Novel schemes of CQI Feedback Compression based on Compressive Sensing for Adaptive OFDM Transmission

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Abstract

In multi-user wireless communication systems, adaptive modulation and scheduling are promising techniques for increasing the system throughput. However, a mass of wireless recourse will be occupied and spectrum efficiency will be decreased to feedback channel quality indication (CQI) of all users in every subcarrier or chunk for adaptive orthogonal frequency division multiplexing (OFDM) systems. Thus numerous limited feedback schemes are proposed to reduce the system overhead. The recently proposed compressive sensing (CS) theory provides a new framework to jointly measure and compress signals that allows less sampling and storage resources than traditional approaches based on Nyquist sampling. In this paper, we proposed two novel CQI feedback schemes based on general CS and subspace CS, respectively, both of which could be used in a wireless OFDM system. The feedback rate with subspace CS is greatly decreased by exploiting the subspace information of the underlying signal. Simulation results show the effectiveness of the proposed methods, with the same feedback rate, the throughputs with subspace CS outperform the discrete cosine transform (DCT) based method which is usually employed, and the throughputs with general CS outperform DCT when the feedback rate is larger than 0.13 bits/subcarrier.

Keywords: CQI, OFDM, feedback compression, compressive sensing

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1. Introduction

Recently, Orthogonal Frequency Division Multiple Access (OFDMA) system with adaptive channel information feedback is considered as one key technique to improve the system performance. OFDMA is a multiple access scheme based on Orthogonal Frequency Division Multiplexing (OFDM), which can achieve high frequency efficiency and less inter-symbol interference[1]. Hence, OFDMA systems have been considered as one of the most promising candidates for the next generation wireless systems, such as the next generation cellular and IEEE 802.16 systems [2][3]. To further increase system throughput, several advanced technologies are widely used in adapted OFDM systems. Adaptive Modulation and Coding (AMC) is one of these key enabling techniques to fully exploit channel information and attain high performance. The essence of AMC is to dynamically adjust the Modulation and Coding Scheme (MCS) in sequential subbands, providing an efficient way of maximizing the instantaneous usage of the wireless channel [4]. In a multi-carrier scheme like OFDM, the overall channel can be divided into several subchannels in time and frequency dimension, called subcarriers, which can be allocated to different connections[5]. In a multi-user system the subcarriers can be adaptively allocated to different users in order to exploit multi-user diversity [6], where knowledge about the channel quality indication (CQI) of the subcarriers has to be available at the transmitter side. Having the prefect channel knowledge at the transmitter, adaptive subchannel allocation schemes can achieve very good performance. However, in order to select among the users and choose modulation and coding scheme, all users need to feedback the CQIs of all the subbands in multi-user multi-carrier OFDM systems. This will lead to overwhelming large CQI feedback overhead. Hence, the feedback compression of CQI is needed.

The challenge of designing a CQI feedback scheme with reasonably low overhead has spurred some research interests. Numerous CQI compression schemes have been proposed, which basically can be grouped into three main categories including scalar quantization methods with optimized SNR thresholds, SNR-limited feedback with max-SNR scheduling and schemes using lossy or lossless compression [7]. In [7], it is shown that the lossy compression scheme based on chunking discrete cosine transform (DCT) gives the best compromise between throughput and feedback rate for multicarrier systems. In [8], CQI feedback compression based on DCT in adaptive OFDM systems using scheduling is proposed. In [9], the performance of compression feedback based on DCT for adaptive MIMO-OFDM transmission with the spatial multiplexing mode is exploited.

The recently introduced principle and methodology of compressive sensing (CS), which has gained a fast-growing interest in applied mathematics and image processing, allows the efficient reconstruction of sparse signals from a very limited number of measurements[10], [11]. The fundamental premise of applying CS is that the signal must be sparse or compressible, i.e., such signals have a representation in terms of a sparsity-inducing basis where most of the coefficients are zeros or small and only a few are large. Rather than uniformly sampling the signal, CS computes the inner products between the signal and column vectors of randomized measurement matrix. The signal is then recovered with high probability by solving an optimization that ensures the recovered signal consistent with the measurements as well as sparse. CS reconstruction has been shown to be robust to multi-level quantization of the measurements [12]. By exploiting the fact that many natural signals are sparse or compressible, CS provides a new framework to jointly measure and compress signals that

allows less sampling and storage resources than traditional approaches based on Nyquist sampling.

In this paper, we mainly exploit the scheme of CQI feedback compression based on CS theory. Our work is an explorative research. The proposed schemes exploit the fact that the channel quality at a certain time and frequency is highly correlated with the channel quality at a neighboring time and/or frequency. Our work provides a new idea to compress CQI and the main target is to cause the attention of peer and make some beneficial discussion.

The main contributions of our work are the following:

(i) The general CS method is firstly introduced to CQI feedback compression for adaptive OFDM systems to reduce the feedback overhead and the processing complexity at terminals.

(ii) A novel CQI feedback scheme based on subspace CS is proposed via further research on the design of measurement matrix with general CS. The proposed CQI feedback scheme based on subspace CS reduces the number of measurements for a given reconstruction performance by exploiting the fact that the sparse signal resides in a low dimension subspace. The feedback rate is greatly decreased and system performance is improved.

It is verified by simulations that the proposed methods have the potential of reducing the CQI feedback overhead under multipath channel conditions. With the same feedback rate, the throughputs with subspace CS outperform the generally used discrete cosine transform (DCT), and the throughputs with general CS outperform DCT when the feedback rate is larger than 0.13 bits/subcarrier.

