

| REPORT DOCUMENTATION PAGE | | | Form Approved OMB NO. 0704-0188 | | |
|---|-------------------|--------------------------------|---|--|---------------------------------------|
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| 1. REPORT DATE (DD-MM-YYYY) 02-12-2010 | | 2. REPORT TYPE Final Report | | 3. DATES COVERED (From - To) 1-Aug-2006 - 31-Aug-2010 | |
| 4. TITLE AND SUBTITLE Final Report: Dynamic Spectrum Sharing with Limited Network State Information | | | 5a. CONTRACT NUMBER W911NF-06-1-0339 | | |
| | | | 5b. GRANT NUMBER | | |
| | | | 5c. PROGRAM ELEMENT NUMBER 611102 | | |
| 6. AUTHORS Michael Honig, Randall Berry | | | 5d. PROJECT NUMBER | | |
| | | | 5e. TASK NUMBER | | |
| | | | 5f. WORK UNIT NUMBER | | |
| 7. PERFORMING ORGANIZATION NAMES AND ADDRESSES Northwestern University Chicago Campus Office of Sponsored Research Northwestern University Evanston, IL 60208 -1110 | | | 8. PERFORMING ORGANIZATION REPORT NUMBER | | |
| 9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) U.S. Army Research Office P.O. Box 12211 Research Triangle Park, NC 27709-2211 | | | 10. SPONSOR/MONITOR'S ACRONYM(S) ARO | | |
| | | | 11. SPONSOR/MONITOR'S REPORT NUMBER(S) 50551-NS.32 | | |
| 12. DISTRIBUTION AVAILABILITY STATEMENT Approved for Public Release; Distribution Unlimited | | | | | |
| 13. SUPPLEMENTARY NOTES The views, opinions and/or findings contained in this report are those of the author(s) and should not be construed as an official Department of the Army position, policy or decision, unless so designated by other documentation. | | | | | |
| 14. ABSTRACT This project is concerned with the costs and benefits of learning and exchanging Network State Information (NSI) among cooperative nodes in a wireless network. NSI includes Channel State Information (CSI), along with information about quality of service requests. This report summarizes our main results on interference management and wireless resource allocation with limited information exchange. We introduce interference prices for optimizing powers and beams in an interference network with multiple antennas per node. We also discuss the | | | | | |
| 15. SUBJECT TERMS interference management, pricing, limited feedback, multi-input multi-output channels, wireless resource allocation | | | | | |
| 16. SECURITY CLASSIFICATION OF: | | 17. LIMITATION OF ABSTRACT | | 15. NUMBER OF PAGES | 19a. NAME OF RESPONSIBLE PERSON |
| a. REPORT UU | b. ABSTRACT UU | c. THIS PAGE UU | UU | | Michael Honig |
| | | | | | 19b. TELEPHONE NUMBER 847-491-7803 |

Report Title

Final Report: Dynamic Spectrum Sharing with Limited Network State Information

ABSTRACT

This project is concerned with the costs and benefits of learning and exchanging Network State Information (NSI) among cooperative nodes in a wireless network. NSI includes Channel State Information (CSI), along with information about quality of service requests. This report summarizes our main results on interference management and wireless resource allocation with limited information exchange. We introduce interference prices for optimizing powers and beams in an interference network with multiple antennas per node. We also discuss the performance of limited feedback schemes for multi-carrier and Multi-Input Multi-Output (MIMO) channels. Additional topics discussed include distributed power allocation (over sub-channels), beamforming, and interference cancellation in a peer-to-peer network, overhead for random network coding with unreliable links, and adaptive techniques for achieving interference alignment in MIMO interference networks.

List of papers submitted or published that acknowledge ARO support during this reporting period. List the papers, including journal references, in the following categories:

(a) Papers published in peer-reviewed journals (N/A for none)

K. Huang, J. G. Andrews, R. W. Heath, Jr., D. Guo, and R. Berry, "Spatial Interference Cancellation for Mobile Ad Hoc Networks: Perfect CSI", submitted to IEEE Transactions on Information Theory, 2009.

