Sparsity Adaptive Expectation Maximization Algorithm for Estimating Channels in MIMO Cooperation systems

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Abstract

We investigate the channel state information (CSI) in multi-input multi-output (MIMO) cooperative networks that employ the amplify-and-forward transmission scheme. Least squares and expectation conditional maximization have been proposed in the system. However, neither of these two approaches takes advantage of channel sparsity, and they cause estimation performance loss. Unlike linear channel estimation methods, several compressed channel estimation methods are proposed in this study to exploit the sparsity of the MIMO cooperative channels based on the theory of compressed sensing. First, the channel estimation problem is formulated as a compressed sensing problem by using sparse decomposition theory. Second, the lower bound is derived for the estimation, and the MIMO relay channel is reconstructed via compressive sampling matching pursuit algorithms. Finally, based on this model, we propose a novel algorithm so called sparsity adaptive expectation maximization (SAEM) by using Kalman filter and expectation maximization algorithm so that it can exploit channel sparsity alternatively and also track the true support set of time-varying channel. Kalman filter is used to provide soft information of transmitted signals to the EM-based algorithm. Various numerical simulation results indicate that the proposed sparse channel estimation technique outperforms the previous estimation schemes.

Keywords: Multi-input multi-output, one-way relay networks, adaptive compressed channel estimation, sparsity adaptive expectation maximization, amplify-and-forward

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1. Introduction

Multiple-input multiple-output (MIMO) relay channel has become one of the promising solutions, because it increases channel capacity, has network reliability, and effectively combats multipath fading. For a three-node MIMO relay network where terminals can be typically divided into three parts, namely, source, relay, and destination. Source and destination can be the base station and mobile station, respectively, or vice versa, and the relay receives a signal from the source and retransmits it to the 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 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 to detect the signals conveyed from the source node. Thus, the overall channel information from the source end to the destination end is estimated at the destination only. The channel estimation issues have been sufficiently studied in MIMO systems with direct point-to-point (P2P) communications [1–6]. For AF relay networks, this study cannot directly appeal to the results of the P2P MIMO systems because the end-to-end channels are often concatenations of channels of multiple communication stages. In [7], parallel factor analysis–based channel estimation method for a two-hop MIMO relay communication system is developed. In [8], the superimposed training strategy into the MIMO AF one-way relay network (OWRN) was introduced to perform the individual channel estimation at the destination. A least squares (LS) channel estimation algorithm under block-based training is proposed for two-way relay MIMO-OFDM relay systems[9]. Furthermore, the expectation conditional maximization (ECM) channel information estimation algorithm is proposed in [10] to estimate the channel for MIMO amplify-and -forward relay networks. A joint channel estimation is proposed for three-hop MIMO relaying systems, which combined alternating least squares algorithm obtains cooperative diversity by fully exploiting the tensor algebraic structures of the available cooperative MIMO links[11]**.** However, most studies on MIMO amplify-and-forward relay networks do not take advantage of channel sparsity, and they 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, particularly when operating at large bandwidths and signaling durations and/or with numbers of antenna elements [12–14]. With the theoretical development of compressed sensing[15], a number of research studies have proposed sparse channel estimation methods on P2P communication systems[16-18]. Group-sparse channel estimation using bayesian matching pursuit is proposed for OFDM systems[18]. Meanwhile, sparse channel estimation methods [19–22] on cooperative networks have also been investigated. All of above methods assumed that the sparsity d is known, whereas the sparsity may not be available in many practical applications.

This study focuses on relay network in which multiple antennas are deployed at the source, relay, and destination nodes. The sparse channel estimation issue under the AF relaying scheme is studied. First, the MIMO relaying model is introduced and the composite channel estimation is formulated as a compressed sensing problem by using sparse decomposition theory. Second, the composite channel is reconstructed by compressive sampling matching pursuit (CoSaMP) [23] algorithm. Last, the proposed methods are verified with computer simulations, and then compared with the traditional methods and compressive sensing-based orthogonal matching pursuit (OMP) algorithm [24]. Then, this paper introduces an adaptive sparse channel estimation technique with compressed sensing for the MIMO relay network and exploits the sparse structure information in the CIR at the end users.

