Blind Multiuser Detection for Frequency-Selective Fading CDMA Channels

X. F. Wang, W.-S. Lu, and A. Antoniou

Department of Electrical and Computer Engineering
University of Victoria
Victoria, B.C., CANADA, V8W 3P6
Email: {xfwang, wslu, andreas}@ece.uvic.ca

Abstract— Linear multiuser detectors for freqency-selective fading CDMA channels are examined within the context of multidimensional adaptive filtering. A blind adaptive multiuser detector, which can suppress multiple-access interference and achieve multipath diversity gain simultaneously, is then proposed. A channel estimator (carrier recovery) for a coherent diversity combining is also presented. The only information required by the proposed detector is the signature and timing of the user of interest. It is shown that the proposed detector outperforms the decorrelating solution and is comparable to the minimum mean-squared-error solution even though the later two require more information.

I. Introduction

The capacity of direct-sequence code-division multiple-access (DS-CDMA) systems is primarily limited by the near-far problem. This has motivated considerable effort to develop near-far resistant multiuser detectors. In particular, for the reverse link (i.e., mobile-to-base), the optimal multiuser detector [1] and various suboptimal multiuser detectors [2-4] were proposed to jointly recover the user signals. These centralized multiuser detectors require information about the signature signals, timing, and sometimes received amplitudes of all active users. For the forward link, however, often the information of interfering users is *not* available at mobile units, which precludes the use of centralized multiuser detectors. Recently, attempts have been made to develop adaptive multiuser detectors to eliminate the need for information about interfering users. A popular adaptive multiuser detector is the minimum mean-squared-error (MMSE) detector which minimizes the mean-squared error (MSE) between the outputs of the detector and the transmitted information data [5-6]. In [7], it was shown that minimizing the output energy of a linear detector under the constraint that the energy of the desired user is maintained is equivalent to minimizing the MSE. A blind adaptive detector, namely, the minimum mean-output-energy (MOE) detector, was then derived to further eliminate the need for training sequences. This blind adaptation mechanism is of particular importance for fading channels where frequent retraining is required by an adaptive detector.

In spite of considerable research effort on multiuser detection, little progress has been made on the development of adaptive multiuser detectors for fading channels. In [8], the MMSE multiuser detector was considered in a flat fading channel. Since the signal bandwidth in mobile radio and indoor DS-CDMA channels is larger than the coherent bandwidth of the channels, practical multiuser detection should also consider *frequency-selective* fading channels. To combat multipath fading, the RAKE receiver is employed in conventional DS-CDMA systems. Like the conventional matched-filter receiver (MFR) for additive white Gaussian noise (AGWN) channels, the RAKE receiver suffers from near-far effects in the presence of multiple-access interference (MAI) [9].

Apparently, a possible way to obtain a near-far resistant diversity receiver for multipath channels is to employ a RAKE structure where each finger is an MMSE adaptive filter instead of a matched filter. As will be shown in the paper, this MMSE solution requires information about the channel coefficients which may not be available at the mobile receiver even during the training period. Furthermore, minimizing the MOE is not equivalent to minimizing the MSE and hence the minimum MOE detector is not applicable. This observation motivates us to develop a new blind multiuser detector for frequency-selective fading channels, which will be referred to as the blind multipath (BM) detector. The proposed BM detector consists of a bank of blind adaptive filters with each adaptor anchored on a designated signal corresponding to a resolvable path. The blind adaptors require only information about the signature signal and timing of the desired user. Following each adaptor, a channel estimator is used to estimate the channel coefficients. This channel estimator essentially resembles the carrier recovery technique for the single-user systems proposed in [11], which was found to be more robust than the conventional phase-locked loop. Having estimated the channel coefficients, a diversity combiner can then be employed to demodulate the data bits coherently and hence achieve frequency diversity gain. The performance of the BM detector is between those of the decorrelating detector and the MMSE detector. Note however that either the decorrelating detector or the MMSE detector requires information that may not be available in practice. Simulation results are included to demonstrate the performance of the proposed detector.

