MSE BASED PRECODING SCHEMES FOR PARTIALLY CORRELATED TRANSMISSIONS IN INTERFERENCE CHANNELS

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ABSTRACT

In this paper, we consider interference channel model in which transmissions from multiple users are partially correlated. This correlation arises in wireless sensor network (WSN) scenarios and temporally correlated models. Considering this model, two minimum mean squared error (MSE) based precoding methods are derived. With these formulations, an iterative convergent procedure is formulated similar to a typical interference alignment (IA) algorithm. Simulations show that the second method provides the best sum rates for different correlation values.

1. INTRODUCTION

Interference is one of the bottlenecks in improving the throughput of multiple-input-multiple-output (MIMO) interference networks. Interference alignment (IA), which aims to achieve interference free communication [1, 2], has therefore naturally attracted significant research interest in the recent past. In MIMO interference channels, each transmitter can employ a suitably designed precoder to align the interference at the receiver, while each receiver can use a decoder (linear combiner) to null the aligned interference from the interfering users [1]. These precoders and decoders for interference alignment enable the users to achieve a sum rate linearly proportional to the number of users [1], when perfect channel state information (CSI) is available.

In literature, IA has been investigated with different scenarios such as cognitive radios, broadcast and multiple access channels, etc, [3]. However, IA has not been investigated for the case when transmissions of multiple users are partially correlated. This type of correlation model is useful in wireless sensor networks (WSN) [4], temporally correlated systems (vehicular mobile systems), etc, [5]. Our investigation show that the same IA precoders in correlated settings do not provide optimal sum rates. Therefore, in this work, we present the two precoding methods based on mean squared error (MSE), when the transmit data of two (or more) users are correlated. After describing an interference channel model with partial correlation in section 2, feasibility conditions are obtained, which show that the presence of correlation reduces the requirements for number of antennas. MSE based precoding solutions are given in section 3. Using these precoding expressions, an iterative algorithm is formulated, whose convergence is illustrated in section 4. Rate expression for this partially correlated model is derived. Simulations verify the sum rate convergence, and improved sum rate performance of both methods over IA precoders. Section 5 concludes the paper.

2. SYSTEM MODEL

We consider an IA-feasible MIMO interference channel $(M \times N, d)^K$ [6–8] with K user pairs, denoted with an index set $\mathcal{K} = \{1, \dots, K\}$. Each user pair has M transmit antennas, N receive antennas and d independent data streams to be communicated. Let $\mathbf{x}_k$ of size $d \times 1$ denote the transmit vector of the k^{th} user. Here, we consider that transmit signals of the two or more users are partially correlated. Without loss of generality, let the index set of correlated users be $\mathcal{S} = \{1, 2\}$ and the correlated signal in general can be expressed as

$$\mathbf{x}_i = \sqrt{1-\alpha_i}\mathbf{x} + \sqrt{\alpha_i}\mathbf{w}_i, i \in \mathcal{S}, \tag{1}$$

where α_i and $\mathbf{w}_i \sim \mathcal{CN}(\mathbf{0}, \frac{P}{d}\mathbf{I}_d)$. Let the correlation factor be denoted as $\bar{\alpha}_i = 1 - \alpha_i$, indicating $\bar{\alpha}_i = 1(0)$ for (no) correlation.

Example 1. In a WSN with two sensors [4], observing a vector parameter ($\mathbf{x} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_d)$) as $\mathbf{x} + \sigma_i\mathbf{w}_i$, where $\sigma_i\mathbf{w}_i \sim \mathcal{CN}(\mathbf{0}, \sigma_i\mathbf{I})$. For amplify and forward (AF) sensors, these observations are scaled to satisfy unity power constraint, i.e., $\frac{\mathbf{x}+\sigma_i\mathbf{w}_i}{\sqrt{1+\sigma_i^2}} = \sqrt{1-\alpha_i}\mathbf{x} + \sqrt{\alpha_i}\mathbf{w}_i$, where $\alpha_i = \frac{\sigma_i^2}{1+\sigma_i^2}$.

