Sparse Channel Estimation for OFDM Based Two-Way Relay Networks

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Abstract—**In this paper, we present a sparse channel estimation method for orthogonal frequency division multiplexing (OFDM) based two-way relay networks (TWRN). Conventional channel estimation methods, such as least squares (LS), have been proposed to obtain channel state information (CSI) at the cost of the training resource, which reduce spectrum efficiency. However, physical measurements have verified that the wireless channels tend to exhibit sparse structures in high-dimensional spaces, e.g., delay spread, Doppler spread and space spread. With the development of compressive sensing (CS), a novel compressive channel estimation method which is called adaptive compressive matching pursuit (ACMP) algorithm is proposed by using the sparse constraint between the terminal nodes and the relay node in the TWRN. Simulation results confirm that ACMP channel estimation method provides significant improvement in mean square error (MSE) performance compared to the conventional channel estimation methods.**

***Keywords*-two-way relay networks (TWRN); orthogonal frequency division multiplexing (OFDM); compressive sensing (CS); sparse channel estimation**

I. INTRODUCTION

Wireless communications advance in development by leaps and bounds [1, 2]. Relay has been intensively researched due to its capability of enhancing the transmission capacity and providing the spatial diversity for single-antenna wireless transceivers by employing the relay nodes as "virtual" antennas [3, 5]. The relay networks have extended from one-way relay networks [5] where the data streams flow in unidirectional manner to two-way relay networks (TWRN) [6] where the data streams flow in bidirectional manner.

For the TWRN, the transmission period is divided into two phases. During phase I, both source terminals transmit the signal simultaneously using the same resource, and a superposed signal is received at the relay node. In phase II, the relay node broadcasts the superposed signal to both terminals, and each terminal is capable of extracting the desired signal through the network coding process. It was reported that there are two relaying schemes: the *amplify-and-forward* (AF) or the *decode-and-forward* (DF). In [7], the optimal channel estimation and training design for AF-based TWRN in flat-fading environments has been proposed. Due to the advantage of orthogonal frequency division multiplexing (OFDM) [8-12] to compensate for the inter-symbol interference (ISI), the channel estimation method for OFDM modulated AF-TWRN has been proposed [13]. However, the above channel estimation methods for the TWRN are based on the assumption that the wireless channels between the terminals and the relay node are rich multipath [14-15]. In recent years, numerous channel measurements have shown that multipath fading channels tend to exhibit clustering sparse structures in which majority of the channel taps end up being either zero or below the noise floor [16]. The conventional linear channel estimation methods, such as LS, cannot exploit this inherent sparse character and result in the waste of the energy and bandwidth. In other words, if we can make full use of the channel sparsity, the resource utilization will be greatly improved [17]. A compressive channel estimation using compressive sampling matching pursuit (CoSaMP) algorithm [18] was proposed for AF-TWRN. The CoSaMP algorithm has been proved to be one of the most suitable reconstruction algorithms after the full consideration of the channel estimation performance and computational complexity [19]. However, the main drawback is the need for a priori knowledge of the number of channel taps, which is rarely available especially nowadays with the huge proliferation of wireless devices/services and the presence of non-collaborative users [20].

Based on the development of the compressive sensing and our previous researches [21-24], we propose a novel sparse channel estimation method using adaptive compressive matching pursuit (ACMP) algorithm for OFDM-based AF-TWRN. The proposed method does not require the knowledge of the channel sparsity. It is verified by simulations that ACMP algorithm performs better than CoSaMP, whatever the channel estimation accuracy and the computational complexity.

The rest of the paper is organized as follows. Section II introduces the AF-TWRN system model. Section III is devoted to a detailed descriptions of the proposed sparse channel estimation method. In Section IV, we provide computer simulations results. Finally, conclusions are drawn in Section V.

II. SYSTEM MODEL

Consider a three-node TWRN with two terminals $\mathbb{T}_1$, $\mathbb{T}_2$ and one relay node $\mathbb{R}$ as shown in Fig. 1. One data transmission period is divided into two phases. During phase I, both $\mathbb{T}_1$ and $\mathbb{T}_2$ send their signals concurrently to the relay node $\mathbb{R}$. During phase II, the relay node $\mathbb{R}$ amplifies the received signal and broadcasts it to both terminals $\mathbb{T}_1$ and $\mathbb{T}_2$.

