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RESEARCH ARTICLE

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Performance analysis of alternating minimization based low complexity detection for MIMO communication system

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ABSTRACT

Several antennas are used for sending and receiving in large MIMO (Multiple-Input-Multiple-Output) devices and assist in enhanced performances of wireless communication systems. One important component of Large MIMO systems is that MIMO detectors are placed at receiver ends, whose functions are to regain symbols broadcasts from multiple antennas. In this paper, novelAMLCD (Alternating Minimizationbased Low Complexity Detections) method is proposed in which AMs (Alternating Minimizations) are applied in initial stages to detect signals. Soft value generation is used for the second stage to estimate the signals. Finally, the more optimal estimated signal value will be chosen by applying the MPSOs (Modified Particle Swarm Optimizations). The system's functions are evaluated using CPMs (Continuous Phase Modulations) and channel's AWGNs (Additive White Gaussian Noises). According to the results obtained, the suggested AMLCD method with modulations of CPMs outperform known methods using QAMs (Quadrature Amplitude Modulations) under multiple antennas in terms of BERs (Bit Error Rates). The AMLCD method also reduces the time complexity and computational complexity compared to the existing methods.

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MIMO; CPM; MPSOs; signal detection; BER; complexity

1. Introduction

The concept of massive MIMO systems involve mounting enormous counts of antenna arrays on BSs (base stations) in order to increase network capabilities, dependability and reduce total transmitted powers. Extremely high data rates may be provided through large-scale MIMO systems, which can quickly meet the growing demands of wireless connections [1]. The linear detectors employ matrix inversions to detect signals in uplink MIMO systems. High computational complexities are produced and performances get reduced [2]. By improving orders in spectrum efficiency and energy efficacy, large-scale MIMO systems may be achieved [3]. In practise, comprehending the benefits of massive MIMO systems present multiple difficulties, one of which is signal recognition algorithms [4] because of increased interferences from several users. ML (Maximum Likelihood) detectors, which have high computational complexities detect the best detector based on antenna sizes in big MIMO systems. In order to reduce BERs and computational complexities, PRUN-MLD-LCDA (Pruning based ML Detection using Low Complexity Detection) algorithm was proposed in [5] with the goal of identifying signal vectors with higher ML values. The soft ML detection for MIMO systems was illustrated which exploits log-likelihood function [6,7].

A low-complexity MIMO algorithm [8] was introduced to develop a soft-output performance with modifications. The low-complexity algorithm which attains significantly better performance in higher-order QAM modulation techniques [9]. ZF (Zero Forcing) detector is proposed to generate optimal BERs for an uncoded MIMO communication system. Including large counts of antennas for broadcasting, the processing costs of ML detectors grow with higher-order modulations [10]. A Generalized Approximate Message Passing Detector (GAMPD) based low complexity detection provides orders-of-magnitude lower complexity and low BERs [11].

A likelihood-based branching criteria was introduced to decrease the amount of Quadratic Programming (QP) that which was needed to be resolved [12]. It uses QAM modulation and combines it with a path technique to provide greater error performance than the previously reported Bound and Branch (BB) method, all while requiring less computational effort [13]. Modulations of CPMs are attractive for their higher powers and spectral efficiencies within classes of constant envelope signals [14]. When such

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AWGNs and phase noise are present, an iterative soft detection algorithm [15] and an iterative identification algorithm [16] were presented for coded signals of CPMs. The complexity of the resulting detector is significantly decreased with respect to that of optimal coherent receivers with negligible performance loss. Full response CPMs with blind estimations of modulations index were discussed [17]. HPSO-BB (hybrid Particle Swarm Optimization-Branch and Bound) detection algorithm mto obtain optimal values for massive MIMO systems were also suggested. The overall evaluation of the performance of large MIMO system employing QAM and modulations of CPMs are analyzed under multiple antennas [18]. Hybrid precoding structures that are directly coupled and partly connected were discussed [19]. In the case of the fully-connected structure, AMs are dependent on manifold optimization is devised to be close to the performance of the completely digital precoder that offers a higher complexity. By the enforcement of an orthogonal constraint on the digital precoder, AMs attain much lesser complexity. Puet al proposed fast AMs to solve predictive control problems [20].

