Joint Antenna Selection and Link Adaptation for MIMO Systems

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Abstract— Based on the observation that link adaptation and antenna selection problems are often coupled, this paper studies the problem of joint antenna subset selection and link adaptation for MIMO systems. After the formulation of the multidimensional joint optimization problem, the main contribution of this paper lies in the designing of efficient algorithms approaching the optimal solution for both uncorrelated and correlated MIMO channels. Specifically, we propose one simplified antenna selection and link adaptation rule based on the expected optimal number of active antennas for uncorrelated MIMO with Raleigh fading, and one for correlated MIMO channels only based on the slowly varying channel correlation information. Our proposed algorithms are verified through numerical results, demonstrating significant gains over traditional MIMO signaling while feasible for practical implementation.

Keywords- Antenna selection, QR-decomposition, Cholesky-decomposition, MIMO systems.

I. INTRODUCTION

The use of multiple antennas at both the transmitter and receiver side, so as to form a multiple-input multiple-output (MIMO) antenna system, is an emerging technology that makes building high data rate wireless networks a reality [6]. Transmitting independent data streams simultaneously from different antennas through spatial multiplexing (see, e.g.,[1]) effectively realizes the high spectral efficiency promised by MIMO systems, but leaves the transmitted data unprotected from random channel impairment. Therefore, it is often desirable to consider link adaptation, such as rate adaptation and power control to improve the system performance and guarantee certain quality of service[4][10].

It is interesting to notice that link adaptation and antenna selection problems are actually coupled for MIMO systems, when practical signal processing techniques such as zero-forcing successive interference cancellation (ZF-SIC) (as used in V-BLAST) are employed at the receiver for data decoupling and detection. This is because the decoupled subchannel gains (post-detection signal-to-noise ratio (SNR)) are determined by the active antenna subset, while some weak subchannels are naturally dropped during link adaptation process. Motivated by this fact, we propose a joint antenna subset selection and link adaptation study for MIMO systems by allowing all the available resources, including the number of active transmit antennas, symbol constellation size and transmit power dynamically adapted to the channel conditions.

This paper is organized as follows. In Section II, we introduce the ZF-SIC receiver, and formulate the problem of joint antenna subset selection and link adaptation based on such receiver. In Section III, we develop the incremental and decremental selection rules with link adaptation for uncorrelated MIMO channels. We also propose a simplified link adaptation rule based on the expected optimal number of active antennas in independent and identically distributed (i.i.d) Rayleigh fading channels. In Section IV, we develop an antenna selection rule with link adaptation for correlated MIMO channels only based on the slowly varying channel correlation information. Simulation results are given and analyzed in Section V. Finally, in Section VI, we make some conclusions.

II. PROBLEM FORMULATION

A. ZF-SIC with QR Decomposition Interpretation

For a narrowband MIMO system with total $K_t$ transmit antennas and $N_r$ receive antennas, when $N_r$ out of $K_t$ transmit antennas are chosen, we denote the channel matrix by $\mathbf{H}(p)$ ($p$ stores the selected antennas’ indexes), and the channel can be modeled as

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

where $x = (x_1, x_2, ..., x_{N_r})^T$ is the transmitted signal vector, $y = (y_1, y_2, ..., y_{N_r})^T$ is the received signal vector, and $n = (n_1, n_2, ..., n_{N_r})^T$ is assumed to be i.i.d Gaussian with zero mean and variance of $\sigma^2_n$. Assume $N_r \geq N_t$, and the QR decomposition of channel matrix is $\mathbf{H}(p) = \mathbf{QR}$, where $\mathbf{Q}$ is a unitary matrix and $\mathbf{R}$ is an upper triangular matrix, we can apply $\mathbf{Q}^T$ to the received vector to obtain

$$\tilde{y} = \mathbf{Q}^T y = \mathbf{Q}^T (\mathbf{R}x + n) = \mathbf{Rx} + \tilde{n},$$

