Interference Management for CDMA Systems Through Power Control, Multiuser Detection, and Beamforming

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***Abstract*—Among the ambitious challenges to be met by the third-generation systems is to provide high-capacity flexible services. Code-division multiple access (CDMA) emerges as a promising candidate to meet these challenges. It is well known that CDMA systems are interference-limited, and interference management is needed to maximally utilize the potential gains of this access scheme. Several methods of controlling and/or suppressing the interference through power control, multiuser detection (temporal filtering), and receiver beamforming (spatial filtering) have been proposed to increase the capacity of CDMA systems up to date. We investigate the capacity increase that is possible by combining power control with intelligent temporal and spatial receiver filter design. The signal-to-interference ratio maximizing joint temporal-spatial receiver filters in unconstrained and constrained filter spaces are derived. Two-step iterative power control algorithms that converge to the optimum powers and the joint temporal and spatial receiver filters in the corresponding filter domains are given. A power control algorithm with a less complex filter update procedure is also given. We observe that significant savings in total transmit power are possible if filtering in both domains is utilized compared with conventional power control and joint optimal power control and filtering in only one domain.**

***Index Terms*—Code-division multiple access (CDMA), interference suppression, MMSE receivers, multiuser detection, power control, receiver beamforming.**

I. Introduction

FUTURE wireless systems are expected to provide high-capacity flexible services. Wide-band code-division multiple access (W-CDMA) [1], [2] has emerged as a promising candidate to meet these challenges. It is well known that CDMA systems are interference-limited and suffer from a phenomenon known as the *near–far effect* where strong users degrade the performance of the weak users significantly. Techniques that control and/or suppress interference help increase the capacity of a CDMA system. Three interference management methods are power control, multiuser detection, and receiver beamforming. In very general terms, power control balances received powers of all users so that no user creates excessive interference to other users in the system; multiuser detection and antenna beamforming exploit the temporal and spatial structure of the interference, respectively, to cancel or suppress it. Current second-generation CDMA standard, IS-95, uses only one of these techniques, power control, whereas the third-generation CDMA proposal, W-CDMA, intends to include all three interference management techniques. In this work, we investigate the capacity gain that these techniques can provide when combined together optimally, and the algorithms that can realize this gain.

The aim of power control is to assign users with transmitter power levels so as to minimize the interference users create to each other while having a certain quality of service which is defined in terms of the signal-to-interference ratio (SIR) [3]. Earlier work identified the power control problem as an eigenvalue problem for nonnegative matrices and the solution is found by a matrix inversion, i.e., in a centralized and noniterative fashion [4], [5]. This is followed by the development of iterative and distributed algorithms that require only local measurements [3], [6], [7]. Traditional iterative power control approaches assume that only one antenna and matched filter receivers are being used at the base stations and each user employs an SIR-based power update where the user's power is multiplied by the ratio of its target SIR to its current SIR, i.e., for user i, the update is

$$p_i(n+1) = \frac{\gamma_i^*}{\gamma_i(n)} p_i(n) \tag{1}$$

where $p_i(n)$ and $\gamma_i(n)$ are the power and SIR of user i at iteration n, and γ_i^* is the SIR *target* of user i. The simple intuition behind this iteration is that if the current SIR $\gamma_i(n)$ of user i is less than the target SIR γ_i^*, then the power of that user is increased; otherwise, it is decreased.

Multiuser detection [8] performs temporal filtering of the received signal to better decode users by exploiting the structure in the multiple-access interference. The optimum multiuser detector is shown to be exponentially complex in the number of users [9]. A number of low-complexity suboptimum receivers have been proposed following this development, e.g., [10]–[12]. Among these low-complexity receivers, the minimum mean-square-error (MMSE) detector [11] minimizes the expected squared error between the transmitted signal and the output of the receiver filter. It is also the linear filter which maximizes the output SIR [13].

Paper approved by R. S. Cheng, the Editor for CDMA and Multiuser Communications Systems of the IEEE Communications Society. Manuscript received November 24, 1999; revised July 28, 2000. This paper was presented in part at the IEEE Vehicular Technology Conference, Houston, TX, May 1999.

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Publisher Item Identifier S 0090-6778(01)05771-3.

Exploiting spatial diversity through the use of array combining to increase the system capacity is a familiar notion in wireless systems [14]. For narrow-band systems, it was shown that multiple antennas can be used to null out interferers and achieve diversity gain [15]. Increasing the capacity of CDMA systems by employing antenna arrays at the base station has been proposed in [16]. The idea is to combine the outputs of multiple antenna array elements to make bit decisions for the user. Reference [16] assumes matched filter receivers in the time domain for each user as well as combining the array observations via a filter that is matched to the array response of the user, i.e., single-user processing is employed in both domains.

Space–time processing for CDMA traditionally refers to receiver beamforming (space processing) and multipath combining (time processing) [17]. The received signals from different paths and antennas are combined to decode the desired user's bits. However, the inherent structure of the multiple interferers is not exploited, i.e., a matched filter to the spreading waveform of the desired user is employed, e.g., [18]–[20]. Suboptimum multiuser detectors for multipath fading channels are studied in [21] and [22]. A recent paper [23] addresses the derivation of the sufficient statistics and the optimum and some suboptimum multiuser detectors when a receiver antenna array is present and the users' transmissions pass through a multipath channel.

Most of the receiver processing literature concentrated on developing signal processing algorithms without considering the issue of optimum transmit power control, assuming the need for power control can be alleviated by intelligent receiver design. More recently, combining power control and multiuser detection for CDMA has been studied in [13] and [24]. In [13], the problem of finding the jointly optimum powers and linear receiver filters was studied. It was shown that a distributed and iterative power control algorithm where each user optimizes its linear receiver filter before each power control update converged to the point where all users expend minimum transmit power and use the corresponding MMSE linear filters. This work assumed a single antenna at each base station. A similar development arose in joint power control and beamforming for wireless networks in [25], where it was shown that a capacity increase is possible with power control if array observations are combined in the MMSE sense. For its applications to CDMA, this work assumed matched filters, i.e., no multiuser detection.

In this work, we combine the three basic interference management approaches, transmit power control, multiuser detection, and beamforming to further increase the uplink capacity of a CDMA system. Linear processing is assumed in both the temporal and the spatial domains. The aim is to assign each user with just enough transmit power and find the best temporal-spatial filter to process the received signal such that each user achieves its target SIR. The reader should note that our approach exploits the spatial diversity (through beamforming) and the inherent temporal structure of the multiple user CDMA system (through multiuser detection) in a *single path* channel. Hence the name temporal-spatial filtering, not to be confused with what is generally referred to as *space–time* processing.

For each user, we first find the jointly optimal temporal and spatial filter that minimizes the mean squared error between the information bit and the decision statistic to be used to decode the user's bit assuming no constraints on the filter space. Motivated by the potential high complexity of this unconstrained optimum filter, we also investigate temporal and spatial filters that are less complex to implement. We constrain the filter space such that the corresponding optimal temporal-spatial filters in this constrained space are separable filters. We then find the iterative power control algorithms that update the filters and the powers of all users that converge to the joint optimal powers and temporal-spatial filters in the associated unconstrained or constrained filter spaces. It is observed that combining the three approaches, i.e., power control and intelligent combining in both spatial and temporal domains, leads to significant savings in total transmit power and can increase capacity by supporting all users in some highly loaded systems that would otherwise be infeasible.

II. System Model

We consider an N-user, multicell direct-sequence CDMA system where each user is assigned a unique signature sequence. For clarity of exposition, we assume a synchronous system with processing gain G. Initially, we will assume that base station assignment has been done for all users. The base station selection will be incorporated into our interference management algorithms in Section IV-B. At each base station, an antenna array of K elements is employed. Following references [16], [25], and [26], over one bit period, the received signal at the output of the antenna array at the assigned base station of user i is

$$\mathbf{r}_i(t) = \sum_{j=1}^{N} \sqrt{p_j h_{ij}} b_j s_j(t) \mathbf{a}_{ij} + \mathbf{n}_i(t) \tag{2}$$

where p_j, b_j, and $s_j(t)$ are the transmit power, bit, and the signature of user j, respectively. The uplink gain of user j to the assigned base station of i is h_{ij}, and $\mathbf{a}_{ij}$ is the array response vector of user j (spatial signature) at the base station of user i. The term $\mathbf{n}_i(t)$ represents the white Gaussian noise vector. Chip matched filtering the received signal and sampling at the chip rate, we have G observations at the output of each of the K antenna elements (see Fig. 1). The observations that will be used to decode the bit of user i can be arranged in a $G \times K$ matrix as

$$\mathbf{R}_i = \sum_{j=1}^{N} \sqrt{p_j h_{ij}} b_j \mathbf{s}_j \mathbf{a}_{ij}^{\top} + \mathbf{N}_i \tag{3}$$

where kth column of $\mathbf{R}_i$ represents the chip sampled outputs at the output of the kth antenna array element. $\mathbf{s}_j$ is the chip-sampled version of $s_j(t)$, $\mathbf{N}_i$ is the matrix that represents the spatially and temporally white noise with variance σ^2, i.e., $E[[N_i]_{kl}^*[N_i]_{mn}] = \sigma^2 \delta_{km}\delta_{ln}$, where $\delta_{nn'} = 0$ for $n \neq n'$, $\delta_{nn} = 1$, and $(\cdot)^*$ denotes the conjugate of a complex number.

Note that one can obtain a different set of sufficient statistics from (2) by using space–time matched filters and derive bit detectors for all users in a centralized fashion [23], [27]. We observe that adopting the model above yields solutions more amenable to decentralized implementation (see Sections III-A and III-B).

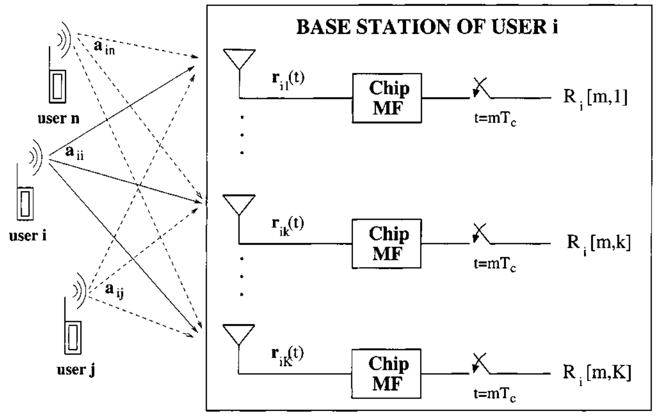

Fig. 1. Received signal model at the base station of user i, $R_i[m,k]$ denotes the (m,k)th element of the received signal matrix $\mathbf{R}_i$ given in (3).

