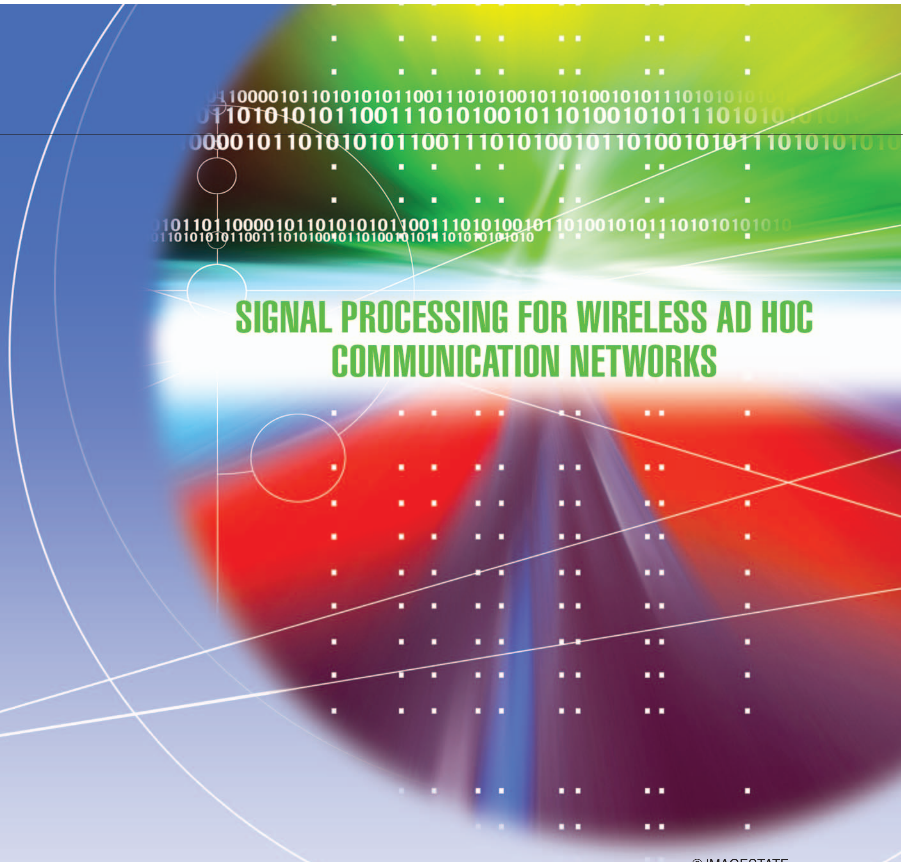
[Hongbin Li and Qiang Zhao]



Distributed Modulation for Cooperative Wireless Communications

[A description of four schemes]

We examine the modulation and signal processing aspect of communications assisted by cooperative relay nodes in wireless ad hoc networks. Several distributed modulation, detection, and combining schemes, utilizing either nonregenerative or regenerative relay nodes, are reviewed and their performances in fading channels are discussed. These schemes offer cooperative diversity against channel fading compared to their noncooperative counterparts. They may or may not require knowledge of the channel state information (CSI) at the receiving nodes, thus suiting both slow and fast fading environments. We bring out connections between such cooperative systems and noncooperative multichannel communication systems, and highlight unique challenges in the design and analysis of the former.

INTRODUCTION

A wireless ad hoc network consists of multiple wireless nodes that can move around and communicate without a fixed network infrastructure. The broadcasting nature of the wireless medium allows neighboring nodes to cooperate in information transport, creating multiple communication routes and offering *cooperative diversity* for fading mitigation (e.g., [1]–[3]). Cooperative diversity is considered particularly useful in wireless ad hoc and sensor networks, where power/bandwidth/size restrictions of the mobile nodes may prevent use of other diversity techniques (e.g., antenna diversity) to combat channel fading.

The purpose of this article is to provide an overview of distributed modulation for cooperative wireless systems. We consider cases when the CSI can be conveniently and accurately estimated as well as when it cannot. CSI estimation, typically performed at the receiving nodes via training, is challenging

1053-5888/06/$20.00©2006IEEE

and costly, especially in fast fading environments. The difficulty is exacerbated in multinode wireless systems since the amount of training grows with the number of links [4]. The modulation techniques discussed in the sequel are *distributed* in nature since the signal is modulated at the source and, subsequently, at the relays for transmission to the destination. We examine both *distributed coherent* and *distributed differential* modulation schemes, which are the counterparts of the conventional noncooperative coherent and differential modulation techniques. Within each category, we consider *nonregenerative* schemes involving amplify-and-forward (AF) as well as *regenerative* schemes involving decode-and-forward (DF) operation performed at the relays. This gives four distributed modulation schemes referred to as coherent amplify-and-forward (CAF), coherent decode-and-forward (CDF, not to be confused with the cumulative denisity function of a random variable), differential amplify-and-forward (DAF), and differential decode-and-forward (DDF), respectively. For each scheme, we discuss several issues including the implementation, detection, combining, and bit error rate (BER) analysis.