The remaining of the paper is organized as follows. Section 2 presents system model and problem description, section 3 addresses the CQI feedback compression based on CS, section 4 compares the throughput performance of CQI feedback compression schemes based on CS with that of DCT and discusses simulation results. Finally, section 5 draws the conclusions and envisions future works.

2. System Model and Problem Description

Fig. 1 shows the system model where the signal processing is divided into multi-user scheduling, adaptive modulation, and OFDM modulation (IFFT). We consider an adaptive OFDMA cellular system, where both the BS and the MS have a single antenna and one BS serves a finite number (U) of users by assigning users with different sub-carriers and time slots. In order to exploit the adaptive modulation schemes, each user has to feed back its channel information periodically according to the speed through control channel to BS. OFDMA is employed to subdivide the downlink bandwidth into N_c orthogonal subcarriers, where the channel response of each subcarrier is assumed to be flat. Note, that a subcarrier can also be interpreted as a representative of a block of subcarriers, called chunks or clusters. The users are assigned to each subcarrier or chunk by multiuser scheduling function depending on CQI which is fed back to base station via feedback channel.

The channel for each user is modeled by a L-tap linear filter, and the response for user u is $\{h_u(0), h_u(1), ..., h_u(L-1)\}$. The time interval between the adjacent paths adopted the channel model of the ITU Vehicular A. $\mathbf{H}_u(n)$ is the channel frequency response of user u at subcarrier with index n at each time slot $k \in \mathrm{N}$. $\mathbf{H}_u(n)$ is expressed as

$$\mathbf{H}_u(n) = \sum_{l=1}^{L} h_l e^{-j2\pi n/Nc} \tag{1}$$

where h_l is channel gain corresponding to the lth path used in the tapped delay line model and N_c is the number of the subcarriers.

From this, it follows that the instantaneous SNR $\gamma_u(n,k)$ of user u of subcarrier with index n in time slot k is given by

$$\gamma_u(n,k) = \bar{\gamma} \cdot |H_u(n,k)|^2 \tag{2}$$

Where $\bar{\gamma}$ is average SNR.

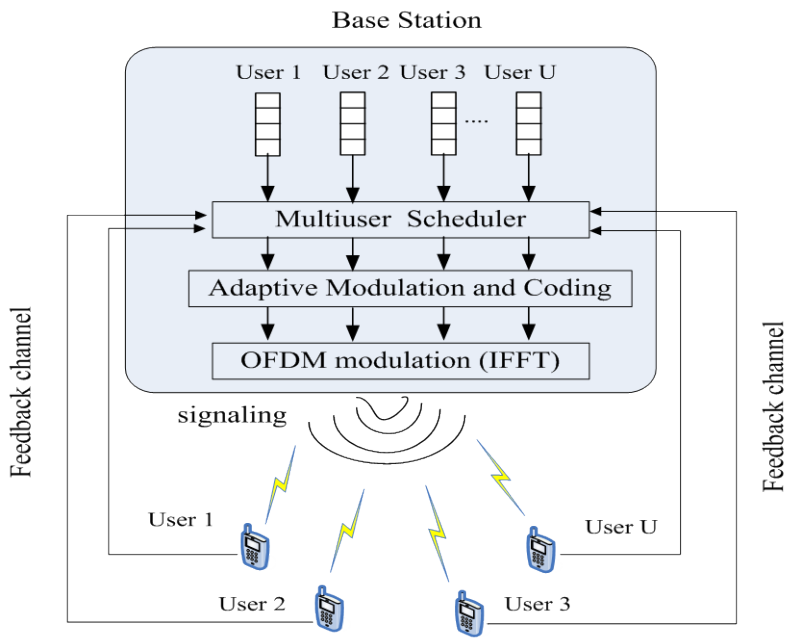

Fig. 1. Block diagram of multi-user downlink OFDMA systems

In this paper, a Max-SNR scheduler is employed to allocate the subcarriers to the user with the best SNR conditions. Also, a modulation scheme is selected for each subcarrier based on the CQI value. In this work, the following modulation schemes are considered: BPSK, 4-QAM, 8-QAM, 16-QAM, 32-QAM, 64-QAM, 128-QAM, and 256-QAM.

At a given time instant k these SNRs are collected in a vector of length N_c, $\gamma_u^k = \{\gamma_u(k,1), \gamma_u(k,2), \ldots, \gamma_u(k,Nc)\}$, at each terminal, the SNRs on all subcarriers are compressed and transmitted to the transmitter. At the transmitter, base station selects the best user and chooses appropriate modulation and coding scheme based on the reconstructed SNRs. The reconstructed SNRs are denoted as

$$\hat{\gamma}_u = \{\hat{\gamma}_u(n,k)\}_{n=1}^{N_c} \tag{3}$$

The mean square error (MSE) between the reconstructed SNRs and the real SNRs on each subcarrier is defined as

$$MSE = E\{\| \hat{\gamma} - \gamma \|^2\} \tag{4}$$

3. CQI Feedback Compression Based on Compressive Sensing

3.1 Compressive Sensing Backgrounds

CS is a new sampling and reconstruction method for signals that are known to be sparse or compressible in some basis. Without loss of generality, we assume an N-dimensional signal $\mathbf{x}$ to be K-sparse in a sparsity-inducing basis $\{\mathbf{b}_i\}$, that is, there are at most K non-zero coefficients $\{\alpha_i\}$ in the basis expansion $\mathbf{x} = \sum_i \alpha_i \mathbf{b}_i$ denoted as $\mathbf{B\alpha}$. The signal is K-compressible if it is well approximated by the K most significant coefficients in the expansion. The basis function widely used includes Inverse Discrete Fourier Transform (IDFT), DCT, Haar, chirplet, Gabor and curvelet basis etc.

