A New Reduced Complexity ML Detection Scheme for MIMO Systems

Jin-Sung Kim, Sung-Hyun Moon, and Inkyu Lee

***Abstract*—For multiple-input multiple-output (MIMO) systems, the optimum maximum likelihood (ML) detection requires tremendous complexity as the number of antennas or modulation level increases. This paper proposes a new algorithm which attains the ML performance with significantly reduced complexity. Based on the minimum mean square error (MMSE) criterion, the proposed scheme reduces the search space by excluding unreliable candidate symbols in data streams. Utilizing the probability metric which evaluates the reliability with the normalized likelihood functions of each symbol candidate, near optimal ML detection is made possible. Also we derive the performance analysis which supports the validity of our proposed method. A threshold parameter is introduced to balance a tradeoff between complexity and performance. Besides, we propose an efficient way of generating the log likelihood ratio (LLR) values which can be used for coded systems. Simulation results show that the proposed scheme achieves almost the same performance as the ML detection at a bit error rate (BER) of 10^{-4} with 28% and 15% of real multiplications compared to the conventional QR decomposition with M-algorithm (QRD-M) in 4-QAM and 16-QAM, respectively. Also we confirm that the proposed scheme achieves the near-optimal performance for all ranges of code rates with much reduced complexity. For instance, our scheme exhibits 74% and 46% multiplication reduction in 4-QAM and 16-QAM, respectively, compared to the sphere decoding based soft-output scheme with rate-1/2 convolutional code.**

***Index Terms*—Multiple-input multiple-output (MIMO), maximum likelihood (ML) detection, spatial multiplexing (SM).**

I. INTRODUCTION

EVER since the information theoretic analysis proved the great potential of multiple-input multiple-output (MIMO) channels in terms of system capacity [1], there has been intensive study on implementation of practical MIMO systems for the past few years. In order to fully exploit the capacity of the MIMO system, appropriate transmission and detection algorithms should be designed.

In spatial multiplexing (SM) systems which support several independent data streams, maximum likelihood (ML) detection is the optimal method in terms of symbol error rate (SER). However, it suffers from extremely high detection complexity because an exhaustive search should be carried out over all possible candidate symbol vectors. Several suboptimal detection schemes have been proposed to reduce the complexity of the ML detection in open loop systems. In linear equalization based schemes [2], zero forcing (ZF) or minimum mean square error (MMSE) criterion is used to determine the estimated symbol vector. Also, non-linear techniques such as vertical Bell Labs layered space-time (V-BLAST) detection [3] [4] are considered for detection to enhance the performance of the linear equalization approaches.

Since most suboptimal detection schemes are unable to provide the satisfactory performance in practical systems, a number of approaches have been presented to approach the near-optimum performance at the cost of additional complexity. Tree search based detection algorithms such as QR decomposition with M-algorithm (QRD-M) [5] and sphere decoding (SD) [6] have been studied as alternative ways to address this problem. Both the QRD-M and the SD schemes employ the QR decomposition [7] to implement the tree search with low complexity compared to the full search ML detector. Also, other reduced complexity approximations of the ML detector have been proposed in [8] [9] [10].

Most techniques described above are not directly applicable to coded systems which require soft-output values. In order to generate the soft output, the QRD-M based approaches [11] [12] obtain a valid set whose candidates are crucial in generating the log likelihood ratio (LLR) values. Similarly, modified SD algorithms [13] [14] have been proposed for coded systems. One approach in [13] keeps a list of candidates instead of just one nearest symbol to generate the soft values. Some other suboptimal approaches [15] [16] are also shown to compute the reliable LLR values with comparable complexity.

In this paper, we introduce a new detection algorithm whose performance approaches the optimal ML solution with significantly reduced complexity. The proposed scheme first employs an MMSE filtering to separate the MIMO channel into several subchannels, and reduces the search space by removing unreliable candidate symbols in each data stream. Using the probability metric which evaluates the reliability with the normalized likelihood functions of each symbol candidate, a near-optimum solution is obtained with the substantially reduced number of candidates. In order to evaluate the performance of our proposed method, we derive the outage probability expression. A threshold parameter is introduced to obtain a balanced tradeoff between performance and complexity. A similar MMSE filtering operation was introduced in [8]. However this requires an iterative filter update and interference cancelation process unlike our scheme. Simulation results show that the proposed scheme performs almost the same as the ML solution in 16-QAM with a 85% reduction in real multiplications compared to the QRD-M at a bit error rate (BER) of 10^{-4} for 4×4 systems. Also our scheme achieves

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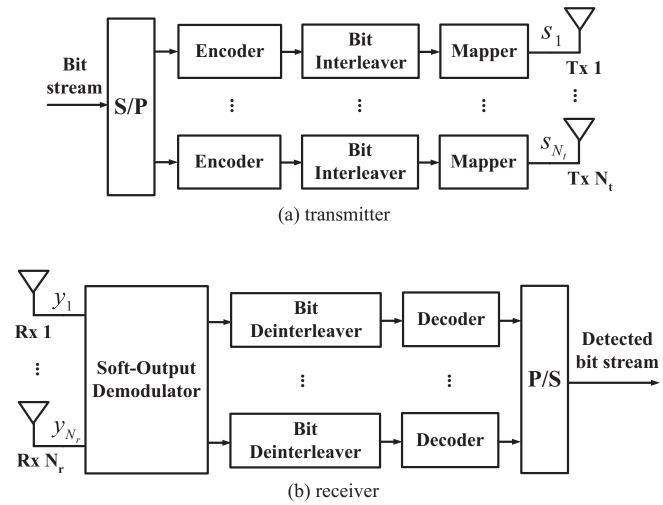

Fig. 1. Block diagram of MIMO systems with N_t transmit and N_r receive antennas: (a) transmitter (b) receiver.

the complexity reduction of 89% and 28% compared with the SD in 4-QAM and 16-QAM, respectively.

Furthermore, we propose an efficient way to generate the LLR values for coded systems. Unlike the modified SD algorithms [13] [14] which show high complexity variations depending on the initial radius of the hypersphere, the proposed algorithm is guaranteed to contain at least one valid candidate. The proposed scheme attains the optimal performance with only half of the real multiplications compared to the QRD-M based method when a rate-1/2 convolutional code is adopted. We also confirm that our scheme outperforms the SD based algorithm in terms of the complexity. Besides, the proposed scheme still maintains its efficiency when the fixed number of search candidates is used.

