Transmit Antenna Selection for Multi-user MIMO Precoding Systems with Limited Feedback

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***Abstract*—Transmit antenna selection techniques are prominent since they exploit the spatial selectivity at the transmitter side. In the literature, antenna selection techniques assume full knowledge of the channel state information (CSI). In this paper, we consider that the CSI is not perfectly known at the transmitter; however, a quantized version of the channel coefficients is fed back by the users. We employ the non-uniform Lloyd-Max quantization algorithm which takes into consideration the distribution of the channel coefficients. Simulation results show that the degradation in the BER of the system with imperfect CSI at the transmitter is tolerable, especially when the transmit diversity order is high.**

***Index Terms*—Multi-user MIMO system, transmit antenna selection, imperfect channel state information, non-uniform quantization, Lloyd-Max quantizer.**

I.INTRODUCTION

IN recent broadband communication standards, multi-user multiple-input multiple-output (MU-MIMO) systems have been considered as a means for increasing the system throughput [1]-[2].In MU-MIMO systems, multiple users are assigned the same time and frequency resources, while the spatial resources can be either shared or orthogonally assigned. In the downlink MU-MIMO system, the base station (BS) has a pre-knowledge of the users' data and the fed back channel state information (CSI) from the users. As such, data can be precoded so that inter-user interference (IUI) can be cancelled, or highly reduced. Optimally, each user receives his data without experiencing the existence of other users.

Dirty paper coding (DPC) is the optimal precoding scheme for downlink MU-MIMO systems [3]. The main idea behind DPC is that it considers the MIMO channel to be a white paper that includes some dirt, i.e., interference. Since the location of the dirt is well-known, the BS only writes on the clean parts of the paper. Therefore, the reader, i.e., the mobile station (MS) receiver, can clearly distinguish between the dirt and the useful writing.

Several practical precoding techniques have been proposed in the literature, including linear precoding techniques [4], Tomlison-Harashimaprecoding [5], [6], and vector perturbation techniquescombined with linear precoders[7]-[10]. Linear zero-forcing precoding(ZFP) can be seen as a beamforming algorithm, where the beamforming weights are the rows of the pseudo-inverse of the channel matrix, while in the minimum-mean square error precoder (MMSEP) the channel matrix is regularized so that a tradeoff between noise amplification and IUI is achieved. On the other hand, THP and VP techniques linearly perturb the data vector such that the required transmit power is reduced. Combining these techniques with linear precoders is interesting in future communication systems such as long-term evolution (LTE) and LTE-advanced (LTE-A). This is because BS is supposed to have a large number of transmit antennas, e.g., up to 8 antennas in LTE-A system, and to communicate simultaneously with several users [11]. Due to its simplicity, we will restrict our discussions in the sequel on the ZFP, unless otherwise mentioned.

Transmit antenna selection improves the system performance by exploiting the spatial diversity at the transmitter side. Therefore, when the number of antennas at the BS is larger than the number of radio frequency (RF) chains, the subset of antennas that achieve the best conditions can be selected and connected to the available RF chains.

In the literature, several antenna selection techniques have been proposed for different scenarios. In [12], [13], various antenna selection techniques have been proposed for single user MIMO systems, and in [14], [15], authors proposed efficient antenna selection algorithms for the MU-MIMO case. Since the evaluation of the antenna selection is out of the scope of this paper, we will consider the optimum algorithm for the ZFP. For more computationally efficient algorithms, readers can refer to [15] and references therein.

The aforementioned references consider perfect channel state information at the transmitter (PCSIT), which is in general not practical, due to mobility, noise, and errors in the channel estimation. In this paper, we investigate transmit antenna selection in MU-MIMO systems with ZFP, when only a quantized version of the channel, a.k.a. limited feedback, is available at the transmitter. In the sequel, this will be referred to as imperfect CSIT (ICSIT). In this paper, the quantization of the channel coefficients is performed using the non-uniform Lloyd-Max iterative quantizer which takes into consideration the probability density function (pdf) of the

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quantized data [16], [17]. The real and imaginary parts of the channel coefficients are quantized separately.

