EFFICIENT FEEDBACK VIA SUBSPACE BASED CHANNEL QUANTIZATION FOR DOWNLINK TRANSMISSION IN DISTRIBUTED COOPERATIVE ANTENNA SYSTEMS

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ABSTRACT

It is one of the biggest challenges of multi-user distributed cooperative antenna (COOPA) systems to provide base stations (BSs) with downlink channel information for transmit filtering (precoding). The analog pilot retransmission method is efficient in terms of resources but is vulnerable to noise enhancement effects. The precoder codebook based feedback schemes are not applicable since they are developed for single user cases. In this paper we propose a new feedback scheme via a subspace based channel quantization method. The proposed scheme adopts the chordal distance as a channel quantizer criterion so as to capture channel characteristics represented by subspaces spanned by the channel matrix. We then develop a channel quantizer codebook construction method based on the Linde, Buzo and Gray (LBG) vector quantization algorithm. Our new codebooks have better minimum distance properties than currently available Grassmannian codebooks. Simulation results show that the proposed subspace based channel quantization method outperforms the analog pilot retransmission method and the Euclidean distance based channel quantization method.

1. INTRODUCTION

Cooperative antenna (COOPA) systems have recently become a hot research topic, as they promise significantly higher performance than conventional cellular systems [1]. The gain is acquired by adopting intercell interference (ICI) cancellation schemes, e.g., joint transmission/joint detection (JT/JD) algorithms. In COOPA, several adjacent BSs are cooperating so as to support multiple MSs which are located in the corresponding cooperative area (CA). Therefore, COOPA can be regarded as a multi-user multiple-input multiple-output (MU-MIMO) systems, with multiple transmit antennas at the BS, which are conventionally considered to be located in one BS, spread over several BSs. This distributed nature, which is attributed to the fact that several geographically distributed BSs are used as transmit antennas, leads to full macro diversity gains. Besides this, COOPA systems have advantageous features compared with conventional cellular systems, like increased degrees of freedom, better ICI cancellation performance, the rank enhancement effect of the channel matrix, etc [1].

COOPA systems are based on the cooperation between multiple distributed BSs. This means COOPA systems need the fast and efficient backbone network as well as the central unit (CU) which manages the cooperation amongst associated BSs. The CU makes the overall network structure more complex by adding one more layer in the hierarchy, and eventually increases the costs. In [5], distributed organization methods have been suggested to address this problem.

One of the main challenges of the distributed COOPA system is channel estimation for the downlink channel. All of the involved BSs in the CA need to know the full channel state information to calculate the corresponding precoding weight matrix. The analog pilot retransmission method has been suggested and tested in [5], but the throughput of this method reaches only 40 % of that of the ideal case, which requires supplementary feedback schemes [1].

In this paper, we propose the subspace based channel quantization method which proves to guarantee much higher performance than the analog pilot retransmission method. The MSs measure the downlink channel and quantize it by using the predefined codebook. Then MSs send only the index of the chosen code to all involved BSs. The BSs reconstruct the channel matrix based on code indices collected from the MSs. The proposed scheme can be used for cellular based MU-MIMO systems as well, which involve one BS for downlink data transmission.

Notation: Vectors and matrices are denoted by lower case bold and capital bold letters, respectively. $(\cdot)^{\mathcal{T}}$ and $(\cdot)^{\mathcal{H}}$ denote transpose and Hermitian transpose, respectively. $\mathrm{tr}(\cdot)$ denotes the trace of a matrix. $\|\cdot\|_2$ and $\|\cdot\|_F$ denote the two-norm of a vector or a matrix and the Frobenius norm of a matrix, respectively. The covariance matrix of the vector process $\mathbf{x}$ is denoted by $\mathbf{R}_{\mathbf{x}} = \mathbb{E}[\mathbf{x}\mathbf{x}^{\mathcal{H}}]$, where $\mathbb{E}[\cdot]$ is used for expectation. $\mathbf{I}_N$ is the $N \times N$ identity matrix and $\mathbf{0}_{M\times N}$ stands for an all-zero matrix of size $M \times N$. $\mathbf{I}_{M\times N}$ is defined as $\mathbf{I}_{M\times N} := \begin{bmatrix} \mathbf{I}_N \\ \mathbf{0}_{(M-N)\times N} \end{bmatrix}$ for $M > N$. $[\mathbf{A}]_{i,j}$ stands for the $(i,j)^{th}$ entry of a matrix $\mathbf{A}$. $|\mathcal{S}|$ is the size of a set $\mathcal{S}$.

