A large-scale MIMO channel information feedback algorithm based on compressed sensing

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Abstract

In order to effectively reduce the feedback overhead of channel state information (CSI), a channel state information feedback algorithm based on compressed sensing was proposed for Large-scale MIMO system. Firstly considering the sparsity of spatial-frequency domain for the large-scale MIMO channel, the channel information was compressed in space domain firstly and in frequency domain subsequently, the receiver acquired the measurement vector based on compressed sensing algorithm; then feedback. CSI observations to the transmitter according to the proposed adaptive feedback protocol, at last the transmitter reconstructed CSI based on the Basis Pursuit (BP) algorithm. It is show in stimulation results that the proposed algorithm can acquire similar BER performance with perfect channel information feedback. The proposed algorithm, which feedbacks the compressed channel information, not only can significantly reduce the feedback overhead, but also ensure that large-scale MIMO performance gain.

Keywords: Large-scale MIMO, Channel State information feedback, Compressed Sensing

1 Introduction

As applications of wireless networks become more and more diverse and users in wireless network increase very rapidly, wireless data grows up dramatically. Enhancing network capacity is still a challenge in the future of wireless communications. The multiple antenna technology has been an important way to improve network capacity. Large-scale MIMO, also known as Massive MIMO, configures a large number (from tens to thousands) of antennas in base station. It can not only greatly improve the system capacity but also reduce transmit power for the large-scale array gain. So Large-scale MIMO has become a hot topic in the research of 5G wireless communication technology [1].

However it is an important issue that how the transmitter acquires the instantaneous and accurate channel state information (CSI). In the time division duplex (TDD) system, the transmitter obtained CSI using the channel reciprocity [2]; in the frequency division duplex (FDD) system, the transmitter obtained CSI by the feedback from the receiver. As the number of antennas increases, the amount of channel state information feedback also grows linearly. Popular CSI feedback schemes, such as vector quantization and codebook-based approaches, may not appropriate for the large-scale MIMO. When the feedback overhead is reduced as to the limited bandwidth and time resource, the accuracy of the feedback will be difficult to ensure [1]. FDD mode is the major mode of current wireless communication systems and will also be one of working modes in the future wireless communications. Therefore, it is necessary to study CSI feedback mechanisms and algorithm in FDD system of Large-scale MIMO to reduce the feedback overhead significantly and ensure a large-scale antenna array gain.

For the CSI feedback of large-scale MIMO on the FDD mode, the following documents provided a good basis for research. Literature [3] assumed the base station and the user shared a common set of training signals in advance, and then proposed open-loop and closed-loop training frameworks. In the open-loop training, the base station transmitted training signals in a round-robin manner, and the user equipment successively estimated the current channel using long-term channel statistics and the previously received training signals. In the closed-loop training, users only received the training signals with best quality. Numerical results proved that this feedback method could obtain better performance for large-scale MIMO systems, especially when the SNR is low. Literature [4] proposed a non-coherent trellis coded quantization (NTCQ) feedback algorithm which combined channel coding with codebook design. Although the above algorithm can reduce the amount of feedback overhead, their computational complexity or encoding complexity linearly scales up with the number of antennas.

Compressed sensing utilizes the sparsity of signals to reduce the number of sampling and breaks the limit of Nyquist sampling theorem. It can not only reduce the sampling number of signals but also achieve good performances for the immense improvement of the sparse

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signal reconstruction [4, 5]. If signals are compressible or sparse in a transform domain, high-dimension signals can be projected onto a low-dimension space through the observation matrix which is uncorrelated with the transformation basis. And then the original signal can be reconstructed from a small number of projections which contains sufficient information of original signals. In this theoretical framework, the sampling rate is not determined by the signal bandwidth, but the structure and contents of information contained in signals. Recently, compressed sensing has been applied to signal processing and communications [7]. For the downlink transmission that services a large number of users, literature [8] proposed a method for channel estimation and user selection which established that full channel state information for each self-selecting user. Full channel state information can be obtained via compressed sensing without increasing the uplink feedback overhead. Literature [9] proposed a compressive sensing feedback method based on the opportunistic feedback protocol. The feedback resources were shared and were opportunistically accessed by high-quality users whose link quality exceeded a certain fixed threshold. Reference [10] proposed channel feedback reduction techniques based on compressive sensing, in which the transmitter can obtain channel information with acceptable accuracy under substantially reduced feedback overhead. At last simulation results showed that CS-based feedback can achieve near optimal rank-1 beamforming performance.