The rest of this paper is organized as follows. In Section II we introduce the MU-MIMO system model and the optimum antenna selection for ZFP. In Section III, we introduce the MU-MIMO precoding system with limited feedback, and in Section IV we present simulation results and some discussions on the performance. Finally, we draw conclusions in Section V.

II. SYSTEM MODEL AND PRELIMINARIES

A. System Model

In this paper, we consider a MU-MIMO system, where a BS equipped with N antennas and M RF chains, communicates on the downlink with K single-antenna MSs. Note that N must be larger than M to use antenna selection and M must be larger than or equal to K to perform DPC precoding. Without loss of generality we consider that $M = K$. Assume that the channel is modeled as narrow-band slow time-varying, then the MU-MIMO system can be modeled as follows.

$$\mathbf{y} = \mathbf{Hx} + \mathbf{n}, \tag{1}$$

Where $\mathbf{y} \in \mathbb{C}^M$ is the received vector whose element y_k is the received signal at the single antenna of the k-th user, $\mathbf{x} \in \mathbb{C}^M$ is the precoded vector and $\mathbf{n} \in \mathbb{C}^M$ is the noise vector whose element n_k is generated in the receiver of the k-th user with zero mean and a variance of σ_n^2. Moreover, $\mathbf{H} = [\mathbf{h}_1^T \ \mathbf{h}_2^T \ \cdots \ \mathbf{h}_M^T]^T$ where $\mathbf{h}_k \in \mathbb{C}^M$ is the vector of channel coefficients coupling the M transmit antennas to the single antenna of the k-th user. Note that the channel coefficients are considered to be independent and follow centered symmetric Gaussian distributions with unit power.

B. Zero-forcing Precoding and Optimum Antenna Selection

Linear ZFP filters the transmitted vector using the pseudo-inverse of the channel matrix. The precoded vector is therefore given by:

$$\mathbf{x}_{\text{zf}} = \frac{1}{\sqrt{\gamma}} \mathbf{H}^{\dagger} \mathbf{s}, \tag{2}$$

Where $\mathbf{s} \in \mathbb{C}^M$ is the data vector and $\mathbf{H}^{\dagger}$ is the pseudo-inverse of the $\mathbf{H}$ matrix. The scaling factor γ is present to fix the average transmit power to a fixed value (P_T). That is

$$\gamma = \frac{1}{P_T} \mathrm{Tr}\left\{ (\mathbf{HH}^H)^{-1} \right\} = \frac{1}{P_T} \sum_{i=1}^{N} \sigma_i^{-2}(\mathbf{H}), \tag{3}$$

where Tr{**A**} denotes the trace of the **A** matrix and $\sigma_i(\mathbf{H})$ is the i-th singular value of **H**. Based on (2) and (3), the expected receive signal-to-noise ratio (SNR) at any receive antenna is given by:

$$\mathrm{SNR} = \frac{\mathrm{E}(ss^*)}{\gamma \sigma_n^2}, \tag{4}$$

assuming an equal noise power at the receivers.

As a consequence of (4), the sum rate capacity of the system is given by:

$$\mathrm{C}_{\text{ZFP}} = M \cdot \mathrm{E}[\log_2(1 + \mathrm{SNR})]. \tag{5}$$

It is clear from (4) that the SNR is inversely proportional to the scaling factor γ. Therefore, smaller values of γ indicate higher receive SNR and consequently higher capacity, and vice-versa.

In light of antenna selection, the set of antennas that minimize γ can be selected to increase the achieved capacity. Therefore,

$$U_{\text{opt}} = \underset{U \in S,\ p = 1,\ \ldots,\ P}{\arg\min} \left(\gamma\{\mathbf{H}_p\} \right), \tag{6}$$

where $P = C_M^N$ and $\gamma\{\mathbf{H}_p\} = \mathrm{Tr}\left\{ (\mathbf{H}_p \mathbf{H}_p^H)^{-1} \right\}\Big|_{P_T = 1}$. For computational efficient antenna selection algorithms, refer to [15] and reference therein. The overall MU-MIMO system with antenna selection and precodingis depicted in Fig. 1.

