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MMSE-SQRD Scheme for MIMO Transmission

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***Abstract*—*Now a day, wireless communication becomes a trend in many ways such as mobile online games, high quality online video calling and mobile multimedia transmissions, etc. So, the requirements of radio spectrum also increase, which makes radio spectrum more and more expensive]. A number of techniques utilize for the radio spectrums and also provide better Efficiency in MIMO communication system. In parallel, MIMO system is one of the promising technology of 5G, which predominance in boosting Spectrum Efficiency and Energy Efficient with low complexity. In MIMO structures, though the multiplexing gain can be obtained with an equal power allocation method , power control among users can help to gain all the benefits brought by antenna arrays Generally, MIMO Provides two types of gain to achieve fair power allocation: one is the spatial multiplexing (SM) gain and other is the diversity gain. In this paper, we present a novel computationally efficient algorithm for detecting QR-OSIC architectures with respect to the MMSE criterion. The QR –OSIC algorithm estimates the BER, this will be minimized by providing the PA scheme at transmitter end and this algorithm improves the SINR. An improved detection ordering for MIMO System an ordered successive interference cancellation detector is determined under the bit error rate minimization. From the convexity of the Q -function, we derive the ordering strategy that makes the channel gains converge to their geometric mean. Based on the approach of this, first we designed the fixed ordering algorithm, for which the geometric mean is used for a constant threshold. Later to improve the performance of the system like SNR, the modified new scheme employing adaptive thresholds is developed using the correlation among ordering results. Comparison of Theoretical analysis and simulation results shows that proposed ordering schemes using QR-decomposition requires reduced computational complexity and improved error performance and SINR*

***Index Terms*—Detection ordering, MIMO, OSIC, power allocation, QR-decomposition.**

I.INTRODUCTION

Multiple Input Multiple Output (MIMO) technology means that multiple antennas are used at the transmitter and receiver sides, has been increases the signal coverage area and also increases spectral efficiency and reliability. The MIMO systems has been an active area of research in wireless communications, as well as practical transceiver implementations of their great potential of enhancing the system's performance [1], [2]. The Vertical-BLAST architecture proposed in this system [3] and [4], also referred to as the BLAST-ordered successive interference cancellation (B-OSIC) detector, is regarded as an attractive and improved solution that exploits this potential. In this BLAST-OSIC (B-OSIC) receiver, the data stream with the strongest signal-to-interference-noise ratio (SINR) is selected first after that it is subtracted from the received signal, and this procedures successively performed for all remaining multiple data streams. For allocating the equal power (power allocation –PA) across all the transmitting antennas, it is optimal in terms of bit error rate (BER) or equivalently minimum-mean-square error (MMSE) [5].At the Transmitter end if the knowledge of the channel is available, a further performance improvement can be achieved using appropriate Power allocation schemes. Based on the PA schemes that the data stream with the smallest SINR degrades the overall error performance, Power allocating schemes for the B-OSIC have been suggested in [6] and [7] which reduces the computational complexity and the feedback overhead by adopting a diagonal precoding matrix for the PA. Most of the PA schemes for the closed-loop systems mainly focus on the transmitter-side processing strategies, while attempts for the joint optimization for the Power Allocation at the transmitter and the OSIC detection ordering scheme at the receiver has not been fully investigated.

In this paper, to reduce the BER and increasing the SINR we derive a new detection ordering strategy and ordering schemes from joint transceiver design, which is a distinct from previous study. To obtain a closed-form solution, a QR-factorization based approach will be employed in our study [6]. In this we extend the ZF-SQRD algorithm to the MMSE solution called MMSE-SQRD and we provide the BER minimization condition, and it is derived from the convexity of the Q-function in the PA scheme. It is demonstrated that the ordering strategy, which makes the channel gains converge to their geometric average, achieves the improved error performance. Based on this observation, we develop the two ordering algorithms, which are identical except for the threshold adaptation. The basic algorithm is used to determine the detection-order using the geometric mean as a constant threshold, whereas the modified ordering scheme is for robust convergence adaptively updates the threshold by taking into an account the previous ordering results. The comparison of the cumulative distribution is conducted to confirm the superiority of the adaptive design. It is also shown that proposed ordering schemes using QR-decomposition obtain not only lower implementation complexity but also better BER performance and good SINR when compared to the conventional BLAST-OSIC algorithm.

