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Channel Estimation for Frequency Division Duplexing Multi-user Massive MIMO Systems via Tensor Compressive Sensing

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ABSTRACT

To make full use of space multiplexing gains for the multi-user massive multiple-input multiple-output, accurate channel state information at the transmitter (CSIT) is required. However, the large number of users and antennas make CSIT a higher-order data representation. Tensor-based compressive sensing (TCS) is a promising method that is suitable for high-dimensional data processing; it can reduce training pilot and feedback overhead during channel estimation. In this paper, we consider the channel estimation in frequency division duplexing (FDD) multi-user massive MIMO system. A novel estimation framework for three dimensional CSIT is presented, in which the modes include the number of transmitting antennas, receiving antennas, and users. The TCS technique is employed to complete the reconstruction of three dimensional CSIT. The simulation results are given to demonstrate that the proposed estimation approach outperforms existing algorithms.

Keywords: Compressive sensing; Tensor decomposition; Channel estimation; Massive MIMO; Multiple-input multiple-output

1. INTRODUCTION

Multi-user massive multiple-input multiple-output (MIMO) technology refers to base stations (BSs) equipped with a large number of transmitting antennas. The concept has been extensively researched and employed in many wireless systems, as it can make full use of space resources, improve system channel capacity and communication quality[1-2]. Precise knowledge of reliable CSIT at the transmitter is necessary to signal detection, beam forming, resource allocation, and so on[3]. In time division duplexing (TDD) massive MIMO systems, it is possible to obtain the CSIT through exploiting the channel reciprocity using uplink pilots[4]. However, the majority of systems in use today require FDD, which is considered more effective as the different frequency bands are employed by uplink and downlink, respectively[5-6]. Thus CSIT corresponding to the FDD system's up and downlink differs. Let each user transmits a sequence of training pilots, the uplink CSIT can be estimated at the BS side.

There are two necessary procedures for obtaining CSIT for the downlink channel in an FDD system. First, the BS sends pilot sequences to all users, then the estimated downlink CSIT are fed back to the BS by all users[7]. As the quantity of BS antennas increases, the number of unknown CSIT coefficients likewise increases. As a result, the traditional downlink CSIT estimation methods for FDD systems, such as least square (LS)[8], minimum mean square error (MMSE)[9], and improved algorithms[10-11] based on them require excessive training pilot and feedback overhead. This illustrates that conventional approaches do not suit today's needs.

Researchers have increasingly focused on compressive sensing (CS) in recent years, as it provides a general signal acquisition framework that enables the reconstruction of sparse signals from a small number of linear measurements[12]. CS applications within the wireless communication and networking field have been researched extensively to date. In many studies on the channel of massive MU-MIMO system[13], the channel coefficient matrices tend to be sparse, as the number of transmitting antennas increases at the BS. Several CSIT estimation approaches have been proposed based on CS techniques to reduce the training pilot and feedback overhead, under the condition that estimation precision is high. Rao[14], *et al*. proposed a joint orthogonal matching pursuit (J-OMP) channel estimation algorithm that can accurately recover the downlink CSIT, by exploiting the hidden joint sparsity in the user channel matrices. Rao[15], *et al.* then proposed a modified subspace pursuit (SP) algorithm to solve conventional CS-based CSIT estimation problems by exploiting the prior support adaptively based on quality information. In addition to existing greedy-based signal reconstruction methods, other researchers utilised the same sparsity structure proposed by Rao[14], *et al*. to build an L1-minimisation-based downlink CSIT recovery scheme[16]. By exploiting the block sparsity of channel matrices in the virtual angular domain among different users, Xu[17], *et al*. proposed a joint block orthogonal matching pursuit (JBOMP) algorithm to estimate CSIT. Whether based on the greedy algorithm or convex optimisation algorithm of CS, the

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CSIT estimation for large and high-order channel coefficient matrices in multi-user massive MIMO requires that each individual user be accounted for; this wastes training pilots and results in excessive feedback overhead. The two types of CS algorithms described above also result in high computational complexity as the iterations progress.

Cesar[18], *et al*. developed a novel reconstruction approach that can reconstruct a tensor through the relatively small amount of multi-way compression measurements, by utilising the low multi-linear-rank structure of tensor. Comparing with conventional sparse representation-based CS algorithms, this Tucker decomposition model-based TCS does not need to assume the sparsity or dictionary-based representation and performs very well. In addition, it works extremely fast as no iteration is involved in the operation. So it is suitable for high-dimensional data processing.