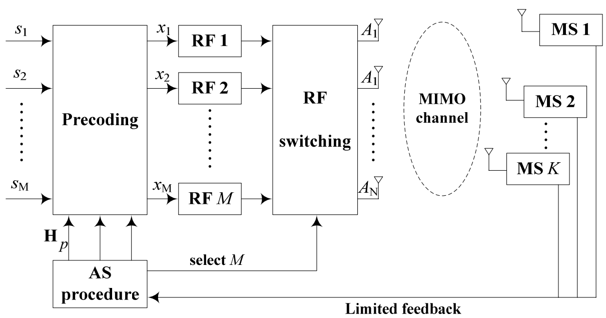

Fig.1. MU-MIMO system with antenna selection and limited feedback.

III. MU-MIMO PRECODING WITH ICSIT

A. Uniform Quantization

The perfect knowledge of the CSI at the transmitter side is not practical, if not impossible. Therefore, the channel coefficients should be quantized and fed back to the transmitter. The intuitive quantization method is to use a *uniform quantizer* where the range of values of the channel coefficient is divided into a number of equal intervals. The quantization levels are then considered as the midpoint between the boundaries of each interval. This quantizer, though simple, is not appropriate for quantizing the channel coefficients which are not uniformly distributed. Hence, it leads to high distortion (see [17], Figure 5). In the following, the non-uniform Lloyd-Max quantization is presented.

B. Non-uniform Lloyd-Max Quantization

Consider the signal to be quantized using a $D = 2^B$quantizer, where D is the number of levels and B is the number of bits required to feed back the real or the imaginary parts of a channel coefficient to the BS. Note that D can be any integer that might not be a power of 2. However, we consider D to be a power of 2 so that each coefficient is fed back as an integer number of bits.

Consider a D level quantizer, where each level y_i is associated with a decision region with boundaries x_k and x_{k-1}. Note that the extreme decision regions are $x_0 = -\infty$ and $x_D = +\infty$. Then,

$$x_k = \frac{y_k + y_{k+1}}{2}, \qquad k = 1, 2, \cdots, D-1 \tag{7}$$

and

$$y_k = \frac{\int_{x_{k-1}}^{x_k} x\, f_X(x)\, dx}{\int_{x_{k-1}}^{x_k} f_X(x)\, dx}, \qquad k = 1, 2, \cdots, D \tag{8}$$

Where $f_X(x)$ is the probability density function of the real/imaginary parts of the channel coefficients. Equations (7) and (8) are the basis for an iterative implementation of Lloyd-Max quantizer, which is given in Table 1 [16]-[18].

TABLE I
LLOYD-MAX ALGORITHM

Inputs:D,$f_X(x)$, convergence condition

1. Start with an initial set of quantization intervals
2. Using the quantization intervals, compute the quantization levels using (8)
3. Update the new boundaries of the quantization intervals using (7). Exit if the algorithm converges, otherwise go to Step 1

Output:the vector **y** of the quantization levels

The vector of the quantization levels is then used to quantize the channel coefficients at the MSs before being fed back to the BS. Note the quantized channel matrix will be referred to as $\mathbf{H}_Q$, where the error matrix $\mathbf{H}_E$ is given by ($\mathbf{H} - \mathbf{H}_Q$).

IV. SIMULATION RESULTS AND DISCUSSIONS

In this section, we evaluate the performance of the MU-MIMO system with precoding. We compare the system performance with PCSIT and with ICSIT. We consider a MU-MIMO system (N, K, M) with N transmit antennas, K users, and M antennas are selected from the available N antennas for transmission.

Fig.2 depicts the bit error rate (BER) performance of the MU-MIMO system for several values of B and system configurations. As the number of feedback bits per the real/imaginary parts increases, the BER performance is improved. As a tradeoff between the feedback overhead and performance, we set $B$to 4 in the following simulations.