A two-step iterative procedure [21] was presented which applies AM approach to solve the precoding vector and the associated precoding factor. The AM method delivers higher BERs quality and has a limited capability, according to analysis data. A new STTS-CPSK receiver is proposed which may be used for digital pass band applications [22]. Compared to STTS-CPSK receiver, our Proposed AMLCD-based receiver uses modulations of CPMs which provide high powers and spectral efficiencies in the presence of AWGNs channel. Potential applications for the proposed AMLCD approach include WIMAX 802, Wireless Local Area Networks, 5G Networks and radar applications. Several machine learning algorithms were used to introduce intrusion detection techniques for security.

In this paper, a novel AMLCD (Alternating Minimization based Low Complexity Detections) method is proposed in which AMs (Alternating Minimizations)are applied in initial stages to detect signals. Soft value generation is used for the second stage to estimate the signals. Finally, the more optimal estimated signal value will be chosen by applying the MPSOs (Modified Particle Swarm Optimizations) also reduces the time complexity and computational complexity compared to the existing methods.

2. Literature survey

Multiple studies on massive MIMO multi-user mobile communication systems have been recently published to enhance the performances of signal detection techniques. Yin et al. [23] proposed algorithmically CG (conjugate gradient) for both data detections and precodes for reducing complexities caused by explicit inverses of channel matrices. The initial solutions of the Gauss-Seidel technique were selected as a 2-term Neumann series expansions for large MIMO systems as Gram matrices are diagonally dominating by nature resulting in effectively speeding up algorithmic convergence.

ADMM (alternating direction technique of multipliers) was suggested as an efficient detection algorithm in [24]. The technique performed infinity-norm or box-constrained equalizations in terms of PER (packet error rates), outperforming conventional linear MMSE detectors. A near-optimal detection approach with very less complexity and based on Richardson's method was proposed in [25], while OCD (optimised coordinate descent) approximated MMSE. These methods produced results that were close to ideal, especially when with a high ratio of BS antennas and user terminals, and having lower temporal complexity than techniques based on n accurate matrix inversions.

A deep unfolded detector presented by Souza et al. [26], modified PDA (probability data association) detector's algorithm for improved learning by neural networks. The work demonstrated that, in spite of being lesser complicated orders-of-magnitude than PDA detectors, their proposed detectors did not significantly degrade performances in terms of BER.

A reduced complexity detector for sQSM schemes was proposed by Alshawaqfeh et al. [27]. The implementations and inherent benefits of their promising system lay in using an optimum low complexity detector for Tree Searches, called TSopt. The computationally challenging ML detectors for sQSM were expanded into tree structure representations by the study's detectors. The goal of the recommended technique was to quickly identify branches that corresponded to a minimal amount of mistakes without the need to trace all nodes, as in the ML example. According to reports, their suggestedTSopt method accomplished equal error performance as ML detectors while significantly reducing computational complexities.

Hybrid BP (Belief Propagation) and EP (Expectation Propagation) receivers, initially addressed BP algorithm's convergence issue using auxiliary variables in factor graph-based near-optimal iterative receivers [28]. Jiang et al. [29] suggested quick processing approaches with low complexity and provided iterative receivers to comprehend linear inverse matrices issues. The iterative technique updated the process separately on a small-size block by using the block matrix attributes. MIMO detection with minimal complexity utilising adaptive mitigation is introduced by Park et al. [30]. Imperfect precoded matrices were used by quantization error-based downlinked multiuser MIMO to lessen interferences and receive required signals at receivers. To achieve reduced complexities, Zhao and

Du [31] suggested LRA (lattice reduction assisted) based MIMO detections.

There has been a lot of studies recently on creating algorithms that replicate biological phenomena like fish schooling, ant foraging behaviour, and bird flocking in order to address optimisation issues in the real world that are challenging to answer using traditional methods. They suggested methods in literature include optimizations using PSO (Particle swarm optimisation), GA (genetic algorithm), ACO (ant colony optimisation), CSO (cuckoo search optimization) and ABC (artificial bee colony). They result in discovering lesser computationally demanding sub-optimal solutions to particular optimisation issues.

