MIMO-OFDM Non-regenerative Relay Channel Estimation using Compressed Sensing

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***Abstract*—In this paper, a compressed sensing (CS)-based channel estimation technique is developed for MIMO-OFDM networks with Amplify-and-Forward (AF) relaying method. The impacts of multiple antennas as well as existing a direct link between source and destination are studied. The proposed CS-based method utilizes the inherent sparse characteristic of wireless channel and improves the bandwidth efficiency as it requires a few measurement units for channel estimation. The simulation results show that the proposed CS-based method outperforms the Least Squares (LS)-based channel estimation.**

I. Introduction

Amplify-and-Forward (AF) relaying method is a promising approach to increase the diversity gain in MIMO systems [1]–[4]. Using coherent modulation techniques involves the knowledge of instant channel state information (CSI) at the receivers. For Decode-and-Forward (DF) mode, channel estimation could be borrowed from point-to-point (P2P) communication, because in DF mode, we are encountered with two P2P system which are cascaded. On the other hand, the computational burden will be increased at the relay node because of the extra channel estimation algorithms. Furthermore, the interference at the destination node will be increased arising by transmitting the estimated channel information from the relay to the destination nodes. The channel estimation in AF mode is different from P2P communication systems. This difference is hidden behind the convolution of two channel responses which is received in the destination node. Compressed sensing (CS) [5], [6] emerged as an appropriate approach to estimate the channel impulse response by fewer training and pilot symbols [7], [8].

Recently, the CS methods are widely used in sparse recovery problems. When, the transmitted signal from the source node propagates through a multipath channel, the received signal could be sparse or compressible in some domain. When the received signal is sparse, using CS could increase the bandwidth efficiency of the system, since the number of transmitted pilots for accurate channel estimation is less than conventional channel estimation approaches. As a result of recent advances in channel measurement techniques, it is confirmed that the wireless channels can present a sparse or block-sparse structure in their time-delay profile [9]. This inherent sparsity of the channel has been never deployed in the conventional channel estimation approaches, however using the CS-based method, one can benefit from sparsity of the channel.

The CS-based techniques are widely used in P2P channel estimation problems [10], [17], [18]. However, the channel estimation in AF based cooperative networks is a more challenging problem and the CS-based channel estimation is rarely used in relay communication. One of the pioneer papers in this field is [11] where the authors developed a compressed sensing based channel estimation method to provide channel state information (CSI) for the receiver in an AF cooperative network. In [11] the authors used the compressed measurements to estimate the compound impulse response together with direct link channel impulse response in a single-carrier AF relay communication system. In [12]–[16], the compressed sensing technique is utilized for channel estimation in two way relay networks (TWRN). All the aforementioned work are based on the assumption that there is no direct link between the source and destination nodes due to the long distance or shadowing. In [12] and [16], the compressed sensing is used to estimate the CIR in a TWRN in a single-input single-output framework. The TWRN system in these two papers are single-carrier. In [13]–[15], CS is used to estimate the channel impulse response in a multi-carrier TWRN in single-input single-output framework.

In this paper, we propose a CS-based channel estimation technique for MIMO-OFDM systems with AF cooperative relaying method for the general case with existence of a direct link between the source and destination. The proposed CS-based method involves a lower number of required pilots for channel estimation than the Least Square (LS)-based channel estimation method.

The rest of the paper is organized as follows: Section II represents a succinct overview of the compressed sensing. In section III, the proposed system model is presented and the channel estimation problem is reformulated for CS to be applicable. Channel estimation techniques are reviewed in section IV. The proposed sparse estimation (SE) is reviewed in section V. Numerical results are presented section VI, followed by the concluding remarks in Section VII.