Let the channel between the j^{th} transmitter and k^{th} receiver be $\mathbf{H}_{kj} \in \mathbb{C}^{N\times M}$ with i.i.d. entries distributed as $\mathcal{CN}(0, 1)$. After receiver processing with $N \times d$ decoder $\mathbf{U}_k$ at k^{th} receiver, the received signal is given as

$$\begin{aligned}\mathbf{U}_k^\dagger\mathbf{y}_k &= \sum_{j\in\mathcal{S}} \mathbf{U}_k^\dagger\mathbf{H}_{kj}\mathbf{V}_j\mathbf{x}_j + \sum_{j\in\mathcal{K}\setminus\mathcal{S}} \mathbf{U}_k^\dagger\mathbf{H}_{kj}\mathbf{V}_j\mathbf{x}_j + \mathbf{U}_k^\dagger\mathbf{n}_k \\ &= \mathbf{U}_k^\dagger\mathbf{H}_{k\mathrm{x}}\mathbf{V}_\mathrm{x}\mathbf{x} + \sum_{j\in\mathcal{K}\setminus\mathcal{S}} \mathbf{U}_k^\dagger\mathbf{H}_{kj}\mathbf{V}_j\mathbf{x}_j + \mathbf{U}_k^\dagger\tilde{\mathbf{n}}_k, \forall k \in \mathcal{S}\end{aligned}$$

$$\mathbf{U}_k^\dagger \mathbf{y}_k = \mathbf{U}_k^\dagger \mathbf{H}_{kk}\mathbf{V}_k\mathbf{x}_k + \sum_{j\in\mathcal{K}\setminus\{\mathcal{S}\cup k\}} \mathbf{U}_k^\dagger \mathbf{H}_{kj}\mathbf{V}_j\mathbf{x}_j + \mathbf{U}_k^\dagger \mathbf{H}_{k\mathrm{x}}\mathbf{V}_{\mathrm{x}}\mathbf{x} + \mathbf{U}_k^\dagger \tilde{\mathbf{n}}_k, \forall k \in \mathcal{K}\setminus\mathcal{S} \quad (2)$$

where (1) is used to simplify from $\mathbf{x}_j$ to $\mathbf{x}$; for $\mathcal{S} = \{1,2\}$, $\mathbf{H}_{k\mathrm{x}} = \left[\sqrt{1-\alpha_1}\mathbf{H}_{k1}, \sqrt{1-\alpha_2}\mathbf{H}_{k2}\right]$; and $\mathbf{V}_{\mathrm{x}} = \begin{bmatrix} \mathbf{V}_1 \\ \mathbf{V}_2 \end{bmatrix}$. In (2), $\mathbf{V}_k$ is $M \times d$ precoder with $\mathrm{tr}\mathbb{E}\left\{\mathbf{V}_k\mathbf{x}_k\mathbf{x}_k^\dagger\mathbf{V}_k^\dagger\right\} \leq P$, yielding $\|\mathbf{V}_l\|_F^2 \leq d$, and $\mathbf{n}_k \sim \mathcal{CN}(\mathbf{0}, \sigma^2\mathbf{I}_N)$ is noise vector, resulting into $\tilde{\mathbf{n}}_k = \sum_{j\in\mathcal{S}} \sqrt{\alpha_j}\mathbf{U}_k^\dagger\mathbf{H}_{kj}\mathbf{V}_j\mathbf{w}_j + \mathbf{n}_k \sim \mathcal{CN}(\mathbf{0}, \mathbf{C}_k)$ with

$$\mathbf{C}_k = \sum_{j\in\mathcal{S}} \alpha_j \frac{P}{d}\mathbf{H}_{kj}\mathbf{V}_j\mathbf{V}_j^\dagger\mathbf{H}_{kj}^\dagger + \sigma^2\mathbf{I}_N. \quad (3)$$