M. Agarwal, M. L. Honig, and B. Ata, "Adaptive Training for Correlated Fading Channels with Feedback", submitted to IEEE Transactions on Information Theory, August 2009.

W. Santipach and M. L. Honig, "Optimization of Training and Feedback Overhead for Beamforming over Block Fading Channels", to appear in IEEE Transactions on Information Theory, Dec. 2010.

M. Agarwal, D. Guo, and M. L. Honig, "Limited Rate Channel State Feedback for Multicarrier Block Fading Channels", to appear in IEEE Transactions on Information Theory, Dec. 2010.

M. Agarwal and M. L. Honig, "Wideband Fading Channel Capacity with Training and Partial Feedback", IEEE Transactions on Information Theory, Vol. 56, No. 10, pp. 4865-4873, Oct. 2010.

D. Schmidt, C. Shi, R. A. Berry, M. L. Honig, and W. Utschick, "Pricing Algorithms for Power Control and Beamformer Design in Interference Networks", IEEE Signal Processing Magazine, Vol. 26, No. 5, pp. 53-63, September 2009.

Number of Papers published in peer-reviewed journals: 4.00

(b) Papers published in non-peer-reviewed journals or in conference proceedings (N/A for none)

Number of Papers published in non peer-reviewed journals: 0.00

(c) Presentations

"Minimum Mean Squared Error Interference Alignment", presented at the Information Theory Applications Workshop, University of Ca., San Diego, Feb. 2010.

Number of Presentations: 1.00

Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Peer-Reviewed Conference Proceeding publications (other than abstracts):

D. Schmidt, W. Utschick, and M. L. Honig,

"Large System Performance of Interference Alignment in Single-Beam MIMO Interference Networks", to appear in Proc. Globecom Conf., Miami, FL, Dec. 2010.

M. Xu, D. Guo, and M. L. Honig, "Two-Cell Downlink Noncoherent Cooperation Without Transmitter Phase Alignment", Proc. Globecom Conf., Miami, FL, Dec. 2010.

D. Schmidt, W. Utschick, and M. L. Honig,

"Beamforming Techniques for Single-Beam MIMO Interference Networks", Proc. Allerton Conf., Monticello, IL, Oct. 2010.

C. Shi, R. Berry, and M. L. Honig,

"Adaptive Beamforming in Interference Networks via Bi-Directional Training", Proc. Conf. on Information Sciences and Systems, Princeton University, March 2010.

M. Xu, D. Guo, and M. L. Honig,

"MIMO Precoding with Limited Rate Feedback: Simple Quantizers Work Well",

IEEE Globecom Conf., Honolulu, Hawaii, December 2009.

D. Schmidt, C. Shi, R. Berry, M. L. Honig, W. Utschick,

"Minimum Mean Squared Error Interference Alignment", Asilomar Conf. on Signals, Systems, and Computers, Pacific Grove, Ca., Nov. 2009.

C. Shi, R. Berry, and M. L. Honig,

"Local Interference Pricing for Distributed Beamforming in MIMO Networks", IEEE Milcom Conf., Boston, Ma., Nov. 2009.

Number of Peer-Reviewed Conference Proceeding publications (other than abstracts):

7

(d) Manuscripts

Number of Manuscripts: 0.00

Patents Submitted**Patents Awarded****Awards****Graduate Students**

| <u>NAME</u> | <u>PERCENT SUPPORTED</u> |
|------------------------|--------------------------|
| Changxin Shi | 0.50 |
| Mingguang Xu | 0.50 |
| FTE Equivalent: | 1.00 |
| Total Number: | 2 |

Names of Post Doctorates

| <u>NAME</u> | <u>PERCENT SUPPORTED</u> |
|------------------------|--------------------------|
| FTE Equivalent: | |
| Total Number: | |