III. Temporal-Spatial Filtering

A. Optimum Temporal-Spatial Filtering (OTSF)

The detection of the information bit of the desired user is done by taking the sign of the decision statistic which is to be found using the observation matrix $\mathbf{R}_i$. Observations over the spatial and temporal domains are to be combined intelligently in making the bit decisions of the desired user. Our aim is to find a two dimensional linear filter $\mathbf{X}_i$ that yields decision statistic $y_i = \sum_{j=1}^{G}\sum_{l=1}^{K}[X_i]^*_{jl}[R_i]_{jl}$. In particular, we aim for a filter that yields the MMSE between y_i and b_i. That is, we want to find a matrix filter $\bar{\mathbf{X}}_i$ such that

$$\begin{aligned}\bar{\mathbf{X}}_i &= \arg\min_{\mathbf{X}} E\left[\left|\sum_{j=1}^{G}\sum_{l=1}^{K} X^*_{jl}R_{i,jl} - b_i\right|^2\right]\\ &= \arg\min_{\mathbf{X}} E[|\mathrm{tr}(\mathbf{X}^H\mathbf{R}_i) - b_i|^2] \qquad (4)\end{aligned}$$

where $\mathrm{tr}(\cdot)$ and $(\cdot)^H$ are the trace and the hermitian transpose operations on a matrix, respectively. The reader should note that an equivalent MMSE problem can be formulated using the space–time matched filter outputs and the resulting centralized solution is given in [23].

The optimization problem (4) can be converted to an optimization problem with vector variables for easier manipulation [26]. Let $\mathbf{r}_i$ be the long vector obtained by stacking the columns of the received signal matrix $\mathbf{R}_i$. The MMSE problem then can be reformulated as follows:

$$\bar{\mathbf{x}}_i = \arg\min_{\mathbf{x}} E[|\mathbf{x}^H\mathbf{r}_i - b_i|^2]. \qquad (5)$$

Let us define $\mathbf{q}_{ij}$ as the combined temporal-spatial signature of user j at the base station of user i. It is constructed by stacking columns of $\mathbf{s}_j\mathbf{a}_{ij}^\top$ as a long vector of size KG. Then, the solution to the optimization problem (5) is given as [8], [11], [28]

$$\bar{\mathbf{x}}_i = k_i\left(\sum_{j\neq i} p_j h_{ij}\mathbf{q}_{ij}\mathbf{q}_{ij}^H + \sigma^2\mathbf{I}\right)^{-1}\mathbf{q}_{ii} \qquad (6)$$

$$= l_i\left(\sum_{j=1}^{N} p_j h_{ij}\mathbf{q}_{ij}\mathbf{q}_{ij}^H + \sigma^2\mathbf{I}\right)^{-1}\mathbf{q}_{ii} \qquad (7)$$

where (7) follows from (6) using the matrix inversion lemma, which states for an invertible matrix $\mathbf{M}$ and vectors $\mathbf{u}$ and $\mathbf{v}$

$$(\mathbf{M}+\mathbf{u}\mathbf{v}^\top)^{-1} = \mathbf{M}^{-1} - \frac{\mathbf{M}^{-1}\mathbf{u}\mathbf{v}^\top\mathbf{M}^{-1}}{1+\mathbf{v}^\top\mathbf{M}^{-1}\mathbf{u}}. \qquad (8)$$

The constants k_i and l_i in (6) and (7) are given as

$$\begin{aligned}k_i &= \frac{\sqrt{p_i h_{ii}}}{1 + p_i h_{ii}\mathbf{q}_{ii}^H\left(\sum_{j\neq i}\mathbf{q}_{ij}\mathbf{q}_{ij}^H + \sigma^2\mathbf{I}\right)^{-1}\mathbf{q}_{ii}}\\ l_i &= \sqrt{p_i h_{ii}}. \qquad (9)\end{aligned}$$

Note that the matrix $\sum_{j\neq i}\mathbf{q}_{ij}\mathbf{q}_{ij}^H + \sigma^2\mathbf{I}$ is necessarily positive definite (and thus has an inverse) for all $\sigma^2 > 0$. $\bar{\mathbf{X}}_i$ then can be constructed by taking every G element of $\bar{\mathbf{x}}_i$ and putting as a column to $\bar{\mathbf{X}}_i$. Note also that it is possible to use adaptive or blind adaptive approaches to find $\bar{\mathbf{x}}_i$ [11], [26], [29].

B. Constrained Temporal-Spatial Filtering (CTSF)

OTSF requires a possibly large matrix $(KG \times KG)$ to be inverted. As this procedure may be computationally costly, or the corresponding adaptive implementation may be slow, one might want to consider less complex filtering procedures that nevertheless present capacity improvements for the system.

To this end, we consider a constrained class of rank 1 matrix filters, i.e., $\mathbf{X}_i \in \mathcal{L}$ where $\mathcal{L}$ is the space of rank 1 matrices in $\mathcal{C}^{G\times K}$. Note that all $\mathbf{X}_i \in \mathcal{L}$ can be expressed as $\mathbf{X}_i = \mathbf{c}_i\mathbf{w}_i^\top$. We call these *separable* temporal-spatial filters. Physically, the scheme is to combine the chip matched filter outputs using a linear filter at the output of each antenna (or equivalently linearly combining all of the antenna array observations for each chip) followed by a linear combination of the resulting statistics. The decision statistic to decode the bit for user i then becomes

$$\begin{aligned}y_i &= \mathrm{tr}\left(\mathbf{w}_i^*\mathbf{c}_i^H\mathbf{R}_i\right) = \mathbf{c}_i^H\mathbf{R}_i\mathbf{w}_i^*\\ &= \sum_{j=1}^{N}\sqrt{p_j h_{ij}}\,b_j\left(\mathbf{c}_i^H\mathbf{s}_j\right)\left(\mathbf{w}_i^H\mathbf{a}_{ij}\right) + \mathbf{c}_i^H\mathbf{N}_i\mathbf{w}_i^*. \qquad (10)\end{aligned}$$

It is possible to choose $\mathbf{c}_i$ and $\mathbf{w}_i$ in many different ways. For example, we may choose to employ matched filters in both spatial or temporal domains, i.e., $\mathbf{c}_i = \mathbf{s}_i$ and $\mathbf{w}_i = \mathbf{a}_{ii}$ [16], or matched filter in one domain and an MMSE filter in the other domain. Here, we consider the joint optimal filter pair in the MMSE sense. In this case, the optimization problem (4) becomes

$$\begin{aligned}[\bar{\mathbf{c}}_i, \bar{\mathbf{w}}_i] &= \arg\min_{\mathbf{c}_i,\mathbf{w}_i} E\left[\left|\mathrm{tr}\left(\mathbf{w}_i^*\mathbf{c}_i^H\mathbf{R}_i\right) - b_i\right|^2\right]\\ &= \arg\min_{\mathbf{c}_i,\mathbf{w}_i} E\left[\left|\mathbf{c}_i^H\mathbf{R}_i\mathbf{w}_i^* - b_i\right|^2\right]. \qquad (11)\end{aligned}$$

Note that the resulting $[\bar{\mathbf{c}}_i, \bar{\mathbf{w}}_i]$ pair yields a matrix filter $\bar{\mathbf{X}}_i = \bar{\mathbf{c}}_i\bar{\mathbf{w}}_i^\top$ that is suboptimal for the optimization problem (4), since it is found in a constrained $\mathbf{X}$ space.

The MSE function in (11) can be expressed as

$$\begin{aligned}\mathrm{MSE} = &\sum_{j=1}^{N} p_j h_{ij}\left|\mathbf{c}_i^H\mathbf{s}_j\right|^2\left|\mathbf{w}_i^H\mathbf{a}_{ij}\right|^2 + \sigma^2\left(\mathbf{c}_i^H\mathbf{c}_i\right)\left(\mathbf{w}_i^H\mathbf{w}_i\right)\\ &- 2\sqrt{p_i h_{ii}}\,\Re\left\{\left(\mathbf{c}_i^H\mathbf{s}_i\right)\left(\mathbf{w}_i^H\mathbf{a}_{ii}\right)\right\} + 1 \qquad (12)\end{aligned}$$

where $\Re\{\cdot\}$ denotes the real part of a complex number. It can be shown that although (12) is convex in $\mathbf{c}_i$ for fixed $\mathbf{w}_i$ and convex in $\mathbf{w}_i$ for fixed $\mathbf{c}_i$, it is not jointly convex in both vector variables, and the minimizer of MSE does not have a closed form expression. In this case, it is first necessary to ensure that the function indeed has a minimum. Fortunately, Weierstrass' theorem [30] ensures that there exists a minimum if the function is continuous and coercive, i.e., $f(x) \to \infty$ when $\|x\| \to \infty$, as is the case for the MSE function given by (12). Unfortunately, this minimum is not attained by a unique pair due to nonconvexity. To see this, simply observe that any two pairs $[\mathbf{c}_i, \mathbf{w}_i]$ and $[\mathbf{c}'_i, \mathbf{w}'_i]$ will produce the same MSE if $\mathbf{c}'_i = \beta \mathbf{c}_i$ and $\mathbf{w}'_i = (1/\beta)\mathbf{w}_i$, where β is any nonzero scalar. Since this argument is true for all MSE values including the MMSE, we are guaranteed to have multiple minima.

Due to the possible multimodality of the MSE function, standard iterative optimization algorithms cannot guarantee convergence to the global minimum. We devise here an iterative algorithm based on block coordinate descent or nonlinear Gauss–Seidel method [30], also known as alternating minimization [31], [32], and investigate its convergence properties.