For clarity, the following notations are used for the description throughout this paper. Boldface letters indicate vectors and boldface uppercase letters designate matrices. Also, $(\cdot)^{-1}$, $(\cdot)^T$ and $(\cdot)^H$ stand for the inverse operation, the transpose and the Hermitian transpose, respectively. Besides, $\mathbf{I}$ represents an identity matrix.

The organization of the paper is as follows: Section II describes the channel model for the SM transmission and reviews conventional detection techniques. In Section III, we introduce a new detection scheme. Section IV presents a method to generate the LLR values based on the proposed scheme, and illustrates an example. In Section V, we provide the complexity analysis of the proposed scheme. Section VI compares the performance of the proposed scheme with conventional schemes. Finally, the paper is terminated with conclusions in Section VII.

II. Conventional Detection Methods

Consider a MIMO system with N_t transmit and N_r receive antennas $(N_r \geq N_t)$ as illustrated in Figure 1. The channel encoding is employed by means of bit-interleaved coded modulation (BICM) [17] [18] at the transmitter, where the data bits are first demultiplexed into N_t parallel data streams. As shown in Figure 1 (a), each data stream is independently encoded with code rate R_c, bit-interleaved and modulated to yield the transmitted symbol vector $\mathbf{s} = [s_1 \cdots s_{N_t}]^T$. Each entry of $\mathbf{s}$ is assumed to have the symbol energy σ_s^2 and belongs to a complex constellation $\mathcal{C}$ of size K.

At the receiver, the baseband system model for discrete time frequency flat-fading channels is given by

$$\mathbf{y} = [y_1 \cdots y_{N_r}]^T = \mathbf{Hs} + \mathbf{n} \tag{1}$$

where $\mathbf{n} = [n_1 \cdots n_{N_r}]^T$ represents the complex additive white Gaussian noise (AWGN) vector whose covariance matrix is assumed to be $\sigma_n^2\mathbf{I}$, and $\mathbf{H}$ stands for the $N_r \times N_t$ channel matrix whose (i,j)-th entry indicates the fading coefficient between the j-th transmit and i-th receive antenna. The entries of $\mathbf{H}$ are drawn from an independent and identically distributed (i.i.d.) complex Gaussian distribution with zero-mean and unit variance, and we assume that $\mathbf{H}$ is perfectly known at the receiver. The received signal vector $\mathbf{y}$ is converted to the LLR values in the soft-output demodulator as shown in Figure 1 (b). We consider the block fading channel model, where the fading coefficients are static within a frame of transmitted symbols and independent over frames.

First we consider uncoded MIMO systems. When estimating the transmitted symbol vector, the optimal ML solution is expressed as

$$\hat{\mathbf{s}} = \arg \min_{\mathbf{s} \in \mathcal{C}^{N_t}} \|\mathbf{y} - \mathbf{Hs}\|^2 \tag{2}$$

where $\mathcal{C}^{N_t}$ denotes the set of constellation symbols in the N_t dimensional complex space. It is clear from (2) that the computational complexity of the ML detector is proportional to K^{N_t} which grows exponentially with the number of transmit antennas N_t and the number of bits per symbol $\log_2 K$.

Although linear equalization techniques such as ZF or MMSE filtering can be implemented with low complexity, their performance often becomes unacceptable for many practical systems since the diversity order reduces to $N_r - N_t + 1$ in contrast to the ML detector which has a diversity order of N_r [2]. The V-BLAST architectures are proposed to enhance the performance of the linear equalizer. However, as the constellation size becomes larger, the performance gain of the V-BLAST is significantly degraded.

Recently, the QRD-M [5] and the SD [6] have been studied to attain the ML performance for practical implementation. These schemes attempt to reduce the search space of the ML solution in (2). Both the QRD-M and the SD scheme start with the QR decomposition on $\mathbf{H}$ to obtain $\mathbf{H} = \mathbf{QR}$ where $\mathbf{Q}$ and $\mathbf{R}$ denote an $N_r \times N_t$ matrix with orthonormal columns and an $N_t \times N_t$ upper triangular matrix, respectively.

By adopting $\mathbf{Q}$ as the receive filter, the received signal becomes

$$\tilde{\mathbf{y}} = [\tilde{y}_1 \cdots \tilde{y}_{N_t}]^T = \mathbf{Q}^H\mathbf{y} = \mathbf{Rs} + \tilde{\mathbf{n}} \tag{3}$$

where $\tilde{\mathbf{n}} = \mathbf{Q}^H\mathbf{n}$ denotes the filtered noise vector with the same covariance matrix $\sigma_n^2\mathbf{I}$ due to the orthonormal columns of $\mathbf{Q}$.

According to (3), the QRD-M converts the ML detection problem (2) to

$$\begin{aligned}\hat{\mathbf{s}} &= \arg\min_{\mathbf{s}\in\mathcal{C}^{N_t}} \|\tilde{\mathbf{y}}-\mathbf{R}\mathbf{s}\|^2 \\ &= \arg\min_{\mathbf{s}\in\mathcal{C}^{N_t}} \sum_{j=1}^{N_t}\left|\tilde{y}_j-\sum_{i=j}^{N_t} r_{j,i}s_i\right|^2 \end{aligned}\tag{4}$$

where $r_{j,i}$ is the (i,j)-th entry of $\mathbf{R}$. In the QRD-M scheme, the search complexity is reduced by keeping only a fraction of the entire branches at each data stream in (4) which have the small accumulated metric values, instead of calculating all possible candidates in the set $\mathcal{C}^{N_t}$ [5]. For the first step $(j=N_t)$ which estimates the N_t-th symbol s_{N_t}, M symbol candidates are selected among the constellation $\mathcal{C}$ by using the metric $\left|\tilde{y}_{N_t}-r_{N_t,N_t}s_{N_t}\right|$ in (4). There is no interference caused by $s_i\,(\forall i\neq N_t)$, since the N_t-th row of the effective channel matrix $\mathbf{R}$ contains only r_{N_t,N_t} corresponding to s_{N_t}. Next, at each subsequent step $(j=N_t-1,\cdots,1)$ which estimates the symbol candidates for s_j, the QRD-M assumes that the symbols $s_{N_t}, s_{N_t-1},\cdots,s_{j+1}$ are already detected at the previous steps by utilizing those M selected candidates. Then the candidates for s_j are obtained similarly by canceling the interference $\sum_{i=j+1}^{N_t} r_{j,i}s_i$ in (4) caused by the symbols $s_{N_t},\cdots,s_{j+1}$. However, the complexity of the QRD-M is still high especially for high modulation and large antenna size.