In the present study, we regarded the entire CSIT in a multi-user massive MIMO system as a 3D tensor expressed as $\mathcal{H} \in \mathbb{R}^{N\times M\times K}$, where M, N, and K are the number of transmitting antennas, receiving antennas and users, respectively. We developed a 3D estimation framework for tensor CSIT. And proposed a novel downlink CSIT recovery algorithm based on TCS, which we tested against conventional CS-based estimation algorithms to find that it yields higher estimation accuracy with less computing time.

2. SYSTEM AND BASIC THEORY

2.1 Multi-user Massive MIMO System

We consider a multi-user massive MIMO system working in FDD mode that containing only one BS and K users. The BS has M transmitting antennas and each user is equipped with N receiving antennas ($M \gg N$). To complete the estimation of downlink CSIT, the BS transmits a sequence of T training pilots by M transmitting antennas. At the i-th user terminal, the received measurement by the pilot can be expressed as follows:

$$Y_i = H_i X + N_i,\ i = 1,\ldots,K \tag{1}$$

where $H_i \in \mathbb{R}^{N\times M}$ is actually the downlink channel coefficient matrix from BS to the i-th user. $X \in \mathbb{R}^{M\times T}$ is the training pilot and $\mathrm{N}_i \in \mathbb{R}^{N\times T}$ is a Gaussian random noise matrix with zero mean and variance σ_n^2. Accurate CSIT estimation at the BS is of great significance for the efficient use of space resources and the improvement of system capacity and performance. For the systems working in FDD mode, the CSIT estimation is performed in two parts:

(a) each user estimates its own local CSI of H_i individually; and

(b) the estimated CSI is fed back to the BS side, as shown in Fig. 1.

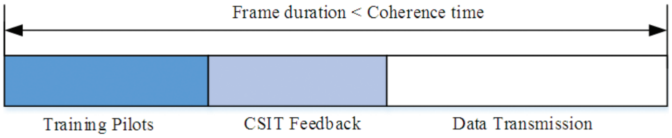

Figure 1. Frame structure in FDD multi-user massive MIMO system.

2.2 Compressive Sensing and Tensor Decomposition

Traditional CS is a method for reconstructing the signals with sparse representations[12]. Given a vector $x \in \mathbb{R}^M$, if it has r nonzero entries, it can be called r-sparse. The CS defines the measurement criterion for the signal x given by:

$$y = \phi x + n \tag{2}$$

with the measurement matrix $\phi \in \mathbb{R}^{N\times M}$ where $N < M$ and $n \in \mathbb{R}^{N\times M}$ is the measurement noise. The reconstruction is a process that knows ϕ and recovers x from y.

A tensor is a multi-dimensional matrix; for example, $\mathcal{X} \in \mathbb{R}^{I_1\times I_2\times\cdots\times I_N}$ is an N-th order tensor[18]. A vector and a matrix can be regarded as a one-order tensor and a second-order tensor, respectively, e.g., $x \in \mathbb{R}^I$ and $X \in \mathbb{R}^{I_1\times I_2}$. The number of modes is actually the dimension (order) of the tensor. $\mathcal{X} \in \mathbb{R}^{I_1\times I_2\times\cdots\times I_N}$ is an N-order tensor and I_n is the dimension of its n-mode. The element of a tensor is referred as $x_{i_1 i_2\cdots i_N}$. A tensor is high-order complex problem and cannot be calculated by general methods. It is necessary to unfold the tensor to the matrix to apply the higher-order singular value decomposition technique and simplify the product of the tensor and measurement matrix. Namely, the tensor should be rearranged to matrices according to the different modes.

Definition 1 (*n-mode unfolding of tensor*): n-mode unfolding of tensor is the process that all elements in n-mode of tensor are arranged in a matrix of column vectors to obtain a new matrix. Assume a tensor $\mathcal{X} \in \mathbb{R}^{I_1\times I_2\times\cdots\times I_N}$, fibers in mode-$n$ are the vectors acquired by fixing all of indices except those that correspond to columns (n=1), rows (n=2), etc. Tensor elements ($a_1, a_2, \cdots a_N$) maps to the matrix elements (a_n, b), with $b = 1 + \sum_{z\neq n}(a_k - 1)B_k$ where $B_k = \prod_{m\neq n}^{z-1} I_m$.