II. SYSTEM MODEL

Let us consider a MIMO system with N_t no of transmitting antennas and N_r receiving antennas. The flat-fading MIMO

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system, channel is expressed by the N_r XN_t matrix H with the element h_{ji} representingthe channel gain from i th transmitting antenna to j th receiving antenna. The N_rX 1 received signal vector y = $[y_{1,\ldots\ldots\ldots}, y_{Nr}]^T$ is written as

$$y = \sqrt{\frac{E_s}{N_t}} HPX + n \qquad (1)$$

where X = $[x_{1,\ldots\ldots\ldots}, x_{Nt}]^T$denotes the N_r X 1 transmitted signal vector, and **n** = $[n_{1,\ldots\ldots\ldots}, n_{Nr}]^T$is the N_r dimensionalnoise vector with elements following complex zero σ_n^2 mean Gaussian distribution with variance of σ_n^2. $E_s$is thetotal transmitted signal energy on N_t transmitting antennas and P = $\sqrt{N_t}$. diag$[P_1,P_{2,}, \ldots\ldots, P_{Nt}]$ denotes the diagonal PA precoding matrix. To express the signal model for the MMSE-QR detector, an $(N_r$+N_t) X$N_t$augmented channel matrix$\bar{\boldsymbol{H}}$, an (N_r + N_t) X 1 extended receive vector$\bar{\boldsymbol{y}}$ and an N_t X 1 zero matrix $0_{N_t,1}$canbe written as [8]–[10]

$$\bar{\boldsymbol{H}}=\begin{bmatrix}\boldsymbol{H}\\ \sigma_n \boldsymbol{I}_{N_t}\end{bmatrix} \rightarrow Ordering \bar{\boldsymbol{Q}}\bar{\boldsymbol{R}} \text{and } \bar{\boldsymbol{y}} = \begin{bmatrix}\boldsymbol{y}\\ 0_{N_t,1}\end{bmatrix}. \qquad (2)$$

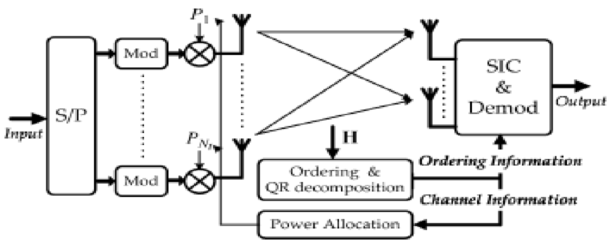

Fig. 1.MIMO transmission model with QR-OSIC detector.

In above equation Q represents the upper triangular matrix , which is differently defined by the detection-order, determines the SINR [9], and the post detection SINRρ_k of thek_{th} data stream is given as [2]

$$\rho_k = \frac{E_s}{\sigma_n^2} P_k^2 \bar{R}_{k,k}^2 - 1, \qquad k = 1, \ldots, N_t. \qquad (3)$$

The QR-decomposition scheme based OSIC detection for BER-minimized transmission can be performed using the architecture shown in Fig. 1. Based on the feedback information of the diagonal elements$\bar{R}_{k,k}$, the transmission power $P_k$is assigned to eachdata stream at transmitting end. The independently encoded symbols are processed through a diagonal PA matrix and then transmitted from $N_t$datastreams. The QR-OSIC receiver detects the transmit symbols sequentiallyin accordance with the designated detection-order.

III. PROPOSED DETECTION ORDERING ALGORITHMS

In Section III-A,MMSE detection is described to extend the MMSE criterion and in section III-B, MMSE Sorted QR Decomposition scheme provided to obtain the optimal detection order. In section III-C , a theoretical approach for BER performance is described. As in the derivation of the post-detection SINR, the error rate is also affected by the channel gains and the transmission power. From the properties of the -function and ordering results, the proposed ordering strategy is derived and the efficient ordering algorithms for the QR-OSIC receiver are presented in Section III-D

