Cooperative Spatial Multiplexing with Hybrid Channel Knowledge

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***Abstract*— We explore the concept of cooperative spatial multiplexing for use in MIMO multicell networks. One key application of this is the transmission of possibly correlated symbol streams jointly by several multiple-antenna access points toward multiple single antenna user terminals located in neighboring cells. To augment the realism of this setting, we consider different levels of channel state information at the transmitter (CSIT). In one case, we further introduce a constraint on *hybrid channel state information* (HCSI) in which any given transmitter knows its own CSI perfectly while it only has *statistical* information about other transmitters' channels. This yield a game situation in which each cooperating transmitter makes a guess about the behavior of the other transmitter. We show different transmission strategies under this setting and compare them with fully cooperative (full CSI) and non cooperative schemes. Our results show a substantial cooperation gain despite the lack of instantaneous information.**

I. Introduction

Recently, there has been increasing interest in so-called cooperative schemes, in which two or more transmitters collaborate to improve the quality of transmission toward a common destination. A prominent scenario for this has so far been cooperative diversity where the devices collaborate to combat the detrimental effects of fading at any one particular device. Typically, the devices are single-antenna user terminals relaying data between a source terminal and the target destination [1], [2], [3]. A specific signaling scheme is distributed space-time block coding (STBC), where the spatial elements of the codewords are distributed over the antennas of the collaborating transmitters [3], [4], [5]. Since this is space time coding, the transmitters can operate with little or no CSI, although it was recently shown that statistical channel information can be very useful there too [6].

Another form of cooperation is that of distributed *spatial multiplexing* in which multiple independent flows of data are jointly transmitted by distributed antennas and captured by one multiple-antenna receiver or several distributed (possibly single antenna) receivers. This is typically relevant in the downlink of a multicell scenario where multiple base stations (access points for a WLAN network) want to transmit data to multiple user terminals at once. This problem bears strong connections with multiuser MIMO. Work in this area include [7], [8], [9], [10] to cite a few.

Importantly, we note that, unlike cooperative diversity, cooperative spatial multiplexing or downlink multi-user MIMO in general requires full CSI at the transmitter(s) when the user terminals have a single antenna. This case is very realistic since we expect a majority of pocket terminals to be single antenna based in the foreseeable future. We consider different levels of CSIT used for cooperation. In one, we assume for all transmitters at the base sites to share the full joint multi-user CSIT. For cases where this would demands unbearable cell-to-cell signaling we also consider a *hybrid* CSI scenario where one transmitting base has full knowledge of its own CSI linking it to the terminals belonging to its coverage region[1] but has only statistical knowledge about the other transmitters' CSI. Here, we limit ourselves to a two cell scenario while more general cases are considered in a companion paper [11]. This scenario is equivalent to a cooperative game where each base station is optimizing a linear spatial filter based on an guess of what the collaborating base might be doing simultaneously. We investigate several possible guess strategies and obtain the corresponding optimal linear transmission schemes. We show that cooperation gains are substantial even when statistical CSI is used. However we show that one benefits a lot from well educated guesses.

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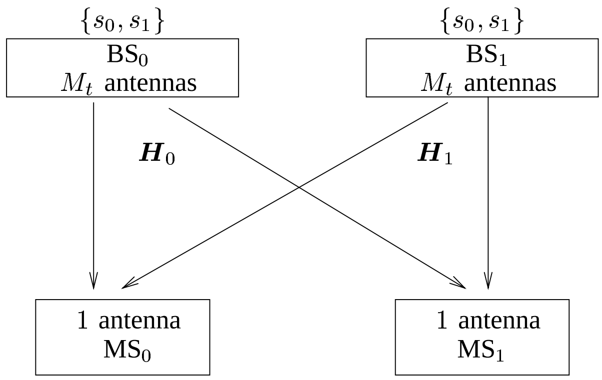

Fig. 1. System studied with two base stations BS_i having M_t antennas and two mobile stations MS_i having one antenna each.