Within the compressive sensing framework, measurements are taken not directly by sampling the sparse signal but by measuring a few of linear projections of the underlying signal. The signal is sampled using M measurements with the measurement vectors $\boldsymbol{\varphi}_i (i = 1, \cdots, M)$, which means $y_i = \langle \mathbf{x}, \boldsymbol{\varphi}_i \rangle$. The compact representation is $\mathbf{y} = \mathbf{\Phi x} = \mathbf{\Phi B \alpha}$, where $\mathbf{y}$ is called vector of measurements, $\mathbf{\Phi}$ is the measurement matrix which models the measurement system and $\boldsymbol{\alpha}$ is the N-dimensional vector of coefficients which includes at most K non-zero coefficients. The reconstruction from $\mathbf{y}$ equals to determining the sparsest signal that explains the measurement $\mathbf{y}$. The strictest measure of sparsity of the signal is the l_0 pseudonorm of the coefficient vector $\boldsymbol{\alpha}$. Unfortunately, the l_0 pseudonorm is combinatorially complex to optimize. Instead, compressive sensing enforces sparsity by minimizing the l_1 norm, $\|\boldsymbol{\alpha}\|_1 = \sum_i |\alpha_i|$. Minimizing the l_1 norm has been theoretically proven equivalent to minimizing the l_0 pseudonorm with very high probability [13].

Specifically, exact recovery requires that the measurement vectors $\{\boldsymbol{\varphi}_i\}$ are sufficiently incoherent with the sparsity basis $\{\mathbf{b}_i\}$. That is, $\{\boldsymbol{\varphi}_i\}$ does not have a compact representation on $\{\mathbf{b}_i\}$ and likewise, $\{\mathbf{b}_i\}$ does not have a compact representation on $\{\boldsymbol{\varphi}_i\}$ [14]. Incoherence can be guaranteed with very high probability if the measurement matrix $\mathbf{\Phi}$ is drawn randomly from a variety of possible distributions such as normal distribution. The number of measurements necessary to guarantee recovery using a random measurement system is approximately $M = O(K \log(N / K))$.

3.2 The Implementation of CQI Feedback Compression Based on CS

Depending on the Doppler effect and the delay spread, the SNRs of neighboring subcarriers in both time and frequency are highly correlated. Therefore, the SNRs on all subcarriers are the sparse and compressible signal. To make the feedback transmission as efficient as possible, both time and frequency correlation should be exploited. Our scheme is to use the CS for exploiting correlation in frequency, due to its efficiency. As for time-domain correlation, we use the method proposed in [8], which suggests that the process is sub-sampled, by transmitting the quantizer indices every G:th block, and estimating the missing blocks with an

MMSE estimator at the base station.

Block diagrams of the encoding and decoding process of feedback information with CS are given in **Fig. 2**. At a given time instant the SNRs on all subcarriers are collected in a vector of length N_c and encoded using CS, quantized by a kind of appropriate design of scalar quantizer and then subsampled (subsampling with the factor G=2 in this work). At the receiver, the inverse process is applied and the compressive sensing reconstruction algorithm is exploited to reconstruct the SNRs of all users. In this work, we don't discuss what kind of quantizer should be employed here because this is not our main concern.

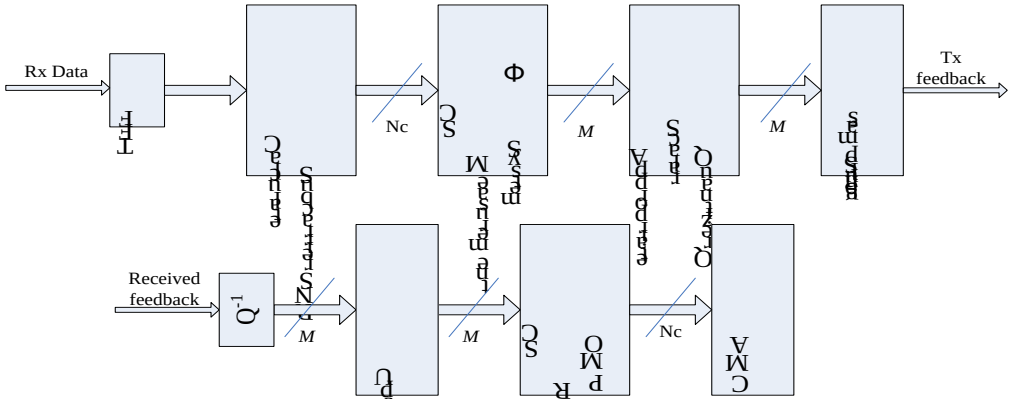

Fig. 2. Diagram of the encoding and decoding of feedback information with CS

The classical compressive sensing reconstruction algorithms include linear programming (LP), matching pursuit (MP), orthogonal matching pursuit (OMP) and etc. In the following, we exploit OMP to reconstruct the CQI feedback information.

This is an iterative algorithm that calculates sequences of partial estimates $\hat{\mathbf{x}}_j$, approximations $\mathbf{y}_j$ to the observation vector $\mathbf{y}$, and residuals $\mathbf{r}_j = \mathbf{y} - \mathbf{y}_j$ as summarized in the following.

Initialization ($j = 0$): define the residual $\mathbf{r}_0 = \mathbf{y}$ and the empty index set $S_0 = \phi$.

Steps at the j th iteration ($j = 1,2,\ldots$):

(1). Determine an index s_j that satisfies

$$\left|\left\langle \mathbf{r}_{j-1}, \phi_{s_j} \right\rangle\right| = \max_{s \in \{1,\ldots,M\} \setminus S_{j-1}} \left|\left\langle \mathbf{r}_{j-1}, \phi_{\mathbf{s}} \right\rangle\right| \tag{5}$$

where $\phi_{\mathbf{s}}$ denotes the s th column of $\mathbf{\Phi}$.