A. MMSE QR Detection

In order to extend the QR based detection with respect to the MMSE criterion, we can apply the similarity of ZF and MMSE detection noted in Section III-B. We introduce the QR decomposition of the extended channel matrix (17)

$$\bar{\boldsymbol{H}}= \begin{bmatrix}\boldsymbol{H}\\ \sigma_n \boldsymbol{I}_{N_t}\end{bmatrix} = \bar{\boldsymbol{Q}}\bar{\boldsymbol{R}} = \begin{bmatrix}\boldsymbol{Q_1}\\ \boldsymbol{Q_2}\end{bmatrix}\bar{R} = \begin{bmatrix}\boldsymbol{Q_1}\bar{R}\\ \boldsymbol{Q_2}\bar{R}\end{bmatrix} \qquad (4)$$

where the (N_r + N_t) X$N_t$matrix $\overline{\boldsymbol{Q}}$ with orthogonal columns was partitioned into the an N_r X$N_t$matrix $\boldsymbol{Q_1}$ and the N_t X$N_t$matrix **Q**2. Obviously,

$$\bar{\boldsymbol{Q}}^H\bar{\boldsymbol{H}} = \boldsymbol{Q}_1^H + \sigma_n^2 \boldsymbol{Q}_2^H = \bar{\boldsymbol{R}} (5)$$

holds and from the relation$\sigma_n \boldsymbol{I}_{N_t}$= $\boldsymbol{Q_2}\bar{R}$ it follows that

$$\bar{R}^{-1} = \frac{1}{\sigma_n}\boldsymbol{Q_2} (6)$$

i.e. the inverse $\bar{R}^{-1}$ is a byproduct of the QR decompositionand **Q**2 is an upper triangular matrix. This relation will be useful for the post-sorting algorithm Using (13) and (14), the filtered receive vector becomes$\tilde{\boldsymbol{s}} = \bar{\boldsymbol{Q}}^H\bar{\boldsymbol{y}} = \boldsymbol{Q}_1^H$ y $= \bar{\boldsymbol{R}}s - \sigma_n \boldsymbol{Q}_2^H$ s + $\boldsymbol{Q}_1^H$ **(7)**The second term on the right hand side of (15) including the lower triangular matrix $\boldsymbol{Q}_2^H$ constitutes the remaining interference that cannot be removed by the successive interference cancellation procedure. This point out the trade-off between noise amplification and interference suppression.

The optimum detection sequence now maximizes the signal-to-interference-and-noise ratio (SINR) for each layer, leading to minimal estimation error for the corresponding detection step. The estimation errors of the different layers in the first detection step correspond to the diagonal elements of the error covariance matrix (11)

$$\emptyset= \sigma_n^2(\bar{\boldsymbol{H}}^H\bar{\boldsymbol{H}})^{-1} = \sigma_n^2\bar{\boldsymbol{R}}^{-1}\bar{\boldsymbol{R}}^{-H} \qquad \textbf{(8)}$$

The estimation error after perfect interference cancellations given byσ_n^2 /$|\bar{\boldsymbol{r}}_{k,k}|^2$. Thus, it is again optimal to choose the permutation that maximizes $|\bar{\boldsymbol{r}}_{k,k}|$ in each detection step.The algorithm proposed in the next section determines anoptimized detection sequence within a single *sorted* QR decomposition and thereby significantly reduces the computational complexity in comparison to standard MMSE-BLAST algorithms.

A. MMSE Sorted QR Decomposition (MMSE-SQRD)

In order to obtain the optimal detection order, first |*rnT ,nT* | has to be maximized over all possible permutations of the $|\bar{\boldsymbol{r}}_{n_T,n_T}|$ has to be maximized over all possible permutations of the columns of the extended channel matrix $\bar{\boldsymbol{H}}$, followed by$|\bar{\boldsymbol{r}}_{n_{T-1},n_{T-1}}|$and so on. Unfortunately, using standard algorithmsfor the QR decomposition, the diagonal elements of$\bar{\boldsymbol{R}}$are calculated just in the opposite order, starting with $\bar{\boldsymbol{r}}_{1,1}$ **.** This makes finding the optimal order of detection a difficult task.