II. System Description

We consider a two-cell downlink situation shown in Figure 1 where two base stations BS_0 and BS_1, equipped with M_t antennas each, communicate with two single-antenna mobile stations MS_0 and MS_1. In our cooperative scenario, MS_i is associated with its base station BS_i but also receives part of his data multiplexed from BS_j, $j \neq i$, in the neighboring cell. Specifically, two symbols $\{s_0, s_1\}$ are sent

[1]coverage regions of different sites are typically overlapping

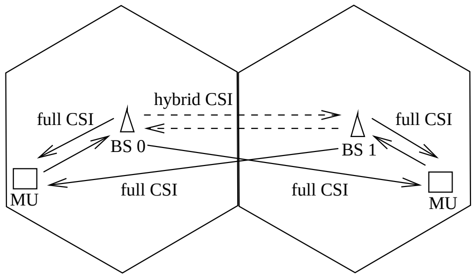

Fig. 2. Hybrid CSI case: the transmitting bases have full CSIT for their own channel but only statistical knowledge about each other's channel.

from the following symbol vector

$$\boldsymbol{s} = \begin{bmatrix} s_0 \\ s_1 \end{bmatrix}, \tag{1}$$

such that $\boldsymbol{s} \in \mathbb{C}^{2\times 1}$, with $s_i \in \mathcal{A}$, where $\mathcal{A}$ is the signal constellation alphabet.

Symbol s_i is intended for mobile station MS_i only, $i \in \{0, 1\}$. However, for cooperation purposes we assume that each base is given a copy of the global symbol vector $\boldsymbol{s}$ (through relay or fibers etc.).

The autocorrelation of the vector $\boldsymbol{s}$ is given by:

$$\boldsymbol{\Phi_s} = \mathbb{E}\left[\boldsymbol{s}\boldsymbol{s}^H\right], \tag{2}$$

where $\boldsymbol{\Phi_s} \in \mathbb{C}^{2\times 2}$. In the case of independent, unit-variance data, we thus get $\boldsymbol{\Phi_s} = \boldsymbol{I}_2$.

A. Complete and Hybrid Channel State Information

Assuming flat-fading, the channel from base station number i to the two mobile stations is given by matrix $\boldsymbol{H}_i \in \mathbb{C}^{2\times M_t}$. In this paper we consider a fully non line of sight situation (channels have zero mean), however the Ricean case is also interesting [11].

Our goal is to test the impact of cooperation given various levels of knowledge shared by the transmitting bases about each other's transmit channels. For this purpose we consider two cases i) complete channel state information, in which both bases know all CSIT from each base to each terminal, and ii) *Hybrid channel state information*. in the latter, CSIT is hybrid in in the sense that, for each i=0,1: Base station BS_i has perfect knowledge of

- its own transmit channel $\boldsymbol{H}_i$,

but only has knowledge of the *statistics* of

- the neighboring base station's CSIT $\boldsymbol{H}_j$, $i \neq j$

In the hybrid CSIT case (illustrated in Fig.2), the statistics are assumed to be exchanged by the base stations via a low rate signaling channel. This scenario can be considered realistic because statistical channel information varies much more slowly than Rayleigh fading and is thus easy to broadcast to the various cells.

III. Linear Transmit Filtering

Each base BS_i transmits the common data vector $\boldsymbol{s}$ by performing linear filtering with the coefficient matrix $\boldsymbol{A}_i \in \mathbb{C}^{M_t\times 2}$ such that the transmitted vector $\boldsymbol{x}_i \in \mathbb{C}^{M_t\times 1}$ from BS_i is given by:

$$\boldsymbol{x}_i = \boldsymbol{A}_i\boldsymbol{s}. \tag{3}$$

The signal received by MS_i is denoted y_i, where $i \in \{0, 1\}$. We set

$$\boldsymbol{y} = \begin{bmatrix} y_0 \\ y_1 \end{bmatrix}. \tag{4}$$

which is the received signal vector $\boldsymbol{y} \in \mathbb{C}^{2\times 1}$ given by

$$\boldsymbol{y} = \boldsymbol{H}_0\boldsymbol{A}_0\boldsymbol{s} + \boldsymbol{H}_1\boldsymbol{A}_1\boldsymbol{s} + \boldsymbol{v}, \tag{5}$$

where $\boldsymbol{v} \in \mathbb{C}^{2\times 1}$ is the additive noise vector with auto correlation matrix

$$\boldsymbol{\Phi_v} = \mathbb{E}\left[\boldsymbol{v}\boldsymbol{v}^H\right], \tag{6}$$

such that $\boldsymbol{\Phi_v} \in \mathbb{C}^{2\times 2}$.