(2). Augment the index set as $S_j = S_{j-1} \cup \{s_j\}$. (Note that $|S_j| = j$.)

(3). Calculate a new estimate $\hat{\mathbf{x}}_j$ such that it has zero entries outside the index set S_j i.e., $\text{supp}\{\hat{\mathbf{x}}_j\} = S_j$, and the nonzero entries (combined into a j -dimensional vector denoted by $\hat{\mathbf{x}}_{j|S_j}$) are given by the solution of a least-squares problem:

$$\hat{\mathbf{x}}_{j|S_j} = \arg\min_{\mathbf{x}\in\square_j} \left\| \mathbf{y} - \Phi_{S_j}\mathbf{x} \right\|_2 = \Phi_{S_j}^{\dagger}\mathbf{y} \tag{6}$$

Here, the $Q \times j$ matrix $\mathbf{\Phi}_{S_j}$ comprises the columns of $\mathbf{\Phi}$ indexed by S_j and $\Phi_{S_j}^{\dagger}$ is its Moore-Penrose pseudoinverse.

(4). Calculate a new approximation to the observation vector $\mathbf{y}$ and a new residual:

$$\mathbf{y}_j = \mathbf{\Phi}_{S_j}\hat{\mathbf{x}}_{j|S_j}, \ \mathbf{r}_j = \mathbf{y} - \mathbf{y}_j. \tag{7}$$

These steps are repeated until a stopping criterion is satisfied. This may be a predefined number of iterations (corresponding to a fixed known sparsity S) or a required approximation quality (e.g., the norm of the residual $\mathbf{r}_j$ is required to be below a given threshold). Upon termination (at the final iteration, say, $j = K$), OMP outputs the K-sparse vector $\hat{\mathbf{x}} = \mathbf{x}_K$.

In our proposed CQI feedback compression methods based on CS, there is a direct connection between the dimension of measurement matrix (scilicet the number of measurement values) and the CQI feedback rate. Thus, it is necessary to explore the compression measurement matrix of CS.

The design of measurement matrix is an important part of compressive sensing theory. The purpose of designing measurement matrix is to obtain M measurement values by sampling and guaranteeing that the original signal or the sparse coefficient vector in certain sparse basis can be reconstructed. Obviously, reconstruction is impossible if the information of $\mathbf{x}$ is destroyed in measurement process. Incoherence characteristic between measurement matrix and sparse basis is the foundation of CS theory's better properties. The measurement matrix, each entry of which is taken from an i.i.d. random Gaussian distribution, is widely employed due to its incoherence to other basis functions. Here, we called the CS method employing random Gaussian measurement matrix 'general CS method'.

3.3 CQI Feedback Compression Based on Subspace CS

Along with the further research on CS, we found that there is certain connection between the required number of measurement values and the design of measurement matrix on condition that the reconstruction effect can be guaranteed. It is clear that the performance depends on the signal energy that the measurement matrix can collect, which is approximately proportional to the number of measurements. Further, on the premise of the reconstruction effect would be guaranteed, the more signal energy information the measurement matrix captures, the smaller number of the measurement values is needed. If the underlying signal's characteristic is considered when we design the measurement matrix, the number of required measurement values will greatly reduced. Luckily, the design of the measurement matrix discussed in [15] just anastomosed our thought.

The i.i.d. random measurement scheme for general compressive sensing provides universality for signals with different structure. However, since the compressive measurements are not tailored to the underlying signals, the measurement matrix is not efficient at gathering signal energy. To improve the performance of general CS, we exploit the fact that a sparse signal resides in a low dimension subspace and we can capture most of the signal energy with as few as K measurements just by projecting the signal into its own subspace. Furthermore, the information of the signal subspace can be inferred from known signal characteristics as a priori or learned from the compressive measurements of training data[16]. The use of training signals is widely employed in communication systems. To this

end, we assume that at the time of acquisition, the signal subspace is known.

Here, we reconsider an N-dimensional signal $\mathbf{x}$ to be K-sparse in a sparsity-inducing basis $\{\mathbf{b}_i\}$, that is, there are at most K non-zero coefficients $\{\alpha_i\}$ in the basis expansion $\mathbf{x} = \sum_i \alpha_i \mathbf{b}_k$ denoted as $\mathbf{B}\boldsymbol{\alpha}$. The signal is K-compressible if it is well approximated by the K most significant coefficients in the expansion.

We assume $\mathbf{D} = [\mathbf{b}_{n_1}, \mathbf{b}_{n_2}, \cdots, \mathbf{b}_{n_K}]$, where $n_i \in \{1, 2, \cdots, N\}$ for $i = 1, \cdots, K$. $\mathbf{b}_{n_k}$ is the vector of $\mathbf{B}$ corresponding to the k-th non-zero entry. The signal $\mathbf{x}$ is represented as $\mathbf{x} = \mathbf{D}\boldsymbol{\theta}$, where $\boldsymbol{\theta}$ is a $K \times 1$ vector with all non-zero entries.

We design the subspace measurement matrix as follow

$$\overline{\boldsymbol{\Phi}} = \mathbf{G}(\mathbf{D}^T\mathbf{D})^{-1}\mathbf{D}^T \tag{8}$$

where $\mathbf{G}$ is a $M \times K$ random matrix, and each entry of $\mathbf{G}$ is taken from an i.i.d. random distribution. Adding of the random matrix $\mathbf{G}$ is required because it leads to measurements equally important in probability. Thus, if any measurement goes wrong, it will not lead to severe performance degradation. Without $\mathbf{G}$, what are measured are the signal transform coefficients. Since failing to measure a large coefficient may lead to wrong results, such transform based schemes are not robust.