2. SYSTEM MODEL AND MOTIVATION FOR CHANNEL QUANTIZATION METHOD

We consider a precoded MU-MIMO system in which a group of BSs transmit data to multiple MSs simultaneously. N_{BS} BSs and N_{MS} MSs have N_t and N_r antennas each, respectively. The data symbol block, $\mathbf{s} = [s_1, \ldots, s_{N_{tr}}]^{\mathcal{T}}$ where $N_{tr} = N_{\mathrm{MS}}N_r$, is precoded by a $N_{tt} \times N_{tr}$ matrix $\mathbf{W}$ where $N_{tt} = N_{\mathrm{BS}}N_t$. Here the first N_r data symbols are intended for the first user, the next N_r symbols for the second user, and so on. When denoting $i_{\mathrm{BS}}/i_{\mathrm{MS}}$ as the BS/MS index and i_t/i_r as the transmit/receive antenna index, respectively, we can denote h_{ij} where $i = N_r(i_{\mathrm{MS}}-1)+i_r, j = N_t(i_{\mathrm{BS}}-1)+i_t$ as the channel coefficient between the i_rth receive antenna of the i_{MS}th MS and the i_tth transmit antenna of the i_{BS}th BS. The $N_{tr}N_{tt}$ channel coefficients can be expressed as the $N_{tr}\times N_{tt}$ channel matrix $\mathbf{H}$ with $[\mathbf{H}]_{i,j} = h_{ij}$. The received signals on N_{tr} receive antennas which are collected in the vector $\mathbf{y}$ can be formulated as

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

where $\mathbf{n}$ is the additive white Gaussian noise (AWGN).

There are several available techniques developed for the downlink transmit filtering in MU-MIMO systems. Linear precoding techniques (e.g., the transmit matched filter (TxMF), the transmit zero-forcing filter (TxZF), and the transmit Wiener filter (TxWF)) have an advantage in terms of computational complexity. Non-linear techniques (e.g., the Tomlinson - Harashima precoding (THP)) have a higher computational complexity but can usually provide a better performance than linear techniques. Some linear techniques (e.g., the block diagonalization (BD) and the successive minimum mean squared error precoding (SMMSE)) are developed for the case in which there are multiple antennas at each receiver. The BD algorithm is designed to eliminate multi-user interference (MUI) [2]. The BD outperforms the TxZF and asymptotically approaches the sum capacity of the channel at high SNR. The SMMSE performs better than some non-linear techniques (e.g., the successive optimization (SO) THP and the MMSE THP) with relatively low computational complexity [3]. In our case, we adopt the TxZF which completely suppresses the interference at the receiver [4]:

$$\{\mathbf{W}, g\} = \arg \min_{\{\mathbf{W},g\}} |g|^2 tr(\mathbf{R_n})$$
$$\text{s.t.: } g\mathbf{HW} = \mathbf{I}_{N_{tr}} \text{ and } tr\left(\mathbf{W R_s W}^{\mathcal{H}}\right) = P_{tx} \tag{2}$$

where P_{tx}, $\mathbf{R_n}$, and $\mathbf{R_s}$ are the maximum transmit power, the covariance matrix of the noise, and the covariance matrix of the data symbol, respectively. The transmit precoding matrix $\mathbf{W}$ which satisfies the design criteria (2) is as follows.

$$\mathbf{W} = g^{-1}\mathbf{H}^{\mathcal{H}}\left(\mathbf{HH}^{\mathcal{H}}\right)^{-1},$$
$$g = \sqrt{\frac{tr\left((\mathbf{HH}^{\mathcal{H}})^{-1}\mathbf{R_s}\right)}{P_{tr}}} \tag{3}$$

The challenge here is that BSs should know the downlink channel matrix $\mathbf{H}$ so as to construct the precoding matrix $\mathbf{W}$. The analog pilot retransmission method has been proposed as a way of transferring channel state information [5]. As shown in [5], the analog pilot retransmission method is vulnerable to noise enhancement effects and this weakness of the analog method brings about a significant performance degradation, even though it is efficient in terms of required resources. As a way of combating noise, the digital method can be used instead of the analog method. The digital method here means that MSs measure the downlink channel and encode this information into the digital code and send it back to the BSs after performing appropriate digital signal processing (modulation, spreading, repetition, or channel coding, etc) to guarantee robust data transmission.