A cooperative communication system utilizes multiple communication routes created by relay nodes for information transport. The distributed modulation and combining techniques discussed in the sequel resemble, to a certain extent, conventional single-hop noncooperative, multichannel communication techniques (e.g., [5, Ch. 12]). But there are major distinctions. Specifically, a cooperative system may involve both a single-hop direct (i.e., source-destination) link and multihop relay (source-relay-destination) links, whereas in noncooperative multichannel systems all links are single hop and usually subject to the same type of fading. The multihop relay link exhibits statistically more complex behaviors that are yet fully understood; meanwhile, the single-hop link has been well studied under various standard fading channel models. When regenerative DF relays are utilized for cooperation, they are prone to fading-induced decision errors (even with the powerful error detection/correction codes), and nonlinear combining has to be employed to offset the effect of such errors. All these factors present unique challenges in the design and analysis of cooperative wireless communication systems. We discuss the connections and distinctions between cooperative systems and noncooperative multichannel communication systems and highlight the challenges in the analysis and design of the former imposed by several unique characteristics of wireless relay channels.

SYSTEM MODEL

We consider a wireless relay system depicted in Figure 1 that consists of a source S, relay R, and destination D node. As simple as it may seem, the system is known for several open theoretical problems that are important for cooperative communications (e.g., [6]) and is expandable to more complex relay networks with multiple relays and multihop transmission. We assume that S and R use orthogonal channels for cooperative transmission; for the sake of presentation, we assume a time-division multiple-access (TDMA) based approach that involves *two-phase* transmission. Specifically, in phase I, S transmits a frame of information symbols while R and D listen; in phase II, S shuts off while R amplifies or decodes the signal received in phase I and retransmits it to D. The CSI is assumed unavailable to the transmitting nodes (i.e., S and R), but may or may not be obtained at the receiver, depending on how fast the channel fades. We consider distributed coherent and differential modulation schemes to handle both cases.

Let $d(n)$ denote the sequence of information symbols to be transmitted from S. The baseband signals received at R and D during time slot n of phase I are

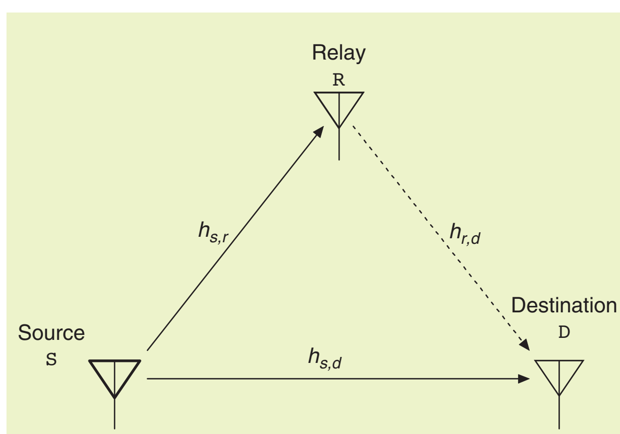
$$x_r(n) = h_{s,r}s(n) + w_r(n),$$
$$x_d(n) = h_{s,d}s(n) + w_d(n),$$

where $s(n)$ denotes the signal transmitted from S, $h_{s,r}$ and $h_{s,d}$ the fading coefficients, and $w_r(n)$ and $w_d(n)$ the channel noise. For coherent modulation, we set $s(n) = d(n)$, while for differential modulation $s(n) = s(n-1)d(n)$, with initial transmission set to $s(0) = 1$. During phase II, R amplifies or decodes the received signal $x_r(n)$, and generate a signal $s_r(n)$ with *unit average power*, which is next transmitted to D. The signal received at D is given by

$$y_d(n) = h_{r,d}s_r(n) + u_d(n),$$

where $h_{r,d}$ and $u_d(n)$ denote the fading and channel noise, respectively. (With a slight abuse of notation, n is used in both phase I and II to denote the index of symbols in a frame.)

Although not required for implementation, Rayleigh fading is assumed for the purpose of analysis. That is, $h_{i,j} \sim \mathcal{CN}(0, \sigma^2_{i,j})$, $(i, j) \in \{(s, r), (s, d), (r, d)\}$, where $\mathcal{CN}(\mu, \sigma^2)$ denotes a complex Gaussian probability density function (PDF) with mean μ and variance σ^2. Some performance analysis for cooperative relays in more general Nakagami fading channels can be found in [7]–[9]. Meanwhile, we assume that the receiver noise $w_r(n)$, $w_d(n)$, and $u_d(n)$ are $\mathcal{CN}(0, N_0)$ random variables. Based on the Rayleigh fading assumption, the instantaneous signal-to-noise ratio (SNR) between nodes i and j, denoted by $\gamma_{i,j} \triangleq |h_{i,j}|^2/N_0$, is exponentially distributed with mean or *average SNR* $\bar{\gamma}_{i,j} \triangleq \sigma^2_{i,j}/N_0$.



[FIG1] A cooperative wireless relay system.

DISTRIBUTED MODULATION

In the following, we discuss four distributed modulation schemes, namely CAF, CDF, DAF, and DDF, along with the corresponding relay strategies, combining methods, and performance analysis. We assume binary phase-shift keying (PSK) modulation for simplicity; however, some of our results can be readily extended to the nonbinary modulation case, as discussed in Section V.

