

A computationally efficient detector for MIMO systems

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ABSTRACT

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1. INTRODUCTION

In the last decade, cooperative and *multiple-input multiple-output* (MIMO) techniques have been extensively studied as their improvements in performance do not require additional power or frequency spectrum [1–13]. In this work, the performance of existing linear and nonlinear decoders [2, 14–20] for MIMO systems is compared with the newly proposed decoder that is particularly suitable for implementation on software-defined-radio architectures. The maximum likelihood (ML) decoder is the optimal detector for MIMO systems [2, 15]. In this decoder, a search over all possible combination of transmitted symbol vectors is performed. The ML detection proves to be optimal, however, at the cost of high complexity which increases exponentially with the increase of the modulation size and the number of transmit antennas [15, 16]. On the other hand, linear detectors such as the zero forcing (ZF) and minimum mean squared error (MMSE) detectors are the simplest and widely used detectors with reasonably lower bit error rate (BER) performances at very low computational complexity [2, 4, 17, 18]. Correspondingly, the vertical Bell laboratories layered space-time (V-BLAST) technique uses an iterative detector that implements the concept of successive interference cancellation (SIC) to find a good trade-off between complexity and performance [2, 18–20]. SIC decoder can be further improved by incorporating appropriate ordering of the symbols, i.e., first decoding the symbols that exhibit small estimation error before detecting the weaker symbols.

In this work, we are interested in implementing, developing and evaluating a MIMO detector that provides the optimal trade-off between the decoding complexity and BER performance as compared to the state of the art detectors. Therefore, we introduce a new MIMO decoding technique which i) enjoys a good complexity-performance trade-off, ii) allows fully parameterizable performance configuration, in the sense that, the performance of the MIMO detector can be adaptively adjusted without the requirement of changing the

implementation, iii) enjoys simple implementation and fully supports massive parallel processing, iv) exhibits a fixed complexity, i.e., unlike the popular sphere decoder, the decoding complexity is deterministic and does not depend on the particular realizations of fading or noise environments, and v) allows natural extension to soft-bit decoding required for modern channel decoders.

2. SYSTEM MODEL

Let us consider a MIMO system with nTx transmit and nRx receive antennas as illustrated in Figure 1 and assume frequency non-selective flat fading channels. If a signal vector \mathbf{x} is sent from the transmit antenna array where symbol x_j emitted from the j th transmit antenna and y_i is received by the i th antenna, then the signal at the receive antennas can be expressed as

$$\mathbf{y} = \mathbf{H} \mathbf{x} + \mathbf{n} \quad (1)$$

where $\mathbf{y} = [y_1, y_2, \dots, y_{nRx}]^T$, $\mathbf{x} = [x_1, x_2, \dots, x_{nTx}]^T$, $\mathbf{n} = [n_1, n_2, \dots, n_{nRx}]^T$, and \mathbf{H} denotes the MIMO channel matrix which describes the input-output relation. In this representation, \mathbf{n} denotes the noise vector which is modeled as independent, zero-mean, complex Gaussian random variables with unit variance.

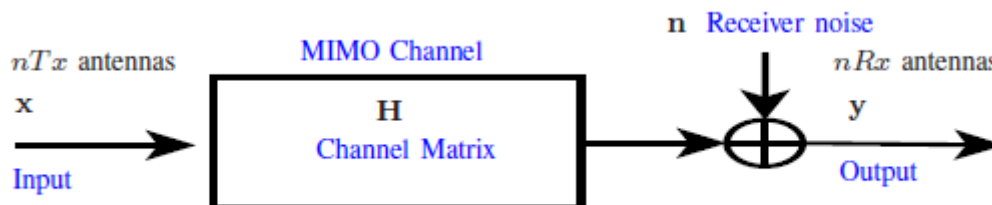


Figure 1. System model of MIMO channel

Let \mathbf{H} be a $nRx \times nTx$ matrix ($nRx \geq nTx$) with $\text{rank}(\mathbf{H}) = nTx$. \mathbf{H} can be decomposed into the QR decomposition, such that

