Sample-by-sample Adaptive Space-Time Processing for Multiuser Detection in Multipath CDMA Systems*

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***Abstract*-- Multiuser detection and space-time processing are two advanced signal-processing techniques for the mitigation of multiple-access interference and intersymbol interference in wireless CDMA communications. The purpose of this work is to investigate techniques for efficient space-time multiuser detection (ST MUD). A companion paper considered batch iterative methods, which assume knowledge of all signals and channels. In this paper sample-by-sample adaptive methods, both data-aided (with training sequences) and blind, which require only the timing and training sequences (for data-aided) or the spreading codes (for blind) of the desired user(s), are considered. For data aided adaptive methods, a decentralized adaptive minimum-mean-square-error space-time multiuser detector and a centralized adaptive decision-feedback space-time multiuser detector are presented. Then a blind adaptive space-time multiuser receiver based on the linear constrained minimum variance criterion and min-max parameter estimation is developed, which is robustified with norm-constrained techniques in the case of signature waveform mismatch. A least mean square implementation of all these adaptive ST MUD receivers is given.**

I. INTRODUCTION

Code-division multiple-access (CDMA) is widely exploited for wireless communications, in which transmitted digital signals experience significant distortion from time and frequency selective fading. The presence of both multiple access interference (MAI) and intersymbol interference (ISI) constitutes a major impediment to reliable CDMA communications in time-varying multipath wireless channels. Multiuser detection (MUD) [10] and space-time (ST) processing [5] are two advanced signal-processing techniques that can be used to combat MAI and ISI in wireless CDMA communications. However, advanced signal processing often improves the system performance at the cost of computational complexity. The purpose of this work is to investigate techniques for efficient space-time multiuser detection (ST MUD). In a companion paper [1], we have discussed batch iterative methods for ST MUD, which assume knowledge of all signals and channels, including spreading codes, powers, array responses, multipath delay and fading. Batch iterative methods are suitable for centralized (e.g. base station) processing after channel parameters have been estimated. In the present paper, we will present sample-by-sample adaptive methods, both data-aided and blind, which require only the timing and training sequences (for data-aided) or the spreading codes (for blind) of the desired user(s). Sample-by-sample adaptive methods are suitable both for mobile end processing, which entails decentralized data detection, and for base station processing due to the time varying nature of wireless communications. We may think of the sample-by-sample adaptive methods discussed here as being most suitable for application at the base station, where it is more practical to install an antenna array. However, most of the described decentralized or blind techniques are readily applied to the mobile user end when multiple antennas can be applied at mobile terminals.

In [6] an adaptive minimum-mean-square-error (MMSE) receiver and a centralized adaptive decision-feedback receiver structure was proposed for single-antenna multiuser detection. Our work is a natural extension of these structures to the space-time domain. Blind adaptive multiuser detection based on the linear constrained minimum variance (LCMV) criterion was proposed in [3], [7]. In our work, a robustified blind space-time multiuser detector based on the LCMV criterion and min-max parameter estimation is presented with improved performance in the presence of signature waveform mismatch.

II. SIGNAL MODEL

Consider a direct-sequence CDMA communication system with K users, employing normalized spreading waveforms $s_1,\dots,s_K$. Throughout this paper, we assume a short-code CDMA system to exploit the cyclostationary nature of signals for effective adaptation. Each user transmits a time-independent equiprobable BPSK symbol sequence $b_k(i)\in\{+1,-1\}$, $1\le k\le K$, $0\le i\le M-1$ with the amplitude A_k, where M is the number of data symbols per user per frame. The transmitted baseband signal due to the kth user is thus given by

$$x_k(t)=A_k\sum_{i=0}^{M-1}b_k(i)s_k(t-iT)\,,\ 1\le k\le K\,. \quad (1)$$

Suppose the transmitted signal of each user passes through a multipath channel before it is received by a uniform linear antenna array (ULA) of P elements. Then the single-input multiple-output vector impulse response between the kth user and the receiving antenna array can be modeled as

$$\mathbf{h}_k(t)=\sum_{l=1}^{L}\mathbf{a}_{kl}g_{kl}\delta(t-\tau_{kl})\,, \quad (2)$$

where L is the number of paths between each user and the receiver array, g_{kl} and τ_{kl} are respectively the complex gain and delay, and $\mathbf{a}_{kl}=[a_{kl,1}\cdots a_{kl,P}]^T$ is the array response vector corresponding to the lth path of the kth user's signal.

