

MIMO Detectors Under Correlated Channels

Detectores MIMO em Canais Correlacionados

Bruno Felipe Costa¹; Alex Miyamoto Mussi²; Taufik Abrão³

Abstract

This contribution analyses the performance of multiple-input multiple-output (MIMO) detectors under correlated fading channels. Two MIMO detection principles, namely minimum mean squared error (MMSE) detector – with and without ordered successive interference cancellation (OSIC) procedure – and the lattice reduction (LR) technique, are analyzed and compared with the maximum likelihood (ML) limit under specific scenarios of interest, namely (a) increasing spectral efficiency configuration, by increasing number of antennas; (b) increasing correlated fading channel scenarios. In this context, the ML-MIMO detector performance is used as reference in order to compare how the bit-error-rate (BER) of those sub-optimal low complexity MIMO detectors are close to the optimum performance.

Keywords: Multiple-input-multiple-output (MIMO). Lattice reduction (LR). Minimum mean squared error (MMSE). Ordered successive interference cancellation (OSIC). Maximum likelihood (ML) detection.

Resumo

Este artigo analisa o desempenho de detectores com múltiplas antenas transmissoras e múltiplas antenas receptoras (MIMO – *multiple-input multiple-output*) em canais com desvanecimento correlacionados. Dois esquemas de detecção MIMO denominados erro quadrático médio mínimo (MMSE – *minimum mean squared error*) – com ou sem a etapa de cancelamento de interferência sucessiva ordenado (OSIC – *ordered successive interference cancellation*) – e técnica de redução treliça (LR – *lattice reduction*) são analisados e comparados com o limite de detecção de máxima verossimilhança (ML – *maximum likelihood*) em cenários específicos de interesse: (a) com incremento da eficiência espectral através do aumento do número de antenas. (b) quando há aumento nos índices de correlação de desvanecimento do canal. Neste contexto, o desempenho do detector ótimo ML-MIMO é utilizado como referência visando caracterizar o comportamento da taxa de erro de bit (BER) destes detectores MIMO e quão próximo esses estão do desempenho ML-MIMO.

Palavras-chave: Múltiplas antenas transmissoras e múltiplas antenas receptoras (MIMO). Redução treliça (LR). Mínimo erro quadrático médio (MMSE). Cancelamento de interferência sucessiva ordenado (OSIC). Detecção de máxima verossimilhança (ML).

¹ Aluno de IC e de Graduação do Departamento de Engenharia Elétrica, Universidade Estadual de Londrina - DEEL-UUEL; bruno.uel.felipe@gmail.com

² Aluno de Doutorado do Programad de Pós-Graduação em Engenharia Elétrica, Escola Politécnica da Universidade de São Paulo; alexmussi@gmail.com

³ Docente do Departamento de Engenharia Elétrica da Universidade Estadual e Londrina - DEEL-UUEL; taufik@uel.br

Introduction

Systems with multiple transmitting antennas and multiple receiving antennas (MIMO) present a remarkable spectral efficiency and/or are able to improve the performance and reliability of wireless communication by deploying multiples antennas at both transmitter and receiver side (FOSCHINI; GANS, 1998). In a spatial multiplexing gain configuration, parallel data streams are transmitted using multiple antennas in order to increase the spectral efficiency at increasing the cost of complexity for data detection at the receiver (WÜBBEN et al., 2011). The MIMO system suffers influences from many effects that can degrade the performance, and consequently reduce its capacity. The knowledge of the channel state information (CSI) is of paramount importance for acceptable system operation, and it can be used at the receiver, transmitter, or both sides, depending on the chosen MIMO architecture. Under realistic scenarios, the CSI cannot be perfectly estimated; therefore, the information available contains a certain amount of errors in which can be modeled by stochastic models. The impact of the imperfect CSI estimation over the MIMO precoder design and respective MIMO performance is investigated for instance in (ANDALIBI; NGUYEN; SALT, 2013).