II. System Model

Consider binary-phase-shift-keying (BPSK) transmission through a frequency-selective multipath fading channel shared by K users in a DS-CDMA system. Since a multiuser detector for synchronous systems can always be extended to asynchronous systems [7], the system is assumed synchronous for the sake of clarity of analysis. The channel for the kth user can be modeled as a discrete wide-sense stationary uncorrelated scattering (WSSUS) channel. Let the number of resolvable paths be $L = W * T_m + 1$, where W and T_m with $W \gg 1/T_m$ are the signal bandwidth and multipath spread, respectively. The impulse response of the channel is given by

$$c_k(\tau, t) = \sum_{l=1}^{L} c_{k,l}(t)\delta[\tau - (l-1)/W] \quad (1)$$

where the channel coefficients $c_{i,n}(t)$ are mutually uncorrelated, each of which is a complex-valued stationary random process [11]. Assuming that the channel coefficients are constant during one transmission interval, a channel coefficient vector for the kth user at the nth transmission interval can be defined as $\mathbf{c}_k(n) = [c_{k,1}(n)\ c_{k,2}(n)\ \cdots\ c_{k,L}(n)]^T$. Without loss of generality, we assume that the desired user is user 1. At the receiver, the received baseband signal during the nth transmission interval of user 1 is of the form

$$r_n(t) = \sum_{k=1}^{K} A_k b_k(n) \sum_{l=1}^{L} c_{k,l}(n) s_k[t-(l-1)/W] + n(t) \quad (2)$$

where A_k, $b_k(n)$, $s_k(t)$ denote the amplitude, the nth bit, and the normalized signature signal of user k, respectively, and $n(t)$ is complex AWGN of zero mean and power spectral density N_0. In (2) we have neglected the intersymbol interference (ISI) since the symbol duration T is usually much larger than T_m. If we denote the critically sampled versions of $s_k(t)$, $r_n(t)$, and $n(t)$ by N-dimensional column vectors $\mathbf{s}_k$, $\mathbf{r}(n)$, and $\mathbf{n}$, respectively, then (2) can be expressed as

$$\mathbf{r}(n) = A_1 b_1(n) \mathbf{S}_1 \mathbf{c}_1(n) + \hat{\mathbf{S}}_2(n) \mathbf{b}_2(n) + \mathbf{n} \quad (3)$$

where

$$\begin{aligned} \hat{\mathbf{S}}_2(n) &= [\mathbf{S}_2\mathbf{c}_2(n)\ \cdots\ \mathbf{S}_K\mathbf{c}_K(n)] \\ \mathbf{b}_2(n) &= [A_2 b_2(n)\ \cdots\ A_K b_K(n)]^T \end{aligned}$$

$\mathbf{S}_k$ is an $N \times L$ Toeplitz matrix whose first column is $\mathbf{s}_k$ and first row is $[s_k(1)\ 0\ \cdots 0]$, and $\mathbf{n}$ is a complex AWGN vector of zero mean and covariance $N_0\mathbf{I}$.

III. Linear Detection for Multipath Channels

In this section, we examine two popular linear multiuser detectors, namely, the decorrelating detector and the MMSE detector from a linear filtering point of view. A linear multiuser detector can be viewed as a linear time-dependent filter followed by a sampler which samples the output of the filter at $t = nT$. For multipath channels, we treat each path signal $\{c_{1,l}(n)b_1(n)\}$ as a bit stream and employ an individual multiuser detector for its detection. Since the ISI can be ignored in this case, the filter for the lth bit stream is an FIR filter of length N. The coefficient vector of the filter, $\mathbf{w}_l(n)$, can be expressed as the sum of a vector in the space spanned by the columns of $\mathbf{S}_1$ and a vector orthogonal to the space, i.e.,

$$\mathbf{w}_l(n) = \mathbf{S}_1 \mathbf{u}_l(n) + \mathbf{x}_l(n) \quad (4)$$

subject to

$$\mathbf{x}_l^H(n)\mathbf{S}_1 = \mathbf{0} \quad (5)$$

where $\mathbf{u}_l(n)$ is a complex weighting vector of length L, and $\mathbf{x}_l(n)$ is a complex steering vector of length N. From (3) and (4), the output of the sampler at $t = nT$ can then be expressed as

$$\begin{aligned} \mathbf{w}_l^H(n)\mathbf{r} &= \mathbf{u}_l^H(n)\mathbf{R}_1\mathbf{c}_1(n)b_1(n) + \mathbf{u}_l^H(n)\mathbf{R}_{12}(n)\mathbf{b}_2(n) \\ &+ \mathbf{u}_l^H(n)\mathbf{S}_1^H\mathbf{n} + \mathbf{x}_l^H(n)\hat{\mathbf{S}}_2(n)\mathbf{b}_2(n) + \mathbf{x}_l^H(n)\mathbf{n} \quad (6) \end{aligned}$$

where $\mathbf{R}_1 = \mathbf{S}_1^T\mathbf{S}_1$ and $\mathbf{R}_{12}(n) = \mathbf{S}_1^T\hat{\mathbf{S}}_2(n)$.