The received signal at the antenna array is the superposition of the channel-distorted signals from the K users and additive spatially and temporally white Gaussian noise given by

$$\mathbf{r}(t)=\sum_{k=1}^{K}x_k(t)\otimes\mathbf{h}_k(t)+\sigma\ \mathbf{n}(t)\,, \quad (3)$$

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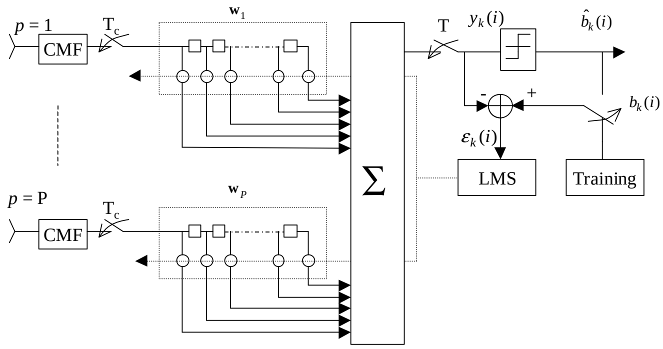

Fig. 1 Structure of an adaptive MMSE space-time multiuser detector

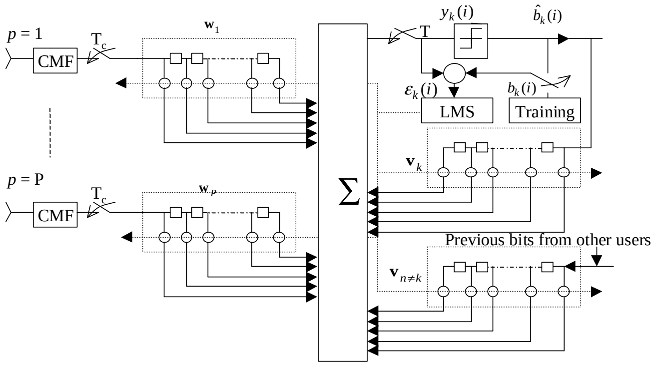

Fig. 2 Structure of an adaptive centralized decision-feedback space-time multiuser detector

where $\otimes$ denotes convolution, and σ^2 is the spectral height of the ambient (normalized) zero-mean complex Gaussian noise $\mathbf{n}(t)$ at each antenna element.

In contrast to batch iterative methods, the observation vector of interest for sample-by-sample adaptive methods is not output of a space-time matched-filter bank [1] but the chip-sampled signal itself. Thus, the cyclostationary character of interfering signals is preserved, which is essential for their removal by adaptive methods. To be specific, supposing the user of interest is the kth user, during the ith symbol interval the received signal at the pth antenna element is passed through a chip-matched filter and then sampled at the chip rate to obtain an $\overline{N}$ -vector of signal samples

$$\mathbf{r}_p{}^{(k)}(i) = [r_{p,0}{}^{(k)}(i), r_{p,1}{}^{(k)}(i), \ldots, r_{p,\overline{N}-1}{}^{(k)}(i)]^T \tag{4}$$

where $\overline{N} = N + \lceil (\tau_{kL} - \tau_{k1}) / T_c \rceil$ (Without loss of generality, we assume $\tau_{k1} \le \cdots \le \tau_{kL}$ here.) is large enough to capture all the information of the desired user from all paths. Then the $P\overline{N}$ -vector $\mathbf{r}^{(k)}(i) = \left[[\mathbf{r}_1^{(k)}(i)]^T, \ldots, [\mathbf{r}_P^{(k)}(i)]^T\right]^T$ becomes the sufficient statistic for the detection of $b_k(i)$ in the various space-time sample-by-sample adaptive receivers discussed in the sequel. Henceforth, we will omit the time index i when no ambiguity is incurred.