The rest of this paper is organized as follows: Section II describes the system model. Section III provides details of the proposed algorithm. Section IV presents the simulation results. Section V concludes the paper.

2. System Model

2.1 System model

A typical dual-hop relay system consists of the source $\mathbb{S}$ sending signals toward the destination $\mathbb{D}$ through the assistance of the relay node $\mathbb{R}$. Nodes $\mathbb{S}$, $\mathbb{R}$ and $\mathbb{D}$ are 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 of 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, the impulse response of which is denoted by $\boldsymbol{h}_{r,\ell}=[\boldsymbol{h}_{r,\ell}(0),\boldsymbol{h}_{r,\ell}(1),\cdots,\boldsymbol{h}_{r,\ell}(L_1-1)]^T$, where $\ell=1,\cdots,M_S$, $r=1,\cdots,M_R$, and L_1 is the length of the channel between $\mathbb{S}$ and $\mathbb{R}$. We assume that $\boldsymbol{h}_{r,\ell}$ 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 $\mathbb{R}$. The direct link between the source and destination is ignored because of the larger distance and additional path loss compared with the relay link. Through this study, we assume perfect synchronization among all terminals and same total transmit power for the source and relay.

2.2 Receive signal model

During the first time slot, the signal vectors from the ℓth antenna of $\mathbb{S}$ $\boldsymbol{x}_\ell=[x(0),x(1),\cdots,x(N-1)]^T$ are cyclic prefix (CP) of length L_P added before transmission, and L_p should satisfy $L_p\geq\max(L_1-1,L_2-1)$. After CP is removed, the received signal vector at the node $\mathbb{R}$ after can be written as

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

where channel matrix H, transmit signal vector x, and received signal vector y_R are denoted as follows:

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

$$x=[x_1\ x_2\ \cdots\ x_{M_S}]^T \tag{3}$$

$$y_R=\left[(y_R^1)^T\cdots(y_R^r)^T\cdots(y_R^{M_r})^T\right]^T \tag{4}$$

The matrix $\boldsymbol{H}_{r,\ell}$ is a $N\times N$ circulant matrix, which is the first column of the form $h_{r,\ell}=\left[h_{r,\ell}(0)\ h_{r,\ell}(1)\ \cdots\ h_{r,\ell}(L_1-1)\ \ 0_{1\times(N-L_1)}\right]^T$. w_R is the $M_R\times 1$ zero-mean additive white Gaussian noise (AWGN) 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 is transmitted from each antenna of the relay $\mathbb{R}$. The vector βy_R^r is CP-added with CP length L_P before being broadcasted to $\mathbb{D}$ during Phase II. We let $\boldsymbol{y}_D^m$ be the received signal vector at the mth antenna of $\mathbb{D}$, $m=1,2,\cdots,M_D$. We construct a vector $y_D\triangleq[(y_D^1)^T,\cdots,(y_D^m)^T,\cdots,(y_D^{M_D})^T]^T$, which is represented as

$$\begin{aligned}y_D&=\beta G y_R+w_D\\&=\beta GHx+\beta G w_R+w_D\\&=\beta GHx+w\end{aligned} \tag{5}$$

where

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

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

The circulant matrices $H_{r,\ell}$ and $G_{r,m}$ can be decomposed as $H_{r,\ell}=F^H\Lambda_{r,\ell}F$, $G_{r,m}=F^H\Xi_{r,m}F$, where

$$\Lambda_{r,\ell}=diag\left\{H_{r,\ell}(0),\cdots,H_{r,\ell}(c),\cdots,H_{r,\ell}(N-1)\right\},\ H_{r,\ell}(c)=\sum_{q=0}^{L_1-1}h_{r,\ell}(q)e^{-j\frac{2\pi qc}{N}},$$

$$\Xi_{r,m}=diag\left\{G_{r,m}(0),\cdots,G_{r,m}(c),\cdots,G_{r,m}(N-1)\right\},\ G_{r,m}(c)=\sum_{q=0}^{L_2-1}g_{r,m}(q)e^{-j\frac{2\pi qc}{N}},$$