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Each terminal then estimates the channel state information for data detection. Assume that the channel impulse responses between $\mathbb{T}_i(i=1,2)$ and $\mathbb{R}$ are $\mathbf{h}=[h_0,h_1,\cdots,h_{L_1-1}]^T$ and $\mathbf{g}=[g_0,g_1,\cdots,g_{L_2-1}]^T$ which are constant within one transmission period. $L_i(i=1,2)$ is the length of the channel between $\mathbb{T}_i(i=1,2)$ and $\mathbb{R}$. The number of non-zero taps in channel vectors $\mathbf{h}$ and $\mathbf{g}$ is much less than the length of the channel which means that the multipath channels exhibit the sparse structures. The variance of the coefficients in $\mathbf{h}$ and $\mathbf{g}$ are $\sigma_{h,l}^2(l=0,\cdots,L_1-1)$ and $\sigma_{g,k}^2(k=0,\cdots,L_2-1)$. The average transmission powers of $\mathbb{T}_1$, $\mathbb{T}_2$ and $\mathbb{R}$ are denoted as P_1, P_2 and P_r respectively.

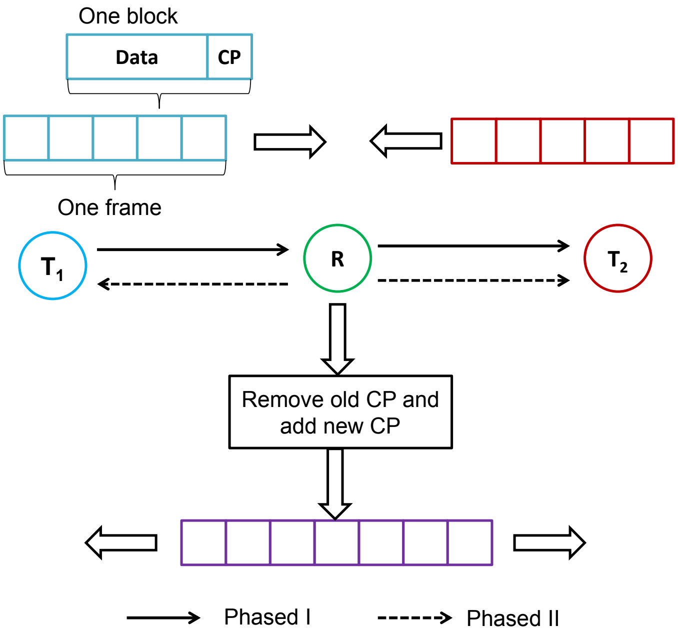


Fig. 1. A typical OFDM based AF-TWRN process

As many sparse channel estimation methods based on compressive sensing have been discussed for conventional point-to-point transmission, the regular method is equivalent to disintegrate the relay process into several point-to-point sections to estimate $\mathbf{h}$ and $\mathbf{g}$ as shown in Fig. 2 [20, 25]. The channel estimation process can be described as follows:

Section 1: $\mathbb{T}_1$ sends its signal to $\mathbb{R}$;
Section 2: $\mathbb{R}$ estimates $\mathbf{h}$, and broadcasts to $\mathbb{T}_1$ and $\mathbb{T}_2$;
Section 3: $\mathbb{T}_2$ sends its signal to $\mathbb{R}$;
Section 4: $\mathbb{R}$ estimates $\mathbf{g}$, and broadcasts to $\mathbb{T}_1$ and $\mathbb{T}_2$;

This way can turn the complex TWRN into several simple point-to-point systems which is easy to understand and implement based on the previous researches achievement. However, it is not recommended for the following reasons:

First, the entire channel estimation process needs to spend two round-trip. The channels between terminal nodes and relay node do not change within one round-trip but vary from round-trip to round-trip, so this way cannot provide accurate channel state information.

Second, the *amplify-and-forward* strategy aims to simplify the process at the relay node. This way requires the relay node be equipped with a channel estimator and feed-back the channel state information which increases the complexity at the relay node.