A. Power Constraints

We wish to optimize the transmit filters $\boldsymbol{A}_i, i = 0, 1$ and we consider per-base power constraints, thus, we set for $i \in \{0, 1\}$:

$$\mathrm{Tr}\left\{\boldsymbol{A}_i\boldsymbol{\Phi_s}\boldsymbol{A}_i\right\} = P_i. \tag{7}$$

IV. Optimal Spatial Filtering

We consider now several strategies for linear filtering based on the transmit MMSE criterion, starting with the case where full CSI is shared by all base stations.

A. Full CSI Optimal Filtering

In this case, full CSIT is assumed however the optimization differs from that of a regular multi-user MIMO problem due to the presence of the per-base power constraints (instead of a single transmit power constraint in regular downlink MIMO) which restricts the scope of optimality. Nevertheless we expect this case to serve as an upper bound on the cooperation gain.

Here, both bases optimize $\boldsymbol{A}_0$ and $\boldsymbol{A}_1$ jointly based on the combined knowledge of $\boldsymbol{H}_0$ and $\boldsymbol{H}_1$. The received signal is given by (5). The optimal filters are optimal in the joint MMSE sense where the mean square error (MSE) is given by

$$\begin{aligned}
\mathrm{MSE} &= \mathbb{E}_{\boldsymbol{s},\boldsymbol{v}}\left[\|\boldsymbol{y}-\boldsymbol{s}\|^2\right] = \mathbb{E}_{\boldsymbol{s},\boldsymbol{v}}\left[\mathrm{Tr}\left\{(\boldsymbol{H}_0\boldsymbol{A}_0\boldsymbol{s} + \boldsymbol{H}_1\boldsymbol{A}_1\boldsymbol{s} + \boldsymbol{v} - \boldsymbol{s})\right.\right. \\
&\quad \left.\left.\left(\boldsymbol{s}^H\boldsymbol{A}_0^H\boldsymbol{H}_0^H + \boldsymbol{s}^H\boldsymbol{A}_1^H\boldsymbol{H}_1^H + \boldsymbol{v}^H - \boldsymbol{s}^H\right)\right\}\right] \\
&= \mathrm{Tr}\left\{\boldsymbol{H}_0\boldsymbol{A}_0\boldsymbol{\Phi_s}\boldsymbol{A}_0^H\boldsymbol{H}_0^H + \boldsymbol{H}_0\boldsymbol{A}_0\boldsymbol{\Phi_s}\boldsymbol{A}_1^H\boldsymbol{H}_1^H - \boldsymbol{H}_0\boldsymbol{A}_0\boldsymbol{\Phi_s}\right. \\
&\quad +\boldsymbol{H}_1\boldsymbol{A}_1\boldsymbol{\Phi_s}\boldsymbol{A}_0^H\boldsymbol{H}_0^H + \boldsymbol{H}_1\boldsymbol{A}_1\boldsymbol{\Phi_s}\boldsymbol{A}_1^H\boldsymbol{H}_1^H - \boldsymbol{H}_1\boldsymbol{A}_1\boldsymbol{\Phi_s} + \boldsymbol{\Phi_v} \\
&\quad \left.-\boldsymbol{\Phi_s}\boldsymbol{A}_0^H\boldsymbol{H}_0^H - \boldsymbol{\Phi_s}\boldsymbol{A}_1^H\boldsymbol{H}_1^H + \boldsymbol{\Phi_s}\right\}
\end{aligned} \tag{8}$$

To optimize the filters under the distributed power constraints, we use the Lagrangian method with the objective function given by

$$\mathrm{MSE} + \mu_0\,\mathrm{Tr}\left\{\boldsymbol{A}_0\boldsymbol{\Phi_s}\boldsymbol{A}_0^H\right\} + \mu_1\,\mathrm{Tr}\left\{\boldsymbol{A}_1\boldsymbol{\Phi_s}\boldsymbol{A}_1^H\right\} \tag{9}$$