The first term in (2) represents the desired signal component, while the second (plus third) and last terms correspond to the interference and noise components respectively. Simplified equation can be written as

$$\mathbf{U}_k^\dagger \mathbf{y}_k = \sum_{j\in\mathcal{K}'} \bar{\mathbf{H}}_{kj}\mathbf{x}_j + \mathbf{U}_k^\dagger\tilde{\mathbf{n}}_k, \quad (4)$$

where $\mathcal{K}' = \{\mathrm{x}\} \cup (\mathcal{K}\setminus\mathcal{S})$, $\bar{\mathbf{H}}_{kj} = \mathbf{U}_k^\dagger\mathbf{H}_{kj}\mathbf{V}_j$, and for index $j = \mathrm{x}$, $\mathbf{x}_{\mathrm{x}} = \mathbf{x}$. The above system is equivalent to the system having $(K-1)$ transmitters and K receivers with the colored receiver noise depending on the channel coefficients. The precoders and decoders are computed to cancel the interference, i.e., we can write

$$\mathbf{U}_k^\dagger\mathbf{H}_{kj}\mathbf{V}_j = \mathbf{0},\ \forall (k,j) \in \mathcal{I} \quad (5)$$

$$\mathrm{rank}(\mathbf{U}_k^\dagger\mathbf{H}_{kk'}\mathbf{V}_{k'}) = d,\ \forall (k,k') \in \mathcal{D}, \quad (6)$$

where $\mathcal{D} = \left\{(k,k')\middle| k\in\mathcal{K}, k' = \begin{cases} \mathrm{x}, & k \in \mathcal{S} \\ k, & k\in\mathcal{K}\setminus\mathcal{S}\end{cases}\right\}$ and $\mathcal{I} = \mathcal{K}\times\mathcal{K}'\setminus\mathcal{D}$ are the desired signal and the interference indices sets, with $|\mathcal{I}| = K(K-|\mathcal{S}|)$. In [7, 8], authors investigate that proper systems are feasible when $M = N$ or M and N are divisible by d. Therefore, the necessary proper condition from (5) can be obtained by simplifying the non-negative difference of number of equations and variables as

$$M + N - (K+1)\left(1 - \frac{|\mathcal{S}|-1}{K}\right)d \geq 0,$$

where for no-correlation (i.e. $|\mathcal{S}| = 1$), it reduces to a typical proper condition. It shows that correlation reduces the feasibility requirements. Therefore, this is useful in the systems where IA-feasibility is not satisfied. By allowing some statistical dependency among transmit signals, the restrictions on feasibility can be reduced. In addition to WSN scenario, this partial correlation occurs when data streams are from finite constellation data.

3. PRECODING SCHEME

In this section, two MSE based methods are derived for the model described above. These two methods employ the similar MMSE receive decoders. Towards, that, the MSE of k^{th} user can be written as

$$\mathcal{E}_k = \mathbb{E}\left\{\|\mathbf{U}_k^\dagger\mathbf{y}_k - \mathbf{x}_k\|^2\right\} \quad (7)$$
$$= \frac{P}{d}\mathrm{tr}\left[\sum_{j\in\mathcal{K}'}\bar{\mathbf{H}}_{kj}\bar{\mathbf{H}}_{kj}^\dagger + \frac{d}{P}\mathbf{U}_k^\dagger\mathbf{C}_k\mathbf{U}_k + \mathbf{I}_d - 2\Re\bar{\mathbf{H}}_{kk'}\right]$$

where for a given k, $(k,k') \in \mathcal{D}$, i.e., $k' = \begin{cases}\mathrm{x}, & \text{if } k\in\mathcal{S} \\ k, & \text{if } k\in\mathcal{K}\setminus\mathcal{S}\end{cases}$.

3.1. MSE based Receive Decoder

The receive decoder is computed in order to minimize the MSE at each receiver. The following lemma provides the required result.

Lemma 2. *The decoder expression to minimize the k^{th} receiver's MSE $\mathcal{E}_k$ is given as*

$$\mathbf{U}_k = \arg\min_{\mathbf{U}_k}\mathbb{E}\left\{\|\mathbf{U}_k^\dagger\mathbf{y}_k - \mathbf{x}_k\|^2\right\} \quad (8)$$
$$= \begin{cases}\mathbf{B}_k^{-1}\mathbf{H}_{k\mathrm{x}}\mathbf{V}_{\mathrm{x}}, & \forall k\in\mathcal{S} \\ \mathbf{B}_k^{-1}\mathbf{H}_{kk}\mathbf{V}_k, & k\in\mathcal{K}\setminus\mathcal{S}.\end{cases} \quad (9)$$

where $\mathbf{B}_k = \sum_{j\in\mathcal{K}'}\mathbf{H}_{kj}\mathbf{V}_j\mathbf{V}_j^\dagger\mathbf{H}_{kj}^\dagger + \frac{d}{P}\mathbf{C}_k$.