II. Compressed Sensing overview

Consider reconstructing of a $N \times 1$ vector signal $\boldsymbol{x}$ which is K sparse in a given dictionary Ψ. Being K sparse, guarantees that $\boldsymbol{x}$ has K non-zero coefficients. We can define $\boldsymbol{x}$ in Ψ

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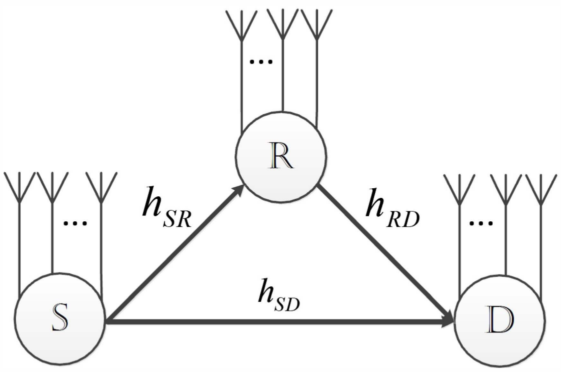

Fig. 1. MIMO Relay communication network with DL

domain as

$$\boldsymbol{x} = \Psi\theta = \sum_{n=1}^{N} \psi_n \theta_n = \sum_{l=1}^{K} \psi_{n_l} \theta_{n_l} \tag{1}$$

where $\Psi = [\psi_1, \psi_2, \ldots, \psi_Z]$ is an $N \times Z$ dictionary and $\boldsymbol{x}$ is a linear combination of $K \ll N$ vector chosen from the dictionary, therefore θ have K non-zero elements which are the coefficients of the combined vectors and $\{n_l\}$ are the indices of the combined vectors from Ψ.

Using the CS framework, $\boldsymbol{x}$ can be reconstructed with much fewer measurements. In fact, by projecting the signal on another basis that is incoherent with Ψ, we can reconstruct the sparse signal with fewer measurements rather that Nyquist rate. To reconstruct $\boldsymbol{x}$ we have

$$\boldsymbol{y} = \Phi\boldsymbol{x} = \Phi\Psi\theta \tag{2}$$

where $\boldsymbol{y}$ denotes the measurements obtained by measurement matrix Φ; Φ is a $M \times N$ basis which is incoherent with Ψ. This reconstruction problem becomes a l_0-norm optimization problem, which counts the number of non-zero elements. Since, l_0-norm optimization is a NP-hard, l_1-norm optimization is used instead as

$$\hat{\theta} = \text{argmin}\|\theta\|_1 \quad \text{s.t.} \quad \boldsymbol{y} = \Phi\Psi\theta \tag{3}$$

This problem can be solved by linear programming techniques including Basis Pursuit (BP) [19] or greedy algorithms such as Compressive Sampling (CoSamp) [20].

As mentioned earlier, having a minimum incoherence matrix in CS result in a better performance comparing to random measurement matrix. The incoherence property is defined as

$$\mu(\Phi, \Psi) = \min_{i \neq j} < \phi_i, \psi_j > \tag{4}$$

where ϕ_i and ψ_j are the rows of measurements matrix and columns of sparsifying matrix, respectively. A more comprehensive review of the CS framework is presented in [5], [6] and the references within.

III. System Model

Fig. 1 illustrates a three-node MIMO relaying system. We consider a source node ($\mathbb{S}$), a relay node ($\mathbb{R}$) and a destination node ($\mathbb{D}$) as the network. In this MIMO network, N_s,N_r and N_d are the number of antennas related to $\mathbb{S}$,$\mathbb{R}$ and $\mathbb{D}$, respectively. An AF relaying method is deployed at the relay node when a direct link (DL) exists between the source and destination nodes. During the first time slot, both the relay and destination nodes receive the transmitted signal by the source node. In this scenario, the destination node can estimate the complement impulse response channel vector and the direct channel between $\mathbb{S}$ and $\mathbb{D}$, simultaneously. In the first time slot, the source $\mathbb{S}$ transmits $\boldsymbol{x}_1^{n_s} = [x_1^{n_s}(0), x_1^{n_s}(1), \ldots, x_1^{n_s}(N-1)]^T$ for $n_s = 1, 2, \ldots, N_s$ antennas with power constraint NP, where N is the number of OFDM sub-carriers and P is the transmit power after pilot placement and Cyclic Prefix (CP)-removal. The received signal in $\mathbb{R}$ at the end of the first time slot after CP-removal is equal to