CAF

The relay strategy for CAF is simple: R amplifies and forwards $x_r(n)$ according to [2]:

$$s_r(n) = G_{\mathrm{CAF}} x_r(n), \tag{1}$$

where G_{CAF} is chosen to meet the unit average power constraint

$$G_{\mathrm{CAF}} \triangleq \frac{1}{(N_0 + |h_{s,r}|^2)^{1/2}}. \tag{2}$$

At D, $x_d(n)$ and $y_d(n)$ can be optimally combined based on the maximum likelihood (ML) principle. Note that $x_d(n)$ and $y_d(n)$ are Gaussian (conditioned on the channels and transmitted symbol), independent but not identically distributed (with different mean and variance). It is straightforward to show that the ML detection based on $x_d(n)$ and $y_d(n)$ reduces to maximum ratio combining (MRC) [10]

$$z(n) = \frac{h_{s,d}^* x_d(n)}{N_0} + \frac{h_{s,r,d}^* y_d(n)}{\sigma_{s,r,d}^2}, \tag{3}$$

followed by thresholding: $\hat{d}(n) = \mathrm{sign}\{\Re\{z(n)\}\}$. Here, $h_{s,r,d}$ and $\sigma_{s,r,d}$ are the *equivalent* channel gain and noise variance of the S–R–D link:

$$h_{s,r,d} \triangleq \frac{h_{s,r} h_{r,d}}{(N_0 + |h_{s,r}|^2)^{1/2}},$$

$$\sigma_{s,r,d}^2 \triangleq \frac{|h_{r,d}|^2 N_0}{N_0 + |h_{s,r}|^2} + N_0.$$

The above combining scheme (3) resembles the MRC combining for standard multichannel communications with independent but not identically distributed branches. Note that CAF requires knowledge of the instantaneous CSI. Specifically, R needs to know the magnitude of $h_{s,r}$, while D requires the magnitude and phase of all channel links including $h_{s,r}$, $h_{s,d}$, and $h_{r,d}$.

Analysis of the above combiner (3) follows similar steps used for standard multichannel systems but with some distinctions. In particular, the instantaneous SNR of the MRC combiner output is the sum of the instantaneous SNRs of the direct link and the relay link

$$\gamma_{\mathrm{CAF}} = \gamma_{s,d} + \gamma_{s,r,d},$$

where

$$\gamma_{s,r,d} \triangleq \frac{\gamma_{s,r}\gamma_{r,d}}{\gamma_{s,r} + \gamma_{r,d} + 1}$$

denotes the equivalent instantaneous SNR of the relay link. By using the moment generating function (MGF) approach, the average BER of the two-branch MRC is given by (e.g., [11])

$$\bar{P}_e = \frac{1}{\pi}\int_0^{\pi/2} \mathcal{M}_{\gamma_{s,d}}\left(-\frac{1}{\sin^2\theta}\right)\mathcal{M}_{\gamma_{s,r,d}}\left(-\frac{1}{\sin^2\theta}\right)d\theta, \tag{4}$$

where $\mathcal{M}_\gamma(\cdot)$ denotes the MGF of random variable γ. The MFG of the exponential variable $\gamma_{s,d}$ is well known (e.g., [11]):

$$\mathcal{M}_{\gamma_{s,r,}}(s) = \frac{1}{1 + s\bar{\gamma}_{s,d}}.$$

Unlike a standard multichannel system, the major difficulty here is that the exact form of $\mathcal{M}_{\gamma_{s,r,d}}(s)$ is very involved. An approximate expression of $\mathcal{M}_{\gamma_{s,r,d}}(s)$ is derived in [12, eq. (15)] by approximating $\gamma_{s,r,d}$ using the harmonic mean of $\gamma_{s,r}$ and $\gamma_{r,d}$, which is still quite complicated and valid only for high SNR cases. Using the results of [12] in (4), we can obtain an approximate expression of the average BER for CAF. The integral in (3) can be computed using standard numerical integration techniques.

CDF

CDF uses a regenerative relaying strategy. Specifically, R first reproduces a copy of the information symbol $d(n)$ by coherently demodulating the signal received in phase I

$$s_r(n) = \mathrm{sign}\{\Re\{h_{s,r}^* x_r(n)\}\}. \tag{5}$$

Then, $s_r(n)$ is retransmitted to D in phase II.

Similar to CAF, optimum ML combing can be performed at D. However, due to possible decision errors occurring in (5), the conditional PDF of $y_d(n)$ [conditioned on the channels and $d(n)$] is a Gaussian mixture density, with two components corresponding to the correct and, respectively, incorrect decision made by R. Meanwhile, $x_d(n)$ is still conditionally Gaussian and independent of $y_d(n)$. Maximizing the joint density of $x_d(n)$ and $y_d(n)$ and after some manipulations, the ML combiner for CDF is given by [13]

$$f(t_1) + t_0 \underset{-1}{\overset{1}{\gtrless}} 0, \tag{6}$$

where

$$f(t_1) \triangleq \ln\frac{(1-\epsilon)e^{t_1} + \epsilon}{\epsilon e^{t_1} + 1 - \epsilon}, \tag{7}$$

$$t_1 \triangleq [h_{r,d}^* y_d(n) + h_{r,d} y_d^*(n)]/N_0, \tag{8}$$

$$t_0 \triangleq [h_{s,d}^* x_d(n) + h_{s,d} x_d^*(n)]/N_0, \tag{9}$$

and ϵ denotes the average probability of error caused by R, which can be computed in closed form for Rayleigh fading channels (see [5, eq. (14.3-7)]). We see that due to decision errors at

R, the ML combiner for CDF is *nonlinear*, in contrast to standard multichannel communication with coherent demodulation which involves *linear* combining [5, Chapter 12].

