Distributed Compressive Sensing Based Channel Feedback Scheme for Massive Antenna Arrays with Spatial Correlation

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Abstract

Massive antenna array is an attractive candidate technique for future broadband wireless communications to acquire high spectrum and energy efficiency. However, such benefits can be realized only when proper channel information is available at the transmitter. Since the amount of the channel information required by the transmitter is large for massive antennas, the feedback is burdensome in practice, especially for frequency division duplex (FDD) systems, and needs normally to be reduced. In this paper a novel channel feedback reduction scheme based on the theory of distributed compressive sensing (DCS) is proposed to apply to massive antenna arrays with spatial correlation, which brings substantially reduced feedback load. Simulation results prove that the novel scheme is better than the channel feedback technique based on traditional compressive sensing (CS) in the aspects of mean square error (MSE), cumulative distributed function (CDF) performance and feedback resources saving.

Keywords: Massive-MIMO, distributed compressive sensing, channel state information, feedback reduction

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1. Introduction

Large scale multiple-input multiple-output (MIMO) techniques, dubbed as Large–scale MIMO or Massive-MIMO, is a promising means to meet the growing demands for larger capacity and improved quality-of-service of next-generation wireless communication systems [1][2]. A tremendous spatial multiplexing gain and array gain can be attained in Massive-MIMO systems. By beamforming technique we can steer the power from a large number of transmit antennas to the targeted direction, which in turn increases the link capacity greatly under a fixed transmission power, or equivalently, remarkably decreases the required transmission power to maintain the desired symbol error rate performance. Massive MIMO systems also have the potential to reduce the operational power consumption at the transmitter and enable the use of low-complexity schemes for suppressing multi-user interference [3].

To acquire the potential benefits of Massive-MIMO, the transmitter must have the instantaneous channel state information (CSI). The transmitter of time division duplexing (TDD) systems can acquire the CSI easily by channel reciprocity. However, in frequency division duplexing (FDD) systems, a dedicated feedback link for the receiver to report CSI is needed, and a lot of spectrum resources for CSI feedback is consumed. Even so, FDD is universally considered to be more effective for systems with symmetric traffic of delay-sensitive applications.

This paper investigates the feasibility of relieving the heavy CSI feedback load in Massive-MIMO systems. If conventional CSI feedback reduction methods, such as vector quantization or codebook-based approaches, are exploited in Massive-MIMO, the codebook size has to be enlarged massively to arrest fine-grain spatial channel structures, which in turn results in more heavier feedback overhead. Therefore, codebook-based design methods may not be suitable for Massive-MIMO. In recent years, the theory of compressive sensing (CS) [4][5] has been applied in various circumstances of signal processing and broadband communications, in which the signal is sparse or compressible. In [6][7], CS has been employed for the receiver to feed channel quality information (CQI) of OFDM subcarriers. In [8], CS has been proposed to support feedback protocols for opportunistic multi-user MIMO downlink transmission. In [9], CS has been applied to channel feedback protocols for spatially-correlated Massive-MIMO systems. In [10], a compressed analog feedback strategy has been studied for spatially correlated massive MIMO system.

Recently, the theory of distributed compressive sensing (DCS) is originated, and it has been applied to some contexts of signal processing and MIMO communications, where the signal satisfies joint sparse model (JSM). In [11], DCS has been employed for multi-user time-correlated MIMO channel information feedback. Different from the aforementioned prior work, this paper employed the strong spatial correlation in massive closely-packed antenna arrays to reduce the feedback load. In our paper, the DCS is used to develop a novel scheme for CSI feedback reduction, which allows CSI recovery with acceptable accuracy at the transmitter and is even better than the CS-based scheme proposed in [9].

The remainder of this paper is organized as follows. Section 2 provides the system model, as well as a review of DCS operation. In Section 3, DCS is applied to the design of the channel feedback scheme. Simulation results are presented in Section 4. Finally, a conclusion is drawn in Section 5.

2. DCS Background and System Model

2.1. Correlated MIMO Channel Model

This paper considers a point-to-point Massive-MIMO wireless communication system with M_t (>>1) transmit antennas and M_r (>>1) receive antennas. For simplicity, a uniform linear array at the transmitter and the receiver is assumed. The spatially-correlated MIMO channel model is studied on the previous work [9]. The $M_r \times M_t$ spatially-correlated MIMO channel matrix can be modeled as,

$$\mathbf{H} = \frac{1}{\sqrt{tr\left(\mathbf{R}_{RX}\right)}} \mathbf{R}_{RX}^{\frac{1}{2}} \mathbf{H}_{iid} \mathbf{R}_{TX}^{\frac{1}{2}} , \tag{1}$$

where $\mathbf{H}_{iid}$ is an $M_r \times M_t$ matrix with independent and identically distributed (i.i.d) zero-mean, unit variance, complex Gaussian random entries; $\mathbf{R}_{TX}$ and $\mathbf{R}_{RX}$ are the correlation matrices at the transmitter side and the receiver side, respectively. We assume that uniformly-spaced linear antenna arrays are installed at both sides of the radio link, and therefore each i-th row and j-th column entry of these matrices ($\mathbf{R}_{TX}$ and $\mathbf{R}_{RX}$) is given by the Jakes model as follows,

$$r_{ij} = J_0\left(\frac{2\pi d_{ij}}{\lambda}\right), \tag{2}$$

where d_{ij} is the distance between the two antennas, λ is the carrier wavelength, and $\boldsymbol{J_0}$ denotes zero-order Bassel function of the first kind. Given that the scope of this paper is focused on CSI compression, we assume $\mathbf{H}$=[$H_1, H_2, \ldots, H_{Mr}$]' can be perfectly estimated at the receiver, and certain channel information, such as $\mathbf{H}$ itself or any spatial signature extracted from $\mathbf{H}$, can be sent to the transmitter via an ideal (error-free) feedback link.