Proof. Proof is obtained by differentiating the simplified MSE and setting it equal to zero. □

3.2. Information Rate Analysis

It is important to observe the changes in sum rate expression, when the transmission are correlated. The following expressions provide the resultant sum rates.

Lemma 3. *Information rate expression for k^{th} user can be obtained as*

$$R_k = \mathcal{H}(\mathbf{U}_k^\dagger\mathbf{y}_k) - \begin{cases}\mathcal{H}(\mathbf{U}_k^\dagger\mathbf{y}_k|\mathbf{x}), & \forall k\in\mathcal{S} \\ \mathcal{H}(\mathbf{U}_k^\dagger\mathbf{y}_k|\mathbf{x}_k), & \forall k\in\mathcal{K}\setminus\mathcal{S}\end{cases} \quad (10)$$
$$= \log_2\left|\mathbf{U}_k^\dagger\mathbf{B}_k\mathbf{U}_k\right| \quad (11)$$
$$- \begin{cases}\log_2\left|\mathbf{U}_k^\dagger\mathbf{B}_k\mathbf{U}_k - \bar{\mathbf{H}}_{k\mathrm{x}}\bar{\mathbf{H}}_{k\mathrm{x}}^\dagger\right|, & \forall k\in\mathcal{S} \\ \log_2\left|\mathbf{U}_k^\dagger\mathbf{B}_k\mathbf{U}_k - \bar{\mathbf{H}}_{kk}\bar{\mathbf{H}}_{kk}^\dagger\right|, & \forall k\in\mathcal{K}\setminus\mathcal{S}\end{cases}$$

where $\mathcal{H}(\cdot)$ denotes entropy.

Proof. Proof follows from simplifying the entropy difference of information rate definition. □

Corollary 4. *Information rate for the decoder expression in* (8) *simplifies to the following*

$$R_k = \begin{cases} -\log_2 \left| \mathbf{I}_d - \bar{\mathbf{H}}_{k\mathrm{x}}^\dagger \right|, & \forall k \in \mathcal{S} \\ -\log_2 \left| \mathbf{I}_d - \bar{\mathbf{H}}_{kk}^\dagger \right|, & \forall k \in \mathcal{K} \setminus \mathcal{S} \end{cases}$$

Corollary 5. *Let an IA algorithm applied on* $\mathbf{H}_{kj}, \forall k, j \in \mathcal{K}$, *yield precoders* $\left(\mathbf{V}_k \mathbf{V}_k^\dagger = \mathbf{I}_d\right)$ *and decoders* $\left(\mathbf{U}_k \mathbf{U}_k^\dagger = \mathbf{I}_d\right)$ *satisfying* $\mathbf{U}_k^\dagger \mathbf{H}_{kj} \mathbf{V}_j = \mathbf{0}, \forall k \neq j$ *and* $\mathbf{U}_k^\dagger \mathbf{H}_{kk} \mathbf{V}_k = \mathbf{D}_k, \forall k$, *where* $\mathbf{D}_k$ *is a diagonal matrix with elements* D_{ki}, $i = 1, \ldots d$. *These* $\mathbf{U}_k$ *and* $\mathbf{V}_k$ *simplify terms as* $\bar{\mathbf{H}}_{k\mathrm{x}} = \sqrt{1-\alpha_k}\bar{\mathbf{H}}_{kk}$, $\mathbf{U}_k^\dagger \mathbf{B}_k \mathbf{U}_k = \bar{\mathbf{H}}_{kk} \bar{\mathbf{H}}_{kk}^\dagger + \frac{\sigma^2 d}{P} \mathbf{I}_d$, *for all* $k \in \mathcal{K}$. *This reduces the information rate to* $R_k = \sum_{i=1}^d R_{ki}$ *with*

$$R_{ki} = \begin{cases} \log_2 \left(1 + \frac{P}{d} \frac{(1-\alpha_k) D_{ki}^2}{D_{ki}^2 \alpha_k \frac{P}{d} + \sigma^2}\right), & \forall k \in \mathcal{S} \\ \log_2 \left(1 + \frac{P}{d} \frac{D_{ki}^2}{\sigma^2}\right), & \forall k \in \mathcal{K} \setminus \mathcal{S} \end{cases}.$$

