A New Compressive Feedback Scheme Based on Distributed Compressed Sensing for Time-Correlated MIMO Channel

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Abstract

In this paper, a new compressive feedback (CF) scheme based on distributed compressed sensing (DCS) for time-corrected MIMO channel is proposed. First, the channel state information (CSI) is approximated by using a subspace matrix, then, the approximated CSI is compressed using a compressive matrix. At the base station, the approximated CSI can be robust recovered with simultaneous orthogonal matching pursuit (SOMP) algorithm by using forgone CSIs. Simulation results show our proposed DCS-CF method can improve the reliability of system without creating a large performance loss.

Keywords: Time-corrected channel, distributed compressed sensing, zero-forcing beamforming, MIMO

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1. Introduction

It is well known that multiple-input multiple-output (MIMO) antenna systems can greatly improve the performance of wireless communication systems[1-2]. MIMO is one of the key concepts for the next generation of cellular systems, such as the 3GPP Long Term Evolution (LTE), to provide high data rates to a large number of different users. In wireless communication systems, a typical scenario has multiple users vying for service from a single transmitter. If multiple antennas are available at the transmitter, multiple users could be served efficiently by transmitting to multiple users simultaneously over user-specific spatial channels. This technique, sometimes known as multiuser (MU) MIMO, is being considered for the downlink of next generation mobile cellular systems to improve spectral efficiency [3]. In the multi-user MIMO broadcast channel, a high capacity can be achieved by coordinating the transmissions to multiple users simultaneously. As an optimal transmit strategy, dirty paper coding (DPC) has been shown to achieve the capacity region of Gaussian MIMO broadcast channels in [4]. However, deploying DPC in real systems is impractical due to the prohibitive complexity at both transmitter and receiver. Linear precoding is a simpler approach that has been shown to achieve a large part of DPC capacity [5]. And it has been suggested one of key techniques for next generation of mobile communication systems.

In general, in order to achieve full MU multiplexing gain and obtain a high system throughput, MU-MIMO techniques require perfect channel state information at the transmitter (CSIT). However, the bandwidth of feedback link is limited in practice scene. CSIT is difficult to obtain and is never perfect. Imperfect CSIT causes residual inter-user interference, which degrades the performance of MIMO broadcast channel [6]. Hence, providing accurate channel state information at the transmitter is very important for MU-MIMO systems. Under time-division duplexing(TDD), the same band is used for uplink and downlink, and CSI at transmitter for the downlink can be obtained through channel estimation on the uplink. On the other hand, under frequency-division duplexing (FDD), the base station must rely on uplink feedback from mobile terminals to obtain CSI at transmitter [7]. Limited feedback of CSI at the transmitter is a very active area of research, especially in the context of FDD systems. In brief, the CSIT feedback for FDD systems can be grouped into two broad families[8]: 1) schemes based on feeding back the unquantized channel coefficients (analog feedback); 2) schemes based on explicit quantization of the channel vectors and on feeding back quantization bites, suitably channel-encoded (digital feedback). In our work, we mainly focus on digital feedback. In digital feedback, the limited feedback schemes based on codebook are mainstream technologies [9][10][11][12]. However, vector quantization codebook (VQC)-based method only achieves a small throughput gain in spite of requiring enormous overhead at larger feedback rates.

To further improve the sum throughput, In [13], a compressive feedback scheme using spare approximation to reduce the CSI feedback rate was proposed. By using the sparse approximation with a unitary codebook and the compression via a “good” compression matrix, compressive feedback method can achieve greater sum throughput than VQC-based method. In this paper, a new compressive feedback (CF) scheme based on distributed compressed sensing (DCS) for time-corrected MIMO channel is proposed. First, the CSI are approximated by using a subspace matrix, then, the approximated CSI is compressed using a compressive matrix. At the base station, the approximated CSI can be robust recovered with SOMP algorithm by using forgone CSIs. Simulation results show our proposed DCS-CF method can improve the reliability of system without creating a large performance loss.

The rest of the paper is organized as follows. Section 2 presents the CSI compressive feedback method based on distributed compressive sensing. Section 3 provides the simulation result. Finally, section 4 draws the conclusion.