The performance of compressive sensing based on compressive measurement can be significantly improved by exploiting the underlying signal structure, leading to the requirement of far fewer measurements. A subspace compressive measurement matrix can be constructed based on the estimated signal subspace model. Although the subspace compressive measurement does not provide universality for all signals in the R^N space, it does provides universality for signals in a specific subspace. We called the compressive sensing method with the subspace measurement matrix 'subspace CS'.

In [15], a set of subspace compressive detectors based on the subspace measurement matrix are proposed for sparse signal detection problem. In our work, we firstly apply subspace CS to solve the problem of CQI feedback compression, thus leading to fewer measurements than general CS. The feedback rate can be greatly reduced on condition that the reconstruction effect can be guaranteed.

4 Experiments and Discussions

In this section, simulation results are provided to investigate the performance of the CQI feedback compression methods based on CS. For comparison purposes, the conventional DCT based method which is widely employed is also illustrated.

In the following, a one cell downlink OFDMA scenario, where both BS and MS have a single antenna and each BS serves 30 users, is considered. The channel is frequency selective Raleigh fading channel with six paths and the average SNR is assumed 20 dB. The number of subcarriers $N_c = 1024$ and a target bit error $BER_T = 10^{-3}$ is assumed. The required SNRs of the different modulation levels (BPSK, 4-QAM, 8-QAM, 16-QAM, 32-QAM, 64-QAM, 128-QAM and 256-QAM) under the target BER are calculated based on [17]. Besides, the vehicular speed is 75 km/h and the carrier frequency is 5GHz. We do not discuss what kind of quantizer should be employed here because this is not our main concern. According to [18], the quantization levels depend on the number of users, and when the quantization law is

designed proportionally most of the multiuser diversity can be efficiently captured with as few as 2-4 quantization bits. In this work the output of quntizer is assumed to be 5 bits. Hence, the bit number of general CS compression feedback amounts to 5×M, where M is the number of measurements.

Finding the optimal sparse representation of signal is the foundation and precondition of compressive sensing theory. Only by choosing suitable basis to represent signal can we guarantee the sparse degree of signal. Consequently, the precision of signal reconstruction can be guaranteed. In our work, OFDM system is employed. To maximally show the superiority of compressive sensing theory, we focus on the performance of CQI feedback compression based on CS by using IDFT in our experiments. In recent years, another hot for sparse representation is sparse decomposition based on redundant dictionaries. This is a new theory of signal representation. A lot of research show that it is more effective to represent sparse signals based on overcomplete redundant dictionaries [19] [20]. Thus, there may be better sparse representation of the underlying class of signals. We will do this work in the future due to the limitation of our knowledge and time.

The measurement matrix of subspace measurement compression, $\overline{\mathbf{\Phi}} = \mathbf{G}(\mathbf{D}^T\mathbf{D})^{-1}\mathbf{D}^T$, is a complex matrix because IDFT basis is composed of complex number. The measurement values which are obtained by using measurement matrix multiply the CQI signal are complex numbers, including real and imaginary parts. If the dimension of measurement matrix in subspace CS method is denoted by M_1 and every real number is quantized to 5 bits, the number of bits of CQI feedback with subspace CS is $2 \times M_1 \times 5$ bits.

As fortraditional methods of orthogonal transformation such as DCT, M key components after orthogonal transformation needs to be saved and more space is needed to store their location information. Thus the bit number of DCT compression feedback is equal to $5 \times M + \log_2 \binom{N_{rb}}{M}$, where M denotes the number of feedback chunks and N_{rb} is the number of chunks.

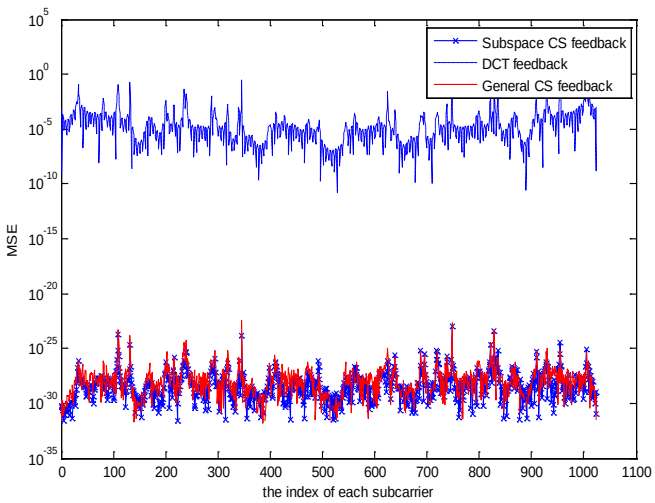

Fig. 3. The MSE between the reconstructed SNRs and the real SNRs on each subcarrier

The MSE between the reconstructed *SNR*s and the real *SNR*s on each subcarrier is given in

Fig. 3 The rates of CQI feedback for the three compression techniques are the same (1 bits/subcarrier). As can be seen from **Fig. 3**, the MSE between the real *SNR*s and the reconstructed *SNR*s (distributing around 10^{-30}) by general CS and subspace CS are far smaller than that (distributing around 10^{-5}) reconstructed by IDCT, which shows that the *SNR*s reconstructed by the corresponding reconstruction algorithm of CS compression are much more accurate.

Fig. 4 shows the rate of CQI feedback on each subcarrier and the corresponding achieved throughput using a max-SNR scheduler with an average SNR per user per symbol of 20 dB with 30 users.