$$\mathbf{H} = \mathbf{Q}\mathbf{R} \quad (2)$$

where \mathbf{Q} is an $nRx \times nRx$ unitary matrix, \mathbf{R} is an $(nRx \times nTx)$ upper triangular matrix, and \mathbf{I}_{nTx} is an $(nTx \times nTx)$ identity matrix. Making use of the QR decomposition, we can transform the channel model (1) into an equivalent triangular channel, such that

$$\tilde{\mathbf{y}} = \mathbf{Q}^H \mathbf{y} = \mathbf{Q}^H (\mathbf{H} \mathbf{x} + \mathbf{n}) = \mathbf{R} \mathbf{x} + \tilde{\mathbf{n}} \quad (3)$$

where $\tilde{\mathbf{n}} = \mathbf{Q}^H \mathbf{n}$. After preprocessing the received data, model (3) becomes in a triangularized form.

3. THE PROPOSED RANDOMIZATION BASED MMSE DECODER

In this section, let us introduce a new MIMO decoding algorithm where this algorithm carries out the following steps:

3.1. Step 1: Preprocessing (Nulling/Channel equalization)

Nulling, i.e. channel equalization, is used to remove the channel effect from the received signal vector. This process is performed using MMSE channel matrix inversion. The linear receiver \mathbf{W}_{MMSE} is computed to minimize the mean squared error (MSE) [2] of the received signal, given by

$$f_{\text{MMSE}}(\mathbf{x}) = \mathbf{E} \left\{ (\mathbf{W}_{\text{MMSE}} \mathbf{y} - \mathbf{x}) (\mathbf{W}_{\text{MMSE}} \mathbf{y} - \mathbf{x})^H \right\} \quad (4)$$

where $\mathbf{E} \{ \cdot \}$ denotes statistical expectation. Therefore, the equalization matrix \mathbf{W}_{MMSE} corresponding to the MMSE decoder is expressed as

$$\mathbf{W}_{\text{MMSE}} = (\mathbf{H}^H \mathbf{H} + \sigma^2 \mathbf{I})^{-1} \mathbf{H}^H \quad (5)$$

where \mathbf{I} denotes the identity matrix. According to the principle of linear receivers, \mathbf{W}_{MMSE} given in (5) is multiplied by \mathbf{y} given in (1) to reconstruct the symbol vector \mathbf{x} by removing the channel effect and suppressing noise enhancement, such that $\hat{\mathbf{x}}_{\text{MMSE}} = \mathbf{W}_{\text{MMSE}}\mathbf{y}$. For convenience of representation and for our derivations in the following, the MMSE decoder can be formulated in another form. Making use of QR decomposition explained in Sec. 2., $\bar{\mathbf{H}}$ can be expressed as

$$\bar{\mathbf{H}} = \begin{bmatrix} \mathbf{H} \\ \sigma\mathbf{I} \end{bmatrix} = \begin{bmatrix} \mathbf{Q}_1 \\ \mathbf{Q}_2 \end{bmatrix} \bar{\mathbf{R}} = \bar{\mathbf{Q}} \bar{\mathbf{R}} \quad (6)$$

where the partitioning is such that $\bar{\mathbf{Q}} = \mathbb{C}^{2nR_x \times nT_x}$, $\mathbf{Q}_1 = \mathbb{C}_1^{nR_x \times nT_x}$, $\mathbf{Q}_2 = \mathbb{C}_2^{nR_x \times nT_x}$ and $\bar{\mathbf{R}} = \mathbb{C}^{nT_x \times nT_x}$. Considering (6), the equalization matrix \mathbf{W}_{MMSE} corresponding to \mathbf{y} in (1) can be expressed as