$$\boldsymbol{y}_R = \mathbf{H}_{SR}\boldsymbol{x}_1 + \boldsymbol{z}_R \tag{5}$$

where $\boldsymbol{y}_R$ is formed by collecting all the received signal vectors in all the N_r antennas at $\mathbb{R}$ in a single vector as $\boldsymbol{y}_R = [(\boldsymbol{y}_R^1)^T, (\boldsymbol{y}_R^2)^T, \ldots, (\boldsymbol{y}_R^{N_r})^T]^T$. Besides, $\mathbf{H}_{SR}$ and $\boldsymbol{z}_R$ are defined as

$$\mathbf{H}_{SR} = \begin{bmatrix} \mathbf{H}_{SR}^{11} & \mathbf{H}_{SR}^{21} & \ldots & \mathbf{H}_{SR}^{N_s1} \\ \mathbf{H}_{SR}^{12} & \mathbf{H}_{SR}^{22} & \ldots & \mathbf{H}_{SR}^{N_s2} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{H}_{SR}^{1N_r} & \mathbf{H}_{SR}^{2N_r} & \ldots & \mathbf{H}_{SR}^{N_sN_r} \end{bmatrix} \in \mathbb{C}^{N_rN \times N_sN},$$

$$\boldsymbol{z}_R = [(\boldsymbol{z}_R^1)^T, (\boldsymbol{z}_R^2)^T, \ldots, (\boldsymbol{z}_R^{N_r})^T]^T \in \mathbb{C}^{N_rN \times 1}. \tag{6}$$

and $\boldsymbol{x}_1 = [(\boldsymbol{x}_1^1)^T, (\boldsymbol{x}_1^2)^T, \ldots, (\boldsymbol{x}_1^{N_s})^T]^T$.

The received signal in terminal $\mathbb{D}$ after CP-removal is represented as

$$\boldsymbol{y}_{D,1} = \mathbf{H}_{SD}\boldsymbol{x}_1 + \boldsymbol{z}_{D,1} \tag{7}$$

where

$$\mathbf{H}_{SD} = \begin{bmatrix} \mathbf{H}_{SD}^{11} & \mathbf{H}_{SD}^{21} & \ldots & \mathbf{H}_{SD}^{N_s1} \\ \mathbf{H}_{SD}^{12} & \mathbf{H}_{SD}^{22} & \ldots & \mathbf{H}_{SD}^{N_s2} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{H}_{SD}^{1N_d} & \mathbf{H}_{SD}^{2N_d} & \ldots & \mathbf{H}_{SD}^{N_sN_d} \end{bmatrix} \in \mathbb{C}^{N_dN \times N_sN},$$

$$\begin{aligned} \boldsymbol{y}_{D,1} &= [(\boldsymbol{y}_{D,1}^1)^T, (\boldsymbol{y}_{D,1}^2)^T, \ldots, (\boldsymbol{y}_{D,1}^{N_d})^T]^T \in \mathbb{C}^{N_dN \times 1}, \\ \boldsymbol{z}_{D,1} &= [(\boldsymbol{z}_{D,1}^1)^T, (\boldsymbol{z}_{D,1}^2)^T, \ldots, (\boldsymbol{z}_{D,1}^{N_d})^T]^T \in \mathbb{C}^{N_dN \times 1} \end{aligned} \tag{8}$$

where $\mathbf{H}_{SD}^{n_sn_d} = \text{diag}\{H_{SD}(0), H_{SD}(1), \ldots, H_{SD}(N-1)\}$ is the diagonal channel matrix between n_s antennas in terminal $\mathbb{S}$ and n_d antennas of terminal $\mathbb{D}$ for $n_s = 1, 2, \ldots, N_s$ and $n_d = 1, 2, \ldots, N_d$, respectively; $\boldsymbol{y}_{D,1}$ is the received vector in the first time slot; $\boldsymbol{z}_{D,1}$ is the AWGN vector satisfying $\mathcal{CN}(\mathbf{0}, \sigma_D^2 \boldsymbol{I}_{N_dN})$.