2.2. Review of Distributed Compressive Sensing and Simultaneous Orthogonal Matching Pursuit Algorithm

The distributed compressive sensing theory, which is capable of solving simultaneous sparse approximation problem, rests on a new concept termed of the joint sparsity of a signal ensemble. DCS enables new distributed coding algorithms that employ both intra-signal and inter-signal correlation structures. DCS is immediately applicable to a range of problems in sensor networks and arrays.

[12] proposed a greedy pursuit algorithm called Simultaneous Orthogonal Matching Pursuit (SOMP) to solve joint sparsity problem of DCS and tested the algorithm with three types of input signal. Each type of input signal is a variant on the form

$$x_j = s_j + v_j , \qquad j = 1, 2, \cdots \quad . \tag{3}$$

where x_j is a target signal and the number of which is $\boldsymbol{J}$, v_j is random noise and s_j called sparse signal or compressible signal can be expressed using a linear combination of K atoms (Each atom is denoted ϕ_w, where w is drawn from an index set Ω) chosen from the N dimensions (K<<N) dictionary, which is denoted as $\mathbf{\Psi} = [\phi_{w_1}, \phi_{w_2}, ..., \phi_{w_N}]$ and also called sparsifying-basis. K is called sparse degree. The form of the first type of input signal is,

$$x_j = \sum_{k=1}^{K} \alpha_{kj} \phi_{w_{kj}} , \qquad j = 1, 2, \cdots \quad . \tag{4}$$

For each signal x_j, K atoms are distributed independently and uniformly from the dictionary, and the coefficients α_{kj} are nonzero but different. SOMP algorithm searches for the best K atoms to represent each signal x_j, which is a linear combination of the K atoms.

The second type of input signal has the form,

$$x_j = \sum_{k=1}^{K} \alpha_{kj} \phi_{w_k}, \qquad j = 1, 2, \cdots \quad . \tag{5}$$

For all J signals, the K atoms are the same, but the coefficients α_{kj} are different.

The third type has the form

$$x_j = \sum_{k=1}^{K} \alpha_k \phi_{w_k} + v_j, \qquad j = 1, 2, \cdots \quad . \tag{6}$$

Each signal x_j is corrupted by i.i.d additive white Gaussian noise v_j.

In this paper, the first type is applied to compressive feedback of CSI for massive antenna arrays system with spatial correlation structure.

3. Massive-MIMO Channel Feedback Based On Distributed Compressive Sensing

We assume that in a Massive-MIMO system, antenna arrays at both transmitter and receiver are on the same platforms and closely-packed. Due to correlations among the antennas on each platform, it is expected from signal processing theory that the channel information has a sparse representation in the spatial domain. Based on this insight, instead of sending **H** on feedback link directly in each feedback time period, the DCS techniques delineated in the above Section could be applied to feedback compression. We note that the common operations for **H** feedback are carried out separately for real and imaginary parts in all proposed methods of this paper. For the sake of convenience, the notation $\tilde{\mathrm{I}}$ is used to denote the target signal in the rest of this paper, which represents either the real part or imaginary part of **H**.

We have assumed in the above content that the receiver has perfect knowledge on **H** and it should be ideally shared with the transmitter through feedback. In order to save the spectrum resources required by the feedback, the information of $\tilde{\mathrm{I}}$ needs to be compressed into comparatively less measurements. In [9], CS operation was used to compress the feedback information into M_{CS} measurements in each feedback time period. In this paper, the feedback information is assumed to be compressed into M_{DCS} measurements via DCS technique.

Just like the operation in [9], in our DCS-based compression scheme, $\tilde{\mathrm{I}}$ should firstly be vectorized into an N×1 (N=M_r×M_t) vector,

$$h = vec(\tilde{\mathrm{I}} \quad . \tag{7}$$

In traditional CS method, h is encoded into a measurement vector as the compressed feedback content,

$$y = \mathbf{\Phi} h, \tag{8}$$

where $\mathbf{\Phi}$ is an M_{CS}×N measurement matrix, the elements of which are random variables generated in accordance with distributions such as Gaussian or Bernoulli. Thus, the channel vector h is compressed into an M_{CS}×1 measurement vector y. Due to the expected sparsity in the spatial domain, M_{CS} can be made to be much smaller than N, while allowing CSI reconstruction at the transmitter to satisfy the required accuracy. Both the transmitter and the receiver are assumed to be aware of the elements of $\mathbf{\Phi}$ with preconfigurations. In order to use

CS to reconstruct CSI, transmitter needs to know a sparsifying-basis ($\mathbf{\Psi}$) of h.

$$S = \mathbf{\Psi} h \,, \tag{9}$$

where S is the sparse representation of h, and $\mathbf{\Psi}$ is an $N \times N$ sparsifying-basis. The transmitter is able to recover the channel information $\hat{h}$ through the following l_1-norm minimization problem,

$$\min \|S\| \qquad s.t. \qquad y = \mathbf{\Phi\Psi} S$$
$$\hat{h} = \mathbf{\Psi} S \quad , \tag{10}$$

The above minimization problem is typically solved by optimization algorithms such as linear programming (LP), basic pursuit (BP), and orthogonal matching pursuit (OMP). OMP is generally considered as the best at the compromise of computation complexity and recovery accuracy. In order to recover S exactly with a high probability, OMP algorithm needs sufficiently large number of measurements M_{CS} which means it is at least $4K$. The feedback load is thereby reduced to a compression ratio of $\eta_{CS} = M_{CS} / N$.