For IA method, the above result yields that the higher α_k is, the lower R_{ki} will be. It can also be concluded that the rate of users ($k \in \mathcal{S}$) is no-longer increasing with SNR. To see that, for $k \in \mathcal{S}$, sum rate at asymptotic SNR is given as

$$\lim_{P \to \infty} R_{ki} = -\log_2 \alpha_k, \; \forall k \in \mathcal{S}, \tag{12}$$

which show that degree of freedom is lost for these users. Therefore, to improve these rates, precoding method exploiting correlation needs to be derived, which is presented next.

3.3. MSE based Transmit Precoder (Method-I)

One can observe from the equation (4) that the joint precoder $\mathbf{V}_\mathrm{x}$ appears. In this first method, we employ MSE method to directly obtain this precoder and decompose it to obtain the precoders $\mathbf{V}_j$, $j \in \mathcal{S}$. In particular, precoder expressions are provided in the following lemma which minimizes total MSE.

Lemma 6. *The precoder expressions to minimize the sum MSE is obtained as*

$$\{\mathbf{V}_\mathrm{x}, \mathbf{V}_j, j \in \mathcal{K} \setminus \mathcal{S}\} = \arg \min_{\mathbf{V}_\mathrm{x}, \mathbf{V}_j} \sum_{k \in \mathcal{K}} \mathcal{E}_k \tag{13}$$

$$\mathbf{V}_\mathrm{x} = \left(\mathbf{A}_\mathrm{x} + \mathcal{D}\left(\alpha_l \mathbf{A}_l, l \in \mathcal{S}\right)\right)^{-1} \mathbf{H}_\mathrm{xx}^\dagger \mathbf{U}_\mathrm{x} \tag{14}$$

$$\mathbf{V}_\mathrm{x} \leftarrow \beta_\mathrm{x} \mathbf{V}_\mathrm{x} \tag{15}$$

$$\mathbf{V}_j = \mathbf{A}_j^{-1} \mathbf{H}_{jj}^\dagger \mathbf{U}_j, \; j \in \mathcal{K} \setminus \mathcal{S} \tag{16}$$

$$\mathbf{V}_j \leftarrow \beta_j \mathbf{V}_j \tag{17}$$

where $\mathbf{A}_j = \sum_{k \in \mathcal{K}} \mathbf{H}_{kj}^\dagger \mathbf{U}_k \mathbf{U}_k^\dagger \mathbf{H}_{kj}$, $\beta_\mathrm{x} = \frac{\sqrt{d}}{\max_{i \in \mathcal{S}} \|\mathbf{V}_i\|_F}$ *and* $\beta_j = \frac{\sqrt{d}}{\|\mathbf{V}_j\|_F}$ *are set to satisfy the power constraint.*

Proof. Proof follows by rearranging the terms in sum MSE expression with respect to $\mathbf{V}_j$, $j \in \mathcal{K}'$, then differentiating and setting it to zero. Normalization β_j is set to obtained $\|\mathbf{V}_j\|_F^2 \leq d$, for all $k = 1, 2, \ldots, K$. Similar scalar is employed for $j \in \mathcal{S}$, since using different scalar for normalization destroyed the structure of $\mathbf{V}_\mathrm{x}$, obtained to minimize the MSE. □

Algorithm 1 MSE based Algorithm for Partially correlated transmissions.

1) Initialize the precoders $\mathbf{V}_\mathrm{x}$ and $\mathbf{V}_k$ for $k \in \mathcal{K} \setminus \mathcal{S}$.
2) Compute decoders using (8).
3) *For Method-I:* compute precoders using (15) and (17),
   For Method-II: compute precoders using (18) and (19).
4) Go to step 2 until maximum iterations are reached.

