Channel-Adaptive Complex K-Best MIMO Detection Using Lattice Reduction

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***Abstract*—Lattice reduction (LR) aided detectors mitigate the exponentially increasing complexity of large multiple-input, multiple-output (MIMO) systems while achieving near-optimal performance with low computational complexity. In this paper, a channel-adaptive complex-domain LR-aided K-best MIMO detector is presented that reduces the gap between the K-best sphere decoding (SD) detector and the maximum likelihood (ML) optimal MIMO detector. While maintaining BER performance, computational complexity is reduced by 50% over a conventional complex domain K-best SD detector by implementing a new on-demand complex-domain candidate symbol selection algorithm. Two tunable variables in the candidate selection process are introduced to enable both coarse-grained and fine-grained adaptation of computational complexity to channel conditions.**

Keywords— Complex K-best detectors, IEEE 802.11n, IEEE 802.11ac, LTE systems, multiple-input multiple-output (MIMO) detector, SE enumeration, lattice reduction, K-best algorithm

I. Introduction

Multiple-input, multiple-output (MIMO) communication systems have been adopted by advanced wireless standards such as IEEE 802.11n, IEEE 802.11ac and 3GPP Long Term Evolution (LTE) to enable increased spectral efficiency and high throughput data rates. For example, the LTE-Advanced Release 10 standard specifies an 8x8 antenna array to increase data rates to 3Gbps in the downlink and 1.5Gbps in the uplink, and improve spectral efficiency to 30bits/sec/Hz in the downlink and 15bits/sec/Hz in the uplink [1]. However, this increase in throughput and spectral efficiency comes at significant computational cost in the receiver. LTE profiling indicates that MIMO detection can consume up to 42% of the compute cycles in the physical downlink baseband processing [2]. This paper presents a channel-adaptive lattice-reduction (LR) aided complex-domain MIMO detection scheme to reduce computational complexity by 50% over conventional complex-domain MIMO detection. Two configurable parameters are introduced to enable adaptation of computation to channel conditions. Hence, compute elements may be disabled during favorable channel conditions to reduce power dissipation.

The rest of this paper is organized as follows. Section II describes the mathematical MIMO system model, summarizes MIMO detection algorithms, and briefly reviews the LR-aided MIMO detection algorithm. Section III presents related prior work and describes the contributions of this work. In Section IV, the focus is on the proposed complex-domain LR-aided K-best MIMO algorithm where K represents a limit on the search radius [2], and on-demand complex-domain candidate expansion and symbol selection. Section VI presents simulation results that demonstrate the performance of the proposed LR-aided MIMO detector implemented in MATLAB and System C. Section V concludes the paper. The notation used throughout this paper is outlined next.

Notation

Superscript ^{T} denotes the transpose. Real and imaginary parts of a complex number are denoted as $\Re[\cdot]$ and $\Im[\cdot]$. Upper- and lower-case bold letters indicate matrices and column vectors, respectively. $A_{i,k}$ indicates the (i,k)th entry of matrix $\boldsymbol{A}$. $\boldsymbol{I_N}$ denotes the $N \times N$ identity matrix, $\boldsymbol{0}_{M\times N}$ denotes the complex valued $M \times N$ matrix with entries all identically zero, and $(\boldsymbol{1}+\boldsymbol{j})_{M\times N}$ denotes the complex valued $M \times N$ matrix with entries all identically $(1+j)$. $\mathbb{C}$ is the set of complex numbers, $E\{\cdot\}$ denotes the statistical expectation, $\|\cdot\|$ denotes the 2-norm, and $\lfloor\cdot\rceil$ denotes rounding to the nearest valid constellation point.

II. MIMO Systems and LR-Aided Detection

A MIMO detector combines complex signals following digital front-end processing in receiver before further processing in the channel decoder as outlined in [2]. Several algorithms have been proposed to address the complexity of MIMO detection in the receiver, offering different tradeoffs between complexity, power, and performance; these tradeoffs are described in [2]. Recently, LR-aided detection has been proposed [4]–[12], to achieve the same diversity as ML detection. However, LR-aided MIMO detection still exhibits some BER performance loss as compared to ML detection [7]. In this paper, the focus is on LR-aided K-best MIMO detection where K represents a limit on the search radius.