The nonlinearity of the above ML combiner creates difficulties for both implementation and analysis. The problem can be partially solved by observing that the nonlinear function $f(t_1)$ can be approximated by a piecewise-linear (PL) function [13]

$$f(t_1) \approx f_{\mathrm{PL}}(t_1) \triangleq \begin{cases} -T_1, & t_1 < -T_1 \\ t_1, & -T_1 \le t_1 \le T_1, \\ T_1, & t_1 > T_1 \end{cases} \tag{10}$$

where $T_1 \triangleq \ln[(1-\epsilon)/\epsilon]$ assuming $\epsilon < 0.5$. The resultant detector obtained by using the above approximation in (6) is henceforth called the *PL demodulator*.

The ML nonlinear demodulator is difficult to analyze. On the other hand, analysis of the PL detector is tractable, which is outlined as follows. The conditional BER (conditioned on the fading channels) of the PL demodulator can be obtained by considering the three exclusive events specified in (10) (supposing $d(n) = 1$):

$$\begin{aligned} P_e(\gamma_{s,d}, \gamma_{r,d}) =& \Pr\{t_0 - T_1 < 0\} \Pr\{t_1 < -T_1\} \\ &+ \Pr\{t_0 + T_1 < 0\} \Pr\{t_1 > T_1\} \\ &+ \Pr\{t_0 + t_1 < 0, -T_1 \le t_1 \le T_1\}, \end{aligned} \tag{11}$$

where $\Pr\{\cdot\}$ denotes the probability of an event and we used the fact that t_0 and t_1 are independent. Based on earlier discussions on the distribution of $x_d(n)$ and $y_d(n)$, it is easy to see from (8) and (9) that t_0 is a Gaussian variable whereas t_1 a Gaussian mixture variable. Therefore, each probability in (11) can be expressed using the Gaussian Q-function. Once we have $P_e(\gamma_{s,d}, \gamma_{r,d})$, the average BER can be obtained by averaging out the fading channels, using either a PDF- or MGF-based approach [10].

DAF

As indicated earlier, CAF cannot be used without knowing the instantaneous CSI, which may be difficult to estimate due to, e.g., mobility-induced fast channel fading. In that case, an alternative approach, namely DAF that facilitates differential demodulation, can be utilized. Specifically, like CAF, R also produces a scaled signal $s_r(n)$ as in (1), but with the gain G_{CAF} changed to[14]

$$G_{\mathrm{DAF}} \triangleq \frac{1}{(\mathrm{var}\{x_r(n)\})^{1/2}} = \frac{1}{(N_0 + \sigma_{s,r}^2)^{1/2}}, \tag{12}$$

where the variance $\mathrm{var}\{x_r(n)\}$ can be estimated by time-averaging over a frame of received signals. The so-obtained $s_r(n)$ again meets the unit average power constraint.

To find combining methods for DAF, we first note that the conditional PDFs of the received signals in phase I and phase II are $x_d(n) \sim \mathcal{CN}(h_{s,d}s(n), N_0)$ and $y_d(n) \sim \mathcal{CN}(h_{s,r,d}s(n), \sigma_{s,r,d}^2)$, where like CAF (with some abuse of notation), we use the same symbols, $h_{s,r,d}$ and $\sigma_{s,r,d}^2$, to denote the effective channel gain and noise variance, respectively, for the relay link, which in the current case are

$$h_{s,r,d} \triangleq \frac{h_{s,r}h_{r,d}}{(N_0 + \sigma_{s,r}^2)^{1/2}},$$

$$\sigma_{s,r,d}^2 \triangleq \frac{|h_{r,d}|^2 N_0}{N_0 + \sigma_{s,r}^2} + N_0.$$

A standard combining method for multichannel systems with differential modulation is the equal-gain combiner (EGC) [5], whose decision variable is

$$x_d^*(n-1)x_d(n) + y_d^*(n-1)y_d(n). \tag{13}$$

EGC is suitable for balanced diversity systems where all diversity branches have identical noise power [5]. This is not the case for DAF, where the direct and relay links has different noise power. A better approach is to mimic MRC by normalizing $x_d(n)$ and $y_d(n)$ by their own variance before combining. Doing so and after some straightforward manipulations, we arrive at the following decision variable:

$$x_d^*(n-1)x_d(n) + \frac{(1+\bar{\gamma}_{s,r})y_d^*(n-1)y_d(n)}{1+\bar{\gamma}_{s,r}+\gamma_{r,d}}. \tag{14}$$

Unfortunately, the above combiner is incompatible with differential demodulation since it requires knowledge of the instantaneous SNR $\gamma_{r,d}$. The dependence on $\gamma_{r,d}$ is because $y_d(n)$ has a conditional variance that is a function of the instantaneous CSI $|h_{r,d}|$. A differential demodulator is proposed in [15], which replaces $\gamma_{r,d}$ by its mean. Doing so we have

$$z(n) = x_d^*(n-1)x_d(n) + \frac{(1+\bar{\gamma}_{s,r})y_d^*(n-1)y_d(n)}{1+\bar{\gamma}_{s,r}+\bar{\gamma}_{r,d}}. \tag{15}$$

Following combining, thresholding is performed for demodulation $\hat{d}(n) = \mathrm{sign}\{\Re\{z(n)\}\}$.