3. MIMO system models

Larger MIMO systems have 'N_t' transmission antennas and 'N_r' receiving antennas with receptions ($N_t \leq N_r$). The relationships are modelled as

$$\bar{\mathrm{Y}} = \bar{\mathrm{H}}\bar{\mathrm{X}} + \bar{\mathrm{N}} \tag{1}$$

where $\bar{\mathrm{X}} = (\bar{\mathrm{x}}_1, \bar{\mathrm{x}}_2, \bar{\mathrm{x}}_3, \ \ldots \bar{\mathrm{x}}_{\mathrm{Nt}})^{\mathrm{T}}$ are transmitted signal vectors, $\bar{\mathrm{Y}} = (\bar{\mathrm{y}}_1, \bar{\mathrm{y}}_2, \bar{\mathrm{y}}_3, \ \ldots \bar{\mathrm{y}}_{\mathrm{Nr}})^{\mathrm{T}}$ are received signal vectors, $\bar{\Omega}$ represent collections of M complex symbols for M-QAM constellations, $\bar{\mathrm{H}}$ implies ($N_r \times N_t$) channel matrices with coefficients $\bar{\mathrm{h}}_{\mathrm{ij}} \sim \mathrm{CN}(0, 1)$., $\overline{\mathrm{N}} = (\bar{\mathrm{n}}_1, \bar{\mathrm{n}}_2, \ \ldots \bar{\mathrm{n}}_{\mathrm{Nr}})^{\mathrm{T}}$ stands for ($N_r \times 1$) i.i.d. AWGNs vectors with zero-means and variances σ^2.

Equation (1) can be rewritten as

$$Y = HX + N \tag{2}$$

where $X = (R\{\bar{\mathrm{X}}\}^T I\{\bar{\mathrm{X}}\}^T)^T$ imply real transmitted vectors, $\Omega = \{\pm 1, \pm 3 \cdot \cdot \cdot \pm(\sqrt{M} - 1)\}$ are collections of $\sqrt{M}$ real symbols, $Y = (R\{\bar{\mathrm{Y}}\}^T I\{\bar{\mathrm{Y}}\}^T)^T$ is ($2\mathrm{N_r} \times 1$) imply real equivalent received vectors.

H provided in Equation (3) is channel matrices and

$$\mathrm{H} = \begin{bmatrix} \mathrm{R}\{\bar{\mathrm{H}}\} & -\mathrm{I}(\bar{\mathrm{H}}) \\ \mathrm{I}(\bar{\mathrm{H}}) & \mathrm{R}(\bar{\mathrm{H}}) \end{bmatrix} \tag{3}$$

$N = (R\{\bar{\mathrm{N}}\}\ \}^T I\{\bar{\mathrm{N}}\}^T)^T$ denotes the noise vector.

The received signal vectors are represented by Equation (4) on receivers.

$$\widehat{\mathrm{X}} = \underset{\mathrm{X} \in \Omega^{2\mathrm{Nt}}}{\operatorname{argmin}} ||\mathrm{Y} - \mathrm{HX}||^2 \tag{4}$$

The vector Y is decomposed as

$$\mathrm{Y} = \sum_{\mathrm{i}=1}^{2\mathrm{N_t}} \mathrm{Y_i} \tag{5}$$

where, In the obtained vector, Yi denotes the participation of the ith broadcast symbol.

The kth element of Y can be represented as

$$\mathrm{Y}^{(\mathrm{k})} = \sum_{\mathrm{i}=1}^{2\mathrm{N_t}} \mathrm{Y}_{\mathrm{u}}^{(\mathrm{k})},\ \mathrm{k} = 1, 2, \ldots 2\mathrm{N_r} \tag{6}$$

To reformulate equation (5) as

$$\min_{\mathrm{X},\ \mathrm{Y_t}} \sum_{\mathrm{i}=1}^{2\mathrm{N_t}} ||\mathrm{Y_i} - \mathrm{H_i X_i}||_2^2 \tag{7}$$

Subject to

$$\sum_{\mathrm{i}=1}^{2\mathrm{N_t}} \mathrm{Y}_{\mathrm{i}}^{(\mathrm{k})} = \mathrm{Y}^{(\mathrm{k})},\ \forall\, \mathrm{k} = 1, \ldots, 2\mathrm{N_r} \tag{8}$$

$$-1 \leq \mathrm{X_i} \leq 1,\ \forall\, \mathrm{i} = 1, \ldots, 2\mathrm{N_t}$$

where $\mathrm{X_i}$ represents the ith transmitted symbol.

In this paper, a novel AM (Alternating Minimization) based LCD (Low Complexity Detection) called AMLCD is proposed where AM techniques are applied in the first stage to detect signals. Soft assessment generations are used in two phases to estimate signals. Finally, more optimal estimated signal values are chosen by applying MPSO (Modified Particle Swarm Optimization).