In the second time slot, the terminal $\mathbb{R}$ amplifies the received signal $\boldsymbol{y}_R$ by factor β and retransmits it to the destination $\mathbb{D}$. At the same time, the source node $\mathbb{S}$ transmits its second time slot signal $\boldsymbol{x}_2$. Hence, the received signal in terminal $\mathbb{D}$ can be written as

$$\begin{aligned} \boldsymbol{y}_{D,2} &= \beta\mathbf{H}_{RD}\boldsymbol{y}_R + \mathbf{H}_{SD}\boldsymbol{x}_2 + \boldsymbol{z}_{D,2} \\ &= \beta\mathbf{H}_{RD}\mathbf{H}_{SR}\boldsymbol{x}_1 + \mathbf{H}_{SD}\boldsymbol{x}_2 + \tilde{\boldsymbol{z}}_{D,2} \end{aligned} \tag{9}$$

where $\mathbf{H}_{SR}$ and $\mathbf{H}_{SD}$ are channel matrices defined in Eq. (6), (8), respectively, and channel matrix $\mathbf{H}_{RD}$ is defined as

$$\mathbf{H}_{RD} = \begin{bmatrix} \mathbf{H}_{RD}^{11} & \mathbf{H}_{RD}^{21} & \cdots & \mathbf{H}_{RD}^{N_r1} \\ \mathbf{H}_{RD}^{12} & \mathbf{H}_{RD}^{22} & \cdots & \mathbf{H}_{RD}^{N_r2} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{H}_{RD}^{1N_d} & \mathbf{H}_{RD}^{2N_d} & \cdots & \mathbf{H}_{RD}^{N_rN_d} \end{bmatrix} \in \mathbb{C}^{N_dN \times N_sN}, \tag{10}$$

$\boldsymbol{x}_2 = [(\boldsymbol{x}_2^1)^T, (\boldsymbol{x}_2^2)^T, \dots, (\boldsymbol{x}_2^{N_s})^T]^T$ is the collected transmitted signal vectors from N_s antennas of source $\mathbb{S}$ in the second time slot; $\tilde{z}_{D,2}$ is the AWGN vector in destination $\mathbb{D}$ satisfying $\mathcal{CN}(\mathbf{0}, \sigma_D^2\boldsymbol{I}_{N_dN} + \beta^2\sigma_R^2|\mathbf{H}_{RD}|^2)$ for the second time slot.

All the channel matrices $\mathbf{H}_{SD}^{n_sn_d} = \text{diag}\{\mathbf{H}_{SD}^{n_sn_d}(0), \mathbf{H}_{SD}^{n_sn_d}(1), \dots, \mathbf{H}_{SD}^{n_sn_d}(N-1)\}$ for $n_s = 1, 2, \dots, N_s$ and $n_d = 1, 2, \dots, N_d$ are diagonal with entries

$$\mathbf{H}_{SD}^{n_sn_d}(k) = \sum_{l=0}^{L-1} h_{SD}^{n_sn_d}(l)e^{-j2\pi lk/N} \tag{12}$$

where $h_{SD}^{n_sn_d}(l)$ is the l-th tap of the channel between n_s-th antenna of $\mathbb{S}$ and n_d-th antenna of $\mathbb{D}$. If one collects Eq. (7) and (9) in a matrix form equation, it can conclude that

$$\boldsymbol{y}_D = \begin{bmatrix} \mathbf{H}_{SD} & \mathbf{0} \\ \beta\mathbf{H}_{RD}\mathbf{H}_{SR} & \mathbf{H}_{SD} \end{bmatrix} \begin{bmatrix} \boldsymbol{x}_1 \\ \boldsymbol{x}_2 \end{bmatrix} + \begin{bmatrix} z_{D,1} \\ \tilde{z}_{D,2} \end{bmatrix} \tag{13}$$

where $\boldsymbol{y}_D = [(\boldsymbol{y}_{D,1})^T, (\boldsymbol{y}_{D,2})^T]^T$ represents $2N_dN$-length total received vector in each of the antennas of terminal $\mathbb{D}$.