Exact performance analysis of the differential detector (15) is involved. In particular, since the signals received through the direct and relay links are unbalanced (with different variance), the well-known tool developed in [5, Appendix B] for the balanced case is inapplicable. On the other hand, noticing that $z(n)$ in (15) is a quadratic form in Gaussian variables, we may use, e.g., a series expansion approach [16] to find the distribution of $z(n)$, and use it for BER analysis. Series expansion is used to analyze DDF in [17]. Here, we follow a different approach. It is observed by computer simulation that the two detectors (14) and (15) have very close BER performance. The analysis of (14) can be pursued using Proakis' tool, since normalization by the noise power effectively converts an unbalanced case to a balanced one. Specifically, the conditional BER is the same as the one for standard multichannel communications using differential binary PSK and two independent channels, which is given by [5, eq. (14.4-26)]:

$$P_e(\gamma_{\mathrm{DAF}}) = \frac{1}{8}(4 + \gamma_{\mathrm{DAF}})e^{-\gamma_{\mathrm{DAF}}},$$

where $\gamma_{\mathrm{DAF}} \triangleq \gamma_{s,r,d} + \gamma_{s,d}$, and $\gamma_{s,r,d}$ denotes the equivalent instantaneous SNR of the relay link:

$$\gamma_{s,r,d} = \frac{\gamma_{s,r}\gamma_{r,d}}{\bar{\gamma}_{s,r} + 1 + \gamma_{r,d}}.$$

The average BER can be obtained by averaging $P_e(\gamma_{\text{DAF}})$ with respect to the PDF of $\gamma_{s,d}$ and $\gamma_{s,r,d}$. For Rayleigh fading, $\gamma_{s,d}$ is a standard exponential variable. However, $\gamma_{s,r,d}$ has a nontrivial PDF, which is obtained in [15, eq. (9)]. Using the PDF for $\gamma_{s,r,d}$ and carrying out statistical averaging yields a closed-form expression of the average BER for (14) expressed in the Whittaker function, as shown in [15, eq. (14)].

DDF

In this case, R first differentially decodes the signal received in phase I

$$\bar{d}(n) = \text{sign}\{\Re\{x_r^*(n-1)x_r(n)\}\}. \quad (16)$$

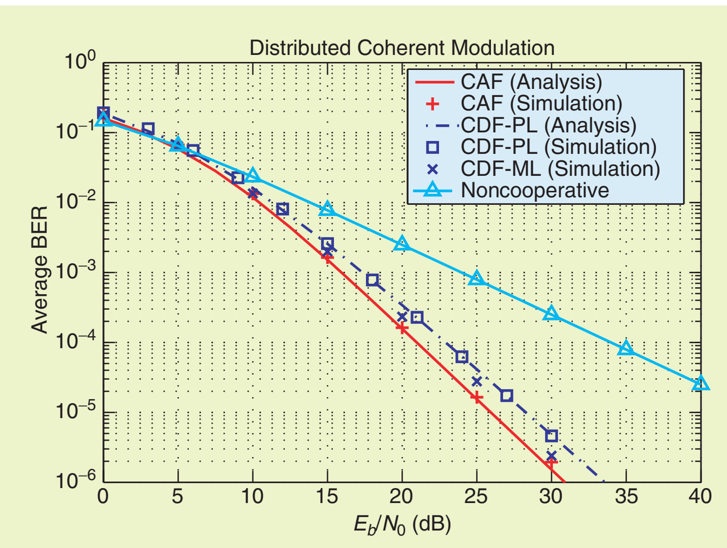
Then, the decoded bits are re-encoded via a differential encoder

$$s_r(n) = s_r(n-1)\tilde{d}(n),$$

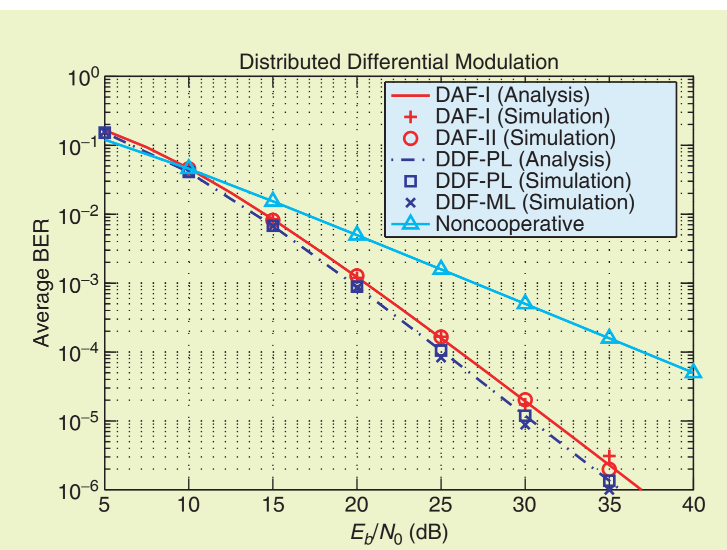
which is transmitted to D during phase II.

