Distributed Queue-Aware Beamforming in MISO Interference Channels

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***Abstract*—We study distributed queue-aware beamforming in a multiple input single output (MISO) interference channel. Instead of assuming full buffer traffic, we adopt a more realistic traffic model where the data arrival rates are finite, and the beamformers are adaptive to the data in the buffer. We propose a simple dynamic beamforming strategy which significantly improves the average sum rate compared to non-adaptive beamformers.**

I. Introduction

The MISO interference channel (IFC) is a well investigated model. Many linear beamforming strategies have been proposed with the object to maximize the instantaneous sum of all user utilities [1], [2], [3], [4]. The beamforming strategies under distributed optimization framework [1], [2] are more interesting due to less requirements on network infrastructures, reduced complexity and latency. The traffic model for all of the above mentioned works is full buffer, i.e. all the transmitters always have infinite amount of data to transmit. However, in real networks, the data arrived at each transmitter is random, and the data in the buffer changes over time.

In this study, we design distributed and dynamic beamformers which take into account the dynamic change of the data buffer. The transmitters update their transmission strategies based on locally available channel state information and exchange the buffer status parameters via the back haul. Our objective is to maximize the time average of the sum user utilities. To our best knowledge, there is not much work in the literature on multiple antenna transmission with random data arrivals. The most similar work is [5], where the authors perform a theoretical analysis on the stability optimal policy in the multiple antenna Multiple Access Channel(MAC). However the optimal policy assumes centralized control and non-linear precoding, so it can only serve as a theoretical upper-bound instead of a practical solution. Another work is [6], where the study is focused on user selection for MU-MIMO systems, and uses only random beamforming. In our work, we are mainly interested in providing simple Queue-aware distributed beamforming solutions which brings big improvement compared to some of the existing Queue-unaware simple distributed solutions.

II. System Model

We consider a data network which can be modeled as a MISO interference channel with K interfering links. Each link has a transmitter equipped with N antennas delivering data intended only for its own single-antenna receiver while causing interference to other links.

In the system, the design variables are the beamforming vectors at the transmitters. We denote the matrix formed by these beamforming vectors as $\mathbf{W}(t) = [\mathbf{w}_1(t)\ \mathbf{w}_2(t)\ ...\ \mathbf{w}_K(t)]^H$. The transmission power is limited at each transmitter, e.g. $\left\|\mathbf{w}_k^H(t)\right\|^2 \leq p_k$. We denote $\mathcal{W}$ as the set of all feasible beamformers.

Associated with each beamformers selection at time instant t is the instantaneous *achievable* user rate vector $\hat{\mathbf{r}}(t) = [\hat{r}_1(t)\ \hat{r}_2(t)\ ...\ \hat{r}_K(t)]^H$, with

$$\hat{r}_k(t) = \log\left(1 + \frac{\left|\mathbf{w}_k^H(t)\mathbf{h}_{kk}(t)\right|^2}{\sum_{l\neq k}\left|\mathbf{w}_l^H(t)\mathbf{h}_{kl}(t)\right|^2 + \sigma_k^2}\right),\ \mathbf{W}(t) \in \mathcal{W}$$

where $\mathbf{h}_{kl}(t),\ k,l \in \{1, 2, ...K\}$ is the channel coefficient from transmitter l to receiver k at time instant t, this coefficient is locally available without involvement of information exchange among transmitters.

The data arrival rate at each transmitter is modeled as a random process with a finite average arrival rate. We denote $\mathbf{a}(t) = [a_1(t)\ a_2(t)\ ...\ a_K(t)]^H$ is the *i.i.d.* random arrival process, and $\bar{\mathbf{a}} = [\bar{a}_1\ \bar{a}_2\ ...\ \bar{a}_K]^H$ is the *average* arrival rate vector, $\bar{\mathbf{a}} = E[\mathbf{a}(t)]$. When the arrived data can not be delivered immediately, they will form a queuing backlog and wait for the next transmission. The dynamic queue length (backlog size) vector is denoted as $\mathbf{s}(t) = [s_1(t)\ s_2(t)\ ...\ s_K(t)]^H$. We assume the channels change slowly and can be estimated accurately, and that the current queue lengths $\mathbf{s}(t)$ could be obtained for all the transmitters (through for example the back haul communications).