One important effect to be considered in realistic MIMO scenarios is the channel correlation between antennas. Some important works have analyzed the capacity gain of MIMO systems assuming independent fading channel, which are in practice difficult to obtain due to the physical constraints of spacing between antennas. Among well-established MIMO detectors, the linear zero forcing (ZF) is known by completely cancel the interference between antennas (WÜBBEN et al., 2004), at the expense of increasing significantly the background noise for ill-conditioned channel matrix. At this point, the minimum mean squared error (MMSE) MIMO detector can be seen as a better alternative, since it takes into account the noise power during the symbol detection process. Besides, the successive

interference cancellation (SIC) detector performs the detection layer-by-layer, using either a ZF or MMSE strategy, and canceling the interference from the previously detected symbols (BÖHNKE et al., 2003). Since errors at the MIMO detection at the first layers can be propagated along the high layers of the algorithm, a remarkable improvement on performance can be achieved detecting the most reliable antennas first, which features the ordered SIC (OSIC) MIMO detectors (WÜBBEN et al., 2003). However, these linear sub-optimum MIMO detection techniques present a performance clearly inferior to the maximum likelihood (ML) MIMO detector. Hence the goal is to analyze promising near-optimum MIMO structures with noticeable improvement in the performance-complexity tradeoff.

Lattice Reduction Technique

Further improvement in MIMO performance-complexity tradeoff can be obtained with a pre-processing technique named lattice reduction (LR). Indeed, LR-aided MIMO detection can be deployed in order to achieve MIMO performance improvement while holds computational complexity manageable. The LR is a mathematical concept deployed to solve many problems involving lattice points. For instance, in the MIMO signal detection problem, the LR can be used to improve the channel matrix conditioning, thus allowing the use of simpler detector structures (WÜBBEN et al., 2011); in other words, less computational complexity is necessary to maintain acceptable performance (MOSTAGI; ABRÃO, 2012).

The main contribution of this work lies in providing a quantitative analysis of the impact on the MIMO system performance when lattice reduction technique is deployed to mitigate the effects of MIMO channel correlation. More precisely, LR technique is applied to improve the MIMO detector performance-complexity tradeoff under correlated channels constrains operating over generic QAM

modulation order M and number of antennas N . Both MMSE and LR-aided MMSE (with and without ordered SIC) detectors are analyzed taking into consideration (a) different levels of fading channels MIMO correlation, ρ ; (b) increasing number of transmit and receive antennas, N_t and N_r , respectively.

MIMO System Model

In this contribution we consider a complex baseband linear transmission system with non-line-of-sight (NLOS) and N_t inputs and N_r outputs corrupted by additive white Gaussian noise (AWGN). The mathematical model of the system under investigation is

$$\mathbf{y} = \mathbf{H}\mathbf{s} + \boldsymbol{\eta}, \quad (1)$$

where \mathbf{H} represents an instantaneous $N_r \times N_t$ fading channel coefficients matrix following a Rayleigh distribution representing a NLOS point-to-point communication, \mathbf{s} is a vector of data symbols and $\boldsymbol{\eta}$ is the independent white noise vector samples with Gaussian distribution.

Correlated MIMO Channels

One important class of MIMO channel model assumes that the correlation between the transmit antennas (Tx) is independent of the correlation among receive antennas (Rx); hence, admitting a MIMO channel Rayleigh flat-fading (ZELST; HAMMERSCHMIDT, 2002), one can express the fading coefficients matrix:

$$\mathbf{H} = \sqrt{\mathbf{R}_{H,Rx}} \mathbf{G} \sqrt{\mathbf{R}_{H,Tx}}, \quad (2)$$

where $\mathbf{G} \in \mathbb{C}^{N_r \times N_t}$ is an independent identically distributed (i.i.d.) complex Gaussian zero-mean unit variance elements. The correlation matrices $\mathbf{R}_{H,Tx} \in \mathbb{R}_{N_t \times N_t}$ and $\mathbf{R}_{H,Rx} \in \mathbb{R}_{N_r \times N_r}$ denote correlation observed among the transmitter antennas and receiver antennas, respectively. Assuming in this work that the Tx and Rx antennas are equally

separated, identical numbers of antennas and equal correlation matrix, results $\mathbf{R}_{H,Rx} = \mathbf{R}_{H,Tx} = \mathbf{R}_H$. Hence, the matrix \mathbf{R}_H , can be written as:

$$\mathbf{R}_H = \begin{bmatrix} 1 & \rho & \rho^4 & \dots & \rho^{(n_r-1)^2} \\ \rho & 1 & \rho & \dots & \vdots \\ \rho^4 & \rho & 1 & \dots & \rho^4 \\ \vdots & \vdots & \vdots & \ddots & \rho \\ \rho^{(n_r-1)^2} & \dots & \rho^4 & \rho & 1 \end{bmatrix} \quad (3)$$

where ρ is the normalized correlation index. Note that a totally uncorrelated scenario means, $\rho = 0$ while a fully correlated scenario implies $\rho = \pm 1$.