Consider fixing the value of one of the filters, say $\tilde{\mathbf{w}}$. It is then possible to find the filter $\hat{\mathbf{c}}$ that maximally decreases the MSE function in (12). The solution is analogous to the MMSE detector described in [11] where user j's received amplitude is modified such that it is $\sqrt{p_j h_{ij}}(\tilde{\mathbf{w}}^H \mathbf{a}_{ij})$. With some abuse of notation, we will call this filter $\hat{\mathbf{c}} = \mathrm{MMSE}(\tilde{\mathbf{w}})$

$$\hat{\mathbf{c}} = \sqrt{p_i h_{ii}}(\tilde{\mathbf{w}}^H \mathbf{a}_{ii}) \left(\sum_{j=1}^{N} p_j h_{ij} |\tilde{\mathbf{w}}^H \mathbf{a}_{ij}|^2 \mathbf{s}_j \mathbf{s}_j^H + \sigma^2 |\tilde{\mathbf{w}}|^2 \mathbf{I} \right)^{-1} \mathbf{s}_i. \tag{13}$$

The same argument can be made for the case where $\mathbf{c}_i$ is fixed to $\tilde{\mathbf{c}}$ and the spatial filter is found to maximally decrease the MSE, $\hat{\mathbf{w}} = \mathrm{MMSE}(\tilde{\mathbf{c}})$

$$\hat{\mathbf{w}} = \sqrt{p_i h_{ii}}(\tilde{\mathbf{c}}^H \mathbf{s}_i) \left(\sum_{j=1}^{N} p_j h_{ij} |\tilde{\mathbf{c}}^H \mathbf{s}_j|^2 \mathbf{a}_{ij} \mathbf{a}_{ij}^H + \sigma^2 |\tilde{\mathbf{c}}|^2 \mathbf{I} \right)^{-1} \mathbf{a}_{ii}. \tag{14}$$

Now, consider the following algorithm. Starting with the filter pair $\mathbf{c}(0), \mathbf{w}(0)$ and keeping $\mathbf{w}(0)$ fixed, one can find $\mathbf{c}(1) = \mathrm{MMSE}(\mathbf{w}(0))$. Then keeping $\mathbf{c}(1)$ fixed, one can find $\mathbf{w}(1) = \mathrm{MMSE}(\mathbf{c}(1))$ that further decreases the MSE in (12). Iteration $n+1$ of this two-step iterative algorithm for user i is given below

$$\mathbf{c}_i(n+1) = \mathrm{MMSE}(\mathbf{w}_i(n)) \tag{15}$$
$$\mathbf{w}_i(n+1) = \mathrm{MMSE}(\mathbf{c}_i(n+1)). \tag{16}$$

Note that the order in which $\mathbf{c}_i$ and $\mathbf{w}_i$ are updated could be reversed. That is, we could devise a similar algorithm where $\mathbf{w}_i$ is updated before $\mathbf{c}_i$. The resulting MSE sequence given by the algorithm (15) and (16) is decreasing since

$$\begin{aligned} \mathrm{MSE}(\mathbf{c}(n-1), \mathbf{w}(n-1)) &\geq \mathrm{MSE}(\mathbf{c}(n), \mathbf{w}(n-1)) \\ &\geq \mathrm{MSE}(\mathbf{c}(n), \mathbf{w}(n)) \end{aligned} \tag{17}$$

and is bounded from below by the MMSE value. Thus, the algorithm is convergent. However, since the function is possibly multimodal, care must be taken to avoid undesirable stopping points. In particular, one can observe that $\mathbf{c} = \mathbf{w} = \mathbf{0}$ is an undesirable fixed point of the algorithm. A moment's thought reveals, however, that this point is reachable only from a point where the filter in either temporal or spatial domains is orthogonal to the desired user's signature in that domain, and this situation can be avoided by judicious choice of starting points.

To see this, we observe that the linear transformation (13) produces $\hat{\mathbf{c}} = \mathbf{0}$ iff $\tilde{\mathbf{w}}^H \mathbf{a}_{ii} = 0$. Similarly, the linear transformation (14) produces $\hat{\mathbf{w}} = \mathbf{0}$ iff $\tilde{\mathbf{c}}^H \mathbf{s}_i = 0$. Thus, $[\mathbf{c}, \mathbf{w}] = [\mathbf{0}, \mathbf{0}]$ is reachable only from one of the following set of points: $[\mathbf{c}, \mathbf{w}_\perp]$ with $\mathbf{w}_\perp^H \mathbf{a}_{ii} = 0$ or $[\mathbf{c}_\perp, \mathbf{w}]$ with $\mathbf{c}_\perp^H \mathbf{s}_i = 0$.

Now, recall the linear transformations in (13) and (14). They are projections onto the corresponding—temporal or spatial—signature spaces. Thus, if we start the algorithm at a point $\mathbf{w}(0)$ that lies in the linear vector space spanned by the spatial signatures, we can never arrive at a point outside the corresponding space for $\mathbf{c}$ or $\mathbf{w}$. Thus, we can avoid the undesirable fixed point $[\mathbf{c}, \mathbf{w}] = [\mathbf{0}, \mathbf{0}]$. Matched filter to the desired user's spatial signature, or any linear combination of the spatial signatures of all users are safe starting points.

Other than the obvious undesirable fixed point $[\mathbf{c}, \mathbf{w}] = [\mathbf{0}, \mathbf{0}]$, we have not encountered any other points where the algorithm would get stuck. Experimentally, we have always observed that the MMSE (global minimum value) is achieved starting from random points and the resulting $[\mathbf{c}, \mathbf{w}]$ vectors are scalar multiples of each other in the form of $[\mathbf{c}, \mathbf{w}]$ and $[\beta \mathbf{c}, \mathbf{w}/\beta]$, where β is a nonzero scalar.

C. Performance of the Temporal-Spatial MMSE Filters

In this section, we will compare the performances of OTSF and CTSF in terms of their asymptotic efficiencies and near–far resistances. Without loss of generality, we will consider a single cell system, and denote the spatial signatures with only one index: the spatial signature of user i will be denoted by $\mathbf{a}_i$; as usual $\mathbf{s}_i$ will denote the temporal signature of the same user. We have seen in the previous sections that for fixed received powers, the OTSF is superior to the CTSF in terms of the achievable MSE and SIR. This was a mere consequence of the fact that the CTSF was constrained to be in the rank 1 matrix space, while the OTSF could take any value in the $G \times K$ dimensional matrix space. We will see in this section that we can arrive at similar conclusions in terms of their asymptotic efficiencies and near–far resistances. Asymptotic efficiency of user i, with energy E_i, and bit-error rate of the user in the multiuser environment, as a function of the background noise power σ^2, $P_i(\sigma)$, is defined as [8]

$$\eta_i = \sup \left\{ 0 \leq r \leq 1; \lim_{\sigma \to 0} \frac{P_i(\sigma)}{Q\left(\frac{\sqrt{rE_i}}{\sigma}\right)} < +\infty \right\} \tag{18}$$

where $Q(x) = \int_x^\infty (1/\sqrt{2\pi}) \exp(-y^2/2)\, dy$. Then the near–far resistance is defined as [8]

$$\bar{\eta}_i = \inf_{E_j, j \neq i} \eta_i. \tag{19}$$

It is well known that the asymptotic efficiency of an MMSE receiver is equal to the asymptotic efficiency of a decorrelating (zero-forcing) receiver [8]. Therefore, in order to study the asymptotic efficiencies of the unconstrained and constrained MMSE receivers (OTSF and CTSF, respectively), we will study the asymptotic efficiencies of the unconstrained and constrained (to rank 1 matrix space) decorrelating receivers. The unconstrained temporal-spatial decorrelating receiver $\mathbf{X}_i$, for the ith user, is defined to be the solution of the following optimization problem [10]:

$$\begin{aligned} \max \quad & \operatorname{tr}\left(\mathbf{X}_i^H \mathbf{s}_i \mathbf{a}_i^\top\right) \\ \text{s.t.} \quad & \operatorname{tr}\left(\mathbf{X}_i^H \mathbf{s}_j \mathbf{a}_j^\top\right) = 0, \qquad \text{for all } j \neq i \\ & \operatorname{tr}\left(\mathbf{X}_i^H \mathbf{X}_i\right) = 1. \end{aligned} \tag{20}$$

Using the long vector notation, the unconstrained decorrelating receiver can be expressed as

$$\mathbf{x}_i = \mathbf{Q}(\mathbf{Q}^H \mathbf{Q})^{-1} \mathbf{e}_i \tag{21}$$

where $\mathbf{Q}$ is a $KG \times N$ matrix whose columns are $\mathbf{q}_i$, i.e., $\mathbf{Q} = [\mathbf{q}_1 \dots \mathbf{q}_N]$, and $\mathbf{q}_i$ are obtained by stacking the columns of $\mathbf{s}_i \mathbf{a}_i^\top$ into a KG dimensional vector, and $\mathbf{e}_i$ is the ith N dimensional unit vector, i.e., all entries of $\mathbf{e}_i$ are zero except the ith entry which is equal to 1. From the construction of the $\mathbf{Q}$ matrix, we have $\mathbf{Q}^H \mathbf{Q} = (\mathbf{A}^H \mathbf{A}) \circ (\mathbf{S}^H \mathbf{S})$, where $\mathbf{A} = [\mathbf{a}_1 \dots \mathbf{a}_N]$ and $\mathbf{S} = [\mathbf{s}_1 \dots \mathbf{s}_N]$, and $\circ$ denotes the Hadamard (elementwise) product of matrices. The asymptotic efficiency of the ith user is given as [8], [10], [23], [27]

$$\eta_X^i = \frac{1}{[(\mathbf{Q}^H \mathbf{Q})^{-1}]_{ii}} = \frac{1}{[((\mathbf{A}^H \mathbf{A}) \circ (\mathbf{S}^H \mathbf{S}))^{-1}]_{ii}}. \tag{22}$$

The constrained temporal-spatial decorrelating filter is given in a similar way, except the addition of $\mathbf{X}_i \in \mathcal{L}$ into the constraint set of (20). Denoting the constrained decorrelating filter as $\mathbf{X}_i = \mathbf{c}_i \mathbf{w}_i^\top$, we can write (20) as

$$\begin{aligned} \max \quad & \left(\mathbf{c}_i^H \mathbf{s}_i\right) \left(\mathbf{w}_i^H \mathbf{a}_i\right) \\ \text{s.t.} \quad & \left(\mathbf{c}_i^H \mathbf{s}_j\right) \left(\mathbf{w}_i^H \mathbf{a}_j\right) = 0, \qquad \text{for all } j \neq i \\ & \left(\mathbf{c}_i^H \mathbf{c}_i\right) \left(\mathbf{w}_i^H \mathbf{w}_i\right) = 1. \end{aligned} \tag{23}$$