2. CSI Compressive Feedback Method Based on Distributed Compressive Sensing

2.1 System Description

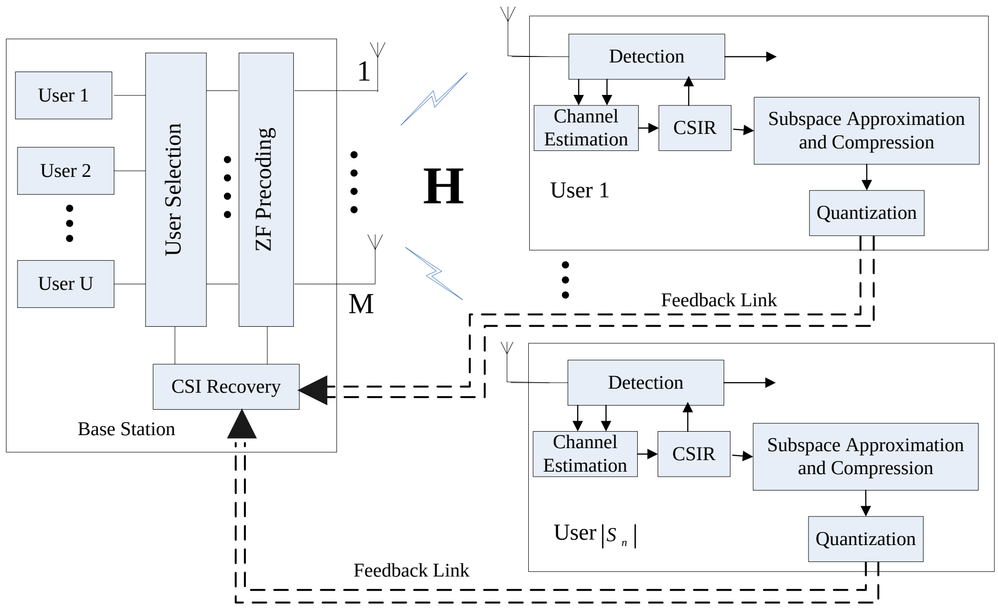

Fig. 1. System Model

As system model, we consider the downlink of a multi-user MIMO system. The base station has M transmit antennas and U users have one antennas each. We consider an FDD system and each user feed back a partial CSI, which is used by the transmitter to schedule downlink transmissions and perform beamforming. The block diagram of the system model is shown in **Fig.1**.

Let $S_n = \{s_n^{(1)}, \cdots, s_n^{(|S_n|)}\}$ be the set of scheduled users receiving data at n-th time and $\mathbf{x}(n)$ the $M \times 1$ transmitted symbol vector which is related to the information symbols $\{d_j(n)\}$ for user $j \in S_n$ via linear beamforming, i.e.

$$\mathbf{x}(n) = \sum_{j \in S_n} \mathbf{F}_j(n) d_j(n) \tag{1}$$

with $\{\mathbf{F}_j(n)\}$ $M \times 1$ beamforming vectors. The signal received by user $k \in S_n$ at n-th time can be written as

$$y_k(n) = \mathbf{h}_k^T(n)\mathbf{x}(n) + w_k(n)$$

$$= [\mathbf{h}_k^T(n)\mathbf{F}_k(n)]d_k(n) + \sum_{j \in S(n), j \neq k} [\mathbf{h}_k^T(n)\mathbf{F}_j(n)]d_j(n) + w_k(n) \tag{2}$$

where $w_k(n)$ is the additive complex Gaussian noise with zero mean and unit variance and the summation term in the second line of (2) accounts for multi-user interference on user k.

The transmit signal is subject to the average power constraint

$$E\left[\left|\mathbf{x}(n)\right|^2\right] \leq P \tag{3}$$

Generally the number of users U is greater than the number of transmit antennas M. In this paper, in order to focus our efforts on the impact of imperfect CSI, we consider a system where the number of mobiles is equal to the number of transmit antennas, i.e. $U = M$.

The channel is modeled as a time-correlated MIMO Rayleigh block-fading channel. The time-correlated channel can be modeled as a first-order Autoregressive process [14], and the channel of each user can be expressed as

$$\mathbf{h}_n = \alpha \mathbf{h}_{n-1} + \sqrt{1-\alpha^2}\mathbf{e}_n \tag{4}$$

where $\mathbf{h}_n$ denotes n-th block-fading channel vector, $\mathbf{e}_n$ is a noise vector, which is independent of $\mathbf{h}_{n-1}$. The parameter $\alpha = J_0(2\pi f_d \tau)$ is the time autocorrelation coefficient, where $J_0(\cdot)$ is the zero-order Bessel function of first kind, f_d is the maximum Doppler frequency and τ is the time interval.