Given the observation about the interdependence of precoders and decoders, an iterative and convergent procedure to obtain these has been provided in Algorithm 1. For simplicity, this algorithm is formulated to follow the same procedure as an IA algorithm [9, 10]. In this algorithm, after an initialization, next two steps respectively computes decoders and precoders until convergence or maximum iterations. Since both the steps minimize the same MSE by construction, the algorithm converges in MSE.

3.4. MSE based Transmit Precoder (Method-II)

The disadvantage of the previous method is that the same scalar was multiplied while satisfying the precoder constraint. This results in inefficient utilization of transmit power constraint, which in turn affects MSE performance, since more transmit power yields less MSE. Therefore, instead of satisfying the power constraint outside the total MSE minimization, the power constraint is incorporated inside the precoder optimization problem, which is presented in the following.

Lemma 7. *The precoder optimization problem to minimize the sum MSE subject to individual transmit power constraint can be written as*

$$\begin{aligned} \{\mathbf{V}_l, l \in \mathcal{S}\} = \arg \min_{\mathbf{V}_l, l \in \mathcal{S}} & \; tr\left[\mathbf{V}_\mathrm{x}^\dagger \left(\mathbf{A}_\mathrm{x} + \mathcal{D}\left(\alpha_l \mathbf{A}_l, l \in \mathcal{S}\right)\right) \mathbf{V}_\mathrm{x}\right] \\ & - 2tr\left[\Re \mathbf{U}_\mathrm{x}^\dagger \mathbf{H}_\mathrm{xx} \mathbf{V}_\mathrm{x}\right] \\ & \text{subject to } \|\mathbf{V}_l\|_F^2 \leq d, \; l \in \mathcal{S} \end{aligned} \tag{18}$$

and for $j \in \mathcal{K} \setminus \mathcal{S}$,

$$\begin{aligned} \mathbf{V}_j = \arg \min_{\mathbf{V}_j} & \; tr\left[\mathbf{V}_j^\dagger \mathbf{A}_j \mathbf{V}_j - 2\Re \mathbf{U}_j^\dagger \mathbf{H}_{jj} \mathbf{V}_j\right] \\ & \text{subject to } \|\mathbf{V}_j\|_F^2 \leq d. \end{aligned} \tag{19}$$

Proof. Proof follows by rearranging the terms for each precoder and formulating as an optimization problem. Decoupling the sum MSE yields the above simplification. □

The above optimizations are convex and can efficiently be solved using CVX tool. However, it involves matrix-

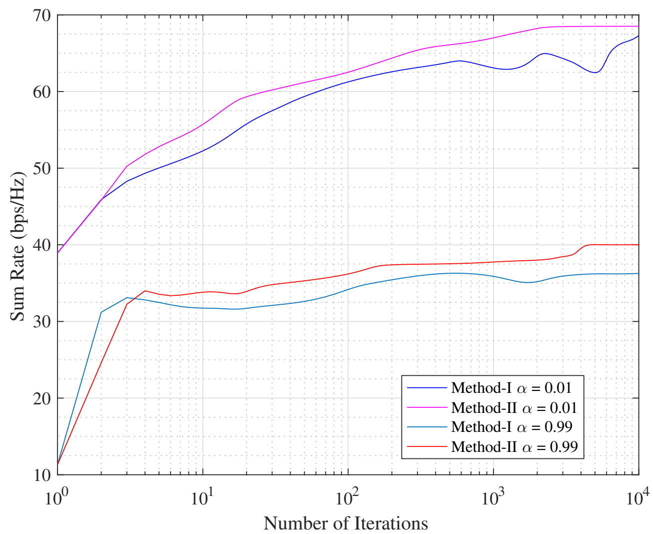

Fig. 1. Figure illustrates the sum rate convergence of two MSE based methods at 25dB SNR with $\alpha = 0.01, 0.99$.