Names of Faculty Supported

| <u>NAME</u> | <u>PERCENT SUPPORTED</u> | National Academy Member |
|------------------------|--------------------------|-------------------------|
| Michael Honig | 0.08 | No |
| Randall Berry | 0.08 | No |
| FTE Equivalent: | 0.16 | |
| Total Number: | 2 | |

Names of Under Graduate students supported

| <u>NAME</u> | <u>PERCENT SUPPORTED</u> |
|------------------------|--------------------------|
| FTE Equivalent: | |
| Total Number: | |

Student Metrics

This section only applies to graduating undergraduates supported by this agreement in this reporting period

- The number of undergraduates funded by this agreement who graduated during this period: 0.00
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Names of Personnel receiving masters degrees

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Names of personnel receiving PHDs

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Sub Contractors (DD882)

Inventions (DD882)

Project Report, November 2010
Dynamic Spectrum Sharing with Limited Network State
Information
ARO Contract Number W911NF-06-1-0339

1 Project Overview and Goals

The performance of a wireless network in general depends on the amount of *Network State Information (NSI)* available to nodes in the network. NSI includes Channel State Information (CSI), along with information about quality of service requests, such as throughput and delay. When available at transmitters, this NSI enables efficient allocation of network resources, such as power and bandwidth, along with effective interference management. Both are necessary to achieve high spectral efficiencies, given a limited supply of bandwidth. However, learning and exchanging NSI requires the expenditure of network resources. Hence there is generally a tradeoff between this overhead cost and the associated benefits. Effectively managing this trade-off is critical for the design of efficient tactical networks. Major goals of this project have been: (1) Design and evaluate distributed algorithms for resource optimization and interference management in peer-to-peer networks with limited exchange of NSI and (2) Characterize the associated tradeoff between overhead costs and associated benefits with multiple Degrees of Freedom (DoFs) in time, frequency, and space.

2 Distributed Interference Compensation

Tactical networks cannot assume the presence of centralized infrastructure and so must rely on peer-to-peer communication. Interference management in a peer-to-peer wireless network is challenging, since the nodes may have only local information about channel and interference conditions. Without exchanging NSI, a transmitter therefore may not be aware of interference it causes to neighboring nodes. This can lead to a substantial degradation in network performance. We have been studying *distributed* interference management techniques with the following properties:

1. Each transmitter optimizes its own resources (e.g., power, spatial beams) based on the information it receives from nearby nodes (i.e., it does not have global knowledge of the network topology and channel gains).
2. The nodes exchange *limited* information about channel and interference conditions.
3. These techniques attempt to maximize a sum utility objective, assuming each user is assigned a utility function, which depends on received Signal-to-Interference Plus Noise Ratio (SINR).

This project has focused on peer-to-peer networks with multi-antenna nodes. The goal is to optimize jointly the powers and spatial beams across users. The additional spatial DoFs allow a transmitter to reduce interference to a neighboring receiver by steering the beam away from that receiver. This centralized optimization problem (e.g., maximize the sum utility over all powers and beams) is typically not convex, which makes it challenging.

2.1 Interference Pricing for Power and Beam Updates

Building on our previous work on distributed power control for single-antenna links [1], we have studied the use of *distributed interference pricing* for adjusting powers and beams. An interference price at a particular receiver is associated with a particular spatial mode, or beam, and is the marginal decrease in utility caused by a marginal increase in interference along that beam. (Interference prices can also be applied to different sub-channels.) This leads to an iterative algorithm in which receivers announce interference prices given a set of transmitter beams, and transmitters update beams and/or powers given a set of announced prices.

