

Research Article

Sparse Channel Estimation for Dual-Hop Amplify-and-Forward Cooperative Communication Systems

¹Guan Gui, ^{2,3}Aihua Zhang, ⁴Aihua Kuang and ¹Wei Peng

¹Department of Communication Engineering, Graduate School of Engineering, Tohoku University, Sendai, 980-8579, Japan

²School of Information Engineering, Zhengzhou University, Zhengzhou, 450001, China

³School of Electronic and Information Engineering, Zhongyuan University of Technology, Zhengzhou, 450007, China

⁴Department of Electronics, School of Electronics and Information Engineering of Zhengzhou, Zhengzhou, 450007, China

Abstract: Cooperative transmission is one of key techniques which can improve system capacity and transmit range with limit power in the next-generation communication systems. However, accurate Channel State Information (CSI) is necessary at the destination for coherent detection. Consider a Dual-Hop Amplify-and-Forward (DHAF) Cooperative Communication System (CCS), traditional linear channel estimation method, e.g., Least Square (LS), based assumption of the rich multipath cascaded channel, is robust and simple while at the cost of low spectrum efficiency. Recent channel measurements have shown that the wireless channel exhibits great sparse in some high-dimensional space. In this study, we confirmed that cascaded channel exhibits sparse distribution if the two individual channels are sparse by using representative simulation results. Later, we propose an efficient sparse channel estimation method to take advantage of the inherent sparse prior information in DHAF CCS. Simulation results confirm the superiority of our proposed methods over LS-based linear channel estimation method.

Keywords: Cascaded channel, Compressive Sensing (CS), Cooperative Communication Systems (CCS), Dual-Hop Amplify-and-Forward (DHAF), Sparse Channel Estimation (SCE)

INTRODUCTION

Relay-based cooperative communication (Cover *et al.*, 1979; Laneman *et al.*, 2004; Yiu *et al.*, 2006; Gao *et al.*, 2008) has been intensively studied in the last decades due to its capability of enhancing the transmission capacity and providing the spatial diversity for single-antenna receivers by employing the relay nodes as virtual antennas. It is well known that utilizing Multiple Input Multiple Output (MIMO) transmission can boost the channel capacity (Telatar, 1999; Goldsmith *et al.*, 2003). In addition, MIMO diversity techniques can mitigate fading and hence enhance the Quality of Service (QoS) (Tarokh *et al.*, 1998; Alamouti, 1998). However, it is very hard to integrate multiple antennas onto a small handheld terminal. To resolve the contradiction between them, one could choose relay-based cooperative communication techniques which have been investigated in last decade years (Cover *et al.*, 1979; Gao *et al.*, 2008). The main reason is that relay nodes in the network can be exploited as diversity antennas, relay nodes can either be

provided by a network operator or be obtained from cooperating terminals of other users.

In the relay network, data transmission is usually divided into two phases as shown in Fig. 1. During phase I, the source broadcasts its own information to relay and destination. During phase II, the relay forwards its received signal to the destination. Usually, there has two kinds of protocols in cooperative networks, one is purely amplify the received signal at relay and forward it to destination, which is termed as Amplify-and-Forward (AF); and the second is to demodulate the received signal and modulated again and retransmit to destination, which is often termed as Decode-and-Forward (DF). Due to coherent detection, accurate Channel State Information (CSI) is required at the destination (for AF) or at both relay and destination (for DF). For DF cooperative networks, the channel estimation methods developed for P2P communication systems can be applied. However, extra computation of channel estimation will increase the computational burden at relay node and broadcasting the estimated channel information will result in further interference at

Corresponding Author: Guan Gui, Department of Communication Engineering, Graduate School of Engineering, Tohoku University, Sendai, 980-8579, Japan

This work is licensed under a Creative Commons Attribution 4.0 International License (URL: <http://creativecommons.org/licenses/by/4.0/>).

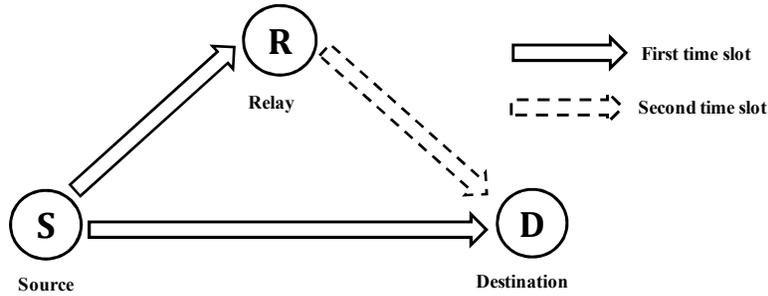


Fig. 1: A typical sparse multipath DHAF CCS

destination. Hence, accurate sparse channel estimation is very critical for multipath fading dual-hop AF CCS. Consider the typical dual-hop AF CCS as shown in Fig. 1, one research object is to estimate the Dual-Hop cascaded channel.