detailed as

$$\begin{pmatrix}
\tilde{y}_1 \\
\tilde{y}_2 \\
\vdots \\
\tilde{y}_{N_r}
\end{pmatrix} =
\begin{pmatrix}
r_{11} & r_{12} & \cdots & r_{1N_r} \\
0 & r_{22} & \cdots & r_{2N_r} \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & r_{N_rN_r}
\end{pmatrix}
\begin{pmatrix}
x_1 \\
x_2 \\
\vdots \\
x_{N_r}
\end{pmatrix} +
\begin{pmatrix}
\tilde{n}_1 \\
\tilde{n}_2 \\
\vdots \\
\tilde{n}_{N_r}
\end{pmatrix},$$ (2)
from which the transmitted symbols $x_k, x_{k-1}, \ldots, x_1$ can be detected successively. Assume no error propagation during detection, it is clear that QR decomposition decomposes an $N \times N$ MIMO channel matrix $H(p)$ into $N$ subchannels with $[r_i]_*$ being the gain for the $i$-th subchannel.

B. Joint Antenna Selection and Link Adaptation

In this paper we assume QAM modulation. For square $M \times M$ QAM with average power $\gamma$, the minimum Euclidean distance $d$ is $\sqrt{6\gamma/(M-1)}$, which is also a good approximation for energy-efficient “non-square” QAM in a large range of interest [2].

Assume there are $N_t$ out of $K_t$ antennas in use, correspondingly, there are $N_t$ decomposed subchannels. For the $i$th subchannel with gain $[r_i]_*$, the minimum Euclidean distance of the output constellation is given as

$$d_{i\text{out}}^2 = \frac{6[r_i]_*^2 \gamma}{M_t - 1}, \quad i = 1, 2, \ldots, N_t,$$  

(3)

where $\gamma$ and $h_i = \log_2(M_t)$ are the power and bits allocated to the $i$-th substream. As with many other multi-channel communications, the performance of a spatial multiplexing system is usually limited by the weakest link. Thus the optimization problem can be sensibly formulated as:

$$\max_{(b_1, b_2, \ldots, b_n)} \sum_{i=1}^{N_t} \min_{\gamma(1, 2, \ldots, N_t)} \frac{d_{i\text{out}}^2}{2\log(1 + \gamma)} = \frac{6\gamma}{2\log(1 + \gamma)}.$$  

(4)

where $b_i$ and $\gamma_i$ are the total throughput and power constraints imposed on the system. Note in (4), $N_t$ is also an optimization parameter.

We can take some effective steps to decouple the optimization problem in (4). First, assuming the set of active antennas and associated bit allocation are given, we would like to allocate power so as to achieve the same minimum Euclidean distances for all subchannels, i.e.,

$$d_{i\text{out}}^2 = \ldots = d_{i\text{out}}^2 = d_{i\text{out}}^2, \quad \text{given as}$$  

$$\frac{6\gamma_i}{2\log(1 + \gamma_i)}.$$  

(5)

Thus our optimization goal is simplified as

$$\min \sum_{i=1}^{N_t} \frac{d_{i\text{out}}^2}{2\log(1 + \gamma)} = \min \{|g(N_t), (m(N_t))\}, 1 \leq N_t \leq K_t,$$  

(6)

subject to $b_i = \log_2(M_t) + \log_2(M_z) + \ldots + \log_2(M_{S_k})$,

where $g(N_t) = \{[r_1]_*, [r_2]_*, \ldots, [r_{N_t}]_*\}$ is called the antenna gain vector, $m(N_t) = (M_t - 1, M_t - 1, \ldots, M_t - 1)$ is called the bit allocation vector, and $\langle \cdot \rangle$ denotes the inner product between them. For the ease of description, we’ll drop the throughput constraint for the minimization problem in the following discussions.

We further decouple the antenna selection and bit allocation problems by exploiting the discrete and finite-alphabet nature of the bit allocation vector $m(N_t)$. When the total throughput and the modulation set are given, the possible choices of the bit allocation vector can be determined in advance by a lookup table. Furthermore, by lemma 1 given below, in order to minimize (6), only one permutation (decreasing order) of the elements in the bit allocation vector needs to be considered for each possible combination. With this decoupling, the optimization problem is finally reduced to an optimal antenna selection problem: we would like to find a matrix $H(p)$ whose “R” factor in the QR decomposition results in a close-to-optimal antenna gain vector $g(N_t)$. Some simple recursive algorithms are proposed in the next section to avoid exhaustive search.

Lemma1. For two increasingly ordered real sequence $\{a_i\}_{i=1}^{n}$ and $\{b_i\}_{i=1}^{n}$, if $c_1, c_2, \ldots, c_n$ is any permutation of $b_1, b_2, \ldots, b_n$, then \( \sum_i^a a_i \geq \sum_i^c c_i \geq \sum_i^a b_i \).