The evolution of the queue length is

$$\mathbf{s}(t+1) = \mathbf{s}(t) + \mathbf{a}(t+1) - \mathbf{r}(t+1).$$

Here, $\mathbf{r}(t+1) = [r_1(t)\ r_2(t)\ ...\ r_K(t)]^H$ denote the *actual* transmitted rate at time $t+1$. i.e.

$$\mathbf{r}(t) = \min\left[\mathbf{s}(t) + \mathbf{a}(t+1),\ \hat{\mathbf{r}}(t)\right].$$

III. Average sum rate maximization

A. Lyapunov drift algorithm

Note that when the data arrival rate $\mathbf{a}(t)$ is an *i.i.d.* random arrival process, the queue length $\mathbf{s}(t)$ is an Markov process. This allows us to use the drift technique to minimize the Lyapunov function of $\mathbf{s}(t)$ as in [7]. The resulting dynamic rate allocation policy is stability-optimal, and is given by

$$\hat{\mathbf{r}}^*(t) = \underset{\hat{\mathbf{r}}(t)}{\text{argmax}} \sum_{k=1}^{K} \hat{r}_k(t)s_k(t). \tag{1}$$

This is a weighted sum rate maximization problem and can be rewritten as

$$\begin{aligned} &\text{maximize} \quad \sum_{k=1}^{K} s_k(t) \cdot \log\left(1 + \frac{\left|\mathbf{w}_k^H(t)\mathbf{h}_{kk}(t)\right|^2}{\sum_{l\neq k}\left|\mathbf{w}_l^H(t)\mathbf{h}_{kl}(t)\right|^2 + \sigma_k^2}\right) \quad (2) \\ &\text{subject to} \quad \left\|\mathbf{w}_k^H(t)\right\|^2 \leq p_k, \quad k = 1, ..., K. \end{aligned}$$

Problem (2) is NP-hard[2] and can be solved via the BRB algorithm for example in [3]. However, such a centralized solution is practically infeasible in terms of computational complexity, back haul signaling, and scalability, and we are more interested in a distributed solution.

B. Distributed algorithm

The algorithm introduced in [2] could be used so solve (2). However, that algorithm still needs a few iterations to converge. Since we are aiming at updating beamformers each time instant, it is preferred to have an even simpler algorithm. In [8] it is shown that each Pareto optimal point is achieved by beamforming vectors which can be parametrized as

$$\mathbf{w}_k(t) = \frac{\left(\frac{\mu_k}{p_k}\mathbf{I}_{N_t} + \sum_{l\neq k}\frac{\lambda_l}{\sigma_l^2}\mathbf{h}_{lk}(t)\mathbf{h}_{lk}^H(t)\right)^{-1}\mathbf{h}_{kk}}{\left\|\left(\frac{\mu_k}{p_k}\mathbf{I}_{N_t} + \sum_{l\neq k}\frac{\lambda_l}{\sigma_l^2}\mathbf{h}_{lk}(t)\mathbf{h}_{lk}^H(t)\right)^{-1}\mathbf{h}_{kk}\right\|}, \quad k = 1, 2, ..., K \qquad (3)$$

where $\{\mu_k\}_{k=1}^K$ and $\{\lambda_l\}_{l=1}^K$ satisfy $\sum_{k=1}^K \mu_k = \sum_{l=1}^K \lambda_l = 1$. From (3) we can see that when μ_k is large compared to $\sum_{l\neq k}\lambda_l$, the beamformer is more selfish like a Maximum Ratio Combining (MRC) beamformer. While μ_k is small compared to $\sum_{l\neq k}\lambda_l$, the beamformer is more altruistic like a zero forcing (ZF) beamformer. Intuitively, we want the links with long queues act more selfish and the links with short queue lengths altruistic. Therefore, we can adjust the parameters μ_k and λ_k in (3) to be monotonically increasing with the queue length. We propose the following strategy,

$$\mu_k = \lambda_k = \frac{s_k^\alpha}{\sum_{k=1}^K s_k^\alpha} \qquad (4)$$

for some choice of $\alpha > 0$. Numerical experiments have shown that a choice of $\alpha = 0.3$ provides good performance (Figure 1).

IV. Simulation Results

While a more realistic simulation scenario will be used in the full paper, here we generate the preliminary results considering a simple MISO interference channel scenario. We consider three transmitter-receiver pairs, each transmitter equipped with three antennas. The channel vector from transmitter l to receiver k, $\mathbf{h}_{kl}$ is i.i.d and modeled as complex Gaussian

$$\mathbf{h}_{lk} \sim \begin{cases} \mathcal{CN}(0, \mathbf{I}_K), & \text{when } k = l \\ \mathcal{CN}(0, \frac{1}{4}\mathbf{I}_K), & \text{when } k \neq l \end{cases},$$

where $\forall k, l \in \{1, 2, 3\}$, $K = 3$. The power constraint at each transmitter is normalized to one, so the system SNR is defined as

$$SNR = \frac{||\mathbf{H}||_2^2}{\sigma^2},$$

where

$$\mathbf{H} = \begin{bmatrix} \mathbf{h}_{11} & \mathbf{h}_{12} & \mathbf{h}_{13} \\ \mathbf{h}_{21} & \mathbf{h}_{22} & \mathbf{h}_{23} \\ \mathbf{h}_{31} & \mathbf{h}_{32} & \mathbf{h}_{33} \end{bmatrix},$$

and σ^2 is the constant noise power at each receiver. We chose an average arrival rate vector $\bar{\mathbf{a}}$ which lies within and near the boundary of the achievable rate region. We run 10 different channel realizations, and for each channel realization10^5 time instances.