4. AMLCD

The optimization problems (9) and (10) were jointly convex based on X, there was no constraint that combined X with $\mathrm{Y_i} \forall$ i. Hence to solve this problem, the following two sub-problems are decomposed into

Given X, obtain $\mathrm{Y_i}\forall$i. by solving

$$\underset{\mathrm{Y_i}}{\operatorname{argmin}} \sum_{\mathrm{i}=1}^{2\mathrm{N_t}} ||\mathrm{Y_i} - \mathrm{H_i}||\mathrm{X}_{\mathrm{i}2}^2 \tag{9}$$

Given $\mathrm{Y_i}\forall$ i, obtain X by solving,

$$\underset{\mathrm{X_i}}{\operatorname{argmin}} \sum_{\mathrm{i}=1}^{2\mathrm{N_t}} ||\mathrm{Y_i} - \mathrm{H_i}||\mathrm{X}_{\mathrm{i}2}^2 \tag{10}$$

Then AM techniques are introduced which solves $\mathrm{Y_i}\forall$ i for X.

The Lagrangian function L is written as,

$$\mathrm{L} = \sum_{\mathrm{i}=1}^{2\mathrm{N_t}} ||\mathrm{Y_i} - \mathrm{H_i X_i}||_2^2 + \sum_{\mathrm{k}=1}^{2\mathrm{N_r}} \lambda^{\mathrm{k}} \left(\mathrm{Y}^{(\mathrm{k})} - \sum_{\mathrm{i}=1}^{2\mathrm{N_t}} \mathrm{Y}_{\mathrm{i}}^{(\mathrm{k})} \right) \tag{11}$$

To solve equation (11), closed expression forms are obtained for λ^{k} and $\mathrm{Y}_{\mathrm{i}}^{(\mathrm{k})}$.

$$\lambda^{(\mathrm{k})} = \mathrm{C}.\frac{1}{\mathrm{N_t}} \left(\mathrm{Y}^{(\mathrm{k})} - \sum_{\mathrm{i}=1}^{2\mathrm{N_t}} \mathrm{H}_{\mathrm{i}}^{(\mathrm{k})} \mathrm{X_i} \right),\ \forall \mathrm{k} \tag{12}$$

$$Y_i^{(k)} = H_i^{(k)} X_i + \frac{\lambda^{(k)}}{2}, \forall i, k \tag{13}$$

When scaling factors C = Nt are used in updates of $\lambda^{(k)}$, iterations needed for convergences decrease dramatically. The update of the i^{th} element solves the sub-problem.

$$\min_{X_i} \sum_{k=1}^{2N_r} (Y_i^{(k)} - H_i^{(k)} X_i)^2 \tag{14}$$

The equivalent Lagrangian function can be defined as Then, the following KKT conditions [25] are both adequate and essential for the convex optimization problem's optimization method

$$2X_i \sum_{k=1}^{2N_r} H_i^{(k)^2} - 2\sum_{k=1}^{2N_r} Y_i^{(k)} H_i^{(k)} - \mu_1^{(i)} + \mu_2^{(i)} = 0 \tag{16}$$

$$\mu_1^{(i)}(1 - X_i) = 0,\ \mu_2^{(i)}(1 + X_i) = 0,\ \mu_1^{(i)}, \mu_2^{(i)} \geq 0 \tag{17}$$

To solve every element in X, among $\{\mu_1^{(i)}, \mu_2^{(i)}, X_i\}$ choices, chose the one that minimizes

$$\mu_1^{(i)} = 0, \text{ and } \mu_2^{(i)} = 0 \rightarrow x_i = \frac{\sum_{k=1}^{2N_r} Y_l^{(k)} H_l^{(k)}}{\sum_{k=1}^{2N_r} H_l^{(k)^2}} \tag{18}$$

$$\mu_1^{(i)} = 0, \text{and } \mu_2^{(i)} \neq 0 \rightarrow X_i = -1 \tag{19}$$

$$\mu_1^{(i)} \neq 0, \text{ and } \mu_2^{(i)} = 0 \rightarrow X_i = 1 \tag{20}$$

Note that the choice $\mu_1^{(i)} \neq 0$ and $\mu_2^{(i)} \neq 0$ is excluded since at the same time, X_t is not equal to -1 and $+1$.

