Distributed MIMO interference alignment in practical wireless systems

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Abstract

In order for interference alignment (IA) techniques to be implemented in future generation mobile multiple-input multiple-output (MIMO) communications systems, they must be shown to be robust to system limitations such as quantisation and delay. Current IA algorithms in the literature assume global and instantaneous channel knowledge. In this paper, a novel IA algorithm is proposed which uses limited feedback and local channel information. Simulations using realistic channel models show that this algorithm can provide viable communications in the overloaded MIMO interference channel.

1 Introduction

One of the main challenges in developing multiple-input multiple-output (MIMO) technologies is maintaining spectral efficiency gains that are theoretically achievable, while incorporating more realistic assumptions and ensuring robustness. Interference alignment (IA) was introduced in [1] as a means of exploiting all spatial and temporal degrees of freedom in a MIMO system for interference rejection. This is accomplished by cooperatively precoding at the transmitters, each with N antenna elements, so that all interference will lie in an $(N-1)$-dimensional subspace at the N-element receivers. Then standard linear reception, e.g., minimum mean square error (MMSE), can be used to completely reject all interference, providing one interference-free channel to each transmitter-receiver pair. While standard beamforming techniques are well-known to null $N-1$ interferers, it has been shown that a single interference-free channel can be provided to $2N-1$ transmitter-receiver pairs using iterative solutions for IA [2]. A closed-form solution is only available for three users with $N = 2$ [1].

Although the methods presented in [1,2] provide theoretically interference-free communication, the assumptions required therein are unrealistic in practice. Perfect and instantaneous channel information of all desired and interfering links is assumed known either throughout the network, or at a central controller. In practice, neither perfect nor instantaneous information is achievable, and the amount of message passing required to make information available globally renders these methods unusable in all but static applications. In this work, a distributed algorithm is proposed which maintains some of the benefits of optimal IA while placing more realistic restrictions on channel information and overhead. Receivers are assumed to have access only to channel information that can realistically be estimated at each receiver; they do not have the information that is available at other receivers. The information fed back from the receivers to the transmitters is effectively quantised by selecting a precoder from a constellation of candidate precoding matrices [3]. Finally, it is assumed that precoding matrices chosen by each receiver in one frame are applied by the respective transmitters in the subsequent frame, introducing a realistic delay in the availability of channel information. Surprisingly, it will be shown that signal-to-interference-and-noise ratios (SINRs) are larger with the proposed distributed algorithm than when simply quantising the output of the optimal algorithm, for the examples shown herein.

2 System Model

Consider a multi-user MIMO interference system with K user pairs, each with N transmit and receive antennas. Each transmitter sends a single data stream precoded across all N antenna elements. In the tth communication frame, the kth transmitter, $k = 1, \ldots, K$, precodes its signal using the $N \times 1$ unit-norm precoding matrix $\mathbf{F}_{t,k}$. The received signal at user k, $\mathbf{y}_k$, is written

$$\mathbf{y}_k = \mathbf{H}_{k,k}\mathbf{F}_{t,k}\mathbf{s}_k + \sum_{j \neq k} \mathbf{H}_{k,j}\mathbf{F}_{t,j}\mathbf{s}_j + \mathbf{n}_k, \tag{1}$$

where $\mathbf{H}_{k,j}$ is the $N \times N$ channel state matrix from transmitter j to receiver k, which is assumed to have Gaussian-distributed zero-mean entries of variance $\sigma^2_{k,j}$, and $\mathbf{n}_k$ is the zero-mean complex Gaussian noise vector with variance $\sigma^2_{n,k}$.

If the choice of precoding matrix is unrestricted, IA algorithms theoretically provide interference-free communication to all user pairs in the system by selecting the $\mathbf{F}_{t,k}$ such that all interference at receiver k lies in an $(N-1)$-dimensional subspace of $\mathbb{C}^N$. This constraint allows the use of standard interference nulling techniques such as zero-forcing (ZF) or MMSE to determine receiver weights, $\mathbf{W}_{t,k}$. Herein, $\mathbf{W}_{t,k}$ is calculated using MMSE as in [2, Eq. 11] to be