$$\begin{aligned} \mathbf{W}_{\text{MMSE}} &= (\bar{\mathbf{H}}^H \bar{\mathbf{H}})^{-1} \bar{\mathbf{H}}^H = (\mathbf{H}^H \mathbf{H} + \sigma^2 \mathbf{I})^{-1} \mathbf{H}^H \\ &= (\bar{\mathbf{R}}^H \bar{\mathbf{R}})^{-1} \bar{\mathbf{R}}^H \mathbf{Q}_1^H = \bar{\mathbf{R}}^{-1} \mathbf{Q}_1^H \end{aligned} \quad (7)$$

where $\bar{\mathbf{H}}$ is given in (6). Making use of the equalization matrix (7), the soft-decoded symbol after MMSE decoding becomes

$$\hat{\mathbf{x}}_{\text{MMSE}} = \mathbf{W}_{\text{MMSE}} \mathbf{y} = \mathbf{x} + \bar{\mathbf{R}}^{-1} \mathbf{Q}_1^H \mathbf{n} = \mathbf{x} + \mathbf{e} \quad (8)$$

where \mathbf{x} denotes the true transmitted symbol vector and the estimation error vector $\mathbf{e} = \hat{\mathbf{x}} - \mathbf{x}$ is Gaussian distributed with zero mean and error covariance matrix given by

$$\mathbf{E} \{ \mathbf{e} \mathbf{e}^H \} = \sigma^2 (\mathbf{H}^H \mathbf{H} + \sigma^2 \mathbf{I})^{-1} = \sigma^2 (\bar{\mathbf{R}}^H \bar{\mathbf{R}})^{-1}. \quad (9)$$

This step is carried out only once and before the randomization is started.

3.2. Step 2: Generating random vector

In this step, the decoder generates a number of instances of a random vector \mathbf{e}_k , $\{k = 1, \dots, No_rand\}$ with mean and variance equal to those of the estimation error \mathbf{e} in (9), i.e., $\mathbf{e}_k \in \mathcal{N}(\mathbf{0}, \sigma^2 (\bar{\mathbf{R}}^H \bar{\mathbf{R}})^{-1})$ where No_rand is the number of generated random vectors and \mathbf{e}_k denotes the k th generated random vector. From $\{\mathbf{e}_k\}_{k=1}^{No_rand}$, a corresponding set for random vectors is computed according to

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_{\text{MMSE}} + \mathbf{e}_k \quad \text{for } k = 1, \dots, No_rand \quad (10)$$

Note that generating more instances of a random vector \mathbf{e}_k will increase the probability to have one of them as close as possible to the optimal one. By doing this, the overall BER performance will improve.

3.3. Step 3: Hard decoding

In this step, the decoder converts for $k = 1, \dots, No_rand$ the soft decoded randomized symbol vector $\hat{\mathbf{x}}_k$ generating according to (10) to hard decoded symbol vector $\tilde{\mathbf{x}}_k$ by finding the nearest constellation point for each soft decoded symbol as shown in Figure 2. Note that this is a symbol by symbol processing step performed using the round operation with almost no additional computational complexity.

3.4. Step 4: Selection

In this step, the decoder selects among the hard decoded symbol vector $\tilde{\mathbf{x}}_k$ for $k = 1, \dots, No_rand$ the vector $\mathbf{x}^{\text{prop.}}$ that maximizes the ML metric, such as

$$\mathbf{x}^{\text{prop.}} = \arg \min_{\tilde{\mathbf{x}}_1, \dots, \tilde{\mathbf{x}}_{No_rand}} \|\tilde{\mathbf{y}} - \bar{\mathbf{R}}\mathbf{x}\|^2. \quad (11)$$