A. MIMO System Model

As in [2], a MIMO system with N_t transmit antennas and N_r receive antennas, operating in a symmetric M-QAM scheme, with $\log_2 M$ bits per symbol is modeled by:

$$\boldsymbol{y} = \boldsymbol{Hs} + \boldsymbol{v}, \tag{1}$$

where $\boldsymbol{s} = \left[s_1, s_2, \ldots s_{N_t}\right]^T$, $(s_i \in \mathcal{S})$ is the N_t-dimensional complex information symbol vector transmitted. The set $\mathcal{S}$ is the constellation set of the QAM symbols, and $\boldsymbol{y} = \left[y_1, y_2, \ldots, y_{N_r}\right]^T$ is the N_r-dimensional complex information symbol vector received. The equivalent baseband model of the Rayleigh fading channel between the transmitter and receiver is modeled as a complex valued $N_r \times N_t$ channel matrix $\boldsymbol{H}$. The vector $\boldsymbol{v} = [v_1, v_2, \dots, v_{N_r}]^T$ represents the N_r-dimensional complex zero-mean Gaussian noise vector with variance σ^2[12].

The ML detector determines the transmitted signal by solving:

$$\hat{\boldsymbol{s}} = \arg\min_{\tilde{\boldsymbol{s}} \in \mathcal{S}^{N_t}} \|\boldsymbol{y} - \boldsymbol{H}\tilde{\boldsymbol{s}}\|^2, \quad (2)$$

where $\tilde{\boldsymbol{s}}$ represents the candidate complex information symbol vector and $\hat{\boldsymbol{s}}$ is the estimated transmitted symbol vector [11]. Eq. (2) represents the closest point problem [14] which is an exhaustive search through the set of all possible lattice points in $\mathcal{S}^{N_t}$ for the global best in terms of Euclidean distance between the received signal $\boldsymbol{y}$ and $\boldsymbol{H}\tilde{\boldsymbol{s}}$. Effectively, Eq. (2) describes a tree search where each of the lattice points in $\mathcal{S}^{N_t}$ is evaluated to find the path through the tree that minimizes the global error. Each transmit antenna contributes two levels to the search tree for real-domain MIMO detection: one real and one imaginary. Only one level in the tree is required for each antenna if complex-domain detection is employed. The goal is to find the closest vector $\tilde{\boldsymbol{s}}$ to the original transmitted symbol vector $\boldsymbol{s}$ given vector $\boldsymbol{y}$. Eq. (2) is generally non-deterministic polynomial hard (NP-hard).

B. Lattice Reduction Aided MIMO Detection

LR-aided detection is used to reduce the complexity of ML detection [9]. Lattice reduction changes the basis of a given integer lattice to one that is as orthogonal as possible with short basis vectors. Lattice reduction effectively reduces the effects of noise and mitigates error propagation in MIMO detection. In Eq. (2), the set $\mathcal{S}$ is bounded resulting in a constrained lattice. However, lattice reduction requires an infinite lattice as a starting point which dictates a modification to Eq. (2) to relax the bounds on $\mathcal{S}$ as follows [15]:

$$\hat{\boldsymbol{s}} = \arg\min_{\tilde{\boldsymbol{s}} \in \mathcal{U}^{N_t}} \|\boldsymbol{y} - \boldsymbol{H}\tilde{\boldsymbol{s}}\|^2. \quad (3)$$

The set $\mathcal{U}$ is an infinite complex constellation set $\{\dots, -3+j, -1-j, -1+j, 1-j, 1+j, 3-j, \dots\}$. Since there are no constraints on $\tilde{\boldsymbol{s}}$, the solution $\hat{\boldsymbol{s}}$ may not be a valid QAM symbol. This is resolved by quantizing the solution $\hat{\boldsymbol{s}}$:

$$\hat{\boldsymbol{s}}^Q = \mathcal{Q}(\hat{\boldsymbol{s}}), \quad (4)$$

where $\mathcal{Q}(\cdot)$ is the symbol-wise quantizer resolving a point in $\mathcal{U}$ to the constellation set $\mathcal{S}$. This equation can be solved by searching for the closest point as in described in [12][14][15]. However, this type of naïve lattice detection (NLD) does not have good diversity-multiplexing tradeoff (DMT) optimality [16]. Regularized lattice decoding is used to improve DMT [11][16]. The most common technique to regularize lattice decoding is minimum mean square error (MMSE) regularization as in [11] and [16] where the channel matrix and received vector are extended as $\overline{\boldsymbol{H}}$ and $\overline{\boldsymbol{y}}$:

$$\overline{\boldsymbol{H}} = \begin{bmatrix} \boldsymbol{H} \\ \sqrt{\dfrac{N_0}{2\sigma_2^2}}\boldsymbol{I}_{N_t} \end{bmatrix}, \qquad \overline{\boldsymbol{y}} = \begin{bmatrix} \boldsymbol{y} \\ \boldsymbol{0}_{N_t \times 1} \end{bmatrix}. \quad (5)$$

