EDICS: 1-ACOM

Iterative Space-Time Processing for Multiuser Detection in Multipath CDMA Channels [*]

Huaiyu Dai*, *Student Member, IEEE*, and H. Vincent Poor, *Fellow, IEEE*
Department of Electrical Engineering, Princeton University
Princeton, NJ 08540
Tel: (609) 258-4634 Fax: (609) 258-1560
Email: **huaiyud@ee.princeton.edu**, **poor@princeton.edu**

Abstract:

Space-time processing and multiuser detection are two promising techniques for combating multipath distortion and multiple-access interference in CDMA systems. To overcome the computational burden that rises very quickly with increasing numbers of users and receive antennas in applying such techniques, iterative implementations of several space-time multiuser detection algorithms are considered here. These algorithms include iterative linear space-time multiuser detection, Cholesky iterative decorrelating decision-feedback space-time multiuser detection, multistage interference cancelling space-time multiuser detection, and EM-based iterative space-time multiuser detection. A new space-time multiuser receiver structure that allows for efficient implementation of iterative processing is also introduced. Fully exploiting various types of diversity through joint space-time processing and multiuser detection brings substantial gain over single-receiver-antenna or single-user based methods. It is shown that iterative implementation of linear and nonlinear space-time multiuser detection schemes discussed in this paper realizes this substantial gain and approaches the optimum performance with reasonable complexity. Among the iterative space-time multiuser receivers considered in this paper, the EM-based (SAGE) iterative space-time multiuser receiver introduced here achieves the best performance with excellent convergence properties.

Index Terms

Antenna arrays, CDMA, iterative processing, multiuser detection, SAGE, space-time processing

---

[*] This research was supported by the National Science Foundation under Grant Nos. CCR-99-80590 and ECS-98-11095, and by the New Jersey Center for Wireless Telecommunications.

I. Introduction

The presence of both multiple-access interference (MAI) and intersymbol interference (ISI) constitutes a major impediment to reliable high-data-rate CDMA communications in multipath channels. These phenomena present challenges as well as opportunities for receiver designers: through multiuser detection (MUD) [23] and space-time (ST) processing [16], the inherent code, spatial, temporal and spectral diversities of multipath multi-antenna CDMA channels can be exploited to achieve substantial gain.

Advanced signal processing typically improves system performance at the cost of computational complexity. It is well known that the optimal maximum likelihood (ML) multiuser detector has prohibitive computational requirements for most current applications. A variety of linear and nonlinear multiuser detectors have been proposed to ease this computational burden while maintaining satisfactory performance [23]. However, in asynchronous multipath CDMA channels with receive antenna arrays and large data frame lengths, direct implementation of these suboptimal techniques still proves to be very complex. Techniques for efficient space-time multiuser detection fall largely into two categories. One includes batch iterative methods, which assume knowledge of all signals and channels and is suitable, for example, for base station processing in cellular systems. The other includes sample-by-sample adaptive methods, which require knowledge only of the signal and (possibly) channel of a desired user and is specifically suitable for mobile-end processing. Sample-by-sample processing is also useful for base station processing due to the time varying nature of mobile communications. In the current paper, we will focus on techniques in the first of these two categories – namely, batch iterative space-time multiuser detectors. Sample-by-sample adaptive methods have been addressed in [4] and the references therein.

There has been considerable research in space-time processing (e.g., [13], [16]), most of which considers single-user-based methods. Combined multiuser detection and array processing has been addressed recently (e.g. [14], [25]). In this paper, we consider iterative implementation of linear and nonlinear space-time multiuser detectors (ST MUD) in multipath CDMA channels with receiver antenna arrays. In particular, we develop several such algorithms, and compare them on the basis of performance and complexity. Ultimately, we conclude that an algorithm based on the expectation-maximization (EM) algorithm offers an attractive tradeoff in this context.

This paper is organized as follows. In Section II a space-time multiuser signal model is presented. Iterative implementation of linear ST MUD is discussed in Section III while that of nonlinear ST MUD, decision-feedback MUD and multistage interference cancellation, is dealt with in Section IV. In Section V, EM-based iterative ST MUD is discussed, and a new ST MUD receiver structure is proposed. Section VI contains simulation results, and Section VII concludes the paper.

II. Space-time Signal Model

Consider a direct-sequence CDMA communication system with K users employing normalized spreading waveforms $s_1, \ldots, s_K$ given by

$$s_k(t) = \frac{1}{\sqrt{N}} \sum_{j=0}^{N-1} c_k(j)\psi(t - jT_c)\,,\ 0 \le t \le T\,,\ 1 \le k \le K\,, \tag{1}$$

where N is the processing gain, $\{c_k(j);\ 0 \le j \le N-1\}$ is a signature sequence of ± 1's assigned to the kth user, and $\psi(\cdot)$ is a normalized chip waveform of duration $T_c = T/N$ with T the symbol interval. User k (for $1 \le k \le K$) transmits a frame of M independent equiprobable BPSK symbols $b_k(i) \in \{+1,-1\}$, $0 \le i \le M-1$; and the symbol sequences from different users are assumed to be mutually independent. The transmitted baseband signal due to the kth user is thus given by

$$x_k(t) = A_k \sum_{i=0}^{M-1} b_k(i) s_k(t - iT)\,,\ 1 \le k \le K\,, \tag{2}$$

where A_k is the amplitude associated with user k's transmission. 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 with inter-element spacing d. Then the single-input multiple-output (SIMO) vector impulse response between the kth user and the receiving array can be modeled as

$$\mathbf{h}_k(t) = \sum_{l=1}^{L} \mathbf{a}_{kl} g_{kl} \delta(t - \tau_{kl}), \tag{3}$$

where L is the maximum number of resolvable paths between each user and the receiver array (for simplicity we assume L is the same for each user), g_{kl} and τ_{kl} are respectively the complex gain and delay of the lth path of the kth user, and

$$\mathbf{a}_{kl} = \begin{bmatrix} a_{kl,1} \\ a_{kl,2} \\ \vdots \\ a_{kl,P} \end{bmatrix} = \begin{bmatrix} 1 \\ e^{j2\pi d \sin(\theta_{kl})/\lambda} \\ \vdots \\ e^{j2\pi d (P-1)\sin(\theta_{kl})/\lambda} \end{bmatrix} \tag{4}$$

is the ULA response corresponding to the signal of the lth path of the kth user with direction of arrival (DOA) θ_{kl} and carrier wavelength λ. $\delta(t)$ denotes the Dirac delta function. The received signal at the antenna array is the superposition of the channel-distorted signals from the K users together with additive Gaussian noise, which is assumed to be spatially and temporally white. This leads to the vector received signal model

$$\mathbf{r}(t) = \sum_{k=1}^{K} x_k(t) \otimes \mathbf{h}_k(t) + \sigma \mathbf{n}(t), \tag{5}$$

where $\otimes$ denotes convolution, and σ^2 is the spectral height of the ambient Gaussian noise at each antenna element.

A sufficient statistic for demodulating the multiuser symbols from the space-time signal (5) is given by [25]

$$\mathbf{y} = [y_1(0), \ldots, y_K(0), y_1(1), \ldots, y_1(M-1), \ldots, y_K(M-1)]^T, \tag{6}$$

where the elements $\{y_k(i)\}$ are defined as follows:

$$y_k(i) = \sum_{l=1}^{L} g_{kl}^* \mathbf{a}_{kl}^H \underbrace{\int_{-\infty}^{\infty} \mathbf{r}(t) s_k(t - iT - \tau_{kl}) dt}_{\mathbf{z}_{kl}(i)}, \; 1 \le k \le K, \; 0 \le i \le M-1. \quad (7)$$

To produce this sufficient statistic, the received signal vector $\mathbf{r}(t)$ is first match-filtered for each path of each user to form the vector observables $\{z_{kl}(i)\}$, after which beams are formed on each path of each user via the dot products with the array responses $\{\mathbf{a}_{kl}\}$, and then all the paths of each user are combined with a RAKE receiver. This process produces one observable for each symbol of each user. Since the system is in general asynchronous and the users are not orthogonal, we need to collect the statistic for all users over the entire data frame. The observable $y_k(i)$ corresponds to the output of a conventional space-time matched filter, matched to the *i*th symbol of user *k*. Therefore, a general space-time multiuser receiver is (as shown in Fig. 1) a space-time matched filter bank, followed by a decision algorithm. In the following, we will present various ST MUD receivers based on this space-time matched filter output. In Section V, however, a new ST MUD receiver structure will be introduced, in which chip-level observables are exploited.

The sufficient statistic (6) can be written as (see [23])

$$\mathbf{y} = \mathbf{HAb} + \sigma\mathbf{v}, \quad (8)$$

where **H** is a $KM \times KM$ matrix capturing the cross-correlations between different symbols and different users, **A** is the $KM \times KM$ diagonal matrix whose $k + iK$ diagonal elements are equal to A_k, $\mathbf{b} = [b_1(0), \ldots, b_K(0), b_1(1), \ldots, b_1(M-1), \ldots, b_K(M-1)]^T$, and $\mathbf{v} \sim \mathcal{N}(0, \mathbf{H})$ (i.e., **v** is Gaussian with zero mean and covariance matrix **H**). An optimal ML space-time multiuser detector will maximize the following log-likelihood function [23], [25]

$$\hat{\mathbf{b}} = \max_{\mathbf{b}} \Omega(\mathbf{b}) = 2\mathrm{Re}\{\mathbf{b}^T \mathbf{Ay}\} - \mathbf{b}^T \mathbf{AHAb}. \quad (9)$$

The multiuser signal and channel parameters (signature waveforms, multipath delay and amplitude, array response) come into play through the $KM \times KM$ block Toeplitz system matrix **H**, which can be written as

$$\mathbf{H} \equiv \begin{bmatrix} \underline{H}^{[0]} & \underline{H}^{[1]} & \cdots & \underline{H}^{[\Delta]} & & & \\ \underline{H}^{[-1]} & \underline{H}^{[0]} & \underline{H}^{[1]} & \cdots & \underline{H}^{[\Delta]} & & \\ & \underline{H}^{[-\Delta]} & \cdots & \underline{H}^{[0]} & \cdots & \underline{H}^{[\Delta]} & \\ & & \underline{H}^{[-\Delta]} & \cdots & \underline{H}^{[-1]} & \underline{H}^{[0]} & \underline{H}^{[1]} \\ & & & \underline{H}^{[-\Delta]} & \cdots & \underline{H}^{[-1]} & \underline{H}^{[0]} \end{bmatrix}, \tag{10}$$

where Δ denotes the multipath delay spread, and $\underline{H}^{[-i]} = (\underline{H}^{[i]})^H$. The *n*, *m*th element of **H** is the cross-correlation between the composite received signatures (after beamforming and RAKE combining) of the *n*th and *m*th elements of **b**. The reader is referred to [25] for further details of **H**. Dynamic programming can be applied to compute the ML estimates of **b**. Due to the binary nature of **b**, the complexity of this computation is on the order of $O(2^{(\Delta+1)K}/K)$ per user per symbol.

