Compressed Channel Estimation for MIMO Amplify-and-Forward Relay Networks

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***Abstract*-In this work, we investigate channel estimation problem in Multi-Input Multi-Output (MIMO) cooperative networks that employ the amplify-and-forward (AF) transmission scheme. Least square (LS) and expectation conditional maximization (ECM) have been proposed in the system. However, both of them never take advantage of channel sparsity and then they cause the estimation performance loss. Unlike the linear channel estimation methods, we propose several compressed channel estimation methods to exploit sparsity of the MIMO cooperative channels based on the theory of compressed sensing. At first, we formulate the channel estimation problem as compressed sensing problem by using sparse decomposition theory. Secondly, the lower bound is derived for the estimation and the MIMO relay channel is reconstructed by compressive sampling matching pursuit（CoSaMP）algorithms. Finally, various numerical simulations are given to confirm the superiority of proposed methods than traditional linear channel estimation methods. Simulation results show that our doubly iterative receiver provides an excellent BER performance.**

Keywords: Multi-input multi-output (MIMO); two-way relay networks (TWRN); sparse channel estimation; compressed sensing (CS); amplify-and-forward (AF).

I. INTRODUCTION

Multiple-input multiple-output (MIMO) relay channel has proved to be one of the promising solutions, as it increases channel capacity, network reliability and combats multipath fading effectively. For a three-node MIMO relay network where terminals can be usually divided into three parts: source, relay, and destination, source and destination can be the base station and mobile station, respectively, or vice versa, and the relay receives signal from source and retransmits to destination. In the amplify-and-forward (AF) mode, the relay amplifies and retransmits its received noisy signal from the source terminal to the destination terminal without decoding it. Compared with the decode-and-forward (DF) scheme, the AF mode requires simpler implementations at the relay and no information about structure of signals from the source terminal.

For the MIMO relay systems where the direct source-destination link is omitted, the instantaneous channel state information (CSI) knowledge of both the source-relay and relay-destination links is required at the destination node in order to detect the signals conveyed from the source node. Hence, the overall channel information from the source end to the destination end is estimated at the destination only. The channel estimation issues have been well studied in MIMO systems with direct point-to-point communications [1-3]. For AF relay networks, we cannot appeal to the results of the point-to-point MIMO systems directly, because the end-to-end channels are often concatenations of channels of multiple communication stages. In [4], parallel factor analysis based channel estimation method for two-hop MIMO relay communication system is developed. In [5] the authors introduce the superimposed training strategy into the MIMO AF one-way relay network (OWRN) to perform the individual channel estimation at the destination. A least square (LS) channel estimation algorithm under block-based training is proposed for MIMO-OFDM relay Systems [6]. Furthermore, expectation conditional maximization (ECM) channel information estimation algorithm proposed in [7] to estimate the channel for MIMO Amplify-and-Forward Relay Networks. However, most of existing studies on MIMO Amplify-and-Forward Relay Networks never take advantage of channel sparsity and then they will cause performance loss. In recent years, numerous channel measurements demonstrate that the multipath wireless channels tend to exhibit cluster or sparse structures in which majority of the channel taps end up being either zero or below the noise floor, especially when operating at large bandwidths and signaling durations and/or with numbers of antenna elements [8-10]. With the theoretical development of compressed sensing [11], a number of researches have proposed sparse channel estimation methods on point-to-point (P2P) communication systems including single-antenna [12] or multiple-antenna [13]. Meanwhile, sparse channel estimation methods [14], [15] on cooperative networks have also been investigated recently. All of the channel estimation methods are limited in either single-antenna or multi-antenna systems for the traditional P2P transmission and single-antenna relay channel. However, corresponding work has not been done for MIMO relay network, to the best of the authors' knowledge.

In this paper, we focus our research on relay network in which multiple antennas are deployed at the source, relay and destination nodes. We study the sparse channel estimation issue under AF relaying scheme. Firstly, we introduce MIMO relaying model and formulate composite channels estimation as compressed sensing problem by using sparse decomposition theory. Secondly, the composite channel is reconstructed by compressive sampling matching pursuit（CoSaMP）[16] algorithm. Lastly, we verify the proposed methods with computer simulations, and then compare with the traditional methods and compressive sensing-based OMP algorithm [17]. The contribution of this paper is that we first introduce a sparse channel estimation technique with compressed sensing for MIMO relay network and exploit the sparse structure information in the CIR at the end users.