Eq. (4) then becomes:

$$\hat{\boldsymbol{s}} = \arg\min_{\tilde{\boldsymbol{s}} \in \mathcal{U}^{2N_t}} \|\overline{\boldsymbol{y}} - \overline{\boldsymbol{H}}\tilde{\boldsymbol{s}}\|^2 \quad (6)$$

Lattice reduction is applied to $\overline{\boldsymbol{H}}$ to find a more orthogonal matrix $\widetilde{\boldsymbol{H}} = \overline{\boldsymbol{H}}\boldsymbol{T}$, where $\boldsymbol{T}$ is a unimodular matrix. This reduction effectively finds a better basis for the lattice defined by the channel matrix. Lattice reduction is an NP Complete problem; however, polynomial time algorithms exist that can find near-orthogonal short basis vectors. The Lenstra-Lenstra-Lovász or LLL algorithm [17] is a popular polynomial time algorithm typically used for lattice reduction. The lattice reduced matrix $\widetilde{\boldsymbol{H}}$ can then be incorporated into MIMO detection algorithms such as K-best SD detection which is a breadth first search through the lattice points configured as nodes in a tree [9][10].

C. Complex K-Best LR-Aided MIMO Detection

The complex K-best search transforms the single $2N_t$-dimensional search into N_t two-dimensional searches that are performed sequentially. The error at each step is measured by the partial Euclidean distance (PED) which represents the accrued error at a given level of the tree, for a given path through the tree. The K best nodes are selected at each level of the tree and passed to the next level for consideration. The search concludes by evaluating K paths through the tree and the path with the minimum Euclidean distance is selected as the most likely solution. If K is arbitrarily large (e.g. to positive infinity), the search becomes exhaustive and is equivalent to the ML detection. If K is set to 1, the algorithm reduces to a linear MMSE detector. Tuning K provides a means of trading computational complexity for performance.

Complex K-best LR-aided MIMO detection factorizes the MMSE regularized and lattice-reduced channel matrix $\widetilde{\boldsymbol{H}}$ using QR decomposition to obtain $\widetilde{\boldsymbol{H}} = \boldsymbol{QR}$ where $\boldsymbol{Q}$ is a $(N_r + N_t) \times N_t$ orthonormal matrix, and $\boldsymbol{R}$ is a $N_t \times N_t$ upper triangular matrix, resulting in:

$$\hat{\boldsymbol{s}} = \arg\min_{\tilde{\boldsymbol{z}} \in \mathbb{C}^{N_t}} \|\breve{\boldsymbol{y}} - \boldsymbol{R}\tilde{\boldsymbol{z}}\|^2, \quad (7)$$

where $\breve{\boldsymbol{y}} = \boldsymbol{Q}^T\overline{\boldsymbol{y}}$. Breadth first search begins at the N_t^{th} layer, and for each nth layer, the algorithm computes the K best partial candidates $[\boldsymbol{z}_1^{(n)}, \boldsymbol{z}_2^{(n)}, \dots, \boldsymbol{z}_K^{(n)}]$, where a partial candidate $\boldsymbol{z}_i^{(n)}$ represents the i^{th} path through the tree from the root node to level n, and is given by $[z_{i,n}^{(n)}, z_{i,n+1}^{n}, \dots, z_{i,N_t}^{(n)}]^T$ [13]. The K candidates at level n represent the K partial candidates with the minimum PED among all the children of the K candidates of the $(n+1)$-st level, where the PED is calculated as:

$$PED_i^{(n)} = \sum_{j=n}^{N_t}\left[\left(\breve{y}_j - \sum_{k=j}^{N_t} R_{j,k} z_{i,k}^{(n)}\right)^2\right]. \quad (8)$$

This algorithm requires a process for selecting children of candidates to expand to determine the K best candidates at the next level. The naïve solution expands all of the children of the candidates at the $(n+1)$st level, and selects the K best.

