Distributed Adaptation of Quantized Feedback for Downlink Network MIMO Systems

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Abstract—This paper focuses on quantized channel state information (CSI) feedback for downlink network MIMO systems. Specifically, we propose to quantize and feedback the CSI of a subset of BSs, namely the feedback set. Our analysis reveals the tradeoff between better interference mitigation with large feedback set and high CSI quantization precision with small feedback set. Given the number of feedback bits and instantaneous/long-term channel conditions, each user optimizes its feedback set distributively according to the expected SINR derived from our analysis. Simulation results show that the proposed feedback adaptation scheme provides substantial performance gain over non-adaptive schemes, and is able to effectively exploit the benefits of network MIMO under various feedback bit budgets.

Index Terms—Network MIMO, base station coordination, limited feedback, co-channel interference.

I. INTRODUCTION

MANAGING inter-cell co-channel interference (CCI) has been a key issue for wireless cellular networks. Traditional ways of CCI mitigation either require extra bandwidth for large reuse factor, or rely on highly complex signal processing which is not practical for mobile devices. Recently, with the development of multiple input multiple output (MIMO) technologies and the enhanced base station (BS) processing capability, network-wise solutions have been proposed to combat inter-cell CCI [1]–[3]. The basic idea is to treat a group of BSs as a "super-BS" with multiple non-colocated antennas, also known as *network MIMO*. By sharing the user data and channel state information (CSI), multiple BSs coherently coordinate the transmission and reception, thus other-cell signals are used to assist transmission instead of acting as interference.

Although significant capacity gain provided by network MIMO has been predicted through theoretical analyses [1][2] and simulations [7] with perfect CSI, little efforts have been made with limited CSI feedback [9]. Practical network MIMO systems only allow restricted number of coordinating BSs to form clusters [3][7]. While larger cluster provides better performance with lower inter-cell CCI[4], the CSI feedback should grow proportionally with the cluster size. Fortunately,

for a specific user, as antennas on the non-collocated BSs have different channel statistics, also known as "channel asymmetry", intuitively BSs with larger path-loss and large-scale fading are less beneficial to cooperate. There are chances for feedback reduction by ignoring the CSI from BSs with relatively weak signals. Nevertheless, very limited work exploits these chances with quantified feedback constraints. Ref. [8] proposes to feedback CSI of the BSs with channel gains larger than a threshold. However, the number of CSI feedback coefficients per user has no closed-form relation with the threshold, and the realistic quantized CSI feedback is not considered, thus the amount of feedback cannot be explicitly controlled. In [4] and [5], quantized CSI feedback and quantization bit allocation are considered, however, for coordinated single-BS transmission (i.e., MIMO interference channel). Other approaches like [14] and [15] only require each BS to have local CSI of its own channel to users, which is more beneficial for reducing CSI exchange over the backhaul, not for feedback reduction.

In this paper, we consider the downlink multi-user (MU) network MIMO where quantized CSI is fed back. The feedback amount is explicitly characterized by the number of feedback bits B. Since the performance of MU-MIMO is very sensitive to CSI error [11], intuitively B should scale proportionally with the cluster size. Therefore, a key tradeoff exists between reducing inter-cell CCI with larger cluster and reducing intra-cluster interference induced by CSI quantization error with smaller cluster. Herein, instead of tuning the cluster size which is generally fixed with the system configuration, we propose to adapt the CSI feedback set in a per-user manner, where the feedback set is defined as the subset of BSs with respect to which the CSI is quantized. We first derive a lower bound of the expected receive SINR, given B, the feedback set, and instantaneous/long-term channel conditions. By maximizing the SINR lower bound, each user independently determines its optimal feedback set, in which the BSs act as an effective coordination cluster to jointly serve the user. The feedback bits are thus optimally utilized to exploit the benefits of network MIMO cooperation.

Notations: $|\cdot|$ denotes the cardinality of a set. $\|\cdot\|$ denotes the Euclidean norm of a vector (or absolute value of a scalar). $(\cdot)^T$ and $(\cdot)^*$ denote the transpose and transpose conjugate of a matrix, respectively. $\mathbb{E}$ represents the expectation operation. Some of the symbol notations that are used throughout this paper are listed in Table I.

II. CLUSTERED NETWORK MIMO COORDINATION

We consider the downlink of a cellular network with universal frequency reuse, where each BS is equipped with
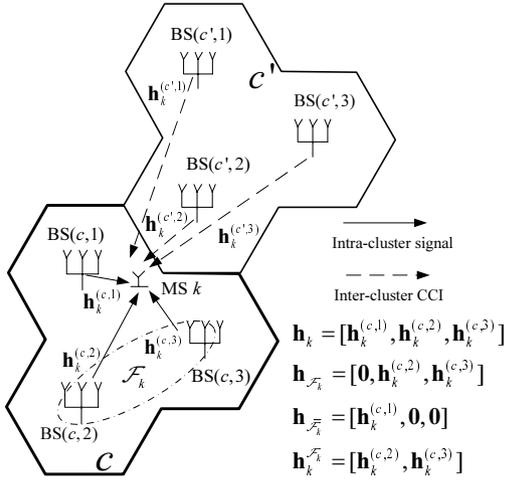
Fig. 1. Example of a clustered network MIMO system, with $|\mathcal{B}_c| = 3$, $N_t = 3$. Three non-sectorized cells form a cluster and each cell has one BS. A CSI feedback set $\mathcal{F}_k = \{(c,2),(c,3)\}$ and corresponding notations are also depicted.