$$\mathbf{W}_{t,k} = \nu\left(\left(\sum_{j\neq k}\mathbf{H}_{k,j}\mathbf{F}_{t,j}\mathbf{F}_{t,j}^H\mathbf{H}_{k,j}^H + \sigma_{n,k}^2\mathbf{I}\right)^{-1}\mathbf{H}_{k,j}\mathbf{F}_{t,k}\mathbf{F}_{t,k}^H\mathbf{H}_{k,k}^H\right) \tag{2}$$

where $(\mathbf{A})^H$ denotes the Hermitian transpose of $\mathbf{A}$ and $\nu(\mathbf{A})$ denotes the right singular vector corresponding to the largest eigenvalue of $\mathbf{A}$. Assuming unit symbol power, i.e., $\sigma_s^2 = 1$, the signal-to-interference-and-noise ratio (SINR) at receiver k is written

$$\gamma_k = \frac{\| \mathbf{W}_{t,k}\mathbf{H}_{k,k}\mathbf{F}_{t,k} \|_F^2}{\sum_{j\neq k} \| \mathbf{W}_{t,k}\mathbf{H}_{k,j}\mathbf{F}_{t,j} \|_F^2 + \sigma_{n,k}^2}. \tag{3}$$

When the interference is perfectly aligned, the summation term in the denominator of (3) becomes zero; however, due to channel delays and quantisation inherent in mobile systems, in practice it is impossible to achieve perfect alignment, resulting in interference which may significantly impact performance.

3 Proposed Algorithm

In this section, a novel cooperative distributed IA algorithm is described which maintains some of the gains available in optimal IA algorithms without requiring global channel knowledge. Due to the interrelation among all precoding matrices in the system, the algorithm is iterative, as are the theoretical solutions. In the initialisation stage, user k's precoding matrix is first calculated using eigenbeamforming; i.e., $\hat{\mathbf{F}}_{0,k}$ is chosen to be the right singular vector corresponding to the maximum eigenvalue of $\mathbf{H}_{k,k}$, i.e., $\nu(\mathbf{H}_{k,k})$. The quantisation process then selects the precoding matrix $\mathbf{F}_{0,k}$ from the constellation as the closest, in the sense of chordal distance, to $\hat{\mathbf{F}}_{0,k}$, i.e., $\mathbf{F}_{0,k} = argmin_{\mathbf{F}_l} \| \mathbf{F}_l\mathbf{F}_l^H - \hat{\mathbf{F}}_{0,k}\hat{\mathbf{F}}_{0,k}^H \|_F$. The constellation of precoding matrices is denoted $\mathbf{F}_l$, $l = 1, \ldots, L$, where $\mathbf{F}_l \in \mathcal{F}$ and $\mathcal{F}$ is the set of all one dimensional subspaces of $\mathbb{C}^N$. This initialisation process is repeated for all k, $k = 1, \ldots, K$. After initialisation, in each subsequent iteration, q, a new set of precoding matrices, $\mathbf{F}_{q,k}$, is selected, each from among the nearest P precoders to those selected in the $q-1$th iteration, $\mathbf{F}_{q-1,k}$, as follows:

- The receiver MMSE beamforming weights are calculated using (2).
- The SINR is estimated at each receiver using (3). It is assumed that receiver k, $k = 1, \ldots, K$, knows $\mathbf{H}_{k,j}$ from all transmitters.
- Receivers test P neighbouring constellation points for all transmitters' current precoding matrices to see which points would potentially improve the SINR. This is accomplished for user k as follows: A lookup table listing the P closest precoders for each constellation point, in a chordal distance sense, is available at every receiver. Receiver k estimates the impact on the SINR, were transmitter j to precode with each of the P nearest constellation precoders to $\mathbf{F}_{q-1,j}$ using (2) and (3). Precoders that would improve receiver k's SINR are given a score of $+1$; conversely, precoders decreasing the SINR are given a score of -1. For precoders making a significant impact on the SINR, herein chosen to be a 30% increase/decrease in SINR, this score is modified to ± 3. Thus, $2P$ bits are fed back to each of the transmitters from receiver k. In this work, for a 4096-point Grassmannian constellation, $P = 8$ neighbours are tested. Choosing P too small slows convergence, whereas choosing P too large allows large changes in the precoders in each iteration, inhibiting convergence.
- Each transmitter collects the $2P$ bits from each of the K receivers. The sum of the scores corresponding to the pth precoder in the lookup table is denoted Σ_p, and is a crude representation of the overall benefit or loss expected in the system by changing to that precoder. $\mathbf{F}_{q,j}$ is selected to be the precoder corresponding to the maximum positive Σ_p measure for each transmitter. In the case where all Σ_p are negative, $\mathbf{F}_{q,k}$ remains equal to $\mathbf{F}_{q-1,k}$.