The decorrelating detector seeks to completely eliminate MAI regardless of the presence of background noise. This so-called zero-forcing (ZF) solution can be achieved if the equations

$$\begin{aligned} \mathbf{u}_l^H(n)\mathbf{R}_1\mathbf{c}_1(n) &= c_{1,l}(n) \quad (7) \\ \mathbf{u}_l^H(n)\mathbf{R}_{12}(n) + \mathbf{x}_l^H(n)\hat{\mathbf{S}}_2(n) &= \mathbf{0} \quad (8) \end{aligned}$$

are satisfied subject to the constraint in (5). If we introduce the projection operator

$$\mathbf{P} = \mathbf{I} - \mathbf{S}_1\mathbf{R}_1^{-1}\mathbf{S}_1^T \quad (9)$$

which projects a vector onto the null space of $\mathbf{S}_1^T$, a solution of (7) and (8) constrained by (5) can then be expressed as

$$\begin{aligned} \mathbf{u}_l &= \mathbf{R}_1^{-1}\mathbf{e}_l \quad (10) \\ \mathbf{x}_l(n) &= \mathbf{P}\hat{\mathbf{S}}_2(n)\Delta_1^{-1}\mathbf{R}_{12}^H(n)\mathbf{R}_1^{-1}\mathbf{e}_l \quad (11) \end{aligned}$$

where

$$\Delta_1 = \mathbf{R}_{12}(n)\mathbf{R}_1^{-1}\mathbf{R}_{12}^H(n) - \mathbf{R}_2(n)^{-1} \quad (12)$$

$\mathbf{R}_2(n) = \hat{\mathbf{S}}_2^H(n)\hat{\mathbf{S}}_2(n)$, and $\mathbf{e}_l$ is the lth coordinate vector. Note that in (10), the time index n in $\mathbf{u}_l(n)$ is omitted since the latter is constant over n. Clearly, in order to implement the above decorrelating filter, knowledge of the signature signals and the channel coefficients of all users is required. By (6), the variance of the output noise is given by

$$V_l = N_0\mathbf{e}_l^T(\mathbf{R}_1 - \mathbf{R}_{12}(n)\mathbf{R}_2(n)^{-1}\mathbf{R}_{12}^H(n))^{-1}\mathbf{e}_l \geq N_0 \quad (13)$$

which shows that the ZF solution is obtained at the cost of an increase in noise power.

In contrast to the decorrelating detector, the MMSE detector seeks to maximize the signal-to-interference-plus-noise ratio (SINR). For the lth path, this is achieved by minimizing the MSE

$$\begin{aligned} E[|c_{1,l}(n)b_1(n) - \langle \mathbf{r}(n), \mathbf{w}_l(n)\rangle|^2] &= \\ |c_{1,l}(n)|^2 - 2\mathrm{Re}\{E[c_{1,l}(n)^* b_1(n)\langle \mathbf{r}(n), \mathbf{w}_l(n)\rangle]\} & \\ + E[|\langle \mathbf{r}(n), \mathbf{w}_l(n)\rangle|^2] & \quad (14) \end{aligned}$$

where E is the expectation operation. Solving the above equation, the minimum MSE is found to be

$$\xi_l^{\min}(n) = \frac{N_0|c_{1,l}(n)|^2}{N_0 + \mathbf{c}_1^H(n)\Delta_2\mathbf{c}_1(n)} \quad (15)$$

where

$$\Delta_2 = \mathbf{R}_1 + \mathbf{R}_{12}(n)[\mathbf{R}_2(n) + N_0\mathbf{I}]^{-1}\mathbf{R}_{12}^H(n) \quad (16)$$

Unlike the MMSE detection for AWGN channels, the value of the second term in the right-hand side of (14) depends on $\mathbf{w}_l(n)$. Hence, minimizing the MOE is not equivalent to minimizing the MSE and the minimum MOE detector is not applicable for multipath channels.