Recently, finite rate feedback strategies in MIMO systems have been extensively investigated. Beamforming codebook design methods are suggested based on Grassmannian packing [7] and systematic unitary design [8], which guarantee substantial gains with just a small number of feedback bits. All of these methods are developed for the single-user MIMO (SU-MIMO) case, which assumes that a user has the knowledge of the channel matrix. Our system requirements invalidate this assumption, since we deal with MU-MIMO systems. Thus it is more feasible for each individual MS to quantize its own channel matrix and send it back to all associated BSs. The BSs can calculate the precoding matrix by making use of channel information reconstructed by collected feedback messages.

There are several ways of quantizing channel matrices. A straightforward method is to view the channel matrix as a set of complex numbers, and to encode every complex number individually. If we allocate N_b bits for representing one floating point number, we need $2N_bN_{\mathrm{MS}}N_rN_{\mathrm{BS}}N_t$ bits in total for every subcarrier. This costs too much.

The alternative is to view the channel matrix as a set of complex matrices, and to quantize every individual matrix by looking up a predefined codebook. As explained above, the overall channel matrix is a $N_{\mathrm{MS}}N_r \times N_{\mathrm{BS}}N_t$ matrix, and is composed of the channel matrix for each user, which is of size $N_r \times N_{\mathrm{BS}}N_t$. (4) depicts this relationship.

$$\mathbf{H} = [\mathbf{H}_1, \cdots, \mathbf{H}_j, \cdots, \mathbf{H}_{N_{\mathrm{MS}}}]^{\mathcal{T}},\ j\text{: user index} \tag{4}$$

Here $\mathbf{H}_j$ is the transpose of the channel matrix for user j, which is a $N_{\mathrm{BS}}N_t \times N_r$ matrix. If we allocate N_{cb} bits for the codebook, we need $N_{cb}N_{\mathrm{MS}}$ bits in total for every subcarrier. The channel quantization method is suitable for the limited feedback in terms of required feedback bits, and the conventional vector quantization (VQ) method can be applied with some modifications.

3. SUBSPACE BASED CHANNEL QUANTIZATION METHOD

As proposed in the previous section, MS j is supposed to quantize its channel matrix $\mathbf{H}_j$. We view $\mathbf{H}_j$ not just as a complex matrix but as a subspace which is spanned by its columns. We perform a singular value decomposition (SVD) to extract the unitary matrix $\mathbf{U}_j$ which includes the basis vectors $\mathbf{U}_{j,S}$ spanning the column space of $\mathbf{H}_j$ ($\mathbf{H}_j$: $N_{tt} \times N_r$, $\mathbf{U}_j$: $N_{tt} \times N_{tt}$, $\mathbf{U}_{j,S}$: $N_{tt} \times N_r$).

$$\mathbf{H}_j = \mathbf{U}_j \mathbf{\Sigma}_j \mathbf{V}_j^{\mathcal{H}} \tag{5}$$

$$\mathbf{U}_j = [\mathbf{U}_{j,S} \mathbf{U}_{j,0}] \tag{6}$$

The channel quantizer uses the chordal distance as a distance metric, since we should measure the distance between subspaces. There are other subspace distance metrics [6], but the chordal distance is the only one which makes the VQ algorithm feasible for designing the codebook [9]. The chordal distance is defined as

$$d_c(\mathbf{T}_i, \mathbf{T}_j) = \frac{1}{\sqrt{2}} \|\mathbf{T}_i \mathbf{T}_i^{\mathcal{H}} - \mathbf{T}_j \mathbf{T}_j^{\mathcal{H}}\|_F \tag{7}$$

for matrices $\mathbf{T}_i$, $\mathbf{T}_j$ which have orthonormal columns.

The quantized version of the column space basis vectors $\mathbf{U}_{j,S}$ is chosen to be the code which has the minimum chordal distance with it. Thus, the subspace quantization process can be written as

$$\hat{\mathbf{U}}_{j,S} = \mathcal{Q}(\mathbf{U}_{j,S}) = \arg \min_{\mathbf{C}_i \in \mathcal{C}} d_c(\mathbf{U}_{j,S}, \mathbf{C}_i) \tag{8}$$

where $\mathbf{C}_i$ is an unitary matrix ($\mathbf{C}_i^{\mathcal{H}} \mathbf{C}_i = \mathbf{I}_{N_r}$). Thus, the code represents only the column space of $\mathbf{H}_j$ and the channel quantizer needs extra information to convey the channel power information. The channel quantizer equation at user j, which takes channel powers as well as subspace distances into account, is given by