In contrast, the SD maintains the optimal performance with the assumption that at least one candidate resides in the sphere [19]. From (4), the SD problem can be represented by

$$\sum_{j=1}^{N_t}\left|\tilde{y}_j-\sum_{i=j}^{N_t} r_{j,i}s_i\right|^2 \leq \mathcal{R}^2 \tag{5}$$

where $\mathcal{R}$ denotes the initial radius of the sphere. In the SD algorithm, after valid lattice points are found at each step, the search space gets smaller by adjusting the radius so that the newly discovered lattice point lies on the surface of the sphere. As a result, the detection complexity can be reduced because the candidate search is restricted to the lattice points found within the sphere. There has been extensive work to reduce the complexity of the SD, including the radius optimization [20] and ordering [21] [22]. An MMSE based SD scheme is introduced in [21] which approximates the ML detector with reduced average complexity.

III. Proposed Detection Algorithm for Uncoded Systems

Now we discuss a new MIMO detection scheme which achieves the near optimal performance with much reduced complexity. Section III-A describes the proposed method, and we prove the validity of our scheme through an outage probability analysis in Section III-B.

A. Proposed Method

First, we apply the linear filter $\mathbf{G}$ based on the MMSE criterion at the receiver given by

$$\mathbf{G}=\left[\mathbf{g}_1\cdots\mathbf{g}_{N_t}\right]=\mathbf{H}\left(\mathbf{H}^H\mathbf{H}+\frac{\sigma_n^2}{\sigma_s^2}\mathbf{I}\right)^{-1}.$$

Then the MMSE estimate symbol vector $\tilde{\mathbf{s}}=[\tilde{s}_1\cdots\tilde{s}_{N_t}]^T$ is obtained as

$$\tilde{\mathbf{s}}=\mathbf{G}^H\mathbf{y}=\mathbf{G}^H\mathbf{H}\mathbf{s}+\mathbf{v} \tag{6}$$

where $\mathbf{v}=[v_1\cdots v_{N_t}]^T$ denotes the filtered output noise vector $\mathbf{v}=\mathbf{G}^H\mathbf{n}$. Denoting $\mathbf{h}_i$ as the i-th column of $\mathbf{H}$, we can represent the i-th symbol estimate $\tilde{s}_i$ in (6) as

$$\begin{aligned}\tilde{s}_i &= \sum_{j=1}^{N_t}\mathbf{g}_i^H\mathbf{h}_j s_j+v_i \\ &= \mathbf{g}_i^H\mathbf{h}_i s_i+\sum_{j=1,j\neq i}^{N_t}\mathbf{g}_i^H\mathbf{h}_j s_j+v_i=\beta_i s_i+w_i \end{aligned}\tag{7}$$

where $\beta_i=\mathbf{g}_i^H\mathbf{h}_i$ is a scale factor introduced by the MMSE equalizer and $w_i=\sum_{j=1,j\neq i}^{N_t}\mathbf{g}_i^H\mathbf{h}_j s_j+v_i$ represents the distortion which consists of the residual interference and the noise.

As the distribution of w_i at the output of the MMSE filter in (7) is well approximated by a Gaussian distribution [23], we assume that the terms in w_i make a complex Gaussian distribution with zero mean and variance $\sigma_{w,i}^2$. Then the conditional probability density function (PDF) of $\tilde{s}_i$ in (7) is given by

$$p\left(\tilde{s}_i|s_i=\rho_k\right)=\frac{1}{\pi\sigma_{w,i}^2}\exp\left(-\frac{|\tilde{s}_i-\beta_i\rho_k|^2}{\sigma_{w,i}^2}\right) \tag{8}$$

where ρ_k for $k=1,\cdots,K$ denotes the constellation symbol candidate and the variance $\sigma_{w,i}^2$ can be obtained as

$$\begin{aligned}\sigma_{w,i}^2 &= \sigma_s^2\mathbf{g}_i^H\left(\mathbf{H}\mathbf{H}^H+\frac{\sigma_n^2}{\sigma_s^2}\mathbf{I}-\mathbf{h}_i\mathbf{h}_i^H\right)\mathbf{g}_i \\ &= \sigma_s^2\left\{\mathbf{g}_i^H\left(\mathbf{H}\mathbf{H}^H+\frac{\sigma_n^2}{\sigma_s^2}\mathbf{I}\right)\mathbf{g}_i-\beta_i^2\right\} \\ &= \sigma_s^2\beta_i(1-\beta_i).\end{aligned}$$

From now on, we illustrate how the ML search candidates can be reduced based on the conditional PDF of (8). First we introduce the threshold value α $(0<\alpha<1)$, which determines the selection range of the candidate symbols. The normalized conditional probabilities for the k-th candidate symbol at the i-th stream $(i=1,\cdots,N_t)$ are defined as

$$\xi_k^i \triangleq \frac{p\left(\tilde{s}_i|s_i=\rho_k\right)}{\sum_{j=1}^{K}p\left(\tilde{s}_i|s_i=\rho_j\right)},\quad 1\leq k\leq K. \tag{9}$$

Note that ξ_k^i indicates the reliability of the symbol candidate ρ_k at the i-th stream. Without loss of generality, let us assume $\xi_1^i\geq\xi_2^i\geq\cdots\geq\xi_K^i$.

Now we select the most reliable symbol candidates independently in each stream based on (9). The number of the survived candidates U_i at the i-th stream is equal to the smallest number of chosen symbols whose probability sum is larger than α, defined by

$$U_i=\arg\min_{1\leq u\leq K}\left(\sum_{j=1}^{u}\xi_j^i-\alpha\right)^+ \tag{10}$$

where $(\cdot)^+$ denotes the operation that the negative value inside the bracket is replaced by ∞. Then the set of these selected candidates for the i-th stream becomes $\widehat{\mathcal{C}}_i = \{\rho_1, \cdots, \rho_{U_i}\}$. From the candidate sets $\{\widehat{\mathcal{C}}_i\}_{i=1}^{N_t}$, we finally obtain the new search set $\mathcal{D}$ as $\mathcal{D} = \widehat{\mathcal{C}}_1 \times \cdots \times \widehat{\mathcal{C}}_{N_t}$. The total number of the candidate symbol vectors is determined as $U = \prod_{i=1}^{N_t} U_i$. Now the ML detection problem of (2) is solved by using the reduced vector set $\mathcal{D}$ as

$$\hat{\mathbf{s}} = \arg\min_{\mathbf{s}\in\mathcal{D}} \|\mathbf{y} - \mathbf{H}\mathbf{s}\|^2. \tag{11}$$

B. Outage Probability Analysis

In what follows, to validate the choice of our candidate set $\widehat{\mathcal{C}}_i$, we investigate the outage probability that the symbol candidate ρ_k is excluded from the set $\widehat{\mathcal{C}}_i$. We assume the actual transmitted symbol is $s_i = \rho_1$. For analytical purpose, we focus on a 2×2 system with binary phase shift keying (BPSK). In this case, the outage probability for ρ_k $(k = 1, 2)$ is equal to $\Pr\left[\xi_k^i < 1-\alpha\right]$ according to (10).