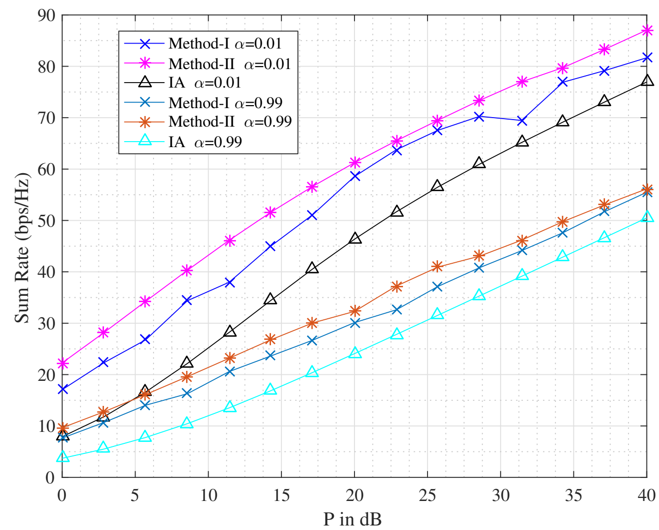

Fig. 2. Figure depicts sum rate versus SNR plots for two MSE based methods with $\alpha = 0.01, 0.99$.

quadratic forms, which is not supported by CVX. Therefore, to proceed with CVX, a trace identity tr$(\mathbf{V}^\dagger \mathbf{F} \mathbf{V} \mathbf{I}_d) = \text{vec}(\mathbf{V})^\dagger (\mathbf{I}_d \otimes \mathbf{F}) \, \text{vec}(\mathbf{V})$ can be utilized.

After getting the solution for precoders, together with the decoder expression in (8), iterative procedure in Algorithm 1 is utilized. This procedure is also convergent due to same MSE minimization in each step.

4. SIMULATION RESULTS

For simulations, we set $M = N = 5$, $K = 4$ and $d = 2$ with $\mathcal{S} = \{1, 2\}$ to satisfy the feasibility conditions. The values of $\alpha_k = \alpha = 0.01$ and 0.99 are selected to observe the effect of correlation in extreme conditions. The value $\bar{\alpha} = 1 - \alpha = 1$ indicates full correlation, while no-correlation for $\bar{\alpha} = 0$. For each of the curves, an algorithm is run for 10^4 iterations.

4.1. Sum rate Convergence

Figures 1 illustrates the sum rate convergence of the two MSE based methods presented above at 25dB SNR. From these curves, it can be observed that for higher values of α, i.e., for lower correlation, the sum rate is lower and vice versa as depicted in Corollary 5. For each of MSE based methods, sum rate can be seen to converge at both the correlation values. These figures also show that sum rates of method-I is lower than that of method-II, which gives smoother curves with respect to number of iterations. The reason of lower sum rate in method-I is due to the fact that the joint precoder is computed, and scaling can be done to satisfy only one of the precoder's constraint. On the other hand, method-II computes individual precoder satisfying the constraint close to equality.

4.2. Sum rate versus SNR

Figure 2 shows sum rates plots with respect to SNR for two methods with correlation values $\alpha = 0.01, 0.99$. It can be observed that method-II yields better sum rates than method-I and typical IA method from [10]. In particular, for $\alpha = 0.01$, more than 10bps/Hz improvement can be observed at high SNR (35dB) for method-II over IA method. At lower SNRs (5dB), the improvement greater than 15 bps/Hz can be seen. The IA method provides better sum rates in uncorrelated system. However, applying those IA precoders in correlated system, the presence of noise terms due to correlation $(\mathbf{C}_k)$ reduces the sum rates significantly as shown in Corollary 5. The trend with respect to α is the same as seen in Figure 1.

5. CONCLUSION

In this paper, we have presented a model where transmissions from two (or more users) are partially correlated. The utility of this type of model arises in wireless sensor networks (WSN) or temporally correlated scenario. Exploiting the correlation, two MSE based precoding methods are derived. In particular, first method is based on joint precoding computation, while the other computes individual user's precoder. In other words, the first method can be considered as a sup-optimal version of the second method. An iterative convergent procedure is formulated, following a typical IA algorithm. Simulation results verify the sum rate convergence and the improved sum rate performance of the second method over the first one and typical IA (precoder and decoders), applied to this system.

6. REFERENCES

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