$$\hat{\mathbf{H}}_j = \hat{\mathbf{U}}_{j,S} \mathbf{\Sigma}_{j,S} \tag{9}$$

where $\mathbf{\Sigma}_j = \begin{bmatrix} \mathbf{\Sigma}_{j,S} \\ \mathbf{0}_{(N_{tt}-N_r)\times N_r} \end{bmatrix}$. Here, $\mathcal{C}$ is the codebook of size N ($N = 2^{N_{cb}}$) which has the code $\mathbf{C}_i \in \mathbb{C}^{N_{tt} \times N_r}$. $\mathbf{\Sigma}_{j,S} \in \mathbb{R}_+^{N_r \times N_r}$ is composed of the upper $N_r \times N_r$ elements of $\mathbf{\Sigma}_j$. $\mathbf{\Sigma}_{j,S}$ is a diagonal matrix which has N_r positive real elements in its diagonal. This constitutes the channel power information. The subspace based channel quantization method works as follows. MS j finds the code $\mathbf{C}_i$ which provides the minimum chordal distance with $\mathbf{U}_{j,S}$, and the corresponding power information. Then it sends back a N_{cb} bit codebook index together with N_r power information to all associated BSs. The reconstructed downlink channel matrix at the BSs is as follows.

$$\hat{\mathbf{H}} = [\hat{\mathbf{H}}_1, \cdots, \hat{\mathbf{H}}_j, \cdots, \hat{\mathbf{H}}_{N_{\mathrm{MS}}}]^{\mathcal{T}},\ j\text{: user index} \tag{10}$$

Extensive simulation results show that the code index alone is enough to achieve a potential performance without extra channel power information when the link strengths (large-scale fading due to path loss and shadowing) are known at the BSs. In this case, the MS needs to send only N_{cb} bits feedback. The channel quantization formula can be simplified as

$$\hat{\mathbf{H}}_j = \hat{\mathbf{U}}_{j,S} = \arg \min_{\mathbf{C}_i \in \mathcal{C}} d_c(\mathbf{U}_{j,S}, \mathbf{C}_i). \tag{11}$$

4. CODEBOOK CONSTRUCTION BASED ON MODIFIED LBG VQ ALGORITHM

The Linde, Buzo, and Gray (LBG) vector quantization (VQ) algorithm [10] is used to construct the codebook $\mathcal{C}$. The LBG VQ algorithm is an iterative algorithm based on the Lloyd algorithm which is known to provide an alternative systematic approach for the subspace packing problem [9]. As in [9], we in this paper acquire the codebook through iteration. The main difference of the proposed method is attributed to the fact that the codebooks in [9] are precoder codebooks, while the codebooks to be constructed here are channel quantizer codebooks. The LBG VQ algorithm is based on a training sequence which is provided by channel realizations simulated in a Monte-Carlo approach, whereas the Lloyd algorithm in [9] is based on an initial codebook which is obtained via a random computer search or the currently best codebook. Thus, codebooks obtained by the LBG VQ algorithm can better capture the statistics of the channel by using channel realizations as a training sequence.

4.1. Design Problem

The LBG VQ based codebook $\mathcal{C}$ design problem can be stated as follows. Given a source vector with its known statistical properties, given a distortion measure, given a codebook evaluation measure, and given the size of the codebook, find a codebook and a partition[1] which result in maximizing the minimum chordal distance of the codebook.

Suppose that we have a training sequence $\mathcal{T}$ to capture the statistical properties of the column space basis vectors $\mathbf{U}_{j,S}$ of size $N_{tt} \times N_r$:

$$\mathcal{T} = \{\mathbf{X}_1, \mathbf{X}_2, \cdots, \mathbf{X}_M\} \tag{12}$$

where $\mathbf{X}_m \in \mathbb{C}^{N_{tt} \times N_r}$ is a sample of $\mathbf{U}_{j,S}$ which can be obtained by taking a SVD of the channel matrix $\mathbf{H}_j$. The

[1]The *partition* of the space is defined as the set of all encoding regions.

channel matrix samples are generated by Monte-Carlo simulations using SCMe[2]. The number of channel samples M is assumed to be large (e.g., $M \geq 1000N$), so that all the statistical properties of the source are captured by the training sequence. The codebook can be represented as the following.