We first study the outage probability of ρ_1 in detail. The normalized probability ξ_1^i is obtained from (9) as

$$\xi_1^i = \left(1 + \exp\left(-\frac{(2\beta_i\sigma_s)^2 + 4\beta_i\sigma_s\Re(w_i)}{\sigma_{w,i}^2}\right)\right)^{-1} \tag{12}$$

where $\Re(w_i)$ indicates the real component of w_i. Denoting the exponential term in (12) as b, the outage probability is presented as

$$\begin{aligned}\Pr\left[\xi_1^i < 1-\alpha\right] &= \Pr\left[\frac{\alpha}{1-\alpha} < b\right] \\ &= \int_0^1 \int_{\frac{\alpha}{1-\alpha}}^{\infty} p(b|\beta_i)db\ p(\beta_i)d\beta_i. \end{aligned}\tag{13}$$

By utilizing the Gaussian assumption on w_i, the conditional PDF $p(b|\beta_i)$ in (13) is given as

$$p\left(b|\beta_i\right) = \frac{\sigma_{w,i}}{4b\beta_i\sigma_s\sqrt{\pi}}\exp\left(-\frac{(\sigma_{w,i}^2\ln b + (2\beta_i\sigma_s)^2)^2}{\sigma_{w,i}^2(4\beta_i\sigma_s)^2}\right).$$

Then the inner integral in (13) is derived as [24]

$$\int_{\frac{\alpha}{1-\alpha}}^{\infty} p(b|\beta_i)db = \frac{1}{2}\left\{1 - \mathrm{erf}\left(\frac{1}{4}\ln\frac{\alpha}{1-\alpha}\sqrt{\frac{1-\beta_i}{\beta_i}} + \sqrt{\frac{\beta_i}{1-\beta_i}}\right)\right\} \tag{14}$$

where $\mathrm{erf}(\cdot)$ indicates the error function.

Also we can yield $p(\beta_i)$ in (13) from the result in [25] as

$$\begin{aligned}p(\beta_i) &= \frac{\lambda\exp(-\lambda z^2)}{(1-\beta_i)^2}\left(1 + \lambda - \frac{1}{(z^2+1)^2} - \frac{\lambda}{(z^2+1)}\right) \\ &\le \frac{\lambda\,(1+\lambda)}{(1-\beta_i)^2}\exp\left(-\lambda z^2\right) \end{aligned}\tag{15}$$

where $z = \sqrt{\frac{\beta_i}{1-\beta_i}}$ and $\lambda = \sigma_n^2/\sigma_s^2$. Applying (14) and (15) into (13) results in [24]

$$\begin{aligned}\Pr\left[\xi_1^i < 1-\alpha\right] &\le \int_0^{\infty}\lambda z(1+\lambda)\exp(-\lambda z^2)\left\{1 - \mathrm{erf}\left(\frac{1}{4z}\ln\frac{\alpha}{1-\alpha} + z\right)\right\}dz \\ &= \frac{1+\lambda-\sqrt{1+\lambda}}{2}\left(\frac{1-\alpha}{\alpha}\right)^{\frac{1+\sqrt{1+\lambda}}{2}}. \end{aligned}\tag{16}$$

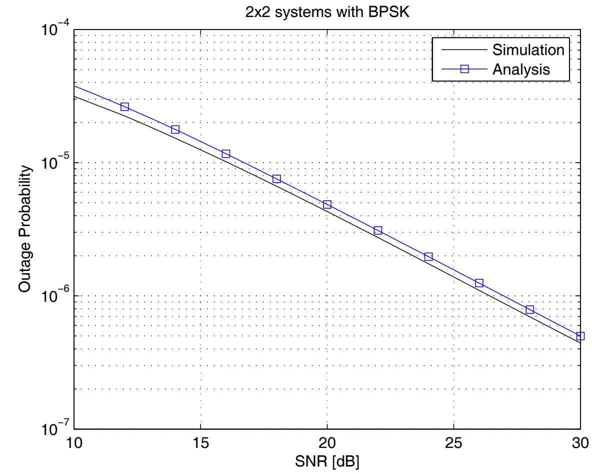

Fig. 2. Outage probability for ρ_1 in a 2×2 system with BPSK.

Since the term $\sqrt{1+\lambda}$ in (16) can be expressed to equal $1+\frac{\lambda}{2}$ for small λ, the outage probability is approximated to

$$\Pr\left[\xi_1^i < 1-\alpha\right] \approx \frac{\lambda}{4}\left(\frac{1-\alpha}{\alpha}\right)^{1+\frac{\lambda}{4}},\ \lambda\to 0. \tag{17}$$

From a similar approach, the outage probability for the other symbol candidate ρ_2 is obtained as

$$\begin{aligned}\Pr\left[\xi_2^i < 1-\alpha\right] &= \Pr\left[b < \frac{1-\alpha}{\alpha}\right] \\ &\le \frac{1+\lambda+\sqrt{1+\lambda}}{2}\left(\frac{1-\alpha}{\alpha}\right)^{\frac{\sqrt{1+\lambda}-1}{2}} \\ &\approx \left(1+\frac{3}{4}\lambda\right)\cdot\left(\frac{1-\alpha}{\alpha}\right)^{\frac{\lambda}{4}},\ \lambda\to 0. \end{aligned}\tag{18}$$

We notice from (17) and (18) that for high SNR $(\lambda\approx 0)$, the outage probability for ρ_1 and ρ_2 exponentially approaches zero and one, respectively. In other words, the reduced set $\widehat{\mathcal{C}}_i$ almost always contains the only actual transmitted symbol $s_i = \rho_1$ at high SNR. Figure 2 depicts the outage probability for ρ_1 using both the analysis in (16) and the simulation result with $\alpha = 0.999$. In this figure, we can see that our analysis provides a tight bound.