Unfortunately this results in excessive expansions which can be improved by the application of Schnorr-Euchner (SE) enumeration techniques [15] which result in on-demand expansion.

D. *Complex On-Demand Child Expansion*

SE-based on-demand expansion enumerates children of a given node in the search tree in a strictly non-decreasing error order [11][12][15]. Child nodes are enumerated until K candidates are selected. The complex-domain enumeration proposed in [13] splits nodes into two different categories: Type I, where the imaginary part of a child is shared with its parent; and Type II, for all other cases.

Figure 1 gives an example of complex on-demand child expansion for a 16-QAM system with $K = 3$. A rounding step is employed to select the best child of a node. The real and imaginary components of the signal are quantized to the nearest valid symbol as in Fig. 1(a). When a Type I node is selected as a next child, both real and imaginary SE enumeration are applied so that two nodes are expanded and added to the set of potential candidates as shown in Fig. 1(b). The best out of the two nodes previously expanded is selected and added to the candidate list and is further expanded as in Fig. 1(c). At this stage, the candidate list has a total of 3 candidate nodes. The next best node is selected for further expansion, which is a Type II node labeled as 3 in Fig. 1(c). When a Type II node is selected, only imaginary SE enumeration is applied to expand to only one node as in Fig. 1(d).

Complexity Analysis

The complexity at any level of the tree, as expressed by number of nodes expanded, is analyzed as follows. The worst case bound is found by assuming that every selected node is Type I, in which case the complexity at any level of the tree is bounded by $K + 2(K - 1)$. Taken over the entire tree, with N_t levels, the complexity for the search is bounded by $3N_tK - 2N_t$ expanded nodes. Similar analysis for the real-domain detection reveals that the real-domain search is bounded by $4N_tK - 2N_t$ expanded nodes, revealing that complex-domain expansion reduces the complexity of the tree search at the cost of 2-dimensional node expansion. In this paper, we present a means to reduce this complexity further.

III. Prior Work and Contributions of This Work

A. *Prior Work*

The constrained LR-aided K-best MIMO detection algorithm was proposed in [9] and [10] and improved in [12]. Compared to a conventional K-Best search, the LR-aided K-best algorithm has no boundary information about the symbols in the lattice-reduced domain. Practically, this means that the set of children in a given layer is infinite. This infinite set is replaced by a finite subset in [9] and [10]. The "on-demand" child expansion based on SE enumeration is employed in [12] to reduce complexity of candidate selection. The algorithm is incrementally improved by the addition of a priority queue for storing and sorting potential candidates in [11]. The real-domain computation described in [9][10][11] is extended to the complex domain in [12]. Additional optimizations for complex-domain LR-aided MIMO detection are outlined in [13] as well [19] to reduce computational complexity and improve BER performance.

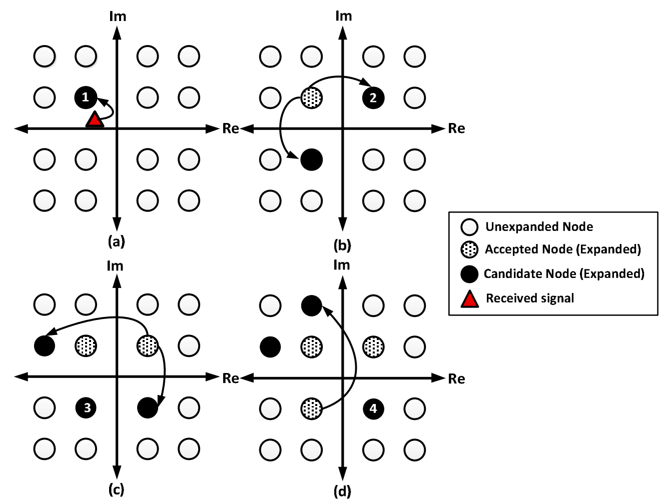

Figure 1. Complex SE enumeration for 16-QAM system

B. *Contributions of This Work*

In this paper, we propose a new channel-adaptive complex-domain LR-aided MIMO detection algorithm with an optimized on-demand expansion scheme that uses a novel enumeration algorithm. The performance of our MATLAB and System C implementation is compared to the work presented in [13]. Results show that our enumeration scheme results in an overall 50% reduction (compared to [13]) in complexity while maintaining BER performance. In contrast to previously published work, we introduce two tunable parameters that adapt the complexity of detection to varying channel conditions. The ability to tune the algorithm complexity enables total power reduction and increased energy-efficiency in the hardware implementation. The next section outlines our algorithm enhancements to complex K-best MIMO detection using lattice reduction.