Definition 2 (*n-mode product of tensor and matrix*): A tensor cannot be directly multiplied by a matrix. Thus, the product of matrix and tensor is actually the n-mode unfolding of this tensor multiplied by the matrix in the same dimension. Assigning $\mathcal{X} \in \mathbb{R}^{I_1\times I_2\times\cdots\times I_N}$ and $U \in \mathbb{R}^{R\times I_n}$ as the tensor and the matrix respectively, the n-mode product of them is $\mathcal{Y} = \mathcal{X} \times_n U \in \mathbb{R}^{I_1\times\cdots\times I_{n-1}\times R\times I_{n+1}\times\cdots\times I_N}$ defined by:

$$y_{i_1 i_2\cdots i_{n-1} r i_{n+1}\cdots i_N} = \sum_{i_n=1}^{I_n} x_{i_1 i_2\cdots i_n\cdots i_N} u_{r i_n} \tag{3}$$

Higher order singular value decomposition (HOSVD) is a common tensor decomposition method that can be used to approximately decompose the tensor $\mathcal{X} \in \mathbb{R}^{I_1\times I_2\times\cdots\times I_N}$ into a core tensor product with multiple matrices. It is defined as follows:

$$\mathcal{X} = \mathcal{S} \times_1 U_1 \times_2 U_2 \times \cdots \times_N U_N \tag{4}$$

where $\mathcal{S} \in \mathbb{R}^{R_1\times R_2\times\cdots\times R_N}$ is a core tensor which is in the same dimension as $\mathcal{X}$ and $U_n \in \mathbb{R}^{R_n\times I_n}$ ($R_n \ll I_n$) are the corresponding mode-n sensing matrices. The HOSVD provides a low-rank approximation with orthogonal factors and a core tensor for the original tensor.

3. THE PROPOSED ALGORITHM

Primary goal of this study was to establish a novel CSIT estimation algorithm for multi-user massive MIMO systems based on TCS. Our algorithm consists of two parts. An estimation framework for the 3D CSIT that makes the tensor CSIT measurable via 2D training pilot, and CSIT reconstruction based on TCS. The proposed CSIT estimation algorithm is illustrated in Fig. 2; the algorithm is introduced step-by-step below.

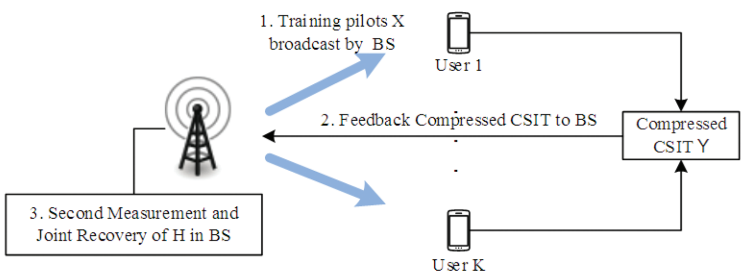

Figure 2. Proposed algorithm.

3.1 Estimation Framework

There are K (number of users) downlink channel matrices $\mathrm{H}_i \in \mathbb{R}^{N\times M}$, each of which is estimated individually in existing algorithms. In the proposed estimation framework, we regard the number of users K as the third dimensionality and combine the all channel matrices, so that the CSIT can be expressed as a three-order tensor $\mathcal{H} \in \mathbb{R}^{N\times M\times K}$, the modes of which include the number of transmitting antennas, receiving antennas and users in the FDD massive MU-MIMO system. The 3D CSIT cannot be measured directly by training pilot $\mathrm{X} \in \mathbb{R}^{M\times T}$. Furthermore, the TCS-based reconstruction algorithm requires multi-way compressive measurements, but the pilot broadcast by the BS can only provide measurement in one mode. To solve this problem, we designed a new measurement strategy that can be divided into two stages.