From **Fig. 4**, we can see that the throughput performance with subspace CS is the best. With the feedback rate smaller than 0.2637 bits/subcarrier, the throughputs with subspace CS present a rising tendency along with the increase of feedback rate. When the feedback rate is near 0.2637 bits/subcarrier, the throughputs with subspace CS approach the ideal throughputs. Comparatively, the throughputs with general CS approach the ideal throughputs when the feedback rate is near 0.3271 bits/subcarrier. As for DCT, the throughputs are continuously rising along with the increase of feedback rate. When the feedback rate is near 0.6592 bits/subcarrier, the throughputs with DCT method gradually approach the ideal throughputs. In addition, from **Fig. 4**, we can also see that the throughputs with DCT are superior to the throughputs with general CS when the feedback rate is smaller than 0.1181 bits/subcarrier. However, this is insignificant because they all suffer from great throughput loss in this situation and the feedback rate with such poor throughputs will not be employed in practical application.

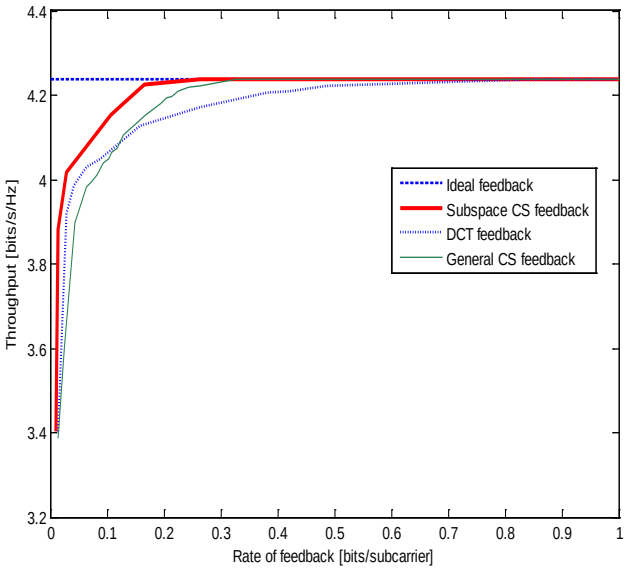

Fig. 4. Throughput as a function of the rate of CQI feedback on every subcarrier

Clustering is widely adopted to reduce feedback overhead in many literatures.It suffers from decline of throughput performance because the subcarriers near the cluster boundary are likely to experience mismatch. The appropriate cluster size is determined by delay profile of channel. In this work, we also exploit the performance of CQI feedback compression based on

CS with different sizes of cluster.

Fig. 5 displays the rate of CQI feedback with cluster size 2 and the corresponding achieved throughput using a max-SNR scheduler with an average SNR per user per symbol of 20 dB with 30 users.We can see from **Fig. 5** that the achieved throughputs of the ideal feedback with cluster=4 are decreased somewhat comparing with the throughputs of the ideal feedback without clustering. The compressive feedback method based on subspace CS has the best throughput performance. The throughputs of the compressive feedback methods based on subspace CS and general CS rise continuously until the feedback rate reaches 0.2246 bits/subcarrier and 0.2637 bits/subcarrier, respectively. When the feedback rate is near 0.542 bits/subcarrier, the throughputs with DCT method gradually approach the ideal throughputs. From **Fig. 5**, we also can see that the throughputs with DCT exceed the throughputs with general CS when the feedback rate is below 0.13 bits/subcarrier.

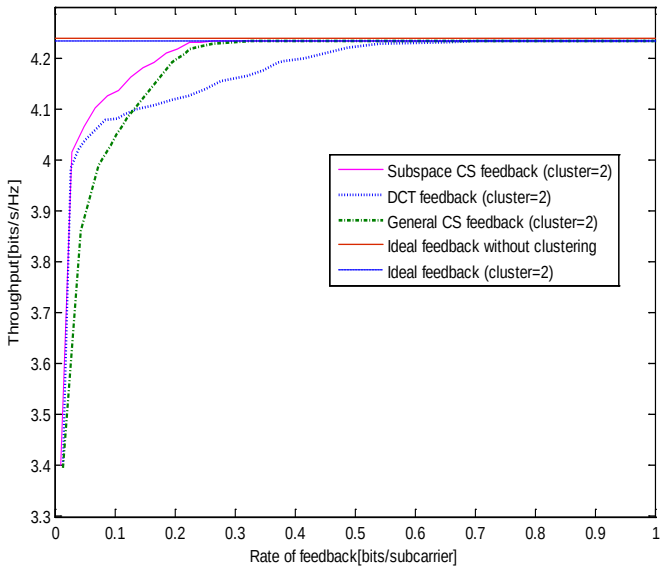

Fig. 5. Throughput as a function of the rate of CQI feedback with cluster=2

Fig. 6 shows the rate of CQI feedback and the corresponding achieved throughput with cluster size 4. We can see that the gap between the ideal feedback without clustering and cluster=4 in **Fig. 6** is much bigger than that in **Fig. 5**. The throughput performance with subspace CS still outperforms that with general CS or DCT. With feedback rate smaller than 0.2246 bits/subcarrier, the throughputs with subspace CS present a rising tendency along with the increasing of feedback rate. When the feedback rate is near 0.2246 bits/subcarrier, the throughputs with subspace CS approach ideal throughputs with clustering, while the throughputs with general CS approach it when the feedback rate is near 0.2832 bits/subcarrier. As for DCT, the throughputs rises continuously along with the increasing of feedback rate. When the feedback rate is near 0.5273 bits/subcarrier, the throughputs with DCT method gradually approach ideal throughputs with clustering. What's more, it is also can be seen from **Fig.6** that the throughputs with DCT are superior to the throughputs with general CS with the feedback rate smaller than 0.1318 bits/subcarrier.