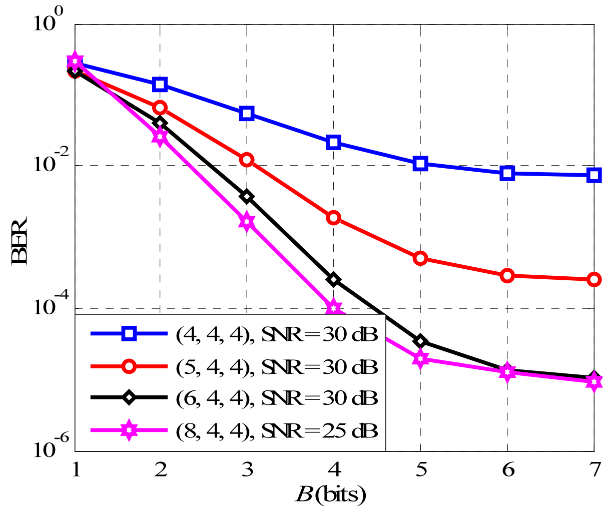

Fig.2. BER performance of the MU-MIMO system versus the number of required feedback bits (B) for several system scenarios.

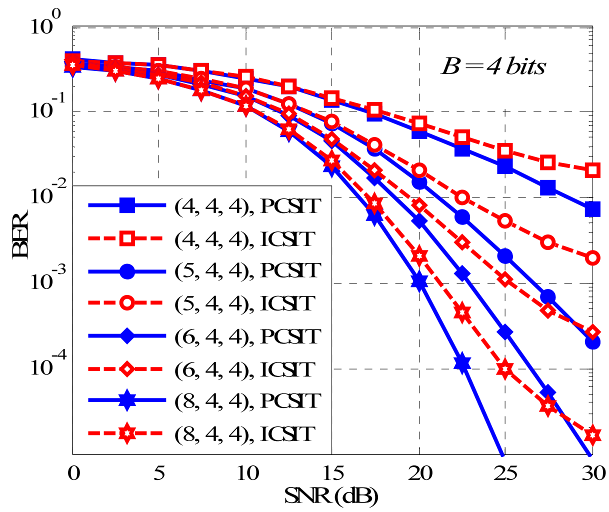

Fig.3.BER performance of the MU-MIMO system with antenna selection and ZFP for PCSIT and ICSIT. Each channel coefficient is fed back using 8 bits equally divided between the real and the imaginary parts.

In [19], it has been shown that for the non-uniform quantizer the elements of the error matrix $\mathbf{H}_E$ have zero mean and a variance of 2^{-B}. This indicates that the quantization error vanishes as the number of the feedback bits increases. It has also been shown that the number of feedback bits depends on the signal-to-noise ratio (SNR), and that relation is given as follows [19].

$$B \approx \log_2(\mathrm{SNR}) - \log_2(d), \tag{9}$$

where*d* is a constant. This indicates that as the SNR increases, the number of feedback bits is increased, which is reasonable. This is due to the fact that at low SNR the number of feedback bits is low because the noise power is dominant. However, when the SNR increases, the noise power is decreased and the quantization error becomes dominant. Therefore, the number of feedback bits should be increased to maintain a fixed effective noise power.

Fig.3depicts the BER performance of the MU-MIMO system with ZFP and antenna selection. The performance with PCSIT and ICSIT are depicted for several scenarios. Although the BER performance of the system with ICSIT is degraded compared the performance the system with PCSIT, the degradation is tolerable especially when the number of additional transmit antennas is high, e.g., when (*N*-*M*) is high.

V. CONCLUSIONS

In this paper, we considered the MU-MIMO precoding system with antenna selection where the quantized channel state information is available by means of feedback from the MSs. In contrast with the uniform quantization, we employed the non-uniform Lloyd-Max quantizer which takes into consideration the probability density function of the channel coefficients, where better performance is achieved. Simulation results show that, for a fixed number of feedback bits, the degradation in BER due to the ICSIT is tolerable for practical scenarios where considering perfect channel knowledge at the transmitter is impossible.

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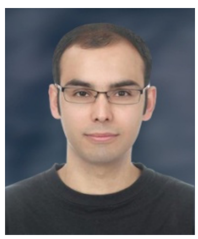

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