In Figure 1, we compare the average sum rate for proposed beamformer with respect to different choice of α in (4), and simulations show that $\alpha = 0.3$ is a good choice.

In Figure 2, we compare the average sum rate for four difference beamformers: distributed beamformer (3) with α in (4) set to 0.3 (blue solid line); Maximum Ratio Combining (MRT); Zero Forcing (ZF) and maximum Signal to Leakage and Noise Ratio (SLNR) beamformers[8].

We can see the beamformer we proposed in this paper performs considerably better than the reference beamformers.

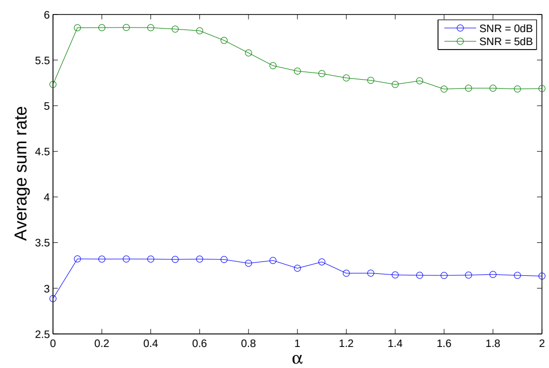

Figure 1. Average sum rate achieved by different beamforming strategies

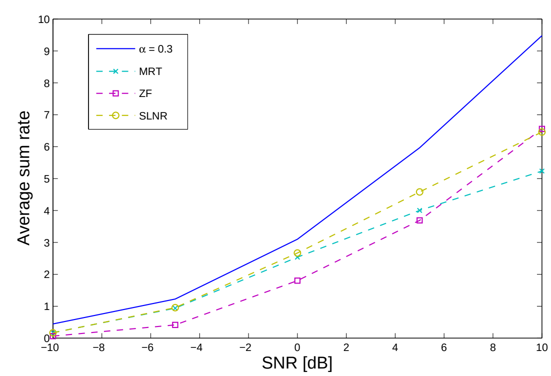

Figure 2. Average sum rate achieved by different beamforming strategies

V. Conclusion

In this study, we propose simple and distributed beamforming strategies considering random data arrival process. The proposed beamformers bring average sum rate gain according to simulations.

REFERENCES

[1] S. Wesemann and G. P. Fettweis, "Distributed asynchronous optimization framework for the MISO interference channel," *IEEE Trans. Signal Process.*, vol. 62, no. 22, pp. 5809–5824, Nov 2014.

[2] Q. Shi, M. Razaviyayn, Z.-Q. Luo, and C. He, "An iteratively weighted MMSE approach to distributed sum-utility maximization for a MIMO interfering broadcast channel," *IEEE Trans. Signal Process.*, vol. 59, no. 9, pp. 4331–4340, Sep 2011.

[3] E. Björnson, G. Zheng, M. Bengtsson, and B. Ottersten, "Robust monotonic optimization framework for multicell MISO systems," *IEEE Trans. Signal Process.*, vol. 60, no. 5, pp. 2508–2523, May 2012.

[4] S. K. Joshi, P. C. Weeraddana, M. Codreanu, and M. Latva-aho, "Weighted sum-rate maximization for MISO downlink cellular networks via branch and bound," *IEEE Trans. Signal Process.*, vol. 60, no. 4, pp. 2090–2095, Apr 2012.

[5] H. Boche and M. Wiczanowski, "Optimization-theoretic analysis of stability-optimal transmission policy for multiple-antenna multiple-access channel," *IEEE Trans. Signal Process.*, vol. 55, no. 6, pp. 2688–2702, June 2007.

[6] J. Chen and V. Lau, "Large Deviation Delay Analysis of Queue-Aware Multi-User MIMO Systems With Two-Timescale Mobile-Driven Feedback," *IEEE Trans. Signal Process.*, vol. 61, no. 16, pp. 4067–4076, Aug 2013.

[7] M. J. Neely, *Stochastic Network Optimization with Application to Communication and Queueing Systems*, Jan. 2010, vol. 3. [Online]. Available: DOI:10.2200/S00271ED1V01Y201006CNT007

[8] E. Björnson, M. Bengtsson, and B. Ottersten, "Optimal multiuser transmit beamforming: A difficult problem with a simple solution structure [lecture notes]," *IEEE Signal Process. Mag.31.4*, pp. 142–148, 2014.