Algorithm 1: AM algorithm

1. Initialization

   $t = 0, xi = 0$ for all i

2. Update $\lambda^{(k)} \forall k$

$$\lambda^{(k)} = C.\frac{1}{N_t}\left(y^{(k)} - \sum_{i=1}^{2N_t} h_i^{(k)} x_i\right), \forall k$$

3. Update $y_i^{(k)} \forall i, k$

$$y_i^{(k)} = h_i^{(k)} x_i + \frac{\lambda^{(k)}}{2}, \forall i, k$$

and $V^{(t)} = \sum_{i=1}^{2N_t} y_i - h_i x_{i2}^2$

$//\delta =$ Convergnece

$//T =$ Number of iterations

4. AM method repeat

$t \leftarrow t + 1$

   update x_i for all i

   update $\lambda^{(k)} \forall k$

   update $y_i^{(k)} \forall i,\ k$

$$V(t) = \sum_{i=1}^{2N_t} ||y_i - h_i x_i||_2^2$$

until $|V^{(t)}$-$V^{(t-1)}| < \delta$ OR $t > T$

To find the best answer to the optimization problem that has been proposed, AM solves $Y_i^{(k)} \forall i$. Set X to 0 and run the process to get the starting value $Y_i^{(k)} \forall$ i; with updated $Y_i^{(k)} \forall$ i, then solve to update X.

4.1. Soft value generation

Assuming QAM symbols $|A| = 2^M$ with $M = \log_2|A|$, and unique vectors can be written as $v = (v_1, \ldots, v_B)^{Tc}B$ then

$$a = \sum_{s=1}^{M} v_s b_s(s) = v^T b(s) \tag{21}$$

For every symbol/l $a \in h$ with a bit vector $x(s) \in \{-1, 1\}B$.

The MIMO symbols are obtained from a QAM symbol in terms of binary and it is represented by

$$y = hx + n \tag{22}$$

The equivalent channel matrix, $h \triangleq H \otimes v^T \in C_r^n \times Mn_t$ and the binary value of the transmit symbol vector an as $x = x(s) \triangleq x^T(s1) \ldots x^T(Snt)^T \in \{-1, 1\}M_{nt}$. The ML recognition rule can be changed at the given index as follows:

$$\hat{x}_{ML}(y) = \underset{x \in \{-1,1\}}{\text{argmin}} = ||y - hx||^2 \tag{23}$$

Computes a few elements $\hat{x}_{ML}(y)$is the first stage for the suggested MIMO detections. The iterative algorithm is used to compute the partial ML bits, which follows as, let $z \triangleq h^H y$, $G \triangleq h^H h$ and $I \triangleq \{1, \ldots, M_{nt}\}$ and x= $(x^T(s1) \ldots x^T(Snt))^T = (x_1 \ldots x_{Mnt})^T$ are the set of elements and x_k, z_k and $G_{k,l}$ are the elements of x, z and G respectively, with $k, l \in I$. For a bit x_k expand the ML metric ||y-hx||2 with k∈I. Let $I_k \triangleq \{1, \ldots, k-1, k+1, \ldots Mnt\}$ and $x_k \triangleq (x_1 \ldots x_{k-1} x_{k+1} \ldots x_{Mnt})^T$.

$$||y - hx||2 = ||y||^2 - X(x) \tag{24}$$

$$X(x) \triangleq 2\mathcal{R}\{z^H x\} - x^T G x \tag{25}$$

$$\begin{aligned} &= 2x_k R\{z_k\} - G_{k,k} x_k^2 - \sum_{l \in I_k} x_k G_{k,l} x_l \\ &- \sum_{k' \in I_k} x_{k'} G_{k',l} x_k + \sum_{k' \in I_k} x_{k'} R\{z_{k'}\} l \\ &- \sum_{k' \in I_k} \sum_{l \in I_k} x_{k'} G_{k',l} x_l \end{aligned} \tag{26}$$

Then ML detection is rewritten as

$$\hat{x}_{ML}(y) = \underset{x \in \{-1,1\}}{\operatorname{argmin}} \; Mnt = X(x) \quad (27)$$

$\widehat{x}_{ML}(y)$ is unknown which can be determined by bounding values as follows,

$$I_k(D) \le \hat{x}_{ML,k} \le u_k(D)$$

$$I_k(D) \triangleq 2\left(\mathcal{R}\{z_k\} - \sum_{I \in D_k} |\mathcal{R}\{G_{k,l}\}| - \sum_{l \in D_k} |\mathcal{R}\{G_{k,l}\}|\hat{x}_{ML,l}\right)$$

$$u_k(D) \triangleq 2\left(\mathcal{R}\{z_k\} - \sum_{I \in D_k} |\mathcal{R}\{G_{k,l}\}| - \sum_{l \in D_k} |\mathcal{R}\{G_{k,l}\}|\hat{x}_{ML}\right)$$

where D – set of already detected bits, d – set of undetected bits.