In a mobile application, these steps are repeated in order to improve the SINR and track changes in the channels. The next section will illustrate this.

4 Simulation Results

In this section, the ability of the IA algorithm outlined in Sec. 3 to sustain multiple users and track changes in mobile channels is demonstrated. Time varying channel data were generated using the IST-WINNER2 model described in [4]. Simulations were run using the WINNER2 urban non-line-of-sight (NLOS) and rural line-of-sight (LOS) scenarios. Fixed transmitters and mobile receivers, each with an $N = 4$-element linear array of omnidirectional antennas, were randomly located in a 500 m by 500 m area. Results presented herein represent 100 independent simulation runs at 2 GHz; for speeds up to and including 10 km/h, in each simulation, the receivers moved 10 λ (1.5 m), while in simulations for speeds of 10 km/h and over the receivers moved 100 λ (15 m). For the evaluation of the proposed algorithm, it was assumed that precoding updates were fed back from the receivers to the transmitters every 2 ms and all SINR calculations were made using precoding matrices determined with a 2 ms delay. It is expected that results based on other delays would be a scaled version of those presented herein. The noise power was selected to ensure interference-limited operation, $E\{\sigma_{k,j}^2/\sigma_{n,k}^2\} = 50$ dB. The precoding matrix constellation consisted of $L = 4096$ points and was designed as outlined in [3].

For the results presented herein, the SINR performance using the algorithm presented in Sec. 3 is compared with that using several other precoding strategies. The first uses a constant precoding matrix for all transmission, thus requiring no feedback. The second is a delayed and quantised version of eigenbeamforming as in the initialisation process of the proposed algorithm, updated every 2 ms. The third is the maximum SINR version of the optimal iterative IA algorithm presented in [2], which requires instantaneous global channel knowledge. The fourth is a quantised version of the optimal iterative IA algorithm, assuming global channel knowledge at the receiver, but incorporating the same level of quantisation and delay found in the proposed algorithm. Cdfs of the receiver SINR for a $K = 6$ user pair system using all precoding methodologies and the urban NLOS scenario are shown in Fig. 1 for receivers moving at 5 km/h. Allowing feedback in the form of quantised eigenbeamforming provides a significant SINR gain over the 'no feedback' case. Another significant gain is obtained with the proposed algorithm through cooperation; transmitters inherently accommodate as many receivers as possible in each iteration of the algorithm, reducing overall interference. Fig. 1 also shows the lack of robustness inherent in the optimal IA algorithm; although, theoretically, it can provide interference-free communication to all 6 user pairs, quantisation and delay surprisingly render its performance worse than the proposed algorithm, despite the assumption of global channel knowledge at all receivers.

Fig. 2 shows the median SINR performance as a function of the number of user pairs at 5 km/h using the urban NLOS scenario. With four antenna elements at each transmitter and receiver, optimal IA is able to provide interference-free communication to seven user pairs, whereas the other precoding methods are able to accomplish this for at most four user pairs. More user pairs can be accommodated, depending on the required median SINR. For example, for a median SINR of 10 dB, the proposed algorithm can provide service to seven user pairs, while quantised eigenbeamforming allows six and zero feedback five. To decrease the spread of SINRs across the users, power control methods could readily be incorporated into the proposed algorithm. Figs. 3 and 4 show the median SINR as a function of receiver speed for the different precoding algorithms in a six user pair system using the urban NLOS and rural LOS scenarios, respectively. Due to the rapidly changing channels in the urban NLOS case, accommodating all users' interference in the proposed algorithm yields diminishing gains at higher speeds; the performance approaches that of quantised eigenbeamforming. Due to the LOS components in the rural scenario, channel variations occur more slowly, allowing significant gains with the proposed algorithm, even at highway velocities.