The above described main procedure in Steps 2-3 can be efficiently implemented using either an iterative or a parallelized implementation as shown in Figure 2. The estimate of a symbol obtained by using MMSE filter has a bias or mean and variance. The randomization algorithm says that there is a high probability to get closer to the actual symbol by searching randomly for a symbol set having same mean as our estimated symbol set and within the limits of the variance circle. By doing this, a better estimate of symbols can be

found. It is clear that we can improve the performance of the decoder by increasing the number of randomization instances, i.e., the value of No_{rand} . This, however, comes at the expense of increased decoding complexity. Therefore, the performance (or complexity) of this decoder can be adaptively adjusted by changing the number of randomization instances without the requirement of changing the structure of the implementation, i.e., the performance to complexity trade-off can be adjusted using system parameter No_{rand} . Furthermore, the proposed algorithm enjoys simple implementation based on the widely used MMSE technique. The proposed algorithm offers a fixed decoding complexity that does not depend on the quality of the received signal vector y .

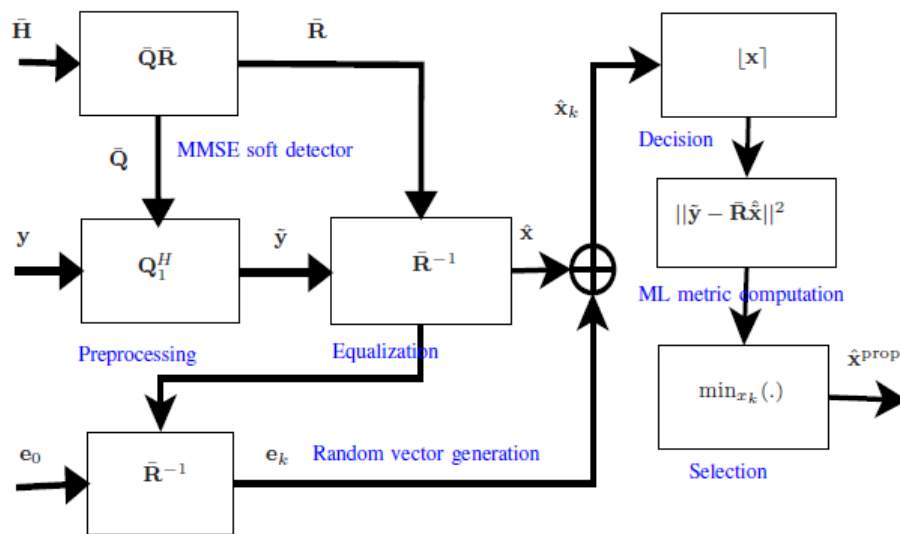


Figure 2. Block diagram of the proposed decoder

4. SIMULATION RESULTS

In the simulations, let us consider MIMO systems with independent flat Rayleigh fading channels and either four transmit and four receive antennas, eight transmit and eight receive antennas, or 20 transmit and 20 receive antennas. All MIMO detectors using 4-QAM, 16-QAM, and 64-QAM constellations are compared. In the proposed decoder, the symbols can also be drawn from any M-PSK constellation. In all illustrated figures, it can be observed that the ZF decoder exhibits the worst performance, however, with linear decoding complexity. On the other hand, the curves which enjoy the optimal decoding performance in any of the figures represent the sphere decoder or ML decoder, however, ML decoder suffers from extremely high (exponential) decoding complexity. Any other decoder has a performance and decoding complexity between that of the ML and the ZF decoder. In the following figures, ZF, MMSE, SIC, SD, ML, K, and $Rand = L$ denote the ZF decoder, MMSE decoder, SIC decoder, sphere decoder, ML decoder, K-best decoder with $K^{n_{Tx}}$ iterations and the proposed decoder using randomization technique with L iterations. From the figures, it is observed that i) the decoders using MMSE outperform those using ZF due to their robustness with respect to noise enhancement as compared to the ZF decoders, ii) the ML decoder enjoys optimal performance at the cost of very high decoding complexity, iii) the proposed decoder can improve the complexity-performance trade-off where it keeps the complexity considerably lower than that of the ML detectors with almost optimal performance, and iv) the sphere decoder which enjoys the optimal performance does not have a fixed complexity and in specific cases the complexity may be as large as the complexity of the ML decoder, however, some sub-optimal sphere decoders enjoy fixed decoding complexity, e.g., K-best decoder with suboptimal performance as shown in Figure 3 [20].