By differentiation with respect to $\boldsymbol{A}_0^*$ and $\boldsymbol{A}_1^*$, the equations for the optimal precoders are given by

$$\begin{bmatrix} \boldsymbol{H}_0^H\boldsymbol{H}_0 + \mu_0\boldsymbol{I}_{M_t} & \boldsymbol{H}_0^H\boldsymbol{H}_1 \\ \boldsymbol{H}_1^H\boldsymbol{H}_0 & \boldsymbol{H}_1^H\boldsymbol{H}_1 + \mu_1\boldsymbol{I}_{M_t} \end{bmatrix}\begin{bmatrix} \boldsymbol{A}_0 \\ \boldsymbol{A}_1 \end{bmatrix} = \begin{bmatrix} \boldsymbol{H}_0^H \\ \boldsymbol{H}_1^H \end{bmatrix}, \tag{10}$$

which is independent of symbol correlation and where μ_0 and μ_1 must be chosen such that the power constraints are satisfied.

B. Hybrid CSI Optimal Filtering

We now turn to the case of hybrid CSI. In this situation, the optimal joint MMSE beamformer cannot be obtained. Instead, each base is optimizing its linear filter in the MMSE sense, based on limited knowledge. We propose to consider a game-like approach in which a base makes a guess as to with what criterion the other base is optimizing its linear filter. We assume first full CSI, then we show how statistical CSI can be incorporated in this setting for two different kinds of guesses, one simplistic namely matched filter

(MRC) guess and and one more computationally advanced, channel inversion guess. More strategies (e.g. single base MMSE guess) are discussed in [11].

C. Transmit MRC Guess

Here, BS_0 is operating under the assumption that BS_1 uses a scaled matched filter for transmission (and vice versa) given by:

$$\boldsymbol{A}_1 = \sqrt{P_1}\frac{\boldsymbol{H}_1^H}{\|\boldsymbol{H}_1\|_F}. \tag{11}$$

In the view of BS_0 the MSE expression, assuming (11), becomes

$$\mathrm{MSE} = \mathbb{E}_{\boldsymbol{s},\boldsymbol{v}}\left[\|\boldsymbol{y}-\boldsymbol{s}\|^2\right] \tag{12}$$

$$= \mathbb{E}_{\boldsymbol{s},\boldsymbol{v}}\left[\mathrm{Tr}\left\{\left(\boldsymbol{H}_0\boldsymbol{A}_0\boldsymbol{s} + \frac{\sqrt{P_1}}{\|\boldsymbol{H}_1\|_F}\boldsymbol{H}_1\boldsymbol{H}_1^H\boldsymbol{s} + \boldsymbol{v} - \boldsymbol{s}\right)\left(\boldsymbol{s}^H\boldsymbol{A}_0^H\boldsymbol{H}_0^H + \frac{\sqrt{P_1}}{\|\boldsymbol{H}_1\|_F}\boldsymbol{s}^H\boldsymbol{H}_1\boldsymbol{H}_1^H + \boldsymbol{v}^H - \boldsymbol{s}^H\right)\right\}\right]. \tag{13}$$

Now, since $\boldsymbol{H}_1$ is actually unknown to base station 0, we average over its realizations to obtain

$$\begin{aligned}\mathbb{E}_{\boldsymbol{H}_1}[\mathrm{MSE}] = \mathrm{Tr}\Big\{&\boldsymbol{H}_0\boldsymbol{A}_0\boldsymbol{\Phi}_{\boldsymbol{s}}\boldsymbol{A}_0^H\boldsymbol{H}_0^H + \\ &\sqrt{P_1}\boldsymbol{H}_0\boldsymbol{A}_0\boldsymbol{\Phi}_{\boldsymbol{s}}\mathbb{E}_{\boldsymbol{H}_1}\left[\frac{\boldsymbol{H}_1\boldsymbol{H}_1^H}{\|\boldsymbol{H}_1\|_F}\right] - \boldsymbol{H}_0\boldsymbol{A}_0\boldsymbol{\Phi}_{\boldsymbol{s}} + \\ &\sqrt{P_1}\mathbb{E}_{\boldsymbol{H}_1}\left[\frac{\boldsymbol{H}_1\boldsymbol{H}_1^H}{\|\boldsymbol{H}_1\|_F}\right]\boldsymbol{\Phi}_{\boldsymbol{s}}\boldsymbol{A}_0^H\boldsymbol{H}_0^H + P_1\mathbb{E}_{\boldsymbol{H}_1}\left[\frac{\boldsymbol{H}_1\boldsymbol{H}_1^H\boldsymbol{\Phi}_{\boldsymbol{s}}\boldsymbol{H}_1\boldsymbol{H}_1^H}{\|\boldsymbol{H}_1\|_F^2}\right] \\ &-\sqrt{P_1}\mathbb{E}_{\boldsymbol{H}_1}\left[\frac{\boldsymbol{H}_1\boldsymbol{H}_1^H}{\|\boldsymbol{H}_1\|_F}\right]\boldsymbol{\Phi}_{\boldsymbol{s}} + \boldsymbol{\Phi}_{\boldsymbol{v}} - \boldsymbol{\Phi}_{\boldsymbol{s}}\boldsymbol{A}_0^H\boldsymbol{H}_0^H - \\ &\sqrt{P_1}\boldsymbol{\Phi}_{\boldsymbol{s}}\mathbb{E}_{\boldsymbol{H}_1}\left[\frac{\boldsymbol{H}_1\boldsymbol{H}_1^H}{\|\boldsymbol{H}_1\|_F}\right] + \boldsymbol{\Phi}_{\boldsymbol{s}}\Big\}.\end{aligned} \tag{14}$$