At the receiver, each user estimates its channel frequency response and feeds back two information for each block: 1) the channel direction information (CDI) given by a quantized version of the normalized channel vector $\bar{\mathbf{h}}(n) = \mathbf{h}(n)/\|\mathbf{h}(n)\|$ and an analog channel quality information (CQI) related to signal to noise ratio. In this paper, we assume that CQI feedback is perfect and all the feedback bits are used for the CDI.

Let $\mathbf{H} = [\mathbf{h}_1, \cdots, \mathbf{h}_k, \cdots \mathbf{h}_M]^T$ denotes the real channel matrix and $\hat{\mathbf{H}} = [\hat{\mathbf{h}}_1, \cdots, \hat{\mathbf{h}}_k, \cdots \hat{\mathbf{h}}_M]^T$ denotes the channel matrix obtained by feedback. $\Delta = \mathbf{H} - \hat{\mathbf{H}} = [\Delta_1, \cdots, \Delta_k, \cdots, \Delta_M]^T$ is the error matrix. The error has variance $E\{\Delta_k \Delta_k^H \mid \hat{\mathbf{H}}\} = DP/M$, where D is the overall average CSI distortion. Then, the maximum achievable sum rate for the limited feedback ZF beamforming scheme is upper bounded by [13]

$$R \leq M \log_2\left(1 + \frac{P(M-D)}{M+PD}\right) \tag{5}$$

2.2. CSI Compressive Feedback Based on DCS

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[15], [16]. 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. Distributed compressive sensing theory rests on a new concept of the joint sparsity of a signal ensemble that exploits both intra- and inter-signal correlation structures[17]. Generally, the distributed compressive sensing theory includes three simple models for jointly sparse signals: 1) Joint sparsity model-1(JSM-1): Sparse common component +innovations; 2) JSM-2: Common sparse supports; 3) JSM-3: Nonsparse common component +sparse innovations. In this paper, we mainly focus on the JSM-2. In JSM-2, all the signals are constructed from the same sparse set of basis vectors, but with different coefficient values. Let $\mathbf{\Psi}$ be the basis matrix, then the signals $\mathbf{x}_j$ with length N can be expressed as $\mathbf{x}_j = \mathbf{\Psi}\boldsymbol{\theta}_j$, $j \in \{1, 2, ..., J\}$, where each $\boldsymbol{\theta}_j$ is nonzero only on the common coefficient set $\Omega \subset \{1, 2, ..., N\}$ with $|\Omega| = K$. Thus all signals are K-sparse in the sparsity-inducing basis $\mathbf{\Psi}$ and they are constructed from the same K basis elements but with arbitrarily different coefficients. In this model, the sparse signals share the same expansion vectors from a basis matrix. The sparse approximation can be recovered via greedy algorithms such as one-step greedy algorithm (OSGA) and simultaneous orthogonal matching pursuit (SOMP).

In the following, the CSI compressive feedback scheme based on distributed compressive sensing is proposed. We named this method “distributed compressive feedback (DCF)” The proposed DCF method consisting of two steps: 1) subspace approximation; 2) compression.

The fundamental premise of the JSM-2 of the DCS theory is that the signals share the same expansion basis vectors. In other words, the signals have the same subspace information in the basis matrix $\mathbf{\Psi}$. In the time-correlated slow fading channel, the channel coefficients of neighboring time instant are highly correlated. So if we approximated the CSIs of the neighboring time blocks by using the same subspace, the approximation error will not be too large. First, we will use a $M \times K$（K<M）subspace matrix $\mathbf{T}$ for CSI subspace approximation. The columns in T can be selected from a $M \times M$ unitary matrix $\mathbf{A}$. The reason for considering a $M \times M$ unitary matrix is that it is the minimum codebook needed to describe an M-dimensional complex vector [13]. The approximation error can be reduced simply by letting $\mathbf{T}$ contain more column vectors of $\mathbf{A}$. Note that when K=M, the approximation error is zero.