Note that in order to satisfy the first constraint in (23) we may decorrelate the ith user from an interfering jth user either in time (by choosing $\mathbf{c}_i^H \mathbf{s}_j = 0$) or in space (by choosing $\mathbf{w}_i^H \mathbf{a}_j = 0$). Decorrelating the ith user from an interfering jth user both in time and space results in more enhanced background noise, and equivalently reduced asymptotic efficiency. Therefore, we have to partition all interfering users (to user i) into two subsets: those that will be decorrelated temporally and those that will be decorrelated spatially. Let us consider an arbitrary partition of interfering users into two sets. Let I_s and I_t denote the indices of the users that will be decorrelated from in space and time, respectively. Let $\mathbf{A}_s$ be a matrix whose first column is the spatial signature of the ith user, and the rest of its columns are the spatial signatures of the users in the set I_s; $\mathbf{S}_t$ be a matrix whose first column is the temporal signature of the ith user and the rest of its columns are the temporal signatures of the users in the set I_t. Then it can be shown that the asymptotic efficiency of the ith user with the constrained temporal-spatial decorrelating filter is given as

$$\eta_{cw}^i = \max_{I_s, I_t} \frac{1}{\left[\left(\mathbf{A}_s^H \mathbf{A}_s\right)^{-1}\right]_{11} \left[\left(\mathbf{S}_t^H \mathbf{S}_t\right)^{-1}\right]_{11}} \tag{24}$$

where the maximization is defined over all possible partitions of the interfering users into two sets. Note that for both the unconstrained and the constrained filters, near–far resistances are equal to the corresponding asymptotic efficiencies, i.e., $\bar{\eta}_X^i = \eta_X^i$ and $\bar{\eta}_{cw}^i = \eta_{cw}^i$, for all i, since the asymptotic efficiencies do not depend on the energies of the users. At first sight, it may seem difficult to compare the quantities in (22) and (24). In order to do this comparison, we will use a slightly different definition of the asymptotic efficiency. For a normalized decorrelating detector $\mathbf{X}_i$, i.e., the solutions of (20) and (23), the asymptotic efficiency is given as [8], [10], [33]

$$\eta_X^i = \left(\operatorname{tr}\left(\mathbf{X}_i^H \mathbf{s}_i \mathbf{a}_i^\top\right)\right)^2. \tag{25}$$

Note that this is the square of the cost function of the maximization problems in (20) and (23). Since the feasible set of (23) is contained in the feasible set of (20), we can conclude that the cost function at the solution of (20) is larger than or equal to the cost function at the solution of (23). Thus

$$\eta_X^i \geq \eta_{cw}^i \tag{26}$$

and the unconstrained temporal-spatial MMSE filter has greater near–far resistance than the constrained temporal-spatial MMSE filter.

A related interesting issue is how many interfering users a given user can cope with, in the sense of having a nonzero asymptotic efficiency, using the constrained and the unconstrained decorrelating receivers. As long as a user has a nonzero asymptotic efficiency, that user can achieve its quality-of-service requirement by increasing its transmit power. With the constrained decorrelating receiver, a user can suppress up to $G-1$ users in time, and up to $K-1$ users in space, as long as the temporal signature sequences of the users to be suppressed in time and the spatial signature sequences of the users to be suppressed in space are linearly independent. Therefore, a user can suppress at most $K+G-2$ interferers by using a constrained temporal-spatial decorrelating receiver. Clearly, the number of interferers a user can suppress by using an unconstrained temporal-spatial decorrelating receiver is higher, since the constrained decorrelating receiver is a special case of an unconstrained decorrelating receiver. Using the long vector formulation in (21), one would conclude that a desired user can suppress up to $KG-1$ interfering users since the dimensionality of the temporal-spatial signatures is KG. However, these “long” temporal-spatial signatures have a repetitive structure. In other words, the temporal-spatial signature of a given user is composed of the temporal signature of the same user concatenated K times after being multiplied by the K antenna gains. This repetitive structure may result in loss of dimensionality. However, in recent work [34], for a large system where $N \to \infty$ and $G \to \infty$ but $\alpha = N/G$ and K are fixed and finite, the dimensionality of the system with unconstrained MMSE receivers has been shown to be KG as long as the temporal signatures are random, and antenna gains are uncorrelated.

IV. Joint Power Control and Temporal-Spatial Filtering

In Sections III-A and III-B, we derived the joint MMSE filters for a CDMA system that employs spatial (through beamforming) and temporal processing (through multiuser detection) at the receiver, using unconstrained ($\mathbf{X}_i \in \mathcal{C}^{G\times K}$) and constrained ($\mathbf{X}_i \in \mathcal{L}$), respectively. Our aim, in this section, is to find optimal powers p_i and matrix filters $\mathbf{X}_i$ for both constrained and unconstrained cases, for $i = 1, \ldots, N$, such that the total transmitter power is minimized while each user i satisfies its quality-of-service requirement, $\mathrm{SIR}_i \geq \gamma_i^*$, where γ_i^*, called the *target* SIR, is the minimum acceptable level of SIR for user i. The SIR of user i at the output of the joint spatial and temporal filter can be expressed as

$$\mathrm{SIR}_i = \frac{p_i h_{ii} \left|\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{s}_i \mathbf{a}_{ii}^\top\right)\right|^2}{\sum_{j\neq i} p_j h_{ij} \left|\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{s}_j \mathbf{a}_{ij}^\top\right)\right|^2 + \sigma^2 \,\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{X}_i\right)}. \tag{27}$$

We can then state the optimization problem as

$$\begin{aligned} \min \quad & \sum_{i=1}^{N} p_i \\ \text{s.t.} \quad & p_i \geq \frac{\gamma_i^*}{h_{ii}} \frac{\sum_{j\neq i} p_j h_{ij} \left|\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{s}_j \mathbf{a}_{ij}^\top\right)\right|^2 + \sigma^2 \,\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{X}_i\right)}{\left|\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{s}_i \mathbf{a}_{ii}^\top\right)\right|^2} \\ & p_i \geq 0, \qquad \mathbf{X}_i \in \mathcal{S} \quad i = 1, \ldots, N \end{aligned} \tag{28}$$

where $\mathcal{S} = \mathcal{C}^{G\times K}$ for unconstrained temporal-spatial filtering and $\mathcal{S} = \mathcal{L}$ for constrained temporal-spatial filtering. Note that as stated above, (28) does not address the constraints on the power level a user can transmit. In practice, each transmitter clearly has a range over which it can transmit, i.e., it has maximum power constraints. We will address the existence of these constraints in Section IV-B.

As in the case for the joint power control and temporal filtering [13], we can write (28) as (29), shown at the bottom of the page. The minimization over $\mathbf{X}_i$, on the right-hand side of each of the power constraints above, is equivalent to maximizing SIR_i given by (27) for a fixed power p_i in the corresponding filter spaces. As stated in the following proposition, temporal-spatial filters that minimize the MSE in the corresponding filter spaces also maximize the SIR.

Proposition 1: The filters that solve (4) and (11) achieve the maximum SIR over all filters in $\mathcal{C}^{G\times K}$ and $\mathcal{L}$, respectively.

The proof of this proposition is given in Appendix A and is a simple extension of the solution to [8, Problem 6.5] (as given in [35]) to include complex numbers and constrained optimization.

A. Iterative Power Control Algorithms

Let us devise an iterative algorithm that converges to the optimum of (28). Iterative power control algorithms of the form

$$\mathbf{p}(n+1) = \mathbf{I}(\mathbf{p}(n)) \tag{30}$$

are analyzed for *standard interference functions* $\mathbf{I}(\mathbf{p})$ in [3]. The definition of a standard interference function and the corresponding convergence result will be used throughout this paper and are restated here for convenience.

Definition 1: $\mathbf{I}(\mathbf{p})$ is a standard interference function if for all $\mathbf{p} \geq \mathbf{0}$ the following properties are satisfied.

- Positivity: $\mathbf{I}(\mathbf{p}) > \mathbf{0}$.
- Monotonicity: If $\mathbf{p} \geq \mathbf{p}'$, then $\mathbf{I}(\mathbf{p}) \geq \mathbf{I}(\mathbf{p}')$.
- Scalability: For all $\alpha > 1$, $\alpha\mathbf{I}(\mathbf{p}) > \mathbf{I}(\alpha\mathbf{p})$.

Theorem 1: If there exists $\mathbf{p}' \geq \mathbf{I}(\mathbf{p}')$, then for any initial power vector $\mathbf{p}(0)$, the sequence $\mathbf{p}(n) = \mathbf{I}(\mathbf{p}(n-1))$ converges to a unique fixed point $\bar{\mathbf{p}}$ such that $\bar{\mathbf{p}} \leq \mathbf{p}'$ for any $\mathbf{p}' \geq \mathbf{I}(\mathbf{p}')$.

The condition that there exists $\mathbf{p}' \geq \mathbf{I}(\mathbf{p}')$ is simply a requirement that a feasible power vector exists. The fixed point $\bar{\mathbf{p}}$ is a minimum power solution in that $\bar{\mathbf{p}} \leq \mathbf{p}'$ for any feasible power vector $\mathbf{p}'$.