5. COMPLEXITY-PERFORMANCE TRADE-OFF

From Figures 3, 4, 5 and 6, both, sphere decoder and ML decoder are optimal and have exactly the same BER performance and the proposed decoder using only 10 iterations outperforms the suboptimal decoders, i.e., ZF, MMSE, and SIC with and without ordering using ZF or MMSE. We emphasize that, in the proposed randomization based decoder, the nulling step, i.e., the matrix inversion step using QR-decomposition, is carried out only once and before the randomization is started as discussed in Sec. 3., while SIC decoder performs the same step every layer [2]. In all investigated decoders, i.e., ZF decoder, MMSE decoder, ML decoder, sphere decoder, SIC decoder, K-best decoder and the proposed randomization based decoder, the QR decomposition stage described in Sec. 2. requires $\mathcal{O}((nTx - i)^3)$ operations. Once the QR decomposition of \mathbf{H} is obtained, the remainder stages in the SIC decoder at the i th layer, the ZF/MMSE decoder, the ML decoder, K-best decoder, and the proposed decoder require $\mathcal{O}((nTx - i)^2)$ operations, $\mathcal{O}((nTx)^2)$ operations, $\mathcal{O}((nTx)^{2.38})M^{nTx}$ operations, $\mathcal{O}((nTx)^{2.38})K^{nTx} + nTx \times \mathcal{O}((nTx)^2)$ operations, and $\mathcal{O}((nTx)^{2.38})No_rand + \mathcal{O}((nTx)^3)$ operations, respectively, as shown in Table 1. Note that, in the proposed decoder, computing the inverse of the channel matrix, i.e., $\mathbf{H}^{-1} = \mathbf{R}^{-1}\mathbf{Q}^H$, requires $\mathcal{O}((nTx)^3)$ after obtaining the QR decomposition of \mathbf{H} .

From Figure 3, it is observed that the BER performance of the proposed decoder with $No_rand = 50$ iterations enjoys the same performance of K -best decoder with $K^4 = 10^4$ iterations. Clearly, the performance of the proposed decoder outperforms K -best decoder at the same decoding complexity where K -best detection algorithm suffers from two main problems which are the expansion and the sorting operations. K -best algorithm expands each K retained paths to its K possible children at each level. The previous step requires sorting the children in each layer before selecting the best K paths. Therefore, its decoding complexity increases exponentially with the increase of the value K where a high decoding complexity is required to enumerate the children nodes especially in the case of large number of transmit antennas and high constellation sizes as shown in Table I, while the complexity of the proposed decoder increases linearly with the value of No_rand . It can be observed from Figures 3, 4, 5 and Table 2 that the proposed decoder using only 200 iterations achieves almost the same performance as the optimal ML decoder which requires $64^4 = 16777216$ iterations. From Table 1, it is observed for low constellation sizes, that the complexity of the proposed decoder is similar to that of the costly ML decoder. This is also the case if $No_rand = M^{nTx}$. However, the value exponential growth of M^{nTx} with the increase of the number of transmit antennas and the constellation size is generally much larger than the corresponding growth rate of No_rand required to achieve similar performance. Particularly for a large constellation size and a large number of transmit antennas as, e.g., in the case 64-QAM constellations and $nTx = 4$ transmit antennas as shown in Table 2, the performance of the proposed decoder using only $No_rand = 200$ iterations enjoys similar performance as the optimal ML decoder.