Stage 1: The BS broadcasts a sequence of T compressive training pilots $\mathrm{X} \in \mathbb{R}^{M\times T}$ with $T \ll M$. The tensor CSIT measurement strategy is then to let the training pilot measure the mode-2 of the tensor CSIT $\mathcal{H} \in \mathbb{R}^{N\times M\times K}$ directly. The process of users observes the compressed measurements from the training pilot, which can be formulated as

$$Y = \mathcal{H} \times_2 X + N \tag{5}$$

which also can be expressed as

$$Y = \mathcal{H}^{(2)} X + N \tag{6}$$

where $\mathcal{H}^{(2)} \in \mathbb{R}^{NK\times M}$ is the mode-2 unfolding expression of tensor $\mathcal{H} \in \mathbb{R}^{N\times M\times K}$ and $\mathrm{N} \in \mathbb{R}^{NK\times T}$ is a Gaussian random noise matrix.

Stage 2: Each user feeds back the observed values, which altogether comprise the final result $Y \in \mathbb{R}^{NK\times T}$ of stage 1 to the BS side. Gaussian sensing matrices $\Phi_1 \in \mathbb{R}^{N\times N}$, $\Phi_3 \in \mathbb{R}^{K\times K}$ are then utilised to measure the other two modes of measured tensor $\mathcal{Y} \in \mathbb{R}^{N\times T\times K}$. The measurement and feedback procedures are then complete. Considering the second measurement is complete in the BS, the sensing matrices used in this stage are not sent to users by the BS. This does not consume the bandwidth or incur any additional cost due to the training pilot or feedback.

3.2 CSIT Reconstruction

We utilise the TCS[18] which is stable, fast, and accurate to decompose and reconstruct tensor CSIT $\mathcal{H}$:

$$\mathcal{Y} = \mathcal{H} \times_1 \Phi_1 \times_2 X \times_3 \Phi_3 \tag{7}$$

$$\hat{\mathcal{H}} = \mathcal{Y} \times_1 Z_1 Y_1^{\dagger} \times_2 Z_2 Y_2^{\dagger} \times_3 Z_3 Y_3^{\dagger} \tag{8}$$

where $Y_{(n)}^{\dagger}$ is the pseudo-inverse matrix of each mode-n of core tensor $\mathcal{Y}$ and the other parameters are as follows:

$$\mathcal{Z}^{(n)} = \begin{cases} \mathcal{H} \times_2 X \times_3 \Phi_3, & for \quad n=1 \\ \mathcal{H} \times_1 \Phi_1 \times_3 \Phi_3, & for \quad n=2 \\ \mathcal{H} \times_1 \Phi_1 \times_2 X, & for \quad n=3 \end{cases} \tag{9}$$

$$Z_n = \left(\mathcal{Z}^n\right)_{(n)} \tag{10}$$

In effect, Z_n is the mode-n unfolding of $\mathcal{Z}^n$ and $\hat{\mathcal{H}}$ is the accurate recovered CSIT. The pseudo code used for the proposed algorithm is as follows.

Algorithm

Input:

1) Tensor CSIT $\mathcal{H} \in \mathbb{R}^{N\times M\times K}$
2) Training pilot $X \in \mathbb{R}^{M\times T}$
3) Sensing matrices $\Phi_1 \in \mathbb{R}^{N\times N}$, $\Phi_3 \in \mathbb{R}^{K\times K}$

Output: Reconstruction of CSIT $\hat{\mathcal{H}}$

Start:

1) Compute core tensor $\mathcal{Y}$ according to formula (7);
2) Compute $Z_n (n = 1,2,3)$ according to Eqns (9)-(10);
3) Compute the MP Pseudo-Inverse $Y_{(n)}^{\dagger}$;
4) Reconstruct $\hat{\mathcal{H}}$ according to equation (8).

End

4. EXPERIMENT RESULTS

Performance of the proposed algorithm is experimentally verified. We compare the performance of the proposed algorithm to the J-OMP recovery algorithm[14], weighted block L1-minimisation algorithm (hereafter referred to as WB L1-minimisation)[16], and JBOMP algorithm[17]. Our simulation experiments consider a narrow band (flat fading) massive MU-MIMO system in FDD mode, where the BS is equipped with M transmitting antennas and there are K users, each of which has N receiving antennas. We utilise the spatial channel model (SCM) for MIMO channel modeling in 3GPP standard[19] to generate the channel coefficients. The angle of departures is uniformly and randomly distributed over $[0, 2\pi]$, and we assume that all spatial paths have same path loss.