In the following, we provide some additional comments on the proposed method compared with the conventional schemes. The probability threshold α determines a tradeoff between performance and complexity, and the search size can be reduced with smaller α at the expense of a little performance loss. As α approaches one, better performance is obtained with the increased number of candidates, and $\alpha = 1$ makes the proposed scheme equivalent to the conventional ML detection. Also the proposed scheme guarantees at least one candidate symbol for every data streams, whereas for the SD it is possible that no valid point is inside the sphere. We will cover more detailed complexity comparison with the SD in Section VI. Note that the proposed scheme does not require the QR decomposition which is critical in the performance of the SD and the QRD-M.

IV. Reduced Complexity Algorithm for Coded Systems

It is well known that a significant improvement in the performance is obtained when a soft-input channel decoder is employed for coded systems. Thus, the generation of a reliable LLR value from the selected candidate symbol vectors is important to obtain acceptable performance [11] [13] [26]. When the LLR values are computed only from a subset of the entire candidate symbol vectors, the reliability of the LLR values become lower which degrades the system performance especially with strong channel codes. In what follows, we present a simple procedure of obtaining the LLR values based on the proposed algorithm.

Utilizing the set $\mathcal{D}$ which contains the reduced candidates, the LLR values can be generated as

$$\mathrm{LLR}\left(b_{i,j}\right)=\log\frac{\displaystyle\sum_{\mathbf{s}\in\mathcal{D}_{i,j,1}}\exp\left(-\frac{\|\mathbf{y}-\mathbf{H}\mathbf{s}\|^2}{\sigma_n^2}\right)}{\displaystyle\sum_{\mathbf{s}\in\mathcal{D}_{i,j,0}}\exp\left(-\frac{\|\mathbf{y}-\mathbf{H}\mathbf{s}\|^2}{\sigma_n^2}\right)} \tag{19}$$

where $b_{i,j}$ $(1\le i\le N_t,\ 1\le j\le \log_2 K)$ denotes the j-th bit of the i-th data stream, and $\mathcal{D}_{i,j,d}$ is defined as $\mathcal{D}_{i,j,d}=\{\mathbf{s}\mid b_{i,j}=d,\ \mathbf{s}\in\mathcal{D}\}$. In computing the LLR values in (19), there may not be enough candidates to produce all the LLR values of $b_{i,j}$. One should note that either $\mathcal{D}_{i,j,0}=\phi$ or $\mathcal{D}_{i,j,1}=\phi$ makes it unable to compute $\mathrm{LLR}\left(b_{i,j}\right)$. To solve this problem, when the LLR values become unavailable because of empty $\mathcal{D}_{i,j,d}$, we obtain the LLR using the MMSE filtered signal $\tilde{s}_i$ in (7) as

$$\begin{aligned}\mathrm{LLR}\left(b_{i,j}\right)&=\log\frac{\displaystyle\sum_{\rho_k\in\mathcal{C}_{j,1}}\exp\left(-\frac{|\tilde{s}_i-\beta_i\rho_k|^2}{\sigma_{w,i}^2}\right)}{\displaystyle\sum_{\rho_k\in\mathcal{C}_{j,0}}\exp\left(-\frac{|\tilde{s}_i-\beta_i\rho_k|^2}{\sigma_{w,i}^2}\right)}\\&=\log\frac{\displaystyle\sum_{\rho_k\in\mathcal{C}_{j,1}}\xi_k^i}{\displaystyle\sum_{\rho_k\in\mathcal{C}_{j,0}}\xi_k^i}\end{aligned} \tag{20}$$

where $\mathcal{C}_{j,d}\in\mathcal{C}$ denotes a subset of the symbol candidates whose j-th bit is d. Since we use the same constellation $\mathcal{C}$ for all the data streams, the subscript i of $\mathcal{C}$ which represents the index of the data stream is omitted in (20).

Note that ξ_k^i for each candidate symbol has been calculated to determine the reduced search set $\widehat{\mathcal{C}}_i$ in (9). Therefore, the additional complexity of obtaining (20) for the case of the undetermined LLR values is negligible compared to uncoded systems. In the simulation section, we verify that the proposed scheme maintains the near optimal performance with much reduced complexity.

Now we provide an example to illustrate the procedure of our method which exploits a significant reduction of the search size. For 4-QAM transmission with two transmit and two receive antennas, given the MMSE symbol estimates $\tilde{s}_1$ and $\tilde{s}_2$, we suppose that the conditional probabilities are equal to $\xi_k^1=\{0.0273,0.0004,0.0145,0.9578\}$ and $\xi_k^2=\{0.0040,0.3228,0.6650,0.0082\}$ as shown in Figure 3.

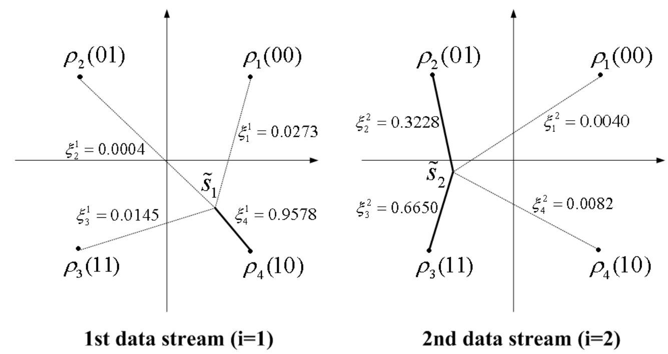

Fig. 3. Example of a 2×2 system with 4-QAM.

The next step is to gather the most reliable symbol candidates in each stream until their probability sum becomes greater than α. Setting $\alpha=0.95$, for the first stream, only ρ_4 is selected $\left(\xi_4^1=0.9578>\alpha\right)$. Also, ρ_2 and ρ_3 are chosen for the second stream $\left(\xi_2^2+\xi_3^2=0.9878>\alpha\right)$. Thus, we have $\widehat{\mathcal{C}}_1=\{\rho_4\}$ and $\widehat{\mathcal{C}}_2=\{\rho_2,\rho_3\}$, and the resulting candidate vector set for our detection becomes $\mathcal{D}=\widehat{\mathcal{C}}_1\times\widehat{\mathcal{C}}_2=\{[\rho_4\ \rho_2],[\rho_4\ \rho_3]\}$. Then the ML search in (11) and the LLR value generation in (19) are performed with the reduced candidate set $\mathcal{D}$. Suppose that the constellation symbols are mapped to $\{00,01,11,10\}$. Then while $\mathrm{LLR}\left(b_{2,1}\right)$ is computed from (19), the LLR values of $b_{1,1}$, $b_{1,2}$, $b_{2,2}$ are undetermined since $\widehat{\mathcal{C}}_{1,1,0}=\widehat{\mathcal{C}}_{1,2,1}=\widehat{\mathcal{C}}_{2,2,0}=\phi$. After $\mathrm{LLR}\left(b_{2,1}\right)$ is evaluated, $\mathrm{LLR}\left(b_{1,1}\right)$, $\mathrm{LLR}\left(b_{1,2}\right)$, and $\mathrm{LLR}\left(b_{2,2}\right)$ are determined as 3.56, -4.19, and 4.39 by using the values of ξ_k^1 and ξ_k^2 in (20).