With DCS technique, SOMP algorithm needs at most K+1 measurements to exactly recover S at each feedback period, the feedback load is thereby reduced to a compression ratio of $\eta_{DCS} = M_{DCS} / N$. On the other hand, SOMP can bring about better recovery performance for it solves simultaneously the joint sparsity problem with J (>=2) input signals, however, it needs more memory resources to store multiple input signals.

The SOMP algorithm description of DCS-based compression technique proposed in this paper is as follows.

1. Initialize the residual matrix R_0=y, the index set $\Lambda_0 = \varphi$, and the iteration counter t=1.
2. Find an index λ_k that solves the easy optimization problem

   $$\max_{w \in \Omega} \sum_{j=1}^{J} \left| \left\langle R_{k-1} e_j , \phi_w \right\rangle \right| .$$

   We use e_j to denote the j-th canonical basis vector.
3. Set $\Lambda_k = \Lambda_{k-1} \bigcup$.
4. Determine the orthogonal projector P_k onto the span of the atoms indexed in Λ_k.
5. Calculate the new approximation and residual:

   $$A_k = P_k S$$
   $$R_k = y - A_k \, .$$
6. Increment t, and return to Step 2 if $k \le K$.

The schematic of the proposed DCS-based feedback method is illustrated in Fig. 1.

The choice of the sparsifying-basis $\mathbf{\Psi}$ plays a key role in recovery performance. Generally speaking, it is desirable to select a sparsifying-basis that provides a more sparse representation (fewer nonzero elements in S, or smaller K) of h. In this paper, we consider

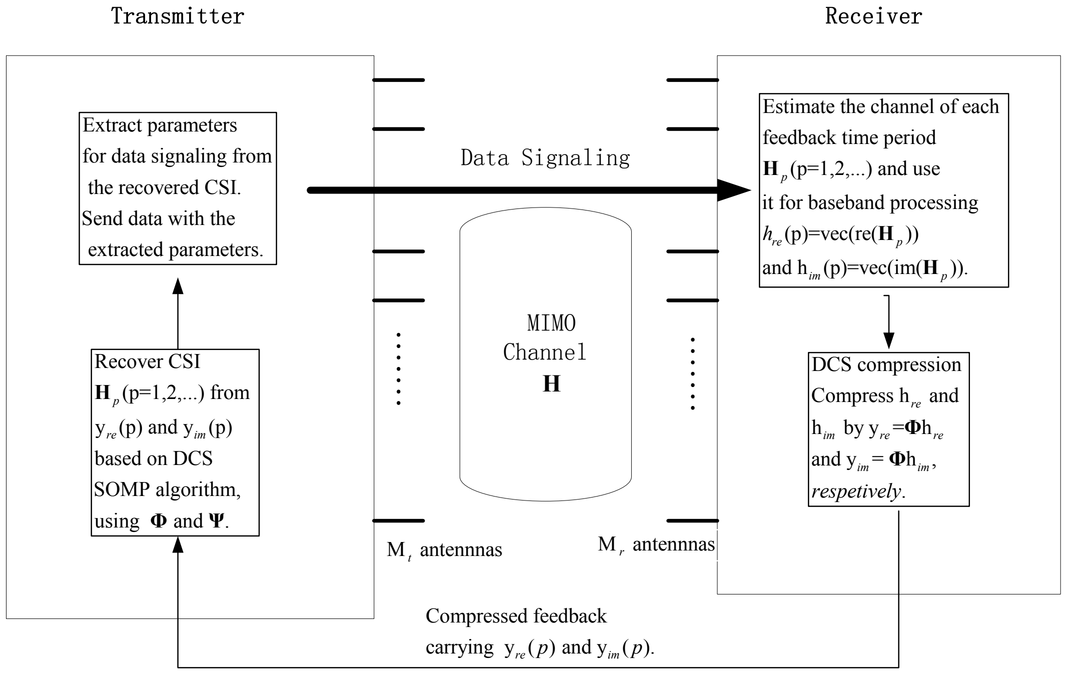

Fig. 1. The schematic of the proposed DCS-based Massive MIMO channel feedback scheme, where re($\mathbf{H}_p$) and im($\mathbf{H}_p$) represent the real and imaginary parts of $\mathbf{H}_p$, respectively.

two-dimensional discrete cosine transform (2D-DCT). As mentioned above, the elements of $\tilde{\Gamma}$ are expected to be strongly correlated in both spatial and frequency domain. In order to achieve a sparse representation of $\tilde{\Gamma}$ in the spatial-frequency domain by fully exploiting such correlation structure, 2D-DCT can be employed as the sparsifying-basis. A DCT matrix with L rows L columns is denoted as C_L, thus, the 2D-DCT matrix used in this paper can be written as $C_{M_t} \otimes C_{M_r}$, therefore,

$$\mathbf{\Psi} = \left(C_{M_t} \otimes C_{M_r}\right)^T, \tag{11}$$

where $\otimes$ is Kronecker product.

The sparse representation of h is

$$S = \left(C_{M_t} \otimes C_{M_r}\right)^T vec(\tilde{\Gamma}) . \tag{12}$$

Generally speaking, the sparse degree is defined as the number of nonzero elements in the sparse representation vector. In fact, we notice that only a few elements in the vector S are of comparatively large numerical values and the others are of comparatively small numerical values but may not be exactly zero. In order to ensure recovery performance being good, enough elements should be selected. We define S_{nz} as the number of selected large elements, which is assumed be the real sparse degree in this paper.

