Data Detection of Amplify-and-Forward User Cooperation in MIMO Broadcasting Systems without Channel State Information Feedback

Shih-Jung Lu, Ronald Y. Chang, and Wei-Ho Chung*
Research Center for Information Technology Innovation, Academia Sinica, Taipei, Taiwan
*E-mail: whc@citi.sinica.edu.tw

***Abstract*—In this paper, we consider the broadcasting of data streams from a multiantenna source to several single-antenna or multiantenna users in a data broadcasting network. To improve the received data quality for all single-antenna users simultaneously while not compromising the data rates of multiantenna users, we propose a new cooperation scheme among single-antenna users. Users cooperate in the amplify-and-forward (AF) mode to jointly detect the spatially multiplexed data streams from the source with estimated channel state information. Simulation results verify the effectiveness of the proposed channel estimation scheme based on very few pilots in conjunction with the maximum likelihood (ML) detection scheme.**

***Index Terms*—Amplify-and-forward (AF) cooperation, MIMO systems, broadcasting, channel estimation, maximum likelihood detection.**

I. Introduction

Cooperative communications gain substantial research interests in recent years due to its capability of improving the performance of physically limited mobile devices. Recent research works [1]– [4] attempt to exploit the cooperation diversity [5] and construct the cooperative multiple-input multiple-output (MIMO) system, where each user shares its antenna with other partners to transmit and decode the data.

In this paper, we consider improving the performance of all single-antenna users through user cooperation in a MIMO broadcasting system. Particularly, we focus on an uncoded system where the base station are equipped with multiple antennas and each user only has a single antenna [6]. We consider using the above setting for the purpose of better representing the physically constrained mobile devices in current real-world scenario. The considered setting is potentially applicable to enabling the multimedia broadcasting services through the current cellular communication systems with hardware-limited mobile devices.

There are two distinguishing features in our considered system, different from the settings considered in the existing works [7]– [11]. The first feature is that our considered single-antenna receivers are to detect multiple data streams without space-time-coding (STC) at the transmitter side. There are several reasons for not considering STC at the transmitter side. One of them is the heterogeneous nature of the real network systems. In the real world, there actually exists multiple-antenna users in the networks, which are already capable of reliably detecting the spatial-multiplexed data streams. Applying STC at the transmitter will limit the acheivable data rate of these users. Another reason is the scalability of the system. For STC, sophisticated design of the codes at the transmitted and corresponding detection at the receivers are essential. However, enlarging the system configuration such as increasing the number of the source antenna will require a re-design of the whole system. Thus, it is reasonable to consider user cooperation in an non-STC coded system.

The second distinguishing feature is that our considered multiple single-antenna receivers are to detect simultaneously the same multiple data streams; thus, the proposed methods must benefit all receivers simultaneously. This is very different from the works in [7], [10], [11], where relays are only to improve the performance of an single user and thus can exploit some existing coding techniques. However, the broadcasting nature of our system becomes the challenge of the cooperation design, since any directional signal processing techniques are not applicable to our system and only simple signal forwarding can be applied.

Another challenge we deal with in this work is the perfect CSI assumption. In most of the existing works assume that the perfect channel knowledge is available. The major reason is that the channel knowledge for cooperation system could be built upon the well-developed channel estimation approach between the individual transmitters and receivers. However, [13] has pointed out that this assumption is not valid for AF relay networks, since separating the channel estimation from the source-relay and the relay-destination links will encounter several drawbacks, including CSI exchange/feedback overhead and the distortions from quantization. As a result, we provide an efficient channel estimate method along with data detection for the AF cooperation system in this work.

This paper is organized as follows. Section II introduces the data broadcasting system model with a multiple-antenna source and multiple single-antenna users. Section III provides a user cooperation scheme where users cooperate in amplify-and-forward (AF) mode to detect the spatial-multiplexed data streams. Section IV investigates the channel estimation and data detection methods for the cooperative system. Section V demonstrates the simulated data detection SER and the channel estimation MSE of the proposed scheme. Section VI concludes this work.