We define $\mathbf{X}_j^i = \text{diag}\{\boldsymbol{x}_{j,\mathcal{P}}^i\}$ for $j = 1, 2$ (transmission time slot) and $i = 1, 2, \dots, N_s$ (source antenna representation) as a diagonal pilot matrix and gather all the compound channel vectors in $\mathbf{b} = [(\mathbf{b}^{11})^T, \dots, (\mathbf{b}^{1N_s})^T, (\mathbf{b}^{21})^T, \dots, (\mathbf{b}^{2N_s})^T, \dots, (\mathbf{b}^{N_dN_s})^T]^T$, where $\mathbf{b}^{n_sn_d}$ is defined as

$$\mathbf{b}^{n_sn_d} = \beta \sum_{n_r=1}^{N_r} \boldsymbol{h}_{SR}^{n_sn_r} * \boldsymbol{h}_{RD}^{n_rn_d}. \tag{14}$$

Furthermore, We can define the channel vector between terminal $\mathbb{S}$ and $\mathbb{D}$ as $\mathbf{d} = [(\mathbf{d}^{11})^T, \dots, (\mathbf{d}^{1N_s})^T, (\mathbf{d}^{21})^T, \dots, (\mathbf{d}^{2N_s})^T, \dots, (\mathbf{d}^{N_dN_s})^T]^T$ where

$$\mathbf{d}^{n_sn_d} = \boldsymbol{h}_{SD}^{n_sn_d} \tag{15}$$

for $n_s = 1, 2, \dots, N_s$ and $n_d = 1, 2, \dots, N_d$. Then, we can rewrite Eq. (13) in a pilot based framework as

$$\boldsymbol{y} = \Phi\theta + \boldsymbol{z} \tag{16}$$

where $\theta = [\mathbf{d}^T\mathbf{b}^T]^T$; $\boldsymbol{z}$ is $2N_dN_\mathcal{P}$-dimensional AWGN vector satisfying $\mathcal{CN}(\mathbf{0}, \text{diag}\{\sigma_D^2\boldsymbol{I}_{N_dN_\mathcal{P}}, \sigma_D^2\boldsymbol{I}_{N_dN_\mathcal{P}} + \beta^2\sigma_R^2\mathbf{F}_{RD}\boldsymbol{h}_{RD}\boldsymbol{h}_{RD}^H\mathbf{F}_{RD}^H\})$; and Φ is defined in Eq. (11), where $\Phi \in \mathbb{C}^{2N_dN_\mathcal{P} \times N_dN_s(3L-1)}$ as pilot matrix is represented. In Eq. (11) $\mathbf{F}_{SRD}$ and $\mathbf{F}_{SD}$ are partial DFT matrices with rows correspond to $S_\mathcal{P}$ and $2L-1$ first columns and L first columns of $\mathbf{W}$, where $\mathbf{W}_{ij} = 1/\sqrt{N}e^{j2\pi ij/N}$ for $i, j = 0, 1, \dots, N-1$, respectively.

Considering Φ in Eq. (11), we can apply compressed sensing to solve channel estimation problem by measurement matrix Φ. In other words, in MIMO-OFDM AF relay network with the existence of direct link between source and destination, the defined measurement matrix in Eq. (11) is used to estimate the compound channel impulse response, together with the direct link channel impulse response using compressed sensing. In the following section, we discuss the approaches to estimate the sparse channels in the aforementioned scenario.