$$\mathcal{C} = \{\mathbf{C}_1, \mathbf{C}_2, \cdots, \mathbf{C}_N\} \tag{13}$$

The each code has the same size as a training matrix ($\mathbf{C}_n \in \mathbb{C}^{N_{tt} \times N_r}$). Let $\mathcal{R}_n$ be the encoding region associated with the code $\mathbf{C}_n$ and let

$$\mathcal{P} = \{\mathcal{R}_1, \mathcal{R}_2, \cdots, \mathcal{R}_N\} \tag{14}$$

denote the partition of the space. If the source matrix $\mathbf{X}_m$ belongs to the encoding region $\mathcal{R}_n$, then it is quantized to $\mathbf{C}_n$:

$$\mathcal{Q}(\mathbf{X}_m) = \mathbf{C}_n, \text{ if } \mathbf{X}_m \in \mathcal{R}_n. \tag{15}$$

Our aim is to find a codebook of which the minimum chordal distance[3] is maximized. The minimum chordal distance of the codebook is given by:

$$d_{c,\min}(\mathcal{C}) := \min d_c(\mathbf{C}_i, \mathbf{C}_j), \text{ for } \mathbf{C}_i, \mathbf{C}_j \in \mathcal{C}, \forall i \neq j. \tag{16}$$

The design problem can be stated as follows: Given $\mathcal{T}$ and N, find $\mathcal{C}$ and $\mathcal{P}$ such that $d_{c,\min}(\mathcal{C})$ is maximized.

4.2. Optimality Criteria

$\mathcal{C}$ and $\mathcal{P}$ must satisfy the following two criteria so as to be a solution to the above mentioned design problem [10]. We should note that the chordal distance is used instead of the Euclidean distance as a distance metric.

- *Nearest Neighbor Condition*:

$$\mathcal{R}_n = \{\mathbf{X} : d_c(\mathbf{X}, \mathbf{C}_n) < d_c(\mathbf{X}, \mathbf{C}_{n'}), \forall n' \neq n\} \tag{17}$$

  This condition says that any channel sample $\mathbf{X}$, which is closer to the code $\mathbf{C}_n$ than any other codes in the chordal distance sense, should be assigned to the encoding region $\mathcal{R}_n$, and be represented by $\mathbf{C}_n$.

- *Centroid Condition*:

$$\mathbf{C}_n = \mathbf{U}_R \mathbf{I}_{N_{tt} \times N_r} \tag{18}$$

  where $\mathbf{U}_R$ is an eigenvector matrix of the sample covariance matrix $\mathbf{R}$ which is defined as

$$\mathbf{R} := \frac{1}{N_{\mathcal{R}_n}} \sum_{\mathbf{X}_m \in \mathcal{R}_n} \mathbf{X}_m \mathbf{X}_m^{\mathcal{H}} \text{ where } N_{\mathcal{R}_n} = |\mathcal{R}_n|, \tag{19}$$

  provided that eigenvalues in the eigenvalue matrix $\mathbf{\Sigma}_R$ of $\mathbf{R} = \mathbf{U}_R \mathbf{\Sigma}_R \mathbf{U}_R^{\mathcal{H}}$ are sorted in the descending order.

  This condition means that the code $\mathbf{C}_n$ of the encoding region $\mathcal{R}_n$ should be the N_r eigenvectors of the sample cavariance matrix $\mathbf{R}$ corresponding to the N_r largest eigenvalues. The centroid condition is designed to minimize the average distortion in the encoding region $\mathcal{R}_n$, when $\mathbf{C}_n^{opt}$ represents $\mathcal{R}_n$ [9]. This process is reproduced here for convenience.

$$\begin{aligned}\mathbf{C}_n^{opt} &= \arg\min_{\mathbf{C}} \frac{1}{N_{\mathcal{R}_n}} \sum_{\mathbf{X}_m \in \mathcal{R}_n} d_c^2(\mathbf{X}_m, \mathbf{C}) \\ &= \arg\min_{\mathbf{C}} \frac{1}{N_{\mathcal{R}_n}} \sum_{\mathbf{X}_m \in \mathcal{R}_n} \operatorname{tr}\left(\mathbf{I}_{N_r} - \mathbf{C}^{\mathcal{H}} \mathbf{X}_m \mathbf{X}_m^{\mathcal{H}} \mathbf{C}\right) \\ &= \arg\max_{\mathbf{C}} \operatorname{tr}\left(\mathbf{C}^{\mathcal{H}} \mathbf{R} \mathbf{C}\right)\end{aligned} \tag{20}$$

  (18) is the optimum solution which minimizes the average distortion.