The channel vector $\mathbf{h}(n)$ of each user at the n-th block is approximated by the subspace matrix $\mathbf{T}$. The optimal coefficient vector for $\mathbf{T}$ in the minimum mean square error sense is given by the least-square solution：

$$\mathbf{G}(n) = (\mathbf{T}^H\mathbf{T})^{-1}\mathbf{T}^H\mathbf{h}(n) \tag{6}$$

Then, the approximated CSI can be achieved by $\tilde{\mathbf{h}}(n) = \mathbf{T}\mathbf{G}(n)$, this is equivalent to $\tilde{\mathbf{h}}(n) = \mathbf{A}\tilde{\mathbf{G}}(n)$, where $\tilde{\mathbf{G}}(n)$ is a $M \times 1$ vector which contains the elements of $\mathbf{G}(n)$ and the others are zero. Thus $\tilde{\mathbf{h}}(n)$ is K-sparse and compressible. Because the $\tilde{\mathbf{h}}(n)$ at the consecutive Q blocks which have the same subspace information are jointly sparse signals, we can use the distributed compressive sensing theory to deal with the approximated CSI.

In [13], the proposed design method of measurement matrix can only find a “good” compression matrix. The compression matrix may be not very effective on that one can ensure the compressed CSI can be reliably recovered at the BS. Thus, we propose a new method of designing compression matrix to guarantee the reliable reconstruction of the compressed CSI. The subspace matrix is known at the step of the subspace approximation, thus we can design the compression matrix by using the subspace matrix to improve the reliability of the CSI reconstruction. Because the CSI is approximated by the same subspace matrix, if the subspace information can be used in the measurement matrix design, the designed compression matrix can be more effective to capture the signal energy and guarantee the reliability of signal reconstruction.

We design the measurement matrix as follow

$$\mathbf{\Phi} = \mathbf{Q}(\mathbf{T}^H\mathbf{T})^{-1}\mathbf{T}^H \quad (7)$$

where $\mathbf{Q}$ is a $C \times K$ matrix. The design method of $\mathbf{Q}$ is following: When C<K, the design method of $\mathbf{Q}$ just like the design method of Θ_t in [13]. When C>K, Q is such a matrix which is composed of K columns of a $C \times C$ random unitary matrix. In the simulation part, we will show the robustness of our proposed measurement matrix.

The compressed CSI can be denoted as

$$\hat{\mathbf{h}}(n) = \mathbf{\Phi}\tilde{\mathbf{h}}(n) \quad (8)$$

Then, the compressed CSI is fed back to base station through an error-free feedback channel after quantization. At the base station, the approximated CSI can be reconstructed based on the compressed CSIs by using the DCS-SOMP[17] algorithm. The previous compressed CSIs can be used to improve the reconstruction probability of the current CSI. The more the available previous compressed CSIs, the higher the reconstruction probability of the current CSI. This is because in JSM-2, the reconstruction probability of the DCS-SOMP algorithm is increase as a function of the number of signals [17]. However, with separate CS reconstruction, each signal will experience an independent probability $p \le 1$ of successful reconstruction. To further improve the superior of distributed compressive sensing, we could use different $\mathbf{Q}$ for different blocks or simply multiply $\mathbf{Q}$ with a unitary rotation matrix which is prior noticed to base station. Note that the dimension of $\mathbf{Q}$ is very small, this will not require too much memory.

We assumed that the available compressed CSIs (inculding the available previous compressed CSIs and the current received CSI) can be described as

$$\mathbf{y} = [\hat{\mathbf{h}}(n-J),...,\hat{\mathbf{h}}(n-1),\hat{\mathbf{h}}(n)] = [\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_J] \quad (9)$$

The DCS-SOMP algorithm is implemented as follows.

(1). Initialize: Set the iteration counter $t = 1$. For each signal index $j \in \{1,2,\ldots,J\}$, initialize the orthogonalized coefficient vectors $\hat{\boldsymbol{\beta}}_j = 0$, $\hat{\boldsymbol{\beta}}_j \in \Re^M$; also initialize the set of selected indices $\hat{\Omega} = \varnothing$. Let $\mathbf{r}_{j,t}$ denote the residual of the measurement $\mathbf{y}_j$ remaining after the first t iterations, and initialize $\mathbf{r}_{j,0} = \mathbf{y}_j$.