Since the direct link between source node S and destination node D can be estimated easily by using estimation method in Point-to-Point communication (P2P) systems. We omit it here and focus our research on dual cascaded channel estimation in dual-hop AF CCS. Based on the assumption of rich multipath channel, linear channel estimation method has been proposed for the Relay-Based AF CCS (Gao *et al.*, 2008). Even though the estimation method can achieve lower bound of performance, low spectral efficiency is unavoidable due to that large space is allocated to transmit training sequence and relatively small space is left to carry user data. In other words, if an insufficient length training sequence is used, sufficiently accurate channel estimate cannot be obtained.

Fortunately, recent channel measurements have confirmed that the wireless channels often exhibit inherent sparse or cluster-sparse structure in delay-spread domain. Consider the cascaded channel in Two-Way Relay Network (TWRN), several sparse channel estimation methods have been proposed in our previous study (Gui *et al.*, 2012a; Zhang and Yang, 2012). In this paper, unlike the linear estimation method, we propose sparse channel estimation methods in order to take advantages of channel sparsity as for prior information. Comparing with the traditional linear method, our propose method can improve estimation performance or spectrum efficiency. Simulation results will confirm the effectiveness of the proposed methods.

SYSTEM MODEL

Dual-hop AF CCS is shown in Fig. 1. Since frequency-selective multipath channels will generate multiple delayed and attenuated copies of the transmitted waveform. Source and relay are assumed to have average power constraints in P_S and P_R respectively. The L_1 length discrete multipath channel

vector h_1 between source S and relay R is represented by:

$$h_1 = \sum_{l=0}^{L_1-1} h_{1,l}(\tau) \delta(\tau - \tau_{1,l}) \quad (1)$$

where, $h_{1,l}$ and $\tau_{1,l}$ denote the complex-valued path gain with $E[\sum_l |h_{1,l}|^2] = 1$ ($E[\cdot]$ denotes the expectation operation) and the symbol-spaced time delay of the l^{th} path, respectively. According to the channel model in Eq. (1), a N -dimensional (complex) signal x transmitted in equivalent complex cooperative channel leads to a received signal at the relay given by (Proakis, 2001):

$$y_1 = h_1 x + n_1 \quad (2)$$

where, H_1 is an $N \times N$ circulant channel matrix with $[h_1^T \ 0_1 \times (N-L)]^T$ as its first column, n_1 represents the complex Additive Gaussian White Noise (AWGN) with zero-mean and covariance matrix $\sigma_n^2 \mathbf{1}_N$ ($\mathbf{1}_N$, denotes a $N \times N$ identity matrix). Due to the same channel property as Eq. (1), channel vector h_2 between relay node R and destination node D can be written as:

$$h_2 = \sum_{l=0}^{L_2-1} h_{2,l}(\tau) \delta(\tau - \tau_{2,l}) \quad (3)$$

where, $h_{2,l}$ and $\tau_{2,l}$ denote the complex-valued path gain with $E[\sum_l |h_{2,l}|^2] = 1$ and the symbol-spaced time delay of the l^{th} path, respectively. Hence, the received signal vector at the destination node D can be given by:

$$y_2 = \beta H_2 y_1 + n_2 = \beta H_2 H_1 X_1 + n \quad (4)$$

where, $n = \beta H_2 Y_1 + n_2$ is the composite noise with zero mean and covariance matrix $(\beta^2 |H_2|^2 + \mathbf{1}_N) \sigma_n^2$, where, $\mathbf{1}_N$ is an $N \times N$ identity matrix and the amplified positive coefficient β is given by:

$$\beta = \sqrt{\frac{P_R}{\sigma_h^2 P_S + \sigma_n^2}} \quad (5)$$

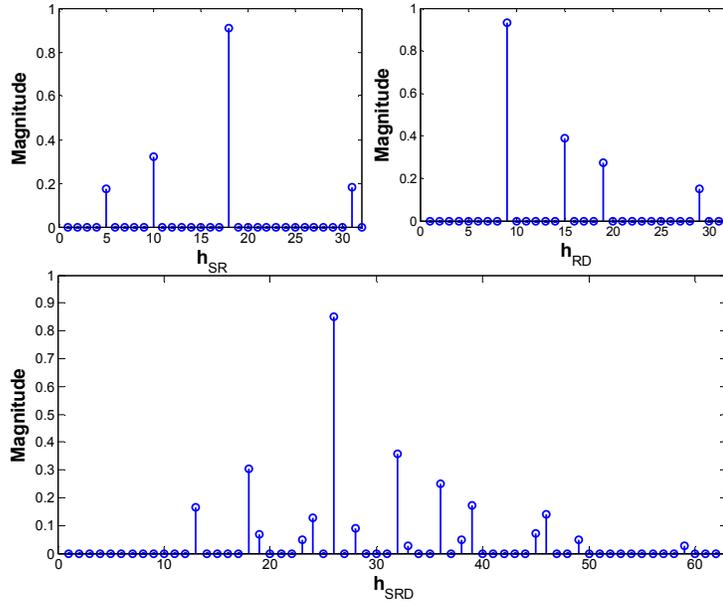


Fig. 2: Two individual channels and its cooperative channel. The numbers of dominant channel taps of individual channels are 4

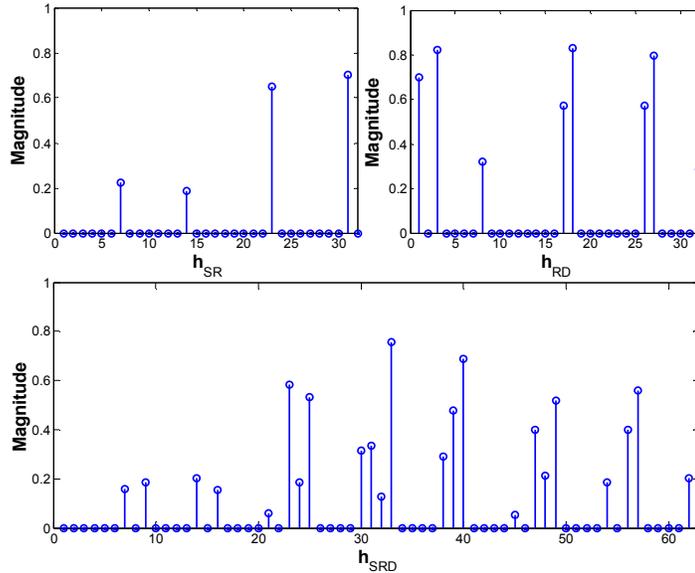


Fig. 3: Two individual channel channels and its cascaded channel. The numbers of dominant channel taps are 4 and 8, respectively

According to the matrix theory (Gray, 2006), circulant channel matrices H_1 and H_2 can be decomposed as $H_1 = W^H \Lambda_1 W$ and $H_2 = W^H \Lambda_2 W$, respectively, where, W is the (unitary) Discrete Fourier Transform matrix (DFT) with $W^{mn} = 1/\sqrt{N} e^{-j2\pi mn/N}$, $m, n = 0, 1, \dots, N-1$. Hence, system model (4) can be rewritten as:

$$y_2 = W^H \beta \Lambda_2 \Lambda_1 W x + n \quad (6)$$

If the (6) is left-multiplied by W , then it can yield:

$$y = Xh + \hat{n} \quad (7)$$

where,
 $h = \beta(h_2 * h_1)$: The dual-hop cascaded channel vector
 $X = \text{diag}(WX)F$: The equivalent training signal matrix
 F : A partial DFT matrix taking the first $(2L-1)$ columns of \sqrt{NW}

$\hat{n} = \Lambda_2 W n_2 + W n_2$: A realization of a complex Gaussian random vector with zero mean and covariance matrix of $(\beta^2 |\Lambda|^2 + 1_N) \sigma_n^2$

By using Maximum Likelihood (ML) algorithm, coherent detection at destination is then obtained by:

$$\tilde{X} = \arg \max_x P(y|X) = \arg \max_x \frac{1}{\pi \sigma_n^2 (\beta^2 |h_1|^2 + 1)} \times \exp \left\{ -\frac{|y-xh|^2}{\sigma_n^2 (\beta^2 |h_1|^2 + 1)} \right\} = \arg \max_x |y-xh|^2 \quad (8)$$