Therefore, $\beta G_{m,r}H_{r,\ell}$ can be written as

$$\beta G_{r,m} H_{r,\ell} = F^H \beta \Xi_{r,m} \Lambda_{r,\ell} F \tag{7}$$

Equation (7) is a circulant matrix that has the first columns of $\left[\beta(g_{r,m} * h_{r,\ell})\ 0_{1\times(N-L+1)}\right]^T$ and a composite channel $k_{\ell,m} = [k_{\ell,m}(0), k_{\ell,m}(1), \cdots, k_{\ell,m}(L-1)]$, $L = L_1 + L_2 - 1$ which is provided as

$$k_{\ell,m} = \beta(h_{\ell,r} \otimes g_{r,m}) \tag{8}$$

$$\beta \Lambda_{r,\ell} \Xi_{r,m} = diag(W k_{\ell \times m}) \tag{9}$$

Thus, by normalized discrete Fourier transformation (DFT) of y_D, system model (5) can be rewritten as

$$z = (I \otimes F) y_D = Xk + n, \tag{10}$$

Where $X = diag(Fx)W$, where F is the DFT matrix and W is a matrix that takes the first $(L-1)$ columns of $\sqrt{N}F, n = (I \otimes F)w$.

3. Compressed Channel Sensing

3.1 Overview of compressed sensing

In this study, we consider the linear model as (10). According to the compressed sensing (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 z. However, the sparsest solution is always a nondeterministic polynomial-time hard problem. According to recent theoretical results, the observation signal can be employed to recover any "sparse enough" signal efficiently provided that the matrix X satisfies the so-called restricted isometric property (RIP) [25]. We suppose that X is a $n \times p$ complex-valued measurement matrix that has unit ℓ_2 norm columns. The X satisfies the RIP of order d with parameter $\delta \in (0,1)$, which can satisfy the inequality.

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

Where $\|k\|_2^2$ denotes the ℓ_2 norm, which is provided by $\|k\|_2^2 = \sum |k_{r,m}|^2$. If (11) is satisfied, then the training sequence satisfies 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, numerous matrices satisfy the restricted isometry constant (RIC) with high property and few measurements. In particular, the random Gaussian, Bernoulli, and partial Fourier matrices have been exponentially shown with high probability to satisfy the RIC with a number of measurements that are nearly linear in the sparsity level.

In this study, we consider the linear model as (10). According to the CS, the magnitudes and nonlinear coefficients of k can be accomplished by the convex program.

$$\hat{k} = \min_{k}\left\{\frac{1}{2}\left\|y - Xk\right\|_{\ell_2}^2 + \lambda\left\|k\right\|_{\ell_1}\right\} \tag{12}$$

Where the ℓ_1 norm provides a convex relaxation ℓ_0 norm, and λ is a regularized parameter that trades off the estimation error and sparsity of k . We define the sparsity of the MIMO relay network. We assume that k is a d-sparse channel vector in the sense that its impulse response satisfies

$$d \triangleq \sum_{\ell=1}^{M_S}\sum_{m=1}^{M_D}\underbrace{\sum_{i=0}^{L-1}\left\|k_{\ell,m}(i)\right\|_0}_{\triangleq d_i} \ll M_S M_D L \tag{13}$$

The mean square error (MSE) in the channel estimate is lower bounded as

$$E\left[\left\|\hat{k} - k\right\|_F^2\right] \geq \frac{M_S M_D d}{\varepsilon} \tag{14}$$