V. Complexity Analysis

In this section, we compare the computational complexity of our proposed scheme with conventional systems. We first evaluate the complexity for uncoded systems by counting the average number of required real multiplications. As for the SD, we consider the scheme in [21] which applies the ordering and the filtering based on the MMSE criterion. This scheme obtains the upper triangular channel by applying a permutation matrix and corresponding MMSE filter vectors, instead of utilizing the QR decomposition. We set the initial radius of the SD to infinity.

The ML detection requires $4N_rN_tK+2N_rK^{N_t}$ real multiplications where the first and the second term indicate, respectively, the computations of $\mathbf{Hs}$ and the norm square operation in (2). When computing $\mathbf{Hs}$ for all $\mathbf{s}\in\mathcal{C}^{N_t}$, we can reduce the number of multiplications by utilizing the following method. First, for each data stream i $(i=1,\cdots,N_t)$, we calculate $\mathbf{h}_is_i$ with all $s_i\in\mathcal{C}$. Then the result of $\mathbf{Hs}$ is obtained easily by summing up all $\mathbf{h}_is_i$. In this way, the computational complexity of $\mathbf{Hs}$ does not grow exponentially with N_t. In the QRD-M, the process in (4) needs $4\left\{\left(\sum_{i=1}^{N_t-1}i+K(N_t-1)\right)M+K\right\}+2\left(MK(N_t-1)+K\right)$ multiplications where the first term accounts for the metric calculations and the second term indicates the square operations for all nodes. As for the SD, it is difficult to derive a closed form expression of the implementation complexity related to the number of the search nodes with detected candidates. Also the complexity of

TABLE I
NUMBER OF MULTIPLICATIONS FOR VARIOUS SCHEMES IN 4×4 UNCODED MIMO SYSTEMS

Detection Schemes	4-QAM (18dB)	16-QAM (26dB)
ML	2304	525312
SD	1054	1056
QRD-M $(M = K)$	408	5088
QRD-M $\left(M = \frac{3}{4}K\right)$	312	3840
QRD-M $\left(M = \frac{1}{2}K\right)$	216	2592
Proposed $(\alpha = 0.9995)$	116	758
Proposed $(\alpha = 0.999)$	110	609

TABLE II
NUMBER OF MULTIPLICATIONS FOR VARIOUS SCHEMES IN 4×4 CODED MIMO SYSTEMS

Code Rate	Schemes	4-QAM		16-QAM	
$R_c = \frac{1}{2}$	LSD	11dB	832	19dB	3432
	Proposed $(\alpha = 0.995)$		214		1846
	Proposed $(\alpha = 0.99)$		184		1317
$R_c = \frac{3}{4}$	LSD	13dB	533	21dB	2915
	Proposed $(\alpha = 0.9995)$		228		2665
	Proposed $(\alpha = 0.999)$		204		2047

the proposed scheme depends on the search set $\widehat{\mathcal{C}}_i$ analyzed in Section III-B. Thus we obtain the complexity of these two schemes by using computer simulations.

Table I represents the computational complexities of various MIMO detection schemes. In the table, SNR values are set to 18dB and 26dB for 4-QAM and 16-QAM, respectively, to achieve the BER of about 10^{-4} for uncoded systems. We exclude the complexity calculation of matrix inversion, QR decomposition, and the pre-processing part of the SD for simple comparisons. However, one should note that the arithmetic operations of the matrix inversion for implementing the proposed scheme are simpler than the QR decomposition, which needs an iterative procedure [27]. Also there exists a method to obtain an MMSE filter without carrying out actual matrix inversion [28]. Besides, the pre-processing for the SD demands high complexity since the SD requires the computation of interference-canceled MMSE filter vectors and the knowledge of the corresponding signal to interference plus noise ratio (SINR) values for each data stream [21].

It is clear from the table that the proposed scheme requires much less complexity compared with conventional near-ML detection schemes. If we set α to 0.9995 in 4-QAM, the reduction in real multiplications is 72% compared to the QRD-M with $M = 4$. Also in 16-QAM, 85% of the real multiplications can be saved compared to the QRD-M with $M = 16$. The comparison with the SD also indicates that the proposed scheme is more efficient in terms of complexity. Note that the complexity of the proposed algorithm can be further reduced by lowering α to a smaller value at the expense of a small performance loss.

Now we address the computational complexity of the proposed scheme in coded systems. The optimal LLR value is obtained by exhaustive search. Note that this optimal LLR value generation does not incur additional computational complexity compared to the uncoded ML detector in (2). An alternative way of generating soft output is introduced in [11] based on the QRD-M. However, it will be shown in the simulation section that this QRD-M based scheme requires much more search candidates to derive reliable LLR values. For the coded SD, the list sphere decoding (LSD) in [13] is considered. We set the search radius of the LSD properly to attain the near-optimal performance. For the LSD, the parameter N_{cand}, which denotes the maximum number of symbol vectors considered in generating the LLR values, is chosen as 32 for 4-QAM and 128 for 16-QAM in order to generate reliable LLR values.

The complexity of both the proposed scheme and the LSD are presented in Table II where the SNR values are determined to achieve the frame error rate (FER) of 10^{-2} for coded systems. Note that the QRD-M based scheme generates the LLR values with almost the same complexity as the QRD-M, regardless of the code rates and the SNR values, thus the results for the QRD-M based scheme are omitted in Table II. Although the complexity is increased for the coded case compared to uncoded results, the proposed scheme still shows a significant reduction in complexity compared to other soft-output schemes. By setting α to 0.995 for both 4-QAM and 16-QAM with $R_c = 1/2$, the proposed scheme leads to a reduction of 74% and 46% in the number of multiplications, respectively, compared to the LSD. Note that the complexity of the SD in uncoded systems is asymptotically subject to $O\left({N_t}^3\right)$ at high SNRs, regardless of the constellation size [29]. In contrast, for coded systems, the SD must keep a sufficiently large list of candidates to generate the LLR values, which makes the complexity of the LSD grow exponentially with N_t [13]. Simulation shows that with $\alpha = 0.99$, the proposed scheme still attains the near-optimal performance with further reduced complexity. When $R_c = 3/4$ is employed, the proposed scheme with $\alpha = 0.999$ achieves a reduction of 62% and 30% in multiplication counts compared to the LSD for 4-QAM and 16=QAM, respectively. Note that in low SNR regime, we observe a similar trend through simulations.