IV. BM Multiuser Detection

A. Closed-Form Solution

In order to derive a linear multiuser detector which allows blind adaptation, we make a compromise by fixing the weighting vector $\mathbf{u}_l$ as that given in (10) and optimizing $\mathbf{x}_l(n)$ such that the SINR at the output of the filter is maximized. By doing so, a new detector named the BM detector is obtained. Substituting (10) into (6), we have

$$E[c_{1,l}^*(n)b_1(n)\langle \mathbf{r}(n), \mathbf{w}_l(n)\rangle] = 2|c_{1,l}(n)|^2 \quad (17)$$

Hence, minimizing (14) subject to (5) and (10) is equivalent to minimizing

$$E[|\langle \mathbf{r}(n), \mathbf{w}_l(n)\rangle|^2] = E[|\langle \mathbf{r}(n), \mathbf{R}_1^{-1}\mathbf{e}_l + \mathbf{x}_l(n)\rangle|^2] \quad (18)$$

The minimizer $\mathbf{w}_l(n)$ of (18) can be obtained as

$$\bar{\mathbf{w}}_l(n) = \mathbf{\Gamma}(n)^{-1}\mathbf{S}_1(\mathbf{S}_1^T\mathbf{\Gamma}(n)^{-1}\mathbf{S}_1)^{-1}\mathbf{e}_l \quad (19)$$

by using the Lagrange multipliers, where $\mathbf{\Gamma}(n) = E[\mathbf{r}(n)\mathbf{r}^H(n)]$. The MOE of the adaptive filter is then given by

$$\begin{aligned} M_l(n) &= E[|\langle \mathbf{r}(n), \bar{\mathbf{w}}_l(n)\rangle|^2] \\ &= \mathbf{e}_l^T(\mathbf{S}_1^T\mathbf{\Gamma}(n)^{-1}\mathbf{S}_1)^{-1}\mathbf{e}_l \end{aligned} \quad (20)$$

On comparing the BM detector with the decorrelating and the MMSE detectors, we have the following propositions:

Proposition 1: The output SINR of the BM detector is lower than or equal to the output SINR of the MMSE, but is higher than the output signal-to-noise ratio (SNR) of the decorrelating detector.

Proof: The BM detector is obtained as a suboptimal solution of (14) and hence its output SINR could not be higher than that of the MMSE. At the output of the decorrelating detector, only the variance of AWGN, which is given by (13), needs to be considered since there is no MAI. Substituting (17) and (20) into (14), we obtain the MSE at the output of the BM detector as

$$J_l^{\min} = N_0\mathbf{e}_l^T\{\mathbf{R}_1 - \mathbf{R}_{12}(n)[\mathbf{R}_2(n)+N_0\mathbf{I}]^{-1}\mathbf{R}_{12}^H(n)\}^{-1}\mathbf{e}_l \quad (21)$$

Comparing (13) with (21), we can see that the MSE at the output of the BM detector is smaller than the average energy of the output noise of the decorrelating detector. This proves the proposition. ∎

Proposition 2: Both the decorrelating detector and the BM detector converge to the MMSE detector as the background noise vanishes ($N_0 \to 0$).

We conclude this section with some comments on the implementation of the BM detector. First, if the fading is sufficiently slow, by (18) a blind MOE adaptor can be used to adaptively search for the optimal filter coefficients. Further, if the SINR at the output of the adaptor is sufficiently high, a channel estimator can be employed to estimate the channel coefficients adaptively. Using this estimated channel coefficients, a maximum-ratio combiner (MRC) can then be applied to achieve the optimal diversity gain.

The structure of the BM detector is illustrated in Fig. 1.

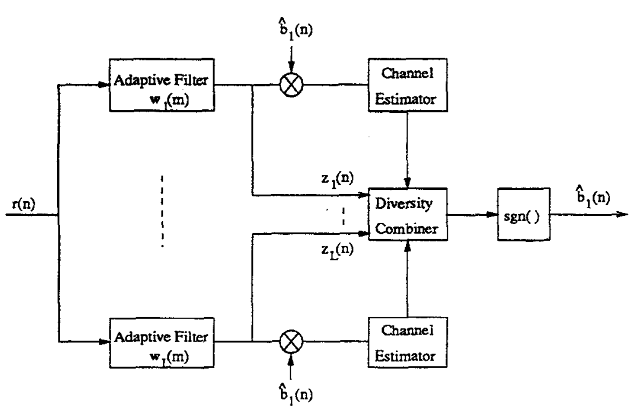

Fig. 1. Block diagram of the proposed blind multipath receiver.