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

$$\hat{k} = \begin{cases} X_T^{\dagger} z, \ T \subseteq supp(k) \\ 0, \ \text{others} \end{cases} \tag{15}$$

where $suup(k)$ denotes the nonzero taps that support the channel vector k, X_T is the submatrix constructed from the columns of X , and T denotes the selected sub columns that correspond to the nonzero index set of the convoluted channel vector h . The MSE of the LS estimator $\hat{k}$ is indicated by

$$\hat{k} = X^{\dagger} z = k + X^{\dagger} n \tag{16}$$

3.2. CoSaMP estimator

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

Input: z, X, d the training signal matrix $X = diag(Fx)W$, the maximum number of dominant channel coefficients is assumed as d .

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

Initialization: The index set of nonzero coefficient as $T_0 = \varnothing$, the residual estimation error as $r_0 = z$, and the iteration index as $q = 1$.

Identification: We select a column index n_q of X that is most correlated with the residual

$$n_q = \left|\left\langle r_{q-1}, X_q \right\rangle\right| \ and \ T_q = T_{q-1} \cup n_q \tag{17}$$

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

Merge: The positions of dominant taps are merged by $T_q = T_{LS} \cup T_q$.

Estimation: The best coefficient for approximating the channel vector with chosen columns is computer as

$$k_q = \arg\min_k \left\| z - X_{T_0} k \right\|_2 \tag{18}$$

Pruning: The T_q largest channel coefficients are selected, as follows:

$$k_q = [k]_d \tag{19}$$

and the left taps $T \setminus T_q$ are replaced by zero.

Iteration: The estimation error is updated, as follows:

$$r_q = z - X_{r_q} k_q \tag{20}$$

The iteration counter k is incremented. Equations (16) to (19) are repeated until the stopping criterion holds. Then $\hat{k}_{CoSaMP} = k_q$ is set.

3.3. Adaptive compressed channel estimation

This section describes the proposed sparsity adaptive expectation maximization (SAEM) algorithm illustrated in **Fig. 1.** Two major blocks exist: The Kalman equalization block and the expectation maximization (EM)–based channel information estimation algorithm block. The Kalman equalization block receives the channel information, i.e., the estimated values of k. Then, it provides the soft information of transmitted signals to the EM-based channel information estimation blocks. The details of the algorithm are explained in **Fig. 1**.

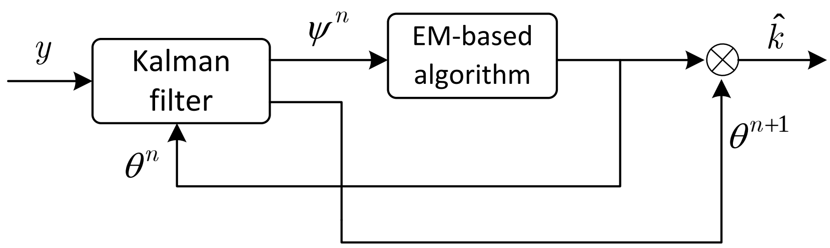

Fig. 1. Block diagram of the sparse channel estimator

The time-variant channel k can be expressed as

$$k_n = k_{n-1} + w_{n,\Delta_0} = k_0 + \sum_{i=1}^{n} w_{i,\Delta_0} \tag{21}$$

Where $k_0 \sim (\bar{k}_0, \sigma_0^2 I_{\Delta_0})$ and Δ_0 denotes the set of the nonzero coefficients of k. The noise vector w_{n,Δ_0} is zero mean Gaussian inside Δ_0, of which the diagonal covariance matrix is $C_{n,\Delta_0} = diag\left[\sigma_{w_1}^2(n), \cdots, \sigma_{w_d}^2(n)\right]$.

We incorporate Equation (14) and the convex program (11) into the EM framework. The resulting adaptive algorithms employ one-time update for computational purposes. We let $\theta = \bar{k}_0$ be the vector of unknown parameters. Under the Gaussian assumption postulated, minimization of (14) is equivalent to maximization of the log-likelihood $p(y_n | \theta)$ augmented by ℓ_1 penalty. To apply the EM method, we have to specify the complete and incomplete data.