The recovery error is defined as,

$$P_{re} = E\left\{ \frac{\left\| h - \hat{h} \right\|_{l_2}}{\left\| h \right\|_{l_2}} \right\}. \tag{13}$$

We assume that $P_{m,th}$ is the threshold of recovery error, i.e., the largest tolerable recovery error, which means that the case with $P_{re} \le P_{m,th}$ is correct recovery. The probability of correct recovery is

$$P_r = \Pr\left\{P_{re} \le P_{m,th}\right\}. \tag{14}$$

We furthermore define the recovery-correct performance as the maximum recovery error level $P_{m,th}$ that is met for 1% of all recovery information.

To compare the recovery-correct performance of different feedback-compressive schemes, we use cumulative distribution function (CDF) defined as

$$CDF(\mathrm{P}_m) = \mathrm{P}\left\{P_{re} \le P_m\right\}. \tag{15}$$

η is defined as the compression ratio, which can be expressed as

$$\eta = \frac{M_{com}}{M} \times 100\%, \tag{16}$$

where M_{com} denotes the needed feedback resources with CS-based or DCS-based feedback method, and M denotes the feedback resources without any compressive methods.

The feedback resources will be saved if a kind of compressive feedback method is adopted. We define η_{saving} as the feedback resources saving, which can be expressed as

$$\eta_{saving} = \frac{M - M_{\mathrm{com}}}{M} \times 100\%. \tag{17}$$

In order to realize a certain probability of correct recovery, such as $P_r = 0.99$, CS-based feedback method and DCS-based feedback method could bring different cost saving of feedback resources compared to the feedback resources without any compressing methods, which are denoted as η_{saving_CS} and η_{saving_DCS}, respectively.

$$\begin{aligned} \eta_{saving\_CS} &= \frac{M - M_{CS}}{M} \times 100\% \\ \eta_{saving\_DCS} &= \frac{M - M_{DCS}}{M} \times 100\% \end{aligned}, \tag{18}$$

where M_{CS} denotes the feedback resources with CS-based feedback method and M_{DCS} denotes that with DCS-based feedback method.

4. Simulation Results

In this section, we present some simulation results for a massive MIMO system with $M_t=M_r=32$, a uniform normalized antenna-spacing (d/λ) of 50. The recovery performance of DCS-based compressive scheme and the traditional CS-based scheme are compared. The real sparse degree $S_{nz} \in (20, 40, 60, 80, 100)$.

Fig. 2 and **Fig. 3** show respectively the average normalized MSE of CS-based and DCS-based MIMO channel feedback recovery using 2D-DCT sparsifying-basis under different compression ratios with different real sparse degrees. **Fig. 4** shows the average normalized MSE of both CS-based and DCS-based schemes together under different compression ratios.

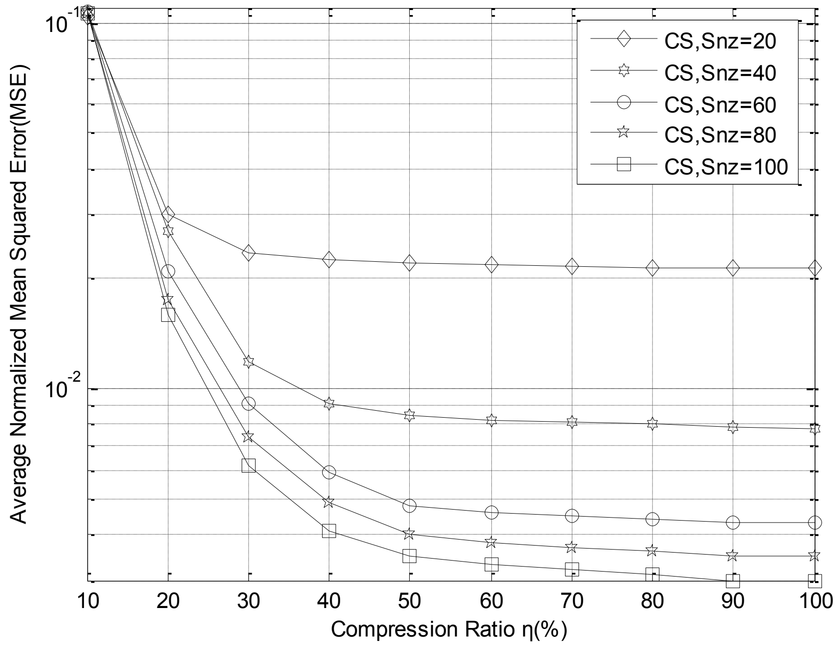

Fig. 2. The average normalized MSE of CS-based MIMO channel feedback recovery using 2D-DCT sparsifying-basis under different compression ratios with different real sparse degrees.