III. JOINT ANTENNA SELECTION AND LINK ADAPTATION FOR UNCORRELATED MIMO CHANNELS

A. Incremental and Decremental Selection Rules with Link Adaptation

Let us first assume that $N_t$ is given. Intuitively, we want $[r_{11}], [r_{22}], \ldots, [r_{N_t}]_*$ as large as possible. Our incremental recursive rule works as follows: starting from a column of $H$ ($H$ denotes the channel matrix between $K_t$ transmit antennas and $N_t$ receive antennas) which results in maximizing $[r_{11}]$ (corresponding to the largest vector norm), we successively choose from the remaining columns of $H$ such that the next subchannel gain is maximized. The subchannel gain of the newly added antenna can be obtained in a closed-form solution, which is described by the following lemma.

Lemma2.a Assume the QR decomposition of a matrix $H^{(k)}$ with $k$ independent columns is $H^{(k)} = Q(k)R(k)$. Then for the enhanced matrix $H^{(k+1)} = \left[ H^{(k)} \ h \right]$ with QR decomposition $H^{(k+1)} = Q(k+1)R(k+1)$, the first $k$ diagonal elements of $R(k+1)$ keep the same with those of $R(k)$, while the $(k + 1)-th$ one is given by $\sqrt{h^*h - h^*Q(k)Q(k)h}.$

Based on Lemma 2.a, in the $(k + 1)-th$ step, we can choose the column vector $h$ from $H - H^{(k)}$, (which represents the remaining columns of $H$) in such a way that $r_{k+1, i+1} = \sqrt{h^*h - h^*Q(k)Q(k)h}$ is maximized. Furthermore, it
can also be shown as follows that the successively generated antenna gains are already ordered.

**Lemma 2.b** In the above incremental selection rule for uncorrelated MIMO, \( r_{i_1} \geq |r_{i_2}| \geq \ldots \geq |r_{i_{K_t}}| \).

Lemma 2.b shows that the elements in the vector \( \mathbf{g}(N_t) = (|r_{i_1}|^2, |r_{i_2}|^2, \ldots, |r_{i_{K_t}}|^2) \) are already in an increasing order. Thus we only need to arrange the elements of candidate bit allocation vectors \( \mathbf{m}(N_t) \) in a decreasing order in the lookup table according to lemma 1, which saves storage space and increases the matching speed for (6).

In case nearly all the \( K_t \) transmit antennas would be deployed, we provide a decremental selection rule for link adaptation. Our proposed decremental selection rule is directly related to the V-BLAST ordering rule first proposed in [8], which successively chooses the antenna (among those not already chosen) that maximizes post-detection SNR under the assumption of perfect feedback. Accordingly, we can successively discard the antenna (among those not already chosen) that minimizes the post-detection SNR under the assumption of perfect feedback. Furthermore, we can avoid computing the inversion of the deflated channel matrix by means of a recursive square-root algorithm introduced in [3]. After successively discarding \( K_t - N_t \) columns from \( \mathbf{H} \), we apply QR decomposition to the deflated matrix to obtain the antenna gain vector \( \mathbf{g}(N_t) \), then find the optimal bit allocation vector \( \mathbf{m}(N_t) \) that minimizes \( \langle \mathbf{g}(N_t), \mathbf{m}(N_t) \rangle \).

**B. Simplified Link Adaptation for Uncorrelated Rayleigh MIMO Channels**

In a general link adaptation problem where \( N_t \) is not fixed in advance, we need to search over all possible \( 1 \leq N_t \leq K_t \) to find the optimal one using either the incremental or decremental selection rule. In this subsection, we propose a simplified selection rule based on the estimation of the optimal number of active transmit antennas to further reduce the complexity. With i.i.d. complex Gaussian channel matrix, \( |r_{i_j}|^2 \) in (6) is a \( \chi^2 \) distributed random variable with \( 2 \times (N_t + 1 - i) \) degrees of freedom, we replace \( 1/|r_{i_j}|^2 \) with its expectation, hence

\[
\min E\left( \langle \mathbf{g}(N_t), \mathbf{m}(N_t) \rangle \right) = \min \sum_{j=1}^{M_t} \frac{1}{2(N_t - j)} \times (M_t - 1).
\]