A heuristic approach of arranging the order of detection into the QR decomposition for the ZF detection was presented in [4], [5]. This sorted QR decomposition algorithm is basically an extension to the modified Gram-Schmidt procedure by reordering the columns of the channel matrix prior to each orthogonalization step. In the sequel we present an adapted version of this algorithm for MMSE detection.

The fundamental idea is that $\bar{\boldsymbol{r}}_{\boldsymbol{k,k}}$is *minimized* in the orderit is computed $(1, \ldots, N_t)$ instead of being *maximized* in the order of detection $(N_t, \ldots, 1)$. This is motivated by the fact that the layers detected last affect only few other layers through error propagation and may therefore have rather small SINR's, which increases the probability of large SINR's in the first layers. Now, $\bar{\boldsymbol{r}}_{\boldsymbol{1,1}}$ is simply the norm of the column vector$\bar{\boldsymbol{h}}_{\boldsymbol{1}}$, so the first optimization in the SQRD algorithm consistsmerely of permuting the column of $\bar{\boldsymbol{H}}$ with minimum norm to this position. During the following orthogonalization of the vectors $\bar{\boldsymbol{h}}_{\boldsymbol{2}}$, $\bar{\boldsymbol{h}}_{\boldsymbol{3}}$, ……$\bar{\boldsymbol{h}}_{\boldsymbol{n_T}}$, with respect to the normalized vector$\bar{\boldsymbol{h}}_{\boldsymbol{1}}$, the first row of$\bar{\boldsymbol{R}}$is obtained. Next, $\bar{\boldsymbol{r}}_{\boldsymbol{2,,2}}$ is determined ina similar fashion from the remaining $\boldsymbol{n_T - 1}$orthogonalizedvectors, etc. Thereby, the extended channel matrix$\bar{\boldsymbol{H}}$issuccessively transformed into the matrix $\bar{\boldsymbol{Q}}$ associated with the desired ordering, while the corresponding $\bar{\boldsymbol{R}}$ is calculated row by row. Note that the column norms have to be calculated only once in the beginning and can be easily updated afterwards. Hence, the computational overhead due to sorting is negligible.

It should be emphasized that MMSE-SQRD does not always lead to the perfect detection sequence, but in many cases of interest the performance degradation is small compared to the reduced complexity. Furthermore, whenever MMSE-SQRD fails to find the optimal order, the post-sorting algorithm described in the sequel may be applied. It assures the optimal sorting and thereby achieves the same performance as MMSEBLAST.

In order to introduce the Post-Sorting-Algorithm (PSA), we investigate the structure of the error covariance matrix in case of optimal sorting in more detail. Due to the relation (14) the error covariance matrix (16) is given by

$$\emptyset = \boldsymbol{Q_2 Q_2^H} \qquad \textbf{(9)}$$

and$\boldsymbol{Q_2}$is a square root of $\emptyset$. As $\boldsymbol{Q_2}$ is upper triangular ,the *k*-th diagonal element of $\emptyset$ is proportional to the norm of the *k*-th row of $\boldsymbol{Q_2}$. Recalling the optimal ordering criterion, the last row of $\boldsymbol{Q_2}$ must have minimum norm of all rows. Assume that this condition is fulfilled, then the last row of the upper left $\boldsymbol{n_{T-1} X n_{T-1}}$ submatrix of $\boldsymbol{Q_2}$ must have minimum norm of all rows of this sub matrix. In case of the correct sorting this condition is accomplished by all upper left sub matrices.

B. Description of the BER Performance

A PA scheme for the average BER minimization under the assumption of the QR-decomposition of the channel matrix and no error propagation in successive cancellation of the data streams has been proposed in [6]. The PA scheme for BPSK modulation can be expressed as minimize

$$\frac{1}{N_t}\sum_{k=1}^{N_t} Q(\sqrt{2}\,\gamma_s P_k \bar{R}_{k,k}) \approx \frac{1}{N_t}\sum_{k=1}^{N_t} Q(\sqrt{2\,\rho_k})$$

s.t $\sum_{k=1}^{N_t} P_k^2 = 1$, $0 < P_k < 1$,
$\bar{R}_{k,k} \geq 0$, k$\in \{1,2,\ldots\ldots, N_t\}$**(10)**

where $Q(x) = \sqrt{1/2\pi}\int_x^{\infty} e^{-(\frac{t^2}{2})}\, dt$and $\gamma_s = \sqrt{\frac{E_s}{\sigma_n^2}}$.