B. Blind Adaptation

In order to obtain an adaptation rule, we extend the stochastic gradient algorithm proposed in [7] to the problem at hand. For the lth path data, the adaptation rule can be obtained from (18) as

$$\begin{aligned} z_l(n) &= \mathbf{w}_l^H(n-1)\mathbf{r}(n) \quad &(22) \\ \mathbf{w}_l(n) &= \mathbf{w}_l(n-1) - \mu\mathbf{P}\mathbf{r}(n)z_l^*(n) \quad &(23) \end{aligned}$$

where μ is the step-size parameter controlling the adaptation speed and stability of the adaptive filter. Since $\mathbf{w}_l(n)$ is not equal to $\bar{\mathbf{w}}_l(n)$ in general, the MSE of the adaptor is no longer given by (21).

In what follows, we examine the behavior of this blind adaptor. To simplify the analysis, assume that the channel is time invariant. Thus, $\mathbf{\Gamma}(n)$ and $\bar{\mathbf{w}}_l(n)$ are independent of n so that we can drop the time index n in them. Defining the coefficient error as

$$\varepsilon_l(n) = \mathbf{w}_l(n) - \bar{\mathbf{w}}_l \quad (24)$$

the MSE of the blind adaptor can be expressed as

$$J_l(n) = J_l^{\min} + J_l^{ex}(n) \quad (25)$$

where

$$J_l^{ex}(n) = \varepsilon_l(n)^H\mathbf{\Gamma}\varepsilon_l(n) \quad (26)$$

Since $\mathbf{P}\varepsilon_l(n) = \varepsilon_l(n)$, (26) leads to

$$\begin{aligned} E[J_l^{ex}(n)] &= E[\varepsilon_l(n)^H\mathbf{P}\mathbf{\Gamma}\mathbf{P}\varepsilon_l(n)] \\ &= \mathrm{tr}\{\mathbf{P}\mathbf{\Gamma}\mathbf{P}E[\varepsilon_l(n)^H\varepsilon_l(n)]\} \end{aligned} \quad (27)$$

where tr stands for the matrix trace. Now a coordinate rotation operator $\mathbf{Q}^H$ can be defined by means of taking the singular value decomposition of $\mathbf{P\Gamma P}$, i.e,

$$\mathbf{P\Gamma P} = \mathbf{Q\Lambda Q}^H \quad (28)$$

where $\mathbf{Q}$ is unitary and $\mathbf{\Lambda}$ is a diagonal matrix whose diagonal entries are the eigenvalues of $\mathbf{P\Gamma P}$. Defining the covariance matrix of the rotated coefficient error as

$$\mathbf{K}_l(n) = E[\mathbf{Q}^H\varepsilon_l(n)^H\varepsilon_l(n)\mathbf{Q}] \quad (29)$$

we obtain

$$E[J_l^{ex}(n)] = \mathrm{tr}[\mathbf{\Lambda}\mathbf{K}_l(n)] \quad (30)$$

It can be shown that

$$\begin{aligned} \mathbf{K}_l(n+1) \approx\ & \mathbf{K}_l(n) + \mu^2\mathbf{\Lambda}\mathrm{tr}[\mathbf{\Lambda}\mathbf{K}_l(n)] - \mu\mathbf{K}_l(n)\mathbf{\Lambda} \\ & -\mu\mathbf{\Lambda}\mathbf{K}_l(n) + \mu^2 M_l\mathbf{\Lambda} \end{aligned} \quad (31)$$

Let $d_i(n)$ be the ith diagonal entry of $\mathbf{K}_l(n)$ and define

$$\mathbf{d}(n) = [d_1(n) \ \cdots \ d_N(n)]^T \quad (32)$$

Then (31) implies that

$$\mathbf{d}(n) = \mathbf{B}\mathbf{d}(n) + \mu^2 \mathrm{M}_l\boldsymbol{\lambda} \quad (33)$$

where

$$\begin{aligned} \mathbf{B} &= \mathbf{I} + \mu^2\boldsymbol{\lambda}\boldsymbol{\lambda}^T - 2\mu\mathbf{\Lambda} \quad &(34) \\ \boldsymbol{\lambda} &= \mathrm{diag}\ \mathbf{\Lambda} \quad &(35) \end{aligned}$$