In [2] we have studied distributed interference pricing for a peer-to-peer network with Multi-Input/Single-Output (MISO) links (i.e., multiple transmit antennas, and a single receive antenna at each node), and in [3] we study beamforming for MIMO links. In [4] we have studied joint optimization of powers and pre-coder matrices (representing multiple beams) for MIMO channels. Distributed optimization of the pre-coding matrices with MIMO links becomes especially difficult, since the number of beams for each link (equivalently, the rank of the pre-coding matrix) must be jointly optimized with the powers and beam directions. (They are all inter-dependent.) We have proposed some heuristic methods in [4], which exchange interference prices for each beam. Numerical results indicate that these methods give near-optimal performance with two users. Furthermore, the results in [3] indicate that substantial performance can be obtained with limited exchange of interference prices. An overview of our work on interference pricing has appeared in *IEEE Signal Processing Magazine* [5].

2.2 MSE Beamforming and Interference Alignment

With more than two users the optimal pre-coding matrices (sets of beams) at high SNRs must achieve *interference alignment*. That is, interfering beams must be *aligned* at each receiver so that the received interference covariance matrix is rank-deficient. As an example, interference alignment allows three users to transmit without interference with 2x2 channels (i.e., two antennas at each transmitter and receiver). Numerical examples indicate that interference pricing does not generally achieve alignment of spatial beams. The reason for this is that the sum rate objective often has a very sharp peak at an aligned solution, making it difficult to reach by gradient-based approaches (including interference pricing). This is illustrated in the following figure, which is a contour plot of sum rate as a function of beamformer weights. (As the sum rate increases the color transition from dark blue to yellow to red.) This is for a network of three users with 2x2 channels, and the contours are shown in a two-dimensional subspace of the beamformer weights (x - and y -axes) that contain the optimal aligned solution (dark red spot in the upper right). The two black curves show trajectories of a gradient algorithm in this subspace starting from two different initial points. In both cases the algorithm converges to a local optimum, which is not an aligned solution.

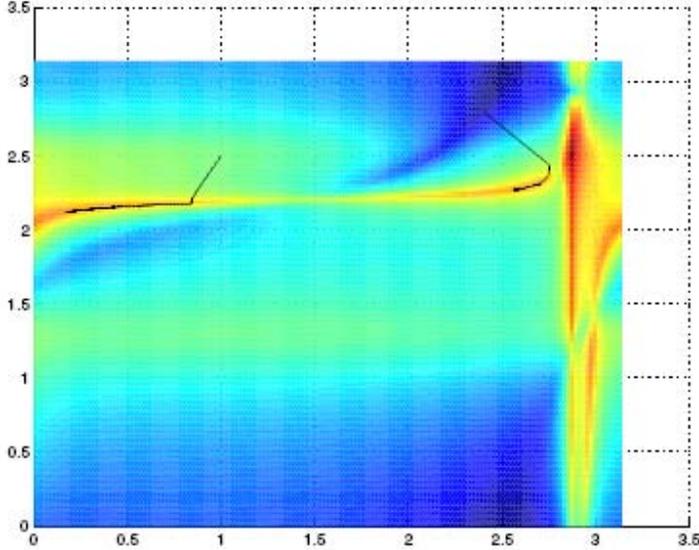


Fig. 1. Contour plot of sum rate as a function of beamformer coefficients.

We have instead proposed a distributed beamforming algorithm using a weighted sum Minimum Mean Squared Error (MMSE) criterion. Specifically, a particular beam is selected to minimize $\sum_k w_k E \left[\|b_k - \tilde{b}_k\|^2 \right]$ where b_k is the transmitted symbol, \tilde{b}_k is the estimated symbol at the output of the receiver filter, w_k is the priority weight assigned to user k , and $E[\cdot]$ denotes expectation [6].¹ Numerical examples have shown that this method typically achieves (essentially) optimal performance over a wide range of SNRs. It therefore achieves alignment at high SNRs. Furthermore, the user weights can be adapted to achieve different points in the rate region. This leads to a two-stage algorithm in which the beams are selected in an inner loop to minimize the sum MSE and the priority weights are adjusted in the outer loop to maximize the sum utility objective. Numerical results show that this method achieves different points in the rate region accounting for the possibility of alignment.