We define the ith element of the interference function $\mathbf{I}(\mathbf{p})$, $I_i(\mathbf{p})$, which is valid for both unconstrained and constrained cases by a proper selection of $\mathcal{S}$ as $I_i(\mathbf{p}) =$

$$\frac{\gamma_i^*}{h_{ii}} \min_{\mathbf{X}_i \in \mathcal{S}} \frac{\sum_{j\neq i} p_j h_{ij} \left|\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{s}_j \mathbf{a}_{ij}^\top\right)\right|^2 + \sigma^2 \,\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{X}_i\right)}{\left|\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{s}_i \mathbf{a}_{ii}^\top\right)\right|^2} \tag{31}$$

Note that the interference function for the unconstrained temporal-spatial filtering, $\bar{\mathbf{I}}(\mathbf{p})$, can be obtained from (31) by choosing $\mathcal{S} = \mathcal{C}^{G\times K}$ as

$$\begin{aligned} \bar{I}_i(\mathbf{p}) &= \frac{\gamma_i^*}{h_{ii}} \min_{\mathbf{X}_i \in \mathcal{C}^{G\times K}} \\ &\quad \cdot \frac{\sum_{j\neq i} p_j h_{ij} \left|\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{s}_j \mathbf{a}_{ij}^\top\right)\right|^2 + \sigma^2 \,\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{X}_i\right)}{\left|\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{s}_i \mathbf{a}_{ii}^\top\right)\right|^2} \\ &= \frac{\gamma_i^*}{h_{ii}} \min_{\mathbf{x}_i \in \mathcal{C}^{GK}} \frac{\sum_{j\neq i} p_j h_{ij} \left|\mathbf{x}_i^H \mathbf{q}_{ij}\right|^2 + \sigma^2 \mathbf{x}_i^H \mathbf{x}_i}{\left|\mathbf{x}_i^H \mathbf{q}_{ii}\right|^2} \end{aligned} \tag{32}$$

where the long vector notation as introduced in (3.1) is used; and the interference function for the constrained temporal-spa-

$$\begin{aligned} \min_{\mathbf{p}} \quad & \sum_{i=1}^{N} p_i \\ \text{s.t.} \quad & p_i \geq \frac{\gamma_i^*}{h_{ii}} \min_{\mathbf{X}_i \in \mathcal{S}} \frac{\sum_{j\neq i} p_j h_{ij} \left|\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{s}_j \mathbf{a}_{ij}^\top\right)\right|^2 + \sigma^2 \,\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{X}_i\right)}{\left|\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{s}_i \mathbf{a}_{ii}^\top\right)\right|^2} \\ & p_i \geq 0 \quad i = 1, \ldots, N \end{aligned} \tag{29}$$

tial filtering case, $\tilde{\mathbf{I}}(\mathbf{p})$, can be obtained from (31), by choosing $\mathcal{S} = \mathcal{L}$ as

$$\begin{aligned}\tilde{I}_i(\mathbf{p}) &= \frac{\gamma_i^*}{h_{ii}} \min_{\mathbf{X}_i \in \mathcal{L}} \\ &\quad \cdot \frac{\sum_{j\neq i} p_j h_{ij} \left|\operatorname{tr}\left(\mathbf{X}_i^H \mathbf{s}_j \mathbf{a}_{ij}^\top\right)\right|^2 + \sigma^2 \operatorname{tr}\left(\mathbf{X}_i^H \mathbf{X}_i\right)}{\left|\operatorname{tr}\left(\mathbf{X}_i^H \mathbf{s}_i \mathbf{a}_{ii}^\top\right)\right|^2} \\ &= \frac{\gamma_i^*}{h_{ii}} \min_{\mathbf{c}_i, \mathbf{w}_i} \\ &\quad \cdot \frac{\sum_{j\neq i} p_j h_{ij} \left|\mathbf{c}_i^H \mathbf{s}_j\right|^2 \left|\mathbf{w}_i^H \mathbf{a}_{ij}\right|^2 + \sigma^2 |\mathbf{c}_i|^2 |\mathbf{w}_i|^2}{\left|\mathbf{c}_i^H \mathbf{s}_i\right|^2 \left|\mathbf{w}_i^H \mathbf{a}_{ii}\right|^2}.\end{aligned} \tag{33}$$

We make the following observation.

Proposition 2: $\mathbf{I}(\mathbf{p})$ in (31) is a standard interference function.

The proof of this proposition is given in Appendix A. Proposition 2 implies that the power control iteration of the form of (30) converges to the optimum power vector.

The resulting power control algorithm for both unconstrained and constrained temporal-spatial filtering cases are two-step iterative algorithms. In both cases, in the first step, the filter is found by solving the minimization problem in (31), and in the second step, the power of the user is updated using (30). Below, we will state the resulting power control algorithms for unconstrained and constrained cases separately.

The implementation of the two-step iterative power control algorithm in the case of unconstrained temporal-spatial filtering for user i at iteration $n+1$ is given by the following Algorithm.

Algorithm A1:

$$\hat{\mathbf{x}}_i = k_i(n) \left(\sum_{j\neq i} p_j(n) h_{ij} \mathbf{q}_{ij} \mathbf{q}_{ij}^H + \sigma^2 \mathbf{I} \right)^{-1} \mathbf{q}_{ii} \tag{34}$$

$$p_i(n+1) = \frac{\gamma_i^* \left(\sum_{j\neq i} p_j(n) h_{ij} \left|\hat{\mathbf{x}}_i^H \mathbf{q}_{ij}\right|^2 + \sigma^2 \hat{\mathbf{x}}_i^H \hat{\mathbf{x}}_i \right)}{h_{ii} \left|\hat{\mathbf{x}}_i^H \mathbf{q}_{ii}\right|^2} \tag{35}$$

where $k_i(n)$ is the scaling factor. Notice that any positive scalar multiple of $\hat{\mathbf{x}}_i$ yields the same power update in (35), so calculation of $k_i(n)$ is actually not needed.

The implementation of the two-step iterative power control algorithm in the case of constrained temporal-spatial filtering for user i at iteration $n+1$ is given by the following algorithm.

Algorithm A2:

$$[\hat{\mathbf{c}}_i, \hat{\mathbf{w}}_i] = \arg\min_{\mathbf{c},\mathbf{w}} E[(\mathbf{c}^H \mathbf{R}_i(\mathbf{p}(n)) \mathbf{w}^*) - b_i)^2] \tag{36}$$

$$p_i(n+1) = \frac{\gamma_i^*}{h_{ii}} \frac{\sum_{j\neq i} p_j(n) h_{ij} \left|\hat{\mathbf{c}}_i^H \mathbf{s}_j\right|^2 \left|\hat{\mathbf{w}}_i^H \mathbf{a}_{ij}\right|^2 + \sigma^2 |\hat{\mathbf{c}}_i|^2 |\hat{\mathbf{w}}_i|^2}{\left|\hat{\mathbf{c}}_i^H \mathbf{s}_i\right|^2 \left|\hat{\mathbf{w}}_i^H \mathbf{a}_{ij}\right|^2}. \tag{37}$$

If the SIR targets are feasible, then starting from any initial power vector and filter coefficients, the algorithms in (34)–(35) and (36)–(37) converge to the minimum power fixed point with best possible temporal-spatial filters in the corresponding filter space.

Note that to implement (36), we need to use the iterative algorithm given by (15) and (16). The filters need to converge to the exact optimum $\hat{\mathbf{c}}_i, \hat{\mathbf{w}}_i$ pair for fixed powers before each power update for the power control algorithm to be standard. So, theoretically, many filter updates in the form of (15) and (16) have to be done before the power of the user is updated. In practice, a finite number L of iterations are performed which is in a way an approximation for the standard power control algorithm. Our observation is that a small number of iterations is sufficient. In all experiments, we used $L = 5$ iterations. Curiously, we have also observed the convergence of the following algorithm with $L = 1$ of each filter update per power iteration, and that the convergence point of the following algorithm and Algorithm A2 are the same (see Section V).

Algorithm A3:

$$\mathbf{c}_i(n+1) = \operatorname{MMSE}(\mathbf{w}_i(n)) \tag{38}$$

$$\mathbf{w}_i(n+1) = \operatorname{MMSE}(\mathbf{c}_i(n+1)) \tag{39}$$

$$p_i(n+1) = \frac{\gamma_i^*}{h_{ii}} \frac{\sum_{j\neq i} p_j(n) h_{ij} \left|\mathbf{c}_i^H \mathbf{s}_j\right|^2 \left|\mathbf{w}_i^H \mathbf{a}_{ij}\right|^2 + \sigma^2 |\mathbf{c}_i|^2 |\mathbf{w}_i|^2}{\left|\mathbf{c}_i^H \mathbf{s}_i\right|^2 \left|\mathbf{w}_i^H \mathbf{a}_{ii}\right|^2}. \tag{40}$$

The intuition behind this algorithm is simple. Before each power control update, each user chooses a *better*, not necessarily the best, filter pair. This is a mere consequence of the fact that in update (38), the SIR of user i is maximized by replacing the temporal filter with $\mathbf{c}_i(n+1)$, for the given power vector and $\mathbf{w}_i(n)$ and in update (40) the SIR is further increased by the maximization when the power vector and $\mathbf{c}_i(n+1)$ are fixed. Thus, $[\mathbf{c}_i(n+1), \mathbf{w}_i(n+1)]$ are a *better* filter pair than $[\mathbf{c}_i(n), \mathbf{w}_i(n)]$ for the power vector $\mathbf{p}(n)$. The simulation results about the performance and convergence of this algorithm are given in Section V.

B. Simple Extensions

It was shown in [3] that standard power iterations in the presence of maximum power constraints are standard and thus convergent. So, it is possible to modify A1 and A2 to incorporate the maximum power constraints. In particular, the transmit power update steps (35) and (37) can be modified, respectively, as follows:

$$p_i(n+1) = \min\{p_{\max}, \bar{I}_i(\mathbf{p}(n))\} \tag{41}$$

$$p_i(n+1) = \min\{p_{\max}, \tilde{I}_i(\mathbf{p}(n))\} \tag{42}$$

where $\bar{I}_i(\cdot)$ and $\tilde{I}_i(\cdot)$ are defined in (32) and (33), respectively.

Another possible extension for the power control algorithms we proposed is to incorporate base station selection into the algorithms. Base station selection as a means of further interference suppression compared to fixed assignment combined with transmit power control has been addressed in [36] and [37]. These works assumed a single antenna at each base station and conventional processing in time and found the best base station assignment that minimized the total power of all users. Similar to that case, by finding the optimum assignment of users to base stations, we can further decrease the total transmit power in the systems where temporal and spatial processing are used. Consider M base stations to which all users will be assigned. $\mathbf{b}$ is the N-dimensional vector that denotes the assigned base station indices. In particular, $b_i = k$ means that user i is assigned to base k. In this case, the optimization problem is

$$\begin{aligned} &\min \sum_{i=1}^{N} p_i \\ &p_i \geq \frac{\gamma_i^*}{h_{b_i i}} \frac{\sum_{j \neq i} p_j h_{b_i j} \left| \mathrm{tr}\left(\mathbf{X}_i^H \mathbf{s}_j \mathbf{a}_{b_i j}^\top\right)\right|^2 + \sigma^2 \, \mathrm{tr}\left(\mathbf{X}_i^H \mathbf{X}_i\right)}{\left|\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{s}_i \mathbf{a}_{b_i i}^\top\right)\right|^2} \\ &p_i \geq 0, \qquad b_i \in \{1, \ldots, M\}; \;\; \mathbf{X}_i \in \mathcal{S}; \;\; i = 1, \ldots, N \end{aligned} \tag{43}$$

where, the optimization is over $\mathbf{p}, \mathbf{b}, \{\mathbf{X}_i \in \mathcal{S}\}_{i=1}^N$, and, again, $\mathcal{S} = \mathcal{C}^{G \times K}$ for unconstrained temporal-spatial filtering and $\mathcal{S} = \mathcal{L}$ for constrained temporal-spatial filtering. We can once again move filter and base station optimization to the constraint set and define (44), shown at the bottom of the page. Simply by extending the proof we had for Proposition 2, we arrive at the following proposition.