5 Conclusion

Although the number of interference-free channels in practical IA system will not match that hypothesised in the literature, significant overloading can be accommodated through cooperative signal processing techniques such as the algorithm proposed herein. Viable communication for overloaded systems is possible, especially at low speeds or in LOS conditions. As with many MIMO applications, IA techniques can be made more robust by incorporating system limitations such as quantisation and delay into their design.

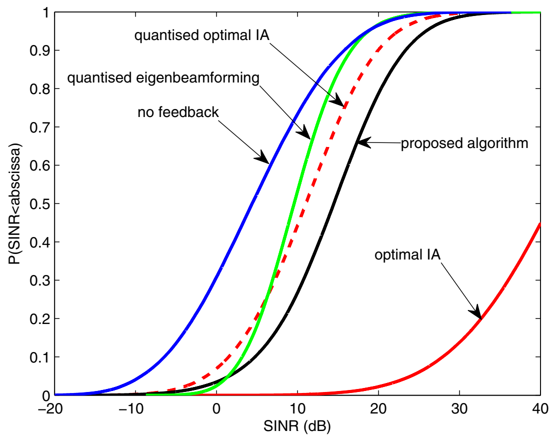

Figure 1: SINR cdf comparison for several interference strategies using the WINNER2 urban NLOS scenario for 6 user pairs at 5 km/h at 2 GHz with 2 ms feedback delay.

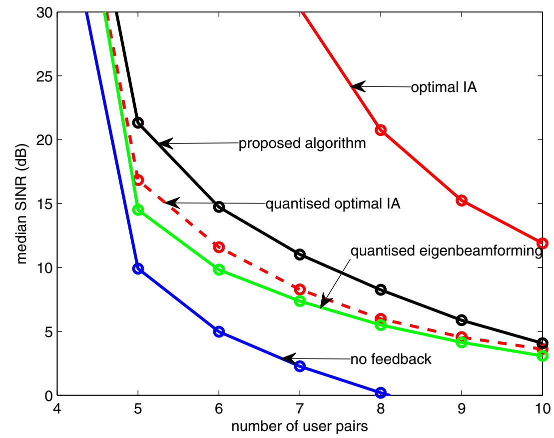

Figure 2: Median SINR comparison for several interference strategies using the WINNER2 urban NLOS scenario for 4-10 user pairs at 5 km/h at 2 GHz with 2 ms feedback delay.

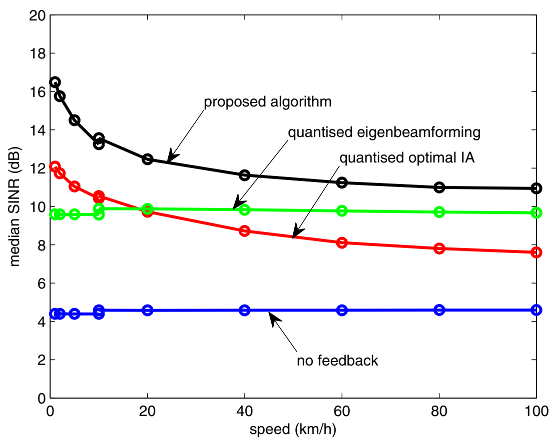

Figure 3: Median SINR comparison as a function of receiver speed for several interference strategies using the WINNER2 urban NLOS scenario for 6 user pairs at 2 GHz with 2 ms feedback delay.

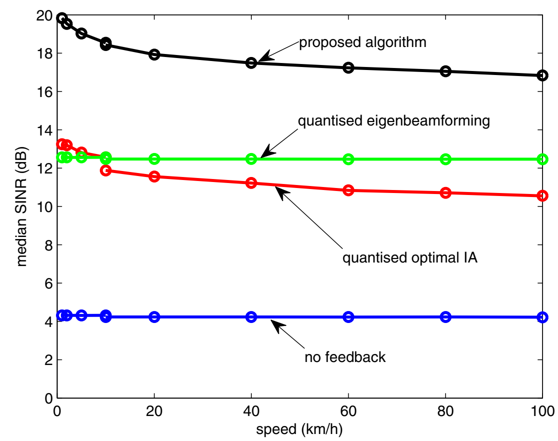

Figure 4: Median SINR comparison as a function of receiver speed for several interference strategies using the WINNER2 rural LOS scenario for 6 user pairs at 2 GHz with 2 ms feedback delay.

Acknowledgements

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6 References

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