This work (in addition to [4], [5]) is joint work with members of the Signal Processing Institute at the Technical University of Munich. One of the PIs (MH) has visited TUM with additional funding from the Humboldt Foundation, and we have hosted M.S. and Ph.D. candidates from TUM in our lab for short-term visits ranging from 3 to 6 months. One of the PIs (RB) has also leveraged funding from the DARPA IT-MANET program to work on these problems.

¹ The corresponding update is similar in form to the ‘Max-SINR’ approach proposed in [7]. Advantages of the weighted sum-MSE approach are that it has provable convergence and can achieve different points in the rate region.

2.3 Convergence

A fundamental issue with any iterative scheme, such as the ones studied here, is whether or not it converges. We have shown in prior work [1] that for a particular class of utility functions and with single-antenna nodes, the sum utility objective converges to the global optimum. However, a shortcoming of this result is that the class of utility functions does not include the rate utility (i.e., $\log(1+\text{SINR})$). More recently, we have shown that if all interference prices are current, meaning that prices are immediately updated and announced after every power and beam update, then the pricing algorithm always converges for a larger class of utility functions, which includes the rate utility [8]. However, depending on the utility functions, it may converge to a local optimum, which is not globally optimal. (This applies to the rate utility, since the problem is not convex, and therefore does not have a unique global optimum.) In contrast to the result in [1], which relies on the application of super-modular game theory, this more recent convergence result is based on a convexity argument. (Note, however, that it does not include the result in [1], since there the prices do not have to be current.) The convergence argument in [8] has also been extended to the combined MSE adaptation of beams with user weights described in [6].

2.4 Performance Analysis

Here we consider a MIMO interference network with K interfering transmitter-receiver pairs and N antennas per node (transmitter or receiver), where each transmitter transmits a single beam. If the channels are independent, random with *i.i.d.* elements, then it has been shown that at high SNRs the maximum slope of the sum rate versus SNR is $2N-1$. (This implies that $2N-1$ users can transmit a single beam with zero interference.) For a given realization of channels there are many sets of beamformers that achieve this maximum slope. (An upper bound on the number of such sets grows as 2^{cN^2} where c is a constant.) However, the sum rate asymptote for each of these sets generally has a different y-axis intercept (or *offset*). This is illustrated in the following figure, which shows a sketch of sum rate versus SNR. (The high SNR slope is s , and the offset is r .)

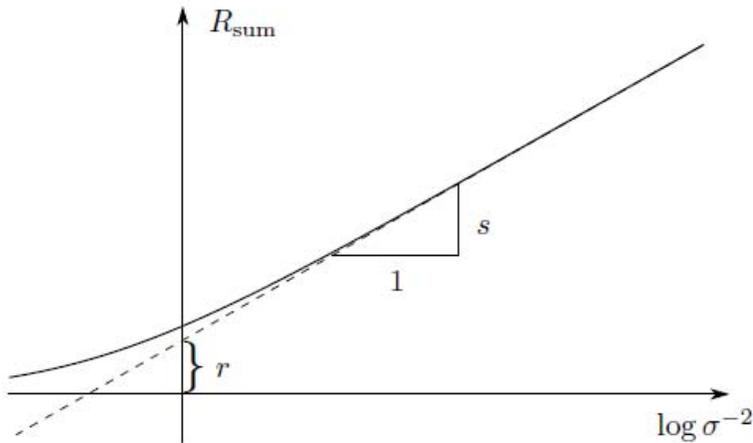


Fig. 2: Illustration of high SNR slope and offset.