I. DATA AIDED ADAPTIVE ST MUD

In this section, we will describe a decentralized adaptive MMSE space-time multiuser detector and a centralized adaptive decision-feedback space-time multiuser detector, both of which operate with the aid of training sequences.

A. Decentralized Adaptive MMSE ST MUD

Fig. 1 depicts the structure of a decentralized adaptive MMSE ST MUD of interest in detecting user k's ith symbol. Each antenna element is equipped with a chip-matched filter followed by a chip-interval-spaced adaptive finite-impulse-response (FIR) filter. The outputs of all FIR filters are summed and sampled at the symbol rate to form a soft decision output, which serves two purposes: to form an estimate for the desired bit through a decision device, and to form an error signal for adjustment of adaptive filter coefficients.

Collect the weights of the FIR filter banks at the pth antenna element into $\mathbf{w}_p^{(k)} = [w_{p,0}{}^{(k)}, w_{p,1}{}^{(k)}, \cdots, w_{p,\overline{N}-1}{}^{(k)}]^T$ and then collect such vectors from all antenna elements into a $P\overline{N}$ -vector $\mathbf{W}_k = [(\mathbf{w}_1^k)^T, (\mathbf{w}_2^k)^T, \ldots, (\mathbf{w}_P^k)^T]^T$. $\mathbf{W}_k$ is thus applied to the signal vector $\mathbf{r}^{(k)}$ given in Section II to make a decision about b_k. Mean square error (MSE) of estimation is defined as

$$\begin{aligned} MSE(\mathbf{W}_k) &= E\left\{(b_k - (\mathbf{W}_k)^H \mathbf{r}^{(k)})^2\right\} \\ &= 1 - (\mathbf{W}_k)^H \mathbf{h}_k - (\mathbf{h}_k)^H \mathbf{W}_k + (\mathbf{W}_k)^H \mathbf{R}_k \mathbf{W}_k \end{aligned}, \tag{5}$$

where $\mathbf{R}_k = E\{\mathbf{r}^{(k)}\mathbf{r}^{(k)H}\}$ and $\mathbf{h}_k = E\{\mathbf{r}^{(k)} b_k\}$. An optimum choice for $\mathbf{W}_k$ is that which minimizes the mean square error $MSE(\mathbf{W}_k)$. This choice, known as the MMSE detector, is given by the Wiener-Hopf solution

$$\mathbf{W}_k{}^{opt} = \mathbf{R}_k{}^{-1}\mathbf{h}_k . \tag{6}$$

For this theoretical optimum solution, the achieved minimum value of the mean square error is given by

$$MMSE_k \overset{\Delta}{=} MSE(\mathbf{W}_k^{opt}) = 1 - (\mathbf{W}_k^{opt})^H \mathbf{R}_k \mathbf{W}_k^{opt} . \tag{7}$$

A number of algorithms are available to seek the solution (6) adaptively, from the simple least-mean-squares (LMS) algorithm to various fast yet complex recursive-least-squares (RLS) methods. The properties and behavior of these algorithms are well known and documented [2]. Here we adopt the LMS algorithm as a simple tool to obtain MMSE FIR filter banks. This choice is illustrated as follows. The soft decision ouput is given by

$$y_k(i) = \mathbf{W}_k{}^H(i)\mathbf{r}^{(k)}(i) , \tag{8}$$

from which a bit estimate is formed as

$$\hat{b}_k(i) = \mathrm{sgn}\{\mathrm{Re}(y_k(i))\}, \tag{9}$$

where "Re" indicates the real part. An error signal is then formed as

$$\varepsilon_k(i) = b_k(i) - y_k(i) , \tag{10}$$

and the filter coefficients are updated as

$$\mathbf{W}_k(i+1) = \mathbf{W}_k(i) + \mu\varepsilon_k{}^*(i)\mathbf{r}^{(k)}(i) , \tag{11}$$