(2). Select the dictionary vector (here, the dictionary $\mathbf{\Psi}$ is described as $\mathbf{\Phi A}$) that maximizes the value of the sum of the magnitudes of the projections of the residual, and add its index to the set of selected indices

$$n_t = \arg\max_{n=1,2,\ldots,N} \sum_{j=1}^{J} \frac{|\langle \mathbf{r}_{j,t-1}, \boldsymbol{\varphi}_{j,n} \rangle|}{\|\boldsymbol{\varphi}_{j,n}\|_2} \quad (10)$$

$$\hat{\Omega} = [\hat{\Omega} \quad n_t] \quad (11)$$

(3). Orthogonalize the selected basis vector against the orthogonalized set of previously selected dictionary vectors

$$\boldsymbol{\eta}_{j,t} = \boldsymbol{\varphi}_{j,n_t} - \sum_{g=1}^{t-1} \frac{|\langle \boldsymbol{\varphi}_{j,n_t}, \boldsymbol{\eta}_{j,g} \rangle|}{\|\boldsymbol{\eta}_{j,g}\|_2^2} \boldsymbol{\eta}_{j,g} \quad (12)$$

(4). Iterate: Update the estimate of the coefficients for the selected vector and residuals

$$\hat{\boldsymbol{\beta}}_j(t) = \frac{|\langle \mathbf{r}_{j,t-1}, \boldsymbol{\eta}_{j,t} \rangle|}{\|\boldsymbol{\eta}_{j,t}\|_2^2} \tag{13}$$

$$\mathbf{r}_{j,t} = \mathbf{r}_{j,t-1} - \frac{|\langle \mathbf{r}_{j,t-1}, \boldsymbol{\eta}_{j,t} \rangle|}{\|\boldsymbol{\eta}_{j,t}\|_2^2} \boldsymbol{\eta}_{j,t} \tag{14}$$

(5). Check for convergence: If $\|\mathbf{r}_{j,t}\|_2 > \varepsilon \|\mathbf{y}_j\|_2$ for all j, then increment t and go to step 2; otherwise, continue to step 6. The parameter ε determines the target error power level allowed for algorithm convergence. Note that due to step 3 the algorithm can only run for up to M iterations.

(6). De-orthogonalize: Consider the relationship between $\boldsymbol{\Gamma}_j = [\boldsymbol{\eta}_{j,1}, \boldsymbol{\eta}_{j,2}, ..., \boldsymbol{\eta}_{j,M}]$ and the Φ_j given by the QR factorization $\boldsymbol{\Psi}_{j,\hat{\Omega}} = \boldsymbol{\Gamma}_j \mathbf{R}_j$, where $\boldsymbol{\Psi}_{j,\hat{\Omega}} = [\boldsymbol{\varphi}_{j,n_1}, \boldsymbol{\varphi}_{j,n_2}, ..., \boldsymbol{\varphi}_{j,n_M}]$. Since $\mathbf{y}_j = \boldsymbol{\Gamma}_j \boldsymbol{\beta}_j = \boldsymbol{\Psi}_{j,\hat{\Omega}} \mathbf{x}_{j,\hat{\Omega}} = \boldsymbol{\Gamma}_j \mathbf{R}_j \mathbf{x}_{j,\hat{\Omega}}$, where $\mathbf{x}_{j,\hat{\Omega}}$ is the mutilated coefficient vector, we can compute the signal estimates $\{\hat{\mathbf{x}}_j\}$ as $\hat{\boldsymbol{\theta}}_{j,\hat{\Omega}} = \mathbf{R}_j^{-1} \hat{\boldsymbol{\beta}}_j$, $\hat{\mathbf{x}}_j = \mathbf{A} \hat{\boldsymbol{\theta}}_j$, where $\hat{\boldsymbol{\theta}}_{j,\hat{\Omega}}$ is the mutilated version of the sparse coefficient vector $\hat{\boldsymbol{\theta}}_j$.

3. Experiment

In this section, we present numerical results for a MIMO system with 4, 8 and 12 transmit and one receive antennas. The channel is modeled as a time-correlated MIMO Rayleigh block-fading channel. The carrier frequency is 1.8 GHz; the duration of block is 2/3 ms and the terminal speed is 5 km/h. The time autocorrelation parameter α can be calculated using the parameters above. The restricted isometry property (RIP) is an important sufficient condition to provide theoretical guarantee for exact sparse signal recovery. The RIP is not a criterion for an optimal compression matrix, any matrix having the RIP can guarantee stable compression and reliable reconstruction [13]. **Fig.2** and **Fig.3** show 2K-resticted isometry constant (δ_{2K}) versus the number of compressed CSI elements with K=2 and K=4, respectively.