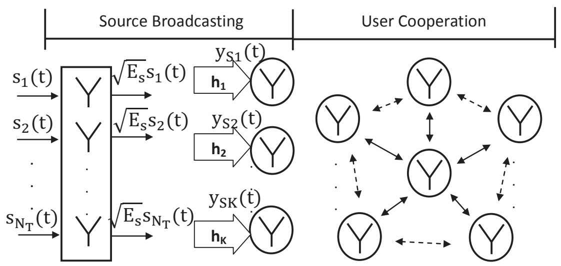

Fig. 1. A broadcasting system with a multiple-antenna source and single-antenna users. The transmission is divided into two phases: the source broadcasting phase and the user cooperation phase. The vector $\mathbf{h}_i = [h_i^{(1)} \; h_i^{(2)} \; \cdots \; h_i^{(N_T)}]$ is the channel vector between the source and the ith user.

II. System Model

We consider a broadcasting system shown in Fig. 1. The source is equipped with N_T antennas and each of the K users is equipped with a single antenna. We assume that the channels are quasi-static flat fading during the transmission of a data frame of length N. For notational consistency, we denote the channel gain from the jth source antenna to the ith user as $h_i^{(j)}$ and the channel gain from the ith user to the kth user as g_{ik}. The transmission is divided into two phases: the source broadcasting phase and the user cooperation phase. In the source broadcasting phase, the source node broadcasts simultaneously its N_T data streams to the K users and we assume that there is no coding applied at the source. The received signal at the ith user in the tth time slots can be expressed as

$$y_{Si}(t) = \mathbf{h}_i \sqrt{E_S}\mathbf{s}(t) + n_{Si}(t), \; i = 1, \ldots, K, \tag{1}$$

where $\mathbf{h}_i = [h_i^{(1)} \; h_i^{(2)} \; \cdots \; h_i^{(N_T)}] \sim CN(0, \sigma_h^2 \mathbf{I}_{N_T})$ and the quantity E_S is the transmit power constraint of each transmit antenna at the source. The vector $\mathbf{s}(t) = [s_1(t) \; \cdots \; s_{N_T}(t)]^T \in \Omega^{N_T \times 1}$ is the data vector of the source at the tth time and the set Ω denotes the modulation constellation set with cardinality of $|\Omega| = M$. The average symbol energy of the symbols in Ω is normalized to unity. The quantity $n_{Si}(t)$ is the additive white Gaussian noise (AWGN) of the ith user with zero mean and variance σ_n^2.

Denote the mth data stream as $\mathbf{s}_m = [s_m(1) \; \cdots \; s_m(N)]$, the received signal vector of the length N data frame is

$$\begin{aligned} \mathbf{y}_{Si} &= [y_{Si}(1) \; \cdots \; y_{Si}(N)] \\ &= \mathbf{h}_i \sqrt{E_S}\mathbf{S} + \mathbf{n}_{Si}, \; i = 1, \ldots, K, \end{aligned} \tag{2}$$

where the matrix $\mathbf{S} = [\mathbf{s}_1^T \; \cdots \; \mathbf{s}_{N_T}^T]^T = [\mathbf{s}(1) \; \cdots \; \mathbf{s}(N)]$ is the data frame of N_T streams and the vector $\mathbf{n}_{Si} = [n_{Si}(1) \; \cdots \; n_{Si}(N)]$ is the AWGN noise vector.

III. Amplify-and-Forward Cooperation

Figure 2 shows the transmission model for users with AF cooperation. In AF cooperation, the L_A selected users ($L_A \geq N_T$) sequentially broadcast their received source signals to all users. These users act as AF relays. Note that any of these users are also destination users when it is not broadcasting.