Conventional MIMO Detectors

In the sequel, a sort of classical MIMO detectors found in the literature are revisited, including the minimum mean squared error (MMSE) criterion, successive interference cancelation (SIC) method, QR decomposition, as well as lattice reduction (LR) aided detection.

MMSE MIMO Detection

In order to reduce the impact of fading and background noise, the MMSE detector employs a linear filter that can take into account the channel matrix and the noise. The MMSE filter can be found by minimizing the mean squared error (MSE) as discussed in (BAI.; CHOI., 2012):

$$\begin{aligned} \mathbf{W}_{\text{mmse}} &= \arg \min_{\mathbf{W}} \mathbb{E}[\|\mathbf{s} - \mathbf{W}^H \mathbf{y}\|^2] \\ \mathbf{W}_{\text{mmse}} &= \left(\mathbb{E}[\mathbf{y}\mathbf{y}^H] \right)^{-1} \mathbb{E}[\mathbf{y}\mathbf{s}^H] \\ \mathbf{W}_{\text{mmse}} &= \mathbf{H} \left(\mathbf{H}^H \mathbf{H} + \frac{N_0}{E_s} \mathbf{I} \right)^{-1} \end{aligned} \quad (4)$$

where $\mathbb{E}[\cdot]$ denotes the statistical expectation operator. The resulting estimated symbol vector can be written as:

$$\mathbf{s}_{\text{mmse}} = \mathbf{W}_{\text{mmse}}^H \mathbf{y} \quad (5)$$

MMSE-SIC MIMO Detection

Assuming that \mathbf{H} is square or tall, where $N_t \leq N_r$ and based on the QR factorization (see section 5.1.6.1 of (BAI.; CHOI., 2012)) of the channel matrix $\mathbf{H}=\mathbf{QR}$, the received signal \mathbf{y} is pre-processing by multiplying it by \mathbf{Q}^H :

$$\begin{aligned} \mathbf{x} &= \mathbf{Q}^H \mathbf{y} \\ \mathbf{x} &= \mathbf{R}\mathbf{s} + \mathbf{Q}^H \boldsymbol{\eta} \end{aligned} \quad (6)$$

where $\mathbf{Q}^H \boldsymbol{\eta}$ is a zero-mean complex Gaussian random vector. Since $\mathbf{Q}^H \boldsymbol{\eta}$ and $\boldsymbol{\eta}$ have the same statistical properties, $\boldsymbol{\eta}$ can be used to denote $\mathbf{Q}^H \boldsymbol{\eta}$.

Assuming initially a square \mathbf{H} matrix, we have from (6):

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_M \end{bmatrix} = \begin{bmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,M} \\ 0 & r_{2,2} & \cdots & r_{2,M} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & r_{M,M} \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_M \end{bmatrix} + \begin{bmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_M \end{bmatrix} \quad (7)$$

where the x_k and η_k denote the k th element of vector \mathbf{x} and $\boldsymbol{\eta}$, respectively. Thus, we have

$$\begin{aligned} x_M &= r_{M,M} s_M + \eta_M \\ x_{M-1} &= r_{M-1,M} s_M + r_{M-1,M-1} s_{M-1} + \eta_{M-1} \\ &\vdots \end{aligned} \quad (8)$$

Now assuming that matrix \mathbf{H} is tall ($N_t \leq N_r$), we have

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_M \\ x_{M+1} \\ \vdots \\ x_N \end{bmatrix} = \begin{bmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,M} \\ 0 & r_{2,2} & \cdots & r_{2,M} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & r_{M,M} \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_M \end{bmatrix} + \begin{bmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_M \\ \eta_{M+1} \\ \vdots \\ \eta_N \end{bmatrix} \quad (9)$$

From bottom to top, each algebraic equation from (9) results:

$$\begin{aligned} x_N &= \eta_N \\ &\vdots \\ x_{M+1} &= \eta_{M+1} \\ x_M &= r_{M,M} s_M + \eta_M \\ x_{M-1} &= r_{M-1,M} s_M + r_{M-1,M-1} s_{M-1} + \eta_{M-1} \\ &\vdots \end{aligned} \quad (10)$$

Since the received signals $\{x_{M+1}, x_{M+2}, \dots, x_N\}$ do not have any useful information, just noise, we can simply ignore them. Hence, provide the same detection information.