Proposition 3: $\mathbf{T}(\mathbf{p})$ is a standard interference function.

Thus, we can devise the algorithm where each user evaluates its SIR at each base station with the best corresponding temporal and spatial filters and then chooses the best base station. The transmit power of the user is then adjusted. This algorithm will converge to the best temporal and spatial filters in the intended filter space with the best base station assignment and transmit power for each user.

V. Simulation Results

We consider a nine-cell CDMA system on a 3×3 grid. We consider fixed base station assignment for simplicity. We assume a linear array of omni directional antennas equispaced at half a wavelength [23]. The positions of the users and their temporal signatures are generated at random, but then kept fixed for the particular experiment. The SIR target value is the same for all users and is set to $\gamma^* = 5$ (7 dB). Results are generated to compare the following algorithms.

1) Conventional power control (C-PC): Each base station has a single antenna and matched filter receivers are employed in the temporal domain [3], [6].
2) Power control and multiuser detection (MMSE-PC): Each base station has a single antenna and MMSE receivers are employed in the temporal domain [13].
3) Power control and beamforming (BF-PC): An antenna array of K elements is employed at each base station. Array outputs are combined in the MMSE sense. Matched filter receivers are employed in the temporal domain [25].
4) Power control with CTSF (CTSF-PC, $L = 5$): Constrained temporal-spatial filtering is employed. We performed $L = 5$ iterations of the algorithm given by (15) and (16) before each power update and observed that the resulting filters $\mathbf{c}, \mathbf{w}$ converged to the global minimizer of the MSE function given by (12) in each case (**Algorithm A2**).
5) Power control with single step CTSF (CTSF-PC, $L = 1$): Constrained temporal-spatial filtering is employed, but only $L = 1$ iteration of the algorithm given by (15) and (16) is employed before each power update (**Algorithm A3**).
6) OTSF (OTSF-PC): Joint unconstrained filtering in temporal and spatial domains is employed as given in (6) (**Algorithm A1**).

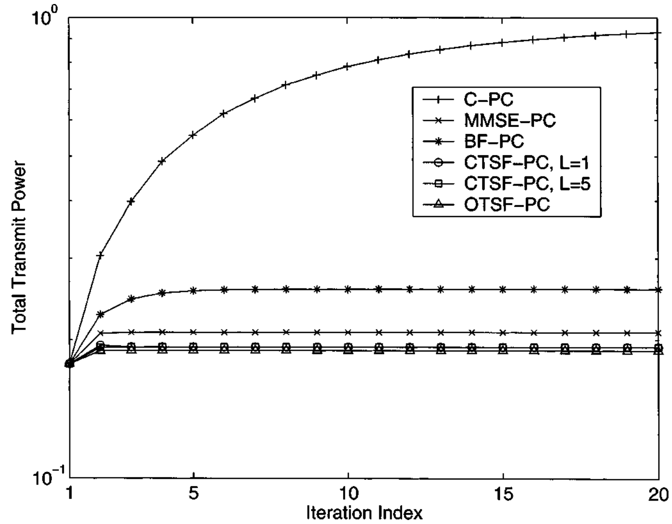

Fig. 2. Total transmit power of all users in the system versus power control iteration index, $N = 12$, $K = 2$, $G = 10$.

Fig. 2 shows the comparison of total transmit power usage when there are $N = 12$ users in the system. An antenna array of $K = 2$ elements is used, and the processing gain is $G = 10$. For this small system, all power control algorithms are feasible, i.e., all users can achieve γ^*. In fact, results of the algorithms are identical for the case when no maximum power constraints are imposed, and the case where each user is assumed to have a maximum power constraint of 1 W. This is a direct result of the fact that no user has to transmit at maximum power at the convergence point for all of the six algorithms considered. We observe that the power control algorithms with temporal-spatial processing (items 4, 5, and 6 above) offer savings in total transmit power over the C-PC (item 1 above) and the combined power control and MMSE filtering in one domain (items 2 and 3 above). Compared to C-PC, the savings are as high as 7.2 dB. Fig. 3 shows the average SIR achieved over all users versus the power control iteration index. Since all power control algorithms are feasible, they all reach the SIR

$$T_i(\mathbf{p}) = \min_{\mathbf{b}, \mathbf{X}_i \in \mathcal{S}} \frac{\gamma_i^*}{h_{b_i i}} \frac{\sum_{j \neq i} p_j h_{b_i j} \left| \mathrm{tr}\left(\mathbf{X}_i^H \mathbf{s}_j \mathbf{a}_{b_i j}^\top\right)\right|^2 + \sigma^2 \, \mathrm{tr}\left(\mathbf{X}_i^H \mathbf{X}_i\right)}{\left|\mathrm{tr}\left(\mathbf{X}_i^H \mathbf{s}_i \mathbf{a}_{b_i i}^\top\right)\right|^2} \tag{44}$$

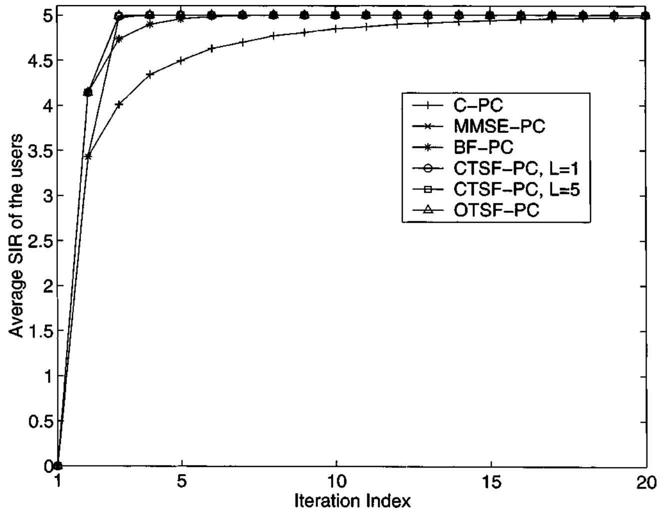

Fig. 3. Average SIR of all users versus power control iteration index, $N = 12$, $K = 2$, $G = 10$.

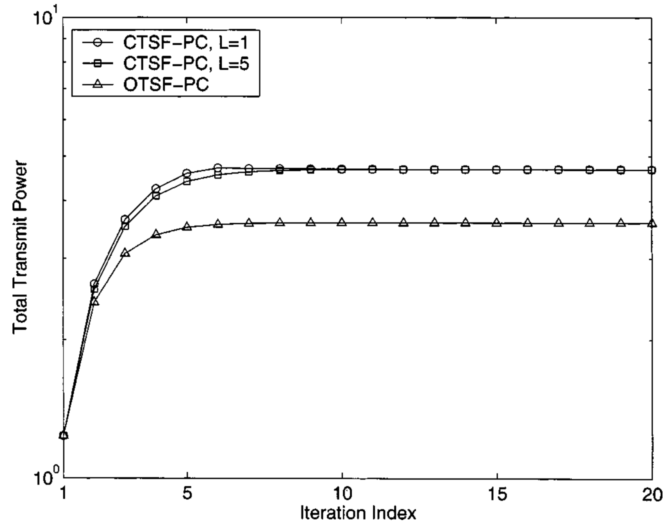

Fig. 5. Total transmit power of all users in the system versus power control iteration index, $N = 60$, $K = 2$, $G = 10$ (Fig. 4 magnified).

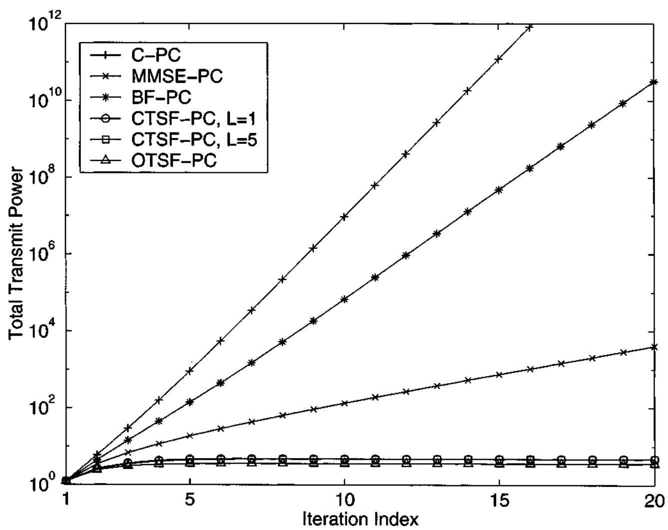

Fig. 4. Total transmit power of all users in the system versus power control iteration index, $N = 60$, $K = 2$, $G = 10$. No power constraints.

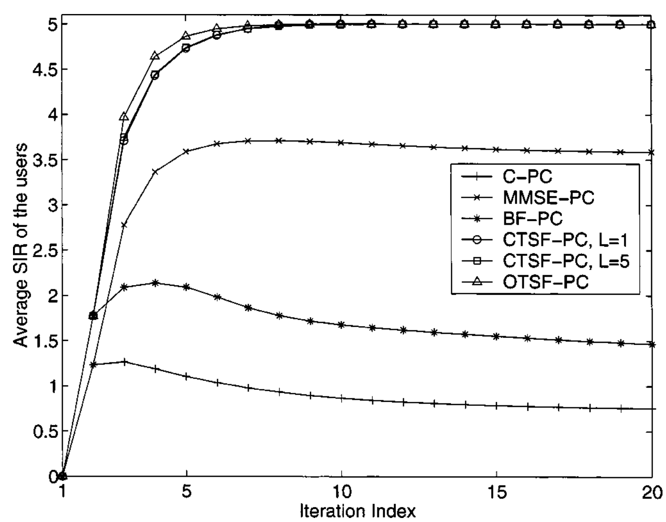

Fig. 6. Average SIR of all users versus power control iteration index, $N = 60$, $K = 2$, $G = 10$. No power constraints.

target of 5 (7 dB). We also observe from Figs. 2 and 3 that the convergence speed of the proposed algorithms are faster than C-PC. For this experiment, C-PC converged in about 20 iterations while the proposed methods converged in three iterations. This observation is consistent throughout our experiments, i.e., we have observed that the joint power control, multiuser detection, and beamforming algorithms converge faster than that of C-PC, BF-PC, and MMSE-PC.