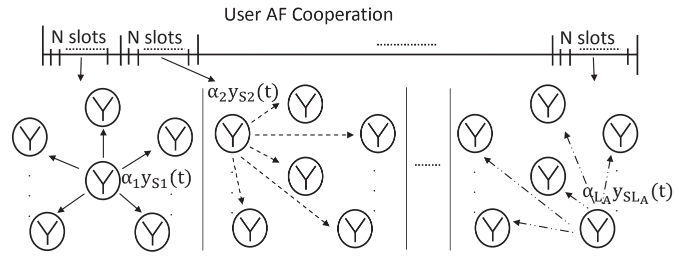

Fig. 2. Transmission model for user cooperation with amplify-and-forward.

After receiving the signals, each user may perform ML or linear detection and obtain its own detection of the source data. The L_A broadcasting users are arbitrarily selected. The selection algorithm may be further improved by selecting the L_A users with the better overall SER benefits based on the CSIs. However, this requires huge amount of computations and signalings between the cooperative users, which can be considered as future directions of research. At current stage, we only consider the arbitrary user selections. Assume that g_{iD}, the channel from the ith broadcasting user to user D remains constant during the broadcasting, the received signal vector is

$$\begin{aligned} \mathbf{y}_{iD} &= g_{iD}\alpha_i \mathbf{y}_{Si} + \mathbf{n}_{iD} \\ &= g_{iD}\alpha_i \mathbf{h_i}\mathbf{S} + (g_{iD}\alpha_i \mathbf{n}_{Si} + \mathbf{n}_{iD}) \end{aligned} \tag{3}$$

where $\alpha_i = \sqrt{E_i / \sum_{j=1}^{N_T} \sigma^2_{h_i^{(j)}}}$ is the power scaling factor applied at the ith broadcasting user to maintain its average transmit power. The vector $\mathbf{n}_{iD}$ is the AWGN noise vector at the user D.

After the broadcastings of all the L_A broadcasting users, the total received signals at user D can be written as

$$\begin{aligned} \mathbf{Y}_D &= [\mathbf{y}_{SD}^T \; \mathbf{y}_{1D}^T \; \cdots \; \mathbf{y}_{L_A D}^T]^T \\ &= \begin{bmatrix} h_{SD}^{(1)} & \cdots & h_{SD}^{(N_T)} \\ g_{1D}\alpha_1 h_1^{(1)} & \cdots & g_{1D}\alpha_1 h_1^{(N_T)} \\ \vdots & \vdots & \vdots \\ g_{L_A D}\alpha_{L_A} h_{L_A}^{(1)} & \cdots & g_{1D}\alpha_{L_A} h_{L_A}^{(N_T)} \end{bmatrix} \mathbf{S} \\ &+ \begin{bmatrix} \mathbf{n}_{SD} \\ g_{1D}\alpha_1 \mathbf{n}_{S1} + \mathbf{n}_{1D} \\ \vdots \\ g_{L_A D}\alpha_{L_A}\mathbf{n}_{SL_A} + \mathbf{n}_{L_A D} \end{bmatrix} \\ &= \mathbf{H}_{eq}\mathbf{S} + \mathbf{n}_{eq}, \end{aligned} \tag{4}$$

where $\mathbf{H}_{eq}$ and $\mathbf{n}_{eq}$ are the equivalent channel and noise matrix, respectively. Note that the first row of $\mathbf{H}_{eq}$ is the direct path from the source to the destinaion, while the other rows are the relay paths from the source through the cooperative users to the destination. To reliably detect the source data, it is required to have the channel state information (CSI) of $\mathbf{H}_{eq}$ at the destination. In the following section, we provide an efficient channel estimation and data detection method achieving near-optimum performance with very few pilot signals.

IV. Channel Estimation and Data Detection

In this section, we investigate the channel estimation and data detection for the AF cooperation system. A least square channel estimation (LSCE) is first introduced to provide an initial estimation of the overall equivalent channel $\mathbf{H}_{eq}$; then the maximum likelihood (ML) data detection is investigated. In the last part of this section, we propose an iterative channel estimation and data detection which efficiently reduced the required pilot use.