III. Iterative Linear Space-Time Multiuser Detection

In this section, we consider the application of iterative processing to the implementation of various linear space-time multiuser detectors in algebraic form. After the introduction to the general form of linear ST MUD, we go on to discuss two general approaches to iteratively solving large systems of linear equations. We reinterpret the results of [25] for the first approach, linear interference cancellation methods, including Jacobi and Gauss-Seidel iteration. Then we extend the idea of [8], [12] to the space-time domain for another approach, gradient based methods. Subsequent sections will treat nonlinear iterative methods.

Linear multiuser detectors in the framework of (8) are of the form

$$\hat{\mathbf{b}} = \mathrm{sgn}(\mathrm{Re}\{\mathbf{W}\mathbf{y}\}), \tag{11}$$

where **W** is a $KM \times KM$ matrix. For the linear decorrelating (zero-forcing) detector, this matrix is given by

$$\mathbf{W}_d = \mathbf{H}^{-1}, \tag{12}$$

while for the linear minimum-mean-square-error (MMSE) detector, we have

$$\mathbf{W}_m = (\mathbf{H} + \sigma^2 \mathbf{A}^{-2})^{-1}. \tag{13}$$

Direct inversion of the matrices in (12) and (13) (after exploiting the block Toeplitz structure) is of complexity $O(K^2 M\Delta)$ per user per symbol [11], [25].

The linear multiuser detection estimates of (11) can be seen as the solution of a linear equation

$$\mathbf{C}\mathbf{x} = \mathbf{y} \tag{14}$$

with $\mathbf{C} = \mathbf{H}$ for the decorrelating detector and $\mathbf{C} = \mathbf{H} + \sigma^2 \mathbf{A}^{-2}$ for the MMSE detector. Jacobi and Gauss-Seidel iteration are two common low-complexity iterative schemes for solving linear equations such as (14) [11]. If we decompose the matrix $\mathbf{C}$ as $\mathbf{C} = \mathbf{C}_L + \mathbf{D} + \mathbf{C}_U$ where $\mathbf{C}_L$ denotes the lower triangular part, $\mathbf{D}$ denotes the diagonal part, and $\mathbf{C}_U$ denotes the upper triangular part, then Jacobi iteration can be written as

$$\mathbf{x}_m = -\mathbf{D}^{-1}(\mathbf{C}_L + \mathbf{C}_U)\mathbf{x}_{m-1} + \mathbf{D}^{-1}\mathbf{y}, \tag{15}$$

and Gauss-Seidel iteration is represented as

$$\mathbf{x}_m = -(\mathbf{D} + \mathbf{C}_L)^{-1}\mathbf{C}_U \mathbf{x}_{m-1} + (\mathbf{D} + \mathbf{C}_L)^{-1}\mathbf{y}. \tag{16}$$

From (15), Jacobi iteration can be seen to be a form of linear parallel interference cancellation [18], [23], the convergence of which is not guaranteed in general. One of the sufficient conditions for the convergence of Jacobi iteration is that $\mathbf{D} - (\mathbf{C}_L + \mathbf{C}_U)$ be positive definite [11]. In contrast, Gauss-Seidel iteration, which (16) reveals to be a form of linear serial interference cancellation, converges to the solution of the linear equation from any initial value, under the mild conditions that **C** is symmetric and positive definite [11], which is always true for the MMSE detector.

Another approach to solving the linear equation (14) involves gradient methods, among which are steepest descent and conjugate gradient iteration [11]. The reader is referred to [4], [17] for sample-by-sample adaptive space-time processing methods, which apply gradient methods in a different setting. Note that solving (14) is equivalent to minimizing the cost function

$$\Phi(\mathbf{x}) = \frac{1}{2}\mathbf{x}^H\mathbf{C}\mathbf{x} - \mathbf{x}^H\mathbf{y} \,. \tag{17}$$

The idea of gradient methods is the successive minimization of this cost function along a set of directions $\{\mathbf{p}_m\}$ via

$$\mathbf{x}_m = \mathbf{x}_{m-1} + \alpha_m \mathbf{p}_m \,, \tag{18}$$

with

$$\alpha_m = \mathbf{p}_m{}^H\mathbf{q}_{m-1} \big/ \mathbf{p}_m{}^H\mathbf{C}\mathbf{p}_m \,, \tag{19}$$

and

$$\mathbf{q}_m = -\nabla\Phi(\mathbf{x})\big|_{\mathbf{x}=\mathbf{x}_m} = \mathbf{y} - \mathbf{C}\mathbf{x}_m \,. \tag{20}$$

Different choices of the set $\{\mathbf{p}_m\}$ in (18) ~ (20) give different algorithms. If we choose the search directions $\mathbf{p}_m$ to be the negative gradient of the cost function $\mathbf{q}_{m-1}$ directly, this algorithm is the steepest descent method, global convergence of which is guaranteed [11]. The convergence rate may be prohibitively slow, however, due to the linear dependence of the search directions, resulting in redundant minimization. If we choose the search direction to be **C**-conjugate as follows

$$\mathbf{p}_m = \underset{\mathbf{p}\in\Lambda_{m-1}^{\perp}}{\operatorname{argmin}} \left\| \mathbf{p} - \mathbf{q}_{m-1} \right\|, \tag{21}$$

where $\Lambda_m = \operatorname{span}\{\mathbf{C}\mathbf{p}_1,...,\mathbf{C}\mathbf{p}_m\}$, then we have the conjugate gradient method, whose convergence is guaranteed and performs well when **C** is near the identity either in the sense of a low rank perturbation or in the sense of norm [11]. The computational complexity of Gauss-Seidel and conjugate gradient iteration are similar, which is on the order of $O(K\Delta\overline{m})$ per user per symbol, where $\overline{m}$ is the number of iterations. The number of iterations required by the Gauss-Seidel and conjugate gradient methods to achieve a stable solution to the associated large system equations has been found on the same order in our simulations.

IV. Iterative Nonlinear Space-Time Multiuser Detection

Nonlinear multiuser detectors are often based on bootstrapping techniques, which are iterative in nature. In this section, we will consider the iterative implementation of decision-feedback and multistage interference cancelling multiuser detection [23] in the space-time domain. We extend the Cholesky iterative detector in [3] to the space-time multipath asynchronous case, and further address the issue of Cholesky factorization of the system matrix $\mathbf{H}$, which is nontrivial for large numbers of antennas and large numbers of users. We also discuss briefly the implementation of multistage interference cancelling ST MUD, which serves as a reference point for introducing a new EM-based iterative ST MUD, to be discussed in the next section.

A. Cholesky Iterative Decorrelating Decision-Feedback ST MUD

Decorrelating decision feedback multiuser detection (DDF MUD) [7], [22], [23] exploits the Cholesky decomposition $\mathbf{H} = \mathbf{F}^H \mathbf{F}$, where $\mathbf{F}$ is a lower triangular matrix, to determine the feedforward and feedback matrix for detection via the algorithm

$$\hat{\mathbf{b}} = \mathrm{sgn}(\mathbf{F}^{-H}\mathbf{y} - (\mathbf{F} - \mathrm{diag}(\mathbf{F}))\mathbf{A}\hat{\mathbf{b}})\,, \tag{22}$$

which should be understood to detect the bits sequentially from that of the first user to the last user, with $\hat{\mathbf{b}}$ a vector containing the detected bits for all users over the whole data frame. The reader is referred to [23] for the implementation of MMSE decision feedback multiuser detection. It is interesting to note that decision feedback multiuser detection has been used in the Bell Labs BLAST techniques for joint detection of data streams of multi-input multi-output (MIMO) systems [10].

Suppose the user of interest is user k (each bit of each user can be treated as a “new” user for asynchronous systems), the purpose of the feedforward matrix $\mathbf{F}^{-H}$ is to whiten the noise and decorrelate against the "future users" $\{s_{k+1},\ldots,s_{KM}\}$; while the purpose of the feedback matrix $(\mathbf{F}-\mathrm{diag}(\mathbf{F}))$ is to cancel out the interference from "previous users" $\{s_1,\ldots,s_{k-1}\}$. Note that the performance of DDF MUD is not uniform. While the first user is demodulated by its decorrelating detector, the last detected user will essentially achieve its single-user lower bound providing the previous decisions are correct. There is another form of Cholesky decomposition, in which the feedforward matrix $\mathbf{F}$ is upper triangular. If we were to use this form instead in (22), then the multiuser detection would be in the reverse order, as would be the performances. The idea of *Cholesky iterative DDF ST MUD* is to employ these two forms of Cholesky decomposition alternatively as follows. For lower triangular Cholesky decomposition $\mathbf{F}_1$, first feedforward filtering is applied as

$$\overline{\mathbf{y}}_1 = \mathbf{F}_1^{-H}\mathbf{y}, \tag{23}$$

where it is readily shown that $\overline{y}_{1,i} = \mathbf{F}_{1,ii}A_i b_i + \sum_{j=1}^{i-1}\mathbf{F}_{1,ij}A_j b_j + \overline{n}_{1,i}$, $i=1,\ldots,KM$, with $\overline{n}_{1,i}$, $i=1,\ldots,KM$, the independent and identically distributed (i. i. d.) Gaussian noise components with zero mean and variance σ^2. We can see that the influence of the "future users" is wiped out and the noise component is whitened. Then we employ the feedback filtering to take out the interference from "previous users" as

$$\mathbf{u}_1 = \overline{\mathbf{y}}_1 - (\mathbf{F}_1 - \mathbf{diag}(\mathbf{F}_1))\mathbf{A}\hat{\mathbf{b}}, \tag{24}$$

where it is easily seen that $u_{1,i} = \overline{y}_{1,i} - \sum_{j=1}^{i-1}\mathbf{F}_{1,ij}A_j\hat{b}_j \approx \mathbf{F}_{1,ii}A_i b_i + \overline{n}_{1,i}$, $i=1,\ldots,KM$. Similarly, for upper triangular Cholesky decomposition $\mathbf{F}_2$, we have

$$\overline{\mathbf{y}}_2 = \mathbf{F}_2^{-H}\mathbf{y}, \tag{25}$$

where $\overline{y}_{2,i} = \mathbf{F}_{2,ii}A_i b_i + \sum_{j=i+1}^{KM}\mathbf{F}_{2,ij}A_j b_j + \overline{n}_{2,i}$, $i=KM,\ldots,1$, and

$$\mathbf{u}_2 = \overline{\mathbf{y}}_2 - (\mathbf{F}_2 - \mathbf{diag}(\mathbf{F}_2))\mathbf{A}\hat{\mathbf{b}}, \tag{26}$$

where $u_{2,i} = \overline{y}_{2,i} - \sum_{j=i+1}^{KM}\mathbf{F}_{2,ij}A_j\hat{b}_j \approx \mathbf{F}_{2,ii}A_i b_i + \overline{n}_{2,i}$, $i=KM,\ldots,1$.