For high enough SNRs, the sum rate is maximized by a set of beamformers that achieves the maximum high SNR slope. However, at finite SNRs this may not be true. In particular, a strategy achieving a slope of only N might allow for a significantly higher offset than a strategy achieving the maximum slope. Assuming that the number of fully aligned beamformer sets that achieve a slope of $2N - 1$ is finite for a given channel realization, we approximate the average offset when the best out of a large number L of these sets is selected. We also derive a simple large system approximation for the sum rate of a successive beam allocation scheme when $K = N$. We show that both approximations accurately predict simulated results for moderate system dimensions and characterize the large-system asymptotes for different relationships between L and N . In this way we can characterize how large the SNR should be so that an aligned solution corresponding to slope $2N-1$ (relatively difficult to compute) is likely to perform better than a solution with slope N (relatively easy to compute). This work is reported in [9].

2.5 Incremental SNR Algorithm

We again consider a network with K users and N antennas per node. Because the number of aligned solutions with $K=2N-1$ can be quite large, and because the aligned solutions are independent of the direct channels (i.e., they need only satisfy the zero interference condition, which depends on the cross-channels), the performance of a randomly chosen aligned solution can be relatively poor. At high SNRs we therefore wish to find an aligned (zero-interference) solution where the beams are as closely aligned as possible with the *direct* channel gains. We also observe that at low SNRs the optimal beamformers are the principal eigenvectors of the direct channels. We have therefore proposed an *incremental SNR* method for adjusting the beamformers in which we initialize the SNR at zero, and set the beamformers as the principal eigenvectors. We then increment the SNR and adjust the beamformers to maximize the sum rate according to gradient updates. We repeat this until the SNR is incremented to the desired value. In this way the beamformers stay close to the principal eigenvectors as the SNR increases.

Numerical results in [10] show that this performs better on average than the sum-MMSE and Max-SINR approaches described previously, the gain becoming significant at high SNRs. This indicates that there are indeed many aligned solutions in the vicinity of the principle eigenvectors, making it quite difficult to find the globally optimal solution.

2.6 Adaptive Beamforming with Bi-Directional Training

The preceding discussion has assumed that the transmitters and receivers know all channel gains in the network. In practice these are initially unknown, so that *adaptive* methods are needed for determining the beamformers and receiver filters. In [11] we propose an adaptive version of the Max-SINR algorithm for a time-division duplex system. This algorithm uses a period of bi-directional training followed by a block of data transmission. Training in the forward direction is sent using the current beamformers and used to adapt the receive filters. Training in the reverse direction is sent using the current receive filters as beamformers and is used to adapt the transmit beamformers. The adaptation of both the receive filters and beamformers is done using a least squares objective for the current block. This is in contrast to bi-directional training for channel

estimation in which the training is used to estimate *channels* (instead of the filters). In a peer-to-peer network, that would require additional exchange of the channel estimates among nodes to compute the beams.

In order to improve the performance when the training data is limited, we also consider using exponentially weighted data from previous blocks. Numerical results in [11] show that this scheme can achieve near-optimal aligned solutions with sufficient training. The amount of training required to achieve near-optimality generally increases with the number of users. This suggests that when training overhead is taken into account, it may be best to restrict the number of active streams even though the maximum multiplexing gain is not achieved.

3 Noncoherent Cooperative Broadcasting

Cooperative transmissions by multiple transmitters in an interference network can mitigate interference and thereby increase the spectral efficiency. While it is optimal to phase-align the transmitters so that signals add coherently at the receivers, this is difficult to achieve in practice. In [12], we study a *noncoherent* cooperative transmission scheme with two interfering links, which does not require phase alignment. It is assumed that the transmitters share their messages through a dedicated link. Each transmitter then transmits a superposition of two codewords, one for each receiver. Each receiver decodes its own message, and treats the signals for the other receiver as background noise.

With narrowband transmissions the achievable rate region and maximum achievable weighted sum rate are characterized by optimizing the power allocation at each transmitter between its two codewords. For a wideband (multicarrier) system, a dual formulation of the optimal power allocation problem across subcarriers is presented, which admits an efficient numerical solution. Results in [12] show that the proposed cooperation scheme can improve the sum rate significantly at low to moderate signal-to-noise ratios when the cross-channel gains are comparable to the direct-channel gains.