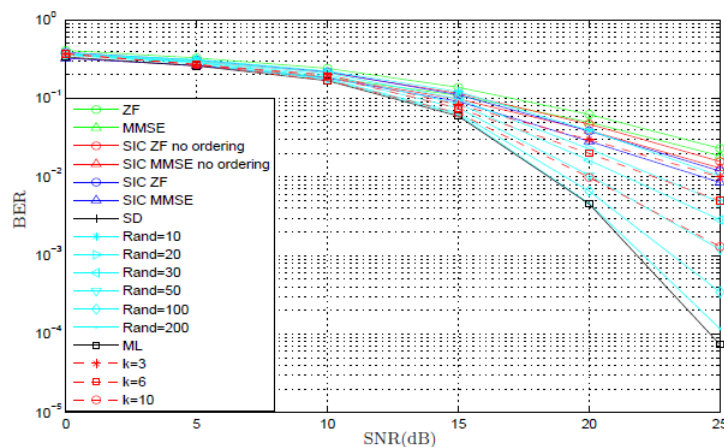


Figure 3. Performance comparison of different decoding schemes using 4×4 system and 16-QAM constellation

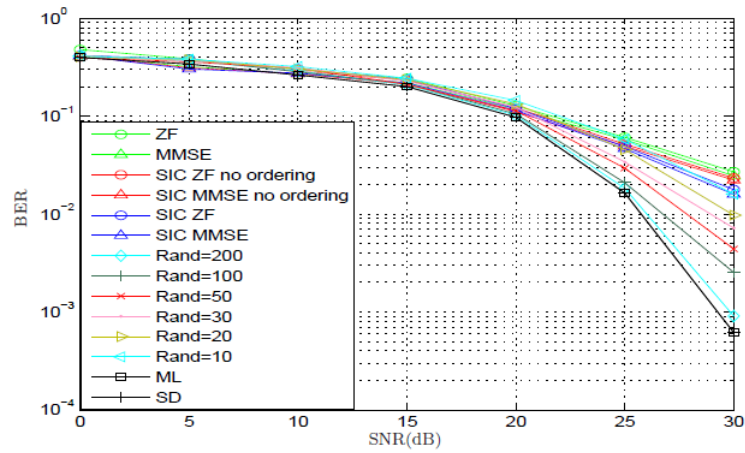


Figure 4. Performance comparison of different decoding schemes using 4×4 system and 64-QAM constellation

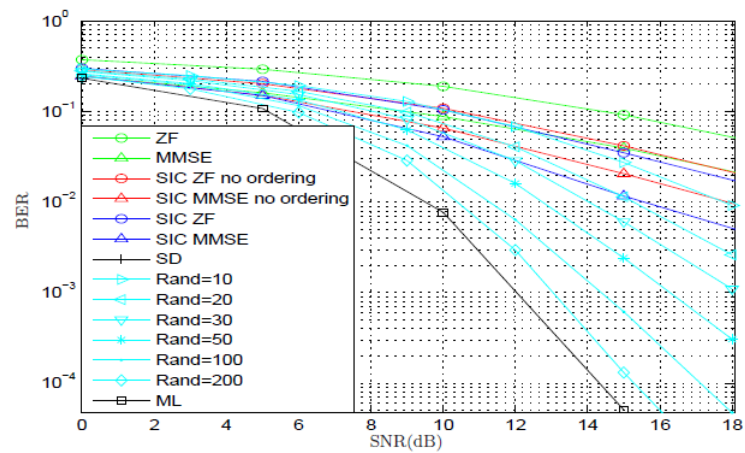


Figure 5. Performance comparison of different decoding schemes using 8×8 system and 4-QAM constellation