TABLE I
SYMBOL NOTATIONS

c	BS cluster
$\mathcal{B}_c$	Set of BSs in cluster c
(c,b)	BS b in cluster c
$\mathcal{S}(c)$	Scheduled users in cluster c
N_t	Number of transmit antennas on a BS
P_k	Allocated power for user k
$\mathbf{h}_k^{(c,b)}$	Channel vector from BS (c,b) to user k
$\mathbf{h}_k$	Aggregate channel vector to user k
$\mathbf{w}_k^{(c,b)}$	Precoding vector from BS (c,b) to user k
$\mathbf{w}_k$	Aggregate precoding vector to user k
$\mathcal{F}_k$	BS Feedback set of user k
$\mathbf{h}_k^{\mathcal{F}_k}$	Aggregate channel vector from $\mathcal{F}_k$ to user k
$\tilde{\mathbf{h}}_k^{\mathcal{F}_k}$	Normalized version of $\mathbf{h}_k^{\mathcal{F}_k}$
$\hat{\mathbf{h}}_k^{\mathcal{F}_k}$	Quantized version of $\tilde{\mathbf{h}}_k^{\mathcal{F}_k}$ to be fed back
$\hat{\mathbf{h}}_k$	Quantized channel vector recovered from $\hat{\mathbf{h}}_k^{\mathcal{F}_k}$
$\theta_k^{\mathcal{F}_k}$	Angle between $\hat{\mathbf{h}}_k^{\mathcal{F}_k}$ and $\tilde{\mathbf{h}}_k^{\mathcal{F}_k}$

N_t antennas and each user has a single antenna. The whole network is divided into *disjointing* cell clusters [3] [7], i.e., each BS belongs to one cluster and each user is served by one cluster, as shown in Fig. 1. A cluster, denoted by c, contains a group of BSs, denoted by $\mathcal{B}_c$, and each of the $|\mathcal{B}_c|$ BSs in $\mathcal{B}_c$ is denoted by (c,b). With fully shared user data, the BSs in the cluster execute joint linear precoding for the scheduled users (denoted by $\mathcal{S}(c)$) based on the available CSI. Block fading model is assumed so that the channel is static over one scheduling interval. The received signal of user k, if scheduled, is given by

$$y_k = \underbrace{\sum_{b=1}^{|\mathcal{B}_c|} \mathbf{h}_k^{(c,b)} \mathbf{w}_k^{(c,b)} d_k}_{\text{desired signal}} + \underbrace{\sum_{b=1}^{|\mathcal{B}_c|} \mathbf{h}_k^{(c,b)} \sum_{i=1,i\neq k}^{|\mathcal{S}(c)|} \mathbf{w}_i^{(c,b)} d_i}_{\text{intra-cluster interference}}$$
$$+ \underbrace{\sum_{c'\neq c} \sum_{b'=1}^{|\mathcal{B}_{c'}|} \mathbf{h}_k^{(c',b')} \sum_{j\in\mathcal{S}(c')} \mathbf{w}_j^{(c',b')} d_j}_{\text{inter-cluster interference}} + n_k, \qquad (1)$$

where we have: $\mathbf{h}_k^{(c,b)} = l_k^{(c,b)} \bar{\mathbf{h}}_k^{(c,b)}$ denotes the $1 \times N_t$ channel vector from BS (c,b) to user k, where $l_k^{(c,b)}$ accounts for the large-scale path-loss and shadowing, and small-scale fast fading is assumed to be uncorrelated Rayleigh fading so that $\bar{\mathbf{h}}_k^{(c,b)^T} \sim \mathcal{CN}(0,\mathbf{I}_{N_t})$; $\mathbf{w}_k^{(c,b)}$ denotes the $N_t \times 1$ precoding vector for user k on BS (c,b); d_k is the intended data signal for user k; n_k is the additive white Gaussian noise at user k, with zero mean and variance σ_n^2. For the ease of further presentations, we denote the aggregate $1 \times N_t|\mathcal{B}_c|$ channel vector from all BSs in cluster c to user k as $\mathbf{h}_k = [\mathbf{h}_k^{(c,1)}, \mathbf{h}_k^{(c,2)}, \ldots, \mathbf{h}_k^{(c,|\mathcal{B}_c|)}]$ (shown in Fig. 1). Similarly, denote the $N_t|\mathcal{B}_c| \times 1$ precoding vector from cluster c to user k by $\mathbf{w}_k = [\mathbf{w}_k^{(c,1)^T}, \mathbf{w}_k^{(c,2)^T}, \ldots, \mathbf{w}_k^{(c,|\mathcal{B}_c|)^T}]^T$. Also, $\mathbf{w}_k$ is normalized to unit norm, and thus $\mathbb{E}(d_k d_k^*) = P_k$ is the transmission power allocated for user k.

In this paper, zero-forcing beamforming (ZFBF) [13] is used to suppress the intra-cluster interference, which satisfies

$\hat{\mathbf{h}}_k \mathbf{w}_i = 0, \forall i \neq k, i \in \mathcal{S}(c)$, where $\hat{\mathbf{h}}_k$ is the quantized channel vector recovered from the feedback of user k. As for the power allocation, we use the sum power constraint (SPC) for each cluster, i.e., $\sum_{k=1}^{|\mathcal{S}(c)|} P_k \leq |\mathcal{B}_c| P_B$, where P_B is the maximum transmit power for single-BS transmission. With much lower calculation complexity, SPC is a good approximation to per-BS power constraint (PBPC), especially when scheduling is adopted among many users due to multi-user diversity [3][6]. Same assumption is made for the performance evaluation of network MIMO systems in [7]. To make the analysis trackable, equal power allocation is assumed in the next section, while more advanced power allocation optimization is adopted in the simulations, which will be described in Section IV.

III. CSI FEEDBACK SET OPTIMIZATION

In this section, a CSI feedback set adaptation scheme is proposed to enhance system performance under feedback bit constraints.