VI. SIMULATION RESULTS

In this section, we present extensive computer simulation results to compare the proposed scheme with conventional schemes. The simulations are carried out in a MIMO system with $N_t = N_r = 4$ where flat fading channels are assumed. For the QRD-M algorithm, we set the parameter M to K, $\frac{3}{4}K$ and $\frac{1}{2}K$.

Figures 4 and 5 illustrate the performance of various schemes for 4-QAM and 16-QAM, respectively, in uncoded systems. Unlike the conventional SD, the MMSE based SD does not yield the optimal ML performance even if the SD has an infinite radius [21]. However, the performance degradation is very small and thus we exhibit the MMSE based SD as a reference of the optimal performance. By setting $\alpha = 0.9995$, the proposed detection algorithm shows the performance almost identical to the SD at a BER of 10^{-4}. Although the QRD-M with $M = K$ achieves the same performance as the proposed scheme, our scheme is substantially simpler. When lowering α to 0.999, we can see that a performance loss is negligible, whereas the performance of the QRD-M schemes with $M = \frac{3}{4}K$ and $\frac{1}{2}K$ is significantly degraded. The performance loss of $\alpha = 0.999$ slightly grows in 16-QAM.

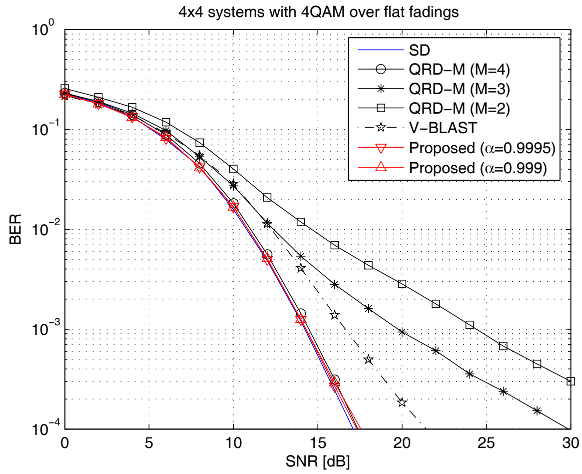

Fig. 4. BER of uncoded detection schemes in a 4×4 system with 4-QAM.

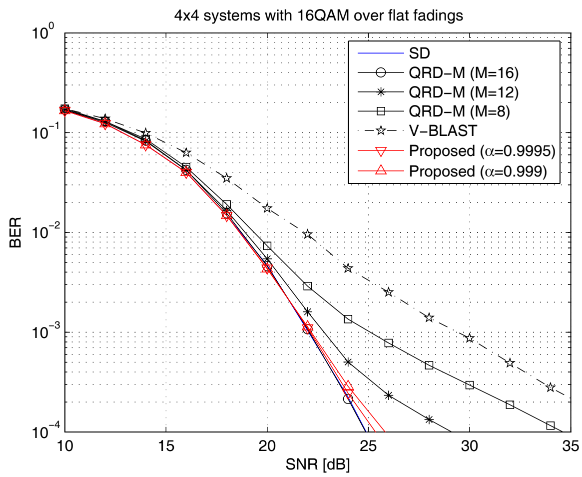

Fig. 5. BER of uncoded detection schemes in a 4×4 system with 16-QAM.

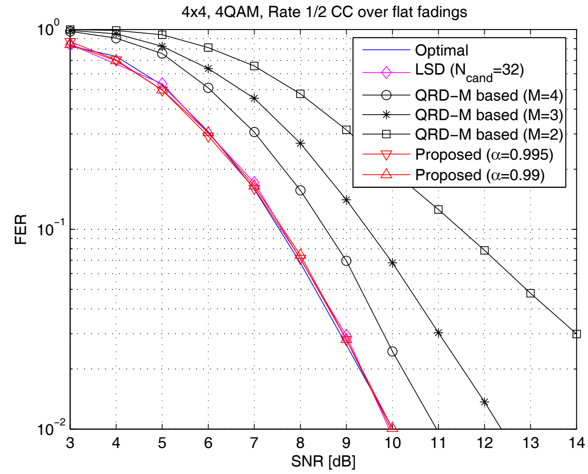

Fig. 6. FER of coded schemes in a 4×4 system with $R_c = 1/2$ and 4-QAM.

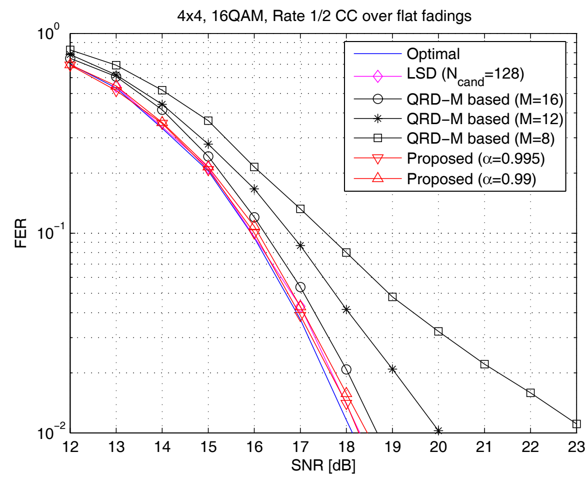

Fig. 7. FER of coded schemes in a 4×4 system with $R_c = 1/2$ and 16-QAM.

Now we examine the performance of various schemes for coded MIMO systems. We employ a convolutional encoder with polynomials (133,171) in octal notation of rate $R_c = 1/2$, where the code of rate $3/4$ is obtained by using the puncturing pattern in [30]. The frame length is set to 64 in all simulations. Also the parameters for both the QRD-M and the SD based soft-output schemes are optimized through computer simulations. Figures 6 and 7 depict the FER plot of coded systems for 4-QAM and 16-QAM, respectively, with $R_c = 1/2$. From the figures, we verify that the proposed scheme with $\alpha = 0.995$ shows the identical performance compared with the optimal exhaustive scheme at a FER of 10^{-2}. Even if we lower α to 0.99 for obtaining the reduced complexity, the proposed scheme still maintains the optimal performance in 4-QAM. In 16-QAM, a performance loss of the proposed scheme with $\alpha = 0.99$ is only a few tenth of a dB. The QRD-M based scheme with $M = K$ shows a loss of 1dB and 0.5dB for 4-QAM and 16-QAM, respectively, compared with the optimal scheme, and the performance degrades as M becomes smaller. We also confirm that the LSD exhibits the near-optimal performance. However the complexity is significantly larger than the proposed scheme as noted in Section V.