MIMO Detection with SIC

Firstly, $\tilde{\mathbf{s}}_M$ can be detected from x_M as follows. Let

$$\tilde{s}_M = \frac{x_M}{r_{M,M}} = s_M + \frac{\eta_M}{r_{M,M}} \quad (11)$$

Then, the contribution of \tilde{s}_M is to be canceled in detecting $\tilde{\mathbf{s}}_{M-1}$ from x_{M-1} . This sequential detection procedure is terminated till all the data symbols of m are detected. The m th symbol of \mathbf{s} , s_m can be detected after canceling $M-m$ data symbols as:

$$\mathbf{s}_m = x_m - \sum_{q=m+1}^M r_{m,q} \tilde{s}_q, \quad m \in \{1, 2, \dots, M-1\} \quad (12)$$

Using the following modifications, the background noise is taken into consideration and then the mean square error is minimized (BAI.; CHOI., 2002):

$$\text{Extended channel matrix: } \mathbf{H}_{\text{ex}} = \begin{bmatrix} \mathbf{H}^T & \sqrt{N_0} \mathbf{I} \end{bmatrix}^T$$

$$\text{Extended receive signal: } \mathbf{y}_{\text{ex}} = \begin{bmatrix} \mathbf{y}^T & \mathbf{0}^T \end{bmatrix}^T;$$

$$\text{Extended noise AWGN: } \mathbf{n}_{\text{ex}} = \begin{bmatrix} \mathbf{n}^T & -\sqrt{\frac{N_0}{E_s}} \mathbf{s}^T \end{bmatrix}^T$$

Sorted QR Decomposition (SQRD)

Further performance improvement on the SIC technique can be achieved through a properly ordering (WÜBBEN et al., 2001), (WÜBBEN et al., 2003), which avoid error propagation in interference

cancellation. The ordering criterion consists in minimize the \mathbf{Q} columns norm, which makes the detection be proceeded from the least noise corrupted symbol to the most. The decomposition assumes the form:

$$\mathbf{HP} = \mathbf{QR} \quad (13)$$

where matrix \mathbf{P} is a permutation matrix, used to reorder the symbols after applying the SIC detection, by multiplying it and the estimated symbol. Therefore the application of decomposition SQRD instead of the QR decomposition introduces ordering in the SIC detection, i.e., the OSIC-MIMO detector.

LR-based MIMO Detection

The lattice (basis) reduction (LR) was elaborated to transform a regular basis to a nearly orthogonal one. Choosing the channel matrix \mathbf{H} as a basis for a lattice, the MIMO problem can be treated as lattice decoding problem. The lattice concept is explored in the sequel; after that, the MIMO LR-aided detector is discussed in details.

Lattices

Let \mathbf{L} be a 2×2 matrix and $\mathbf{u} = [u_1 \ u_2]^T$ a 2×1 vector.

A lattice Λ_L is the set of points:

$$\Lambda_L = \{ \mathbf{L}\mathbf{u} \mid u_1, u_2 \in \mathbb{Z}[i] \} \quad (14)$$

where $\mathbb{Z}[i]$ is the set of Gaussian integers. The set of Gaussian integers is the complex numbers $\alpha = a + bi$ whose components a and b are both integers. \mathbf{L} is called a *generator matrix* for the lattice Λ_L . The minimum distance of Λ_L is defined as (JAMES, 2010):

$$d_{\min}^2(\Lambda_L) = \min_{\mathbf{u} \neq \mathbf{v}} \|\mathbf{L}(\mathbf{u} - \mathbf{v})\|^2 \quad (15)$$

where \mathbf{u} and \mathbf{v} are Gaussian integer vectors.

From the definition of Λ_L , there are infinitely different bases in a lattice and they all span the

same lattice Λ_L . Assume that \mathbf{L}' is another basis for Λ_L , then follows that $\mathbf{L}' = \mathbf{L}\mathbf{Z}$, where \mathbf{Z} is a unimodular matrix; therefore, \mathbf{Z} has Gaussian integers entries and $\det(\mathbf{Z}) \in \{\pm 1, \pm i\}$. From the definition of $d_{\min}^2(\Lambda_L)$ follows that:

$$d_{\min}^2(\Lambda_{\mathbf{QLZ}}) = d_{\min}^2(\Lambda_L) \quad (16)$$

where \mathbf{Q} is a unitary matrix. A matrix \mathbf{U} is said to be unitary if $\mathbf{U}^H \mathbf{U} = \mathbf{I}$ (HORN; JOHNSON, 1985).