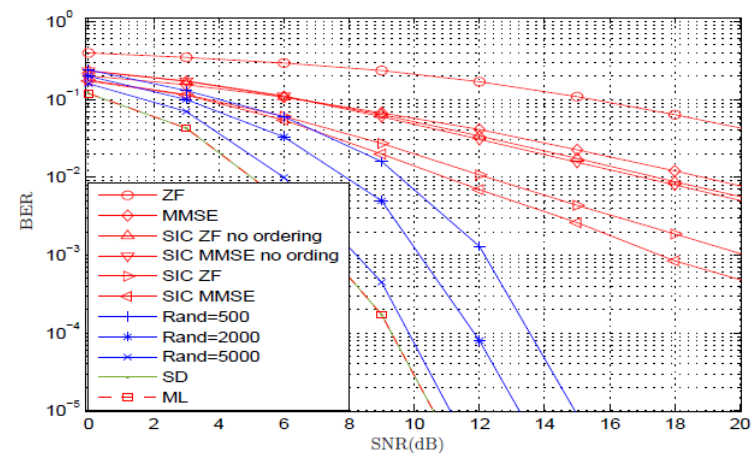


Figure 6. Performance comparison of different decoding schemes using 4-QAM constellation and 20×20 system

Table 1. Coding complexity of the investigated MIMO detectors

	ZF or MMSE decoder	SIC decoder	ML decoder	K-best decoder	The proposed decoder
Decoding	$\mathcal{O}\left(\binom{nTx}{+}^3\right)$	$\mathcal{O}\left(\binom{nTx}{+}^3\right)$	$\mathcal{O}\left(\binom{nTx}{+}^{2.38}\right) \times M^{(nTx)}$	$\mathcal{O}\left(\binom{nTx}{+}^{2.38}\right) \times K^{nTx}$	$\mathcal{O}\left(\binom{nTx}{+}^{2.38}\right) \times No_rand$
complexity	$\mathcal{O}\left(\binom{nTx}{+}^2\right)$	$\sum_{i=0}^{nTx-1} \mathcal{O}\left(\binom{nTx-i}{+}^2\right)$	$\mathcal{O}\left(\binom{nTx}{+}^3\right)$	$\sum_{i=0}^{nTx-1} \mathcal{O}\left(\binom{nTx-i}{+}^2\right)$ + $\mathcal{O}\left(\binom{nTx}{+}^3\right)$	$2\mathcal{O}\left(\binom{nTx}{+}^3\right)$

Table 2. Comparison of the relative decoding complexity of the proposed decoder with respect to the ML decoder

Scenario	Number of iterations <i>No_rand</i>	Relative complexity of the proposed decoder w.r.t. the ML decoder
(4×4) MIMO with 16-QAM	200	0.3052 %
(4×4) MIMO with 64-QAM	200	0.0012 %
(8×8) MIMO with 4-QAM	200	0.3052 %
(20×20) MIMO with 4-QAM	5000	4.5×10^{-7} %

6. EFFECT OF NOISE VARIANCE

In this section, let us compare the robustness of the proposed decoder with respect to a mismatch between the true and the noise variance at the receiver. In the simulations, let us consider a MIMO system with four transmit and four receive antennas and a true noise variance of 0-dB. We assume that the SNR at the receiver amounts to $SNR = P_t/\sigma^2 = 12dB$ in Figure 7 and $SNR = P_t/\sigma^2 = 17dB$ in Figure 8, and the estimated (presumed) SNR at the receiver side is varied between 0-dB to 20-dB. From Figures 7 and 8, it is observed that for a number of randomization instances exceeding $N_rand = 20$ the performance of the proposed algorithm in terms of BER remains approximately constant as the estimated receive SNR is varied across the entire range considered in the simulations. This shows that the proposed algorithm is fairly robust with respect to a mismatch in the noise variance or SNR estimation. This is due to the idea of the proposed decoder which depends on generating random vectors. These random vectors could be far away from the optimal one, however, there is a high probability that some of them will lie very close to it even if the variance of the noise is changed.