In iterations, if $l_k(D) \ge 0$ then $\hat{x}_{ML,k} = 1$, the updates sets D i.e, $D^{(new)} = D \cup \{k\}$ and $u_k(D) \le 0$ thus $\hat{x}_{ML,k} = -1$ updates respective elements of the D set. Lower $l_k(D_{ML})$ and upper $u_k(D_{ML})$ bounds satisfy the conditions. $L_k(D_{ML}) < 0$ and $u_k(D_{ML}) > 0$, for all $k \in D_{ML}$. The iterative process ends if no additional bits are discovered. DML is the collection of the observed ML bits after termination i.e. $\hat{x}_{ML,k}$ bits at the partial ML detection step are detected bits.

Using the anticipated value of, create the soft value $S_k \hat{x}_{ML,k}$

$$S_k \triangleq E\{\hat{x}_{ML,k}\}, k \in D_{ML} \quad (28)$$

Soft values S_k can be computed from bounds $l_k(D_{ML})$ and $u_k(D_{ML})$,

$$S_k = \frac{I_k(D_{ML}) + \mu_k(D_{ML})}{u_k(D_{ML}) - l_k(D_{ML})}, \; k \in D_{ML} \quad (29)$$

Here $-1 < S_k < 1$. More bits are discovered, and the soft values get better and better. The MPSO method is used to obtain the ideal value following the production of soft values. The set of QAM symbol alphabet A, B and C represent the people in MIMO detection based on modified PSO where $|A| = 2^M$ with $M = \log_2|A|$ transmitted by transmitting antennas. The initial set $\{x^{(1)}, \ldots, x^{(1)}{}_{Mmax}\}$ are generated at first, subsequently individuals with best fitnesses by use of local search techniques. MPSO algorithm, which selects poorest as well as best placements. The poorest component in this scenario will have the highest function value. For this MPSO technique, results must not get much worse compared to PSO. Even though for few sophisticated problems, MPSO produces better results.

Algorithm 2: MPSO algorithm

1. Initialize

(a) Determine the population needs (s, c1, c2, number of iterations). (p) w_{start} and w_{end}.

(b) Produce a swarm of s particles dispersed at random inside the design domain S.

(c) Generate a random beginning velocity for each particle, $-V_{max} < V^i < V_{max}$.

(d) Determine each starting particle's effectiveness.

(e) Locate the ideal location of global $Gbestg_{id}$.

(f) Locate the worst location on the global Gworst, g_{iw}.

2. By updating the velocities, the optimizing process can be improved.

For each particle $i \in S$

If iteration $< = p$

(a) Change the switch matrix, the velocity and the position

(i) Find the worst s1 particles

(ii) Update switch matrix k according to bad particles

(iii) Update particles velocity $v_{id}(j+1)$

(iv) Update particle position $x_{id}(j+1)$

(b) Update the particle's best position

Evaluate fitness value using coordinates $x_{id}(j+1)$ in design space

If $f(x_{id}(j+1)) \le f(p_{id}(j))$

Set $p_{id}(j+1) = x_{id}(j+1)$

Else

Set $p_{id}(j+1) = p_{id}(j)$

If $f(p_{id}(j+1) \le f(g_{id}(j)))$

Set $g_{id}(j+1) = p(j+1)$

Else

Set $g_{id}(j+1) = g_{id}(j)$

(c) If the stopping requirements are not met, proceed to step 2; else, stop.

5. Results and discussion

In this chapter, the characteristics of the AMLCD technique and current strategies are discussed. There are, correspondingly, 64 transmitting antennas and 64 receiving antennae. Using 64-QAM and CPM modulations, the suggested AMLCD method's BER performance is examined for (64 × 64) antennas is shown in Figure 1. From Figure 1, it is observed that AMLCD with 64-QAM has BERs of 0.0031. The AMLCD with CPMs has 0.0017 which is superior to AMLCD with QAM.

The proposed AMLCD method and HPSO-BB detection algorithm are using modulations of CPMs and other existing methods such as Zero Forcing Maximum Likelihood (ZFML), Residue Number System(RNS), Quadrature Programming (QP) detector, modified BB algorithm, PRUN-MLD-LCDA, NRLCD,