Since the difference equation (33) is exactly the same as that for the conventional least-mean-square (LMS) algorithm, it follows from [12] that the adaptive filter described in (22) and (23) is convergent in the mean square if and only if

$$0 < \mu < \frac{2}{\mathrm{tr}(\mathbf{\Lambda})} \tag{36}$$

Notice that $\mathrm{tr}(\mathbf{\Lambda})$ is equal to $\mathrm{tr}(\mathbf{P\Gamma P})$, which is the total energy of the input signal at the null space of $\mathbf{S}_1^T$. This result is clearly different from that obtained in [7]. The steady-state excess MSE can be derived as

$$J_l^{ex}(\infty) = \frac{\mu M_l}{2 - \mu \mathrm{tr}(\mathbf{\Lambda})} \tag{37}$$

Let us now compare this blind adaptation algorithm to the conventional decision-directed LMS algorithm. Recall that the steady-state MSE of the LMS algorithm is given by

$$\xi_l = \xi_l^{\min} + \xi_l^{ex} \tag{38}$$

where ξ_l^{ex} is the steady-state excess MSE of the LMS algorithm which is given by

$$\xi_l^{ex} = \frac{\mu \xi_l^{\min}}{2 - \mu \mathrm{tr}(\mathbf{\Gamma})} \tag{39}$$

When the user signature signals are nearly orthogonal as is often encountered in practice, $\xi_l^{\min}$ can be accurately approximated by $J_l^{\min}$. Since M_l is usually much larger than $J_l^{\min}$, by (37) and (39) the blind adaptation algorithm is noisier as compared with the LMS algorithm. However, if μ is small, the values of ξ_l and J_l will be dominated by the first terms in the right-hand sides of (25) and (38), respectively, and their difference will be small. Notice that the results stated in (38) and (39) for the LMS algorithm were obtained under the assumption of perfect decision feedback. In practice, the performance of the LMS algorithm can be even worse than that of the blind adaptation algorithm due to the possibility of incorrect decision feedback. In summary, if the fading is slow such that a small μ is preferred, the blind adaptation algorithm can be used throughout the data transmission; on the other hand, if a large μ has to be used, the adaptive filter should switch from blind mode to decision-directed mode once the filter is close to its steady state.

C. Channel Estimation and Diversity Reception

The use of a channel estimator is motivated by the potential performance improvement of coherent combining as compared to noncoherent combining. Since the output of the adaptive filter can be fairly approximated as Gaussian [9], the techniques used for channel estimation in single user systems can also be used here. When the fading processes are Markov processes, the optimal channel estimator is a Kalman filter. Under the assumption that the fading process is wide-sense stationary, an MMSE estimator, which is asymptotically equivalent to the Kalman filter, can be used for each path independently. Let the autocorrelation function of the lth fading process be $R_c(\tau)$. The coefficients of a pth-order MMSE estimator can be derived as

$$\mathbf{a} = (A_1^2 \mathbf{R}_c + J_l^{\min} \mathbf{I})^{-1} A_1 \mathbf{v} \tag{40}$$

where $\mathbf{R}_c$ is a $p \times p$ matrix with the (i,j)th entry as

$$\mathbf{R}_c(i,j) = R_c(iT - jT) \tag{41}$$

and $\mathbf{v}$ is a vector of length p whose ith entry is $v_i = R_c(-iT)$. The channel coefficients at time n can then be estimated as

$$\hat{c}_{1,l}(n) = \sum_{i=1}^{p} \mathbf{a}_i \tilde{c}_{1,l}(n-p) \tag{42}$$

where $\tilde{c}_{1,l}(n) = \hat{b}_1(n) z_l(n)$ is the estimate of $c_{1,l}(n)$ by using the decision feedback $\hat{b}_1(n)$. The MSE of this estimator is given by

$$P_l = R_c(0) - \mathbf{v}^H \mathbf{a} \tag{43}$$

For the WSSUS model, the autocorrelation function of the fading process is given by

$$R_c(\tau) = \frac{1}{2} E[|c_{1,l}|^2] J_0(2\pi f_d \tau) \tag{44}$$

where f_d is the Doppler shift and J_0 is the zeroth-order Bessel function of the first kind. The order of the estimator can be determined by examining the singular values of the corresponding $\mathbf{R}_c$. It was found that an order of 2 or 3 is usually sufficient.