The remainder of this paper is organized as follows. Section II describes the system model. Section III provides the details of the proposed algorithm. Simulation results are given in IV. Finally, conclusions are given in Section V.

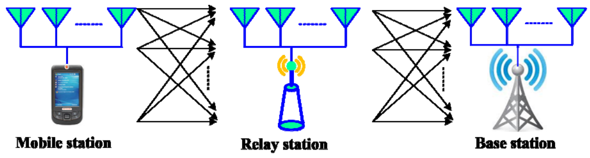

Fig.1. MIMO relay network

II. System Model

A. System model

A typical dual-hop relay system, as shown in Fig. 1, consists of the source $\mathbb{S}$ sending signals towards the destination $\mathbb{D}$ via the assistance of the relay $\mathbb{R}$. Nodes $\mathbb{S}$, $\mathbb{R}$ and $\mathbb{D}$ equipped with M_S, M_R and M_D antennas. The average transmit power of $\mathbb{S}$, $\mathbb{R}$ and $\mathbb{D}$ are denoted as P_S, P_R, and P_D, respectively. All the channels are assumed to be quasi-statistic frequency-selective fading.

We suppose that the channel between the lth antenna of $\mathbb{S}$ and the rth antenna of $\mathbb{R}$ is a frequency selective fading channel whose impulse response is denoted by $\boldsymbol{h}_{r,l}=[\boldsymbol{h}_{r,l}(0),\boldsymbol{h}_{r,l}(1),\cdots,\boldsymbol{h}_{r,l}(L_1-1)]^T$, where $l=1,\cdots,M_S$, $r=1,\cdots,M_R$, and L_1 is the length of the channel between $\mathbb{S}$ and $\mathbb{R}$. We assume that $\boldsymbol{h}_{r,l}$ is a complex Gaussian random variable with zero mean and variance α_1^2. Meanwhile, the channel coefficient between the mth antenna of $\mathbb{D}$ and the rth antenna of $\mathbb{R}$ is denoted by $\boldsymbol{g}_{r,m}=[\boldsymbol{g}_{r,m}(0)\ \boldsymbol{g}_{r,m}(1)\ \cdots\ \boldsymbol{g}_{r,m}(L_2-1)\ ]^T$, $(m=1,\cdots,M_D;r=1,\cdots,M_R)$ which is a complex zero mean Gaussian random variable with variance α_2^2 and L_2 is the length of the channel between $\mathbb{D}$ and $\mathbb{R}$. It is assumed that the direct link between the source and destination is ignored due to the larger distance and additional path loss compared to the relay link. Through this paper, we assume perfect synchronization among all terminals and the total transmit power for the source and the relay is the same.

B. Receive signal model

During the first time slot, the signal vectors from the lth antenna of $\mathbb{S}$ $\boldsymbol{x}_l=[x(0),x(1),\cdots,x(N-1)]^T$ are CP-added with CP length L_P before transmission, $L_P\geq\max(L_1-1,L_2-1)$. The received signal vector at the node $\mathbb{R}$ after removing CP can be written as

$$\boldsymbol{y}_R=\boldsymbol{Hx}+\boldsymbol{w}_R \tag{1}$$

where channel matrix $\boldsymbol{H}$, transmit signal vector $\boldsymbol{x}$, received signal vector $\boldsymbol{y}_R$ are denoted as follows:

$$\boldsymbol{H}=\begin{bmatrix} \boldsymbol{H}_{1,1} & \boldsymbol{H}_{1,2} & \cdots & \boldsymbol{H}_{1,M_S} \\ \boldsymbol{H}_{2,1} & \boldsymbol{H}_{2,2} & \cdots & \boldsymbol{H}_{2,M_S} \\ \vdots & \vdots & \vdots & \vdots \\ \boldsymbol{H}_{M_R,1} & \boldsymbol{H}_{M_R,2} & \cdots & \boldsymbol{H}_{M_R,M_S} \end{bmatrix} \tag{2}$$

$$\boldsymbol{x}=[\boldsymbol{x}_1\ \boldsymbol{x}_2\ \cdots \boldsymbol{x}_{M_S}]^T \tag{3}$$

$$\boldsymbol{y}_R=[(\boldsymbol{y}_R^1)^T\ \cdots\ (\boldsymbol{y}_R^r)^T \cdots\ (\boldsymbol{y}_R^{M_r})^T]^T \tag{4}$$

The matrix $\boldsymbol{H}_{r,l}$ is a $N\times N$ circulant matrix which the first column of the form $\boldsymbol{h}_{r,l}=[h_{r,l}(0)\ h_{r,l}(1)\ \cdots\ h_{r,l}(L_1-1)\ \ 0_{1\times(N-L_1)}]^T$, $\boldsymbol{w}_R$ is the $M_R\times 1$ zero-mean additive white Gaussian noise vector.