In Figures 8 and 9, we examine the performance of coded systems with $R_c = 3/4$. Again the proposed method with $\alpha = 0.9995$ shows almost the same performance as the optimal method at a FER of 10^{-2}. The proposed scheme outperforms the QRD-M based scheme with $M = K$ by about 0.5dB for 4-QAM with much reduced complexity. Although the QRD-M based method approaches the performance of the proposed scheme for 16-QAM, the complexity of our scheme is substantially lower. In addition, setting $\alpha = 0.999$ maintains the performance almost identical to the optimal scheme with much lower complexity.

As a final simulation, we address the effect of the fixed complexity on our proposed scheme. Although the reduced vector set $\mathcal{D}$ in (19) usually contains a small number of the reliable search candidates in average, occasionally there might exist channel realizations which require a large number of candidates. Figure 10 will illustrate that fixing the number of candidates in the set $\mathcal{D}$ causes only a small loss. By exploiting

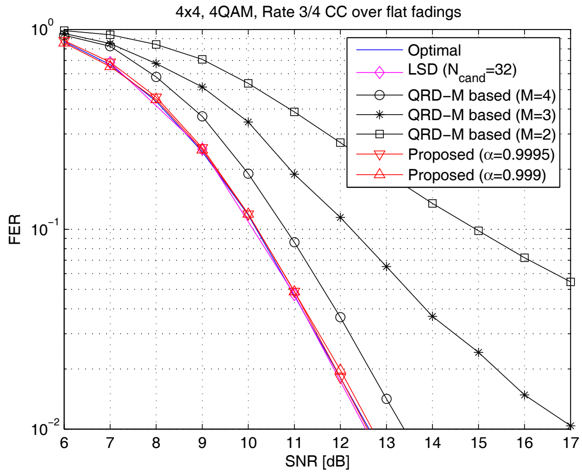

Fig. 8. FER of coded schemes in a 4×4 system with $R_c = 3/4$ and 4-QAM.

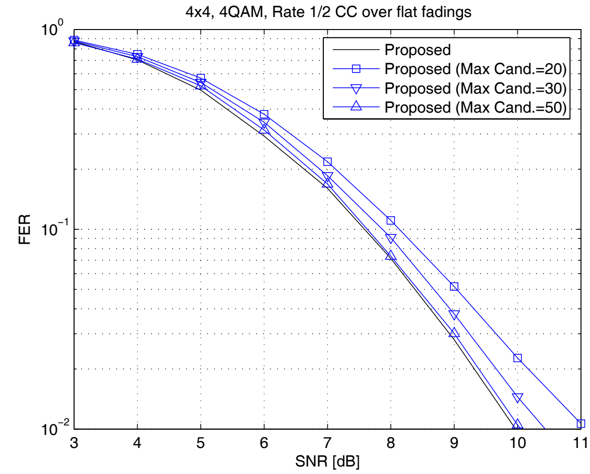

Fig. 10. FER of the proposed scheme with the fixed number of candidates in a 4×4 system.

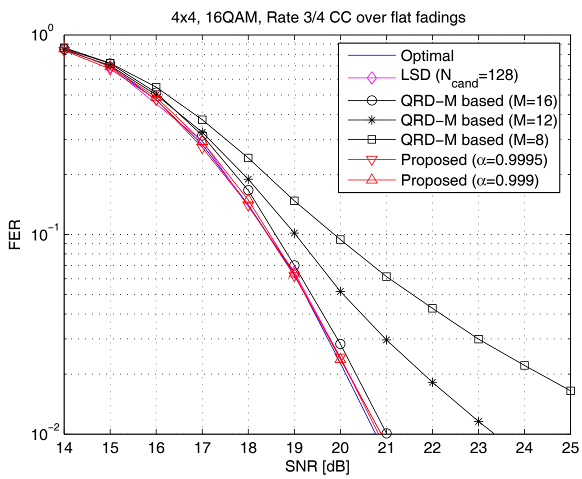

Fig. 9. FER of coded schemes in a 4×4 system with $R_c = 3/4$ and 16-QAM.

the normalized probabilities obtained in (9), we can choose the fixed number of candidates from the set $\mathcal{D}$, and this can be beneficial in actual implementation. Figure 10 exhibits the performance of our scheme with different candidate numbers in the set set $\mathcal{D}$ with 4-QAM and $R_c = 1/2$. Without restriction, $K^{N_t} = 256$ candidates are necessary for the worst case. When we limit this number to 20, only a 1dB loss is observed. Also, the performance loss is negligible when the maximum of 50 candidates is allowed. Thus we confirm that the proposed scheme can be applied with fixed complexity, which is important for practical implementation.

VII. Conclusions

In this paper, we have presented a new low-complexity ML detection scheme for multiple antenna systems. By utilizing the MMSE criterion, reliable symbol candidates are selected in each data stream based on their conditional probabilities. We also analyze the outage probability of the reduced candidate set $\widehat{\mathcal{C}}_i$ for our proposed scheme. The threshold parameter α is introduced to balance the tradeoff between the performance and the complexity. Compared to other conventional near-ML detection algorithms, the complexity of the proposed scheme is substantially smaller with limited search candidates. Simulation results indicate that the proposed scheme achieves the near optimal performance. The proposed method requires only 28% and 15% of real multiplications at a BER of 10^{-4} compared to the QRD-M in 4-QAM and 16-QAM, respectively. Also we identify that the proposed scheme shows its efficiency in terms of the complexity compared to the SD.

In addition, we have proposed an efficient way of generating the LLR values for coded systems from limited candidates with reduced complexity. In rate-1/2 convolutional coded systems for 4-QAM and 16-QAM, only 52% and 36% of real multiplications, respectively, are required for the proposed method to achieve the optimal performance at a FER of 10^{-2} compared to the QRD-M based soft-output scheme. Also our scheme exhibits a significantly low complexity compared to the LSD. Besides, we verify our proposed scheme attains its performance even when the fixed number of candidates is used. The simulation results show that the choice of α is relatively robust for various system configurations and modulation sizes. Therefore, the proposed scheme is a good choice for efficient MIMO detection methods for both uncoded and coded systems.

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