IV. Channel-Adaptive Complex K-Best MIMO Detection Using Lattice Reduction

The channel-adaptive complex K-best MIMO detector proposed in this paper uses lattice reduction to reduce computational complexity and employs a new two-dimensional on-demand child expansion scheme based on complex SE enumeration. The top-level block diagram of the implementation is shown in Fig. 2. The first step in the detection is to regularize the received symbol vector and channel matrix using MMSE regularization. Then we utilize the LLL algorithm with $\delta = 0.99$ for the lattice reduction on $\bar{\boldsymbol{H}}$. QR decomposition is applied to the output of lattice reduction to begin K-best MIMO detection using an enhanced complex SE enumeration algorithm. A priority queue is used to optimize candidate storage and sorting. The search radius K is made configurable from 1 through 4, where the maximum

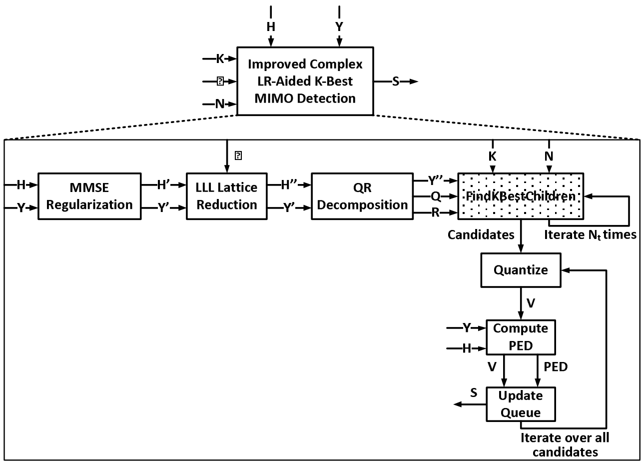

Figure 2. Overview of Matlab and System C Implementation

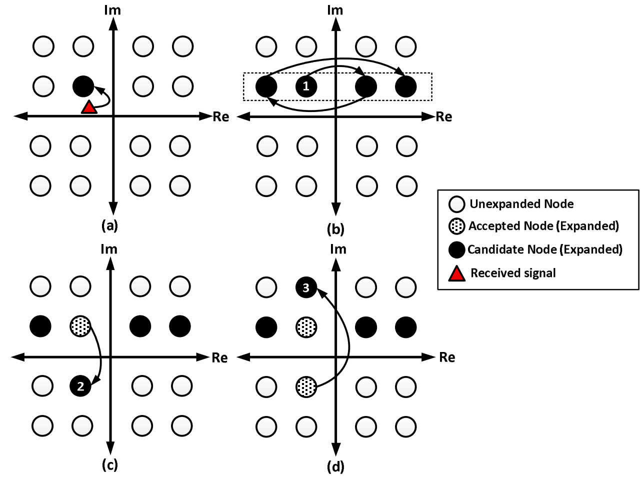

Figure 3. Improved complex on-demand expansion

value is determined through worst-case analysis and simulation of an 8x8 64-QAM MIMO system in different channel conditions. It should be noted that we have introduced an additional tunable input, N, in our implementation which controls the number of additional nodes expanded during the first step in findKBestChildren, discussed in the next section. The channel-adaptive complex-domain K-best MIMO detector using lattice reduction is implemented in System C and Matlab and its performance is compared to work presented in [13]. Next we outline our proposed complex on-demand child expansion strategy, denoted as findKBestChildren in Fig. 2.

A. Improved Complex On-Demand Child Expansion

As noted earlier, symbol detection begins at the N_t^{th} level of the tree. A simple example is provided for a 16-QAM system in Fig. 3 to contrast this approach to the one presented in [13] that was summarized in Fig. 2. For the same level of the tree considered in Fig. 2, the real and imaginary components of the received signal are rounded to the nearest symbol as shown in Fig. 3(a). In Fig. 3(b) node expansion begins by expanding the best node (shown as node 1) until all K nodes are expanded. Real SE enumeration is used to expand the first N nodes of each of the K nodes while keeping the imaginary component of the signal fixed and enumerating over only the real component as in Fig. 3(b). Then an additional node is selected via imaginary SE enumeration by fixing the real component. As proven in [13], this method will yield an enumeration in strictly non-decreasing error magnitude.