For coherent detection in dual-hop AF CCS, destination node D performs the ML detection well if we can obtain cascaded channel estimator. In my previous study (Gui *et al.*, 2012b), we have confirmed that the cascaded channel exhibits sparse by using sparse measure function (Hoyer, 2004). To simplify our discussion, we only give two typical examples to show the sparse property of the cascaded channel h in the CCS. In Fig. 2, we set the channel length of h_i , $i = 1, 2$ is $L_1 = L_2 = 32$ with number of nonzero taps $K_1 = K_2 = 4$. It is easy found that its cascaded channel h is sparse. If we reset nonzero number of the h_2 as $K_2 = 8$, the cascaded channel still keeps sparse in the Fig. 3. Hence, sparse channel estimation could be utilized to get the accurate estimation of h .

SPARSE CHANNEL ESTIMATION

Based on the system model in Eq. (7), the optimal sparse channel estimator \tilde{h}_{opt} is given by Candes *et al.* (2006) and Donoho (2006):

$$\tilde{h}_{opt} = \arg \min_h \left\{ \frac{1}{2} \|y - xh\|_2^2 + \lambda \|h\|_0 \right\} \quad (9)$$

where,

λ : A regularized parameter which tradeoffs the estimation error and sparsity of h

$\|h\|_2^2$: The ℓ_2 -norm which is given by $\|h\|_2^2 = \sum |h_i|^2$

$\|h\|_0$: ℓ_0 -norm which counts the number of nonzero coefficients

Unfortunately, Eq. (10) is nonconvex optimization problem and is NP-hard (Donoho, 2006). In other words, optimal sparse estimators are unlikely to be calculated efficiently. However, numerous practical suboptimal algorithms exist for the cascaded channel h if the training measurement matrix satisfies the Restricted Isometry Property (RIP) (Candes, 2008). Usually, these sub-optimal algorithms can be classified in two kinds. The first kind is greedy algorithms such as Orthogonal Matching Pursuit (OMP) (Tropp and Gilbert, 2007) and Compressive Sampling Matching

Pursuit (CoSaMP) (Needell and Tropp, 2009), which select each nonzero tap in channel by iteration. The second kind is convex relation methods such as Lasso (Ribshirani, 1996). Here we also consider the LS channel estimator (known channel position of h) for comparison. The lower bound of h is given by:

$$h_b = \begin{cases} X_T^\dagger y, & T \subseteq \text{supp}(h) \\ 0, & \text{others} \end{cases} \quad (10)$$

where,

$\text{supp}(h)$: The nonzero taps supporting the channel vector h

X_T : The sub matrix constructed from the columns of X

T : The selected sub columns corresponding to the nonzero index set of the cascaded channel vector h

The Normalized Mean Square Error (NMSE) of LS estimator \tilde{h} is given by:

$$NMSE(\tilde{h}) = \sigma_n^2 \text{Tr}\{(X_T^\dagger X_T)^{-1}\} \quad (11)$$

By utilizing CS recovery algorithms for sparse channel estimation, we propose sparse channel estimation for dual-hop AF CCS by using Orthogonal Matching Pursuit (OMP) (Tropp and Gilbert, 2007) and Compressive Sampling Matching Pursuit (CoSaMP) (Needell and Tropp, 2009). They are termed as SCE-OMP and SCE-CoSaMP. Two propose sparse channel estimation methods are described as follows:

SCE-OMP: Given the received signal Y , W and F and x , CCS-OMP estimator performs as follows:

Initialize: Set the nonzero coefficient index set $T_0 = \emptyset$ the residual estimation error $r_0 = Y$ and put the initialize iteration counter as $k = 1$.

Identification: Select a column index n_k of X that is most correlated with the residual:

$$n_k = | \langle r_{k-1}, x_{n_k} \rangle | \text{ and } T_{k-1} \cup n_k \quad (12)$$

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

$$h_k = \arg \min_h \|y - x_{T_k} h\|_2 \quad (13)$$

Iteration: Update the estimation error:

$$r_k = y - x_{T_k} h_k \quad (14)$$

Increment the iteration counter k . Repeat (12)-(14) until stopping criterion holds and then set $\tilde{h}_{OMP} = h_k$.

SCE-CoSaMP: Given the received signal y , the unitary DFT matrix W and F , training signal x (training signal matrix $X = \text{diag}(WX)F$ the maximum number of dominant channel coefficients is assumed as S . The CCS-CoSaMP performs as follows:

Initialization: Set the nonzero coefficient index set $T_0 \neq \emptyset$ the residual estimation $r_0 = y$ and put the initialize iteration counter as $k = 1$.