A. Framework of CSI Feedback Set Adaptation

Frequency division duplex (FDD) is considered so that the CSI required for downlink transmission should be obtained through quantized feedback [9]. In this paper, CSI feedback set adaptation is proposed, i.e., the equivalent channel vector $\mathbf{h}_k^{\mathcal{F}_k}$ with any subset of the BSs $\mathcal{F}_k \subseteq \mathcal{B}_c$ can be quantized and fed back by user k to its home BS[1], where

$$\mathbf{h}_k^{\mathcal{F}_k} = [\mathbf{h}_k^{(c,b_1)}, \mathbf{h}_k^{(c,b_2)}, \ldots, \mathbf{h}_k^{(c,b_{|\mathcal{F}_k|})}], \qquad (2)$$

and $\mathcal{F}_k = \{(c,b_i)|i = 1, \ldots, |\mathcal{F}_k|\}$. Note that the dimension of $\mathbf{h}_k^{\mathcal{F}_k}$ is $1 \times N_t|\mathcal{F}_k|$. To assist limited feedback, the channel direction information (CDI) $\tilde{\mathbf{h}}_k^{\mathcal{F}_k} = \mathbf{h}_k^{\mathcal{F}_k}/\|\mathbf{h}_k^{\mathcal{F}_k}\|$ is quantized to a unit norm vector $\hat{\mathbf{h}}_k^{\mathcal{F}_k}$, which is chosen from a codebook $\mathcal{V}_k$ with unit norm $1 \times N_t|\mathcal{F}_k|$ vectors of size $N = 2^B$, according

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[1]The home BS is the one that user k associates to, and is generally with the largest $l_k^{(c,b)}$. After user feedback, the CSI is shared among the cluster BSs over the backhaul.

to the minimum distance criterion: $\hat{\mathbf{h}}_k^{\mathcal{F}_k} = \arg\max_{\mathbf{v}\in\mathcal{V}_k} \|\tilde{\mathbf{h}}_k^{\mathcal{F}_k}\mathbf{v}^*\|$ [11][12]. Then the B-bit index of the codeword is fed back. We assume perfect CSI estimation at the users, and the feedback channel is error-free and without delay.

In this paper we use random vector quantization (RVQ) [10], where the vectors in $\mathcal{V}_k$ are independently and isotropically distributed on the $|\mathcal{F}_k|N_t$-dimensional unit sphere. Simple for analysis, RVQ also serves as a close lower-bound to the system performance [10][11]. In practice, when a specific codebook design is adopted, because the user codebooks $\mathcal{V}_k$ are different in terms of vector dimension $|\mathcal{F}_k|N_t$, the storage of all the possible subset codebooks seems to be large at first glance. In fact, they can be generated on demand from a "basic codebook" $\mathcal{V}$ containing N vectors with dimension $1 \times C_{\max}N_t$, where $C_{\max}$ is the largest cluster size the system can support. Then $\mathcal{V}_k$ is obtained by cutting out and normalizing a predefined combination of $|\mathcal{F}_k|N_t$ dimensions of the vectors in $\mathcal{V}$. As a result, *no* storage increase is required.

At the BS side, the unit norm $1 \times N_t|\mathcal{B}_c|$ equivalent channel vector $\hat{\mathbf{h}}_k$ should be recovered from the feedback version $\hat{\mathbf{h}}_k^{\mathcal{F}_k}$. Specifically, if $\mathcal{F}_k = \mathcal{B}_c$, $\hat{\mathbf{h}}_k = \hat{\mathbf{h}}_k^{\mathcal{F}_k}$. Otherwise $\mathcal{F}_k \subset \mathcal{B}_c$, then $\hat{\mathbf{h}}_k$ equals $\hat{\mathbf{h}}_k^{\mathcal{F}_k}$ on the corresponding dimensions, and equals 0 elsewhere, see Fig. 1. For example, if $\mathcal{F}_k$ corresponds to the first $|\mathcal{F}_k|$ BSs in the cluster c, i.e., in (2), $b_i = 1,\ldots,|\mathcal{F}_k|$, we have $\hat{\mathbf{h}}_k = [\hat{\mathbf{h}}_k^{\mathcal{F}_k}, \mathbf{0}_{1\times N_t(|\mathcal{B}_c|-|\mathcal{F}_k|)}]$, where the unit norm property still holds. It is assumed that the channel quality information (CQI) is fed back without quantization, because CQI feedback does not scale with the cluster size and thus is not the focus of this paper.

B. Impact of Quantized Feedback

For the analysis, assume that $N_t|\mathcal{B}_c|$ users are scheduled in the cluster, and the transmit power is equally allocated among users with P_B/N_t. Let $z_k = \sum_{c'\neq c}\sum_{j\in\mathcal{S}(c')}\|\sum_{b'=1}^{|\mathcal{B}_{c'}|}\mathbf{h}_k^{(c',b')}\mathbf{w}_j^{(c',b')}\|^2 P_j + \sigma_n^2$ denote the inter-cluster interference plus noise at user k. The SINR of user k is given by

$$\gamma_k = \frac{\|\mathbf{h}_k\mathbf{w}_k\|^2}{\sum_{j=1,j\neq k}^{N_t|\mathcal{B}_c|}\|\mathbf{h}_k\mathbf{w}_j\|^2 + \frac{z_k N_t}{P_B}}. \quad (3)$$

The following discussions concentrate on a specific cluster c, so the pairwise notation of BS (c,b) is simplified to b. From the kth user's point of view, the expected SINR follows the following theorem.

Theorem 1: Given $\mathbf{h}_k$, CSI feedback set $\mathcal{F}_k$, codebook size $N = 2^B$, the expected SINR of user k over recovered channel vector $\hat{\mathbf{h}}_k$ and beamformers $\{\mathbf{w}_j\}_{j=1}^{N_t|\mathcal{B}_c|}$ is lower bounded by[2]

$$\mathbb{E}\{\gamma_k\} \geq \bar{\gamma}_k^{\mathrm{LB}}$$
$$\triangleq \frac{\mathbb{E}\{\|\mathbf{h}_k\mathbf{w}_k\|^2\}}{\frac{z_k N_t}{P_B} + 2^{-\frac{B}{N_t|\mathcal{F}_k|-1}}\sum_{b\in\mathcal{F}_k}\|\mathbf{h}_k^{(b)}\|^2 + \sum_{b'\notin\mathcal{F}_k}\|\mathbf{h}_k^{(b')}\|^2}. \quad (4)$$

[2]Note that in the case of $N_t = 1$, $\frac{B}{N_t|\mathcal{F}_k|-1}$ would be singular when the feedback set only has one BS. Nevertheless, $2^{-\frac{B}{N_t|\mathcal{F}(k)|-1}}$ approaches zero, and it is reasonable because in this case the equivalent channel reduces to a scalar channel and we assumed perfect CQI.