The rate of CQI feedback and the corresponding achieved throughput with cluster size 8 is

shown in **Fig.7**. From **Fig.7,** we can see that the throughput of the ideal feedback with cluster=8 reduced to 4.171 bits/subcarrier and the gap between the throughputs of ideal feedback without clustering and cluster=8 is very large. The throughputs of three methods based on subspace CS, general CS and DCT present a rising tendency along with the increase of feedback rate. Their throughputs gradually approach the ideal throughputs when the feedback rate reached 0.2246, 0.2832 and 0.4766 bits/subcarrier, respectively. When the feedback rate is larger than 0.1514 bits/subcarrier, the throughputs with general CS outperform the throughputs with DCT.

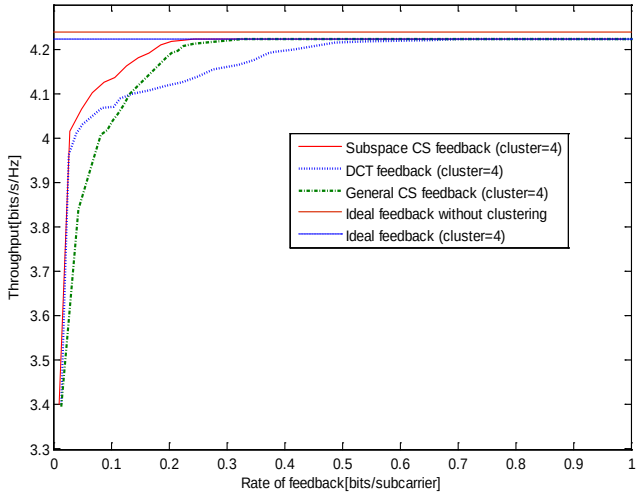

Fig. 6. Throughput as a function of the rate of CQI feedback with cluster=4

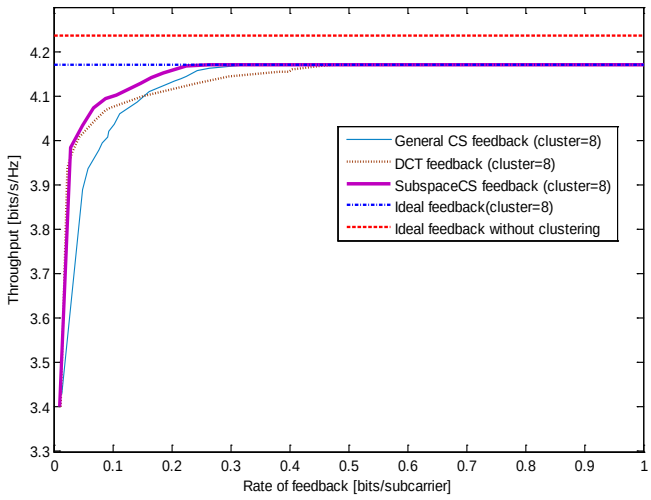

Fig. 7. Throughput as a function of the rate of CQI feedback with cluster=8

From **Fig. 4**, **Fig. 5**, **Fig. 6** and **Fig.7**, we can oberserve that the gap between the throughputs of ideal feedback with clustering and without clustering became larger with the

increase of cluster size. This is because that clustering suffers from decline of performance due to mismatch between subcarriers at the edges of the cluster boundaries. The performance of the CQI compressive feedback methods based on subspace CS and general CS also decreased with the increase of cluster size. The application precondition of the methods based on compressive sensing is that the signal is sparse. The correlation between the values of CQI signal, decreases gradually as the size of cluster increases. In other words, the sparse level is gradually decreasing. This is one reason why methods based on compressive sensing performs worse and worse when the size of cluster increases. Despite the above-mentioned problem, the method based on subspace CS still maintains good performance, because it is much easier to capture the energy information of signals due to the special design of measurement matrix. In contrary, DCT based method, with the increase of cluster size, N_{rb} in $5\times M+\log_2\binom{N_{rb}}{M}$ which calculates the rate of feedback is decreasing, and the required bit number of indicating the location information of M most important coefficients is further decreasing.

The above analysis and simulation assumed an error-free feedback link. However, in practical systems, noise exists in feedback channel. Hence, signals at the receiver are corrupted by different kinds of noise such as quantization noise and feedback noise. In the following simulations, we exploit the performance of different feedback methods influence by noise. **Fig. 8** shows the throughput performance of different methods without clustering under varying SNR. **Fig. 9** is the throughput performance with cluster size 4 under varying SNR. From the two figures, we can see that the throughputs of three methods are continuously raising with the increasing SNR. The throughputs performance of subspace compressive feedback method is the best ,followed by general CS. The performance of DCT based method is worst and its throughputs outperform general CS only with SNR below 2 dB.