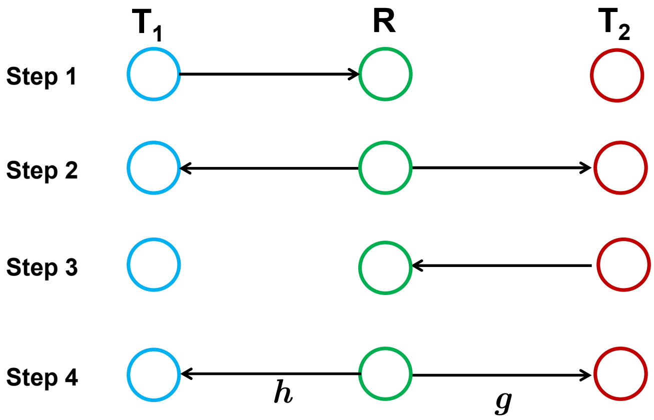


Fig. 2. The disintegration process for AF-TWRN.

For all things considered, it is the best way to estimate the channel state information at the terminal nodes within one round-trip. The entire process can be described as follows:

A. *Phase I Process*

Assume that the transmitted N subcarriers at terminal $\mathbb{T}_i$ is denoted as $\tilde{\mathbf{x}}_i=[\tilde{x}_{i,0},\tilde{x}_{i,1},\cdots\tilde{x}_{i,N-1}]^T$, $i=1,2$. The time-domain signal vector can be obtained by inverse discrete Fourier transformation (IDFT) as

$$\mathbf{x}_i=\mathbf{F}^H\tilde{\mathbf{x}}_i=[x_{i,0},x_{i,1},\cdots x_{i,N-1}]^T. \quad (1)$$

where $\mathbf{F}$ is the discrete Fourier transformation (DFT) matrix with the (p,q)-th entity given by $1/\sqrt{N}\,e^{-j2\pi(p-1)(q-1)/N}$. After the cyclic prefix (CP) insertion, the time-domain signal vector is

$$\mathbf{s}_i=[x_{i,N-L_{CP}},\cdots,x_{i,N-1},x_{i,0},\cdots,x_{i,N-1}] \quad (2)$$

L_{CP} is the length of CP which should satisfied with $L_{CP}>\max\{L_1,L_2\}$. In phase I, both terminals $\mathbb{T}_i(i=1,2)$ send out signal simultaneously. At the relay node $\mathbb{R}$, the received signal after CP removing, can be represented by

$$\mathbf{r}=[r_0,\cdots,r_{N-1}]^T=\mathbf{H}\mathbf{x}_1+\mathbf{G}\mathbf{x}_2+\mathbf{n}_r \quad (3)$$

where $\mathbf{H}$ and $\mathbf{G}$ are the $N\times N$ circulant matrices with the first columns of $[\mathbf{h}^T,\mathbf{0}_{1\times(N-L_1)}]^T$ and $[\mathbf{g}^T,\mathbf{0}_{1\times(N-L_2)}]^T$ respectively. $\mathbf{n}_r=[n_{r,0},n_{r,1},\cdots n_{r,N-1}]^T$ denotes the noise vector whose entries are i.i.d. random variables according to $\mathcal{CN}(0,\sigma_n^2)$.

B. Relay and Phase II Process

For AF mode, the received signal in (3) is amplified by a relay factor β. The typical choice of β is

$$\beta = \sqrt{\frac{P_r}{\sum_{l=0}^{L_1-1}\sigma_{h,l}^2 P_1 + \sum_{k=0}^{L_2-1}\sigma_{g,k}^2 P_2 + \sigma_n^2}}. \tag{4}$$

Finally, $\mathbb{R}$ adds new CP and broadcasts the signal to both source terminals.