The vector k_n at time n is taken to represent the complete data vector, whereas y_{n-1} accounts for the incomplete data [9]. In this context, the conditional density $p(k_n \mid y_{n-1})$ plays a major role. This density is Gaussian with mean and covariance

$$\psi_n = E[k_n \mid y_{n-1}] \tag{22}$$

$$P_n = E[(k_n - \psi_n)(k_n - \psi_n)^H] = \sigma_0^2 I + \sum_1^n diag\left[\sigma_{q_i}^2(t)\right] \tag{23}$$

Expectation step computes the conditional expectation

$$\begin{aligned} Q(\theta, \hat{\theta}_{n-1}) &= E_{p(k_n | y_{n-1}; \hat{\theta}_{n-1})}\left[\log p(k_n; \theta)\right] \\ &= \delta + \theta \mathrm{P}_n^{-1} \psi_n - \frac{1}{2}\theta^H P_n^{-1} \theta \end{aligned} \tag{24}$$

Where $\log p(k_n;\theta) = \delta - \frac{1}{2}(k_n - \psi(\theta))^H P_n^{-1}(k_n - \psi(\theta))$. .

Maximization step maximizes the Q-function minus the ℓ_1 penalty with respect to θ, as follows:

$$\hat{\theta} = \arg\max_{\theta}\left\{Q(\theta, \hat{\theta}_{n-1}) - \lambda \|\theta\|_{\ell_1}\right\} \tag{25}$$

Maximization of the Q-function leads to the soft thresholding function

$$\hat{k} = \mathrm{sgn}(\psi_n)\left[|\psi_n| - \lambda(\sigma_0^2 + f_n)I\right]_{\max} \tag{26}$$

The parameter ψ_n is recursively computed by the Kalman smoothing algorithm, which can be expressed as follows:

$$\psi_n = k_{n-1} + r_n * (y_n - x_n^T k_{n-1}) \tag{27}$$

4. Simulation results

In this section, the MSE performance of the proposed method with sparsity adaptive expectation maximization (SAEM) algorithm is evaluated by simulations. The performance of the proposed estimators is compared with that of the CoSaMP channel estimator, OMP channel estimator, and oracle channel estimator (LS-based known position of dominant taps). The MIMO relay network with $M_S = M_R = M_D = 2$ antennas is considered. A total of 10^4 symbols are generated; QPSK modulation is used, and the numbers of training symbols and data symbols are set to 200 and 1200, respectively. The number of nonzero taps is set to 3 out of a total of 20 taps for each channel link, the sparse structure of channels does not change during the block, and the positions of nonzero channel taps are generated randomly. The auto regressive (AR) parameters are chosen such that an autocorrelation of fading process derived from Jakes model is closely approximated by an AR process, and the parameters for the Kalman smoother are chosen accordingly. 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 $10\log\left(P/\sigma_n^2\right)$.