Two Lagrangian multipliers are introduced for the two power constraints and then the optimization with respect to the precoder in BS_0 can be done. Here, the necessary conditions for optimality of $\boldsymbol{A}_0$ under the considered cooperation strategy is given by:

$$\boldsymbol{H}_0^H\boldsymbol{H}_0\boldsymbol{A}_0\boldsymbol{\Phi}_{\boldsymbol{s}} + \sqrt{P_1}\boldsymbol{H}_0^H\mathbb{E}_{\boldsymbol{H}_1}\left[\frac{\boldsymbol{H}_1\boldsymbol{H}_1^H}{\|\boldsymbol{H}_1\|_F}\right]\boldsymbol{\Phi}_{\boldsymbol{s}} - \boldsymbol{H}_0^H\boldsymbol{\Phi}_{\boldsymbol{s}} + \mu_0\boldsymbol{A}_0\boldsymbol{\Phi}_{\boldsymbol{s}} = \boldsymbol{0}_{M_t\times 2}. \tag{15}$$

Assuming that the matrix $\boldsymbol{\Phi}_{\boldsymbol{s}}$ is invertible, the necessary conditions for optimality can be rewritten as:

$$\boldsymbol{A}_0 = \left[\boldsymbol{H}_0^H\boldsymbol{H}_0 + \mu_0\boldsymbol{I}_{M_t}\right]^{-1}\boldsymbol{H}_0^H\left[\boldsymbol{I}_2 - \sqrt{P_1}\mathbb{E}_{\boldsymbol{H}_1}\left[\frac{\boldsymbol{H}_1\boldsymbol{H}_1^H}{\|\boldsymbol{H}_1\|_F}\right]\right]. \tag{16}$$

By symmetry we argue that BS_1 will operate with the following linear filter:

$$\boldsymbol{A}_1 = \left[\boldsymbol{H}_1^H\boldsymbol{H}_1 + \mu_1\boldsymbol{I}_{M_t}\right]^{-1}\boldsymbol{H}_1^H\left[\boldsymbol{I}_2 - \sqrt{P_0}\mathbb{E}_{\boldsymbol{H}_0}\left[\frac{\boldsymbol{H}_0\boldsymbol{H}_0^H}{\|\boldsymbol{H}_0\|_F}\right]\right]. \tag{17}$$

Note that these equation can be interpreted as modified MMSE transmit filters, where the modification makes the use of the cooperating base's channel statistics.

Note also that in the equations derived, the following statistic $\boldsymbol{S}_i \triangleq \mathbb{E}_{\boldsymbol{H}_i}\left[\frac{\boldsymbol{H}_i\boldsymbol{H}_i^H}{\|\boldsymbol{H}_i\|_F}\right]$ is needed. An estimate of this matrix $\hat{\boldsymbol{S}}_i$ can simply be found by the following estimator:

$$\hat{\boldsymbol{S}}_i = \frac{1}{Q}\sum_{q=0}^{Q-1}\frac{\boldsymbol{H}_i^{(q)}\left(\boldsymbol{H}_i^{(q)}\right)^H}{\|\boldsymbol{H}_i^{(q)}\|_F}, \tag{18}$$

where $\boldsymbol{H}_i^{(q)}$ is a realization of the channel found from the following relation:

$$\mathrm{vec}\left(\boldsymbol{H}_i\right) = \boldsymbol{R}_{\boldsymbol{H}_i}^{1/2}\,\mathrm{vec}\left(\boldsymbol{H}_w\right), \tag{19}$$

where $\mathrm{vec}\left(\boldsymbol{H}_w\right) \sim \mathcal{CN}\left(\boldsymbol{0}_{M_tM_r\times 1}, \boldsymbol{I}_{M_tM_r}\right)$ is used to indicate the distribution of the vector $\mathrm{vec}\left(\boldsymbol{H}_w\right)$, and where $\boldsymbol{R}_{\boldsymbol{H}_i} \triangleq \mathbb{E}_{\boldsymbol{H}_i}\left[\mathrm{vec}\left(\boldsymbol{H}_i\right)\mathrm{vec}^H\left(\boldsymbol{H}_i\right)\right]$ is the covariance matrix.

D. Transmit Zero-Forcing Guess

Here, we look at the case where BS_0 assumes that BS_1 uses a scaled-down zero-forcing (ZF), on the form of

$$\boldsymbol{A}_1 = \sqrt{P_1}\frac{\boldsymbol{H}_1^H(\boldsymbol{H}_1\boldsymbol{H}_1^H)^{-1}}{\|\boldsymbol{H}_1^H(\boldsymbol{H}_1\boldsymbol{H}_1^H)^{-1}\|_F}. \tag{20}$$

The expected MSE under this assumption, averaged over all realizations of the unknown $\boldsymbol{H}_1$, becomes:

$$\begin{aligned}&\mathbb{E}_{\boldsymbol{H}_1}[\mathrm{MSE}] = \mathbb{E}_{\boldsymbol{H}_1,\boldsymbol{s},\boldsymbol{v}}\left[\|\boldsymbol{H}_0\boldsymbol{A}_0\boldsymbol{s} + \boldsymbol{H}_1\boldsymbol{A}_1\boldsymbol{s} + \boldsymbol{v} - \boldsymbol{s}\|^2\right] \\ &= \mathbb{E}_{\boldsymbol{H}_1,\boldsymbol{s},\boldsymbol{v}}\left[\mathrm{Tr}\left\{\left(\boldsymbol{H}_0\boldsymbol{A}_0\boldsymbol{s} + \frac{\sqrt{P_1}\boldsymbol{I}_2}{\|\boldsymbol{H}_1^H(\boldsymbol{H}_1\boldsymbol{H}_1^H)^{-1}\|_F}\boldsymbol{s} + \boldsymbol{v} - \boldsymbol{s}\right)\left(\boldsymbol{s}_0^H\boldsymbol{A}_0^H\boldsymbol{H}_0^H + \frac{\sqrt{P_1}\boldsymbol{I}_2}{\|\boldsymbol{H}_1^H(\boldsymbol{H}_1\boldsymbol{H}_1^H)^{-1}\|_F}\boldsymbol{s}^H + \boldsymbol{v}^H - \boldsymbol{s}^H\right)\right\}\right] \\ &= \mathrm{Tr}\Big\{\boldsymbol{H}_0\boldsymbol{A}_0\boldsymbol{\Phi}_s\boldsymbol{A}_0^H\boldsymbol{H}_0^H + \mathbb{E}_{\boldsymbol{H}_1}\left[\frac{\sqrt{P_1}}{\|\boldsymbol{H}_1^H(\boldsymbol{H}_1\boldsymbol{H}_1^H)^{-1}\|_F}\right]\boldsymbol{H}_0\boldsymbol{A}_0\boldsymbol{\Phi}_s \\ &\quad - \boldsymbol{H}_0\boldsymbol{A}_0\boldsymbol{\Phi}_s + \mathbb{E}_{\boldsymbol{H}_1}\left[\frac{\sqrt{P_1}}{\|\boldsymbol{H}_1^H(\boldsymbol{H}_1\boldsymbol{H}_1^H)^{-1}\|_F}\right]\boldsymbol{\Phi}_s\boldsymbol{A}_0^H\boldsymbol{H}_0^H + \\ &\quad \mathbb{E}_{\boldsymbol{H}_1}\left[\frac{P_1}{\|\boldsymbol{H}_1^H(\boldsymbol{H}_1\boldsymbol{H}_1^H)^{-1}\|_F^2}\right]\boldsymbol{\Phi}_s - \mathbb{E}_{\boldsymbol{H}_1}\left[\frac{\sqrt{P_1}}{\|\boldsymbol{H}_1^H(\boldsymbol{H}_1\boldsymbol{H}_1^H)^{-1}\|_F}\right]\boldsymbol{\Phi}_s \\ &\quad + \boldsymbol{\Phi}_v - \boldsymbol{\Phi}_s\boldsymbol{A}_0^H\boldsymbol{H}_0^H - \mathbb{E}_{\boldsymbol{H}_1}\left[\frac{\sqrt{P_1}}{\|\boldsymbol{H}_1^H(\boldsymbol{H}_1\boldsymbol{H}_1^H)^{-1}\|_F}\right]\boldsymbol{\Phi}_s + \boldsymbol{\Phi}_s\Big\}.\end{aligned} \tag{21}$$