We assume$\bar{R}_{k,k} \geq 0$ because it is defined as the norm of thek_{th}column of the augmented channel matrix [8]. For generalconstellations, the average BER of the PA can be approximatedwith a constellation-specific constant [7], [11].

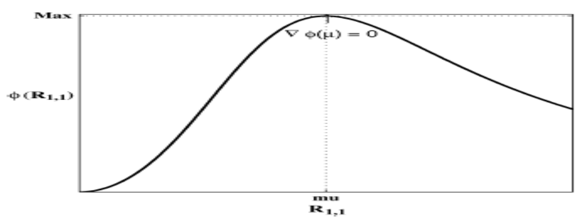

Fig. 2. Graph of$\emptyset(\bar{R}_{1,1})$.

As can be observed in (4), the average BER as well as the post-detection SINR is determined by the allocated power and the channel gain . Because of the convexity property of the -function, the resulting BER is minimized by (i)the detection ordering of the QR-OSIC receiver such that all diagonal elements of the matrix are equal to their geometrical average $\mu = \sqrt[N_t]{\det(\bar{R})} = \sqrt[N_t]{\prod_{k=1}^{N_t} \bar{R}_{k,k}}$, and alternatively(ii) the PA scheme at the transmitter which makes the product of two variables $P_K$and$\bar{R}_{k,k}$ identical for all data streams. Asthe real MIMO channel is characterized by several spatio –temporal properties, the condition (i) is not practical in spite of its optimality. On the other hand, in (ii), different detection-order leads to different$\bar{R}_{k,k}$, and hence$P_K$should be also differently assigned. This indicates that an appropriate detection ordering strategy incorporates with the PA scheme can achieve the improved BER performance.

D. Proposed Ordering Strategy and Algorithms

Since the Q–function has convex and decreasing properties, the average BER minimization problem (4) can be simplified to maximize the product of two variables $P_K$and$\bar{R}_{k,k}$

Maximize $P_1\bar{R}_{1,1}$
s. t. $P_1\bar{R}_{1,1} = P_2\bar{R}_{2,2} = \ldots\ldots\ldots = P_{N_t}\bar{R}_{N_t,N_t}$
$\sum_{k=1}^{N_t} {P_k}^2$, $0 < P_k < 1$ **(11)**

Using the following properties of .

$P_1\bar{R}_{1,1} = P_2\bar{R}_{2,2} = \sqrt{1 - {P_1}^2}\,(\det(\bar{R})\,/\bar{R}_{1,1})$

${P_1}^2 = (det^2(\bar{R})\ /\ (\bar{R}_{1,1}^4 + \det(\bar{R})))$ and $\max P_1\bar{R}_{1,1} \cong max{P_1}^2\bar{R}_{1,1}^2$, the problem for two transmit antennas can be written as

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Maximize $\frac{\bar{R}_{1,1}^2 det^2(\bar{R})}{\bar{R}_{1,1}^4 + det^2(\bar{R})} = \emptyset(\bar{R}_{1,1})$.**(12)**

s . t $P_1\bar{R}_{1,1} = P_2\bar{R}_{2,2}$, $P_1^{\ 2} + P_2^{\ 2} = 1$

To find the direction of increasing, a plot of the objective function $\emptyset(\bar{R}_{1,1})$ versus $\bar{R}_{1,1}$ is given in Fig. 2. It is observed that $\emptyset(\bar{R}_{1,1})$ increases as $\bar{R}_{1,1}$ tends to μ. When differential calculusis applied to $\emptyset(\bar{R}_{1,1})$, we also obtain

$$2\bar{R}_{1,1}(\bar{R}_{1,1}^4 + det^2(\bar{R})) = 0$$

$$\bar{R}_{1,1} = \sqrt{\det(\bar{R})} = \mu \quad \textbf{(13)}$$

Note that ,$\rho_K \propto P_K^{\ 2}\bar{R}_{k,k}^2$ and therefore the above consideration simply that ρ_K is gradually increasing as $\bar{R}_{k,k}$ approaches to μ. In other words, the ordering strategy that makes $\bar{R}_{k,k}$ converge to μ achieves higher post-detection SINR, which also further improves the overall BER performance. From (18), it can be extended to the system with transmit antennas. To satisfy the derived strategy, we establish the fixed ordering algorithm, the architecture of which arranges the channel gains to minimize$|\bar{R}_{k,k} - \mu|$for all k.