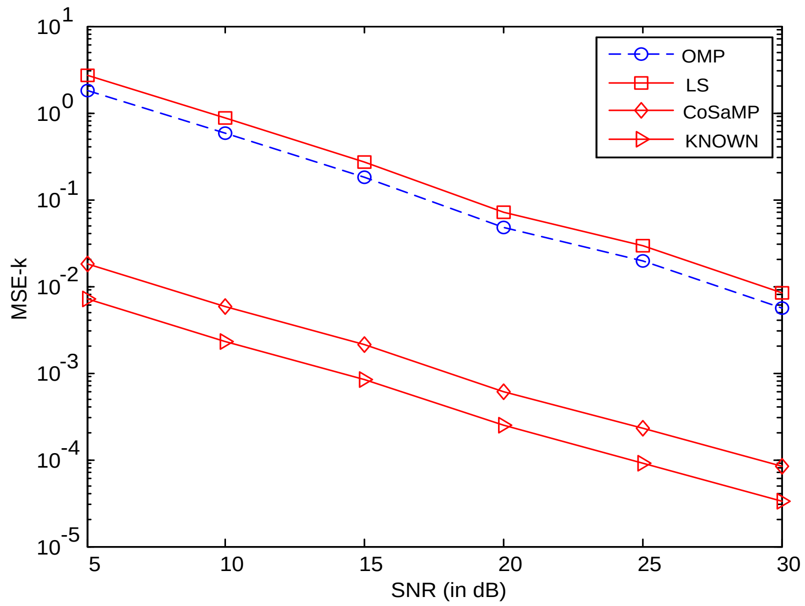

Fig. 2. MSE performance of channel estimation for the case when d=2

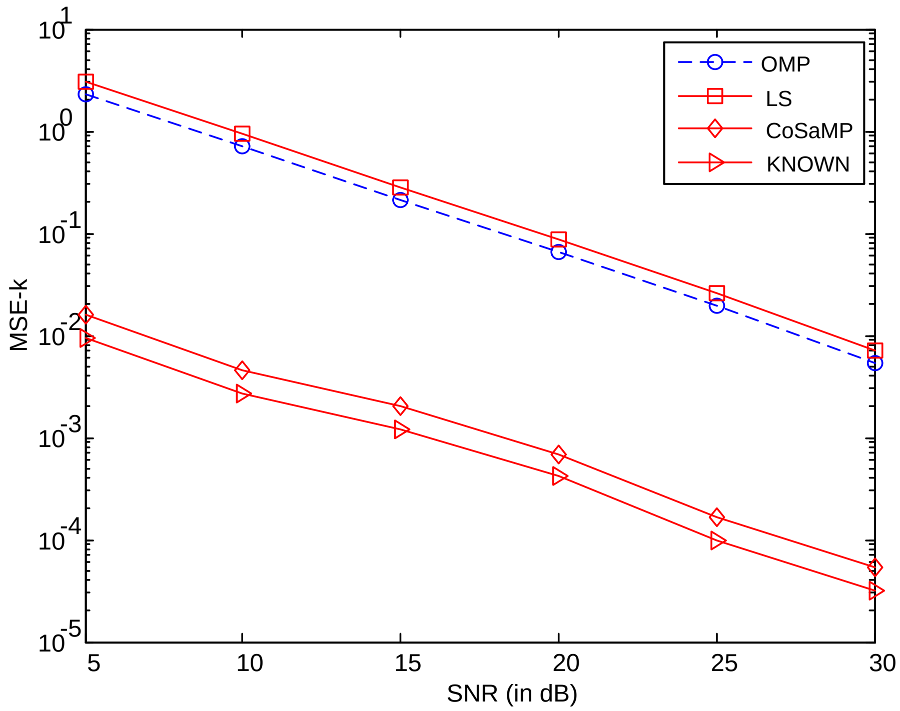

Fig. 3. MSE performance of channel estimation for the case when d=4.

Figs. 2 to **6** show the simulation results when the number of nonzero taps in cooperation channels is changed. These figures show the average MSE performance improves as the SNR increases. **Fig. 2** to **4** based the channel mode (10), and we can see that CS-based method has a small gap to oracle bound but is better than the LS-based linear channel estimation. The CoSaMP algorithm also performed better than OMP.

This study provides MSE performance comparisons of channel estimators versus different channel sparsities. The numbers of dominant channel taps are assumed to be 2 and 4. According to the figures, the LS-based average MSE performances are not changed because the linear channel estimation method neglected channel sparsity. However, the proposed method employed channel structure as for prior information and has a better MSE performance than the LS algorithm. The figures indicate that the fewer the nonzero taps in the channel, the better the MSE performance is.