where μ is the step size of the adaptive algorithm. Note that after the training period, the receiver is switched to decision-directed mode and the error signal is formed as

$$\varepsilon_k(i) = \hat{b}_k(i) - y_k(i) . \tag{12}$$

B. Centralized Adaptive Decision-Feedback ST MUD

Fig. 2 gives the structure for a centralized adaptive decision-feedback ST MUD. In contrast with the structure of Fig. 1, in Fig. 2 previously detected bits of all active users are exploited through a symbol-spaced FIR feedback filter to help detect the bit of interest $b_k(i)$. The length of the feedback filter can be taken as the maximum delay spread (more than one symbol), while that of the chip-spaced feedforward filter can just span one symbol. Compared with its counterpart in Subsection III-A, this type of receiver is suitable for base station processing, and is expected to achieve great improvement over decentralized MMSE receivers in the case of large delay spread and severe near-far problem.

Now the input signal is augmented to include the previous bits from all users; i.e., we consider

$$\mathbf{r}_a^{(k)}(i) = \left[[\mathbf{r}_1^{(k)}(i)]^T, \ldots, [\mathbf{r}_P^{(k)}(i)]^T, [\mathbf{e}_1(i)]^T, \ldots, [\mathbf{e}_K(i)]^T\right]^T$$

with $\mathbf{e}_n(i) = [b_n(i-1), \ldots, b_n(i-D)]^T$, $1 \le n \le K$, where D is the maximum delay spread in units of symbol interval. Again, collect the feedforward filter coefficients at the pth antenna element into $\mathbf{w}_p = [w_{p,1}, w_{p,2}, \cdots, w_{p,N}]^T$, $1 \le p \le P$, and the feedback filter coefficients for the nth user with the vector $\mathbf{v}_n = [v_{n,1}, \ldots, v_{n,D}]^T$, $1 \le n \le K$. Collect all these feedforward and feedback filter vectors into a $(PN + KD)$-vector $\mathbf{W}_k^a = [\mathbf{w}_1^T, \mathbf{w}_2^T, \ldots, \mathbf{w}_P^T, \mathbf{v}_1^T, \ldots, \mathbf{v}_K^T]^T$. Detection then proceeds by applying this vector to the augmented input signal. The adaptation of the algorithm readily follows that in Section III-A.

C. Simulation Examples

In this subsection, the performance of the above described data-aided adaptive space-time multiuser detectors is examined through computer simulations. We assume a K = 16-user CDMA system with spreading gain N = 16, which is heavily loaded with severe near-far problem. Each user travels through L = 3 paths before it reaches a ULA with P =3 elements and half-wavelength spacing. The maximum delay spread is set to be 4T. The complex gains and delays of the multipath and the directions of arrival are randomly generated and kept fixed for all the simulations. The number of symbols per frame is M = 250. The step size of the LMS algorithm is fixed to be $\mu = 0.001$.

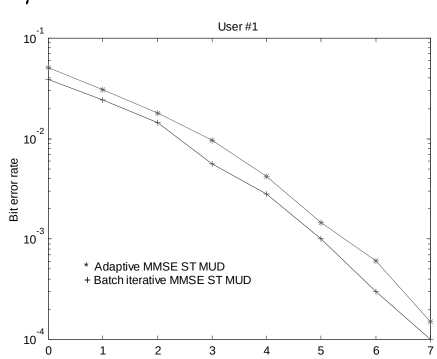

Fig. 3 Bit error rate of the decentralized adaptive MMSE space-time multiuser detector in the steady state

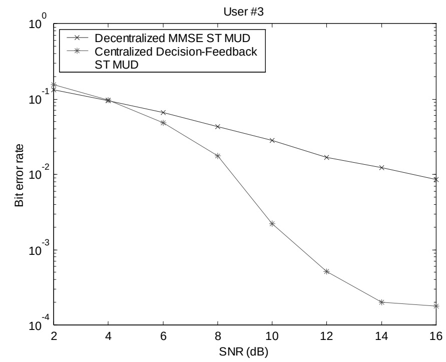

Fig. 4 Comparison of steady state BER of the two adaptive receivers

Fig. 3 compares the steady-state bit error rate (BER) of the decentralized adaptive MMSE ST MUD with that of the batch iterative MMSE ST MUD (see [1]). The error is counted and averaged for consecutive 400 data frames after an initial 4 data frames (1000 iterations) of adaptation. These results show that this adaptive ST MUD structure approaches the optimum MMSE ST MUD, while using only knowledge of the timing and training sequence of the desired user. This simple adaptive structure effectively combines the function of beamforming, RAKE combining and multiuser detection.