Next, we consider a highly loaded system with $N = 60$ users. The number of antenna array elements is $K = 2$ and processing gain is $G = 10$. In Fig. 4, we see that only power control algorithms with joint processing in both domains are feasible (items 4, 5, and 6 above). The infeasible algorithms (items 1, 2, and 3 above) result in total transmit power values that increase without bound since users have no maximum power constraints and keep increasing their powers at each iteration to increase their SIRs, but never can achieve the target SIR value. The system can support this many users at the SIR target level of 5 only by utilizing the structure in both temporal and spatial domains to suppress the interference in conjunction with power control. Fig. 5 is a magnified version of Fig. 4, which emphasizes the fact that the OTSF with power control offers more savings in total transmit power as compared to CTSF with power control (see Section III-B). This figure also emphasizes our observation about the convergence of the $L = 1$ algorithm implemented as in (38)–(40) to the optimal power vector with optimal CTSFs. Fig. 6 shows the average SIRS after each iteration. The proposed algorithms (items 4, 5, and 6 above) achieve the SIR target of 5 (7 dB) while the C-PC, BF-PC, and MMSE-PC result in lower average SIRs. Figs. 7 and 8 show the performance of the same system when a maximum power constraint of 1 W is imposed on each user. Although the total transmit powers of the infeasible algorithms converge to finite levels due to the presence of the maximum power constraints (Fig. 7), the average SIR levels achieved are below the target SIR value for C-PC, BF-PC, and MMSE-PC (Fig. 8). The target SIR level is achieved by each user only when temporal and spatial filtering and power control algorithms are employed.

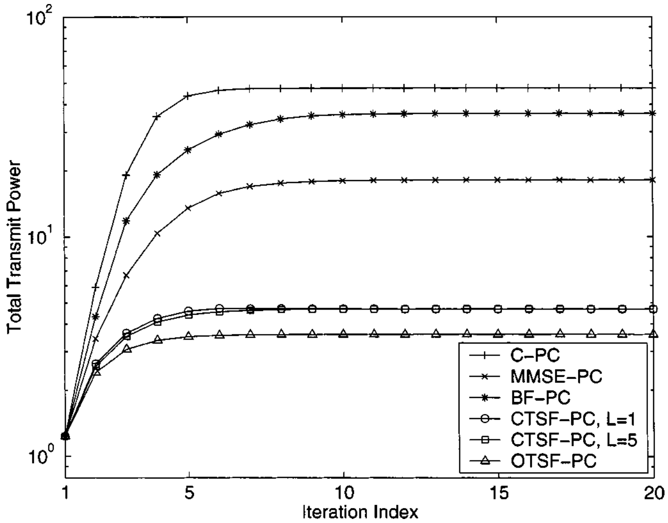

Fig. 7. Total transmit power of all users in the system versus power control iteration index, with maximum power constraint of 1 W, $N = 60$, $K = 2$, $G = 10$.

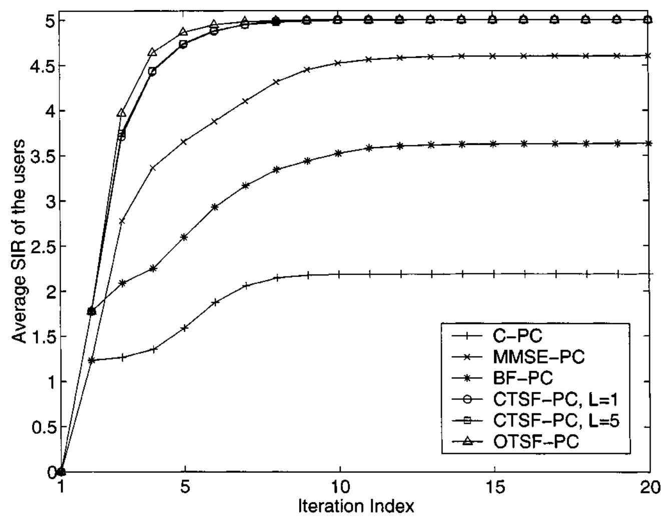

Fig. 8. Average SIR of all users versus power control iteration index, with maximum power constraint of 1 W, $N = 60$, $K = 2$, $G = 10$.

Similar observations are obtained for a larger system with processing gain $G = 64$ and $K = 4$ antennas. Fig. 9 shows the distribution of the $N = 300$ users in nine cells for this experiment.In this p The corresponding total transmit power curves are plotted in Fig. 10. Once again, intelligent signal combining methods in both temporal and spatial domains used with optimal power control are superior to that of single domain combining with power control. C-PC and BF-PC are simply infeasible for this example. Fig. 11 shows an even more crowded system with the same parameters and $N = 500$ users. For this example, only the temporal and spatial filtering with power control methods (items 4, 5, and 6) are feasible, i.e., the system can support this many users only if all three interference management methods are combined as proposed in this paper.

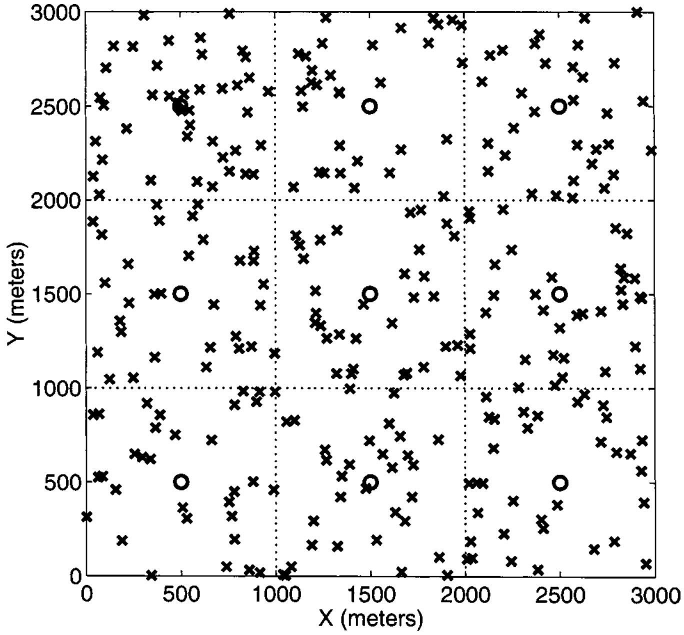

Fig. 9. Distribution of $N = 300$ users on a nine-cell grid. x and o denote users and bases, respectively.

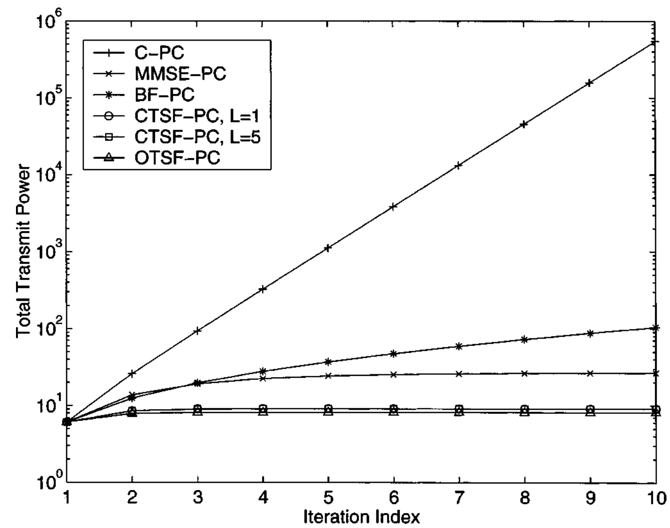

Fig. 10. Total transmit power of all users in the system versus power control iteration index, $N = 300$, $K = 4$, $G = 64$. No power constraints.

VI. Conclusion

aper, we have shown that when antenna arrays are employed at each base station, the system performance can be improved by jointly combining the array observations and the temporal observations and employing power control. The total transmit power expended by all users is less as compared to algorithms that do not utilize both temporal and spatial domains. In cases where other algorithms result in an infeasible system, power control with multiuser detection and beamforming can convert the system into a feasible one. Thus, it increases the system capacity by allowing the SIR targets of the users to be higher, or by increasing the number of users supportable at a fixed SIR target level.

One should note that the results we have presented assume knowledge of all users' parameters in the system, e.g., spreading codes, timing information, spatial signatures, and link gains. In practice, especially for out of cell interferers, all parameters may not be available to the system. In such cases, adaptive [11] or

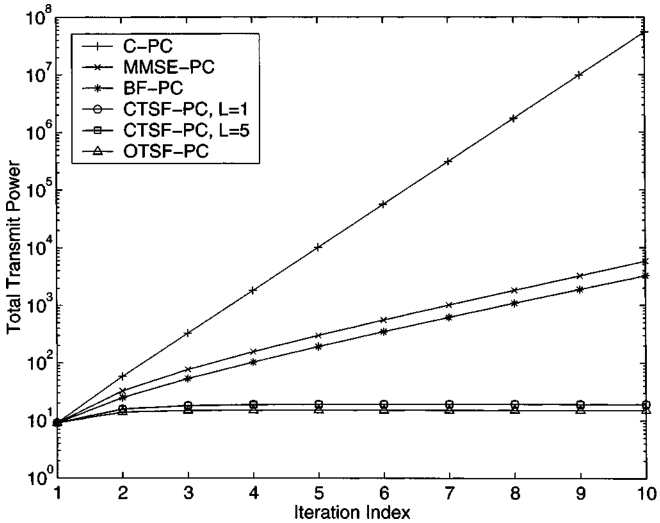

Fig. 11. Total transmit power of all users in the system versus power control iteration index, $N = 500$, $K = 4$, $G = 64$. No power constraints.

blind adaptive [26], [29] methods should be used to find the filters in power control iterations (34), (36), (38), and (39). The speed of convergence of these adaptive algorithms brings a natural constraint on the time frame in which the power updates in (35), (37), and (40) can be done. Moreover, updates (35), (37), and (40) require the SIR, or equivalently the interference function, measured at the output of the user's *updated* receiver filter to calculate the next transmit power value. We have assumed perfect measurements of interference functions for the power control algorithms proposed here and proved deterministic convergence. When perfect measurements of these quantities are replaced by their noisy estimates, the algorithms we proposed here become stochastic algorithms. Stochastic power control algorithms were studied only for conventional power control (with matched filter receivers at the base station) in [38]. Stochastic convergence results need to be studied for the algorithms proposed here as well as the ones in [13] and [25]. Lastly, the SIR (or the interference) is a real number and requires many bits to be transmitted to the mobile user with enough precision. In this work, as in most of the previous power control studies [3], [6], [7], [13], [25], [36]–[38], we assumed that this feedback channel has infinite precision. In contrast with this methodology, the second- and third-generation CDMA systems employ the so-called *up-down* power control algorithms which have fixed power steps and require considerably less feedback from the base station to the mobile. The implementation of such limited feedback corresponds to quantization of the SIR value to be fed back to the mobile. The effects of this quantization on the convergence of the power control algorithms and also the system performance need to be investigated.