Taps identification: Select a column index n_k of X that is most correlated with the residual:

$$n_k = \left\langle r_{k-1}, X_n \right\rangle, \text{ and } T_k = T_{k-1} \cup n_k, \quad (15)$$

Using LS method to calculate a channel estimator as $T_{LS} = \arg \min \|y - Xh\|_2$ and select T maximum dominant taps h_{LS} . The positions of the selected dominant taps in this sub step are denoted by T_{LS} .

Taps merge: The positions of dominant taps are merged by $T_k = T_{LS} \cup T_k$.

Taps estimation: Compute the best coefficient for approximating the channel vector with chosen columns:

$$h_k = \arg \min_h \|y - X_{T_k} h\|_2 \quad (16)$$

Taps pruning: Select the T_k largest channel coefficients:

$$h_k = [h]_s \quad (17)$$

and replace the left taps by zeros.

Iteration: Update the estimation error:

$$r_k = y - X_{T_k} h_k \quad (18)$$

Increment the iteration counter k . Repeat 15 to 18 until stopping criterion holds and then set $\tilde{h}_{\text{CoSaMP}} = h_k$.

SIMULATION RESULTS

In this section, we will compare the performance of the proposed estimators with LS-based linear estimator and adopt 1000 independent Monte-Carlo runs for

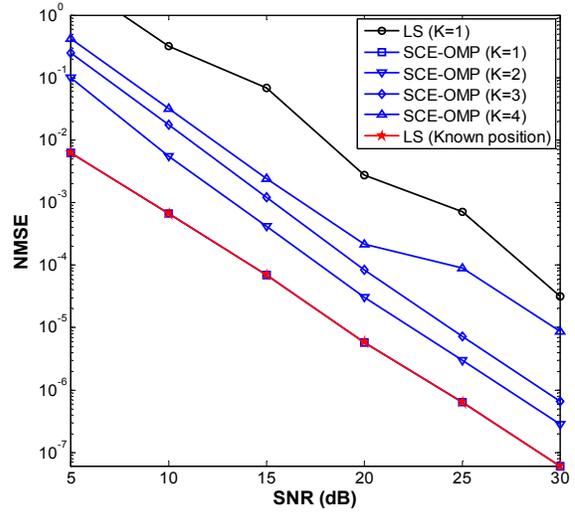


Fig. 4: NMSE performance as a function of SNR

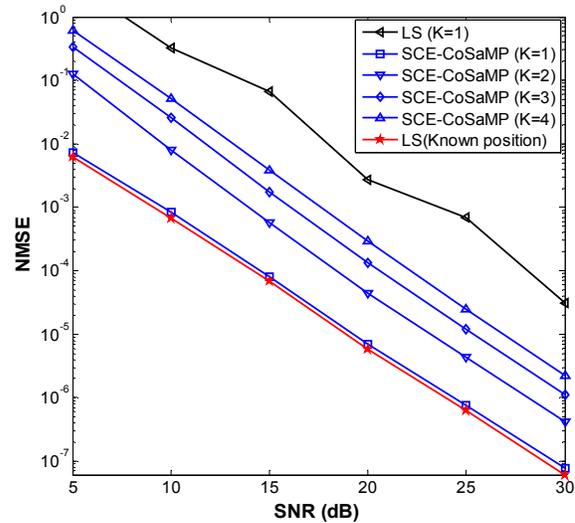


Fig. 5: NMSE performance as a function of SNR

average. The length of training sequence is $N = 64$. All of the nonzero taps of sparse channel vectors h_1 and h_2 are generated following Gaussian distribution and subject to $\|h_1\|_2^2 = \|h_2\|_2^2 = 1$. The length of the two channel is $L_1 = L_2 = 32$ and the positions of nonzero channel taps are randomly generated. Transmit power is set as $P_S = N$ and AF relay power is set as $P_R = N$. The Signal to Noise Ratio (SNR) is defined as $10 \log \left(\frac{p}{\sigma_n^2} \right)$. When the number of nonzero taps of h_i , $i = 1, 2$ is changed, the simulation results are shown in Fig. 3, 4. Channel estimators (LS, SCE-OMP and SCE-CoSaMP) are evaluated by NMSE standard which is defined by:

$$NMSE(\hat{h}) = \frac{E \left\{ \|h - \hat{h}\|_2^2 \right\}}{\|h\|_2^2}, \quad (19)$$

where, h and \hat{h} denote cascaded channel vector and its estimator, respectively. In Fig. 3, we evaluate the estimation performance of SCE-OMP which works at different channel sparsity. As shown in the Fig. 3, the estimation performance of the proposed SCE-OMP estimators is much better than LS estimator and is close to the lower bound by using known position of the channel. Figure 4 and 5 evaluates estimate performance of SCE-CoSaMP which better than LS-based channel estimation method. From the two figures, we can find that the sparser channel is estimated and better estimation performance is obtained.