A. Least Square Channel Estimation

In the beginning of the length N frame, a length N_P pilot matrix $\mathbf{P}$ is first transmitted for channel estimation. The matrix $\mathbf{P}$ is predefined and known to the users. The remaining $N_data = N - N_P$ time slots are used for data transmission. The transmitted frame is therefore written as $\mathbf{S} = [\mathbf{P}\ \mathbf{S}_{data}]$. The received training signals at user D can be expressed by substituting $\mathbf{S}$ in eq. (4) with $\mathbf{P}$, which gives

$$\mathbf{Y}_{D,pilot} = \mathbf{H}_{eq}\mathbf{P} + \mathbf{n}_{eq,pilot}, \tag{5}$$

where the dimension of $\mathbf{Y}_{D,pilot}, \mathbf{P}$ and $\mathbf{n}_{eq,pilot}$ are $(1+L_A) \times N_P, N_T \times N_P$ and $(1+L_A) \times N_P$, respectively. Since $\mathbf{P}$ is known at user D, an initial LSCE can be derived from eq. (5) as

$$\check{\mathbf{H}}_{LSCE} = \mathbf{Y}_{D,pilot}\mathbf{P}^H(\mathbf{P}\mathbf{P}^H)^{-1}. \tag{6}$$

Note that the design of the pilot matrix $\mathbf{P}$ affects the complexity and performance of channel estimation. A typical choice of $\mathbf{P}$ would be an orthogonal matrix, which reduces the computation complexity of the matrix inverse.

B. Data Detection

To begin this subsection, assume that the equivalent channel $\mathbf{H}_{eq}$ is known at user D. The ML detection criterion for time-instance of $\mathbf{S}_{data}$, i.e., $\mathbf{s}(t)$, for $t = N_P + 1, \ldots, N$, is

$$\begin{aligned}\hat{\mathbf{s}}(t) &= \arg\max_{\mathbf{s}(t)\in\Omega^{N_T\times 1}} prob(\mathbf{Y}_D(t)|\mathbf{H}_{eq}\mathbf{s}(t)) \qquad (7)\\ &= \operatorname*{argmin}_{\mathbf{s}(t)\in\Omega^{N_T\times 1}} [(\mathbf{Y}_D(t) - \mathbf{H}_{eq}\mathbf{s}(t))^H\mathbf{D}^{-1} \\ &\qquad (\mathbf{Y}_D(t) - \mathbf{H}_{eq}\mathbf{s}(t))].\end{aligned}$$

The matrix $\mathbf{D}$ is the covariance matrix of the equivalent noise $\mathbf{n}_{eq}(t)$ and can be derived as

$$\begin{aligned}\mathbf{D} &= E[\mathbf{n}_{eq}(t)\mathbf{n}_{eq}(t)^H] \qquad (8)\\ &= diag([\sigma^2_{n_{SD}}, \alpha_1^2\sigma^2_{g_{1D}}\sigma^2_{n_{S1}} + \sigma^2_{n_{1D}}, \cdots, \\ &\quad \alpha^2_{L_A}\sigma^2_{g_{L_A D}}\sigma^2_{n_{SL_A}} + \sigma_{n_{L_A D}}]).\end{aligned}$$

Now with the LSCE result $\check{\mathbf{H}}_{LSCE}$ from eq. (6), an initial ML detection of $\mathbf{s}(t)$ is obtained as

$$\begin{aligned}\hat{\mathbf{s}}_{init}(t) = \operatorname*{argmin}_{\mathbf{s}(t)\in\Omega^{N_T\times 1}} &[(\mathbf{Y}_D(t) - \check{\mathbf{H}}_{LSCE}\mathbf{s}(t))^H\mathbf{D}^{-1} \\ &(\mathbf{Y}_D(t) - \check{\mathbf{H}}_{LSCE}\mathbf{s}(t))]. \qquad (9)\end{aligned}$$