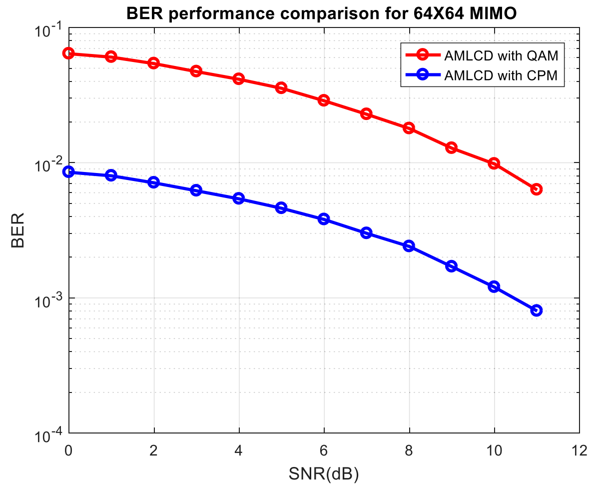

Figure 1. Performance of AMLCD method using QAM and CPMs.

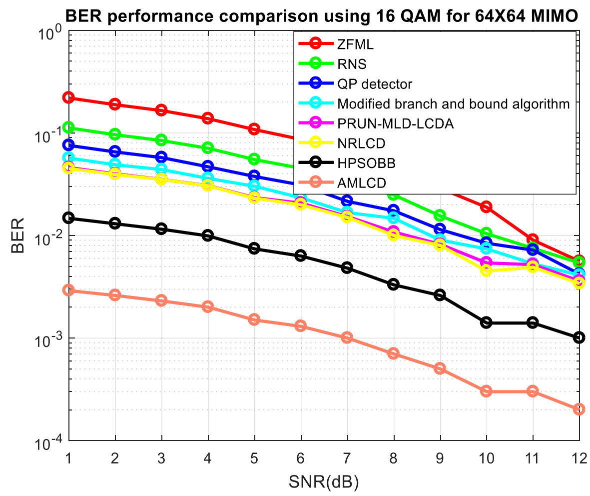

Figure 2. BERs performance of AMLCD and existing methods using 16-QAM.

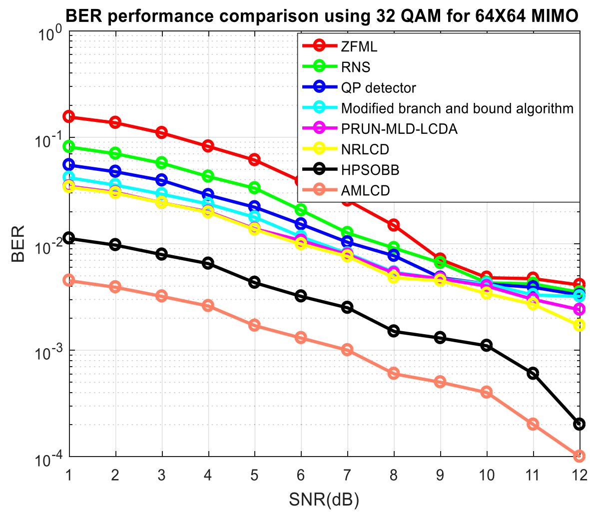

Figure 3. BERs vs SNR for AMLCD and existing methods using 32-QAM.

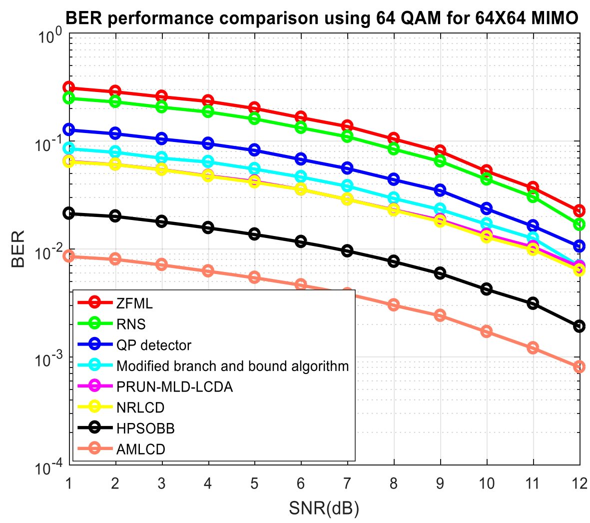

Figure 4. BERs performance comparison for AMLCD and existing methods using 64-QAM.