The vector $\boldsymbol{y}_R$ is then amplified at $\mathbb{R}$ by a real coefficient β. The value of β is to guarantee that the average power transmitted from each antenna of $\mathbb{R}$. The vector $\beta\boldsymbol{y}_R^r$ is CP-added with CP length L_P before being broadcasted to $\mathbb{D}$ during Phase II. Let $\boldsymbol{y}_D^m$ is the received signal vector at the mth antenna of $\mathbb{D}$, $m=1,2,\cdots,M_D$. We construct a vector $\boldsymbol{y}_D\triangleq[(\boldsymbol{y}_D^1)^T,\cdots(\boldsymbol{y}_D^m)^T,\cdots(\boldsymbol{y}_D^{M_D})^T]^T$, and it is represented as

$$\begin{aligned}\boldsymbol{y}_D&=\beta\boldsymbol{G}\boldsymbol{y}_R+\boldsymbol{w}_D\\&=\beta\boldsymbol{G}\boldsymbol{H}\boldsymbol{x}+\beta\boldsymbol{G}\boldsymbol{w}_R+\boldsymbol{w}_D\\&=\beta\boldsymbol{G}\boldsymbol{H}\boldsymbol{x}+\boldsymbol{w}\end{aligned} \tag{5}$$

where

$$\boldsymbol{G}=\begin{bmatrix} \boldsymbol{G}_{1,1} & \boldsymbol{G}_{2,1} & \cdots & \boldsymbol{G}_{M_R,1} \\ \boldsymbol{G}_{1,2} & \boldsymbol{G}_{2,2} & \cdots & \boldsymbol{G}_{M_R,2} \\ \vdots & \vdots & \vdots & \vdots \\ \boldsymbol{G}_{1,M_D} & \boldsymbol{G}_{2,M_D} & \cdots & \boldsymbol{G}_{M_R,M_D} \end{bmatrix} \tag{6}$$

The matrix $\boldsymbol{G}_{r,m}$ is a $N\times N$ circulant matrix which the first column of the form $\boldsymbol{g}_{r,m}=[g_{r,m}(0)\ g_{r,m}(1)\ \cdots\ g_{r,m}(L_2-1)\ \ 0_{1\times(N-L_2)}]^T$. $\boldsymbol{w}_D$ is the $M_D\times 1$ complex circular AWGN vector at the destination with zero mean and covariance matrix $\sigma_D^2\mathrm{I}_{M_D}$, $\boldsymbol{w}$ is the overall noise at the destination.

The circulant matrices $\boldsymbol{H}_{r,l}$ and $\boldsymbol{G}_{m,r}$ can be decomposed as $\boldsymbol{H}_{r,l}=\boldsymbol{F}^H\Lambda_{r,l}\boldsymbol{F}$, $\boldsymbol{G}_{r,m}=\boldsymbol{F}^H\boldsymbol{\Xi}_{r,m}\boldsymbol{F}$, where

$$\boldsymbol{\Lambda}_{r,l}=diag\left\{\boldsymbol{H}_{r,l}(0),\cdots\boldsymbol{H}_{r,l}(c),\cdots,\boldsymbol{H}_{r,l}(N-1)\right\},$$

$$\boldsymbol{H}_{r,l}(c)=\sum_{q=0}^{L_1-1}\boldsymbol{h}_{r,l}(q)\ e^{-j\frac{2\pi qc}{N}},$$

$$\boldsymbol{\Xi}_{r,m}=diag\left\{\boldsymbol{G}_{r,m}(0),\cdots\boldsymbol{G}_{r,m}(c),\cdots,\boldsymbol{G}_{r,m}(N-1)\right\},$$

$$\boldsymbol{G}_{r,m}(c)=\sum_{q=0}^{L_2-1}\boldsymbol{g}_{r,m}(q)\ e^{-j\frac{2\pi qc}{N}},$$

therefore $\beta\boldsymbol{G}_{m,r}\boldsymbol{H}_{r,l}$ can be written as

$$\beta\boldsymbol{G}_{r,m}\boldsymbol{H}_{r,l}=\boldsymbol{F}^H\beta\boldsymbol{\Xi}_{r,m}\boldsymbol{\Lambda}_{r,l}\boldsymbol{F}, \tag{7}$$