After the above operations are (alternately) executed, the following log-likelihood ratio is calculated,

$$L_i = 2\,\mathrm{Re}(\mathbf{F}_{1/2,ii}{}^{*} A_i u_{1/2,i}) / \sigma^2 \,, \tag{27}$$

where $\mathbf{F}_{1/2}$ and $u_{1/2}$ are used to give a shorthand representation for both alternatives. Then the log-likelihood ratio is compared with the last stored value, which is replaced by the new value if the new one is more reliable, i.e.,

$$L_i^{stored} = \begin{cases} L_i^{stored} & if \left|L_i^{stored}\right| > \left|L_i^{new}\right| \\ L_i^{new} & otherwise \end{cases}. \tag{28}$$

Finally we make soft decisions $\hat{b}_i = \tanh(L_i / 2)$ at an intermediate iteration, which has been shown to offer better performance than making hard intermediate decisions, and make hard decisions $\hat{b}_i = \mathrm{sgn}(L_i)$ at the last iteration. Three or four iterations are usually enough for the system to achieve an improved steady state without significant oscillation. The structure of Cholesky iterative decorrelating decision-feedback ST MUD is illustrated in Fig. 2.

The Cholesky factorization of the block Toeplitz matrix $\mathbf{H}$ (see (10)) can be done recursively, as in [26] for $\Delta = 1$

$$\mathbf{F} = \begin{bmatrix} \underline{F}_1(0) & 0 & & 0 & 0 \\ \underline{F}_2(1) & \underline{F}_2(0) & \cdots & 0 & 0 \\ 0 & & & & \\ \vdots & & & & \\ 0 & 0 & & \underline{F}_M(1) & \underline{F}_M(0) \end{bmatrix}, \tag{29}$$

where the element matrices are obtained recursively as follows.

$$\underline{V}_M = \underline{H}^{[0]}, \tag{30}$$

and, for $i = M, M-1, \ldots, 1$, we do the Cholesky decomposition for the reduced-rank matrix $\underline{V}_i$ to get $\underline{F}_i(0)$

$$\underline{V}_i = \underline{F}_i{}^H(0)\underline{F}_i(0), \tag{31}$$

while $\underline{F}_i(1)$ is obtained as

$$\underline{F}_i(1) = (\underline{F}_i^H(0))^{-1}\underline{H}^{[-1]}. \tag{32}$$

Finally we have

$$\underline{V}_{i-1} = \underline{H}^{[0]} - \underline{H}^{[1]}\underline{V}_i^{-1}\underline{H}^{[-1]} \tag{33}$$

for use in the next iteration. The extension of this algorithm to $\Delta > 1$ is straightforward and is omitted here.

B. Multistage Interference Cancelling ST MUD

Multistage interference cancellation (IC) [21], [23] is similar to Jacobi iteration except that hard decisions are made at the end of each stage in place of the linear terms that are fed back in (15). Thus we have

$$\hat{\mathbf{b}}_m = \mathrm{sgn}\left(\mathbf{y} - (\mathbf{C}_L + \mathbf{C}_U)\hat{\mathbf{b}}_{m-1}\right) = \mathrm{sgn}\left(\mathbf{y} - (\mathbf{H} - \mathbf{D})\hat{\mathbf{b}}_{m-1}\right). \tag{34}$$

The underlying rationale of this method is that the estimator-subtracter structure exploits the discrete-alphabet property of the transmitted data streams. This nonlinear hard-decision operation typically results in more accurate estimates, especially in high SNR situations. Although the optimal decisions are a fixed point of the nonlinear transformation (34), there are problems with the multistage IC such as a possible lack of convergence and oscillatory behavior. In the following section we consider some improvements on space-time multistage IC MUD.

Except for the Cholesky factorization, the computational complexity for Cholesky iterative DDF ST MUD is the same as multistage IC ST MUD, which is essentially the same as that of linear interference cancellation, i.e., $O(K\Delta\overline{m})$ per user per symbol.

V. EM-based Iterative Space-Time Multiuser Detection with a New Structure

In this section, EM-based multiuser detection is introduced to avoid the convergence and stability problem of the multistage IC MUD. After the introduction of EM and space-alternating generalized EM (SAGE) algorithms, we follow the approach of [15] to apply the SAGE algorithm to the space-time multipath asynchronous CDMA systems. To address the problems caused by long spreading codes, namely, the large computational burden to obtain the cross-correlation matrix $\mathbf{H}$, a new space-time multiuser receiver structure is also introduced. The SAGE algorithm is then applied nontrivially to group spatial-domain multiuser detection based on different directions of arrival for different paths of different users. The SAGE iterative ST MUD with this new structure retains its excellent performance but with greater adaptability; it is easily adjusted for use in time-varying environments and for non-CDMA space-time processing.

A. EM and SAGE Algorithm with Application to ST MUD

The EM algorithm [5] provides an iterative solution of maximum likelihood estimation problems such as

$$\hat{\boldsymbol{\theta}}(\mathbf{Y}) = \arg\max_{\boldsymbol{\theta}\in\Lambda} \log f(\mathbf{Y};\boldsymbol{\theta}), \tag{35}$$

where $\boldsymbol{\theta}\in\Lambda$ are the parameters to be estimated, and $f(\cdot)$ is the parameterized probability density function of the observable $\mathbf{Y}$. The idea of the EM algorithm is to consider a judiciously chosen set of "missing data" $\mathbf{Z}$ to form the complete data $\mathbf{X} = \{\mathbf{Y},\mathbf{Z}\}$ as an aid to the parameter estimation, and then to iteratively maximize the following new objective function

$$Q(\boldsymbol{\theta};\bar{\boldsymbol{\theta}}) = E\{\log f(\mathbf{Y},\mathbf{Z};\boldsymbol{\theta}) \big| \mathbf{Y}=\mathbf{y};\bar{\boldsymbol{\theta}}\}, \tag{36}$$

where $\boldsymbol{\theta}$ are the parameters in the likelihood function, which are to be estimated, while $\bar{\boldsymbol{\theta}}$ represent *a priori* estimates of the parameters from the previous iteration. Together with the observations, these previous estimates are used to calculate the expected value of the log-likelihood function with respect to the complete data $\mathbf{X}=\{\mathbf{Y},\mathbf{Z}\}$. To be specific, given an initial estimate $\boldsymbol{\theta}^0$, the EM algorithm alternates between the following two steps:

1) E-step, where the complete-data sufficient statistic $Q(\boldsymbol{\theta};\boldsymbol{\theta}^i)$ is computed;

2) M-step, where the estimates are refined by $\boldsymbol{\theta}^{i+1}=\arg\max_{\boldsymbol{\theta}\in\Lambda} Q(\boldsymbol{\theta};\boldsymbol{\theta}^i)$.

It has been shown that EM estimates monotonically increase the likelihood, and converge stably to an ML solution under certain conditions [5].

An issue in using the EM algorithm is the tradeoff between ease of implementation and convergence rate. One would like to add more “missing data” to make the complete data space more informative so that the implementation of the EM algorithm is simpler than the original setting (35). However, the convergence rate of the algorithm is inversely proportional to the Fisher information contained in the complete data space [9]. Thus, convergence of the EM algorithm is notoriously slow, especially for multidimensional parameter estimation, due to the simultaneous updating nature of the M-step of the EM algorithm. The SAGE algorithm has been proposed in [9] to improve the convergence rate for multidimensional parameter estimation. The idea is to divide the parameters into several groups (subspaces), with only one group being updated at each iteration. Thus, we can associate multiple less-informative “missing data” sets to improve the convergence rate while maintaining overall tractability of optimization problems. For each iteration, a subset of parameters $\boldsymbol{\theta}_{S_i}$ and the corresponding missing data $\mathbf{Z}^{S_i}$ are chosen, which is called the definition step. Then similarly to the EM algorithm, in the E-step we calculate

$$Q^{S_i}(\boldsymbol{\theta}_{S_i};\boldsymbol{\theta}^i)=E\{\log f(\mathbf{Y},\mathbf{Z}^{S_i};\boldsymbol{\theta}_{S_i},\boldsymbol{\theta}^i_{\tilde{S}_i}\,|\,\mathbf{Y}=\mathbf{y};\boldsymbol{\theta}^i)\}, \tag{37}$$

where $\boldsymbol{\theta}_{\tilde{S}_i}$ denotes the complement of $\boldsymbol{\theta}_{S_i}$ in the whole parameter set; in the M-step, the chosen parameters are updated while the others remain unchanged as

$$\begin{cases}\boldsymbol{\theta}_{S_i}{}^{i+1}=\arg\max\limits_{\theta_{S_i}\in\Lambda_{S_i}} Q^{S_i}(\boldsymbol{\theta}_{S_i};\boldsymbol{\theta}^i)\\ \boldsymbol{\theta}^{i+1}_{\tilde{S}_i}=\boldsymbol{\theta}^i_{\tilde{S}_i}\end{cases}, \tag{38}$$

where Λ_{S_i} denotes the restriction of the entire parameter space to those dimensions indexed by S_i. Like the traditional EM estimates, the SAGE estimates also monotonically increase the likelihood and converge stably to an ML solution under appropriate conditions [9].