Having estimated the channel coefficients, an MRC can then be applied, i.e.,

$$\hat{b}_1(n) = \mathrm{sign}[\hat{\mathbf{c}}_1^H(n) \mathbf{R}_n \mathbf{z}(n)] \tag{45}$$

where $\mathbf{z}(n) = [z_1^*(n) \ \cdots \ z_L^*(n)]^H$, and $\mathbf{R}_n$ is the covariance matrix of noise at the output of L adaptive filters and can be estimated as $\mathrm{diag}[J_1^{\min} \ \cdots \ J_L^{\min}]$.

V. Numerical Examples

Extensive simulations have been conducted to study the behavior of the blind adaptation algorithm and evaluate the performance of the proposed detector. In all simulations, there were 9 interfering users, each had an energy 10 dB higher than the energy of the desired user; the signature signals with a rectangular chip waveform were selected from a family of 127-chip Gold code, and the Rayleigh fading channel was simulated by using the method proposed in [12].

As the first example, we compare the blind adaptation algorithm with the conventional LMS algorithm for time-invariant channels. Illustrated in Fig. 2 are learning curves for these two algorithms. The learning curves for the LMS algorithm were obtained under the assumption of perfect decision feedback. As is expected, the MSE of the LMS algorithm is always smaller than that of the blind adaptation algorithm; the difference of their MSE's is quite small when μ is small (i.e., $\mu/tr(\mathbf{\Gamma}) < 0.1$), and becomes significant when a large μ is used.

As the second example, we examine the performance of the proposed detector. Differentially encoded signaling was used in the simulation to eliminate the possible 180-degree phase ambiguity. The bit-error rate versus SNR of the proposed detector under two fading environments is shown in Fig. 3. In the first fading environment, all users were assumed to be moving at a speed of 96 km/hour which corresponds to a Doppler shift of $f_d = 80$ Hz; in the second fading environments, a speed of 20 km/hour ($f_d = 16$ Hz) was assumed. In order to clarify the effect of imperfect channel estimation, the performance of the proposed detector under the assumption of perfect channel estimation is also presented. As expected, the BER of the proposed detector is reduced as the user speed is reduced. The effect of imperfect channel estimation is also clear from the figure: Since the normalized variance of the channel estimation error will converge to the variance of the excitation noise of the Markov channel model as SNR increases, an error floor is imposed on the performance of the detector. For comparison, the performance of the MFR is also illustrated in the figure. As can be seen from the figure, even though the channel coefficients were assumed to be known to the MFR, its performance is still poor and does not increase too much as the SNR increases since the performance of the MFR is MAI limited.

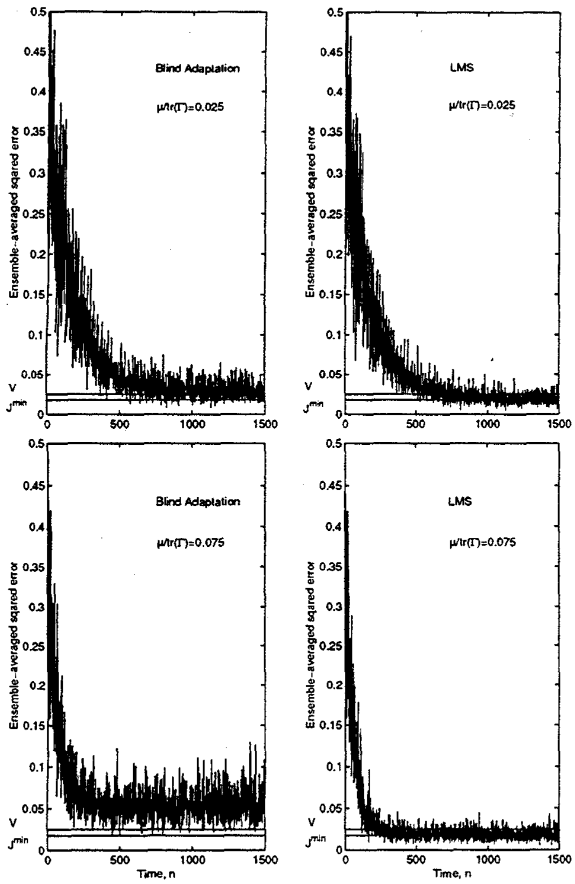

Fig. 2. Learning curves for the blind adaptation algorithm and the LMS algorithm for multiuser detection in static frequency-selective fading channels, where $J^{min} = \sum_{l=1}^{L} J_l^{min}$, and $V = \sum_{l=1}^{L} V_l$.