IV. Channel Estimation Methods

A. LS based channel estimation

The conventional approach to solve the equation as

$$\boldsymbol{y} = \Phi\theta + \boldsymbol{z} \tag{17}$$

where θ is to be estimated by known matrix Φ and vector $\boldsymbol{y}$ with contamination $\boldsymbol{z}$ referred as LS approach. In this framework, we have no knowledge of the channel vector θ to be available. As a consequence, we can estimate the channel from known pilot matrix Φ and received vector $\boldsymbol{y}$ using LS approach as

$$\theta_{LS} = \boldsymbol{y}\Phi^\dagger = \boldsymbol{y}\Phi^H(\Phi\Phi^H)^{-1}. \tag{18}$$

B. CS based channel estimation

Sparse recovery algorithms which have been emerged recently, enable efficient reconstruction of especial kinds of signals called sparse signals in the estimation framework (Eq. (17)). Sparse signals could be recovered from highly fewer linear measurements using CS. A K-sparse vector $\boldsymbol{h} \in \mathbb{C}^L$ can be recovered from Eq. (16) with deliberately designed $\Phi \in \mathbb{C}^{M \times N}$ by solving l_0-norm minimization problem

$$\min_\theta \|\theta\|_0 \quad \text{s.t.} \quad \|\boldsymbol{y} - \Phi\theta\|_2 < \sigma \tag{19}$$

where $\|\theta\|_0$ represents the number of non-zero elements of θ; σ is the variance of contamination $\boldsymbol{w}$. Since, this problem is combinatorial and NP hard, it has been shown in [6], [21] that this can be replaced by a convex dual problem

$$\min_\theta \|\theta\|_1 \quad \text{s.t.} \quad \|\boldsymbol{y} - \Phi\theta\|_2 \le \sigma. \tag{20}$$

Methods to solve this convex optimization problem is categorized in two main groups including greedy algorithms and convex optimization algorithms [21]. Here we mainly focus on convex optimization algorithm and the sparse estimation is carried out using convex optimization algorithm.

V. Proposed Sparse Estimation

Proposed Sparse Estimation (SE) approach is based on the compressed sensing. At first, the pilots are placed randomly, and then in the destination, the measurement matrix is formed. It is considerable that forming the measurement matrix needs the destination to know the place and the values of pilots. These two amounts are defined before by a unique protocol between source node and destination node. By forming measurement matrix, the compressed sensing reconstruction algorithm is used to estimate the channel impulse responses. The first $2L-1$ coefficients in the recovered vector will be the compound channel impulse response between source and destination considering relay node and the next L coefficients would be the direct link channel impulse response between source node and destination node.

$$\Phi = \begin{bmatrix} \mathbf{X}_1^1\mathbf{F}_{SD} & \dots & \mathbf{X}_1^{N_s}\mathbf{F}_{SD} & \dots & \mathbf{0}_{N\times(L)} & \dots & \dots & \dots & \dots & \mathbf{0}_{N\times(2L-1)} \\ \mathbf{0}_{N\times(2L-1)} & \mathbf{X}_1^1\mathbf{F}_{SD} & \dots & \mathbf{X}_1^{N_s}\mathbf{F}_{SD} & \mathbf{0}_{N\times(2L-1)} & \dots & \dots & \dots & \dots & \mathbf{0}_{N\times(2L-1)} \\ \mathbf{0}_{N\times(L)} & \ddots & \ddots & \ddots & \mathbf{0}_{N\times(L)} & \dots & \dots & \ddots & \ddots & \mathbf{0}_{N\times(2L-1)} \\ \mathbf{0}_{N\times(L)} & \dots & \mathbf{X}_1^1\mathbf{F}_{SD} & \dots & \mathbf{X}_1^{N_s}\mathbf{F}_{SD} & \dots & \dots & \dots & \dots & \mathbf{0}_{N\times(2L-1)} \\ \mathbf{X}_2^1\mathbf{F}_{SD} & \dots & \mathbf{X}_2^{N_s}\mathbf{F}_{SD} & \dots & \mathbf{0}_{N\times(L)} & \mathbf{X}_1^1\mathbf{F}_{SRD} & \dots & \mathbf{X}_1^{N_s}\mathbf{F}_{SRD} & \dots & \mathbf{0}_{N\times(2L-1)} \\ \mathbf{0}_{N\times(L)} & \mathbf{X}_2^1\mathbf{F}_{SD} & \dots & \mathbf{X}_2^{N_s}\mathbf{F}_{SD} & \mathbf{0}_{N\times(2L-1)} & \mathbf{0}_{N\times(2L-1)} & \mathbf{X}_1^1\mathbf{F}_{SRD} & \dots & \mathbf{X}_1^{N_s}\mathbf{F}_{SRD} & \mathbf{0}_{N\times(2L-1)} \\ \mathbf{0}_{N\times(L)} & \ddots & \ddots & \ddots & \mathbf{0}_{N\times(L)} & \mathbf{0}_{N\times(2L-1)} & \ddots & \ddots & \ddots & \mathbf{0}_{N\times(2L-1)} \\ \mathbf{0}_{N\times(L)} & \dots & \mathbf{X}_2^1\mathbf{F}_{SD} & \dots & \mathbf{X}_2^{N_s}\mathbf{F}_{SD} & \mathbf{0}_{N\times(2L-1)} & \dots & \mathbf{X}_1^1\mathbf{F}_{SRD} & \dots & \mathbf{X}_1^{N_s}\mathbf{F}_{SRD} \end{bmatrix} \quad (11)$$