The initial detection of the source data $\mathbf{S}_{data}$ is therefore given by

$$\hat{\mathbf{S}}_{data,init} = [\hat{\mathbf{s}}_{init}(N_P{+}1)\ \hat{\mathbf{s}}_{init}(N_P{+}2)\ \cdots\ \hat{\mathbf{s}}_{init}(N)] \tag{10}$$

C. Iterative Channel Estimation and Data Detection

Accurate channel estimation is essential for reliably detecting the source data. In general, channel estimation is more accurate when the length of the training, N_P, is larger. The cost is the decreased length N_{data} for source data transmission, or, the loss of data rate. As a result, it is not possible to use a large taining length. However, the detected source data $\hat{\mathbf{S}}_{data}$ can be fed back to the channel estimator. The entire frame can serve as a new virtual pilot matrix $\check{\mathbf{P}} = [\mathbf{P}\ \hat{\mathbf{S}}_{data}]$. Then the new channel estimate can be fed again to the data detector and exploited to new detection $\hat{\mathbf{S}}_{data}$ with lower error probability. The process can be iteratively repeated to yield further performance improvement. Simulation in the next section will show that this iterative channel estimation and data detection mechanism is very effective and achieves large performance gain within few iterations, even for very short training length.

We now summarize the proposed iterative channel estimation and data detection scheme for the AF user cooperation system.

1) Compute initial LSCE: $\check{\mathbf{H}}^{(0)} = \check{\mathbf{H}}_{LSCE}$ from eq. (6).
2) Compute initial ML data detection: $\hat{\mathbf{S}}^{(0)}_{data}$ from eq. (9) and (10).
3) Perform iterative channel estimation and data detection: for ($i = 1; i \le N_I; i++$) {
   a) Compute LSCE with the new virtual pilot $\check{\mathbf{P}} = [\mathbf{P}\ \hat{\mathbf{S}}^{(i-1)}_{data}]$:
   $\check{\mathbf{H}}^{(i)} = \mathbf{Y}_D\check{\mathbf{P}}^H(\check{\mathbf{P}}\check{\mathbf{P}}^H)^{-1}$.
   b) ML data detection with the new channel estimation:
   $\hat{\mathbf{s}}^{(i)}(t) = \operatorname{argmin}_{\mathbf{s}(t)\in\Omega^{N_T\times 1}}(\mathbf{Y}_D(t) - \check{\mathbf{H}}^{(i)}\mathbf{s}(t))^H\mathbf{D}^{-1}(\mathbf{Y}_D(t) - \check{\mathbf{H}}^{(i)}\mathbf{s}(t))$, for $t = N_P, \ldots, N$.
   c) $\hat{\mathbf{S}}^{(i)}_{data} = [\hat{\mathbf{s}}^{(i)}(N_P+1)\ \hat{\mathbf{s}}^{(i)}(N_P+2)\ \cdots\ \hat{\mathbf{s}}^{(i)}(N)]$.

   }
4) Output the final results: $\hat{\mathbf{H}} = \check{\mathbf{H}}^{(i)}$ and $\hat{\mathbf{S}}_{data} = \hat{\mathbf{S}}^{(i)}_{data}$

V. Simulation Results

In this section, we present the simulation results of the proposed AF cooperation scheme. In the following simulations, we use an individual user's average SER as our performance metric. The SER is averaged over the $N_T = 4$ data streams. We use QPSK in the simulations. The channel gains are realized as i.i.d. complex Gaussian random variables with zero mean and variance $\sigma_h^2 = 1 = \sigma_g^2$ and remain invariant during the transmission of a length $N = 100$ data frame. The AWGNs at the users are i.i.d. complex Gaussian with zero mean and variance $\sigma_n^2 = 1$. The transmission power of the source and the users are set as $E_s = E_i = 2E_b$ and the transmit signal-to-noise ratio (Tx SNR) is defined as E_b/σ_n^2.