Therefore in the pre-processing stage, we can estimate the optimal number of active antennas, which is described below: given \( \mathbf{g}(N_t) \), for all possible bit allocation vectors \( \mathbf{m}(N_t) \)'s that satisfy throughput constraint, find the one that minimizes (7), assume \( \hat{N}_t = \arg \min E\left( \langle \mathbf{g}(N_t), \mathbf{m}(N_t) \rangle \right) \). Then find \( \hat{N}_t = \arg \min \sum_{j=1}^{M_t} \frac{1}{2(N_t - j)} \times (M_t - 1) \), which is our estimate of the optimal number of active antennas in i.i.d Raleigh fading MIMO channels. Thus we can decide to use either the incremental (if \( \hat{N}_t < K_t \)) or decremental selection rule (if \( \hat{N}_t = K_t \) ) for joint antenna selection and link adaptation for different system settings based on the value of \( \hat{N}_t \).

Furthermore, we can restrict ourselves to search optimal \( N_t \) only in the range around \( \hat{N}_t \) to further reduce the computational complexity. Simulations results show that searching \( N_t \) in the range of \( \hat{N}_t - 1, \hat{N}_t + 1 \) and storing only three bit allocation vectors \( \hat{\mathbf{m}}(N_t - 1), \hat{\mathbf{m}}(N_t) \) and \( \hat{\mathbf{m}}(N_t + 1) \) in the bit allocation lookup table incur little performance loss (See Section V).

**IV. JOINT ANTENNA SELECTION AND LINK ADAPTATION FOR CORRELATED MIMO CHANNELS**

**A. Correlated MIMO Channels**

We assume correlation only exists at the transmitter side, as described by the “one-ring” model in [5]. For an \( N_t \times K_t \) MIMO system, the channel can be modeled as \( \mathbf{H} = \mathbf{H}_w \mathbf{R}_y^{1/2} \), where \( \mathbf{H}_w \) is an \( N_t \times K_t \) matrix containing i.i.d. complex Gaussian random variables and \( \mathbf{R}_y \) is a \( K_t \times K_t \) Hermitian semi-positive definite matrix representing the covariance matrix for each row of \( \mathbf{H} \).

Again, we assume \( N_t \) out of \( K_t \) antennas are to be selected ( \( p \) denotes the active antenna indexes), then the channel matrix can be modeled as:

\[
\mathbf{y} = \mathbf{H}_w(p) \mathbf{R}_y^{1/2}(p) \mathbf{x} + \mathbf{n},
\]

where \( \mathbf{R}_y(p) \) is a submatrix of \( \mathbf{R}_y \) corresponding to the correlation matrix of the selected antennas. Since \( \mathbf{R}_y(p) \) (correlation information) varies much more slowly than \( \mathbf{H}_w(p) \mathbf{A}_t^T(p) \) (full channel information), in the next subsection, we will describe a joint antenna selection and link adaptation algorithm for correlated MIMO only based on the channel correlation information \( \mathbf{R}_y(p) \).

**B. Antenna Selection and Link Adaptation Only Based on Channel Correlation Information**

By applying QR decomposition successively to the correlation matrix \( \mathbf{R}_y^{1/2} = \mathbf{Q} \mathbf{R} \) and \( \mathbf{H}_w \mathbf{Q} = \mathbf{Q} \mathbf{R}_w \), (8) becomes (index \( p \) is dropped for simplicity)

\[
\mathbf{y} = \mathbf{Q} \mathbf{R}_w \mathbf{R} \mathbf{x} + \mathbf{n}.
\]

Apply \( \mathbf{Q}^T \) to the right hand side of (9), we can obtain

\[
\tilde{\mathbf{y}} = \mathbf{Q}^T \mathbf{y} = \mathbf{R}_w \mathbf{R} \mathbf{x} + \tilde{\mathbf{n}}.
\]

Compare (10) with (2) and (6), we can obtain the optimization goal for correlated MIMO channels as:
\[\min \sum_{j} R_{r,j} R_{r,j}^* \times (M_j - 1) = \min \{ \mathbf{g}(N_j), \mathbf{m}(N_j) \} \tag{11}\]

where

\[
\mathbf{g}(N_j) = \begin{bmatrix} |R(1,1)|^2 & \ldots & |R(N_j,N_j)|^2 \end{bmatrix}^T, \tag{12}\]

\[
\mathbf{m}(N_j) = (M_j - 1, M_j - 2, \ldots, M_{N_j} - 1)^T. \tag{13}\]