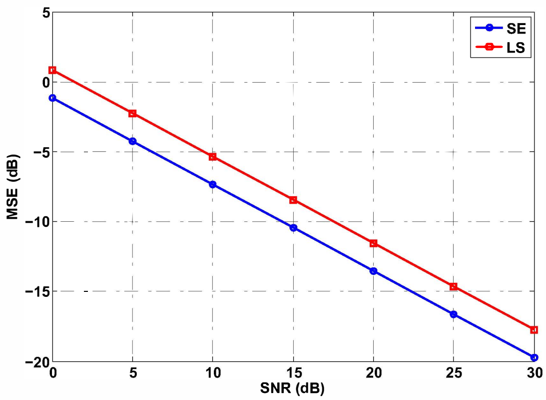

Fig. 2. Mean square error for a cooperative MIMO system for sparse estimation (SE) and LS.

VI. Numerical results

In this section, the simulation results are presented to validate the performance of the proposed method. As a measure of comparison, the mean square error (MSE) for the estimated channel and the original one are calculated. All of the available channels are assumed to have the same length of $L = 64$ with $K = 4$ non-zero taps whose positions are randomly generated. Each non-zero tap follows a complex Gaussian distribution. We compare the performance of the proposed estimator with the LS-based linear estimator. For each of the channels, we adopt 10000 independent realization and average over them. An OFDM system with 512 sub-carriers is used whence 12.5% of them are pilot symbols. Each of the OFDM symbols are QPSK modulated.

To solve sparse problems in the simulations, a Convex Programming tool called cvx is used. In other words, for sparse estimation (SE) of channels l_1 norm minimization is solved by cvx [22].

In Fig. 2, the performance of the proposed sparse estimation (SE) is compared by LS channel estimation. Mean Square Error (MSE) of the estimated channels is used as a comparison tool. The simulation is performed for a 4×4 MIMO-OFDM system, in which the source node transmits its own signal to the destination through a relay. The complement channel impulse response is estimated using the both aforementioned techniques. As shown in Fig. 2, the proposed CS-based method outperforms the conventional LS method through utilizing the sparsity of the channel.

VII. Conclusion

Channel estimation in MIMO-OFDM relay network is considered in this paper. Compressed sensing is used as a sparse solution for estimating the compound channel impulse response and the direct link between $\mathbb{S}$ and $\mathbb{D}$. The simulation results demonstrate the superior performance of the proposed sparse estimation technique comparing to the LS method. One of the main advantages of the proposed approach is utilizing the sparsity of the channel during the estimating. This in turn allows the estimation technique to remove the non-sparse channels, which minimizes the l_1-norm optimization problem and reduces the search space.

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