Equation (7) is circulant matrix which has the first columns of $[\beta(\boldsymbol{g}_{r,m}*\boldsymbol{h}_{r,l})\ \ 0_{1\times(N-L+1)}]^T$, and we have a composite channel $\boldsymbol{k}_{l,m}=[\boldsymbol{k}_{l.m}(0),\boldsymbol{k}_{l.m}(1),\cdots\boldsymbol{k}_{l.m}(L-1)]$, $L=L_1+L_2-1$, which is given as

$$\boldsymbol{k}_{l,m}=\beta(\boldsymbol{h}_{r,l}\otimes\boldsymbol{g}_{r,m}), \tag{8}$$

$$\beta\boldsymbol{\Lambda}_{r,l}\boldsymbol{\Xi}_{r,m}=diag(\boldsymbol{W}\boldsymbol{k}_{l\times m}), \tag{9}$$

Hence, by normalized DFT of $\boldsymbol{y}_D$, system model (5) can be rewritten as

$$\boldsymbol{z}=(I\otimes\boldsymbol{F})\boldsymbol{y}_D=\boldsymbol{X}\boldsymbol{k}+\boldsymbol{n}, \tag{10}$$

where $\boldsymbol{X}=diag(\boldsymbol{F}\boldsymbol{x})\boldsymbol{W}$, where F is the discrete Fourier transformation (DFT) matrix, and $\boldsymbol{W}$ is a matrix taking the first ($L-1$) columns of $\sqrt{N}\boldsymbol{F}$, $\boldsymbol{n}=(\boldsymbol{I}\otimes\boldsymbol{F})\boldsymbol{w}$.

III. COMPRESSED CHANNEL SENSING

A. Overview of compressed sensing

In this paper, we consider the linear model as (10). According to the CS, if an unknown signal vector satisfies the sparse or approximate sparse requirements, the conditions under which CS succeeds depends on the structure of the measurement matrix X. Thus, these kinds of unknown signals can be robustly reconstructed from observation signal $\boldsymbol{z}$. However, the sparsest solution is always a non-deterministic polynomial-time hard (NP-hard) problem. According to recent theoretical results, the observation signal can be used to efficiently recover any "sparse enough" signal provided that the matrix X satisfies the so-called restricted isometric property (RIP) [18]. We suppose that X is a $n\times p$ complex-valued measurement matrix that has unit ℓ2-norm columns. The X satisfies the RIP of order d with parameter $\delta_d\in(0,1)$, which can satisfy the inequality

$$(1-\delta_d)\|\mathbf{k}\|_2^2\le\|X\mathbf{k}\|^2\le(1+\delta_d)\|\mathbf{k}\|_2^2, \tag{11}$$

where $\|\mathbf{k}\|_2^2$ denotes the ℓ2-norm, which is given by $\|\mathbf{k}\|_2^2=\sum\left|k_{r,m}\right|^2$. If (11) is satisfied, the training sequence is said to satisfy the RIP of order d, and the accurate channel estimator with high probability can be obtained by using CS methods. Although verifying whether a given matrix satisfies this condition is difficult, many matrices satisfy the restricted isometry constant (RIC) with high property and few measurements. In particular, it has been shown exponentially with high probability that the random Gaussian, Bernoulli, and partial Fourier matrices satisfy the RIC with a number of measurements that are nearly linear in the sparsity level.

B. Compressed channel estimation

As the MIMO relay system model (10) shows, the LS estimator is expressed as

$$\hat{\boldsymbol{k}} = \begin{cases} \boldsymbol{X}_T^{\dagger}\boldsymbol{z}, & T \subseteq supp(\boldsymbol{k}) \\ \boldsymbol{0}, & others \end{cases} \tag{12}$$

where $\mathrm{supp}(\boldsymbol{k})$ denotes the nonzero taps supporting the channel vector $\boldsymbol{k}$, $\boldsymbol{X}_T$ is the sub matrix constructed from the columns of $\boldsymbol{X}$, and T denotes the selected sub columns corresponding to the nonzero index set of the convoluted channel vector h. The MSE of LS estimator $\hat{\boldsymbol{k}}$ is given by

$$\hat{\boldsymbol{k}} = \boldsymbol{X}^{\dagger}\boldsymbol{z} = \boldsymbol{k} + \boldsymbol{X}^{\dagger}\boldsymbol{n}. \tag{13}$$