Since the distribution of \( \mathbf{H}_w \mathbf{Q}_i \) is the same as \( \mathbf{H}_w \), \( \mathbf{R}_r(j,j) \) is still \( \chi^2 \) distributed with degree of freedom \( 2 \times (N_j + 1 - j) \). We replace \( |\mathbf{R}_r(j,j)|^2 \) in (12) with its expectation value to get

\[
\overline{\mathbf{g}}(N_j) = \begin{bmatrix} |R(1,1)|^2 & \ldots & |R(N_j,N_j)|^2 \end{bmatrix}^T. \tag{14}\]

Hence (11) is turned into:

\[
\min \sum_{j} |R_{r,j}|^2 \times (M_j - 1) = \min \{ \overline{\mathbf{g}}(N_j), \mathbf{m}(N_j) \}. \tag{15}\]

In recognition of \( \mathbf{R}_r = \mathbf{R}_r^{\text{CH}} \mathbf{R}_r \), for correlated MIMO, our goal is to find a submatrix of \( \mathbf{R}_r \) whose Cholesky factor \( \mathbf{R}_r^{\text{CH}} \) will result in minimization of (14).

**Lemma3.a.** Assume matrix \( R_r^{(i)} \) is Hermitian positive definite with size \( k \), whose Cholesky decomposition is given by \( R_r^{(k)} = R^{(k)} v R^{(k)} \), then for the enhanced matrix \( R_r^{(k+1)} = \begin{bmatrix} R_r^{(k)} & v \v^H \end{bmatrix} \) with Cholesky decomposition \( R_r^{(k+1)} = R^{(k+1)} v R^{(k+1)} \), the first \( k \) diagonal elements of \( R^{(k+1)} \) keep the same with those of \( R^{(k)} \), while the \((k+1)\)-th one is given by \( \sqrt{1 - v^H R_r^{(k)}} v \).

Based on Lemma 3.a, in the \((k+1)\)-th step, we will choose the antenna whose covariance vector \( v \) will maximize \( r_{k+1} = \sqrt{1 - v^H R_r^{(k)}} v \). Note that the diagonal elements of the covariance matrix \( R_r \) are all 1’s, thus \( r_{1,1} \) is always 1 no matter which antenna is selected first. However, we can determine the first and second active antennas jointly by means of maximizing \( r_{2,2} \). Also note that the condition number of \( R_r \) is high, hence we can set a positive threshold value \( C_r \) in practice to discard those essentially zero-gain subchannels. Furthermore, the following lemma facilitates the optimization of (15).

**Lemma3.b** In the above incremental selection rule for correlated MIMO, \( r_{1,1} \geq \ldots \geq r_{k,1} \geq r_{k+1,1} \).

Lemma3.b shows the elements in \( \overline{\mathbf{g}}(N_j) \) are already in a decreasing order. Thus we only need to arrange the elements of candidate bit allocation vectors \( \mathbf{m}(N_j) \) in a deceasing order according to lemma 1. For correlated MIMO, a decremental selection rule is usually not necessary, since the ill-conditioning of the channel matrix typically results in much fewer antennas being selected compared with the uncorrelated MIMO of the same size. Furthermore, antenna selection and link adaptation modes need to be updated only when the channel covariance matrix changes, which happens far less frequently compared to that based on the instantaneous channel fading.

**V. NUMERICAL RESULTS**

In this section, we evaluate the performance of our proposed joint antenna selection and link adaptation algorithms for both uncorrelated and correlated MIMO channels through two representative examples. Due to space limitations, some results are omitted here, but will be presented at the conference. Square QAM modulation is employed in all simulations with 256-QAM the largest constellation to be used.

Example1: This example demonstrates the application of our proposed algorithms on a large MIMO system, emphasizing the demand of complexity reduction. The MIMO system considered is of size \( 16 \times 16 \), and the target throughput is 32 bits/s/Hz. To evaluate our proposed algorithms, link adaptation based on singular value decomposition (SVD) of the channel matrix [9] is also included, which can be viewed as a performance upper bound since the decomposed subchannels are interference free.