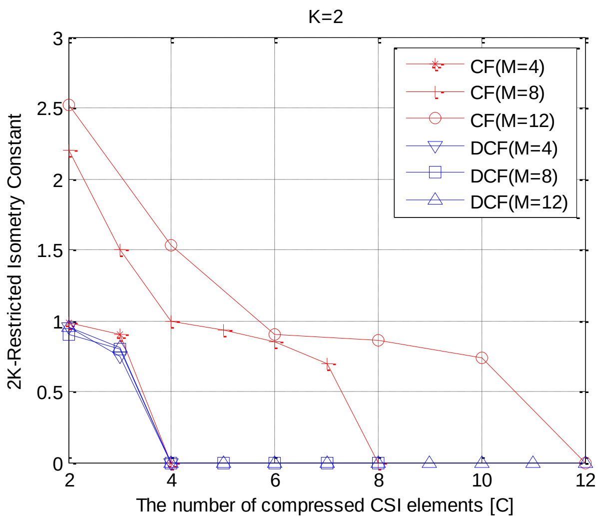

Fig. 2. δ_{2K} versus the number of compressed CSI elements with K=2 (M: the number of transmit antennas)

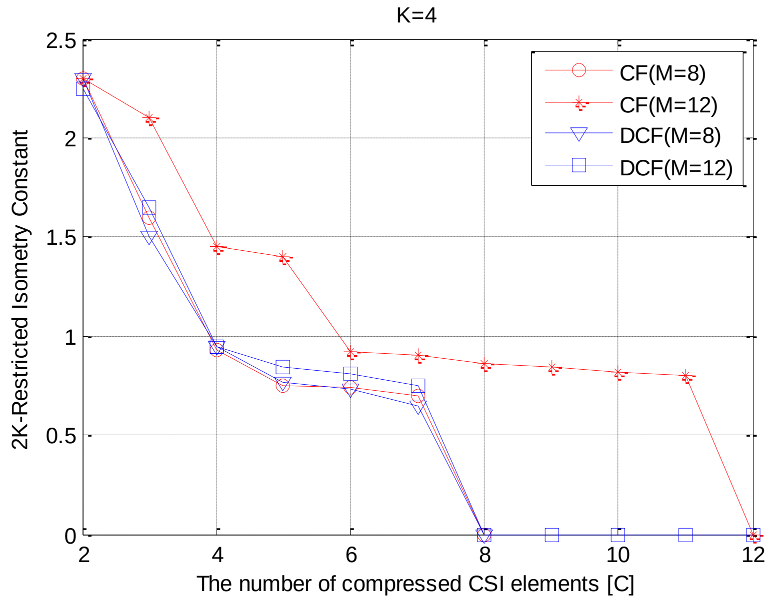

Fig. 3. δ_{2K} versus the number of compressed CSI elements with K=4 (M: the number of transmit antennas)

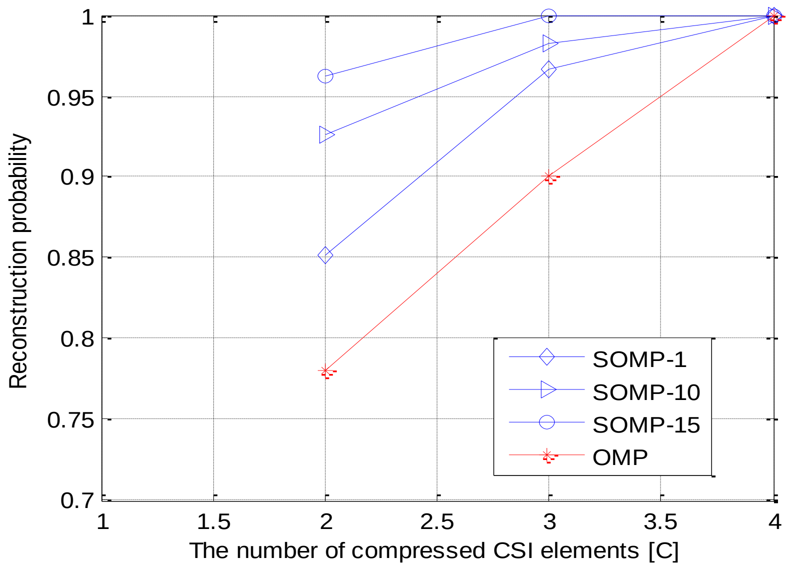

Fig. 4. Reconstruction probability versus the number of compressed CSI elements (SOMP-1: SOMP algorithm with one available block, SOMP-10: SOMP algorithm with 10 available blocks, SOMP-15: SOMP algorithm with 15 available blocks.)