The differential ML demodulator is developed in [17], which takes the same form as (6), but with the t_1 and t_0 replaced by

$$t_1 = [y_d^*(n-1)y_d(n) + y_d(n-1)y_d^*(n)]/N_0,$$
$$t_0 = [x_d^*(n-1)x_d(n) + x_d(n-1)x_d^*(n)]/N_0.$$



[FIG2] Cooperative distributed coherent modulation versus noncooperative coherent modulation.



[FIG3] Cooperative distributed differential modulation versus noncooperative differential modulation.

In addition, the ϵ in $f_1(t_1)$ is the error probability associated with (16), which can also be computed in closed form for Rayleigh fading channels (see [5, eq. (14.3–10)]). Like CDF, the differential ML demodulator is nonlinear. We can again use the PL approximation (10), which leads to a differential PL demodulator that is easier to implement and analyze.

Similar to CDF, the analysis of the nonlinear ML detector for DDF is intractable. The PL detector can be analyzed in a similar fashion as in the previous case, using conditional probabilities as in (11). Finding these conditional probabilities for DDF, however, is considerably more involved. The reason is that while for CDF t_0 and t_1 and Gaussian and Gaussian mixture variables, respectively, for DDF they are *quadratic forms* of Gaussian and Gaussian mixture variables, respectively. In general, their PDFs are involved except for a few special cases [16]. An exact average BER expression for the PL detector is obtained in [4] and [17] using series expansion. Convergence of such results is usually slow. At high SNRs, we can ignore the cross noise terms in $x_d^*(n-1)x_d(n)$ and $y_d^*(n-1)y_d(n)$ (as in [5, p. 273]). This leads to an approximate average BER expression obtained in [4].

NUMERICAL RESULTS

We present some numerical results to compare the performance of the various distributed modulation schemes and verify the analysis. We consider the cooperative system depicted in Figure 1 with Rayleigh fading. For fair comparison between the cooperative schemes, which involve two transmissions from S and R to D, and the noncooperative schemes that involve a single transmission from S to D, we scale the transmission power of S and R for the cooperative schemes so that the total transmitted power is the same as that of the noncooperative schemes.

We first consider a *symmetric* scenario where the average SNRs of all hops are identical:

$$\bar{\gamma}_{s,d} = \bar{\gamma}_{s,r} = \bar{\gamma}_{r,d} = E_b/N_0,$$

where E_b/N_0 denotes the average SNR of the noncooperative schemes. Figure 2 shows the average BER of the cooperative CAF and CDF as well as the noncooperative scheme using binary PSK. For the cooperative schemes, both results obtained by simulation and analysis are included, which are seen to agree with each other. For CDF, both the PL and ML detectors are shown, yielding very similar performance except at relatively high SNRs. We see that CAF and CDF achieve a diversity gain over the noncooperative scheme.

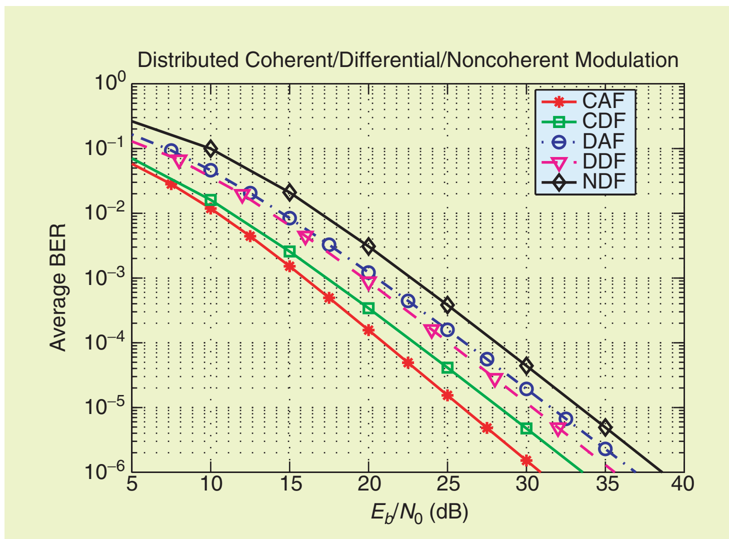
Figure 3 depicts the counterpart results for the case with differential modulation, where DAF-I refers to the detector using (14) while DAF-II refers to that of (15). Additional comparisons that include DAF with EGC detection can be found in [4], where it is shown that EGC is in general inferior to DAF-I and DAF-II. We note that DAF-I and DAF-II indeed have very similar performance. Like the coherent case, the cooperative DAF and DDF also outperform the noncooperative differential scheme.

Figure 4 compares the cooperative schemes discussed earlier as well as another cooperative noncoherent modulation using DF and binary frequency shift keying (labeled as NDF) considered in [18]. The results suggest that CAF has an advantage over CDF, and DDF does better than DAF; meanwhile, the differential DAF and DDF outperform the noncoherent NDF. However, it should be noted that the performance of all cooperative schemes depends on the relative locations of the cooperating nodes. Indeed, there are relay nodes at some locations that are more preferable for cooperation than others. Hence, in ad hoc networks with dense node distribution, the problem of selecting good cooperating nodes is of practical interest.