MIMO Channels described by Lattice

Consider a basis \mathbf{B} consisting of M real-valued linearly independent basis vectors which is given by

$$\mathbf{B} = \{b_1, b_2, \dots, b_M\} \quad (17)$$

Since a lattice can be generated from an integer linear combination of a basis, with \mathbf{B} , we can have a lattice defined by

$$\Lambda = \left\{ \mathbf{u} \mid \mathbf{u} = \sum_{m=1}^M \mathbf{b}_m z_m, \quad z_m \in \mathbb{Z}[i] \right\} \quad (18)$$

So adopting \mathbf{H} as a basis and \mathbf{s} to produce an integer linear combination of the basis, the \mathbf{y} becomes a vector in the lattice generated by the basis \mathbf{H} .

LR-based MIMO Detection

Since a lattice can be generated by different bases or channel matrices, with the goal to reduce the noise and interference between multiple signals, it is convenient to find a matrix whose columns vectors are nearly orthogonal to generate the same lattice. So the LR can be applied to improve the performance of the detection, these methods are regarded as the LR-based detection for MIMO systems.

In order to use this technique, the original constellation must be defined in terms of consecutive integers lattice. This symbol is represented by \mathbf{x} . Hence, considering two bases \mathbf{H}

and \mathbf{G} that span the same lattice, it also shown that

$$\mathbf{H} = \mathbf{G}\mathbf{U} \quad (19)$$

where \mathbf{U} and $\mathbf{T} = \mathbf{U}^{-1}$ is an unimodular matrix.

Then the receive signal can be rewritten as

$$\begin{aligned} \mathbf{y} &= \mathbf{H}\mathbf{x} + \eta \\ \mathbf{y} &= \mathbf{H}\mathbf{T}\mathbf{T}^{-1}\mathbf{x} + \eta \\ \mathbf{y} &= \mathbf{G}\mathbf{z} + \eta \end{aligned} \quad (20)$$

$$\text{where } \mathbf{z} = \mathbf{U}\mathbf{x} = \mathbf{T}^{-1}\mathbf{x} \quad (21)$$

Since the received signal can be treated as the lattice points spanned by the basis, MIMO system detection with lattice can be developed, where conventional low-complexity detectors are able to be carried out in order to detect \mathbf{z} .

LR-aided Linear MIMO Detection

The LR-based linear detectors are carried out to detect \mathbf{z} as

$$\mathbf{z} = \mathbf{W}^H \mathbf{y}, \quad (22)$$

where for the LR-based MMSE detector the linear filter is describe by $\mathbf{w}^H = (\mathbf{G}^H \mathbf{G} + \frac{N_0}{E_s} \mathbf{U}^{-H} \mathbf{U}^{-1})^{-1} \mathbf{G}^H$.

Shift and Scale Method

After the detection of \mathbf{z} , it is necessary implement shifting and scaling operations in order to estimate the symbols \mathbf{s} . The solution to this quantization problem is to use a combination of shifting and scaling operations aiming to ensure that both the original \mathbf{x} and reduced constellation \mathbf{z} symbols are defined in terms of consecutive integer lattices (MILFORD; SANDELL, 2011). In doing so, the conventional symbols are related to a consecutive integer lattice by:

$$\mathbf{x}_i = \alpha s_i + \beta \quad (23)$$

where s_i is a complex integer, α is a scalar and β a complex offset. The symbol vector can be represented as

$$\mathbf{x} = \alpha \mathbf{s} + \beta \mathbf{1} \quad (24)$$

where \mathbf{s} is a vector of symbols in the complex integer lattice and $\mathbf{1}$ is a vector of ones. From eqs. (21) and (24) we can write

$$\begin{aligned} \mathbf{T}^{-1}\mathbf{x} &= \mathbf{T}^{-1}(\alpha \mathbf{s} + \beta \mathbf{1}) \\ \mathbf{z} &= \alpha \tilde{\mathbf{s}} + \beta \rho \end{aligned} \quad (25)$$