Figures 3 and 4 show the data detection SER and the mean squared error (MSE) of the channel estimation. In the simulation, we simply select a basic pilot matrix $\mathbf{P}_{basic}$ as a 4×4 DFT matrix due to its orthogonal and constant-power properties. Other choices of the basic pilot matrix give similar simulation results and thus are not shown here. For pilot matrix

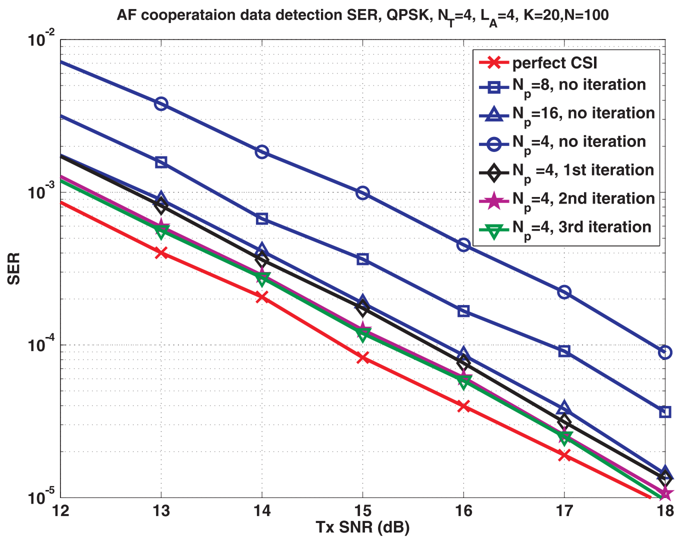

Fig. 3. The data detection SER for $N_T = 4, L_A = 4, K = 20, N = 100$.

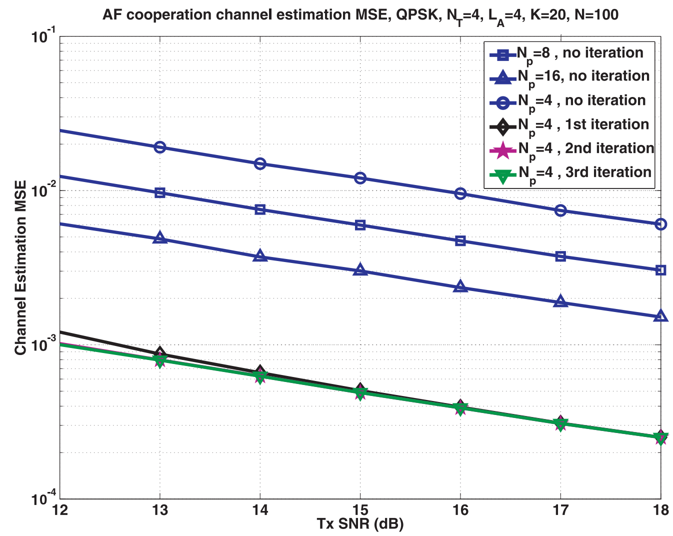

Fig. 4. The channel estimation MSE for $N_T = 4, L_A = 4, K = 20, N = 100$.

length $N_P = 4$, the basic pilot matrix is transmitted. For $N_P = 8$ and $N_P = 16$, the basic pilot matrix is transmitted two and three times, respectively, in the beginning of each data frame.

In Fig. 3, the curve labeled "perfect CSI" represents the ML detection peformance with exact $\mathbf{H}_{eq}$. The curves labeled "no iteration" represent the result of ML detection with the conventional least square channel estimation. The curves labeled "1st iteraition", "2nd iteration", and "3rd iteration" are the results of the proposed iterative channel estimation and data detecion. As we can see from the figure, the detection performance of "$N_P = 4$, no iteration" case is about 2 dB worse than that of "$N_P = 16$, no iteration" case. However, the performance of "$N_P = 4$, 1 iteration" case is slightly better than that of "$N_P = 16$, no iteration" case. The performance is further improved with 2 and 3 iterations and is only 0.5 dB worse than the perfect CSI case.