Without loss of generality, we only illustrate the process at $\mathbb{T}_1$ while the same process goes at $\mathbb{T}_2$. At the terminal node $\mathbb{T}_1$, the signal after the CP removal is given by

$$\begin{aligned}\mathbf{y} &= \beta\mathbf{H}\mathbf{r} + \mathbf{n}_1 \\ &= \beta\mathbf{H}(\mathbf{H}\mathbf{x}_1 + \mathbf{G}\mathbf{x}_2 + \mathbf{n}_r) + \mathbf{n}_1 \\ &= \beta\mathbf{H}\mathbf{H}\mathbf{x}_1 + \beta\mathbf{H}\mathbf{G}\mathbf{x}_2 + \mathbf{n}_2\end{aligned} \tag{5}$$

$\mathbf{n}_2 = \beta\mathbf{H}\mathbf{n}_r + \mathbf{n}_1$ is an $N\times 1$ complex Gaussian noise, its mean vector is $\mathbf{0}$ and covariance matrix is $\mathrm{E}\{\mathbf{n}_2\mathbf{n}_2^H\} = \sigma_n^2(\beta^2|\mathbf{H}|^2 + \mathbf{I}_N)$. $\mathbf{n}_1$ is complex Gaussian noise according to $\mathcal{CN}(\mathbf{0}_{N\times 1}, \sigma_n^2\mathbf{I}_N)$.

According to the circulant matrix theory, $\mathbf{H}$ and $\mathbf{G}$ can be decomposed as

$$\begin{aligned}\mathbf{H} &= \mathbf{F}^H\mathbf{\Lambda}\mathbf{F} \\ \mathbf{G} &= \mathbf{F}^H\Xi\mathbf{F},\end{aligned} \tag{6}$$

where $\mathbf{\Lambda} = diag\{H_0,\cdots,H_n,\cdots,H_{N-1}\}$ is diagonal matrix with frequency-domain channel coefficients $H_n = \sum_{l=0}^{L_1-1} h_l e^{-j2\pi nl/N}$, and $\Xi = diag\{G_0,\cdots,G_n,\cdots,G_{N-1}\}$ is diagonal matrix with frequency-domain channel coefficients $G_n = \sum_{l=0}^{L_2-1} g_l e^{-j2\pi nl/N}$, $n = 0,\cdots N-1$. Therefore, (5) can be rewritten as

$$\mathbf{y} = \mathbf{F}^H\beta\mathbf{\Lambda}\mathbf{\Lambda}\mathbf{F}\mathbf{x}_1 + \mathbf{F}^H\beta\mathbf{\Lambda}\Xi\mathbf{F}\mathbf{x}_2 + \mathbf{n}_2. \tag{7}$$

According to (5) and (7), it is hard to get $\mathbf{h}$ and $\mathbf{g}$ separately, but we can get their self- and cross- products. Define the convolution impulse response vectors $\mathbf{b} = \beta(\mathbf{h}*\mathbf{h})$ and $\mathbf{c} = \beta(\mathbf{h}*\mathbf{g})$. The length of $\mathbf{b}$ and $\mathbf{c}$ are $(2L_1-1)$ and (L_1+L_2-1). After left-multiplied by $\mathbf{F}$, the signal can be rewritten as

$$\mathbf{Y} = diag(\mathbf{F}\mathbf{x}_1)\mathbf{F}_1\mathbf{b} + diag(\mathbf{F}\mathbf{x}_2)\mathbf{F}_2\mathbf{c} + \mathbf{n}, \tag{8}$$

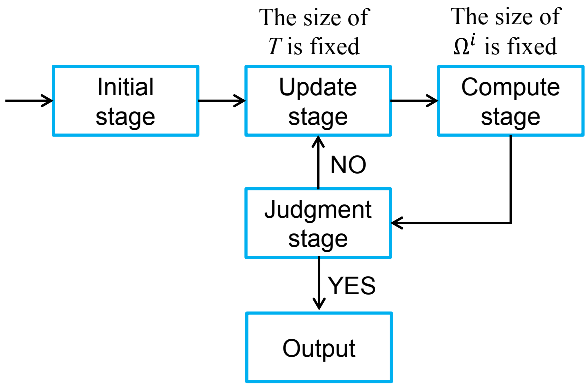
where $\mathbf{F}_1$ and $\mathbf{F}_2$ are the first $(2L_1-1)$ and (L_1+L_2-1) columns of $\mathbf{F}$. $\mathbf{n} = \beta\mathbf{\Lambda}\mathbf{F}\mathbf{n}_r + \mathbf{F}\mathbf{n}_1$ is the complex Gaussian random vector whose mean vector is $\mathbf{0}$ and covariance matrix is $\mathrm{E}\{\mathbf{n}\mathbf{n}^H\} = \sigma_n^2(\beta^2|\mathbf{\Lambda}|^2 + \mathbf{I}_N)$. For simplicity, equation (8) can be expressed as

$$\mathbf{Y} = \mathbf{X}_1\mathbf{b} + \mathbf{X}_2\mathbf{c} + \mathbf{n}, \tag{9}$$