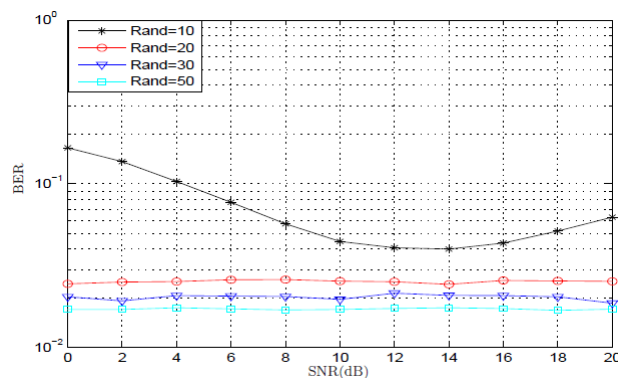


Figure 7. Robustness of the proposed decoder to a mismatch between the true SNR value ($P_t/\sigma^2 = 12dB$) and the presumed SNR value in a 4×4 system using 4-QAM

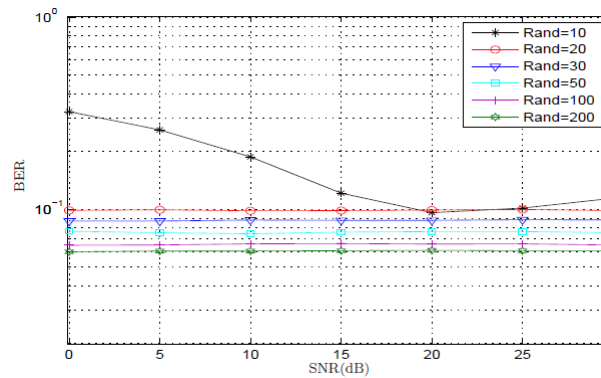


Figure 8. Robustness of the proposed decoder to a mismatch between the true SNR value ($P_t/\sigma^2 = 17dB$) and the presumed SNR value in a 4×4 system using 16-QAM

7. CONCLUSION

The proposed decoder appears to find the optimal compromise between competing interests encountered in the implementation of advanced MIMO detectors in practical hardware systems. The proposed detector exhibits a number of desirable properties such as: i) deterministic latency where the proposed decoder exhibits configurable and fully deterministic decoding complexity, which offers the benefit of a fixed decoding complexity, ii) full parameterizable performance/complexity tradeoff where the modification of the number of randomization instances used in the proposed decoder allows to balance at runtime the tradeoff between performance and computational complexity, iii) simple implementation where the proposed algorithm enjoys simple implementation with a minimum requirement of control structures and the proposed detector allows a high degree of parallelization, iv) extension to soft-bit output where the proposed decoder can naturally be extended to create soft-bit outputs as required in modern cellular communication standards.

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BIOGRAPHY OF AUTHORS



Samer Alabed Samer Alabed joined American University of the Middle East as an assistant professor of electrical engineering in 2015. He received his PhD degree in electrical engineering and information technology with great honor ("magna cum laude"), from Darmstadt University of Technology, Darmstadt, Germany and his Bachelor and Master degree with great honor. During the last 16 years, he has served as an assistant professor, (post-doctoral) researcher, teaching assistant, and lecturer in several universities in Germany and Middle East and supervised tens of master theses and several PhD students. Dr. Alabed received several awards from IEE, IEEE, DAAD ... etc., where the last one was the best paper award from the International IEEE WSA in March, 2015. Dr. Alabed has worked as a researcher in several universities and companies and was invited to many conferences and workshops in Europe, US, and North Africa. The main idea of his research is to develop advanced DSP algorithms in the area of wireless communication systems and networks including (Massive) MIMO systems, distributed systems, co-operative communications, relay networks, space-time block and trellis coding, differential and blind multi-antenna techniques, MIMO channel estimation, MIMO decoders, channel coding and modulation techniques, distributed communication systems, two-way relaying, baseband communications, multi-carrier transmission (OFDM), modeling of wireless channel characteristics, adaptive beamforming, sensor array processing, transceiver design, multi-user and multi-carrier wireless communication systems, convex optimization algorithms for signal processing communications, channel equalization, and other kinds of distortion and interference mitigation. Further information on his homepage: <http://drsamerlabed.wixsite.com/samer>