Fig. 4 compares the performance of the decentralized adaptive MMSE ST MUD and the centralized adaptive decision-feedback ST MUD. The user of interest is user 3 (a weak user with strong interference). It clearly demonstrates the significant improvement of the centralized adaptive decision-feedback ST MUD over the decentralized adaptive MMSE ST MUD in the situation of large delay spread and severe near-far problem.

II. BLIND ADAPTIVE ST MUD

We see from the previous section that data aided adaptive space-time multiuser detectors achieve very good performance with simple algorithms, while no side information is needed. However, these receivers require training sequences from the desired user(s), which consume system resources. Moreover, whenever there is a dramatic change in the interference environment, decision directed adaptation becomes unreliable, and new training sequences have to be transmitted. These observations indicate the need for blind adaptive receivers that require no more information than the conventional single-user receivers: the timing and signature waveform of the desired user.

A. LCMV Blind ST MUD and its GSC Implementation

In this section we adopt this LCMV criterion to design a blind adaptive space-time multiuser detector. Suppose again the user of interest is the kth user. The received signal at the pth antenna element is passed through a chip-matched filter and then sampled at the chip rate to obtain a $\overline{N}$-vector $\mathbf{r}_p^{(k)}$ as shown in (4), which can be expressed as

$$\mathbf{r}_p^{(k)} = A_k b_k \sum_{l=1}^{L} a_{kl,p} g_{kl} \mathbf{s}_{kl} + \mathbf{i}_p + \sigma \mathbf{n}_p, \qquad (13)$$

where $\mathbf{n}_p$ is the ambient noise vector, $\mathbf{i}_p$ comprises both MAI and ISI, and the $\bar{N}$-vector $\mathbf{s}_{kl}$ is the discretized version of the delayed signature waveform of user *k*. As in subsection III-A, at the *p*th antenna element, we would like to design a linear filter with coefficients $\mathbf{w}_p^{(k)} = [w_{p,1}{}^{(k)}, w_{p,2}{}^{(k)}, \cdots, w_{p,\bar{N}}{}^{(k)}]^T$, $1 \le p \le P$. But now we trade the knowledge of a training sequence for the desired user for its spreading code. According the LCMV criterion, we should choose $\mathbf{w}_p^{(k)}$ via the optimization problem

$$\begin{aligned}\mathbf{w}_p{}^{(k)} &= \arg\min_{\mathbf{w}_p{}^{(k)} \in C^{\bar{N}\times 1}} E\left\{ \left\| (\mathbf{w}_p{}^{(k)})^H \mathbf{r}_p{}^{(k)} \right\|^2 \right\} \\ &= \arg\min_{\mathbf{w}_p{}^{(k)} \in C^{\bar{N}\times 1}} (\mathbf{w}_p{}^{(k)})^H \mathbf{R}_p{}^{(k)} \mathbf{w}_p{}^{(k)}\end{aligned}, \quad (14)$$

where $\mathbf{R}_p^{(k)} = E[\mathbf{r}_p{}^{(k)} \mathbf{r}_p{}^{(k)H}]$, subject to a linear constraint

$$\mathbf{C}_k{}^H \mathbf{w}_p{}^{(k)} = \mathbf{f}_p{}^{(k)}, \quad (15)$$

where

$$\mathbf{C}_k = [\mathbf{s_{k1}}, \mathbf{s_{k2}}, \ldots, \mathbf{s_{kL}}], \quad (16)$$

and

$$\mathbf{f}_p{}^{(k)} = [a_{k1,p} g_{k1}, \quad a_{k2,p} g_{k2}, \quad \cdots, \quad a_{kL,p} g_{kL}]^T. \quad (17)$$

The constraints (15) ~ (17) ensure that, after summing the filtered outputs of all antenna elements, the desired signal energy is optimally combined.