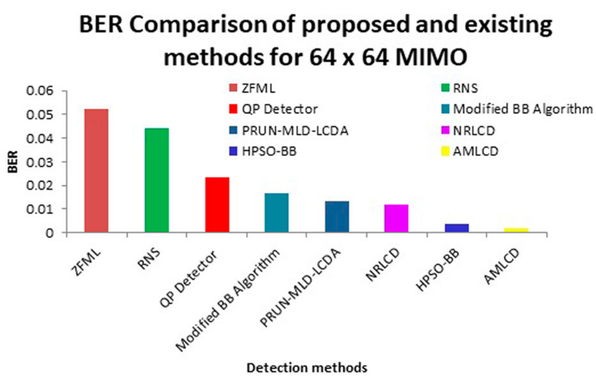

Figure 5. Bar graph comparison of AMLCD and existing methods at SNR = 10 dB.

are using 16-QAM, 32-QAM and 64-QAM modulation techniques. The proposed AMLCD and conventional approaches' BERs performance is shown in Figures 2–4. The BERs performance of the suggested method is clearly enhanced when the value of SNR is increased, as shown in Figures 2–4, when compared to other current methods.

Figure 5 illustrates a bar graph comparison of the proposed AMLCD's BERs performance vs existing approaches. From Figure 5, at 10 dB SNR, the proposed AMLCD method has 0.0017 BERs which is superior to the other existing methods.

5.1. Time complexity

The computation cost of algorithms are determined by time taken to process input values. Figure 6 compares the temporal complexity of existing techniques and the suggested technique. The proposed AMLCD method and HPSO-BB method are using modulations of CPMs and other existing methods are using 64-QAM.

From Figure 6, it can be observed that AMLCD method results in reduced time complexity i.e. 8.7% than HPSO-BB, 23.9% than NRLCD, 36.58% than PRUN-MLD-LCDA, 46.75% than modified BB algorithm, 50.15% than QP detector, 52.72% than RNS

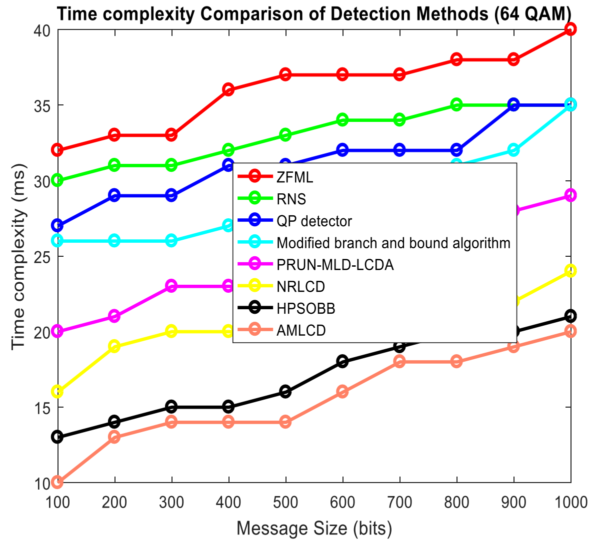

Figure 6. Time complexity vs message size for AMLCD and existing methods.

Table 1. Computational complexity comparison of proposed AMLCD and existing methods.

	Number of arithmetic operations			
Detection methods	Addition	Subtraction	Multiplication	Division
ZFML	445	390	510	195
RNS	450	378	560	312
QP detector	415	298	515	216
Modified BB algorithm	379	250	495	175
PRUN-MLD-LCDA	354	195	460	119
NRLCD	265	210	436	131
HPSO-BB	289	181	485	127
AMLCD	233	174	395	114

and 56.78% than ZFML. The proposed method tends to have reduced time complexity than the existing methods.

5.2. Computational complexity

The number of arithmetic operations present in the proposed AMLCD method and existing methods are shown in Table 1. From Table 1, the complexity in terms of arithmetic operations of AMLCD method is less than the other methods.

6. Conclusion

Massive deployment of MIMO configuration antennas dramatically improves the performance of wireless communication networks. It is suggested to use a unique AMLCD identification approach for large MIMO systems in which the signal is first detected using an AM methodology. The second technique estimates the signals via soft value generation. Finally, the MPSO method is used to determine the best value for an estimated signal. For numerous antennas, the performance characteristics of the proposed AMLCD approach employing CPM modulations and the currently used QAM methods are compared. Based on the results of simulations, it can be concluded that a unique AMLCD approach that modulates CPMs outperforms other ones already in use, including ZFML, RNS, QP detector, modified BB algorithm, PRUN-MLD-LCDA, NRLCD and HPSO-BB detection. The suggested AMLCD methodology delivers reduced temporal complexity and computational complexity while outperforming the earlier approaches in terms of BER performance. WIMAX 802, Wireless Local Area Networks, 5G Networks, Radar and other communication applications are a few possible uses for the suggested AMLCD method.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data avaliablity statement

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

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