Based on the above-described research, we put forward a compressed sensing feedback algorithm for Massive MIMO system. The channel information is compressed in space domain firstly and in frequency domain subsequently. Compressed channel information is feedback to the receiver according to a new adaptive feedback mechanism. The receiver acquires accurate CSI recovery using Basis Pursuit (BP) reconstruction algorithm. In especial, the adaptive feedback mechanism will modify the compressing rate based on the channel sparsity to improve the feedback efficiency and assure the feedback performance. At last, numerical results proved that the proposed CSI feedback algorithm can not only greatly reduce the feedback overhead, but get similar BER performance to the perfect CSI feedback.

2 Compressed sensing theory

The theory of compressed sensing (CS) mainly includes three steps: get the sparsifying transformation of original signals; acquire the measurement vector of sparsifying signals; and reconstruct original signals.

2.1 SPARSIFYING TRANSFORMATION

Original signal $\mathbf{x}$ of length N can be expressed by the following sparsifying transformation:

$$\mathbf{S} = \mathbf{\Psi x}, \tag{1}$$

where $\mathbf{S}$ is the sparse transformation of $\mathbf{x}$, $\mathbf{\Psi}$ is an $N \times N$ sparsifying-basis. In this case, original signals $\boldsymbol{x}$ have K non-zero coefficients on this sparsifying-basis and $\boldsymbol{x}$ are called as K-sparse. Discrete cosine transform (DCT) matrix, discrete fourier transform (DFT) matrix and wavelet transform (DWT) matrix are some typical sparsifying-basis. These transformations are usually orthogonal and (1) can be expressed as following too:

$$\mathbf{x} = \mathbf{\Psi}^T \mathbf{S}, \tag{2}$$

where $(\cdot)^T$ represents matrix transpose.

2.2 DESIGN THE MEASUREMENT MATRIX

In the measurement of compressed sensing, it does not directly measure the K-sparse original signals $\boldsymbol{x}$ itself. Instead, the signal $\boldsymbol{x}$ is projected with a set of measurement matrix $\boldsymbol{\Phi}$ onto CS measurement vector $\mathbf{y}$:

$$\boldsymbol{y} = \boldsymbol{\Phi x}. \tag{3}$$

We substitute (2) into an equation (3), the equation (3) can be rewritten as:

$$\mathbf{y} = \mathbf{\Phi \Psi}^T \mathbf{S} = \mathbf{\Theta S}, \tag{4}$$

where $\boldsymbol{y}$ is an $M \times 1$ CS measurement vector, and M satisfies $M \geq K \log_2(N/K)$. $\boldsymbol{\Theta}$ is an $M \times N$ sensing matrix. If original signals are K-sparse and $\boldsymbol{\Phi}$ satisfies the Restricted Isometry Property (RIP) [7], K coefficients can be accurately reconstruct from M measurements.

The related literature proved that independent and identically distributed Gaussian random measurement matrix can become universal compressed sensing measurement matrix.

2.3 SIGNAL RECONSTRUCTION

We can obtain the sparse coefficients $\boldsymbol{S}$ via solving inverse problem of formula (4), then the K-sparse signal $\boldsymbol{x}$ can be reconstructed from M dimensional measurement vectors $\boldsymbol{y}$. This can be formulated as the following l_0 norm (also called 0-norm, that is the number of non-zero elements in the vector) minimization problem:

$$\min \|\mathbf{S}\|_{l_0} \quad s.t. \quad \mathbf{y} = \mathbf{\Phi \Psi^T S}. \tag{5}$$

When the estimation of sparse transformation $\boldsymbol{S}'$ is solved by (5), and then original signals $\boldsymbol{x}$ can be reconstructed as $\boldsymbol{x}'$ via $\boldsymbol{x}' = \boldsymbol{\Psi}\boldsymbol{S}'$. Reconstruction algorithms contain Matching tracking algorithm (MP) Orthogonal Matching pursuit (OMP) algorithm and Linear Programming (LP), basic Pursuit (BP), etc.

3 System Model

In the Large-scale MIMO system, assume that the number of subcarriers is N_c , the number of OFDM symbol is N_l , the number of transmit antennas is $N_t >> 1$, the number of receive antennas is $N_r > 1$, the received signal of users:

$$\mathbf{g}(t,\omega) = \sqrt{P_d}\,\mathbf{H}(t,\omega)\mathbf{W}(t,\omega)\mathbf{f}(t,\omega) + \mathbf{n}(t,\omega), \qquad (6)$$