The EM algorithm is applied to space-time multipath asynchronous CDMA multiuser detection as follows. For ease of illustration, we reindex the vectors and matrices in the system model (8) as

$$\mathbf{y} = [y_1, \ldots, y_K, y_{K+1}, \ldots, y_{K(M-1)+1}, \ldots, y_{KM}]^T,$$

$$\mathbf{b} = [b_1, \ldots, b_K, b_{K+1}, \ldots, b_{K(M-1)+1}, \ldots, b_{KM}]^T,$$

and

$$\mathbf{A} = \mathrm{diag}[a_1, \ldots, a_K, a_{K+1}, \ldots, a_{K(M-1)+1}, \ldots, a_{KM}]^T.$$

Suppose we would like to detect a bit b_k, $k \in \{1, 2, \cdots, KM\}$, while the interfering users' bits $\mathbf{b}_{\tilde{k}} = \{b_j\}_{j \neq k}$ are treated as the missing data. The complete-data sufficient statistic is given by ($\mathbf{H}_{km}$ is the element of matrix $\mathbf{H}$ at the kth row and mth column)

$$Q(b_k; b_k^i) = \frac{a_k^2}{2\sigma^2}\left(-b_k^2 + 2\frac{b_k}{a_k}(y_k - \sum_{m \neq k} \mathbf{H}_{km} a_m \tilde{b}_m)\right), \tag{39}$$

with

$$\tilde{b}_m = E\{b_m \mid \mathbf{Y} = \mathbf{y}; b_k = b_k^i\} = \tanh(\frac{a_m}{\sigma^2}(y_m - \mathbf{H}_{mk} a_k b_k^i)), \tag{40}$$

which forms the E-step of the EM algorithm. The M-step is given by

$$b_k^{i+1} = \arg\max_{b_k \in \Lambda} Q(b_k; b_k^i) = \begin{cases} \mathrm{sgn}(y_k - \sum_{m \neq k} \mathbf{H}_{km} a_m \tilde{b}_m) & \Lambda = \{\pm 1\} \\ \frac{1}{a_k}(y_k - \sum_{m \neq k} \mathbf{H}_{km} a_m \tilde{b}_m) & \Lambda = \Re \end{cases}, \tag{41}$$

where $\Lambda = \Re$ (the set of real numbers) means a soft decision is needed, e.g., in an intermediate stage. Note that in the E-step (40), interference from users $j \neq k$ is not taken into account, since these are treated as "missing data". This shortcoming is overcome by the application of the SAGE algorithm, where the bit vector of all users $\mathbf{b} = \{b_j\}_{j=1}^{KM}$ is treated as the parameter to be estimated and no missing data is needed. The algorithm is described as follows: for $i = 0,1,\cdots,$

1) Definition step: $S_i = 1 + (i \mod KM)$

2) M-step: $$\begin{cases} b_k^{i+1} = \mathrm{sgn}(y_k - \sum_{m \neq k} \mathbf{H}_{km} a_m b_m^i) & k \in S_i \\ b_m^{i+1} = b_m^i & m \notin S_i \end{cases}. \quad (42)$$

Note that there is no E-step since there is no missing data, and interference from all other users are recreated from previous estimates and subtracted. The resulting receiver is similar to the multistage interference cancelling multiuser receiver (see (34)), except that the bit estimates are made sequentially rather than in parallel. However, with this simple concept of sequential interference cancellation, the resulting multiuser receiver is convergent, guaranteed by the SAGE algorithm. The multistage interference cancelling multiuser receiver discussed in IV-B, on the other hand, does not always converge. The computational complexity of this SAGE iterative ST MUD is also $O(K\Delta\overline{m})$ per user per symbol.

B. SAGE Iterative ST MUD with a New Structure

So far when we discuss computational complexity, we have ignored the computational burden for calculating the matrix **H**. In a CDMA system exploiting short spreading codes as we have assumed, the system matrix will exhibit the block-Toeplitz structure as shown in (10). The computation of $\underline{H}^{[j]}$, $1 \leq j \leq \Delta$, though involved (see [25]) for details), would become insignificant when *M* is large. This is not the case, however, when a long spreading code is employed so that spreading sequences vary from symbol to symbol (e.g. in IS-95). In this situation, the sub-matrices $\underline{H}^{[j]}$, $1 \leq j \leq \Delta$, have to be calculated for each symbol, which results in an additional complexity of $O(K^3L^3\Delta)$ per user per symbol. To circumvent this problem, a new space-time processing structure is introduced, where we separate the spatial and temporal processing, and apply the SAGE algorithm to spatial-domain multiuser detection based on different directions of arrival for different paths of different users, as shown in Fig. 3. From (5), we can write

$$\mathbf{r}(t) = \sum_{i=0}^{M-1} \sum_{k=1}^{K} A_k b_k(i) \sum_{l=1}^{L} \mathbf{a}_{kl} g_{kl} s_k(t - iT - \tau_{kl}) + \sigma \mathbf{n}(t) . \tag{43}$$

After chip-matched filtering and chip-rate sampling, the model can be represented in discrete time as

$$\mathbf{z}(n) = \int_{nT_c+\tau_{\min}}^{(n+1)T_c+\tau_{\min}} \mathbf{r}(t)\psi(t - nT_c - \tau_{\min})dt\,,\ 0 \le n \le MN - 1 + \left\lceil \frac{\tau_{\max} - \tau_{\min}}{T_c} \right\rceil, \tag{44}$$

where $\tau_{\min}$ and $\tau_{\max}$ denote the minimum and maximum value, respectively, of the delay spreads for all users. For simplicity, we assume the delays are integer numbers of chip intervals. (The results can straightforwardly be extended to the fractional delay case by oversampling.) On denoting

$$s_{kl}(n) = \int_{nT_c+\tau_{\min}}^{(n+1)T_c+\tau_{\min}} \sum_{i=0}^{M-1} s_k(t - iT - \tau_{kl})\psi(t - nT_c - \tau_{\min})dt\,, \tag{45}$$

we have

$$\mathbf{z}(n) = \sum_{k=1}^{K}\sum_{l=1}^{L} A_k b_k \left(\left\lfloor \left(n + \frac{\tau_{kl} - \tau_{\min}}{T_c} \right) \Big/ N \right\rfloor \right) \mathbf{a}_{kl} g_{kl} s_{kl}(n) + \sigma \mathbf{e}(n) = \sum_j \tilde{A}_j \tilde{\mathbf{a}}_j d_j(n) + \sigma \mathbf{e}(n)\,,$$

$$1 \le j \le K \times L\,, \tag{46}$$

where for the last equality we reformulate the system model so that chips received from different paths of each user are treated as different users in a synchronous system, according to the following translation

$$\tilde{A}_j \leftrightarrow A_k g_{kl}\,,\ \tilde{\mathbf{a}}_j \leftrightarrow \mathbf{a}_{kl}\,, \text{ and } d_j \leftrightarrow b_k s_{kl}\,, \tag{47}$$

through $j = (k-1)*L + l,\ 1 \le k \le K\,,\ 1 \le l \le L$. Here $\mathbf{e}(n)$ denotes i.i.d. background noise with zero mean and unit variance. The parameters to be estimated are $\boldsymbol{\theta} = \mathbf{d} = [d_1(n), \ldots, d_{K\times L}(n)]^T \in \{\pm 1\}^{KL}$ which correspond to the chips from all paths of all users. The index sets cycle through $1, \ldots, KL$, with L chips (of a user) being updated at a time. The algorithm is implemented without any missing data so there is no need for the E-step. Each iteration thus comprises the following steps:

1) Definition step: $S_i = [1, \cdots, L] + (i \mod K) \times L$;

2) M-step: $\begin{cases} \tilde{d}_j^{i+1} = g_\Lambda\left(\tilde{\mathbf{a}}_j^H (\mathbf{z} - \sum_{m \neq j} \tilde{\mathbf{a}}_m \tilde{A}_m d_m^i) \right) & j \in S_i \\ d_m^{i+1} = d_m^i, \quad m \notin S_i \end{cases}$. (48)

Since the spatial processing is one of the components of our proposed space-time receiver, whose outputs are provided to the next stage for temporal processing, we choose to use the linear function $g_\Lambda(x) = x$ in the above M-step to produce soft outputs $\tilde{d}_j(n)$, $j \in S_i$, which is better for overall performance than the hard-decision function $g_\Lambda(x) = \text{sgn}(x)$.

After the spatial processing described above, the chips from the different paths of one user are combined through a RAKE combiner to get a chip estimate for that user ($k = (i \mod K)$),

$$\hat{d}_k(n) = \sum_{l=1}^{L} A_{kl}^* g_{kl}^* \tilde{d}_{kl}(n + \tau_{kl} / T_c),\ 0 \le n \le MN - 1 + \left\lceil \frac{\tau_{\max} - \tau_{\min}}{T_c} \right\rceil, \tag{49}$$

where the index conversion is made through the translation of (47). Finally, the spreading code is employed to get the bit estimate

$$\hat{b}_k(i) = \text{sgn}\left(\text{Re}\left(\sum_{n=1}^{N} \hat{d}_k^*(iT + n) c_k(n) \right) \right),\ 0 \le i \le M - 1. \tag{50}$$

The obtained bit estimates are then respread and remodulated as (46) and (47) to get d_j^{i+1}, $j \in S_i$ for spatial domain interference cancellation (48) for the next iteration.

Our proposed space-time multiuser receiver structure in Fig. 3 has several advantages. As we mentioned earlier, the multiuser signals and multipath channel parameters come into play through the system matrix **H**. For a CDMA system employing long spreading codes, **H** must be calculated for each symbol interval, which is quite cumbersome. More generally, for any time-varying communication system, **H** has to be updated on the order of the coherence time. Furthermore, any part of the algorithm that is related to this system matrix, e.g., the Cholesky factorization for Cholesky iterative DDF ST MUD, should also be calculated for each symbol. This problem is circumvented by our structure, which effectively distributes the operations combined in the system matrix **H** into the different stages of spatial IC, beamforming, temporal RAKE combining, and despreading. Further, since the front end processing is at the chip level, these "users" are synchronous. Therefore, the algorithm can be implemented chip-by-chip or symbol-by-symbol in a pipelined version. This structure also has the benefit that it can be applied in non-CDMA (e.g. space-division multiple-access (SDMA)) cellular networks to exploit the spatial and temporal knowledge to suppress interference and improve system capacity. All we need in such cases is to omit the despreading stage.