Proof: See Appendix. ∎

The value of $\mathbb{E}\{\|\mathbf{h}_k\mathbf{w}_k\|^2\}$ in the numerator is related to how scheduling is performed. Two representative cases for calculating $\mathbb{E}\{\|\mathbf{h}_k\mathbf{w}_k\|^2\}$ are illustrated.

Case 1: If the $N_t|\mathcal{B}_c|$ users are selected randomly (or equivalently round-robin scheduling), beamformer $\mathbf{w}_k$ is statistically independent of $\mathbf{h}_k$. Due to the same reason as described in the proof of Theorem 1 for $\{\mathbf{w}_i\}_{i\neq k}$, it is also reasonable for each user k to view $\mathbf{w}_k$ isotropically distributed in the unit sphere of $\mathbb{C}^{N_t|\mathcal{B}_c|\times 1}$. In this case, we have $\|\mathbf{h}_k\mathbf{w}_k\|^2 \sim \|\mathbf{h}_k\|^2\beta(1, N_t|\mathcal{B}_c|-1)$ [11]. Therefore

$$\mathbb{E}_{\mathbf{w}_k}\{\|\mathbf{h}_k\mathbf{w}_k\|^2\} = \|\mathbf{h}_k\|^2/(N_t|\mathcal{B}_c|) = \sum_{b=1}^{|\mathcal{B}_c|}\|\mathbf{h}_k^{(b)}\|^2/(N_t|\mathcal{B}_c|). \quad (5)$$

Case 2: When advanced scheduling scheme is utilized [13][17], and if the number of users is large, the channel vectors of selected users are mutually orthogonal. Thus the two vectors $\hat{\mathbf{h}}_k^*$ and $\mathbf{w}_k$ are aligned. Note that $\hat{\mathbf{h}}_k$ is zero on the dimensions corresponding to the BSs outside $\mathcal{F}_k$, and so does $\mathbf{w}_k$. Hence we have $\|\mathbf{h}_k\mathbf{w}_k\|^2 = \|\mathbf{h}_k^{\mathcal{F}_k}\|^2\cos^2\theta_k^{\mathcal{F}_k} = \sum_{b\in\mathcal{F}_k}\|\mathbf{h}_k^{(b)}\|^2\cos^2\theta_k^{\mathcal{F}_k}$. Then the expectation $\mathbb{E}_{\mathbf{w}_k}\{\|\mathbf{h}_k\mathbf{w}_k\|^2\}$ can be derived with the results in [12]. Or the upper bound for $\mathbb{E}\{\sin^2\theta_k^{\mathcal{F}_k}\}$ from [11] can be utilized to lower bound the expectation as

$$\mathbb{E}_{\mathbf{w}_k}\{\|\mathbf{h}_k\mathbf{w}_k\|^2\} \geq \left(1 - 2^{-\frac{B}{N_t|\mathcal{F}_k|-1}}\right)\sum_{b\in\mathcal{F}_k}\|\mathbf{h}_k^{(b)}\|^2. \quad (6)$$

We remark that the proposed feedback set adaptation algorithm, which will be detailed next, is not restricted to any specific scheduling scheme. One should choose from the above two cases based on the scheduling scheme adopted. We will also illustrate the usage of the two cases in the next sub-section when the overhead of the proposed algorithm is discussed.

C. Distributed Feedback Set Optimization Algorithm

For the denominator in the expression of $\bar{\gamma}_k^{\mathrm{LB}}$, $\sum_{b\in\mathcal{F}_k}\|\mathbf{h}_k^{(b)}\|^2$ represents the co-user CCI due to quantization error, and $z_k N_t/P_B + \sum_{b'\notin\mathcal{F}_k}\|\mathbf{h}_k^{(b')}\|^2$ represents the inter-cell CCI that has not been tackled by network MIMO coordination. The BSs of $\mathcal{B}_c$ outside $\mathcal{F}_k$ behave equivalently as interference sources as those BSs of other clusters, i.e., reducing $\mathcal{F}_k$ is like shrinking the effective cluster for the user. Therefore, given B, there exists a tradeoff between CCI mitigation (prefers larger $\mathcal{F}_k$) and CSI quantization precision (prefers smaller $\mathcal{F}_k$). The best CSI feedback set $\mathcal{F}_k^*$ should be determined based on the channel conditions $\{\mathbf{h}_k^{(b)}, b\in c\}$ as

$$\mathcal{F}_k^* = \arg\max_{\mathcal{F}_k}\bar{\gamma}_k^{\mathrm{LB}}. \quad (7)$$

Naturally it requires to search all the possible BS subsets of $\mathcal{B}_c$. However, the following corollary assures simple linear search for both case 1 and case 2.

Corollary 1: The optimal CSI feedback set $\mathcal{F}_k^*$ that maximizes the expected SINR low bound $\bar{\gamma}_k^{\mathrm{LB}}$ satisfies: $\forall b \in \mathcal{F}_k^*$ and $\forall b' \notin \mathcal{F}_k^*$, $\|\mathbf{h}_k^{(b)}\|^2 \geq \|\mathbf{h}_k^{(b')}\|^2$ always holds.