where $\mathbf{g}(t,\omega)$ is the received signal of OFDM symbol t and subcarriers ω , the dimension of $\boldsymbol{g}$ is $N_r \times 1 \times N_c \times N_l$. P_d is the transmission power of the base station, $\boldsymbol{W}(t,\omega)$ is the $N_t \times N_{sts} \times N_c \times N_l$ downlink precoding matrix,. N_{sts} is the number of spatial data streams of transmitted signals. $\boldsymbol{f}(t,\omega)$ is the $N_{sts} \times 1 \times N_c \times N_l$ transmitted signals. $\boldsymbol{n}(t,\omega)$ is the additive white Gaussian noise (AWGN) with zero mean and variance σ^2. $\boldsymbol{H}$ is $N_r \times N_t \times N_c \times N_l$ dimension channel matrix, and $\boldsymbol{H}(t,\omega)$ is the $N_r \times N_t$ spatial channel matrix from the transmitter to the receiver of OFDM symbol t and subcarriers ω.

4 Large-scale MIMO channel information feedback based on compressed sensing

We assume that large-scale antenna array of the base station is in a same platform and arranged closely. The correlation of antennas is expected, the channel information can has a sparse representation in both the spatial and frequency domain according to the signal processing theory. Based on this assumption, CS (compressed sensing) techniques can be applied to compress the CSI feedback information. We can carry out the two-dimension compression in space and frequency domain, then feedback the measurement vector to the transmitter, instead of $\boldsymbol{H}$.

The detailed process should be explained as follows: Firstly compress channel matrix $\boldsymbol{H}(t,\omega)$ in the spatial domain and get its sparse transformation; secondly make a secondary compression in frequency domain, then find a suitable measurement matrix to obtain the measured value (this paper employs the random matrix obeying Gaussian distribution); finally reconstruction algorithm was introduced to reconstruct the original channel matrix from the measured values. So channel matrix $\boldsymbol{H}(t,\omega)$ should be vectorized into an $N_r N_t \times 1$ vector firstly:

$$\boldsymbol{h}(t,\omega) = \mathrm{vec}(\boldsymbol{H}(t,\omega)). \qquad (7)$$

After choosing the suitable sparsifying-basis in space domain and compress $\boldsymbol{h}$, we can get $\boldsymbol{S}_1 = \boldsymbol{\Psi}_1\boldsymbol{h}(t,\omega)$. The channel matrix of frequency domain is $N_r N_t \times N_c$, while the elements of each column are the elements of S_1 obtained from spatial domain compression. Then the channel matrix in frequency domain should be vectorized into an $N_r N_t N_c \times 1$ vector, after the second compression, we can obtain sparse coefficients $\boldsymbol{S}_2 = \boldsymbol{\Psi}_2\boldsymbol{h}(t)$.

Then $\boldsymbol{H}$ is encoded into measurement vector which is used as the content of compressing feedback:

$$\boldsymbol{y} = \boldsymbol{\Phi}\boldsymbol{h} = \boldsymbol{\Phi}\boldsymbol{\Psi}_2\boldsymbol{S}_2 = \boldsymbol{\Theta}\boldsymbol{S}_2 . \qquad (8)$$

Thus, the channel vector $\boldsymbol{h}(t)$ with dimension $N_r N_t N_c \times 1$ is compressed into $M \times 1$ measurement vector $\boldsymbol{y}$ through equation (8). M is much smaller than $N_r N_t N_c$ because the channel matrix is sparse in spatial-frequency domain , while CSI recover can be achieved accurately at the transmitter. Feedback load reduced by the compression $\eta = M / N_r N_t N_c$, transmitter and receiver can both get $\boldsymbol{\Phi}$ by pre-configured. The transmitter can recover the channel information accurately through reconstruction algorithm after receiving the feedback of $\boldsymbol{y}$. The feedback flow chart is depicted in Figure 1.

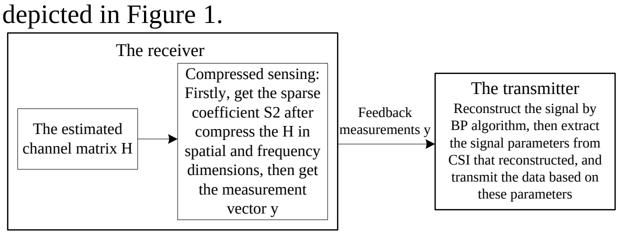

FIGURE1 The flow chart of the proposed CS-based channel feedback method

4.1 SPARSE REPRESENTATION OF THE CHANNEL MATRIX

The choice of sparsifying-basis $\boldsymbol{\Psi}$ plays a key role in sparsifying and reconstructing the information. Generally, an ideal sparsifying-basis would be associated with a more sparse representation or approximated sparse representation for $\boldsymbol{h}$. Due to the fact that Wavelet transform (DWT) has a strong ability to remove the correlation, this paper uses wavelet transform to get the corresponding sparse representation of channel matrix $\boldsymbol{H}$ in its spatial-frequency domain. Then construct the orthogonal wavelet transform matrix $\boldsymbol{\Psi}$ [11]:

$$\boldsymbol{\Psi} = [P_n]\cdots[P_2][P_1], \tag{9}$$

$$[P_n] = \begin{bmatrix} \boldsymbol{L}_{(N/2^n)\times(N/2^{n-1})} & \\ \boldsymbol{G}_{(N/2^n)(N/2^{n-1})} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix}, \tag{10}$$

where L, G are two matrices which are constructed by low-pass filter l and high-pass filte g . Each row of them is a vector of length $N/2^{n-1}$: $[l(0), l(1), \cdots l(2P-2), l(2P-1), 0, 0, \cdots 0]$ and $[g(0), g(1), \cdots g(2P-2), g(2P-1), 0, 0, \cdots 0]$ that can be obtained by circumference 2 shifts separately. According to the Orthogonality of the filter, it can be proved that $\mathbf{\Psi\Psi}^T = \mathbf{\Psi}^T\mathbf{\Psi} = \mathbf{I}$.

As mentioned above, the sparse representation of $\boldsymbol{H}$ could be generated after compression in both spatial domain and frequency domain:

$$\boldsymbol{S}_2 = \boldsymbol{\Psi}_2\boldsymbol{h}(t). \tag{11}$$

4.2 RECONSTRUCT THE CHANNEL MATRIX

This paper applies the Basis Pursuit (BP) [12] to reconstruct the channel matrix, which can be formulated as the following l_1 norm minimization problem:

$$\min_S \|\boldsymbol{S}_2\|_1 \ \ s.t.\ \boldsymbol{\Theta S}_2 = \boldsymbol{y}. \tag{12}$$

Solving equation (12) can be equivalent to optimization of the linear programing problem [13], the standard form of which is as follows:

$$\min \boldsymbol{C}^T\boldsymbol{S}_2 \ s.t.\ \boldsymbol{AS}_2 = \boldsymbol{b}\ \boldsymbol{S} \geq 0, \tag{13}$$

where $\boldsymbol{S}_2$ is called decision vector that can be used to find the reconstructed channel, $\boldsymbol{C}$ is called the coefficient vector of the objective function. In this paper, the coefficient vector is specified as a unit vector, In addition, $\boldsymbol{S}_2$ and $\boldsymbol{C}$ are both column vector with dimension N; $\boldsymbol{b}$ is the M-dimension column vector called the constant vector of constraint equation; $\boldsymbol{A}$ is an $M \times N(M \leq N)$ matrix called the coefficient matrix of constraint equations.

The value of vector $\boldsymbol{S}_2$ should be decomposed into two parts, positive and negative, in order to solve the above formula. Let $\boldsymbol{u}_2$ and $\boldsymbol{v}_2$ have the same dimension with $\boldsymbol{S}_2$ and $\boldsymbol{u}_{2,i} = (\boldsymbol{S}_{2,i})_+, \boldsymbol{v}_{2,i} = (-\boldsymbol{S}_{2,i})_+, i = 1,2.....N$. Then, the vector $\boldsymbol{S}_2$ can be rewriten as

$$\boldsymbol{S}_2 = \boldsymbol{u}_2 - \boldsymbol{v}_2, \boldsymbol{u}_2 \geq 0, \boldsymbol{v}_2 \geq 0. \tag{14}$$

And let $\boldsymbol{A} = (\boldsymbol{\Theta}, -\boldsymbol{\Theta})$, $\boldsymbol{S}_2 = \begin{pmatrix} \boldsymbol{u}_2 \\ \boldsymbol{v}_2 \end{pmatrix}$, $\boldsymbol{b} = \boldsymbol{y}$, the value of $\boldsymbol{S}_2$ can be solved with the combination of formula (14), then the reconstructed channel matrix $\hat{\mathbf{h}}$ was got by $\boldsymbol{h} = \boldsymbol{\Psi}_2^{\mathrm{T}}\boldsymbol{S}_2$.

4.3 ADAPTIVE FEEDBACK PROTOCOLS BASED ON SPARSITY OF THE CHANNEL MATRIX

According to the feedback mechanism in large-scale MIMO systems described above, this paper proposed an adaptive feedback protocols based on CS which configures the feedback dynamically according to the sparsity of the channel state matrix to improve system efficiency.