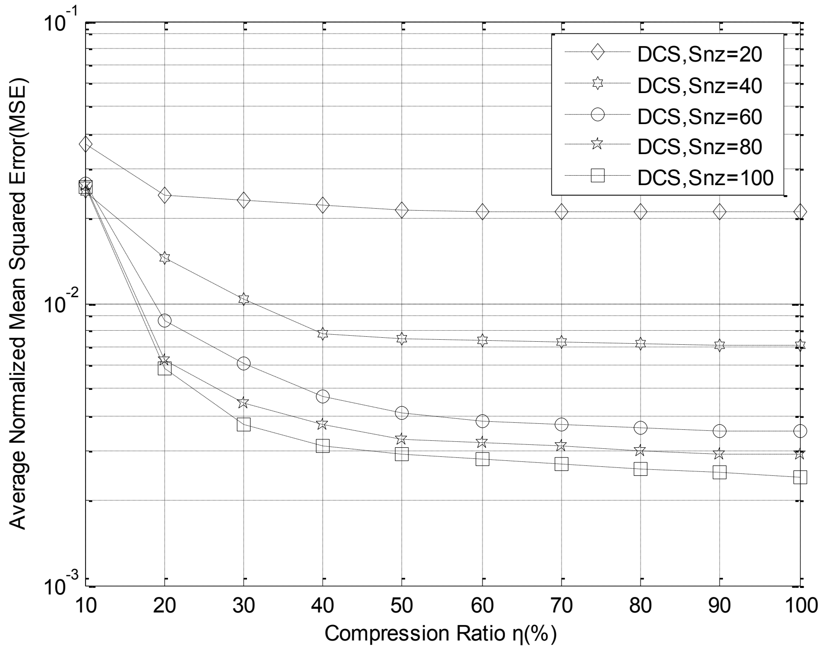

Fig. 3. The average normalized MSE of DCS-based MIMO channel feedback recovery using 2D-DCT sparsifying-basis under different compression ratios with different real sparse degrees.

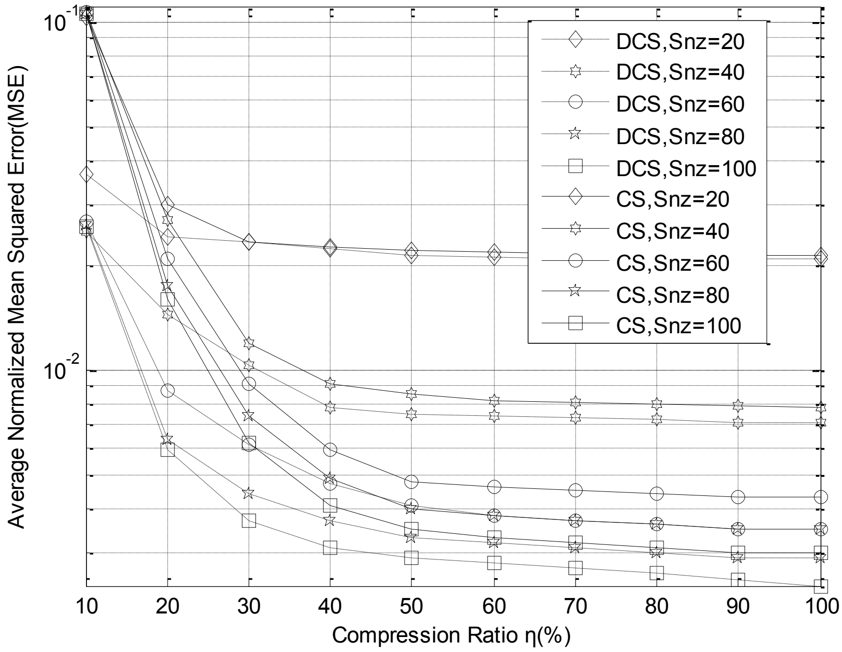

Fig. 4. The average normalized MSE of DCS-based and CS-based MIMO channel feedback recovery using 2D-DCT sparsifying-basis under different compression ratios with different real sparse degrees.

Fig. 2 and **Fig. 3** show that exact recovery can be achieved with both DCS-based and CS-based schemes. From **Fig. 2** and **Fig. 3**, both the MSE performance of CS-based scheme and that of DCS-based scheme become better as the real sparse degree or the compression ratio becomes larger. However, from Fig. 4 it is very clear that DCS-based scheme has smaller average normalized MSE than CS-based scheme, which means that DCS-based scheme has relatively better recovery performance.

Fig. 5, **Fig. 6**, **Fig. 7**, **Fig. 8**, and **Fig. 9** show the CDF of the threshold of recovery error P_m of CS-based scheme under different compression ratios with the real sparse degree S_{nz} being 20, 40, 60, 80 and 100 respectively.

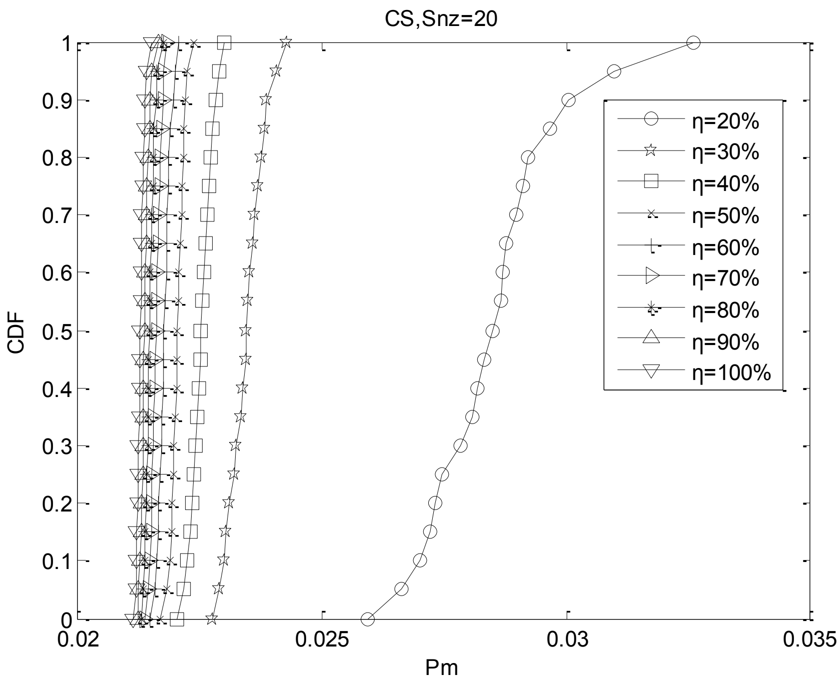

Fig. 5. The CDF of the threshold of recovery error P_m of CS-based scheme under different compression ratios with the real sparse degree S_{nz}=20.