The performance of the CoSaMP estimator is also compared with that of the ECM estimator algorithm in this section. According to **Fig. 4,** the performance of the proposed compressed channel estimation (CCE) method is considerably better than that of the ECM algorithm when channel impulse responses are sufficiently sparse. However, as the number of nonzero taps of all the channels increases, the performance of CoSaMP gets closer to that of the ECM algorithm.

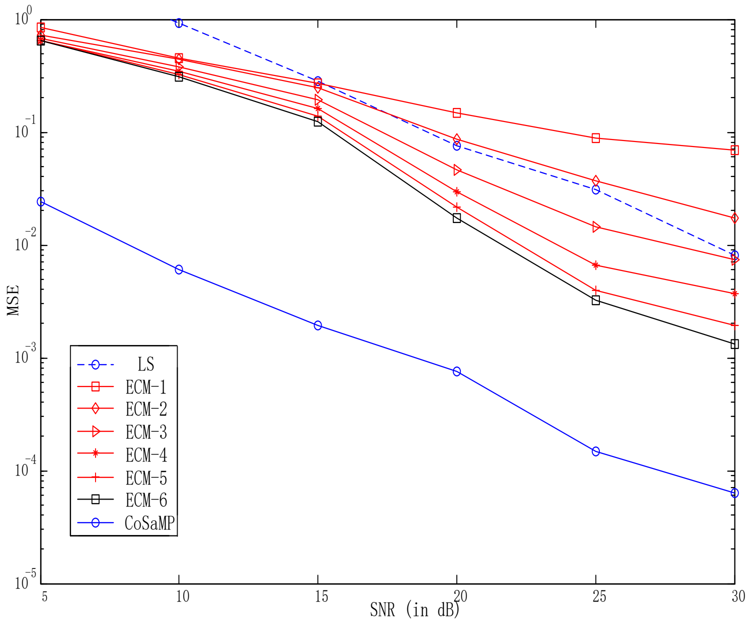

Fig. 4. MSE performance of channel estimation for the case when channel impulse responses are sparse enough

According to **Figs. 5** and **6**, the average MSE performance improves as the SNR increases. The CS-based method has a small gap to oracle bound, but is better than OMP and sparsity adaptive matching pursuit (SAMP) algorithm [26]. **Fig. 5** presents the normalized MSE versus SNR when the Doppler rate is 0.002. The MSE of the proposed sparse channel estimator is close to the lower bound, which implies that the SAEM channel estimator can detect the sparse structure with reasonably good accuracy. In **Fig. 6**, the performance of the SAEM estimator is compared with that of the CoSaMP estimator algorithm and the proposed channel estimator shows lower normalized MSE compared with the OMP channel estimator.