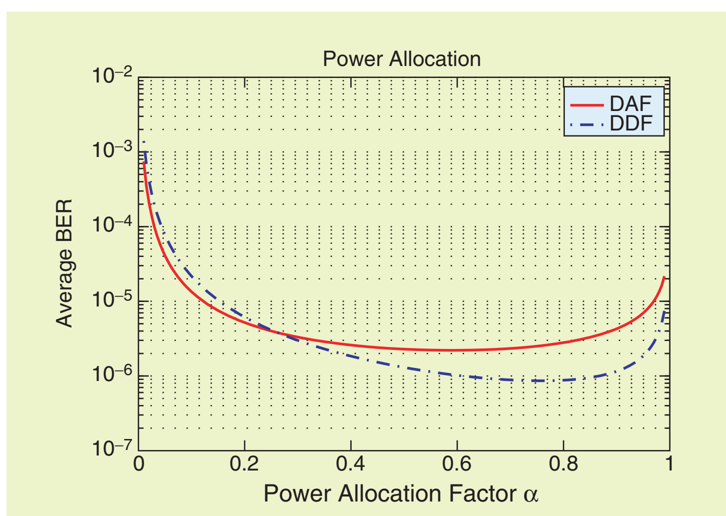
It is not difficult to see that the above *relay selection* problem is equivalent to the following *power allocation* problem: supposing that the internode distances are identical but the total transmission power from the source and relay(s) is fixed, how to split the power among the source and relay nodes to optimize the BER performance? To show the impact of power allocation, let $0 < \alpha < 1$ be the *power allocation factor* that controls power allocation as follows: $\bar{\gamma}_{s,r} = \bar{\gamma}_{s,d} = \alpha E_b/N_0$ and $\bar{\gamma}_{r,d} = (1-\alpha)E_b/N_0$. In effect, $\alpha > 0.5$ means more power allocated to S than to R, and vice versa. Equivalently, $\alpha > 0.5$ also corresponds to the case when R is closer to S than to D as in the relay selection problem. Using the analytical results in [4] and [15], we show in Figure 5 the average BER of DAF and DDF as a function of α when $E_b/N_0 = 35$ dB. It is seen that DAF favors approximately equal power allocation ($\alpha = 0.5$), which agrees with the prior result for CAF [3], [19], while DDF yields the lowest BER when $\alpha \approx 0.75$, viz., when the power allocated to S is approximately three times that allocated to R. The performance of DDF is intuitive, since the less power that is allocated to S, the more likely R is expected to make incorrect decoding, and the less gain that can be produced by cooperation. Similar observation has been made for CDF as well.

CONCLUSIONS AND FURTHER DISCUSSIONS

We have provided an overview of distributed modulation for cooperative wireless communications and, in particular, described four such schemes that can be categorized as being nonregenerative (i.e., AF) or regenerative (i.e., DF) and coherent or differential. For each scheme, we have discussed issues such as relay strategies, combining methods, and BER analysis. A major motivation of this article is to explore the relations



[FIG4] Cooperative distributed coherent, differential, and noncoherent modulation.



[FIG5] Power allocation.

between cooperative communications and noncooperative multichannel communications. The latter have been widely studied with numerous results and tools that may benefit the analysis and design of cooperative wireless systems. We have shown that while there are many connections between the two, there are also major distinctions, such as the statistical complexity of the cooperative wireless relay channel and error proneness of regenerative relays that cannot be neglected in a wireless environment. Because of such, the preliminary results presented here and in the references for cooperative wireless communications are usually complicated and sometimes inconvenient to use (due to, e.g., multiple folds of integrations and/or summations). This points to the need for alternative statistical/mathematical tools and perhaps even more fundamentally, a better understanding of the underlying wireless relay channel, which may lead to simpler and more insightful results and performacne bounds for the optimization of cooperative wireless systems.

We briefly comment on extensions of the results reported here to the case of M-ary modulation, say M-ary PSK. For CAF and DAF, the extension is straightforward. As we has shown, the key to the analysis of such nonregenerative schemes is to find the statistics (PDF, MGF, etc.) of the decision variable. Since the decision variable before thresholding is the same for both binary and M-ary PSK, the symbol error rate (SER) for M-ary PSK can easily be obtained by using our results (i.e., the statistics of the decision variable) and modifying the integration region of the decision variable (based on an appropriate M-ary PSK demodulation rule). A similar extension for the regenerative CDF and DDF is conceptually simple, since $y_d(n)$, the signal received at D in phase II, also has a Gaussian mixture PDF and hence, the analytical approach developed for the binary case is still applicable; on the other hand, such an extension is also practically tedious, since the mixture PDF now has M instead of two components. As such, implementations of the ML or PL detector as well as their SER analysis are considerably more involved. One simplifying strategy is to consider only nearest neighbor errors, i.e., confusing $d(n)$ to its nearest neighbors on the constellation, instead of all possible errors made by D. This reduces the number of components in the mixture density. Finally, we remark that it is also possible to extend our results to cases with multiple relays and/or multihop transmission. The extension for the regenerative relays is again more involved, since the number of error events increases with the number of relays and/or hops.