After compressed in both spatial and frequency domain, the channel matrix $\boldsymbol{H}$ will be transformed into its sparse representation in wavelet domain after the joint compression in space and frequency domain, and wavelet sparsifying-basis satisfies Restricted Isometry Property(RIP), then the K coefficients can be accurately reconstructed from the M measured values $(K < M << N)$. Since the compression ratio, $\eta = M / N_r N_t N_c$, is proportional to M , K can be used as the threshold of its sparsity (Because the channel matrix is impossible sparsed absolutely, so we need to set smaller sparse coefficients to 0 to get approximated sparse). Only when the channel matrix is $\geq K$ -sparse, the feedback scheme with a larger compression ratio should be employed, if the channel matrix is $< K$ -sparse, a smaller compression ratio should be employed. We adjust the value of M at the receiver, in accordance with the sparsity of instantaneous channel. In this case the feedback can be reduced by using a lower default value of M . In the simplest form, the compression ratio is switched between two possible levels. Note that the extension to adaptation among more than two levels is also possible, where the sparsity of channel range is partitioned into several regions, and each region corresponds to a specific compression ratio.

Consider that M changes between M_1 and

M_2 $(M_1 < M_2)$, and $\boldsymbol{\Phi}$ is an $M_2 \times N_t N_r N_c$ random measurement matrix stored at both transmitter and receiver. When the lower compression ratio is used ($M = M_1$), only the first M_1 rows of $\boldsymbol{\Phi}$ are useful for compression at the receiver and for reconstruction at the transmitter. If $M = M_2$, then the full matrix of $\boldsymbol{\Phi}$ is applied for computation. Thus, besides the CS measurements, the feedback should also include an indication of M so that the transmitter is able to determine an appropriate portion of $\boldsymbol{\Phi}$ for CSI recovery.

5 Performance analysis and simulation results

In this section, we analysed and evaluated the performance of channel information feedback scheme based on compressed sensing by simulation. Simulation parameters are shown in Table 1. To more clearly evaluate the performance, we compared a fixed compression ratio feedback, an adaptive compression ratio feedback according to the sparsity and a perfect channel information feedback. Simulation results in Figure 2 show the bit error rate (BER) performance of SVD precoding.

TABLE 1 simulation parameters of channel feedback algorithm based on CS

Simulation parameters	Values
Wavelength	0.375m
Antenna spacing	0.01m
Carrier frequency	800MHz
Subcarrier number	512
Antenna Configuration	BS:16 antennas UE:16 antennas
Channel Model	
Simulation Data	20000bit
Modulation and coding scheme	QPSK,1/2 Convolutional coding
Channel estimation	Ideal Channel Estimation
Precoding	SVD
Channel feedback	Feedback cycle in time domain:5ms;CS-based feedback in Spatial frequency domain, compared with perfect channel information feedback

As the simulation results shown, the BER performance is better when the compression rate is adaptive to the sparsity channel compared with the compression ratio fixed at 40%, and it is very close to the BER of the perfect channel information feedback. The proposed algorithm not only can significantly reduce the feedback overhead, but obtain highly-accurate channel information recovery and ensure large-scale MIMO performance gain. The simulation results are shown in Figure (2):

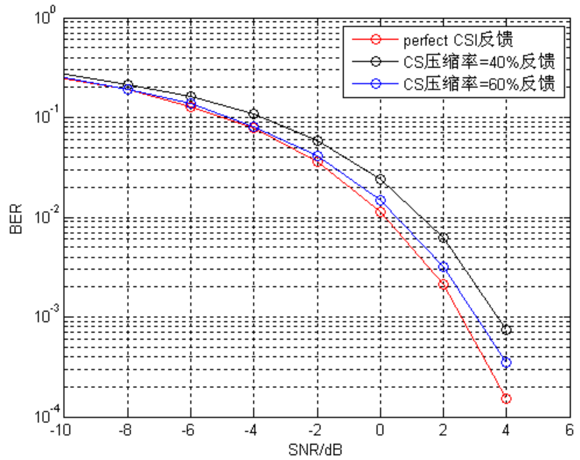

FIGURE 2 Comparison of BER performance

6 Conclusions

To reduce the CSI feedback overhead, we proposed a CS feedback algorithm for Large-scale MIMO systems. CSI Feedback can be compressed by sparsifying projections, feedback with an adaptive compression ratio and reconstructed to highly-accurate channel information. The compression ratio is dynamically adjusted based on the sparsity of instantaneous channel, so the proposed feedback algorithm can acquire a perfect balance between performance and feedback overhead. But in the real implementation process, many practical problems e.g. channel estimation errors, quantization noise, need more investigations in the future.

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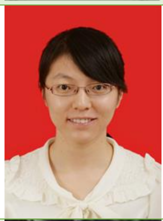

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