The computational complexity of this new-structure-based SAGE iterative ST MUD is $O(KNL^2\overline{m})$ per user per symbol, which can easily be implemented with $O(KL\overline{m})$ or even less time complexity per user per symbol with modern VLSI techniques. The basic idea would be to build multiple parallel hardware processing units, which can be done due to the synchronous chip-level processing nature of the new structure. The multistage IC ST MUD can also be implemented with this structure in a straightforward way. The performance of these ST MUD receivers with this new structure is the same as that implemented with the conventional structure of Fig. 1, which will be discussed further in the next section.

VI. Simulation Results

In this section, the performance of the above described space-time multiuser detectors is examined through computer simulations. We assume a K = 8-user CDMA system with spreading gain N = 16. 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 $\Delta = 1$. The complex gains and delays of the multipath and the directions of arrival are randomly generated and kept fixed for the whole data frame. This corresponds to a slow fading situation. The spreading codes of all users are randomly generated and kept fixed for all the simulations. We assume $A_1 = \ldots = A_K$ for simplicity, but the received signal powers of different users are unequal due to the effects of multipath.

First we compare the performance of various space-time multiuser receivers and some single-user space-time receivers in Fig. 4. Five receivers are considered: the single-user matched filter (Matched-Filter), the single-user MMSE receiver (SU MMSE), the multiuser MMSE receiver (MU MMSE) implemented in Gauss-Seidel or conjugate gradient iteration method (the performance is the same for both), the Cholesky iterative decorrelating decision-feedback multiuser receiver (Cholesky Iterative MU DF), and the multistage interference cancelling multiuser receiver (MU Multistage IC). All these receivers are implemented on the conventional space-time multiuser receiver structure shown in Fig. 1. (The reader is referred to [25] for derivations of the single-user based receivers.) The performance is evaluated after the iterative algorithms converge. Due to the bad convergence behavior of the multistage IC MUD, we measure its performance after three stages. The single-user lower bound is also depicted for reference. We can see that the multiuser approach greatly outperforms the single-user based methods; nonlinear MUD offers further gain over the linear MUD; and the multistage IC seems to approach the optimal performance (not always though, as is seen in Fig. 4(c)), when it has good convergence behavior. Note that due to the introduction of spatial (receive antenna) and spectral (RAKE combining) diversity, the SNR for the same BER is substantially lower than that required by normal receivers without these.

Figure 5 shows the performance of Cholesky iterative decorrelating decision-feedback ST MUD for two users, which is also typical for other users. Note that we use a different parameter set for this simulation, so there is no correspondence between Figs. 4 and 5. We find that the Cholesky iterative method offers uniform gain over its noniterative counterpart. This gain may be substantial for some users and negligible for others due to the individual characteristics of signals and channels.

In Section V-B, a new space-time multiuser receiver structure was introduced to reduce complexity and enhance adaptability of the algorithms while keeping the same performance. In this new structure, different paths of each user are treated as separate users in a synchronous system, while in the original structure, different paths are combined prior to interference cancellation. One may be concerned that the new structure is more susceptible to saturation ("dimensional crowding") than the traditional structure by a factor of L. We implemented the SAGE ST MUD with both structures for a fully loaded $K = N = 16$ system. The results shown in Fig. 6 are measured after three iterations. It is seen that the performance is almost identical for these two structures. We believe that this should be always the case as long as the number of paths L is no larger than the number of antenna elements P.

Finally, we show the advantage of our new EM-based (SAGE) iterative method over the multistage IC method with regard to the convergence of the algorithms. These receivers are implemented on the new space-time multiuser receiver structure shown in Fig. 3, and long random spreading codes are employed. We assume again a K = 8-user CDMA system with spreading gain N = 16. From Fig. 7 we find that, while the multistage interference cancelling ST MUD converges slowly and exhibits oscillatory behavior, the SAGE ST MUD converges quickly and outperforms the multistage IC method. The oscillation of the performance of the multistage IC corresponds to a performance degradation as no statistically best iteration number can be chosen.

VII. Conclusions

In this paper, we have considered several iterative space-time multiuser detection schemes for multipath CDMA channels with multiple receive antennas. Fully exploiting diversities through space-time processing and multiuser detection offers substantial improvement over alternative processing methods. It is shown that iterative implementation of these linear and nonlinear multiuser receivers realizes this substantial gain and approaches the optimum performance with reasonable complexity. Among these iterative implementations the SAGE space-time multiuser receiver outperforms the others. The complexity of the new SAGE detector with the traditional structure is no higher than the existing methods but with better performance and smoother convergence. The SAGE detector with the new structure retains its excellent performance but with greater adaptability, and its complexity is comparable to the existing methods. Furthermore, with the long (pseudo-random) spreading codes (e.g. IS-95 and its 3G version) or in the rapidly time-varying environments, the SAGE detector with the new structure exhibits some advantage as it circumvents the system matrix update problem. The reader is referred to [4] for the issue of sample-by-sample adaptive methods in this latter structure.

References

[1] P. D. Alexander, et al., “Iterative multiuser interference reduction: turbo CDMA,” *IEEE Trans. Commun.*, vol. 47, no. 7, pp. 1008-1014, July 1999.

[2] S. Beheshti and G. W. Wornell, “Joint intersymbol and multiple-access interference suppression algorithms for CDMA systems,” *European Trans. Telecomm*., vol. 9, no. 5, pp. 403-418, Sept.-Oct., 1998.

[3] A. Boariu and R. E. Ziemer, “Cholesky-iterative detector: a new multiuser detector for synchronous CDMA systems,” *IEEE Commun. Lett*., vol. 4, no. 3, Mar. 2000.

[4] H. Dai and H. V. Poor: “Sample-by-sample Adaptive Space-Time Processing for Multiuser Detection in Multipath CDMA Systems,” *Proc. 2001Fall IEEE Vehicular Technology Conference*, Atlantic City, NJ, Oct. 7 – 11, 2001.

[5] A. P. Dempster, et al., “Maximum likelihood from incomplete data via the EM algorithm,” *J. Royal Statistical Soc*., *Ser. B*, vol. 39, no. 1, pp. 1-38, 1977.

[6] D. Divsalar, et al., “Improved parallel interference cancellation for CDMA,” *IEEE Trans. Commun.*, vol. 46, no. 2, pp. 258-268, Feb. 1998.

[7] A. Duel-Hallen, “A family of multiuser decision-feedback detectors for asynchronous code-division multiple access channels,” *IEEE Trans. Commun.*, vol. 43, no. 2/3/4, pp. 421-434, Feb./Mar./Apr. 1995.

[8] H. Elders-Boll, et al., “Efficient implementation of linear multiuser detectors for asynchronous CDMA systems by linear interference cancellation,” *European Trans. Telecomm*., vol. 9, no. 5, pp. 427-437, Sept.-Oct., 1998.

[9] J. A. Fessler and A. O. Hero, “Space-alternating generalized EM algorithm,” *IEEE Trans. Signal Processing*, vol. 42, no. 10, pp. 2664-2677, Oct. 1994.

[10] G. J. Foschini, G. D. Golden, R. A. Valenzuela and P. W. Wolniansky, “Simplified processing for high spectral efficiency wireless communication employing multi-element arrays,” *IEEE J. Selected Areas Comm.*, vol. 17, pp. 1841-1852, 1999.

[11] G. H. Golub and C. F. Van Loan, *Matrix Computation*, The John Hopkins University Press, Baltimore, MD, 1996

[12] M. Juntti, et al., “Iterative implementation of linear multiuser detection for dynamic asynchronous CDMA systems,” *IEEE Trans. Commun.*, vol. 46, no. 4, pp. 503-508, Apr. 1998.

[13] H. Liu and M. D. Zoltowski, "Blind equalization in antenna array CDMA systems," *IEEE Trans. Signal Processing*, vol. 45, no. 1, pp. 161-172, Jan. 1997.

[14] S. Miller and S. C. Schwartz, "Integrated spatial-temporal detectors for asynchronous Gaussian multiple access channels," *IEEE Trans. Commun.*, vol. 43, no. 2/3/4, pp. 396-411, Feb./Mar./Apr. 1995.

[15] L. B. Nelson and H. V. Poor, "Iterative multiuser receivers for CDMA channels: An EM-based approach," *IEEE Trans. Commun.*, vol. 44, no. 12, pp. 1700-1710, Dec. 1996.

[16] A. J. Paulraj and C. B. Papadias, "Space-time processing for wireless communications," *IEEE Signal Processing Mag.*, pp. 49-82, Nov. 1997

[17] P. B. Rapajic and B. S. Vucetic, "Adaptive receiver structures for asynchronous CDMA systems," *IEEE J. Select. Areas Commun*., vol. 12, no. 4, pp. 685-697, May 1994

[18] L. K. Rasmussen, T. J. Lim, and A. Johansson, "A matrix-algebraic approach to successive interference cancellation in CDMA," *IEEE Trans. Commun*., Vol. 48, pp. 145-151, Jan. 2000.

[19] J. B. Schodorf and D. B. Williams, "Array processing techniques for multiuser detection," *IEEE Trans. Commun.*, vol. 45, no. 11, pp. 1375-1378, Nov. 1997.

[20] B. D. Van Veen and K. M. Buckley, "Beamforming: a versatile approach to spatial filtering," *IEEE ASSP Mag*., pp. 4-24, Apr. 1988.

[21] M. Varanasi and B. Aazhang, "Multistage detection in asynchronous code-division multiple access communications," *IEEE Trans. Commun.*, vol. 38, no. 4, pp. 509-519, Apr. 1990.

[22] M. Varanasi, "Decision feedback multiuser detection: a systematic approach," *IEEE Trans. Inform. Theory*, vol. 45, No.1, pp. 219-240, Jan. 1999.

[23] S. Verdú, *Multiuser Detection*, Cambridge University Press: Cambridge, UK, 1998.

[24] X. Wang and H. V. Poor, "Iterative (turbo) soft interference cancellation and decoding for coded CDMA", *IEEE Trans. Commun.*, vol. 47, no. 7, pp. 1046-1061, July 1999.

[25] X. Wang and H. V. Poor, "Space-time multiuser detection in multipath CDMA channels," *IEEE Trans. Signal Processing*, vol. 47, no. 9, pp. 2356-2374, Sept. 1999.

[26] L. Wei and L. K. Rasmussen, " A near ideal noise whitening filter for an asynchronous time-varying CDMA systems," *IEEE Trans. Commun*., vol. 44, no. 10, pp. 1355-1361, Oct. 1996.