The theoretical optimum solution to the above problem (14) - (15) is given by

$$(\mathbf{w}_p{}^{(k)})^{opt} = (\mathbf{R}_p{}^{(k)})^{-1} \mathbf{C}_k [\mathbf{C}_k{}^H (\mathbf{R}_p{}^{(k)})^{-1} \mathbf{C}_k]^{-1} \mathbf{f}_p{}^{(k)}, \quad (18)$$

with the theoretical minimum ouput energy in (14) given by

$$MOE = (\mathbf{f}_p^{(k)})^H [\mathbf{C}_k{}^H (\mathbf{R}_p^{(k)})^{-1} \mathbf{C}_k]^{-1} \mathbf{f}_p^{(k)}. \quad (19)$$

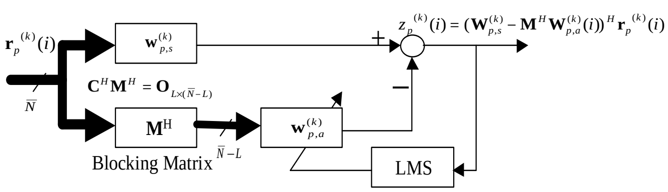

Fig. 5 GSC implementation of LCMV blind adaptive space-time multiuser detector (*p*th antenna FIR for desired user *k*)

The LCMV criterion has been applied in many signal processing fields, one of which is spatial filtering or beamforming [9]. The generalized sidelobe canceller (GSC) structure for adaptive beamforming represents an effective implementation of the LCMV beamformer, changing a constrained minimization problem into an unconstrained form. We borrow this idea for implementation of our LCMV blind ST MUD, which is shown in Fig. 5. The basic idea is to decompose the weight vector $\mathbf{w}_p^{(k)}$ into two orthogonal components: nonadaptive part $\mathbf{w}_{p,s}^{(k)}$ and adaptive part $\mathbf{M}^H \mathbf{w}_{p,a}^{(k)}$: $\mathbf{W}_p{}^{(k)} = \mathbf{W}_{p,s}^{(k)} - \mathbf{M}^H \mathbf{W}_{p,a}^{(k)}$. The nonadaptive part $\mathbf{w}_{p,s}^{(k)}$ lies in the range of $\mathbf{C}_k$ and fulfills the constraint (15) as

$$\mathbf{w}_{p,s}^{(k)} = \mathbf{C}_k (\mathbf{C}_k{}^H \mathbf{C}_k)^{-1} \mathbf{C}_k{}^H \mathbf{W}_p{}^{(k)} = \mathbf{C}_k (\mathbf{C}_k{}^H \mathbf{C}_k)^{-1} \mathbf{f}_p. \quad (20)$$

The adaptive part lies in the null space of $\mathbf{C}_k$, whose orthogonality is guranteed by the $(\bar{N}-L)\times\bar{N}$ blocking matrix $\mathbf{M}$, which satisfies $\mathbf{C}_k{}^H \mathbf{M}^H = \mathbf{O}_{L\times(\bar{N}-L)}$.With the constraint of (15), the optimization problem has $\bar{N}-L$ degrees of freedom. After this decompositon, the constrained minimization problem is transformed to an unconstrained problem for the $\bar{N}-L$-vector $\mathbf{w}_{p,a}^{(k)} =$

$$\arg\min_{\mathbf{W}_{p,a}^{(k)} \in C^{(\bar{N}-L)\times 1}} (\mathbf{w}_{p,s}^{(k)} - \mathbf{M}^H \mathbf{W}_{p,a}^{(k)})^H \mathbf{R}_p{}^{(k)} (\mathbf{w}_{p,s}^{(k)} - \mathbf{M}^H \mathbf{W}_{p,a}^{(k)}), \quad (21)$$

whose theoretical optimum solution is given by

$$\mathbf{w}_p^{(k)opt} = (\mathbf{M}\mathbf{R}_p^{(k)} \mathbf{M}^H)^{-1} \mathbf{M}\mathbf{R}_p{}^{(k)} \mathbf{w}_p^{(k)}. \quad (22)$$