Figure 3 compares the proposed algorithm, J-OMP, WB L1-minimisation algorithm, and JBOMP for different SNRs and the parameters were set according to our references[16]. Namely, the number of transmitting antennas at BS M = 160, the number of receiving antennas at MS N = 2, the number of users K = 40, and the number of training pilot symbols T = 45. The proposed algorithm outperforms the other algorithms, though it does show worse normalised mean square error (NMSE) at low SNR (<3 dB) than the Tseng's method[16].

As shown in Fig. 4, the NMSE of the estimated CSIT versus the number of pilot symbols T were compared, with the parameter settings M = 100, N = 2, K = 40, and transmit SNR = 30 dB. We found that the estimation accuracy of CSIT

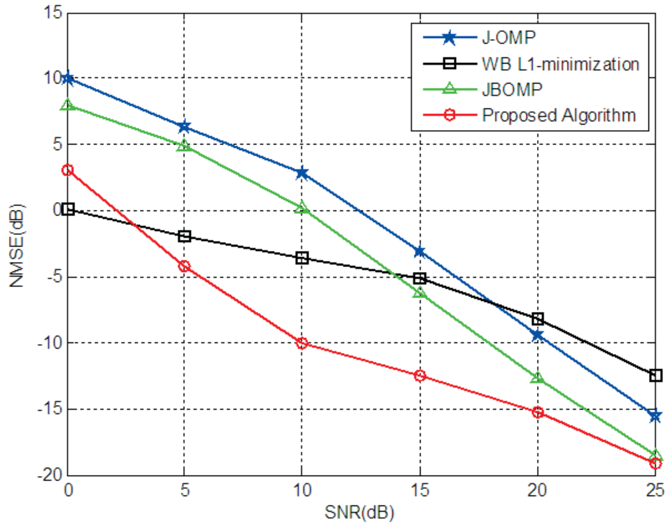

Figure 3. NMSE of the proposed algorithm, J-OMP[14], WB L1-minimisation[16] and JBOMP[17] for different SNRs.

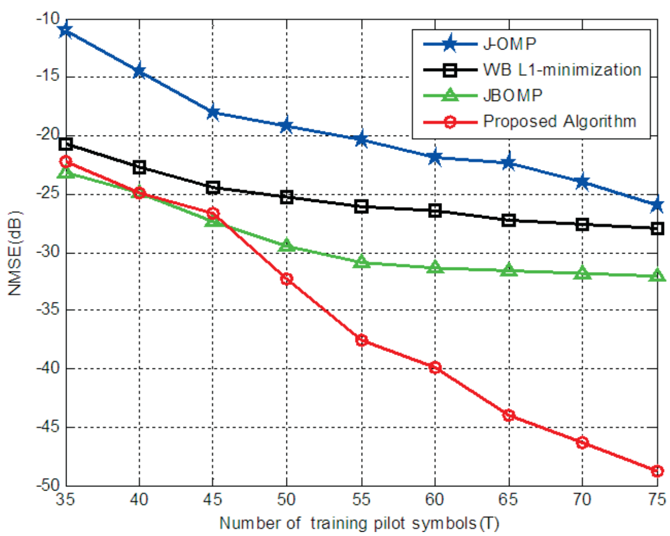

Figure 4. NMSE of the proposed algorithm, J-OMP[14], WB L1-minimisation[16] and JBOMP[17] with different number of training pilot symbols T.

increases as T increases. The proposed algorithm also showed a substantial performance gain from $T = 45$.

We also compared the NMSE of the estimated CSIT versus the number of antennas at BS under $N = 2$, $K = 40$, $T = 45$, and $SNR = 30$dB. As shown in Fig. 5, the proposed algorithm achieved better performance than the other three algorithms, especially when the number of transmitting antennas was small (<100). On the contrary, we found that the quality of CSIT estimation decreases as M increases. The dimensions of the channel coefficient matrices grow larger as M increases, suggesting under CS theory that more measurements are required. Thus the estimation accuracy decreases as M increases regardless of which of the four algorithms is utilised.