This is depicted in Fig. 3(c) where the best node out of the N nodes expanded in Fig. 3(b) is selected and complex SE enumeration is used to determine a new candidate. In Fig. 3(c), node labeled as 2 is the new candidate for expansion. This node is then used as the starting point for complex SE enumeration to determine the next new candidate as shown in Fig. 3(d). The final K candidates are quantized and their PED is computed to evaluate the current accrued error through the lattice search.

Introduction of the variable N enables fine-grain control over the complexity of complex SE enumeration and candidate symbol selection. Increasing N results in increased complexity but also yields an improvement in MIMO detection BER performance. Decreasing N reduces the amount of computation required but can degrade BER performance. Both K and N can be adapted to channel signal-to-noise (SNR) conditions so that K and N can be set to low values when channel conditions are favorable and increased when channel conditions deteriorate. This can potentially result in overall energy savings in the MIMO detector.

B. Complexity Analysis

The complexity analysis of our modified complex SE enumeration proceeds as follows. At an arbitrary level of the tree, NK nodes must be expanded to perform the initial row expansions. Then, for each of K selected nodes, one node is expanded via imaginary SE enumeration. Thus, the bound for a level is given by $(NK + K - 1)$. Taken over the entire tree, the bound for a search is therefore $N_T K(N+1) - N_t$ expanded nodes.

V. Simulation Results

This section demonstrates the performance of the proposed LR-aided complex-domain K-best algorithm for MIMO detection using an improved complex on-demand child expansion scheme. First, an analysis of the runtime complexity of this work relative to conventional LR-aided real-domain and complex-domain K-best MIMO detectors is presented. Then a comparison of BER performance of this work to conventional real-domain and complex-domain LR-aided K-best detectors is detailed.

A. Analysis of Runtime Complexity

Table 1 shows the computational complexities of the conventional real-domain and complex-domain LR-aided K-best MIMO detectors, and the complex-domain LR-aided K-best MIMO detector proposed in this paper. As outlined in the table, a complex-domain detector will always have reduced complexity relative to the real-domain detector [11] for the same value of K. This gap grows with increasing K. When N is set to 1 and K is fixed at 4, the computational complexity of the proposed detection scheme is 50% lower than [11] and 30% lower than the complexity of [13] for an 8x8 MIMO array. Table 1 also shows that when N is set to 2 for the proposed complex-domain detector, the computational complexity is slightly higher than [13].

However, for a given BER target and channel SNR as shown in the next section, the proposed MIMO detector in this work requires a lower K as compared to the K value required for the complex-domain detector presented in [13]. The MIMO detection using the modified SE enumeration scheme and the channel-adaptive complex K-best detection that has been proposed in this work results in overall reduced complexity compared to [13].

Table 1. Complex K-best MIMO detection complexity analysis

	Symbolic Bound
Real-Domain [11]	$4N_tK - 2N_t$
Complex-Domain [12]	$3N_tK - 2N_t$
This Work	$N_tK(N+1) - N_t$

B. BER Performance Comparison

Figure 4 shows the performance of the proposed complex-domain K-best MIMO detection algorithm for the flat fading Rayleigh channel compared to the real-domain LR-aided K-best detector [11]. Results show that the complex MIMO detector outperforms the real-domain LR-aided MIMO detector for the same value of K. We note that as K and N are increased the proposed detector comes closer to approximating optimal ML detection.

Key results from Fig. 4 are highlighted in Table 2. When $K = 2$ and $N = 2$ the proposed complex detector is able to match the performance of the real detector for $K = 2$ with 17% reduction in computational complexity. A 10% increase in computational complexity, resulting from increasing K to 4 and keeping $N = 2$, yields 1.0dB SNR gain at a BER target of 10^{-3}, relative to $K = 3$ for the real-domain K-best detector. As K is increased for the real-domain MIMO detector, the computational complexity increases dramatically with only minor improvement in SNR gain as compared to the proposed K-best MIMO detector using the enhanced complex SE enumeration scheme.