In the normalized lattice we can write:

$$\mathbf{z}' = \left(\frac{2}{\alpha} \right) \mathbf{z} = 2\tilde{\mathbf{s}} + \beta' \rho \quad (26)$$

where $\beta' = \left(\frac{2\beta}{\alpha} \right)$ and has the value $1+j$ for all M-QAM constellations. Isolating the $\tilde{\mathbf{s}}$, results:

$$\tilde{\mathbf{s}} = \frac{1}{2}(\mathbf{z}' - \beta' \rho) \quad (27)$$

while the symbol estimate in the reduced lattice should be based on quantization in the consecutive integer lattice

$$\hat{\tilde{\mathbf{s}}} = \left\lfloor \frac{1}{2}(\mathbf{z}' - \beta' \rho) \right\rfloor \quad (28)$$

where $\lfloor \cdot \rfloor$ represents rounding (floor) to the nearest integer less than the argument. Finally, from eqs. (26) and (28), the estimate in the reduced lattice is

$$\hat{\mathbf{z}}' = 2 \left\lfloor \frac{1}{2}(\hat{\tilde{\mathbf{s}}} - \beta' \rho) \right\rfloor + \beta' \rho \quad (29)$$

These combinations of operations lead to a correct solution to the quantization problem in LR-based MIMO detectors.

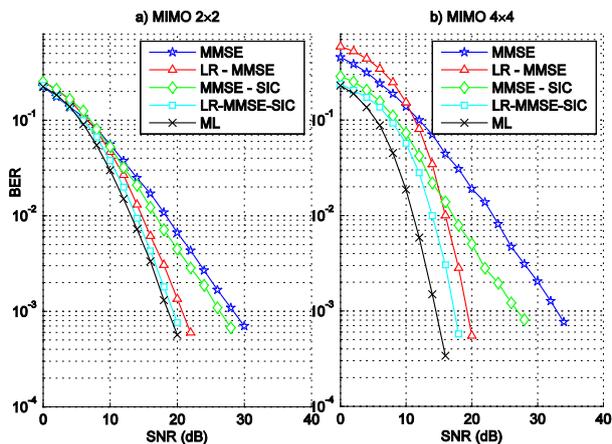
Numerical Results

In this section, the BER *versus* SNR under perfect channel estimation is analyzed; further realistic MIMO detection performance analyses have been conducted considering low, medium and high correlated MIMO channels scenarios. Along this numerical section, Monte-Carlo simulation (MCS) results are examined. Different system and channel configurations have been considered: a) non-correlated channels; b) different levels of channel correlation ($\rho > 0$).

Fig. 1 depicts the bit error rate (BER) performance

of different detectors for a 4-QAM MIMO system with $N_t = N_r = 2$ and $N_t = N_r = 4$ antennas with perfect channel estimation and uncorrelated MIMO channels ($\rho = 0$), respectively. In Fig. 1.a), the performance of MMSE-OSIC detector shows a slightly improvement compared with the MMSE, although this detector also presents slightly higher complexity; however, the performance of these detectors, due to the noise enhancement, is poor in comparison to ML. In contrast, the LR-aided MIMO detectors clearly outperform the others MIMO detectors, noticeably in high SNR region, indicating that the LR technique is robust against the fading effect specially in this region, although its performance in low SNR region has proved worse, especially with the increase of the numbers of antennas, as shown in Fig. 1.b). The LR-based MMSE-OSIC detector achieves near-ML performance especially in the medium and high SNR regions, where the additive noise is manageable and negligible, respectively.

Figure 1 – BER performance for the MIMO detectors under 4-QAM, perfect channel estimation and uncorrelated channels for a) 2×2 antennas; b) 4×4 antennas.



Source: author.

Fig. 2 and 3 show the bit error rate performance of the detectors for a 4-QAM MIMO system with $N_t = N_r = 2$ and $N_t = N_r = 4$ antennas, respectively, and perfect channel estimation, but under four different levels of channel correlation,