Proof: The proof can be done by contradiction. Suppose there exist BS $b \in \mathcal{F}_k^*$ and BS $b' \notin \mathcal{F}_k^*$, so that $\|\mathbf{h}_k^{(b)}\|^2 < \|\mathbf{h}_k^{(b')}\|^2$. Because $2^{-\frac{B}{N_t|\mathcal{F}_k^*|-1}} < 1$, in $\mathcal{F}_k^*$, replacing b by b' always increases $\bar{\gamma}_k^{\mathrm{LB}}$ for both case 1 and case 2. It then contradicts the fact that $\mathcal{F}_k^*$ is the optimal CSI feedback set. As a result, the original corollary holds. ∎

Based on Corollary 1, each user distributively determines its feedback set by Algorithm 1, where we explicitly write the SINR lower bound as a function of $\mathcal{F}_k$ by $\bar{\gamma}_k^{\mathrm{LB}}(\mathcal{F}_k)$. Since it is not practical to have z_k when executing Algorithm 1, z_k is approximated by its expectation

$$
z_k \approx \sum_{c' \neq c} \mathbb{E}\left\{ \sum_{j \in \mathcal{S}(c')} \| \sum_{b'=1}^{|\mathcal{B}_{c'}|} \mathbf{h}_k^{(c',b')} \mathbf{w}_j^{(c',b')} \|^2 P_j \right\} + \sigma_n^2
$$
$$
= \sum_{c' \neq c} \sum_{b'=1}^{|\mathcal{B}_{c'}|} \|\mathbf{h}_k^{(c',b')}\|^2 P_B/N_t + \sigma_n^2, \tag{8}
$$

where the last equality holds because: 1) Full load scheduling is assumed with $|\mathcal{S}(c')| = N_t|\mathcal{B}_{c'}|$; 2) Equal power allocation is assumed so that $P_j = P_B/N_t$; 3) $\mathbf{h}_k^{(c',b')}$ and $\mathbf{w}_j^{(c',b')}$ are mutually independent, and the direction of $\mathbf{w}_j = [\mathbf{w}_j^{(c',1)^T}, \mathbf{w}_j^{(c',2)^T}, \ldots, \mathbf{w}_j^{(c',|\mathcal{B}_{c'}|)^T}]^T$ can be considered isotropic so that $\mathbb{E}\left\{ \| \sum_{b'=1}^{|\mathcal{B}_{c'}|} \mathbf{h}_k^{(c',b')} \mathbf{w}_j^{(c',b')} \|^2 \right\} = \sum_{b'=1}^{|\mathcal{B}_{c'}|} \|\mathbf{h}_k^{(c',b')}\|^2/(N_t|\mathcal{B}_{c'}|)$ [3].

Algorithm 1 CSI Feedback Set Adaptation

Initialization: Set $\mathcal{F}_k = \emptyset$ and $\mathcal{L} = \mathcal{B}_c$
  while $\mathcal{L} \neq \emptyset$ **do**
    Find $b^* = \arg\max_{b \in \mathcal{L}} \|\mathbf{h}_k^{(b)}\|^2$
    if $\bar{\gamma}_k^{\mathrm{LB}}(\mathcal{F}_k \cup \{b^*\}) > \bar{\gamma}_k^{\mathrm{LB}}(\mathcal{F}_k)$ **then**
      $\mathcal{F}_k = \mathcal{F}_k \cup \{b^*\}$ and $\mathcal{L} = \mathcal{L} \setminus \{b^*\}$
    else
      Return $\mathcal{F}_k^* = \mathcal{F}_k$
    end if
  end while

It is important to note that indicating the feedback set introduces extra feedback overhead. To address this issue, we consider two extreme scenarios about how frequently Algorithm 1 is performed: In one case Algorithm 1 is executed at each scheduling interval (denoted by *fast adaptation*, with *Case 2* matric); The other is the scenario when the feedback set is merely determined by large-scale path-loss and shadowing $l_k^{(b)}$, which varies very slowly. One can simply replace the $\|\mathbf{h}_k^{(b)}\|$ by its expectation $l_k^{(b)}\sqrt{N_t}$ in the expressions of $\bar{\gamma}_k^{\mathrm{LB}}$ (denoted by *slow adaptation*, with *Case 1* metric, as in the *long-term*, users got almost equal scheduling opportunities with fairness scheduling schemes). It is confirmed by simulations that slow adaptation works very close to fast adaptation. This indicates that the large-scale path-loss and shadowing is the main factor that determines the optimal feedback set, and thus the update rate of the feedback set can be made very low, which introduces negligible feedback overhead compared to

CSI feedback. In practice, the appropriate feedback set update frequency is between the above two cases according to the stability of the channel.

Although in the analysis we assume RVQ, the extension to other codebook design can be accomplished by replacing $2^{-\frac{B}{N_t|\mathcal{F}_k|-1}}$ in the expression of $\bar{\gamma}_k^{\mathrm{LB}}$ with the expectation of $\sin^2 \theta_k^{\mathcal{F}_k}$ for the corresponding codebook.

It has been shown that SINR feedback is superior over channel norm feedback under limited CDI feedback [13]. Therefore $\bar{\gamma}_k^{\mathrm{LB}}$ can also be used as CQI for scheduling by replacing $2^{-\frac{B}{N_t|\mathcal{F}_k|-1}}$ with the actual value of $\sin^2 \theta_k^{\mathcal{F}_k}$, which is adopted in our simulations.