Figure 6 compares the proposed algorithm, J-OMP, WB L1-minimisation algorithm, and JBOMP versus the number of users under $M = 160$, $N = 2$, $T = 45$, and $SNR = 30$ dB. The proposed algorithm outperforms other algorithms, especially when K is less than 30. Moreover, the estimated accuracy

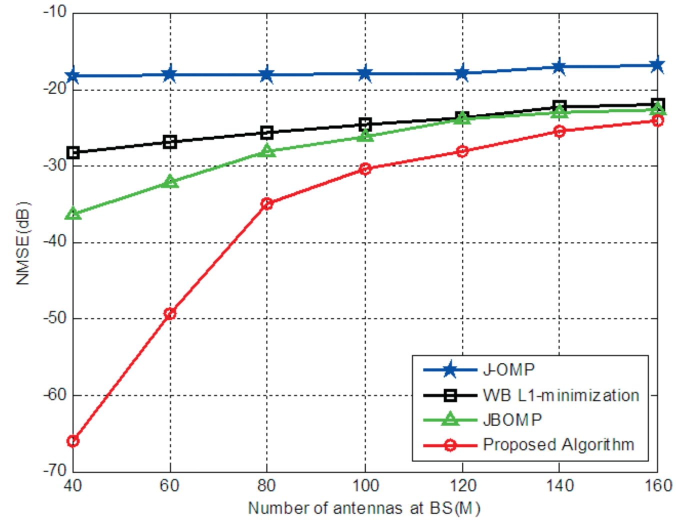

Figure 5. NMSE of the proposed algorithm, J-OMP[14], WB L1-minimisation[16] and JBOMP[17] with different number of antennas at BS.

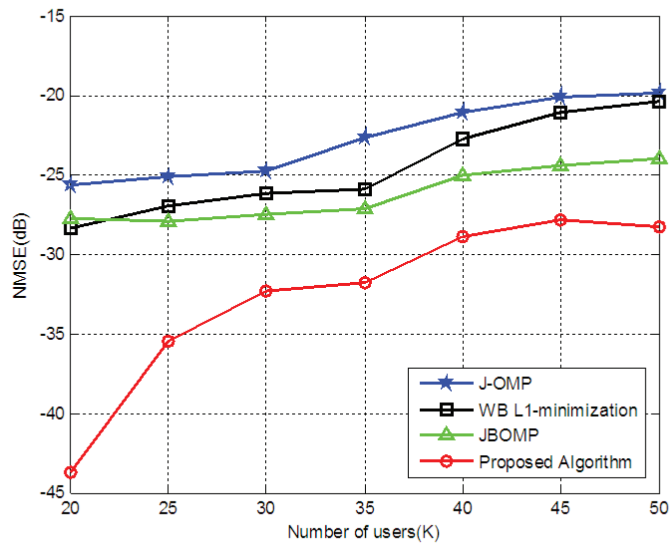

Figure 6. NMSE of the proposed algorithm, J-OMP[14], WB L1-minimisation[16] and JBOMP[17] with different number of users.

decreases as the number of users increases, but the magnitude of the reduction is not significant. In the proposed algorithm, the accuracy is always kept at a higher level, although it reduces a lot when $20 \le K \le 25$.

In Table 1, we compare the average computation time in terms of different quantities of transmitting antennas at the BS side. Simulation experiments were performed in Matlab2010b on the work station with a 2.1 GHz Intel Celeron CPU and 6 GB RAM. The parameter settings of the multi-user massive MIMO system were $N = 2$, $K = 40$, $T = 45$, and SNR=30dB. The proposed algorithm requires much less computation time than the weighted block L1-minimisation algorithm, but is slightly slower than the J-OMP and JBOMP.

5. CONCLUSIONS

This paper proposed a novel 3D method based on TCS to

Table 1. Comparison of computation time (s)

Number of transmitting antennas (M)	Computation time (s)			
	J-OMP	JBOMP	WB L1-minimisation	Proposed algorithm
40	0.07	0.14	261.23	0.46
100	0.16	0.28	438.45	1.22
160	0.22	0.34	752.39	1.65

estimate the CSIT for multi-user massive MIMO systems in FDD mode. The proposed algorithm first presents an estimation framework to measure the tensor CSIT via a general training pilot, then the downlink CSIT is accurately recovered via the TCS reconstruction algorithm. By comparison against the J-OMP estimation algorithm, weighted block L1-minimisation algorithm, and JBOMP algorithm, the NMSE of our approach is remarkably low. The proposed algorithm has better estimation quality than other existing algorithms. It is also non-iterative, meaning it yields complete estimation results faster than other algorithms.

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Contribution in the current study, conception, foundations.