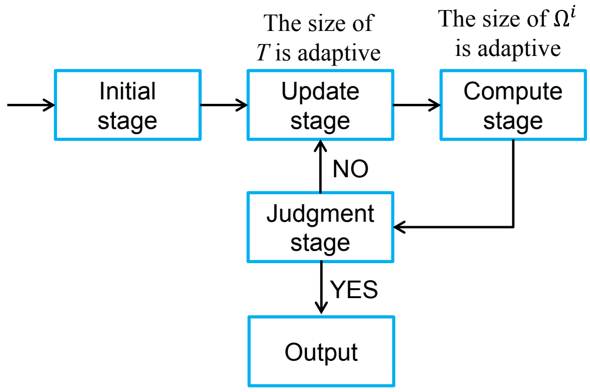
where $\mathbf{X}_i = diag(\mathbf{F}\mathbf{x}_i)\mathbf{F}_i$, $(i = 1,2)$ denotes the virtual training signal matrices. We define $\mathbf{X} = [\mathbf{X}_1, \mathbf{X}_2]$ and $\boldsymbol{\theta} = [\mathbf{b}^T, \mathbf{c}^T]^T$ so that (9) can be written as

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\theta} + \mathbf{n}, \tag{10}$$

So far we have turned the problem of solving two variables ($\mathbf{h}$ and $\mathbf{g}$) to the problem of solving one variable ($\boldsymbol{\theta}$). What is more, the system model like equation (10) is suitable for spare channel estimation using compressive sensing.



(a) The process of the CoSaMP.



(b) The process of the proposed algorithm (ACMP).

Fig. 3. The Comparison of the CoSaMP algorithm and ACMP algorithm

III. COMPRESSIVE CHANNEL ESTIMATION

A. Overview of Compressive Sensing

Compressive sensing aims to recover the high dimensional sparse signals with considerably fewer linear measurements. So far compressive sensing theory has been successfully applied in several fields, such as imaging, radar and signal processing [17]. The detailed descriptions can be found in [26-28]. In this paper, we consider the following linear model:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\theta} + \mathbf{n}, \tag{11}$$

where $\mathbf{Y}$ denotes the $P\times 1$ observation vector and $\mathbf{X}$ denotes the $P\times Q$ known measurement matrix. $\mathbf{n}$ is the stochastic noise. $\boldsymbol{\theta}$ denotes the unknown $Q\times 1$ sparse vector with the nonzero entities $S(S \ll Q)$. The process of compressive sensing recovery is to reconstruct the sparse vector $\boldsymbol{\theta}$ in terms of $\mathbf{Y}$, $\mathbf{X}$ and the sparsity S. In addition, the recovery algorithms have been proved that recovery $\boldsymbol{\theta}$ reliably depends on some property of the measurement matrix $\mathbf{X}$ and the sparsity of S. The property of the $\mathbf{X}$ is called restricted isometry property (RIP) [26]. The basic definition of the RIP is given as follows:

Definition 1 (Restricted Isometry Property) Suppose that $\mathbf{X}$ is an $P \times Q$ measurement matrix which can satisfy the following inequality in order of S with parameter $\delta_S \in (0,1)$:

$$(1-\delta_S)\|\boldsymbol{\theta}\|_2^2 \le \|\mathbf{X}\boldsymbol{\theta}\|_2^2 \le (1+\delta_S)\|\boldsymbol{\theta}\|_2^2 \quad (12)$$

for all sparse vectors $\boldsymbol{\theta}$ having no more than S nonzero coefficients. Where $\|\boldsymbol{\theta}\|_2^2 = \sum_{i=1}^{Q}|\theta_i|^2$ denotes the l_2 norm. While it is a complicated issue to identify whether the matrix $\mathbf{X}$ satisfies the RIP, it is proved that many kinds of matrix satisfy the RIP with high probability. As [27] shows, the matrices, such as random Gaussian, Bernoulli, and partial Fourier matrices, obey the RIP with high probability.