IV. SIMULATION RESULTS

A sectorized cellular network is tested [7], where each hexagonal cell has 3 collocated BSs. Each BS corresponds to a 120-degree sector with $N_t = 2$, and the antenna angular pattern is $-\min\{12(\theta/70^o)^2, 20\}$dB, where θ is the angle with respect to the antenna broadside direction. The path-loss exponent is 3.5, and the lognormal shadowing deviation is 8 dB. The P_B and σ_n^2 are set so that the cell edge reference SNR[4] is 20dB. One simulation includes 80 topology drops, and in every drop 20 users are randomly distributed in each cell. Multiuser proportional fair scheduling (MPFS) is executed, where we use a greedy user selection algorithm based on [17] with weighted sum-rate as optimization object, i.e., the weight $\omega_k = 1/T_k$, where T_k is the average throughput perceived by user k up to last time slot, and is updated with fairness factor $\tau = 10$(time slots) [16]. Then power allocation is adopted to maximize the weighted sum-rate of the scheduled users in cluster c

$$
\max_{P_k, k=1,\ldots,|\mathcal{S}(c)|} \sum_{k=1}^{|\mathcal{S}(c)|} \omega_k R_k, \quad \text{s.t.} \quad \sum_{k=1}^{|\mathcal{S}(c)|} P_k \leq |\mathcal{B}_c| P_B, \tag{9}
$$

where $R_k = \log(1 + \gamma_k)$ is the expected rate of user k, and the received SINR γ_k is given by (3). Also, in order to decouple the power allocation optimization among clusters, the approximation of z_k can be further derived from (8). Therefore (9) is convex and can be efficiently solved. The reason for using MPFS is that fairness should be considered for the performance evaluation in the multi-cell environment, otherwise the system will always schedule users in cell or cluster centers. We use the cellular network simulation methodologies provided in [7]. Utilizing the statistics of RVQ [11][12], the quantization procedure can be precisely emulated without having to do actual quantization.

Denoted by no-C as no BS coordination, and K-C as the clustering of K adjacent cells with $3K$ BSs, and the clustering patterns can be found in [3] [7]. Fig. 2 and Fig. 3 show the cumulative distribution function (CDF) of per user spectral efficiency, with $B = 20$ and $B = 5$ respectively. It is shown that the performance of network MIMO without feedback adaptation degrades severely under limited feedback, and is even worse than no-C. On the contrary, the proposed 3-C fast

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[3]In this case, $\| \sum_{b'=1}^{|\mathcal{B}_{c'}|} \mathbf{h}_k^{(c',b')} \mathbf{w}_j^{(c',b')} \|^2 \sim \sum_{b'=1}^{|\mathcal{B}_{c'}|} \|\mathbf{h}_k^{(c',b')}\|^2 \beta(1, N_t|\mathcal{B}_{c'}| - 1)$.

[4]The reference SNR is defined as the SNR assuming a single antenna at the cell center transmits at full power and accounting only for the distance-based path-loss.
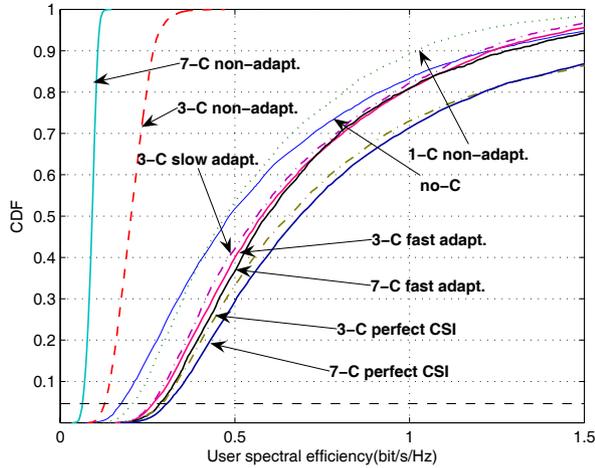
Fig. 2. CDF of spectral efficiency per user (bps/Hz), with $B = 20$. The cross points with the horizontal dashed line indicate the 5% outage rate.

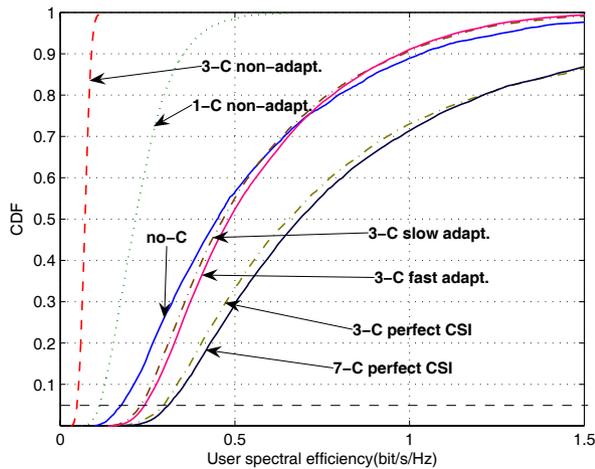Fig. 4. Average spectral efficiency per user versus B.

Fig. 3. CDF of spectral efficiency per user (bps/Hz), with $B = 5$. The cross points with the horizontal dashed line indicate the 5% outage rate.
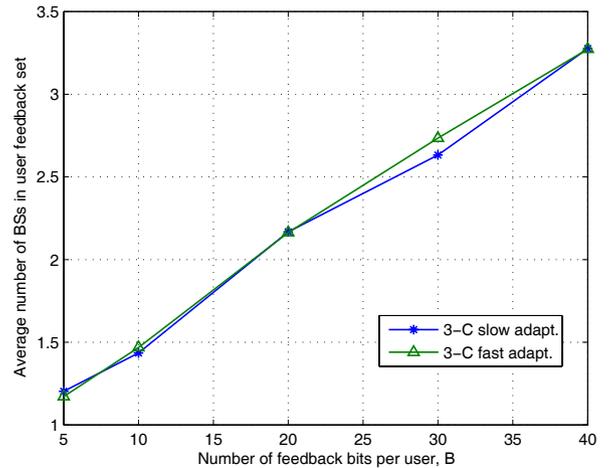
Fig. 5. Average number of BSs in CSI feedback set $|\mathcal{F}_k|$ versus B.

adaptation provides substantial gain over no-C, by 15% on average, and 60% for 5%-outage rate with $B = 20$. Even with $B = 5$, 3-C fast adaptation still maintains 45% gain for 5%-outage rate. Slow adaptation works very close to fast adaptation, which means that the proposed scheme is robust to rapid channel variation. It is also observed that even under perfect CSI, 7-C does not provide evident gain over 3-C, and so does the proposed scheme, where only 7-C fast adaptation is depict in Fig. 2. This is mainly because remote BSs have little values on CCI mitigation.