CONCLUSION

In this study, we have investigated sparse channel estimation problem for dual-hop AF CCS. Unlike the conventional linear channel estimation methods, we proposed sparse channel estimation method by using OMP and CoSaMP algorithm. The cascaded channel is confirmed sparse if its two individual channels satisfy sparse. The proposed methods can take advantage of cascaded channel sparsity well. Simulation results have confirmed the performance superiority of the proposed method over the conventional linear LS method.

REFERENCES

Alamouti, S., 1998. A simple transmit diversity technique for wireless communications. *IEEE J. Select. Areas Commun.*, 16(8): 1451-1458.

Candes, E., J. Romberg and T. Tao, 2006. Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information. *IEEE T. Inform. Theor.*, 52(2): 489-509.

Candes, E.J., 2008. The restricted isometry property and its implications for compressed sensing. *Comptes. Rendus. Math.*, 1(346): 589-592.

Cover, T.M. and A.A. El Gamal, 1979. Capacity theorems for the relay channel. *IEEE T. Inform. Theor.*, 25(5): 572-584.

Donoho, D.L., 2006. Compressed sensing. *IEEE T. Inform. Theor.*, 52(4): 289-1306.

Gao, F., T. Cui and A. Nallanathan, 2008. On channel estimation and optimal training design for amplify and forward relay networks. *IEEE Trans. Wireless Commun.*, 7(5): 1907-1916.

Goldsmith, A., S.A. Jafar, N. Jindal and S. Vishwanath, 2003. Capacity limits of MIMO channels. *IEEE J. Select. Areas Commun.*, 21(5): 684-702.

Gray, R.M., 2006. Toeplitz and circulant matrices: A review. *Foundat. Trends Commun. Inform. Theor.*, 3(2): 155-239.

Gui, G., Q. Wan and F. Adachi, 2012a. Compressed channel estimation of two-way relay networks using mixed-norm sparse constraint. *Res. J. Appl. Sci. Eng. Technol.*, 4(15): 2279-2282.

Gui, G., P. Wei, A. Mehbodniya and F. Adachi, 2012b. Compressed channel estimation for sparse multipath non-orthogonal amplify-and-forward cooperative networks. *IEEE 75th Vehicular Technology Conference*, Yokohama, Japan.

Hoyer, P.O., 2004. Non-negative matrix factorization with sparseness constraints. *J. Mach. Learn. Res.*, 5: 1457-1469.

Laneman, J.N., D.N.C. Tse and G.W. Wornell, 2004. Cooperative diversity in wireless networks: Efficient protocols and outage behavior. *IEEE T. Inform. Theor.*, 50(12): 3062-3080.

Needell, D. and J.A. Tropp, 2009. CoSaMP: Iterative signal recovery from incomplete and inaccurate samples. *Appl. Computat. Harmonic Anal.*, 26(3): 93-100.

Proakis, J.G., 2001. *Digital Communications*. 4th Edn., McGraw-Hill, New York.

Ribshirani, T., 1996. Regression shrinkage and selection via the lasso. *J. Royal Statist. Soc. (B)*, 58(1): 267-288.

Tarokh, V., N. Seshadri and A.R. Calderbank, 1998. Space time codes for high data rate wireless communication: Performance criterion and code construction. *IEEE T. Inform. Theor.*, 44(2): 744-765.

Telatar, E., 1999. Capacity of multi-antenna gaussian channels. *Europ. Trans. Telecommun.*, 10(6): 585-595.

Tropp, J.A. and A.C. Gilbert, 2007. Signal recovery from random measurements via orthogonal matching pursuit. *IEEE T. Inform. Theor.*, 53(12): 4655-4666.

Yiu, S., R. Schober and L. Lampe, 2006. Distributed space-time block coding. *IEEE Trans. Commun.*, 54(7): 1195-1206.

Zhang, A.G. and S. Yang, 2012. Compressive channel estimation for ofdm cooperation networks. *Res. J. Appl. Sci. Eng. Technol.*, 4(08): 897-901.