TABLE I. THE PROCESS OF THE ACMP ALGORITHM

Input: $\boldsymbol{Y}$ and $\boldsymbol{X}$
Output: Channel estimator $\hat{\boldsymbol{\theta}}$.
$\Omega^0 \leftarrow \emptyset$;
$\boldsymbol{r}^0 \leftarrow \boldsymbol{Y}$;
$i \leftarrow 1$;
$j \leftarrow 1$.
while $\|\boldsymbol{w}_j^i - \boldsymbol{h}\|_2^2 \le 0.1 * 10^{-SNR/20}$ **do**
  $i \leftarrow i+1$;
  $\boldsymbol{u}_i \leftarrow \boldsymbol{X}^* \boldsymbol{r}^{i-1}$;
  $S^i \leftarrow \mathrm{supp}(|\boldsymbol{u}_i|, j)$;
  $\hat{\theta}_j^i \leftarrow \boldsymbol{X}_T^{\dagger} \boldsymbol{Y}$;
  $\Omega^i \leftarrow \mathrm{supp}(|\hat{\theta}_j^i|_T|, j)$;
  $\hat{\theta}_j^i|_{(\Omega^i)^c} \leftarrow 0$;
  $\boldsymbol{r} = \boldsymbol{Y} - \boldsymbol{X}_{\Omega^i}\hat{\boldsymbol{\theta}}_j^i|_{\Omega^i}$;
  if *stopping criterion is true* **then**
    $\hat{\boldsymbol{\theta}} = \hat{\boldsymbol{\theta}}_j^i|_T$;
  else
    $\boldsymbol{r}_i \leftarrow \boldsymbol{r}$;
    $j \leftarrow j+1$;
  end
end

B. Compressive Channel Estimation

As the channel impulse responses $\mathbf{h}$ and $\mathbf{g}$ are sparse, their self- and cross- products $\mathbf{b}$ and $\mathbf{c}$ have been verified to be sparse or approximate sparse [29]. Based on the equation (10), compressive channel estimation with ACMP algorithm is carried out without the prior knowledge of the number of the non-zero taps of the channel (the channel dominant taps). The ACMP algorithm is a kind of iterative algorithm which updates the number of non-zero taps stage by stage until the stopping criterion is satisfied. It adopts the similar process to the CoSaMP algorithm to refine the support set during each iteration. The biggest advantage is that the optional value of the channel dominant set is an open question in each iteration for the ACMP algorithm. For the CoSaMP algorithm, the selectable range of the channel dominant set is fixed at the first iteration by making use of the prior knowledge of the channel sparsity. In other words, the size of the channel dominant set is adaptive in ACMP algorithm, while it is fixed in CoSaMP algorithm as shown in Fig. 3. The detailed process of the ACMP algorithm is described as Table I.

Remark: $S^i = \mathrm{supp}(|\mathbf{u}_i|, j)$ denotes that S^i is the index set of the maximum j channel coefficients in $|\mathbf{u}_i|$. $(\Omega^i)^c$ is the complementary set of Ω^i. $\hat{\boldsymbol{\theta}}_j^i|_{\Omega^i}$ is a vector consisted of the elements in the index set Ω^i of $\hat{\boldsymbol{\theta}}_j^i$. The stopping criterion can be set as

$$\left\{ i, j : \begin{matrix} i \ge (3L_1 + L_2 - 2) \\ j \le (3L_1 + L_2 - 2) \end{matrix} \left\| \mathbf{w}_j^i - \mathbf{h} \right\|_2^2 \le 0.1 \times 10^{-SNR/20} \right\}. \quad (13)$$