At first, we would like to give a definition to the sparsity of MIMO relay network. Assume that $\boldsymbol{k}$ is a d-sparse channel vector, in the sense that its impulse response satisfies [19]

$$d \triangleq \sum_{m=1}^{M_D} \underbrace{\sum_{i=0}^{L-1} \left\| \boldsymbol{k}_{l,m}(i) \right\|_0}_{\triangleq d_i} \ll M_S M_D L \tag{14}$$

The MSE in the channel estimate is lower bounded as

$$\mathrm{E}\left[\left\|\hat{\boldsymbol{k}} - \boldsymbol{k}\right\|_{\mathrm{F}}^2\right] \geq \frac{M_S d}{\varepsilon}. \tag{15}$$

The compressive sensing-based CoSaMP has been considered as an effective method when the sparsity d of the channel is known [20]. The accurate channel estimator is obtained by refining the support set at each iteration step.

***Input**:* $\boldsymbol{z}, \boldsymbol{X}$, d , the training signal matrix $\boldsymbol{X} = diag(\boldsymbol{F}\boldsymbol{x})\boldsymbol{W}$, the maximum number of dominant channel coefficients is assumed as d.

Output: channel estimator $\hat{\boldsymbol{k}}_{CoSaMP}$.

Initialization: The index set of nonzero coefficient as $\boldsymbol{T}_0 = \varnothing$, the residual estimation error $\boldsymbol{r}_0 = \boldsymbol{z}$ and put the iteration index as $q = 1$.

Identification: Select a column index n_q of $\boldsymbol{X}$ that is most correlated with the residual:

$$\boldsymbol{n}_q = \left|\langle \boldsymbol{r}_{q-1}, \boldsymbol{X}_q \rangle\right| \text{ and } \boldsymbol{T}_q = \boldsymbol{T}_{q-1} \cup \boldsymbol{n}_q, \tag{16}$$

Using LS method to calculate a channel estimator as $\boldsymbol{T}_{LS} = \arg\min \left\|\boldsymbol{z} - \boldsymbol{X}\boldsymbol{k}\right\|$, and select $\boldsymbol{T}$ maximum dominant taps d. The positions of the selected dominant taps in this sub step are denoted by $\boldsymbol{T}_{LS}$.

Merge: The positions of dominant taps are merged by $\boldsymbol{T}_q = \boldsymbol{T}_{LS} \cup \boldsymbol{T}_q$.

Estimation: Compute the best coefficient for approximating the channel vector with chosen columns,

$$\boldsymbol{k}_q = \arg\min_k \left\|\boldsymbol{z} - \boldsymbol{X}_{T_q}\boldsymbol{k}\right\|_2, \tag{17}$$

Pruning: Select the $\boldsymbol{T}_q$ largest channel coefficients

$$\boldsymbol{k}_q = [\boldsymbol{k}]_d, \tag{18}$$

and replace the left taps $\boldsymbol{T} \setminus \boldsymbol{T}_q$ by zero.

Iteration: Update the estimation error:

$$\boldsymbol{r}_q = \boldsymbol{z} - \boldsymbol{X}_{T_q}\boldsymbol{k}_q, \tag{19}$$

Increment the iteration counter k. Repeat (16)-(19) until stopping criterion holds and then set $\hat{\boldsymbol{k}}_{CoSaMP} = \boldsymbol{k}_q$.

IV. SIMULATION RESULTS

In this section, the mean square error (MSE) performance of the proposed method with CoSaMP algorithm is evaluated by simulations. Here we compare the performance of the proposed estimators with LS channel estimator, OMP channel estimator and oracle channel estimator (LS-based known position of dominant taps). We consider the MIMO relay network with $M_S = M_R = M_D = 2$ antennas; the number of carrier is 128. We assume that the channel vectors have the same length $L_1 = L_2 = 32$ and hence the length of convolution channel vectors is $L = L_1 + L_2 - 1 = 63$. And we also model the MIMO channel as frequency-selective block fading so that the signal can be transmitted in a data block. The positions of nonzero channel taps are randomly generated. QPSK modulation is used. Transmit power is set as $P_S = P$ and AF relay power is set as $P_R = P$. The signal to noise ratio (SNR) is defined as a as $10\log\left(P/\sigma_n^2\right)$. When the number of nonzero taps in cooperation channels is changed, the simulation results are shown in Fig. 2 ~ Fig. 4.

From Fig.2 and Fig. 3, we find that the average MSE performance becoming better as the SNR increases. The CS-based method has a small gap to oracle bound but better than the LS-based linear channel estimation. We also find that CoSaMP algorithm is much better than OMP.