APPENDIX
PROOFS

Proof: Proposition 1: Let us assume a general matrix receiver filter $\mathbf{X}$. Let us represent the desired signal part of the received signal, i.e., the signal of user i, with $b_i\mathbf{S}_i$, and the multiaccess interference and additive white Gaussian noise part of the received signal with $\mathbf{Y}_i$, i.e., $\mathbf{R}_i = b_i\mathbf{S}_i + \mathbf{Y}_i$

$$\begin{aligned}\mathbf{S}_i &= \sqrt{p_i h_{ii}}\mathbf{s}_i\mathbf{a}_{ii}^\top \\ \mathbf{Y}_i &= \sum_{j\neq i}\sqrt{p_j h_{ij}}b_j\mathbf{s}_j\mathbf{a}_{ij}^\top + \mathbf{N}_i.\end{aligned} \tag{45}$$

The MSE and SIR with filter $\mathbf{X}$ are given by

$$\begin{aligned}\mathrm{MSE}(\mathbf{X}) &= E[|\mathrm{tr}(\mathbf{X}^H\mathbf{R}_i) - b_i|^2] \\ &= |\mathrm{tr}(\mathbf{X}^H\mathbf{S}_i)|^2 + E[|\mathrm{tr}(\mathbf{X}^H\mathbf{Y}_i)|^2] \\ &\quad - 2\Re\{\mathrm{tr}(\mathbf{X}^\top\mathbf{S}_i^*)\} + 1\end{aligned} \tag{46}$$

and

$$\mathrm{SIR}(\mathbf{X}) = \frac{|\mathrm{tr}(\mathbf{X}^H\mathbf{S}_i)|^2}{E[|\mathrm{tr}(\mathbf{X}^H\mathbf{Y}_i)|^2]} \tag{47}$$

Now let us consider the MSE with a scaled version of the filter $\mathbf{X}$

$$\begin{aligned}\mathrm{MSE}(\alpha\mathbf{X}) &= |\alpha|^2\{|\mathrm{tr}(\mathbf{X}^H\mathbf{S}_i)|^2 + E[|\mathrm{tr}(\mathbf{X}^H\mathbf{Y}_i)|^2]\} \\ &\quad - 2\Re\{\mathrm{tr}(\alpha\mathbf{X}^T\mathbf{S}_i^*)\} + 1.\end{aligned} \tag{48}$$

Setting the derivative of $\mathrm{MSE}(\alpha\mathbf{X})$ with respect to the real and the imaginary parts of α equal to zero, the complex scalar α that minimizes $\mathrm{MSE}(\alpha\mathbf{X})$ can be found as

$$\bar{\alpha} = \arg\min_{\alpha}\mathrm{MSE}(\alpha\mathbf{X}) = \frac{\mathrm{tr}(\mathbf{X}^H\mathbf{S}_i)}{|\mathrm{tr}(\mathbf{X}^H\mathbf{S}_i)|^2 + E[|\mathrm{tr}(\mathbf{X}^H\mathbf{Y}_i)|^2]}. \tag{49}$$

Thus

$$\min_{\alpha}\mathrm{MSE}(\alpha\mathbf{X}) = 1 - \frac{|\mathrm{tr}(\mathbf{X}^H\mathbf{S}_i)|^2}{|\mathrm{tr}(\mathbf{X}^H\mathbf{S}_i)|^2 + E[|\mathrm{tr}(\mathbf{X}^H\mathbf{Y}_i)|^2]}. \tag{50}$$

Using (50) and (47) we can write

$$\frac{1}{\min_\alpha \mathrm{MSE}(\alpha\mathbf{X})} = 1 + \mathrm{SIR}(\mathbf{X}). \tag{51}$$

Equation (51) is true for any complex filter $\mathbf{X}$. In the unconstrained temporal-spatial filtering case, $\mathbf{X}$ can take any value in $\mathcal{C}^{G\times K}$, and the constrained case it is constrained to be in the rank 1 matrix space denoted by $\mathcal{L}$. In order to represent the constrained and unconstrained cases in a unified fashion, we will restrict $\mathbf{X}$ to be $\mathbf{X} \in \mathcal{S}$ with $\mathcal{S} = \mathcal{C}^{G\times K}$ for the unconstrained and $\mathcal{S} = \mathcal{L}$ in the constrained case. Maximizing both sides of (51) with respect to $\mathbf{X} \in \mathcal{S}$, i.e.,

$$\max_{\mathbf{X}\in\mathcal{S}}\frac{1}{\min_\alpha \mathrm{MSE}(\alpha\mathbf{X})} = 1 + \max_{\mathbf{X}\in\mathcal{S}}\mathrm{SIR}(\mathbf{X}) \tag{52}$$

is equivalent to

$$\frac{1}{\min_{\mathbf{X}\in\mathcal{S}}\min_\alpha \mathrm{MSE}(\alpha\mathbf{X})} = 1 + \max_{\mathbf{X}\in\mathcal{S}}\mathrm{SIR}(\mathbf{X}). \tag{53}$$

Combining continuous variables $\mathbf{X}$ and α into one variable and noting that, for both unconstrained and constrained cases, if $\mathbf{X} \in \mathcal{S}$, then $\alpha\mathbf{X} \in \mathcal{S}$ yields

$$\frac{1}{\min_{\mathbf{X}\in\mathcal{S}}\mathrm{MSE}(\mathbf{X})} = 1 + \max_{\mathbf{X}\in\mathcal{S}}\mathrm{SIR}(\mathbf{X}) \tag{54}$$

where we also used the fact that $\mathrm{SIR}(\mathbf{X})$ is insensitive to the scaling of its argument.

Therefore, (54) verifies that the filter $\mathbf{X} \in \mathcal{S}$ that minimizes the MSE is the one that maximizes the SIR. As shown above, this result is valid for both $\mathcal{S} = \mathcal{C}^{G \times K}$ and $\mathcal{S} = \mathcal{L}$. We conclude that the MMSE filters in both the unconstrained and the constrained spatial-temporal filter spaces maximize the SIR. □

Proof: Proposition 2: We first define

$$J_i(\mathbf{p}, \mathbf{X}_i) = \frac{\gamma_i^*}{h_{ii}} \frac{\sum_{j \neq i} p_j h_{ij} \left|\operatorname{tr}\left(\mathbf{X}_i^H \mathbf{s}_j \mathbf{a}_{ij}^\top\right)\right|^2 + \sigma^2 \operatorname{tr}\left(\mathbf{X}_i^H \mathbf{X}_i\right)}{\left|\operatorname{tr}\left(\mathbf{X}_i^H \mathbf{s}_i \mathbf{a}_{ii}^\top\right)\right|^2}. \tag{55}$$

Therefore

$$I_i(\mathbf{p}) = \min_{\mathbf{X}_i \in \mathcal{S}} J_i(\mathbf{p}, \mathbf{X}_i). \tag{56}$$

To show that $\mathbf{I}(\mathbf{p})$ is standard, we need to check that the three conditions in Definition 1 are satisfied for (31). Similar to [13]:

- Positivity: For any fixed $\mathbf{X}_i \in \mathcal{S}$, we have $J_i(\mathbf{p}, \mathbf{X}_i) > 0$. Therefore, this is true for the minimizer filter also, i.e., $I_i(\mathbf{p}) = \min_{\mathbf{X}_i \in \mathcal{S}} J_i(\mathbf{p}, \mathbf{X}_i) > 0$.
- Monotonicity: For any fixed $\mathbf{X}_i$, $\mathbf{p} \geq \mathbf{p}'$ implies $J_i(\mathbf{p}, \mathbf{X}_i) \geq J_i(\mathbf{p}', \mathbf{X}_i)$. If the minimum of $J_i(\mathbf{p}, \mathbf{X}_i)$ in $\mathcal{S}$ is achieved at $\mathbf{X}_i^*$, then

$$I_i(\mathbf{p}) = \min_{\mathbf{X}_i \in \mathcal{S}} J_i(\mathbf{p}, \mathbf{X}_i) \tag{57}$$

$$= J_i(\mathbf{p}, \mathbf{X}_i^*) \tag{58}$$

$$\geq J_i(\mathbf{p}', \mathbf{X}_i^*) \tag{59}$$

$$\geq \min_{\mathbf{X}_i \in \mathcal{S}} J_i(\mathbf{p}', \mathbf{X}_i) = I_i(\mathbf{p}'). \tag{60}$$

- Scalability: For any fixed $\mathbf{X}_i$ and $\alpha > 1$, we have $\alpha J_i(\mathbf{p}, \mathbf{X}_i) > J_i(\alpha\mathbf{p}, \mathbf{X}_i)$. Again, let $\mathbf{X}_i^*$ be the minimizer of $J_i(\mathbf{p}, \mathbf{X}_i)$ in $\mathcal{S}$. Then

$$\alpha I_i(\mathbf{p}) = \min_{\mathbf{X}_i \in \mathcal{S}} \alpha J_i(\mathbf{p}, \mathbf{X}_i) \tag{61}$$

$$= \alpha J_i(\mathbf{p}, \mathbf{X}_i^*) \tag{62}$$

$$> J_i(\alpha\mathbf{p}, \mathbf{X}_i^*) \tag{63}$$

$$\geq \min_{\mathbf{X}_i \in \mathcal{S}} J_i(\alpha\mathbf{p}, \mathbf{X}_i) = I_i(\alpha\mathbf{p}). \tag{64}$$

□

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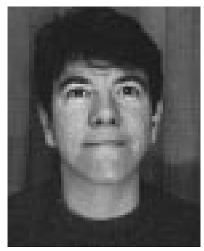

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