$k_l = \arg\min|\bar{R}_{w,w} - \mu|$

s ,t w∈ $\{k_1, \dots \dots \dots . k_{l-1}\}$

$\mu = \sqrt[N_t]{\det(\bar{R})}$**(14)**

where the list of N_t elements {1,2,….,are rearranged with the parenthesized subscript implying the reverse order in which the elements are to be detected and the ordered set$k = \{k_1, \dots \dots \dots . k_{N_t}\}$is a permuted sequence of them [8], [10].

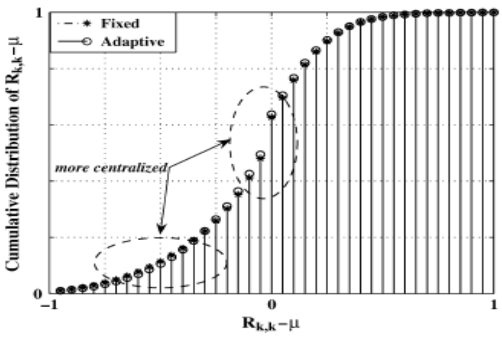

Fig. 3. Comparison of cumulative distribution of $\bar{R}_{k,k} - \mu$

Using the correlation among ordering results, the modified ordering algorithm employing adaptive criteria can be developed for robust convergence. For instance, in $N_t = 3$ system, selectingan element 1 as $k_1$will, in general, result in a different$\bar{R}_{1,1}$than if element 2 or 3 was selected. It also affects the remainingsets which decide k_2, k_3 . Moreover, channel gains are constrained via $\mu = \sqrt[N_t]{\prod_{k=1}^{N_t}\bar{R}_{k_l,k_l}}$ Motivated by the aboveproperties, we propose the adaptive ordering design which continually renews the thresholds by controlling the weights with reference to previously determined channel gains. Substituting the variable thresholds into the fixed method, we get$k_l = \arg\min|\bar{R}_{w,w} - \mu_l|$

s . t $\mu_1 = \mu$; $\mu_{l+1} = \frac{N_{t-l+1}}{N_t - l}\sqrt{\frac{\mu_l}{\bar{R}_{l,l}^{\ N_{t-l+1}}}}$**(15)**

Where μ_l denotes the threshold for k_l . The adaptive ordering algorithm can be considered as the reduced-sized fixed ordering process extracting the already decided gains thus it plays a large part in balancing among ordering results. If the sign of$\bar{R}_{k,k} - \mu$is distributed to one side serially, the adaptive ordering algorithm enables the following channel gain to be on the opposite side by adjusting μ_{l+1}. This allows more channel gains to converge to . To identify it, the cumulative distributions of$\bar{R}_{k,k} - \mu$with four transmit/receive antennas are drawn in Fig. 3. Thesmall gap between two similar schemes is noticeable because the adaptive algorithm is equivalent to the fixed one for slight differences in .$|\bar{R}_{k,k} - \mu|$.

The complexity comparison between the B-OSIC and the QR-OSIC receiver is not discussed in this paper. Fortunately, the efficiency of the QR-OSIC receiver which reduces the computational complexity by an order of magnitude is proven in [5].In a B-OSIC detector with $N_t = Nr$, the total numbers of multiplicationsand additions are $(43/12)N_t^4 + (22/3)N_t^3 + \vartheta(N_t^2)$,and $(43/12)N_t^4 + (20/3)N_t^3 + \vartheta(N_t^2)$, respectively. On theother hand, the OSIC receiver using QR-factorization requires are $(2/3)N_t^3 + 7N_t^2N_r + 2N_r^2N_t + \vartheta(N_t^2)$ multiplications and additions. Because of the multiple calculations of pseudo-inverse for nulling and ordering, the B-OSIC requires higher computational cost [10]. When ,$N_t = N_r$ the numbers of multiplications and additions are given with the complex floating point operations(flops).