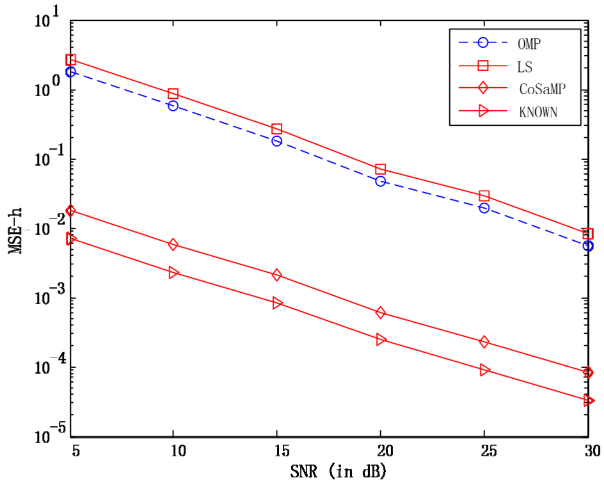

Fig.2. MSE performance of channel estimation for the case when d=2.

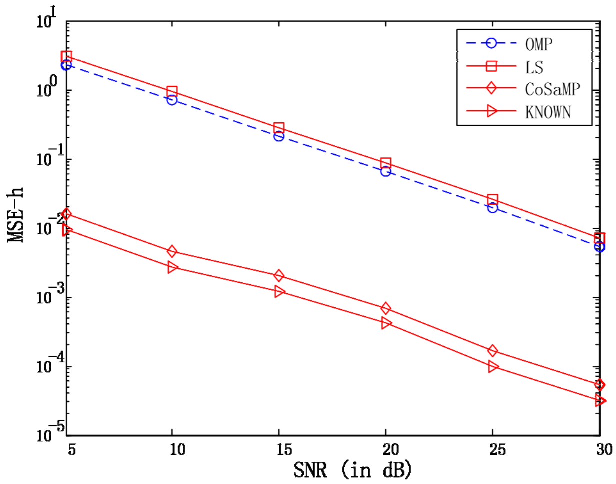

Fig.3. MSE performance of channel estimation for the case when d=4.

We give MSE performance comparisons of channel estimators versus different channel sparsity. We suppose that the number of dominant channel taps is 2 and 4. From the figures, we can see that LS-based average MSE performances are not changed due to the linear channel estimation method neglected channel sparsity. However the proposed method utilized channel structure as for prior information, and has a better MSE performance than LS algorithm. The figures show that the less number of nonzero tap in channel the better MSE performance obtained.

We also compare the performance of the CoSaMP estimator with ECM estimator algorithm in this section. From Fig.4, we can see that performance of the proposed CCE estimator method is much better than ECM algorithm when channel impulse responses are sparse enough. However, as the number of nonzero taps of all the channels increasing, the performance of CoSaMP is closer to ECM algorithm.

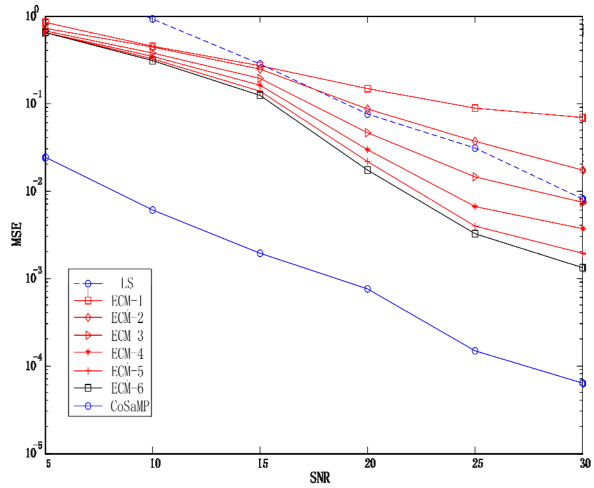

Fig.4. MSE performance of channel estimation for the case when channel impulse responses are sparse enough

V. Conclusion

This paper investigated the channel estimation problem in sparse multipath MIMO relay networks. To address the shortcomings of conventional linear channel estimation methods, we proposed compressed channel estimation methods for MIMO relay networks under the AF protocol. The sparseness of convoluted sparse channels was demonstrated by a measure function. The proposed methods exploited the sparsity in the MIMO OWRN channel. The simulation results confirmed the superior performance of the proposed method compared with conventional linear methods, e.g., LS and ECM.

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