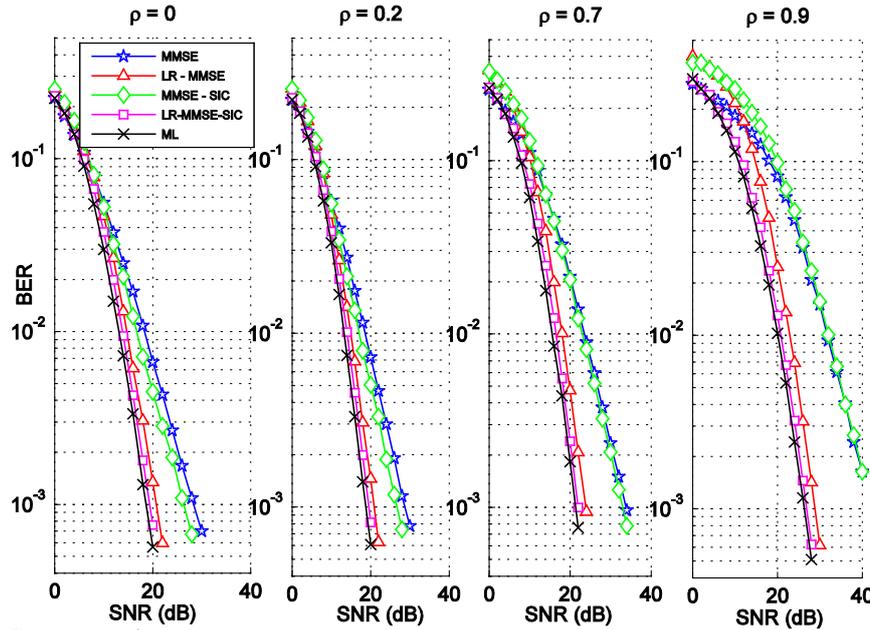
$\rho = [0; 0.2; 0.7; 0.9]$. The performance of the MIMO detectors under channels weakly correlated ($\rho = 0.2$) results very close to the uncorrelated channel condition, although with the increase of the levels of correlation implies in an increasing degradation in the BER performance. The MIMO detection with the aid of lattice-reduced has demonstrated be robust against correlation between antennas. In strongly correlated channels with 2×2 antennas, the detectors ML and LR-aided MMSE-OSIC in high SNR region present very similar performance; the same behavior happens with MMSE and MMSE-OSIC detectors. Under same channel and system scenario but with 4×4 antennas, one can note that with the increasing of the level of correlation provokes a larger degradation in the performance, especially for the MMSE and MMSE-OSIC detectors, which under strongly correlated channels present a really poor performance. As a conclusion, the LR-based MMSE-OSIC detector performance for any number of antennas presents a slightly worst performance than the optimal ML-MIMO, but with the same diversity order, indicated by the slope of BER performance curve, determined in high SNR region, as well as a much less complexity, producing an excellent performance-complexity tradeoff.

Conclusion

The effects of the correlated channels have demonstrated very significant on the MIMO performance. Among the analyzed MIMO detectors, the LR-aided technique has been proved useful in order to improve the performance of several MIMO detectors under correlated channel estimation constrains. Indeed, our numerical results and analysis of correlated channel effects over the BER performance of MIMO system equipped with different detectors and number of antennas have indicated notable gains in the performance and in robustness of those versions of MIMO detectors aided by lattice reduction. The MMSE and MMSE-OSIC showed a really poor performance in channels strongly correlated indicating that detectors aided

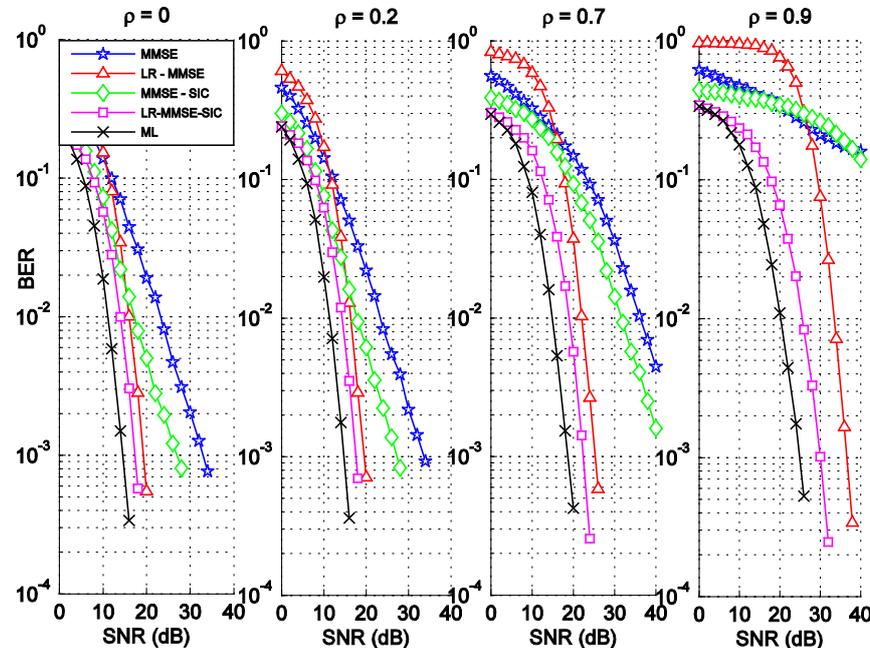
by LR technique can be effectively an alternative to this scenario. Among them, the LR-MMSE MIMO OSIC detector has achieved the smaller degradation regarding the devastating effect of the MIMO channel correlation.