$(43/6)N_t^4 + 14N_t^3 + \vartheta(N_t^2)$, for B-OSIC ;

$(29/3)N_t^3 + \vartheta(N_t^2)$, for QR-OSIC ;**(16)**

IV. SIMULATION RESULTS

We consider an un coded MIMO system with 3 X 3, 4 X 4transmit/receive antenna configurations and BPSK modulation. The effects of error propagation are not ignored, an d simulations are used to obtain the actual performance. For each of the MIMO systems and for a specific value of SNR, a quasi-static channel is assumed for the performance evaluation, for which the channel gain is constant over a frame and changed independently from frame to frame. To concentrate our point on comparing ordering algorithms, we postulate the perfect channel estimation at the receiver and error-free PA information at the transmitter.

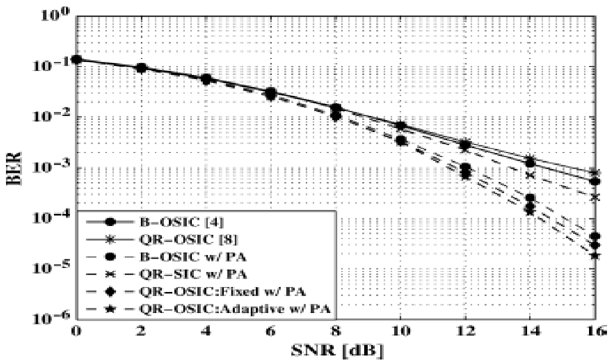

Fig. 4. Average BER performance of MIMO systems with three transmit/receive antennas.

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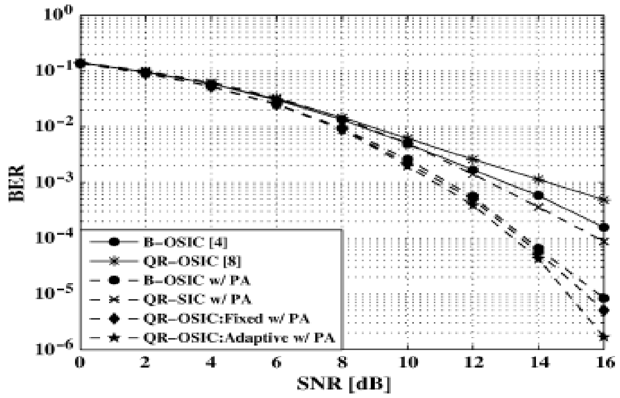

Fig. 4. Average BER performance of MIMO systems with four transmit/receive antennas.

Fig. 4 shows the average BER performance comparison for MIMO systems with three transmit/receive antennas and the simulation results of four transmit/receive antennas are depicted in Fig. 5. Here, the dashed line indicates a system with the BER-minimized PA scheme, whereas the solid line represents a system without the PA. The QR receiver with the PA but no ordering, denoted as QR-SIC w/ PA, has similar performance to the open-loop OSIC systems without the PA. This demonstrates the importance of the detection-order for successive detection. As expected, without the PA, the B-OSIC outperforms the QR-OSIC receiver. Despite the reduced complexity, however, power controlled MIMO systems employing the proposed ordering strategy achieve the improved error performance compared to those with the B-OSIC algorithm. It is sufficient to confirm the superiority of the proposed design because the ordering algorithms of previous studies comply with the strategy of the B-OSIC [5]–[8]. A further performance improvement in the high SNR region can be explained in terms of the error propagation,
since the PA scheme as well as the proposed QR-OSIC receiver is designed under the assumption of the error-free decision in previous detection stages.

V. CONCLUSION

In this study, we investigate the QR-OSIC receiver design for the transmitter-side power allocated MIMO system. Based on the properties of the Q -function and ordering results, we develop the efficient ordering algorithms in combination with the PA scheme. In spite of less computational effort, the proposed ordering schemes decrease the overall BER in comparison with the previously derived B-OSIC scheme. Because of the post-detection SINR increment, the coded systems with the derived approach can also be expected to achieve the performance improvement.

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