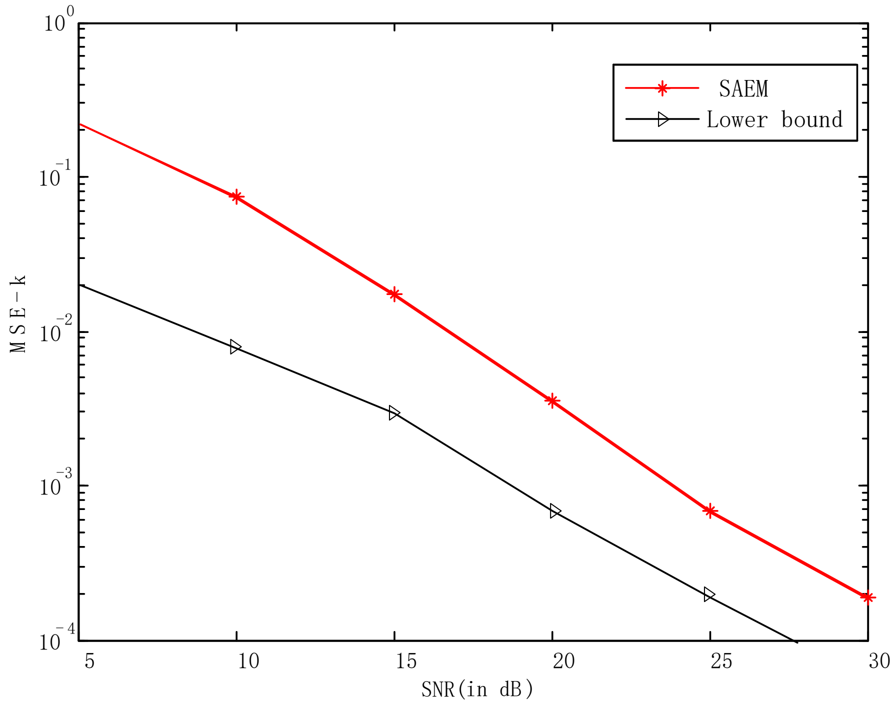

Fig. 5. MSE performance of SAEM

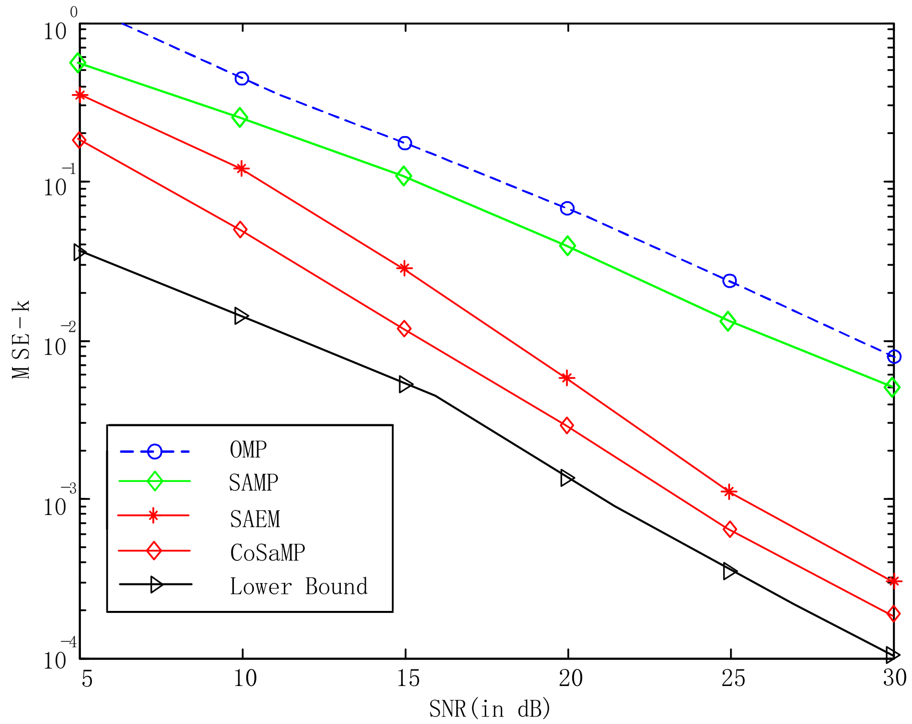

Fig. 6. MSE performance of several channel estimators

5. Conclusion

This study investigated the channel estimation problem in sparse multipath MIMO relay networks. To address the limitations 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, and the proposed CS method CoSaMP exploited the sparsity in the MIMO OWRN channel when the sparsity as a prior. According to the proposed SAEM algorithm in this work, this reconstruction algorithm is most featured of not requiring information of sparsity of target signals as a prior. It not only releases a common limitation of existing greedy pursuit algorithms but also keeps performance comparable with that of strongest algorithm CoSaMP and better than OMP and SAMP. The underlying intuition of SAEM which is similar to that of the EM algorithm is to alternatively estimate the sparsity and the true support set. Extensive experiment results confirm that SAEM is very appropriate for reconstructing compressible sparse signal where its magnitudes are decayed rapidly. The proposed algorithm can be applied in signal receiver by using FPGA and high-speed real-time digital signal processor, which will increase the performance of signal receiver.

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