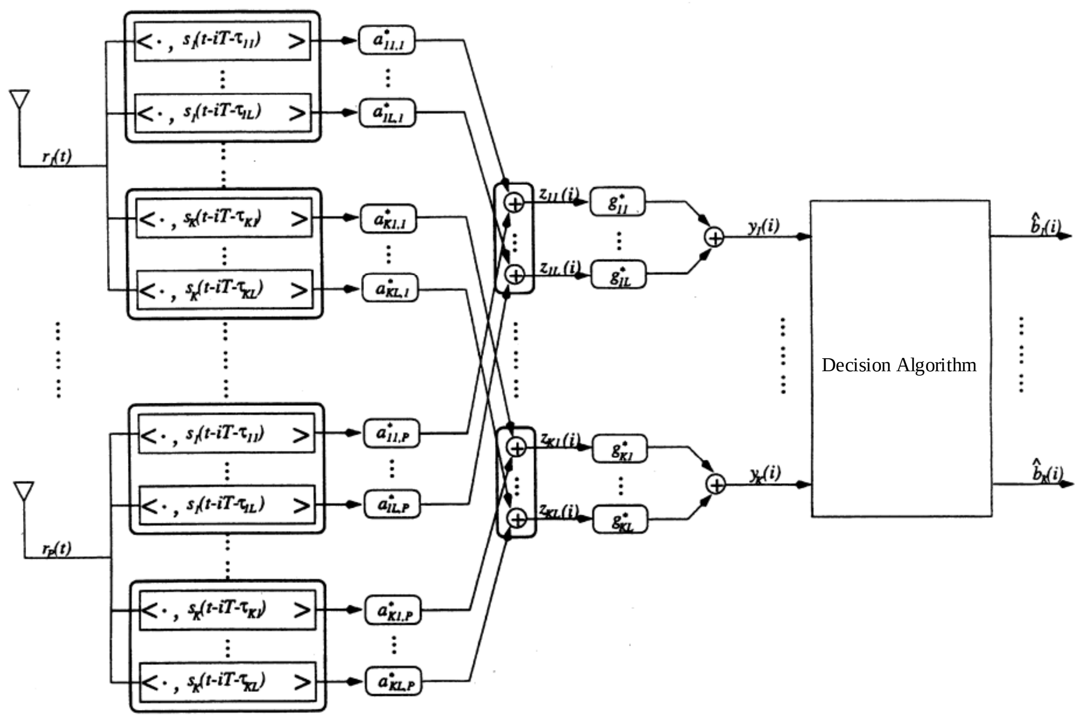


Fig. 1 A conventional space-time multiuser receiver

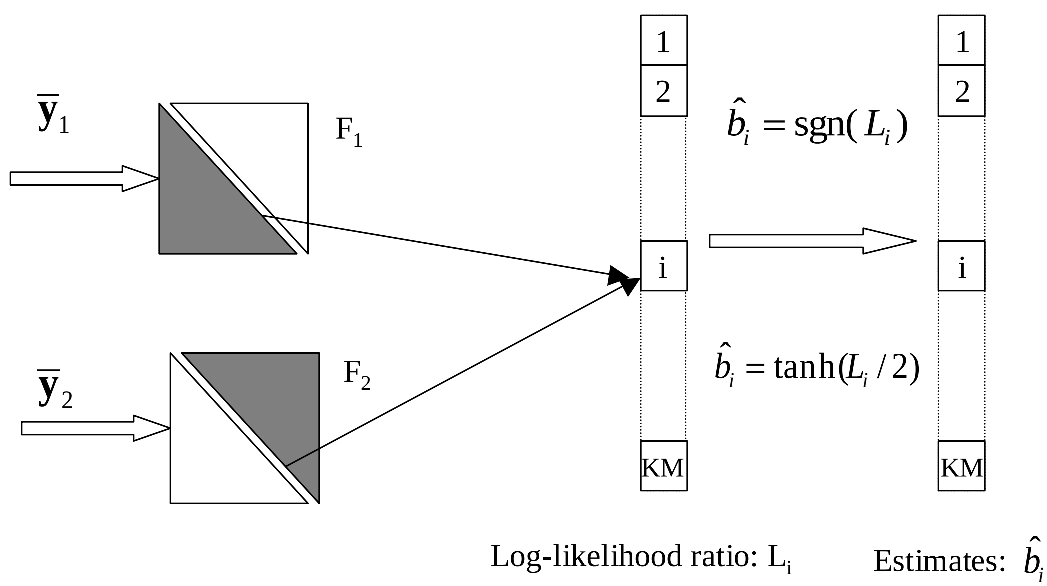


Fig. 2 Cholesky iterative decorrelating decision-feedback ST MUD

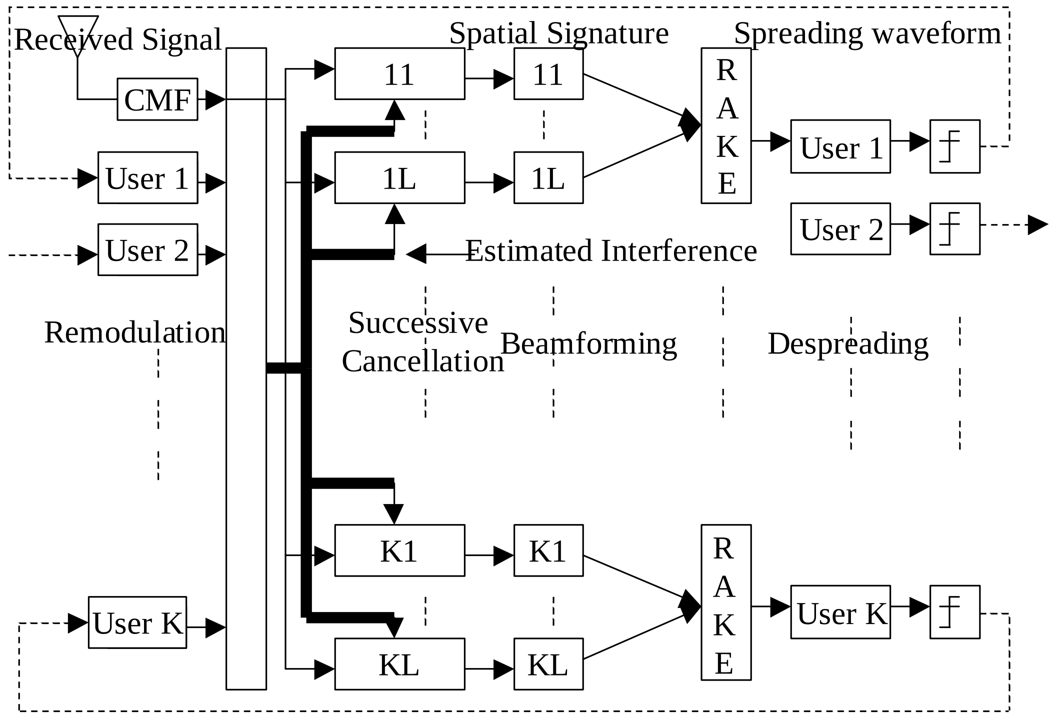
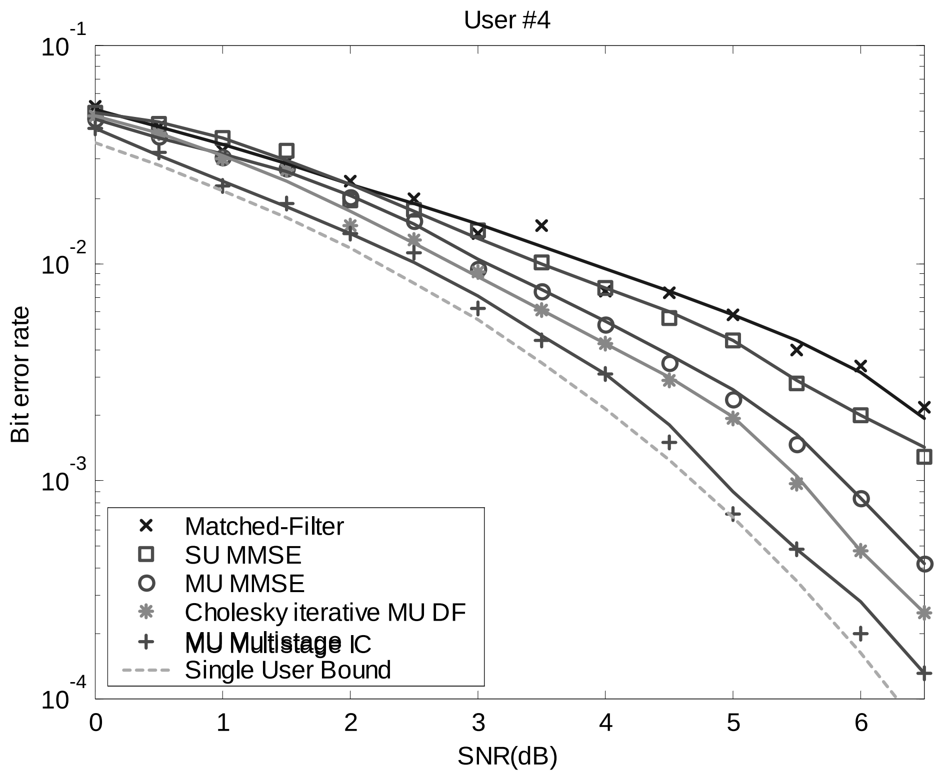
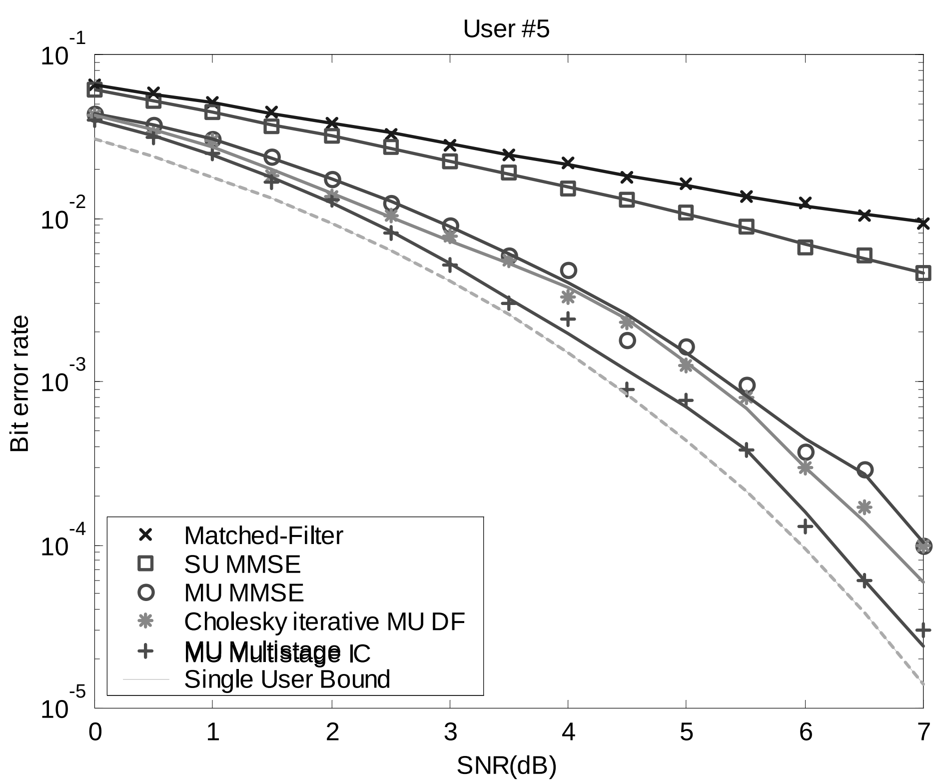