Note from Fig. 5 that if $(\mathbf{w}_{p,s}^{(k)})^H \mathbf{r}_p^{(k)}$ is taken as the desired user while $\mathbf{M}\mathbf{r}_p^{(k)}$ is taken as the observations, then the GSC implementation readily lends itself to LMS adaptation with no need of training sequences. The adaptation rule is given as follows:

$$z_p{}^{(k)}(i) = (\mathbf{w}_{p,s}^{(k)} - \mathbf{M}^H \mathbf{w}_{p,a}^{(k)}(i))^H \mathbf{r}_p{}^{(k)}(i), \quad (23)$$

$$\mathbf{w}_{p,a}^{(k)}(i+1) = \mathbf{w}_{p,a}^{(k)}(i) + \mu z_p{}^{(k)*}(i) \mathbf{M}\mathbf{r}_p{}^{(k)}(i). \quad (24)$$

Finally the detected bits are given by

$$\hat{b}_k(i) = \mathrm{sgn}(\mathrm{Re}(z_p^{(k)}(i))). \quad (25)$$

B. MIN-MAX Channel Parameter Estimation

The above LCMV ST MUD assumes knowledge of the channel parameters of the desired user (see (17)), which in practice should be estimated in advance. This problem can be overcome by using a technique of [8] which incorporates the parameter estimation into the LCMV receiver design with a min-max approach, i.e., the idea is to find a constraint vector $\mathbf{f}_p^{(k)}$ that maximizes the theoretical minimum output energy (19). The problem can be stated as

$$\hat{\mathbf{f}}_p{}^{(k)} = \arg\max_{\mathbf{f}} MOE(\mathbf{f}) \text{ subject to } \|\mathbf{f}\| = 1, \quad (26)$$

where $MOE(\mathbf{f})$ is defined as in (19) in the obvious way. The solution to the above problem is readily given by the minimum-eigenvalue eigenvector of $[\mathbf{C}_k{}^H (\mathbf{R}_p^{(k)})^{-1} \mathbf{C}_k]^{-1}$. It is shown in [8] that if the vectorized signature waveforms of all users and all their delayed versions are linearly independent, then $\hat{\mathbf{f}}_p{}^{(k)} \to \mathbf{f}_p{}^{(k)} / \|\mathbf{f}_p{}^{(k)}\|$ asymptotically in the sense of norm.

C. Robustified Blind ST MUD

In practice, the receiver may assume the original spreading waveform of the desired user as its nominal choice in data detection, whereas the actual received waveform may be distorted during transmission or may include additional unmodeled multipath components. In this situation of signature waveform mismatch, the blocking matrix used in the GSC structure is no longer orthogonal to the desired signal. This lack of orthogonality will lead the adaptive filter $\mathbf{w}_{p,a}^{(k)}$ to cancel the desired signal in its effort to minimize the output energy. To overcome this problem, we adopt the approach in

[3] to constrain the norm of the weight vector to avoid desired signal cancellation; i.e., we introduce a constraint $\|\mathbf{w}_p\| \le \chi_I$, where an approximate choice of χ_I can be determined experimentally. The LMS adaptation of this robustified LCMV blind ST MUD is given as follows:

$$z_p{}^{(k)}(i) = (\mathbf{w}_{p,s}^{(k)} - \tilde{\mathbf{w}}_{p,a}^{(k)}(i))^H \mathbf{r}_p{}^{(k)}(i) \,, \qquad (27)$$

$$\mathbf{x}(i) = \tilde{\mathbf{w}}_{p,a}^{(k)}(i) + \Delta z_p{}^{(k)^*}(i)\mathbf{M}^H \mathbf{M}\mathbf{r}_p{}^{(k)}(i) \,, \qquad (28)$$