4.3. Modified LBG VQ Algorithm

The modified LBG VQ (mLBG VQ) design algorithm is an iterative algorithm which finds the solution satisfying the two optimality criteria in section 4.2. The algorithm requires an initial codebook $\mathcal{C}^{(0)}$. $\mathcal{C}^{(0)}$ is obtained by the splitting of an initial code, which is the centroid of the entire training sequence, into two codes. The iterative algorithm runs with these two codes as the initial codebook. The final two codes are split into four and the same process is repeated until the desired number of codes is obtained. The codebook design steps are as follows for a given $\mathcal{T}$ and $\epsilon > 0$ ('small' number). $centroid(\mathcal{S})$ denotes the optimum code calculated for a given encoding region $\mathcal{S}$.

1. (Preparation) Let $N = 1$ and calculate $\mathbf{C}_1^* = centroid(\mathcal{T})$.
2. (Splitting) For $i = 1, 2, \ldots, N$, set $\mathbf{C}_i^{(0)} = (1+\epsilon)\mathbf{C}_i^*$, $\mathbf{C}_{N+i}^{(0)} = (1-\epsilon)\mathbf{C}_i^*$ and $N = 2N$.
3. (Iteration) Set the iteration index $k = 0$ and calculate $d_{c,\min}^{(0)}(\mathcal{C})$.
   (a) Find $n^* = \arg\min_{n \in \{1,\ldots,N\}} d_c(\mathbf{X}_m, \mathbf{C}_n^{(k)})$ for $m = 1, \ldots, M$ and set $\mathcal{Q}(\mathbf{X}_m) = \mathbf{C}_{n^*}^{(k)}$.
   (b) Update the codes by finding the centroid $\mathbf{C}_n^{(k+1)} = centroid(\{\mathbf{X}_m : \mathcal{Q}(\mathbf{X}_m) = \mathbf{C}_n^{(k)}\})$ for $n = 1, \ldots, N$.
   (c) Set $k = k + 1$.
   (d) Calculate $d_{c,\min}^{(k)}(\mathcal{C})$ and if $d_{c,\min}^{(k)}(\mathcal{C}) > d_{c,\min}^{(k-1)}(\mathcal{C})$, then save $d_{c,\min}^{(k)}(\mathcal{C})$ and $\mathbf{C}_n^{(k)}$ for $n = 1, \ldots, N$, and go back to step (a). Otherwise, go to step (e).

[2] extended 3GPP Spatial Channel Model [12]

[3] There are several subspace distance metrics, e.g., the Fubini-Study distance, the projection two-norm distance, and the chordal distance metrics. It has been shown that the chordal distance is the only distance measure which makes the iterative algorithm feasible [9].

(e) Set $\mathbf{C}_n^* = \mathbf{C}_n^{(k-1)}$ for $n = 1, \ldots, N$ as the final codes.

4. Repeat steps 2 and 3 until the desired number of codes is obtained.

The minimum distances of the codebooks are collected in Table 1. It shows that the codebooks acquired by the modified LBG VQ algorithm have better distance properties than Grassmannian codebooks listed in [11].

Table 1. The minimum codebook distances $d_{c,\min}(\mathcal{C})$

(N_{tt}, N_r)	N_{cb}	mLBG VQ	Grassmann
$(2, 1)$	3	0.3895	0.3820
$(3, 1)$	3	0.5706	0.5429
	4	0.4882	0.4167

5. SIMULATION RESULTS

Simulations have been performed for the 2 BSs - 2 MSs and 3 BSs - 2 MSs cases. Two (three) BSs are cooperating to transmit data signal for two MSs through the same resources at the same time. Both BSs and MSs have a single antenna, so it yields 2×2 and 2×3 overall channel matrices, respectively. SCMe[4] is used for the simulations and the proposed methods are tested for an Urban Macro channel with a mobile speed of 10 m/s. The system performance is evaluated in terms of the received SINR at the MS. Simulations are performed for 30000 channel realizations and the culmulative distribution function (cdf) at one MS is obtained. OFDMA is assumed as the data transmission scheme and we focus on one subcarrier. The transmit power at the BS is set to be 10 W and it is equally allocated to 1201 subcarriers. The cooperative area (CA) topology is shown in Fig. 1. As in the conventional cellular topology, one cell is composed of three sectors and the hexagonal area, which is composed of three sectors which are served by three BSs, forms a CA. Two MSs in the CA are served by three BSs simultaneously. In case of the 2 BSs - 2 MSs case, two BSs which maintain the strongest two links with MSs are chosen for downlink transmission. The cell radius is 600 m and MSs are equally distributed in the CA for every drop. The transmit zero-forcing filter formula follows (3), based on downlink channel information which is either perfect channel (pCh), or is provided by a downlink channel estimation method which is shared by the BSs through a prompt and error free backbone network (centralized CA, cCA), or is acquired by the analog pilot retransmission method (distributed CA, dCA), or is captured and reconstructed by looking up an n bit codebook (n bit channel quantization, nbCQ). The BSs are assumed to be aware of the large-scale fading of the channel, and the channel quantization process (12) is based on true channel information. The codebooks are acquired by the modified LBG VQ algorithm. The feedback link is error free and delay free.