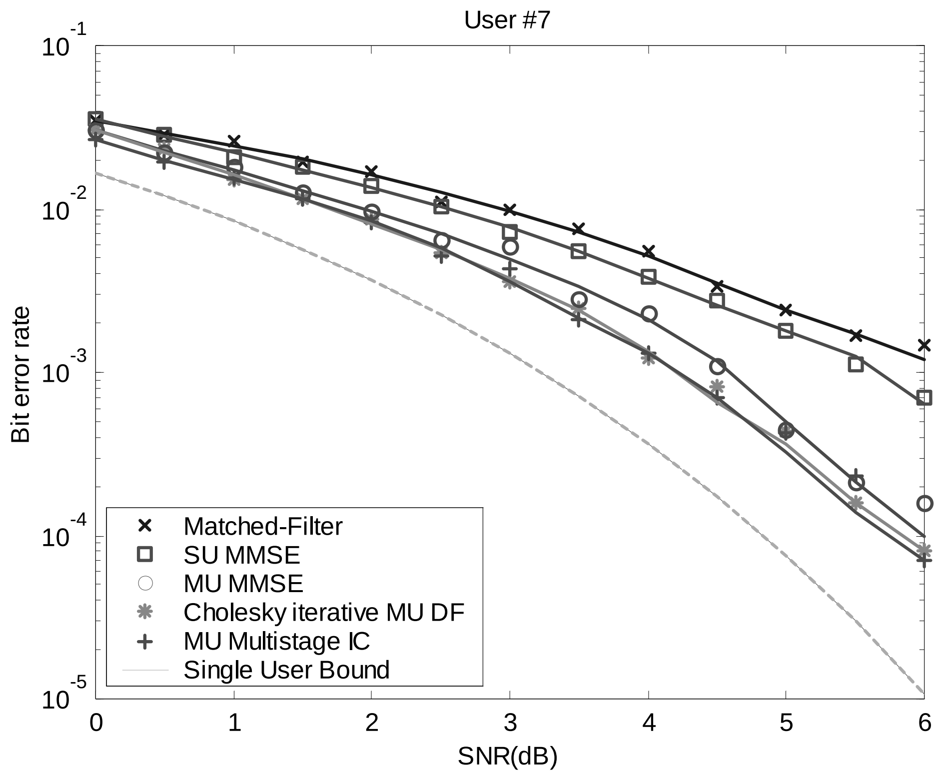
Fig. 3 A new space-time multiuser receiver structure


User #4
Bit error rate
SNR(dB)
Matched-Filter
SU MMSE
MU MMSE
Cholesky iterative MU DF
MU Multistage IC
Single User Bound

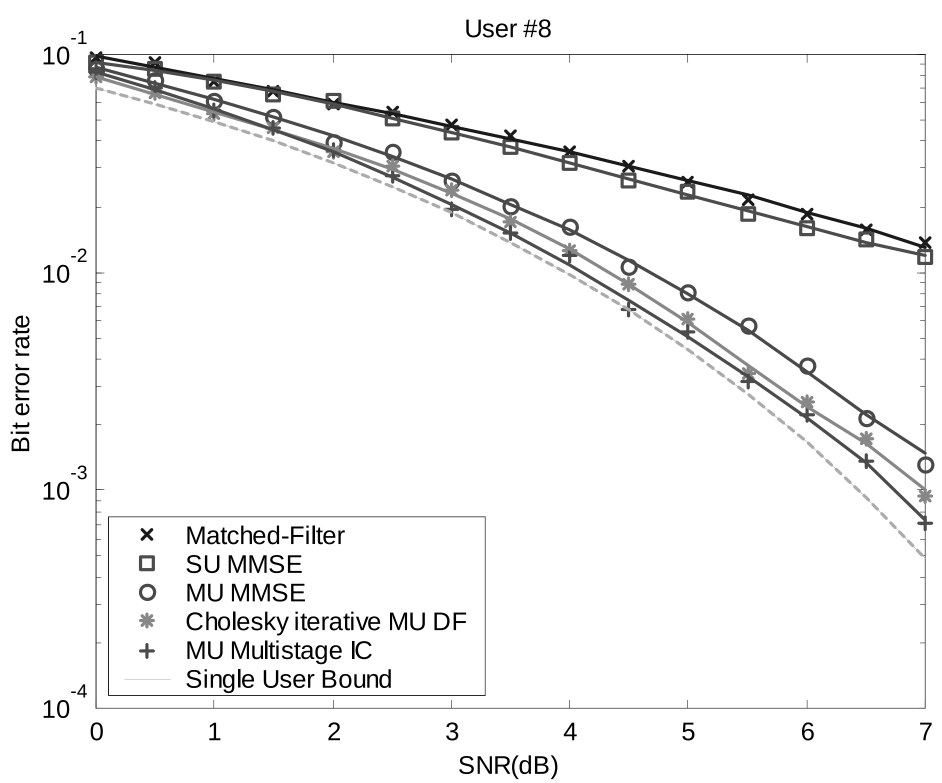
(a)


User #5
Bit error rate
SNR(dB)
Matched-Filter
SU MMSE
MU MMSE
Cholesky iterative MU DF
MU Multistage IC
Single User Bound

(b)

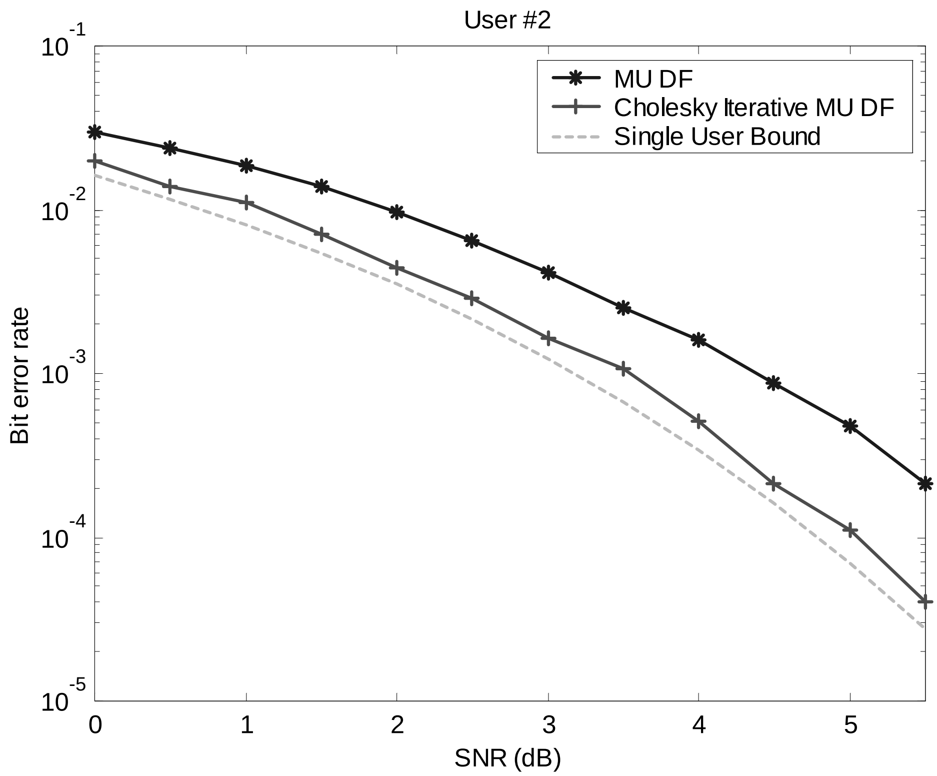


(c)

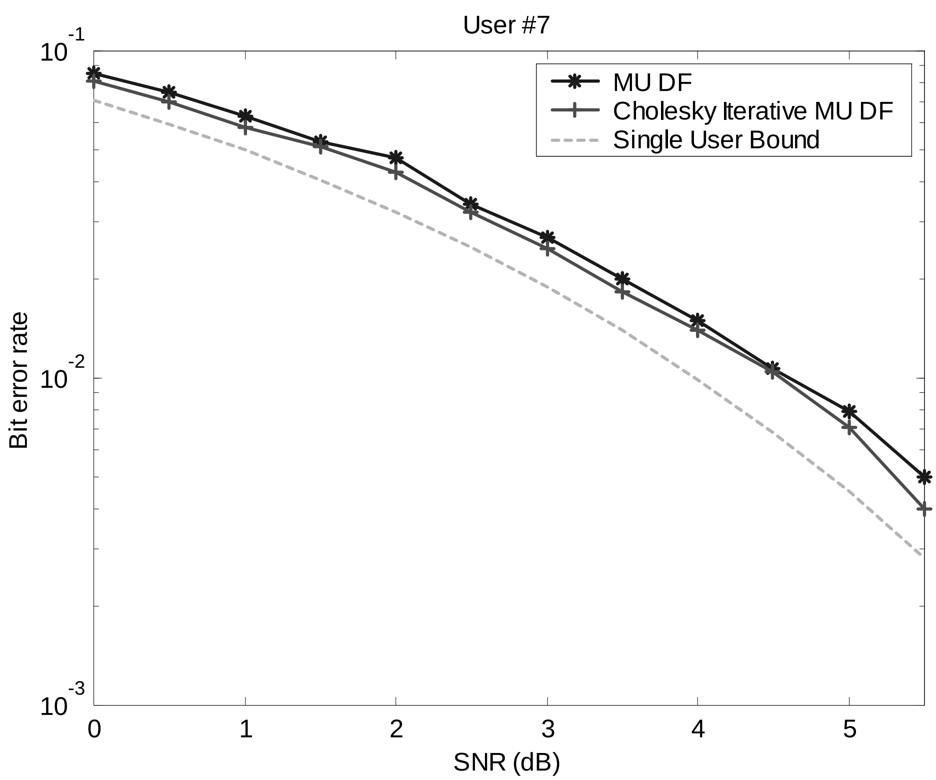


(d)