From **Fig. 2** and **Fig. 3**, we can see that our proposed measurement matrix has better RIP than that of compression feedback (CF) in [13]. This means that our proposed measurement matrix can guarantee more stable compression and more reliable reconstruction than that of the CF method.

Fig. 4 shows the reconstruction probability of DCS-SOMP and CF-OMP methods when

M=4. From the figure, we can see that the recovery probability of DCF-SOMP is superior to CF-OMP. The recovery probability of DCF-SOMP is improving as the increase of the number of available blocks. In practice, the algorithm which has a better reliability will be adopted.

Fig. 5, **Fig. 6** and **Fig. 7** show the achievable sum rate versus the number of feedback bits for DCF, CF and VQC with SNR=5 dB and the number of available blocks are 60, 80 and 100. The numbers of feedback bits are 4, 8,12,16,20 and 24. The performance results are the mean for 2000 realizations. Since there is no perfect channel estimation in practice, the influence of the channel estimation error is considered. In this paper, we assume the variance of maximum likelihood (ML) channel estimation error is 0.05 [14]. From **Fig. 6**, **Fig. 7** and **8**, we can see that the performance of our proposed DCF method is slightly worse than that of CF but better than that of the traditional VQC method. As the increase of the available blocks, the performance gap between DCF and CF become a little larger. This is because the CF method can find the best K columns to approximate each block's CSI, but the same subspace is used to approximate the CSI of all the blocks in our proposed DCF method, as the increase of the available blocks, the correlation between the CSIs in the current and the foregoing blocks decreases. This will lead to more mismatch in subspace approximation and create performance loss. To reduce performance loss, it is better to adjust the subspace matrix after a period of time. Then, two benefits will be obtained: robustness of reconstruction and a good throughput performance.

Fig. 8 shows the sum throughputs for DCF, CF and VQC as the SNR increases. The values of SNR are 0~15 dB. The performance results are the mean for 1000 realizations. The number of available blocks is 60. Assumed the variance of channel estimation error is also 0.05. We can see that as the increase of SNR, the performance of DCF is only slightly worse than CF with both cases of M=8, B=10 and M=4, B=5. DCF and CF has a much greater throughput than VQC with the same case.

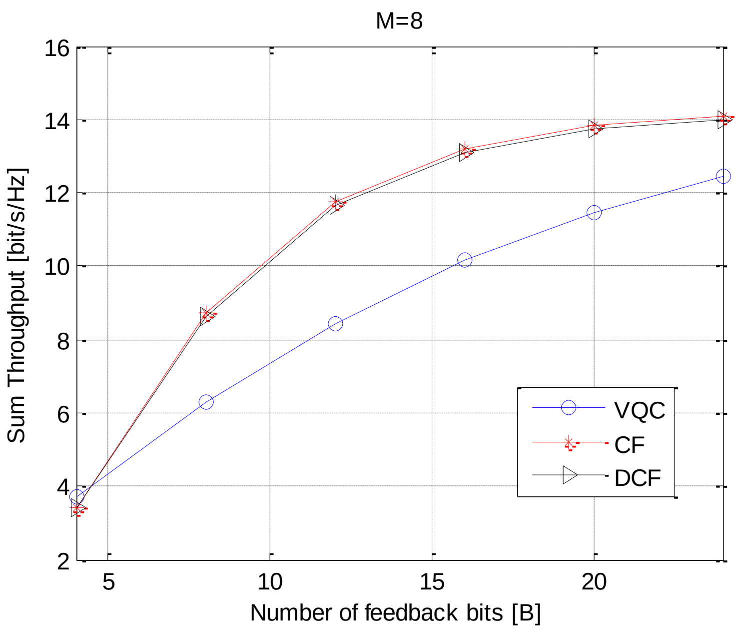

Fig. 5. The achievable sum rate versus the number of feedback bits with the number of available blocks is 60.