Fig. 2 shows the cdf of the SINR for the 2 BSs - 2 MSs case. At 50 % outage SINR, the 3 bit channel quantizer (3bCQ) shows 5.3 dB gain over the analog pilot retransmission case (dCA) and it is only 0.7 dB away from the centralized CA (cCA). The channel matrix at MS j $\mathbf{H}_j (j = 1, 2)$ is in this case a 2×1 complex vector and this is represented by a codebook of size $2^3 = 8$. Compared with the channel quantization method, the resource efficient dCA case requires 3 pilot tones per MS for FDD. Therefore, the proposed scheme outperforms the pilot retransmission method without requiring extra resources. Fig. 3 deals with simulation results of the 3 BSs - 2 MSs case. The 3bCQ, 4bCQ, and 5bCQ cases have 3.2 dB, 5.0 dB, and 6.1 dB gains over the dCA case, respectively.

The proposed method is to quantize the channel matrix based on the chordal distance, and the LBG VQ algorithm is modified as such. Conventional VQ methods use the Euclidean distance instead. Is the subspace based method better than the conventional method? A performance comparison result is shown in Fig. 4. The Euclidean distance based CQ ($n$beCQ) adopts the Euclidean distance as a distance metric for channel quantization. Its optimality criteria for codebook construction are as follows, accordingly.

- *Nearest Neighbor Condition*:

$$\mathcal{R}_n = \{\mathbf{X} : \|\mathbf{X} - \mathbf{C}_n\|_2^2 \leq \|\mathbf{X} - \mathbf{C}_{n'}\|_2^2, \forall n' \neq n\} \tag{21}$$

- *Centroid Condition*:

$$\mathbf{C}_n = \frac{\sum_{\mathbf{X}_m \in \mathcal{R}_n} \mathbf{X}_m}{\sum_{\mathbf{X}_m \in \mathcal{R}_n} 1} \tag{22}$$

The simulation results show that the subspace based CQ has a substantial gain over the Euclidean distance based CQ. At 50 % outage SINR, the 4bCQ and 5bCQ outperform the 4beCQ and 5beCQ by 2.9 dB and 2.6 dB, respectively.

6. CONCLUSIONS

In this paper, we considered precoded MU-MIMO systems assisted by limited feedback. We proposed a subspace based channel quantization method as a way of providing BSs with downlink channel state information, which is applicable to the distributed COOPA systems as well as MU-MIMO systems. The subspace based channel quantizer improves the system performance significantly, compared to the analog pilot retransmission method and the Euclidean distance based channel quantization method. We also developed an efficient codebook construction algorithm based on well known LBG

[4] The MATLAB code provided in [13] supports a channel matrix generation function for links between multiple BSs and multiple MSs.