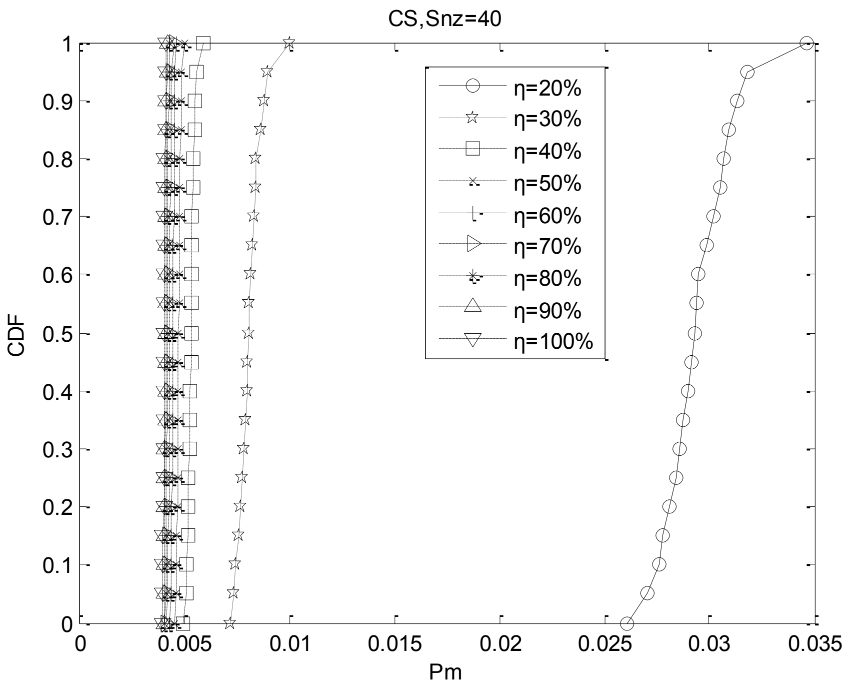

Fig. 6. The CDF of the threshold of recovery error P_m of CS-based scheme under different compression ratios with the real sparse degree S_{nz} =40.

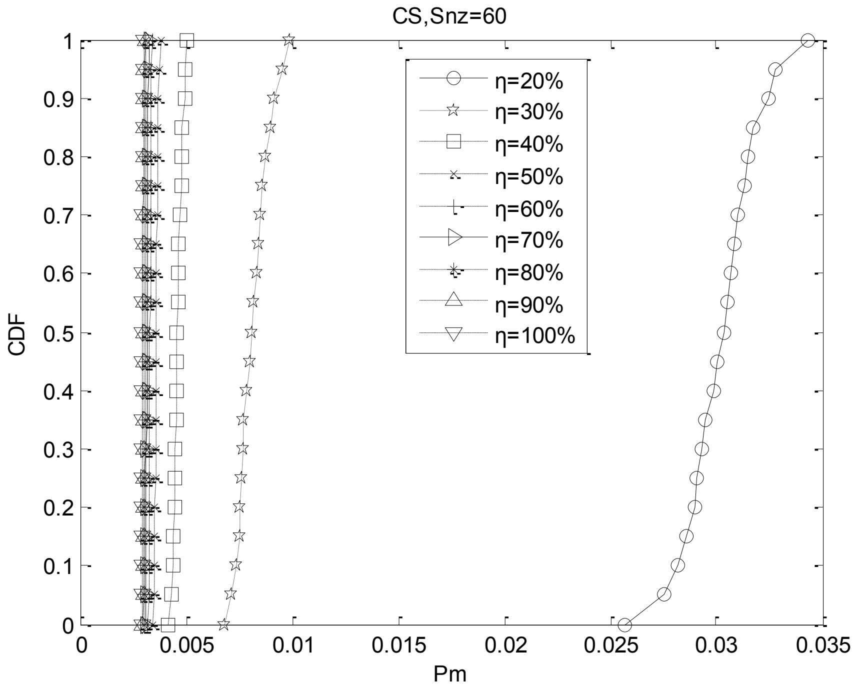

Fig. 7. The CDF of the threshold of recovery error P_m of CS-based scheme under different compression ratios with the real sparse degree S_{nz} =60.