Figure 2 – BER performance for the MIMO detectors under correlated channels with 2x2 antennas; ρ variable



Source: author.

Figure 3 – BER performance for the MIMO detectors under correlated channels with 4x4 antennas; ρ variable



Source: author.

References

- ANDALIBI, Z.; NGUYEN, H. H.; SALT, J. E. Precoder design for BICM-MIMO systems under channel estimation error. *Wireless Personal Communications*, v. 72, n. 4, p. 2823-2835, 2013.
- BAI, L.; CHOI, J. Low Complexity MIMO Detection. 1. ed. New York: Springer, 2012. 230 p. ISSN 9781441985828.
- BÖHNKE, R.; WÜBBEN, D.; KÜHN, V.; KAMMEYER, K.-D. Reduced complexity mmse detection for blast architectures. In: *IEEE Global Telecommunications Conference, 2003. GLOBECOM '03*. San Francisco, CA: 2003. v. 4, p. 2258–2262, vol. 4.
- FOSCHINI, G. J.; GANS, M. J. On limits of wireless communications in a fading environment when using multiple antennas. *Wireless Personal Communications*, v. 6, p. 311-335, 1998.
- HORN, R. A.; JOHNSON, C. R. *Matrix analysis*. Cambridge University Press, 1985.
- JAMES, G. *Modern engineering mathematics*. 4. ed. New York, NY, USA: Prentice Hall, 2010. ISBN 0521837162.
- MILFORD, D.; SANDELL, M. Simplified quantization in a reduced-lattice MIMO decoder. *IEEE Communications Letters*, v. 15, n. 7, p. 725-727, July 2011. ISSN 1089-7798.
- MOSTAGI, Y. M.; ABRÃO, T. Lattice-reduction-aided over guided search MIMO detectors. *International Journal of Satellite Communications Policy and Management*, p. 142-154, 2012.
- WÜBBEN, D.; BÖHNKE, R.; KÜHN, V.; KAMMEYER, K.-D. MMSE extension of V-BLAST based on sorted QR decomposition. In: *Vehicular Technology Conference, 2003. VTC 2003-Fall. 2003 IEEE 58th*. Orlando, Florida USA: 2003. v. 1, p. 508–512. Vol.1. ISSN 1090-3038.
- WÜBBEN, D.; BÖHNKE, R.; KÜHN, V.; KAMMEYER, K.-D. Near-maximum likelihood detection of MIMO systems using MMSE-based lattice reduction. *IEEE International Conference on Communications*, v. 2, p. 798-802, 2004.
- WÜBBEN, D.; BÖHNKE, R.; RINAS, J.; KAMMEYER, K.-D.; KÜHN, V. Efficient algorithm for decoding layered space-time codes. *IEEE Electronic Letters*, v. 37, n. 22, p. 1348-1350, Nov. 2001.
- WÜBBEN, D.; SEETHALER, D.; JALDÉN, J.; MATZ, G. Lattice reduction - a survey with applications in wireless communications. *IEEE Signal Processing Magazine*, v. 28, n. 3, p. 70-91, 2011.
- ZELST, A. V.; HAMMERSCHMIDT, J. S. A single coefficient spatial correlation model for multiple-input multiple-output (MIMO) radio channels. In: *Proc. URSI XXVIIth General Assembly*. Maastricht, The Netherlands, 2002. p. 1-4.

Recebido em 28 Julho, 2014 – Received on July 28, 2014
 Aceito em 19 Agosto, 2015 – Accepted on August 19, 2015