Table 2. Summary of key results from Fig. 4

K	N	Nodes Expanded [this work]	K [13]	Nodes expanded [13]	Complexity Change	SNR Gain (dB)
2	2	40	3	56	0.71x	0.5
2	2	40	4	80	0.50x	0.0
3	2	64	4	80	0.80x	0.7

Figure 5 shows the performance of the proposed complex-domain K-best MIMO detector compared to the complex-domain K-best detector in [13]. The graph shows that for the same value of K the detector algorithm presented in this work outperforms the detector in [13] while reducing computational complexity as shown in the complexity analysis section. Key results from Fig. 5 are summarized in Table 3.

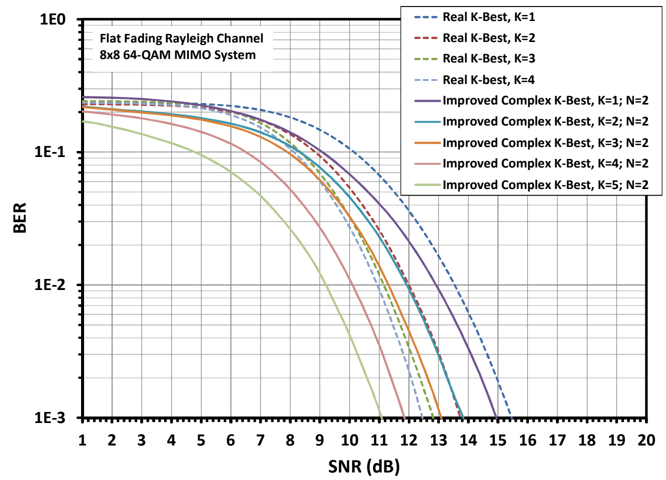

Figure 4. BER performance of real-domain and improved complex-domain LR-aided K-best MIMO detectors

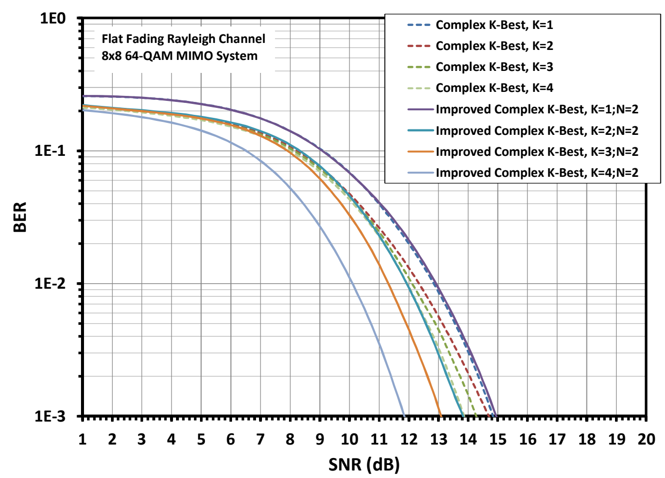

Figure 5. BER performance of complex-domain and improved complex-domain LR-aided K-best MIMO detectors

Table 3. Summary of key results from Fig. 5

K	N	Nodes Expanded [this work]	K [13]	Nodes expanded [13]	Complexity Change	SNR Gain (dB)
2	2	40	3	56	0.71x	0.5
2	2	40	4	80	0.50x	0.0
3	2	64	4	80	0.80x	0.7

When $K = 2$ and $N = 2$ for the proposed MIMO detector, BER performance matches the complex K-best detector performance in [13] for $K = 4$. This results in a 50% computational complexity reduction for the same BER performance, which is a significant improvement over the work presented in [13]. If the configurable parameters in the proposed MIMO detection scheme are set to $K = 4$ and $N =$

2, resulting in 10% increase in computational complexity over [13], then we can achieve an SNR gain of 2.0dB (at a BER target of 10^{-3}) relative to [13].

VI. Conclusion

In this paper, we developed an improved complex-domain LR-aided K-best MIMO detector. A 50% complexity reduction and gains in BER performance were primarily obtained through an improved on-demand complex child expansion scheme. Two complexity tuning parameters were introduced that can be adapted to channel conditions to improve computational complexity further and potentially reduce total power of MIMO detection. The performance of the algorithm was modeled and compared against conventional real-domain and complex-domain LR-aided K-best detectors. The proposed detector provides the ability to tune complexity of computation and match or exceed BER performance of conventional real-domain and complex-domain LR-aided K-best MIMO detectors.

Future work will include evaluating the detector performance using additional channel models along with comparisons with similar detectors such as [19].

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