4 Limited Feedback

Another theme of this project has been limited feedback for point-to-point and multi-user channels. We are interested in characterizing the increase in achievable forward rate as a function of the amount of available feedback.

4.1 Resource Allocation for Broadcast OFDM

In a broadcast channel a single transmitter transmits (possibly different) messages to a set of mobile receivers. We have studied limited feedback schemes for both single-user Orthogonal Frequency Division Multiplexing (OFDM) and broadcast Orthogonal Frequency Division Multiple Access (OFDMA). For both scenarios we have analyzed the performance (e.g., total rate summed over users) of limited feedback schemes *explicitly taking into account the feedback overhead*. Specifically, each sub-channel is assumed to be block Rayleigh fading, and all feedback must occur within the coherence time. Hence

more feedback of Channel State Information increases the achievable rate per symbol, but decreases the time (number of symbols) left for useful data transmission.

Our more recent work has focused on limited feedback schemes for MIMO OFDMA, assuming multiple antennas at an access point. Limited feedback becomes more important in this scenario since the number of channel coefficients grows rapidly with the system size (users, antennas, and sub-channels). We have proposed a scheme in which the broadcast node sequentially receives feedback from the mobiles and decides when to stop receiving additional feedback and begin data transmission [13]. In this way the broadcast node optimizes the feedback duration. We explicitly characterize the optimal stopping rule at the base station, assuming each user feeds back their best beam selected from a beamforming codebook on groups of OFDM sub-channels. We also characterize the performance (sum rate) as the number of users and OFDM sub-channels both become large with fixed ratio. Namely, the total throughput scales linearly with the number of users, and as the log of the amount of feedback per coherence time.

4.2 Evaluating Optimal Limited Feedback Methods

In prior work we have studied the performance of limited feedback schemes for single-user MIMO and multi-carrier channels. The feedback is used to optimize the precoder (beam directions) and power allocation over available DoFs. In general, finding the optimal quantization scheme for CSI is a vector quantization problem, and the associated performance with a large number of degrees of freedom (i.e., sub-channels or antennas) is characterized by a rate-distortion function. We have used this rate-distortion approach to characterize how the maximum achievable rate varies with the feedback rate for a single-user multi-carrier channel [14]. In contrast with other limited feedback schemes, which designate a subset of good sub-channels in a lossless manner, optimal rate-distortion codes activate a small number of bad sub-channels (with small probability) in order to activate a larger percentage of good channels. Our results in [14] show that rate-distortion codes used to quantize sub-channels and beams can provide a significant increase in forward rate at low SNRs.

We have also studied the performance of optimal vector quantizers for a MISO multi-carrier channel with *iid* sub-channels [15]. Each entry in the vector quantizer is a *set* of beamformers across sub-channels. The loss in forward rate due to quantization, which is the distortion criterion, can be computed as a function of the feedback rate. Numerical results show that when the feedback rate is small, the rate-distortion bound significantly outperforms separate vector quantization of each sub-channel vector. For a narrowband MIMO channel we have studied the performance of simple (scalar) quantizers, and have shown that the degradation relative to optimal (vector) quantizers is relatively small [16].

4.3 Adaptive Training for Correlated Channels

We have previously reported on a model for optimizing pilot and data power over a time-selective, correlated (first-order Markov) Rayleigh fading channel with feedback, subject to an average power constraint. Specifically, the channel is estimated at the receiver with a pilot signal, and the estimate is fed back to the transmitter. The estimate is used for coherent demodulation, and to adapt the data and pilot powers. More recently, we have

