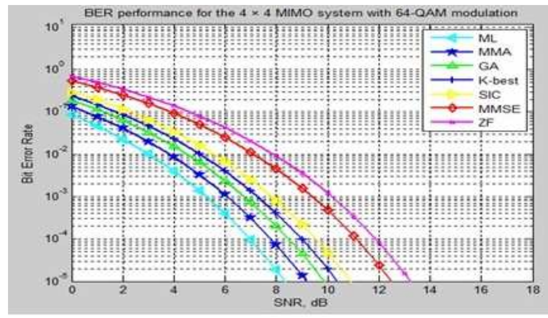
(a) BER vs. SNR for 16-QAM for 4×4 MIMO system.



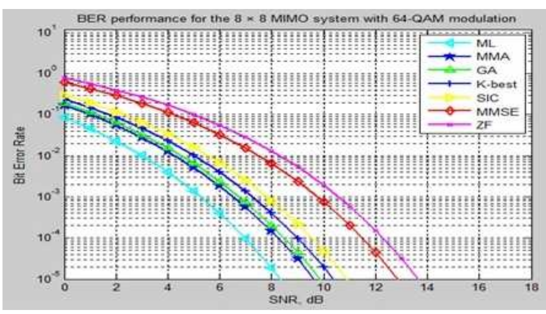
(b) BER vs. SNR for 16-QAM for 8×8 MIMO system.



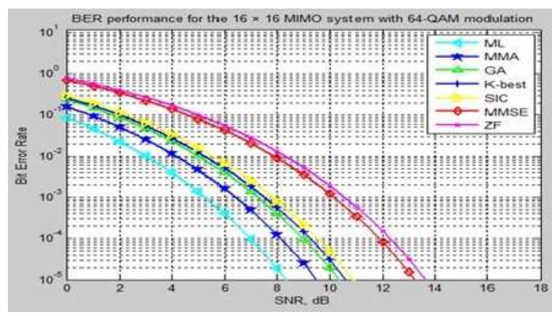
(c) BER vs. SNR for 16-QAM for 16×16 MIMO system.



(d) BER vs. SNR for 64-QAM for 4×4 MIMO system.



(e) BER vs. SNR for 64-QAM for 8×8 MIMO system.



(f) BER vs. SNR for 64-QAM for 16×16 MIMO system.

Fig. 4

configurations. They reach effectively optimum (ML) performance with 16 QAM and 64 QAM. Furthermore, they are significantly less complex than conventional GA.

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