IV. COMPUTER SIMULATIONS

The theoretical analysis has been deduced in previous section. In this section, we numerically examine the performance of the proposed compressive channel estimation method using ACMP algorithm. We only consider the channel estimation at $\mathbb{T}_1$. Assume that the system parameters are constant within an OFDM frame. The channel lengths between $\mathbb{T}_i (i=1,2)$ and $\mathbb{R}$ is $L_1 = L_2 = 32$, and the number of channel nonzero taps is 4, which means that the channels from $\mathbb{T}_i (i=1,2)$ to $\mathbb{R}$ are totally sparse. Fix $2P_1 = 2P_2 = P_r$ and define the signal to noise ratio (SNR) at $\mathbb{T}_i (i=1,2)$ as $10\log(P_i/\sigma_n^2)$ and SNR at relay node $\mathbb{R}$ as $10\log(P_r/\sigma_n^2)$. The length of OFDM block is assumed as $N = 64$. We adopt the mean square error (MSE) to quantize the channel estimation error. The MSE is expressed as

$$e_{MSE} = \frac{1}{M}\sum_{m=1}^{M}\left\|\mathbf{h} - \hat{\mathbf{h}}_m\right\|_2^2, \quad (14)$$

where M is the number of Monte Carlo simulation runs.

We give the MSE performance comparisons of the proposed channel estimation method-ACMP, CoSaMP and the LS-based linear channel estimation method under SNR ranged from 0dB to 30dB. In Fig. 4, the average MSE performance gets better as the SNR increases. One can see clearly that the CS-based channel estimation methods have better performance than LS-based linear method. In addition, the ACMP algorithm which does not need the prior knowledge of the channel sparsity has almost the same performance as the CoSaMP algorithm which requires the number of channel taps as the priori knowledge.

As the core algorithms of the ACMP and the CoSaMP in each iteration are almost the same (LS), their computational complexity belongs to the same order of magnitude. The process of the CS-based channel estimation methods is a little more complex than that of LS but still within acceptable limits. Table II gives the comprehensive comparison of these three methods from the point of the channel estimation precision, computational complexity, and whether need of prior knowledge.

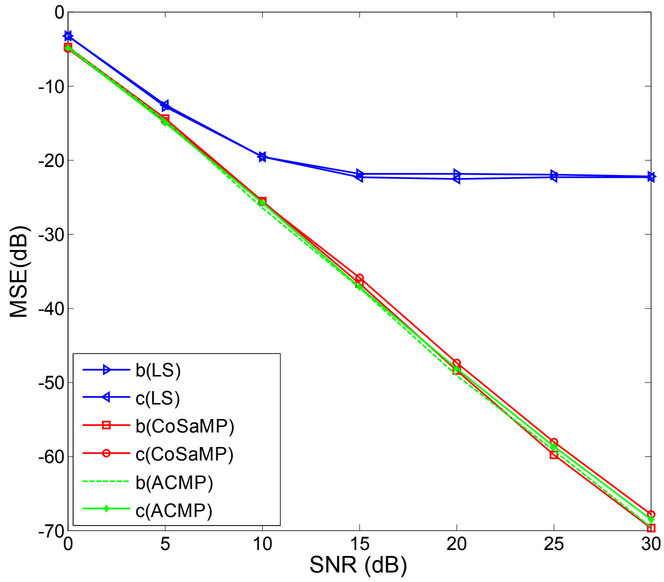


Fig. 4. MSE performance of b and c versus SNR.

TABLE II. THE COMPREHENSIVE COMPARISON OF LS, COSAMP, AND ACMP.

	ESTIMATION PRECISION	COMPUTATIONAL COMPLEXITY	PRIOR KNOWLEDGE
LS	bad	good	needless
COSAMP	good	moderate	need
ACMP	good	moderate	needless

V. CONCLUSION

In this paper, we developed a new compressive channel estimation method for OFDM based two-way relay systems. By using the channel sparsity, an effective compressive sensing recovery algorithm was introduced. This CS-based channel estimation method simplifies the process of the conventional LS channel estimation method, and turns the solution of the complicated channel impulse responses to the solution of their relatively simple self- and cross- products. In addition, as its name suggests, the ACMP algorithm can keep the performance comparable with one of the most suitable algorithms, such as CoSaMP, without the prior knowledge of the channel sparsity. Simulation results demonstrate the effectiveness of the proposed method for OFDM based two-way relay systems.

ACKNOWLEDGMENT

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