In Fig. 4, the iterative mechanism significantly improves the accuracy of the channel estimate and only 2 to 3 iterations suffice to converge. When the detection error probability is sufficiently low, the new channel estimate with new virtual pilots is more accurate than the previous. The above results show that the proposed iterative algorithm provides accurate overall channel estimates for AF cooperation system with the aid of very few pilots. The overall CSIs are obtained directly at the destination users without individual channel estimations and complicated CSI exchange.

VI. Conclusion

In this paper, we investigated an AF user cooperation scheme for a MIMO broadcasting system, in which single-antenna users receive multiple data streams from the multiple-antenna source. We considered the data detection of the system without perfect CSI assumption. Instead of estimating the channels separately at each user and then exchanging the required CSIs between the users, we estimate the overall channels directly at the destination users, which avoids the CSI quantization problem and the high overhead of CSI exchange between users. Simulation results show that the proposed method can obtain accurate channel estimates with the aid of very few pilots.

References

[1] A. Sendonaris, E. Erkip, and B. Aazhang, "User cooperation diversity-part I: system description," *IEEE Trans. Commun.*, vol. 51, no. 11, pp. 1927-1938, Nov. 2003.

[2] A. Nosratinia, T. Hunter, and A. Hedayat, "Cooperative communication in wireless networks," *IEEE Commun. Mag.*, vol. 42, no. 10, pp. 74-80, Oct. 2004.

[3] N. Jindal, "MIMO broadcast channels with finite rate feedback," in *Proc. IEEE GLOBECOM*, Nov. 2005, pp. 1520-1524

[4] R. Dabora and S. D. Servetto, "Broadcast channels with cooperating decoders," *IEEE Trans. Inf. Theory*, vol. 52, no. 12, pp. 5438-5454, 2006.

[5] A. Sendonaris, E. Erkip, and B. Aazhang, "Increasing uplink capacity via user cooperation diversity," in *Proc. IEEE Int. Symp. Information Theory*, Cambridge, MA, Aug. 1998.

[6] H. Kwon and J. M. Cioffi, "Multi-user MISO broadcast channel with user-cooperating decoder," in *IEEE VTC 2008-Fall*, Calgary, Canada, Sept., 2008.

[7] I. Krikidis, J. Thompson, S. McLaughlin and N. Goertz, "Optimization issues for cooperative amplify-and-forward systems over block-fading channels," *IEEE Trans. Veh. Technol.*, vol. 57, no, 5, pp. 2868-2884, Sept., 2008.

[8] I. Krikidis, and J. S. Thompson, "Opportunistic relay selection in cooperative systems with dirty-paper coding," *IEEE Trans. Veh. Technol.*, vol. 58, no, 7, pp. 3322-3332, Sept., 2009.

[9] S. Chen, W. Wang, X. Zhang and Z. Sun, "Performance analysis of OS-TBC transmission in amplify-and-forward cooperative relay networks," *IEEE Trans. Veh. Technol.*, vol. 59, no, 1, pp. 105-113, Jan., 2010.

[10] A. H. Bastami and A. Olfat, "Selection relaying schemes for cooperative wireless networks with adaptive modulation," *IEEE Trans. Veh. Technol.*, vol. 60, no, 4, pp. 1539-1558, May, 2011.

[11] L. Chen, R. Carrasco and I. Wassell, "Distributed amplify-and-forward cooperation through message partitioning," *IEEE Trans. Veh. Technol.*, vol. 60, no, 7, pp. 3054-3065, Sept. 2011.

[12] M. Rupp and C. F. Mecklenbr$\ddot{a}$uker, "On extended Alamouti schemes for space-time coding," *Proc. WPMC*, pp. 115–119, Honolulu, Oct. 2002.

[13] F. Gao, T. Cui, and A. Nallanathan, "On channel estimation and optimal training design for amplify and forward relay networks," *IEEE Trans. Wireless. Commun.*, vol. 7, no. 5, pp. 1907–1916, May 2008.