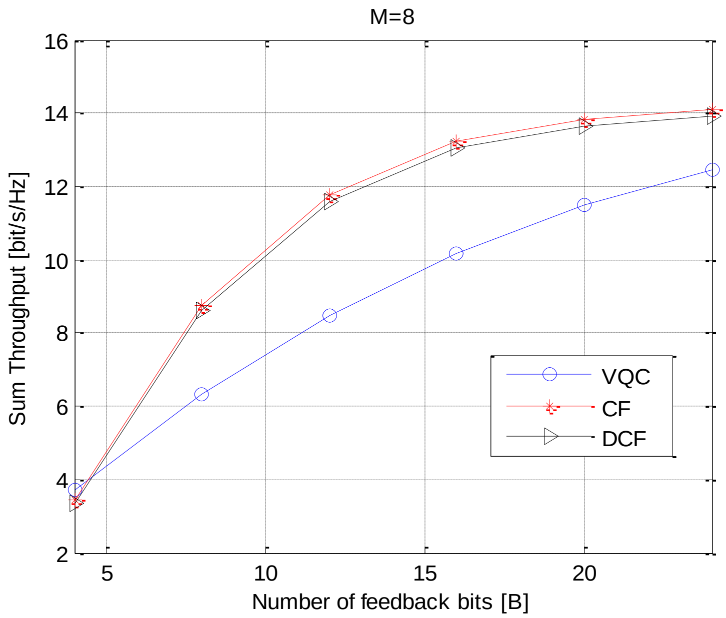

Fig. 6. The achievable sum rate versus the number of feedback bits with the number of available blocks is 80.

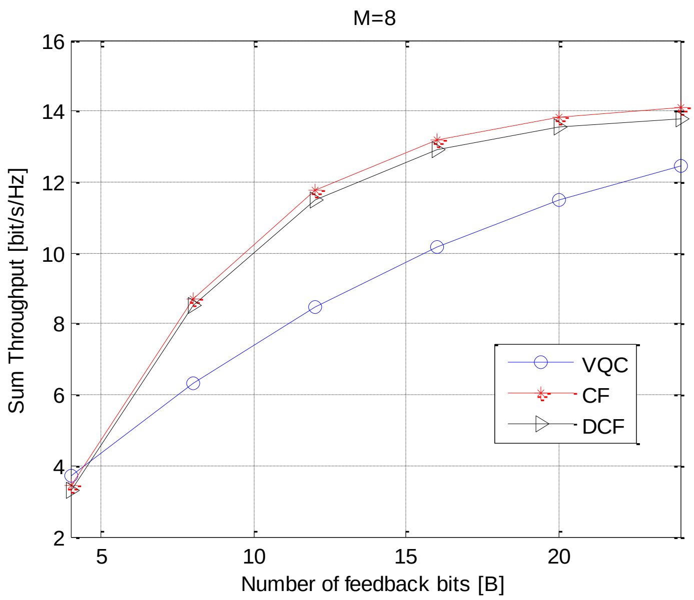

Fig.7. The achievable sum rate versus the number of feedback bits with the number of available blocks is 100.

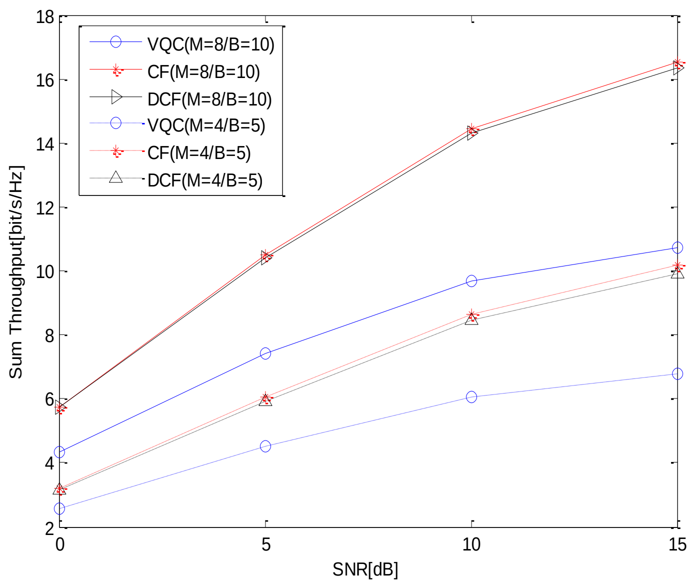

Fig. 8. Sum throughput versus SNR (M: the number of transmit antennas, B: the number of feedback bits.)

3. Conclusion

In this paper, distributed compressed sensing is proposed to apply to CSI compressive feedback for time-corrected MIMO channel. We proposed a more robust method of designing compression matrix. First, the CSI will experience two steps: subspace approximation and compression. At the base station, the approximated CSI can be robust recovered with SOMP algorithm by using forgone CSIs. Simulation results show our proposed DCS-CF method can improve the reliability of system without creating a large performance loss.

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