By changing B, Fig. 4 clearly shows the tradeoff between CCI mitigation and feedback precision. For small B, the bad CSI precision with large cluster introduces severe co-user interference, which outweighs the mitigated inter-cell CCI. As B increases, large cluster gradually shows the performance gain. Since the effective cluster size of users can be tuned according to B (as shown in Fig. 5 that the average number of $|\mathcal{F}_k|$ increases in proportional to B), the proposed feedback set adaptation guarantees the gain of network MIMO coordination under various feedback budgets, as 3-C fast adaptation
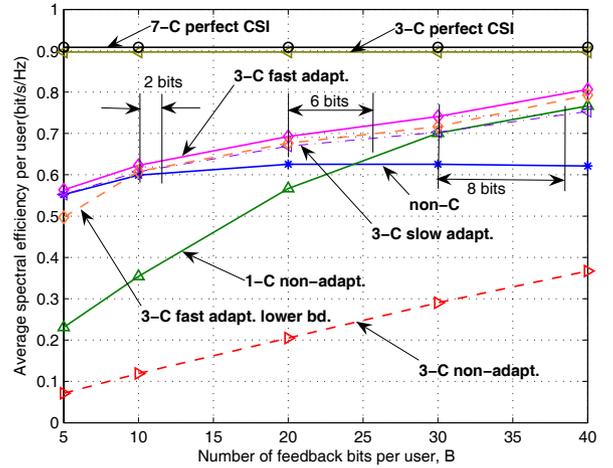
performs the best over all the tested B. This also indicates that the fixed method to feedback the CSI of M BSs with the largest channel gains proposed in [8] is not suitable for quantized feedback scenario, as it fails to adapt M according to B. The performance gap between slow and fast adaptation is more evident with larger B, because more details of the CSI variation can be described by the increased bits with fast adaptation. From a different perspective, the bit budget offsets are also shown in Fig. 4, which represents the additional feedback bits for indicating BS set that can be exploited to get performance gain over slow adaptation. Naive approach requires 9 bits (9 sector BSs in the 3-C scenario), which is larger than the offsets. Therefore, intelligent bit compression for fast adaptation, based on the results of slow adaption and the temporal correlation of the channels, is a valuable design problem for the future work. Note that in Fig. 4, we also show the tightness of the lower bound in (4) for the 3-C fast adaptation scenario. We record the bound $\bar{\gamma}^{\mathrm{LB}}$ for the *scheduled* users corresponding to its selected feedback set, with (6) as the numerator. Then we average over $\log(1 + \bar{\gamma}^{\mathrm{LB}})$ with the recorded $\bar{\gamma}^{\mathrm{LB}}$ to get the curve.

$$\mathbb{E}\{\gamma_k\} \geq \frac{\mathbb{E}\left\{\|\mathbf{h}_k\mathbf{w}_k\|^2\right\}}{\frac{z_k N_t}{P_B} + \left(\mathbb{E}\left\{\sin^2\theta_k^{\mathcal{F}_k}\right\}\sum_{b\in\mathcal{F}_k}\|\mathbf{h}_k^{(b)}\|^2 + \sum_{b'\notin\mathcal{F}_k}\|\mathbf{h}_k^{(b')}\|^2\right)\sum_{j\neq k}\mathbb{E}\left\{\|\tilde{\mathbf{g}}_k\mathbf{w}_j\|^2\right\}} \tag{13}$$

$$= \frac{\mathbb{E}\left\{\|\mathbf{h}_k\mathbf{w}_k\|^2\right\}}{\frac{z_k N_t}{P_B} + \left(\mathbb{E}\left\{\sin^2\theta_k^{\mathcal{F}_k}\right\}\sum_{b\in\mathcal{F}_k}\|\mathbf{h}_k^{(b)}\|^2 + \sum_{b'\notin\mathcal{F}_k}\|\mathbf{h}_k^{(b')}\|^2\right)\sum_{j\neq k}\frac{1}{N_t|\mathcal{B}_c|-1}} \tag{14}$$

$$\geq \frac{\mathbb{E}\left\{\|\mathbf{h}_k\mathbf{w}_k\|^2\right\}}{\frac{z_k N_t}{P_B} + 2^{-\frac{B}{N_t|\mathcal{F}_k|-1}}\sum_{b\in\mathcal{F}_k}\|\mathbf{h}_k^{(b)}\|^2 + \sum_{b'\notin\mathcal{F}_k}\|\mathbf{h}_k^{(b')}\|^2}, \tag{15}$$

V. CONCLUSION

In this paper, we have proposed a CSI feedback adaptation scheme for clustered network MIMO coordination. Based on the analysis for the impact of quantized CSI feedback on network MIMO, the optimal set of BSs, with respect to which the CSI is quantized and fed back, is determined by each user in a distributed way. Simulation results show that network MIMO is extremely sensitive to CSI error and could perform even worse than no BS coordination under limited feedback, while the proposed scheme guarantees the substantial gain of network MIMO under various feedback budgets and is robust to rapid channel variation. For future work, we will also consider joint feedback and BS clustering adaptation [18] for network MIMO systems.