Clearly with this system, any exhaustive search will lead to tremendous computational complexity. Our proposed algorithms exhibit their simplicity advantage while closely approaching the SVD performance upper bound, as shown in Fig. 4. By using the reduced-size lookup table, the computation complexity is significantly reduced further. From (7) the estimated optimal number of active antennas is \( N_j = 12 \), hence in the lookup table, we only need to store the optimal bits pattern for \( N_j = \{11, 12, 13\} \), which is shown below.

\[
\text{Bits_table_reduced=} \begin{bmatrix} 4 & 4 & 4 & 4 & 4 & 4 & 4 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}.
\]

We do not provide the full size lookup table here because of its large size. From Fig.1, we can see that little performance loss is incurred when using the reduced-size lookup table. It is also shown that the incremental and decremental selection rules achieve almost the same performance and approach the SVD upper bound quite closely. (Note that the four curves for joint antenna selection and link adaptation are almost indistinguishable in Fig.1.)

Example2: This numerical example demonstrates the performance of link adaptation only based on correlation information, compared with that based on the full channel information. Consider a \( 6 \times 6 \) correlated MIMO with correlation matrix generated using the model introduced in [7], and the target throughput is 12 bits/s/Hz. We consider three correlated fading scenarios whose parameters (mean angle departure \( \bar{\theta} \) and variance of angle departure \( \sigma \)) are listed in Table I with an increasing order of fading.

---

**Table I**

<table>
<thead>
<tr>
<th>Scenario</th>
<th>( \bar{\theta} ) (deg)</th>
<th>( \sigma^2 ) (deg)²</th>
<th>( \delta ) (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>30</td>
<td>25</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>15</td>
<td>15</td>
<td>7</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>5</td>
<td>9</td>
</tr>
</tbody>
</table>

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Figure 1. Performance comparison of the proposed joint antenna and link adaptation algorithms in 16x16 MIMO with throughput 32 bits/s/Hz

Fig2 demonstrates the BER performance among link adaptation only based on the correlation information, link adaptation based on the full channel information and the conventional V-BLAST. From the simulation results, we can see the performance of the traditional V-BLAST degrades greatly in the correlated MIMO channels. On the other hand, antenna selection and link adaptation achieves more substantial gains for correlated MIMO than for uncorrelated MIMO, and the performance gap between link adaptation only based on channel correlated information and link adaptation based on the full channel information decreases as the degree of correlation increase.

Table I. FADING CORRELATION SCENARIOS

<table>
<thead>
<tr>
<th>Fading scenario</th>
<th>$\theta = \pi / 6$</th>
<th>$\theta = \pi / 10$</th>
<th>$\theta = \pi / 15$</th>
<th>$\theta = \pi / 30$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fading scenario 1</td>
<td>$\sigma = \pi / 6$</td>
<td>$\sigma = \pi / 10$</td>
<td>$\sigma = \pi / 15$</td>
<td>$\sigma = \pi / 30$</td>
</tr>
<tr>
<td>Fading scenario 2</td>
<td>$\sigma = \pi / 6$</td>
<td>$\sigma = \pi / 10$</td>
<td>$\sigma = \pi / 15$</td>
<td>$\sigma = \pi / 30$</td>
</tr>
<tr>
<td>Fading scenario 3</td>
<td>$\sigma = \pi / 6$</td>
<td>$\sigma = \pi / 10$</td>
<td>$\sigma = \pi / 15$</td>
<td>$\sigma = \pi / 30$</td>
</tr>
</tbody>
</table>

VI. CONCLUSION

In this paper, we propose joint antenna selection and link adaptation algorithms for both uncorrelated and correlated MIMO channels. Simulation results show that in most situations, significant performance gains are achieved compared with traditional equal power and equal rate V-BLAST. We also propose a simplified link adaptation algorithm based on the estimation of optimal number of active transmit antennas for Rayleigh i.i.d. MIMO channels. For correlated MIMO, we propose a link adaptation algorithm only based on channel correlation information, which is more practical in realization than that based on the instantaneous channel information, while approaching the latter in performance as the fading correlation increases. Finally, our antenna selection and link adaptation algorithms can be readily extended to other antenna selection applications, such as capacity maximization for both uncorrelated and correlated MIMO systems.

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