Using again Lagrangian multipliers, we obtain the following necessary conditions for optimality of $\boldsymbol{A}_0$:

$$\boldsymbol{H}_0^H\boldsymbol{H}_0\boldsymbol{A}_0 + \mathbb{E}_{\boldsymbol{H}_1}\left[\frac{\sqrt{P_1}}{\|\boldsymbol{H}_1^H(\boldsymbol{H}_1\boldsymbol{H}_1^H)^{-1}\|_F}\right]\boldsymbol{H}_0^H - \boldsymbol{H}_0^H + \mu_0\boldsymbol{A}_0 = \boldsymbol{0}_{M_t\times 2}$$

This can be rewritten as:

$$\boldsymbol{A}_0 = \left[\boldsymbol{H}_0^H\boldsymbol{H}_0 + \mu_0\boldsymbol{I}_{M_t}\right]^{-1}\boldsymbol{H}_0^H\left[1 - \mathbb{E}_{\boldsymbol{H}_1}\left[\frac{\sqrt{P_1}}{\|\boldsymbol{H}_1^H(\boldsymbol{H}_1\boldsymbol{H}_1^H)^{-1}\|_F}\right]\right].$$

By symmetry, we obtain for the transmit filter for BS_1:

$$\boldsymbol{A}_1 = \left[\boldsymbol{H}_1^H\boldsymbol{H}_1 + \mu_1\boldsymbol{I}_{M_t}\right]^{-1}\boldsymbol{H}_1^H\left[1 - \mathbb{E}_{\boldsymbol{H}_0}\left[\frac{\sqrt{P_0}}{\|\boldsymbol{H}_0^H(\boldsymbol{H}_0\boldsymbol{H}_0^H)^{-1}\|_F}\right]\right].$$

Let the operator $(\cdot)^\dagger$ denote the Moore-Penrose inverse. In an analogous way as before, finding the matrix $\boldsymbol{U}_i \triangleq \mathbb{E}_{\boldsymbol{H}_i}\left[\frac{1}{\|\boldsymbol{H}_i(\boldsymbol{H}_i\boldsymbol{H}_i^H)^{-1}\|_F}\right] = \mathbb{E}_{\boldsymbol{H}_i}\left[\frac{1}{\|\boldsymbol{H}_i^\dagger\|_F}\right]$ can be done using

$$\hat{\boldsymbol{U}}_i = \frac{1}{Q}\sum_{q=0}^{Q-1}\frac{1}{\|\boldsymbol{H}_i^\dagger\|_F}. \tag{22}$$

These results again correspond to *modified* MMSE filters, where the modification takes into account the statistics of the unknown channel and the guess on the filtering strategy of the cooperating base.

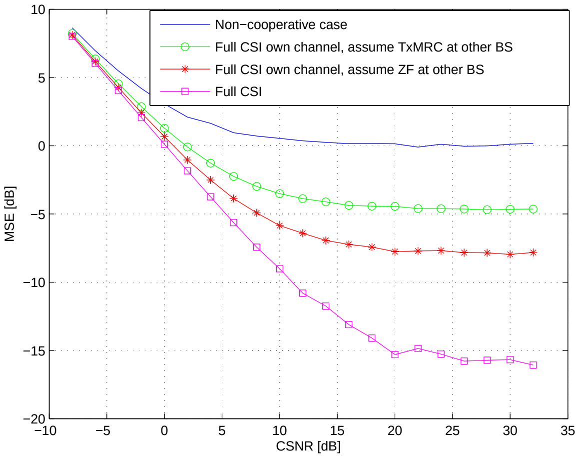

Fig. 3. MSE versus CSNR for cooperative transmission, using two two-antenna BSs and two single-antenna MSs, with $P = 0.5$ and $r_{\rm ipl} = 0$ dB.