and

$$\tilde{\mathbf{w}}_{p,a}^{(k)}(i+1) = \begin{cases} \mathbf{x}(i), & \|\mathbf{x}(i)\| \le \sqrt{\chi_I^2 - \left\|\mathbf{w}_{p,s}^{(k)}\right\|^2} \\ \sqrt{\chi_I^2 - \left\|\mathbf{W}_p^S\right\|^2}\,\dfrac{\mathbf{x}(i)}{\|\mathbf{x}(i)\|} & \|\mathbf{x}(i)\| > \sqrt{\chi_I^2 - \left\|\mathbf{w}_{p,s}^{(k)}\right\|^2} \end{cases} . \qquad (29)$$

The detected bits are then given by

$$\hat{b}_k(i) = \mathrm{sgn}(\mathrm{Re}(z_p^{(k)}(i))) \,. \qquad (30)$$

D. Simulation Results

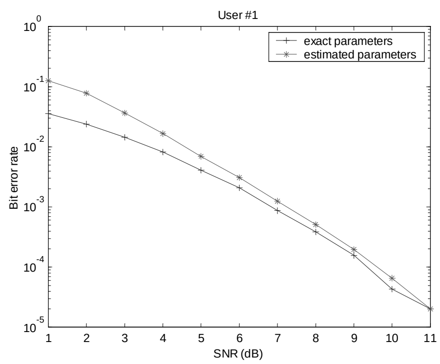

Fig. 6 Performance comparison of LCMV blind adaptive ST MUD with exact and estimated chaneel parameters

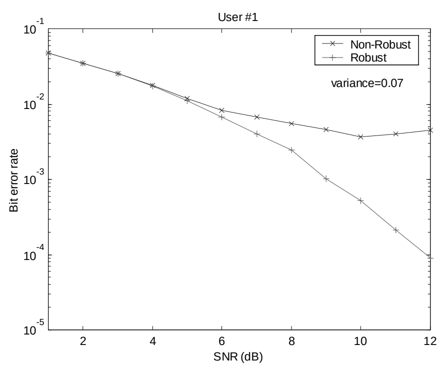

Fig. 7 Performance comparison of non-robust and robust LCMV blind adaptive ST MUD in the situation of signature waveform mismatch

In this subsection, the performance of the blind adaptive space-time multiuser detectors is examined through computer simulations. The simulation parameters are similar to those used in subsection III-C, with the following exceptions. We assume a K = 8-user CDMA system with spreading gain N = 16. The user of interest is user 1. The delay spread is set to be T. A variable step size is used for the LMS algorithm as follows: 0.01 for the first 250 iterations, 0.005 for the next 250 iterations, and 0.002 afterwards.

Fig. 6 compares the performance of the LCMV blind ST MUD with exact and estimated channel parameters. It is seen that min-max channel parameter estimation leads to almost no performance loss.

Fig. 7 shows the robustness of the norm-constrained LCMV blind adaptive ST MUD in the situation of signature waveform mismatch. To simulate the effects of signature distortion, the signature waveform of the desired user is disturbed by Gaussian noise with zero mean and standard deviation 0.07. Note that the performance of the non-robustified LCMV blind adaptive ST MUD worsens as the SNR increases because of the signal cancellation; while that of the robustified LCMV blind adaptive ST MUD greatly outperforms its counterpart, with a 2 dB loss relative to the ideal case without signature waveform mismatch.

III. CONCLUSIONS

In this paper, sample-by-sample adaptive space-time multiuser detectors have been presented. The alternative blind adaptive space-time multiuser receiver is based on the LCMV criterion and min-max parameter estimation, and is robustified against signature waveform mismatch with norm-constrained techniques. Issues for further study include faster adaptive algorithms implementation such as RLS, and the performance gap narrowing between blind adaptive techniques and data aided adaptive techniques, using, for example, techniques developed in the context of blind source separation or blind equalization, like fourth-order cumulant-based methods and the constant modulus algorithm (CMA).

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