VI. APPENDIX: PROOF OF THEOREM 1

Proof: Let $\cos\theta_k^{\mathcal{F}_k} = \|\tilde{\mathbf{h}}_k^{\mathcal{F}_k}\hat{\mathbf{h}}_k^{\mathcal{F}_k*}\|$, then $\theta_k^{\mathcal{F}_k}$ is the angle between $\hat{\mathbf{h}}_k^{\mathcal{F}_k}$ and $\tilde{\mathbf{h}}_k^{\mathcal{F}_k}$. Denote $\mathbf{h}_{\mathcal{F}_k}$ as the variation to $\mathbf{h}_k$ that replaces the dimensions of BSs *outside* $\mathcal{F}_k$ with 0, and denote $\mathbf{h}_{\bar{\mathcal{F}}_k} = \mathbf{h}_k - \mathbf{h}_{\mathcal{F}_k}$ as the variation to $\mathbf{h}_k$ that replaces the dimensions of BSs *in* $\mathcal{F}_k$ with zero, as the example shown in Fig. 1.

Decompose $\tilde{\mathbf{h}}_k^{\mathcal{F}_k} = (\cos\theta_k^{\mathcal{F}_k})\hat{\mathbf{h}}_k^{\mathcal{F}_k} + (\sin\theta_k^{\mathcal{F}_k})\mathbf{g}_k^{\mathcal{F}_k}$, where $\mathbf{g}_k^{\mathcal{F}_k}$ is a $1 \times N_t|\mathcal{F}_k|$ unit norm vector representing the direction of quantization error, which is orthogonal to $\hat{\mathbf{h}}_k^{\mathcal{F}_k}$. According to the description of the recovered $1 \times N_t|\mathcal{B}_c|$ CDI vector $\hat{\mathbf{h}}_k$ in section III-A, we have $\mathbf{h}_{\mathcal{F}_k} = \|\mathbf{h}_k^{\mathcal{F}_k}\|\left((\cos\theta_k^{\mathcal{F}_k})\hat{\mathbf{h}}_k + (\sin\theta_k^{\mathcal{F}_k})\mathbf{g}_{\mathcal{F}_k}\right)$, where $\mathbf{g}_{\mathcal{F}_k}$ is the $1 \times N_t|\mathcal{B}_c|$ unit norm vector that equals $\mathbf{g}_k^{\mathcal{F}_k}$ on the corresponding dimensions of BSs in $\mathcal{F}_k$, and equals 0 elsewhere. Then

$$\mathbf{h}_k = \|\mathbf{h}_k^{\mathcal{F}_k}\|(\cos\theta_k^{\mathcal{F}_k})\hat{\mathbf{h}}_k + \|\mathbf{h}_k^{\mathcal{F}_k}\|(\sin\theta_k^{\mathcal{F}_k})\mathbf{g}_{\mathcal{F}_k} + \mathbf{h}_{\bar{\mathcal{F}}_k}. \tag{10}$$

Denote $\mathbf{g}_k = \|\mathbf{h}_k^{\mathcal{F}_k}\|(\sin\theta_k^{\mathcal{F}_k})\mathbf{g}_{\mathcal{F}_k} + \mathbf{h}_{\bar{\mathcal{F}}_k}$. Since $\mathbf{g}_k^{\mathcal{F}_k}$ is orthogonal to $\hat{\mathbf{h}}_k^{\mathcal{F}_k}$, $\mathbf{g}_{\mathcal{F}_k}$ is orthogonal to $\hat{\mathbf{h}}_k$. Also $\mathbf{h}_{\bar{\mathcal{F}}_k}$ is orthogonal to $\hat{\mathbf{h}}_k$. Hence $\mathbf{g}_k$ is orthogonal to $\hat{\mathbf{h}}_k$. With ZFBF, $\hat{\mathbf{h}}_k\mathbf{w}_j = 0$, $j \neq k$, therefore

$$\|\mathbf{h}_k\mathbf{w}_j\|^2 = \|\mathbf{g}_k\mathbf{w}_j\|^2 = \|\mathbf{g}_k\|^2\|\tilde{\mathbf{g}}_k\mathbf{w}_j\|^2, \quad j \neq k, \tag{11}$$

where $\tilde{\mathbf{g}}_k$ is the normalized version of $\mathbf{g}_k$, and $\|\mathbf{g}_k\|^2 = \sin^2\theta_k^{\mathcal{F}_k}\sum_{b\in\mathcal{F}_k}\|\mathbf{h}_k^{(b)}\|^2 + \sum_{b'\notin\mathcal{F}_k}\|\mathbf{h}_k^{(b')}\|^2$.

Here both $\tilde{\mathbf{g}}_k$ and $\mathbf{w}_j$ are unit vectors on the $N_t|\mathcal{B}_c| - 1$ dimensional hyperplane orthogonal to $\hat{\mathbf{h}}_k$. Moreover, since $\mathbf{w}_j$ is merely determined by $\hat{\mathbf{h}}_i$, $i \neq j$, $i \neq k$ within

the hyperplane, also due to the fact that $\hat{\mathbf{h}}_i$ are mutually independent and do not have certain preference in direction[5], it is reasonable to consider that $\mathbf{w}_j$ is isotropic within the hyperplane and independent of $\tilde{\mathbf{g}}_k$. As a result, from [11], we have $\|\tilde{\mathbf{g}}_k\mathbf{w}_j\|^2 \sim \beta(1, N_t|\mathcal{B}_c| - 2)$, $j \neq k$, where $\beta(x, y)$ is a Beta-distribution random variable with parameters (x, y), then

$$\mathbb{E}_{\mathbf{w}_j}\left\{\|\tilde{\mathbf{g}}_k\mathbf{w}_j\|^2\right\} = \frac{1}{N_t|\mathcal{B}_c| - 1}. \tag{12}$$

Finally, given $\mathbf{h}_k$, the expected SINR over $\hat{\mathbf{h}}_k$ and $\mathbf{w}_j$ at user k is given by Eq.(13)-(15), where (13) follows from Jensen's inequality and (11). Eq. (14) follows from (12). Eq. (15) follows from the results in [11] that a tight upper bound for $\mathbb{E}\left\{\sin^2\theta_k^{\mathcal{F}_k}\right\}$ is $2^{-B/(M-1)}$, where $N = 2^B$ and M is the number of transmit antennas. This completes the proof. ∎

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