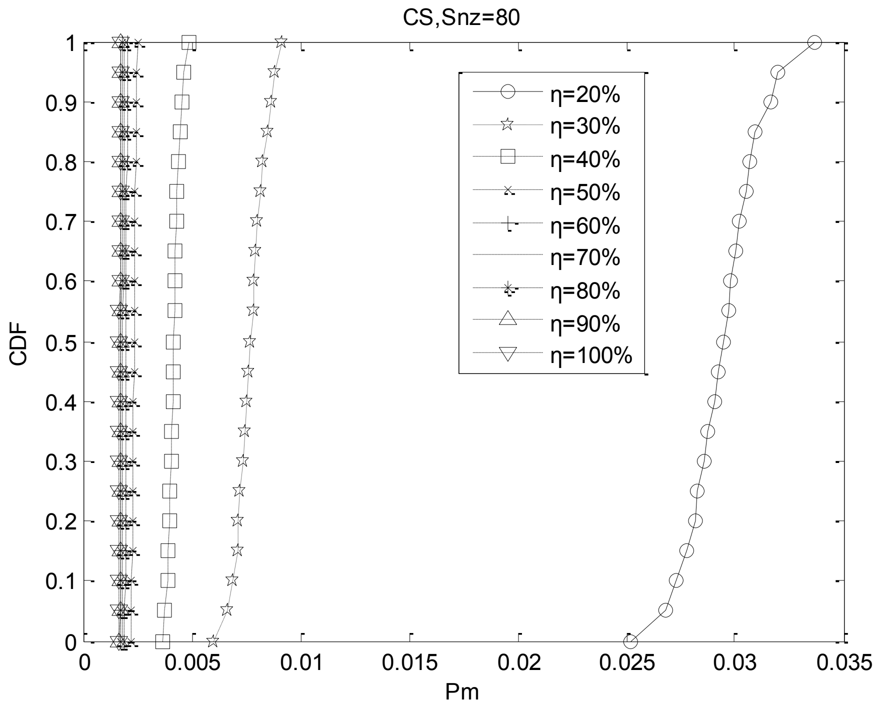

Fig. 8. The CDF of the threshold of recovery error P_m of CS-based scheme under different compression ratios with the real sparse degree S_{nz} =80.

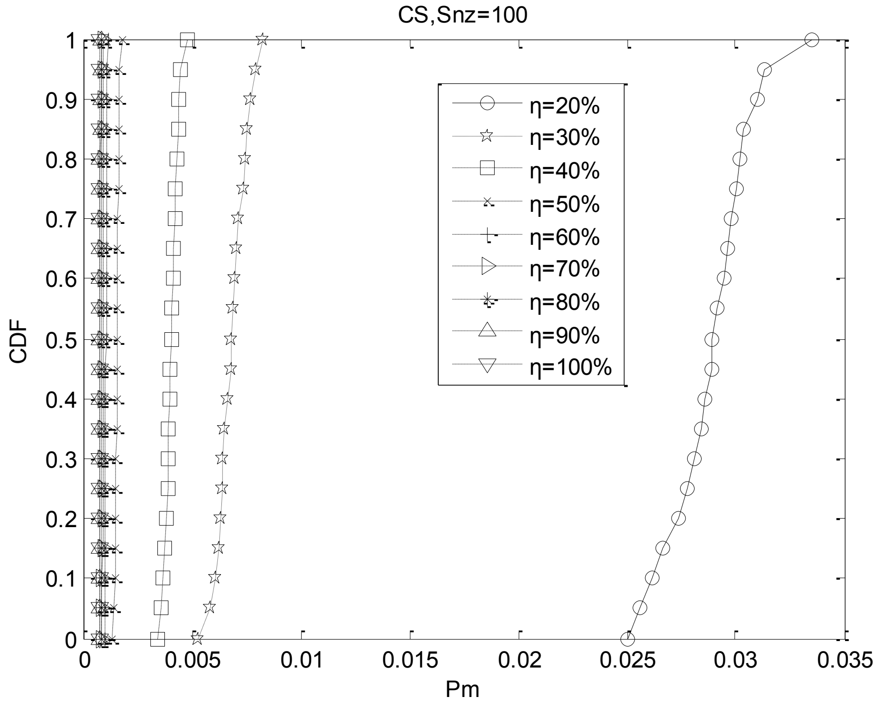

Fig. 9. The CDF of the threshold of recovery error P_m of CS-based scheme under different compression ratios with the real sparse degree S_{nz} =100.

From **Fig. 5**, **Fig. 6**, **Fig. 7**, **Fig. 8** and **Fig. 9** we all can see that when the real sparse degree is a constant, the P_m of CS-based scheme becomes smaller as the compression ratio becomes larger. The compression ratio becoming larger means that the occupied feedback resource becomes much more. It is easy to understand that the recovery-correct performance will improve as feedback resource becomes much more. Comparing **Fig. 5**, **Fig. 6**, **Fig. 7**, **Fig. 8** and **Fig. 9**, it is obvious to find that the P_m of CS-based scheme becomes smaller as the real sparse degree becomes larger. The real sparse degree becoming larger means that the more elements within the sparse vector are selected. The recovery-correct performance will surely improve as the real sparse degree becomes larger.

Fig. 10 and **Fig. 11** show the CDF of the threshold of recovery error P_m of DCS-based scheme under different compression ratios with the real sparse degree S_{nz} being 40 and 60 respectively.

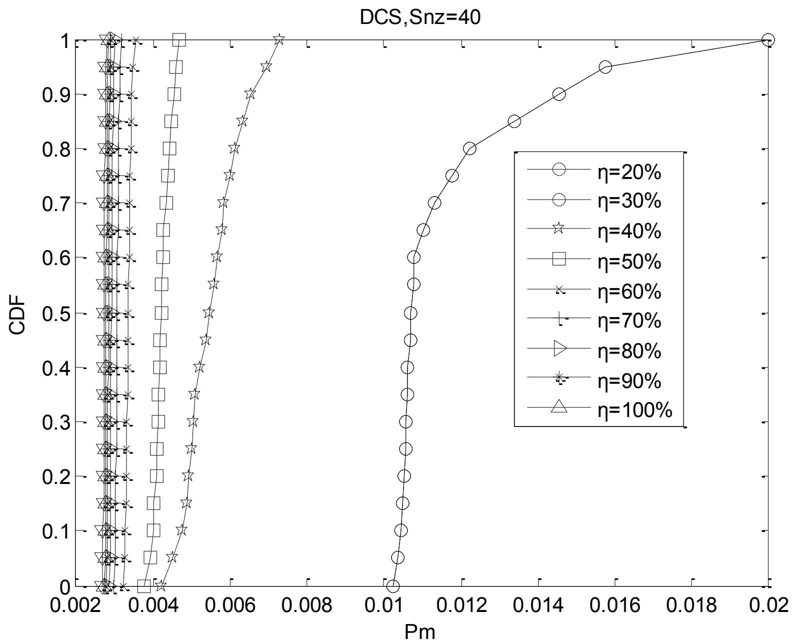

Fig. 10. The CDF of the threshold of recovery error P_m of DCS-based scheme under different compression ratios with the real sparse degree S_{nz} =40.