VI. Conclusion

We have shown that for frequency-selective fading channels, both the decorrelating detector and the MMSE detector require information that may not be available at the mobile receiver. Motivated by this observation, we have proposed a new linear multiuser detector which requires only information about the signature and timing of the desired user. This new detector can be adapted blindly and its performance is comparable to those of the decorrelating detector and the MMSE detector. A study of the output MSE and the stability condition of the blind adaptation rule has been conducted to clarify several implementation issues. A robust channel estimator has also been presented to achieve a coherent diversity combining.

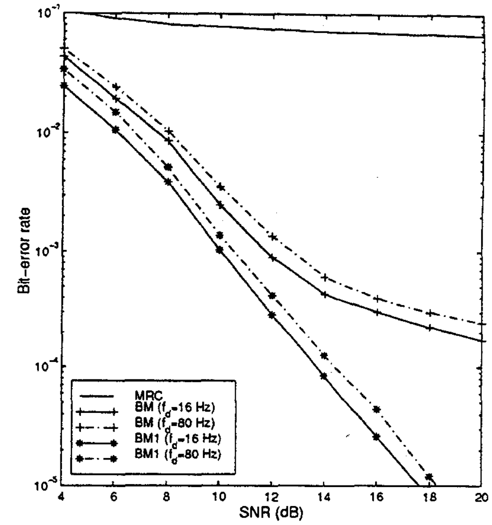

Fig. 3. BER of user 1 versus SNR in frequency-selective Rayleigh fading channels, where "BM1" stands for the proposed detector with perfect channel estimation, and the SNR is defined as $A_1^2 * tr(E[\mathbf{c}_1(n)\mathbf{c}_1^H(n)])/N_0$ (f_D = 80 Hz).

Acknowledgement

The authors would like to acknowledge Micronet, Networks of Centers of Excellence Program, for supporting this research.

References

[1] S. Verdú, "Minimum probability of error for asynchronous Gaussian multiple-access channels," *IEEE Trans. Inform. Theory*, vol. 32, pp. 85-96, Jan. 1986.

[2] R. Lupas and S. Verdú, "Near-far resistance of multiuser detectors in asynchronous channels," *IEEE Trans. Commun.*, pp. 725-736, April 1990.

[3] Z. Xie, R. T. Short, and C. K. Rushforth, "A family of suboptimum muti-user detectors," *IEEE JSAC*, vol. 8, pp. 683-90, May 1990.

[4] M. Varanasi and B. Aazhang, "Multi-stage detection in asynchronous code-division multiple-access communications, " *IEEE Trans. Commun.*, vol. 38, pp. 509-519, Apr. 1990.

[5] U. Madhow and M. Honig, "MMSE interference suppression for direct-sequence spread spectrum CDMA, " *IEEE Trans, Commun.*, vol. 42, pp. 3178-3188, Dec. 1994.

[6] S. L. Miller, "An adaptive direct-sequence code-division multiple-access receiver for multiuser interference rejection," *IEEE Trans, Commun.*, vol. 43, pp. 1746-1754, Feb./March/April. 1995.

[7] M. Honig, U. Madhow, and S. Verdú, "Blind adaptive multiuser detection," *IEEE. Trans. Inform. Theory.*, vol. 41, pp. 944-960, July, 1995.

[8] A. N. Barbosa and S. L. Miller, "Adaptive Detection of DS/CDMA signals in Fading Channels ," *IEEE. Trans. Commun.*, vol. 46. pp. 115-124, Jan. 1998.

[9] C. Kchao and G. Stüber, "Performance analysis of a single cell direct sequence mobile radio system," *IEEE Trans. Commun.*, vol. 41, pp. 1507-1516, Oct. 1993.

[10] J. G. Proakis, *Digital Communications*, 3rd ed., New York: McGraw-Hill, 1995.

[11] S. Haykin, *Adaptive Filter Theory,* Prentice-Hall, 1986.

[12] *JTC(AIR)/94.09.23-065R6.*