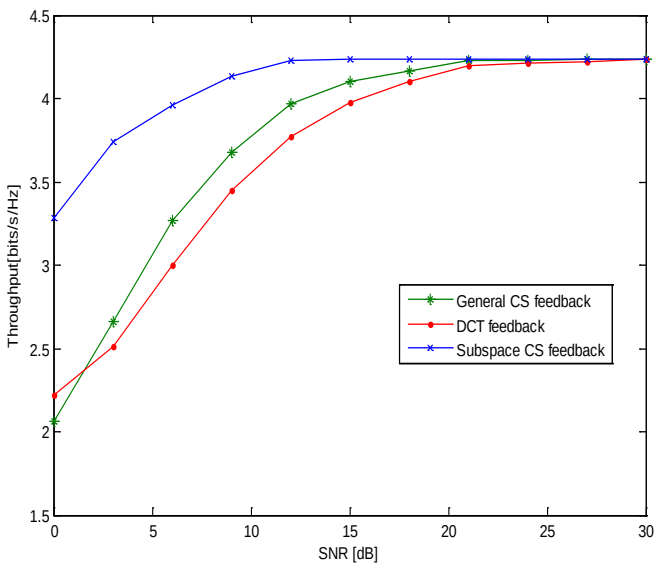

Fig. 8. Throughput without clustering as a function of SNR

As can be seen from the two figures, the methods above have better performance with SNR beyond 15 dB. This is because the reconstructed CQI sequence is used for scheduling or AMC,

which could tolerate certain degree of noise. Moreover, for DCT based method, if one or several key components of the M most important components are lost in transmission processes, the reconstruction performance decreased seriously. Thus the method based on DCT has poor anti-interference ability. By contrast, the methods based on CS have better anti-interference ability. Because every entry in the measurement vector is equally importantand the loss of one or several enties in trasmission will result in little unfavorable effect on the reconstruction performance.

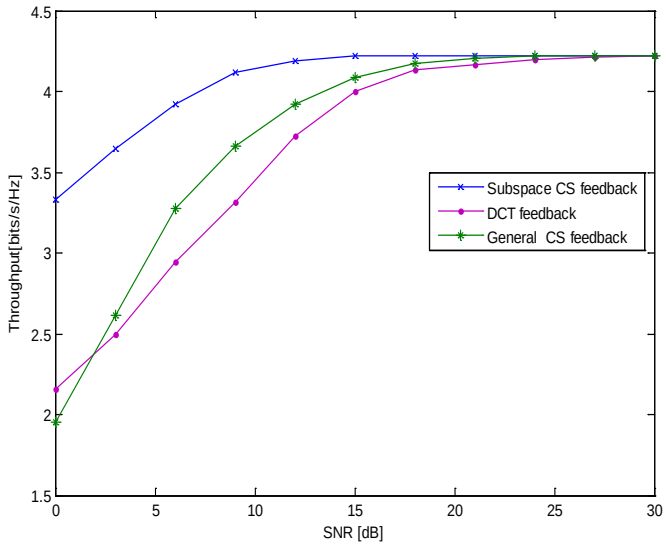

Fig. 9. Throughput with cluster size 4 as a function of SNR

According to our experiments, it is very clear that with far fewer measurements, the CQI feedback compression based on subspace CS has greatly improved the throughput performance by exploiting subspace information. Although CQI feedback compression based on general CS might require more measurements than subspace CS, it has a better throughput performance than the DCT based method does.

The general CS method has a simple design because it only needs a measurement matrix at the user side and the reconstruction algorithm which has a high computational complexity is processed at base station. Comparatively, in order to design measurement matrix, the subspace CS method needs to obtain the underlying signal characteristics by using training sequence. It increases the system overhead although the high-comutational reconstruction algorithm is also processed at base station. However, it is worth mentioning that the subspace CS method greatly reduces the rate of CQI feedback, which is what we expected. From **Fig. 4**, **Fig. 5**, **Fig. 6** and **Fig. 7**, we can see that the performance of subspace CS method is superior to general CS method at the same feedback rate no matter with clustering or without clustering.

The special design of measurement matrix with subspace CS can guarantee the exact recovery of signal before the measurement number M_1 becomes smaller than K. However, $4\times K \sim 5\times K$ or more measurement values are required to guarantee the exact recovery of signal with general CS method. Because the random measurement matrix with each entry taken from an i.i.d. random distribution is employed by general CS, the lower-dimension random Gaussian measurement matrix can not guarantee that it can capture enough signal

energy information for the reconstruction algorithm to perfectly reconstruct signal with high probability. To ensure that general CS method can stably reconstruct signal with high probability, we must increase the dimension of measurement matrix to get more measurement values.

5. Conclusions and Future Works

In this work, we have shown that exploiting correlation in frequency with compressive sensing can achieve considerable reduction in CQI feedback rate. Firstly, the general CS method is introduced to reduce CQI feedback overhead for adapted OFDM system. Secondly, via further research on the design of measurement matrix with general CS, a novel CQI feedback scheme based on subspace CS is proposed by exploiting the subspace information of the underlying signal and the feedback rate is greatly decreased. Finally, Simulation results show both of the proposed two methods have better throughput performance than the commonly used Discrete Cosine Transform based method. Therefore, CS is a good choice from the viewpoint of trade-off between system throughput and feedback rate for adapted OFDM transmission.

So far, the simulations results have shown the effectiveness of the proposed two methods. From our experiments, we found that one realization of $\mathbf{\Phi}$ in general CS and $\mathbf{G}$ in subspace CS can be selected for each feedback to avoid the worst scenario. Especially with general CS, one realization of $\mathbf{\Phi}$ would lead to different reconstruction effect when the number of measurements is small. It has been shown in [21] that the performance of CS sampling can be improved if the random measurement matrices are optimized to some extent. However, the method in [21] leads to optimized but unstructured measurement matrices. Therefore, large memory space and computation demanding resources are needed, making the implemetation prohibitively expensive. Hence, it is not the best choice. One of our future works is to find better schemes to optimize the measurement matrices and exploit the impact on our CQI feedback compression caused by different measurement matrices. In addition, since the quantization is very important in feedback link, future research may also include investigating the impact of different kinds of quantization. Another future focus is how to find the best sparse representation to CQI signal of OFDM model from overcomplete redundant atom dictionary or numerious orthogonal basis dictionaries, which can further reduce the feedback rate.

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