Fig. 4 Performance comparison of BER versus SNR for five space-time multiuser receivers

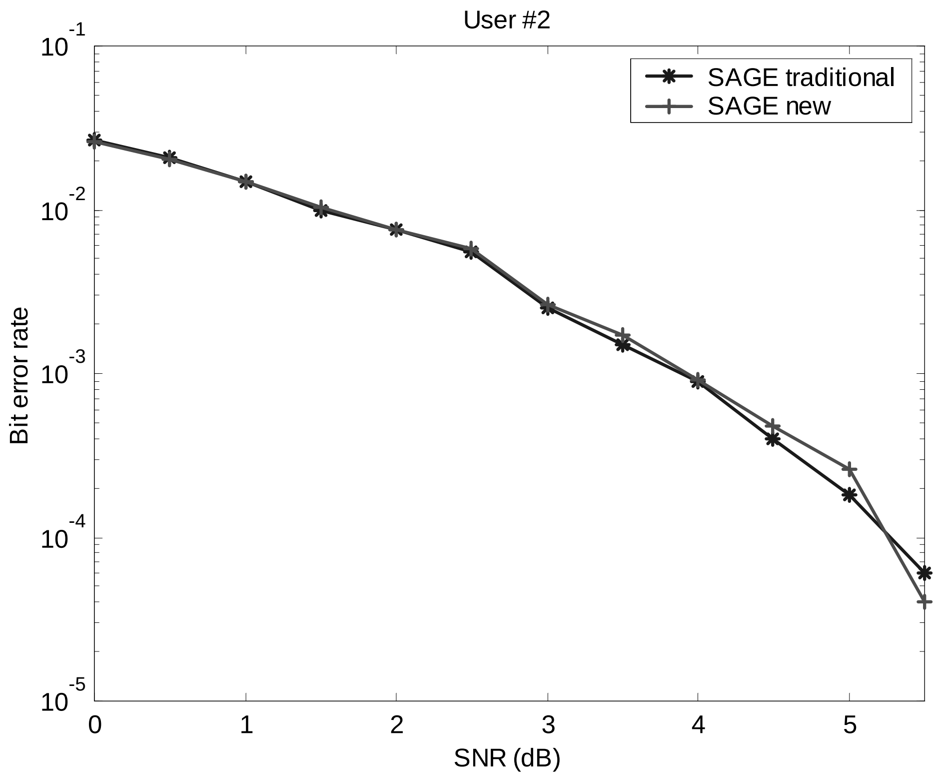


(a)



(b)

Fig. 5 Performance comparison of decision-feedback ST MUD and Cholesky iterative ST MUD



(a)

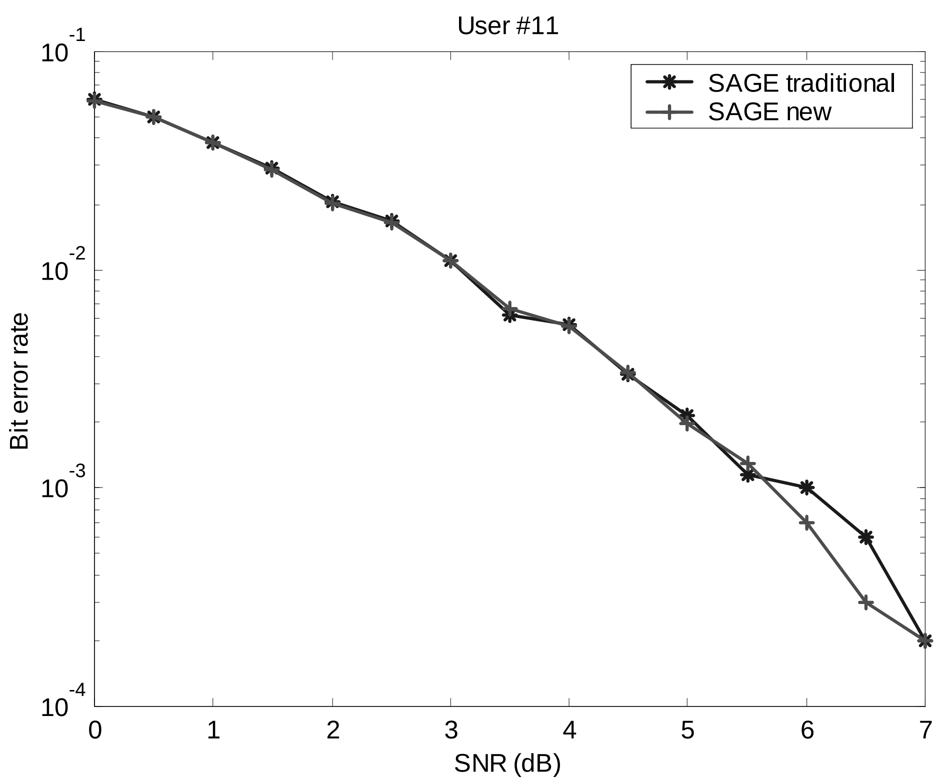
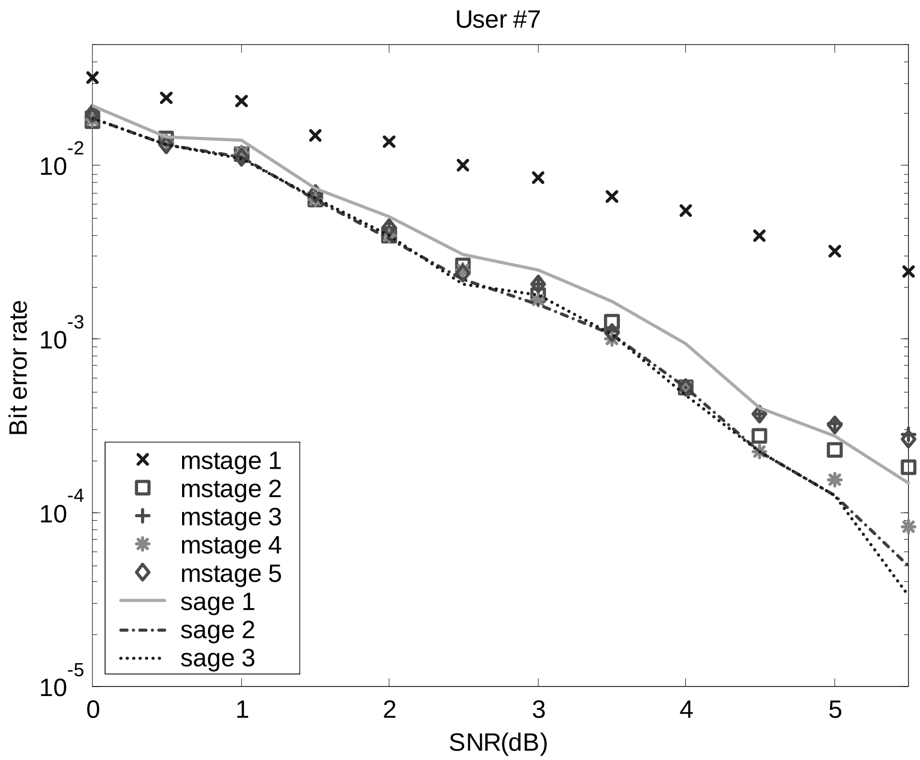
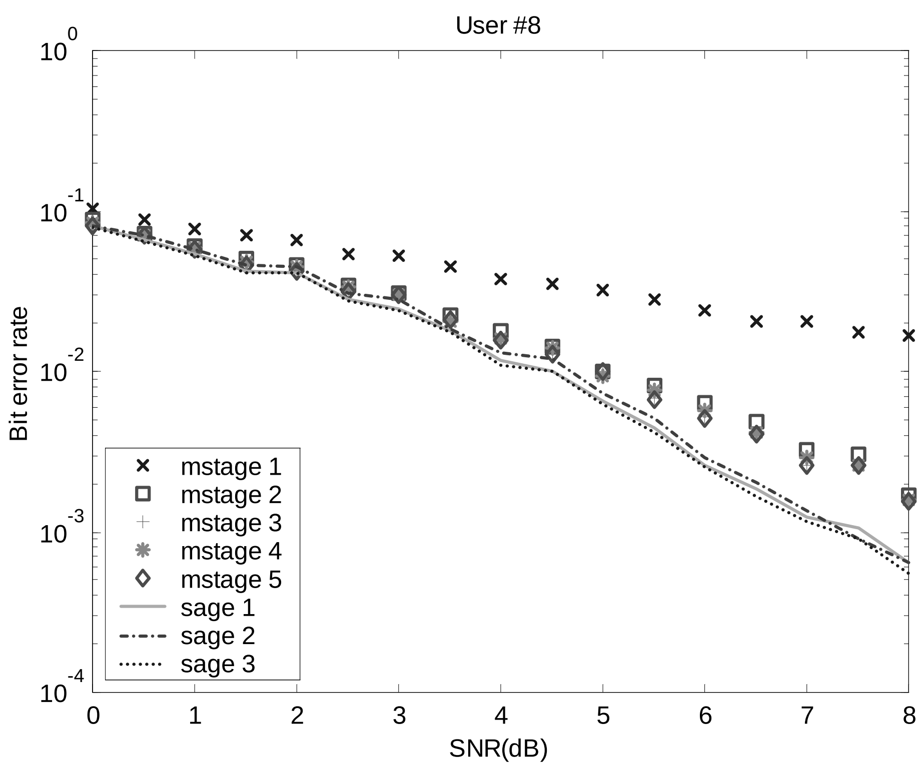


Fig. 6 Performance comparison of SAGE ST MUD with traditional and new ST structure



(a)



(b)

Fig. 7 Performance comparison of convergence behavior of multistage interference cancelling ST MUD and EM-based iterative ST MUD