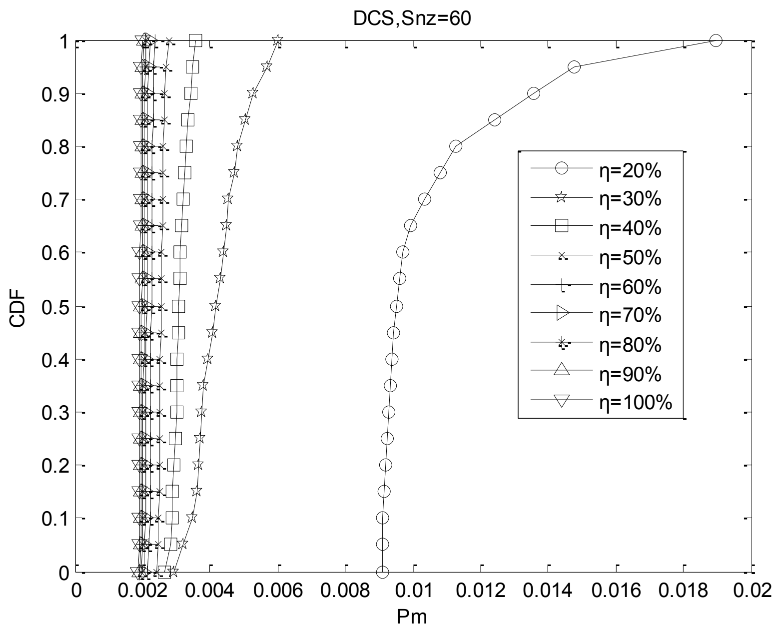

Fig. 11. The CDF of the threshold of recovery error P_m of DCS-based scheme under different compression ratios with the real sparse degree S_{nz} =60.

Both **Fig. 10** and **Fig. 11** show that when the real sparse degree is a constant, the P_m of DCS-based scheme under different compression ratios becomes smaller as the compression ratio becomes larger. Comparing **Fig. 10** and **Fig. 11** we can see that the P_m of DCS-based scheme becomes smaller as the real sparse degree becomes larger. We can also do some comparisons among **Fig. 6** and **Fig. 10**, or **Fig. 7** and **Fig. 11**. The P_m of DCS-based scheme is obviously much smaller than that of CS-based scheme, therefore the CDF performance of DCS-based scheme is better than that of CS-based scheme.

Fig. 12 shows the feedback resources saving of both DCS-based and CS-based schemes under different real sparse degrees.

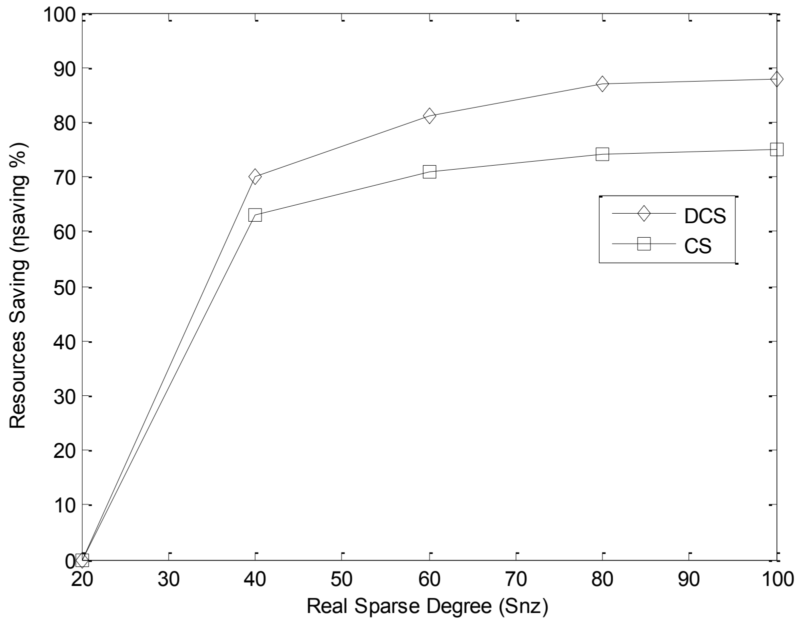

Fig. 12. The feedback resources saving of both DCS-based and CS-based schemes under different real sparse degrees.

Fig. 12 shows that the resources saving of DCS-based feedback scheme is obviously more than that of CS-based feedback scheme. In other words, DCS-based compressive feedback scheme needs comparatively less feedback resources than CS-based one.

5. Conclusion

In this paper, a novel channel feedback reduction scheme based on the theory of distributed compressive sensing is proposed to apply to massive antenna arrays with spatial correlation, which permits the transmitter to obtain channel information with acceptable accuracy but with substantially reduced feedback load. Simulation results show that DCS-based compressive scheme has better MSE performance and CDF performance than that of traditional CS-based compressive scheme, and DCS-based channel feedback scheme needs comparatively less feedback resources than CS-based scheme.

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