ACKNOWLEDGMENTS

This work was supported in part by the U.S. National Science Foundation under Grant CCF-0514938, the U.S. Army Research Office under Grant DAAD19-03-1-0184, and the National Natural Science Foundation of China under Grant 60502011.

AUTHORS

Hongbin Li (hli@stevens.edu) received the B.S. and M.S. degrees from the University of Electronic Science and Technology of China, Chengdu, in 1991 and 1994, respectively, and the Ph.D. degree from the University of Florida, Gainesville, in 1999, all in electrical engineering. He was a summer visiting faculty member at the Air Force Research Laboratory, Rome, New York, in the summers of 2003 and 2004. He joined Stevens Institute of Technology, Hoboken, New Jersey, in 1999, where he is an associate professor of electrical and computer engineering. His current research interests include wireless communications, statistical signal processing, and radars. He is a member of Tau Beta Pi and Phi Kappa Phi. He received the 2003 Harvey N. Davis Teaching Award in 2003, the 2001 Jess H. Davis Memorial Award for excellence in research, and the 1999 Sigma Xi Graduate Research Award. He is an editor for *IEEE Transactions on Wireless Communications* and an associate editor for *IEEE Signal Processing Letters*. He is a Member of the IEEE.

Qiang Zhao (qzhao@stevens.edu) received his Ph.D. degree in electrical engineering from Stevens Institute of Technology, Hoboken, New Jersey, in 2006. In 2002, he received the M.S. degree in electrical engineering from Virginia Tech, Blacksburg, Virginia. His interests include cooperative diversity and wireless relay networks.

REFERENCES

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

[2] J. N. Laneman, D.N.C. Tse, and G.W. Wornell, "Cooperative diversity in wireless networks: Efficient protocols and outage behavior," *IEEE Trans. Inform. Theory*, vol. 50, no. 12, pp. 3062–3080, Dec. 2004.

[3] Y. Hua, Y. Mei, and Y. Chang, "Wireless antennas—Making wireless communications perform like wireline communications," in *Proc. IEEE Topical Conf. Wireless Communication Technology*, Honolulu, Hawaii, Oct. 2003, pp. 47–73.

[4] Q. Zhao and H. Li, "Differential modulation for cooperative wireless networks," submitted for publication.

[5] J.G. Proakis, *Digital Communications*, 4th ed. New York: McGraw-Hill, 2000.

[6] T.M. Cover and J.A. Thomas, *Elements of Information Theory*. New York: Wiley, 1991.

[7] M.O. Hasna and M.S. Alouini, "Outage probability of multihop transmission over Nakagami-fading channels," *IEEE Commun. Lett.*, vol. 7, no. 5, pp. 216–218, May 2003.

[8] Q. Zhao and H. Li, "Performance analysis of an amplify-based differential modulation for wireless relay networks under Nakagami-*m* fading channels," in *Proc. 6th IEEE Int. Workshop Signal Processing Advances for Wireless Communications*, New York, June 2005, pp. 211–215.

[9] Q. Zhao and H. Li, "Performance of decode-based differential modulation for wireless relay networks in Nakagami-*m* channels," in *Proc. 2006 IEEE Int. Conf. Acoustics, Speech, Signal Processing*, Toulouse, France, May 2006.

[10] Q. Zhao, "Distributed modulations for wireless relay networks," Ph.D. dissertation, Dept. Elec. Comput. Eng., Stevens Inst. Technol., Hoboken, NJ, 2006.

[11] M.K. Simon and M.-S. Alouini, *Digital Communications over Fading Channels: A Unified Approach to Performance Analysis*. New York: Wiley, 2000.

[12] M.O. Hasna and M.S. Alouini, "End-to-end performance of transmission systems with relays over Rayleigh-fading channels," *IEEE Trans. Wireless Commun.*, vol. 2, no. 6, pp. 1126–1131, Nov. 2003.

[13] J.N. Laneman and G.W. Wornell, "Energy-efficient antenna sharing and relaying for wireless networks," in *Proc. 2000 IEEE Wireless Commun. Networking Conf.*, Chicago, IL, Sept. 2000, vol. 1, pp. 7–12.

[14] Q. Zhao and H. Li, "Differential BPSK modulation for wireless relay networks," in *Proc. 38th Annual Conf. Information Sciences and Systems*, Princeton Univ., NJ, Mar. 2004.

[15] Q. Zhao and H. Li, "Performance of differential modulation with wireless relays in Rayleigh fading channels," *IEEE Commun. Lett.*, vol. 9, no. 4, pp. 343–345, Apr. 2005.

[16] A.M. Mathai and S.B. Provost, *Quadratic Forms in Random Variables*. New York: Marcel Dekker, 1992.

[17] Q. Zhao and H. Li, "Decode-based differential modulation for wireless relay networks," in *Proc. 2005 IEEE Int. Conf. Acoustics, Speech, Signal Processing*, vol. 3, Philadelphia, PA, Mar. 2005, pp. 513–516.

[18] D. Chen and J.N. Laneman, "Modulation and demodulation for cooperative diversity in wireless systems," *IEEE Trans. Wireless Commun.*, to be published.

[19] A. Ribeiro, X. Cai, and G. B. Giannakis, "Symbol error probabilities for general cooperative links," *IEEE Trans. Wireless Commun.*, vol. 4, no. 3, pp. 1,264–1,273, May 2005.

SP