been able to explicitly determine the optimal pilot and data power control policies in the continuous-time limit where the channel state evolves as an Ornstein-Uhlenbeck diffusion process, and is estimated by a Kalman filter at the receiver [20]. We showed previously that the optimal pilot policy switches between zero and the maximum (peak-constrained) value (“bang-bang” control), and approximates the optimal discrete-time policy at low Signal-to-Noise Ratios (equivalently, large bandwidths). The switching boundary is determined in terms of the system state (estimated channel mean and associated error variance). Our more recent results compute this boundary explicitly, and show that under the optimal policy, the transmitter conserves power by decreasing the training power when the channel is faded, thereby increasing the data rate. Numerical results show a significant increase in achievable rate due to the adaptive training scheme with feedback, relative to constant (non-adaptive) training, which does not require feedback. The gain is more pronounced at relatively low SNRs and with fast fading.

5 Interference Cancellation in Ad Hoc Networks

Another approach for utilizing multiple antennas in an ad hoc network is to attempt to simply cancel the interference to neighboring nodes. Given full channel state information, such an approach is sub-optimal, but in a distributed implementation, it avoids the need for iteratively updating pre-coding and receiver matrices. In [17] we study the gains of such an approach in large random ad hoc networks, using the notion of *transmission capacity*, which is defined as the maximum number of successful communication links per unit area given constraints on the received SINR and outage probability. For a network of Poisson distributed transmitters with Rayleigh fading, we have characterized the scaling of the metric as the outage probability goes to zero. For small outage probabilities, transmission capacity increases following a power law, whose exponent depends on the inverse of the size of the antenna arrays. This suggests that the use of multiple antennas can potentially yield large gains in transmission capacity with only a few antennas per node. We have also studied the effect of channel state uncertainty on these results.

6 Network Coding

6.1 Comparison of Analog and Digital Relay Methods

Adding cooperative relays to a network can help to extend coverage and increase the overall throughput. This work was motivated by the possibility of combining simple analog relays with power control and linear filtering. We considered wireless multicasting from two sources to two destinations with the assistance of a single half-duplex relay [18]. The objective was to evaluate the throughput and error performance of different analog and digital relay schemes with linear network coding at the relay. The analog relay node forwards either a scaled version of the received signal to the destinations, or alternatively, first filters the received signals to generate a linear Minimum Mean Squared Error (MMSE) estimate, which is subsequently forwarded. The digital relay scheme first decodes the source transmissions, combines the packets with a network code, and forwards the resulting symbols to the destinations. For all schemes the

destinations recover the source and relay signals by first applying linear MMSE filters, followed by decoding of the source bits.

The performance of the schemes were compared in terms of normalized throughput (bits per channel use accounting for the delay due to the relay) and uncoded error probability, given a normalized power constraint. Both narrowband and wideband (spread-spectrum) transmission schemes were evaluated. Our results show that the analog relay schemes outperform the digital network coding scheme with respect to both throughput and error probability because of error propagation through the relay (and because the digital relay does not perform any intermediate decoding/coding operations other than combining packets). Numerical results in [18] illustrate throughput-reliability trade-offs for all schemes considered.

6.2 Training Overhead for Random Network Coding

For multicast communications linear network coding maximizes the achievable (min-cut) rate. A distributed code assignment can be realized by choosing codes randomly at the intermediate nodes, but then additional signaling overhead is needed to communicate the network coding matrix to each destination. This overhead may be significant for a wireless network with unreliable links and varying topology. In [19] we have considered a training method for communicating the network coding matrices to the destinations in which training bits are appended to data bits at the source. To balance the protection of overhead with protection of data, the source can jointly code across both the training and information bits. Each destination can then jointly decode the network coding matrix along with the data. We have shown how the resulting data throughput depends on the network size, channel properties (i.e., error and erasure probabilities), number of independent messages, and field size. Using the combination network as an example, we have specified conditions under which throughput is limited by training overhead.

7 Technology Transfer

The PIs have given talks and seminars about this work over the past few years at the Army Research Laboratory and at Motorola. Additional discussions with colleagues in industry have indicated that interference pricing, based on [1], is being considered as a means for mitigating other-cell interference in cellular networks.

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