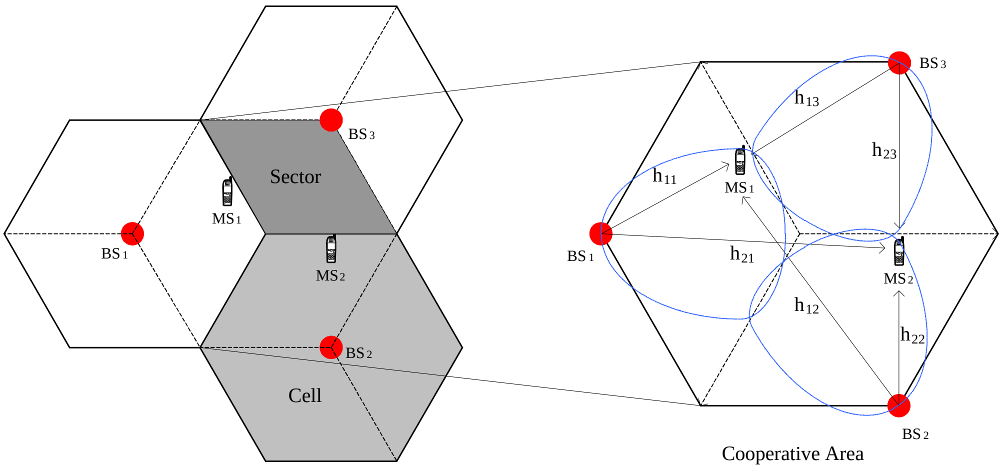

Fig. 1. CA topology based on 3 sector - cell system

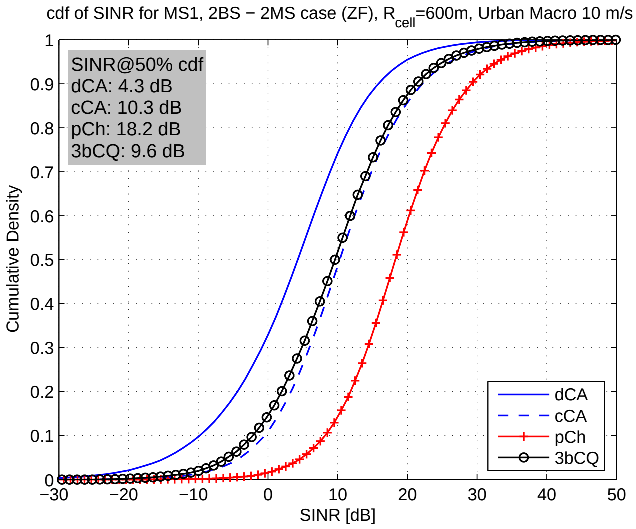

Fig. 2. 2 BSs - 2 MSs case simulation results

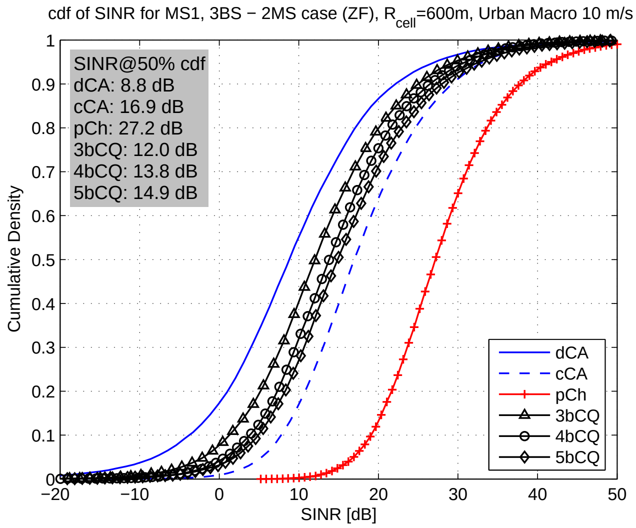

Fig. 3. 3 BSs - 2 MSs case simulation results

VQ by adopting the chordal distance and modifying the optimality criteria accordingly. The codebooks generated by the proposed algorithm have better distance properties than Grassmannian codebooks that are currently available.

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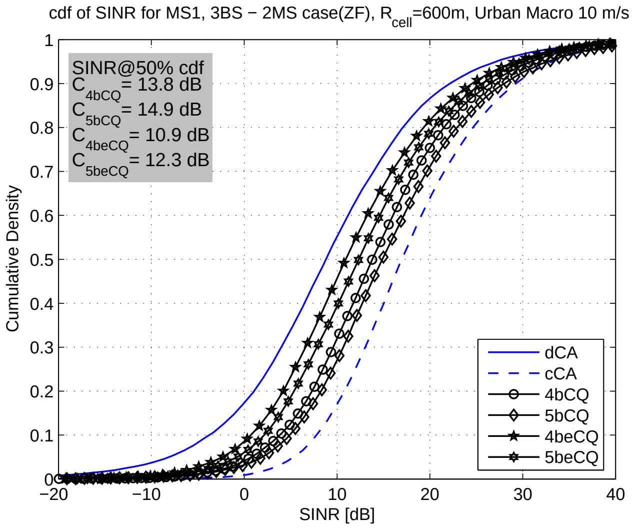

Fig. 4. Performance comparison of the Euclidean distance based CQ and the Subspace based CQ

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