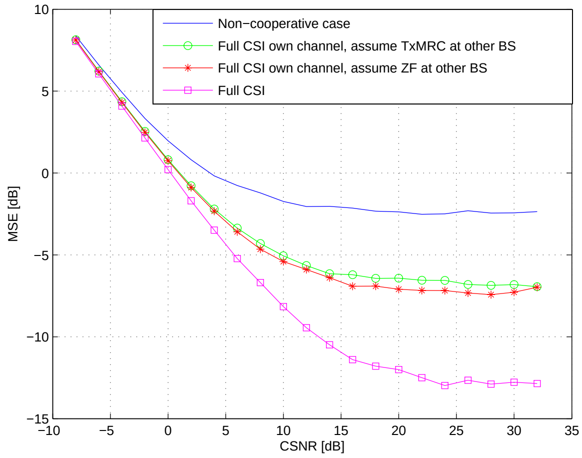

Fig. 4. MSE versus CSNR for cooperative transmission, using two two-antenna BSs and two single-antenna MSs, with $P = 0.5$ and $r_{\rm ipl} = 3$ dB.

V. Simulation Results

We have simulated a system consisting of two transmitting base stations (BS) and two receiving MSs. Each of the BSs are equipped with $M_t = 2$ antennas, while there are only $M_r = 1$ antenna on each MS.

We obtain the mean square error (MSE) versus CSNR (channel signal to noise ratio), for 4 different approaches at optimizing the precoders $\boldsymbol{A}_0$ and $\boldsymbol{A}_1$, based on different cases of channel state information at the BS side. The CSNR is defined as CSNR $= P/\sigma_v^2$, where $P = P_0 = P_1 = 0.5$ is the power available at both BS. Thus the noise level is what is varied to change the CSNR. Note that no receiver optimization is used, although this problem is tackled in [11]. The MSE at each CSNR-point is averaged over 1000 channel realizations.

With the fully cooperative (full CSI) case as an example, we observe that the optimal precoders $\boldsymbol{A}_0$ and $\boldsymbol{A}_1$ are found by jointly optimizing with respect to $\boldsymbol{A}_i$ and μ_i, $i \in \{0, 1\}$. The precoders are given by (10), using the per-base power constraint in (7) to determine the Lagrangian multipliers μ_i, $i \in \{0, 1\}$.

We define the intercell loss ratio $r_{\rm ipl}$ as the ratio between own-cell average channel gain and inter-cell channel gain. In Figure 3, $r_{\rm ipl} = 0$ dB, i.e., signals from both BS experience the same average large-scale path loss on their way to *both* MS. Figure 4 shows the case of $r_{\rm ipl} = 3$ dB.

In Figure 3, the best MSE-results are obtained by the full CSI cooperative approach. As expected the proposed hybrid CSI schemes yield performance in between the optimal and the non cooperative scenarios. Clearly playing the cooperative game yields better result using the ZF assumption than assuming transmit MRC, as the optimal MMSE filter is much closer to the ZF in moderate to high SNR levels.

In Figure 4, understandably we observe that $r_{\rm ipl} = 3$ dB (more intercell loss) hurts the full CSI cooperative scheme, while it benefits the suboptimal but more practical approaches using hybrid CSI, as well as the non-cooperative approach. This means that there is clearly an interesting trade-off between the use of aggressive reuse factors of the frequency resource which increases interference but in turn amplifies cooperation gains. The trade-off seems clearly in favor of cooperation.

VI. Conclusions

We investigate spatial multiplexing signaling between two cooperating base stations/access points communicating each with users in two neighboring cells. We propose practical transmission strategies that exploit either complete or hybrid (mixed instantaneous and statistical) channel state information at the transmitters. We show that cooperation is possible thanks to a game scenario where each base station is making certain assumptions about the behavior of the cooperating base in terms of the spatial filter being used.

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