Blind Adaptive Minimum Output Energy Rake Receiver for DS/CDMA over Multipath Fading Channels

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Abstract—**To achieve a better tracking of time-varying channel parameters, a structure using blind adaptive *minimum output energy* (MOE) detection in conjunction with a Rake combining diversity for direct-sequence code-division multiple-access (DS/CDMA) communications over the frequency selective multipath fading channels is introduced. In this MOE-RAKE structure, the signal replicas received from multiple fading paths are first independently produced by a bank of adaptive MOE detectors and then combined by a Rake receiver for final symbol decision. A normalized, complex-valued *stochastic gradient descent* (SGD) algorithm is developed for blind adaptation used in the MOE-RAKE. Simulation results show that, in the time-varying channel, the MOE-RAKE provides a better performance than the other blind multiuser detection techniques. In practice, to further improve the detector performance, a hybrid scheme started with blind adaptation for initial updates and then switched to the decision-directed algorithm is desired.**

I. Introduction

Many multiuser detection schemes assume the knowledge of the signature waveforms, timing information, and even received power of all the active users. Therefore, their applications can be limited in practice, especially in the forward link channel from the base station to the mobile users, where the mobile receivers know only the signature waveform and timing of the desired signal. In that situation, the *minimum mean square error* (MMSE) detection [1] has attracted a considerable attention and it can achieve the optimum resistance to the multiple-access interference (MAI). For this detector, a training sequence is usually needed and may require extra channel bandwidth and complicate the signaling. As an alternative solution to suppress the MAI without the aid of any training sequence, blind multiuser detectors [2, 3] have been proposed. In particular, [2] presented the blind minimum output energy (MOE) detector, for which a stochastic gradient descent (SGD) algorithm and a recursive lease square (RLS)-type algorithm were developed for blind adaptation. The MOE-SGD has a computational complexity of O(N), much lower than that of MOE-RLS which is O(N^2) where N is the length of the PN codes. On the other hand, the MOE-RLS has a faster convergence rate than the MOE-SGD. In [3], the subspace approach was developed for the multiuser detection and channel estimation. The *singular-value decomposition* (SVD) [4] and the *projection approximation subspace tracking with deflation* (PASTd) algorithms [5] were adopted for estimating the eigenvectors and eigenvalues of the signal subspace, and for developing the blind subspace MMSE (BS-MMSE), and decorrelating (BS-DECO) detectors. Compared with the MOE-RLS, the BS-MMSE is shown to have better performance and lower computational complexity [3]. Its computational complexity, by using the PASTd algorithm, is O(NK) where K is the number of active users and also represents the rank of the subspace. However, the low-complexity PASTd has a slow convergence rate and thus the complicated SVD is needed in the initial estimation as mentioned in [3]. Besides, the inaccurate estimation of the subspace may incur the performance degradation and the effect of errors has not yet been investigated in detail [6].

In this paper, we focus on the MOE-SGD for its low complexity and examine techniques to improve its performance in time-varying multipath fading channels. We consider a structure using a bank of L complex-valued MOE detectors to independently produce the signal replicas received from multiple paths, and a Rake combining diversity receiver to collect all these replicas for final symbol detection. In order to improve the convergence rate, a normalized, complex-valued SGD algorithm for weight adaptation is developed. The computational complexity for the L-diversity MOE-RAKE is O(NL), lower than those of the BS-MMSE [3] and MOE-RLS.

The performance of the introduced MOE-RAKE is studied by simulation in a multiuser system over a time-varying multipath fading channel. The results show that all the blind detectors and the decision-directed MMSE can outperform the conventional RAKE. In the presence of a large number of users, the MOE-RAKE is robust and outperforms other blind techniques and even the decision-directed MMSE with the normalized LMS (NLMS). Furthermore, for its fast convergence capability, the decision-directed MMSE-RLS has a better performance than the other MMSE and blind detectors. This suggests that, to improve the performance of the MOE-RAKE, it is desired to switch the blind adaptation to the decision-directed one after the initial updates.

II. System Description

Consider a *synchronous* DS/CDMA system with K active users over multipath fading channels. We assume that the channel has a large coherence time so that the fading parameter exhibits a slowly time-varying characteristic and over the several bit intervals could be treated as a constant. The received signal, after demodulation and being sampled at a chip rate ($1/T_c$), can be written as (within the n-th bit interval, $j = 0, 1, ..., N-1$)

$$\begin{aligned} V_{n,j} \quad = \quad & \sum_{k=1}^{K} A_k \sum_{l=1}^{L_f} \alpha_l \left[B_{j-m_l}^{(k)} a_{j-m_l}^{(k)} (T_c - \tau_l') \right. \\ & \left. + B_{j-m_l-1}^{(k)} a_{j-m_l-1}^{(k)} \tau_l' \right] + \eta_{n,j} \qquad (1) \end{aligned}$$

where $A_k := \sqrt{2\rho_k/(2N)}$ is the signal amplitude of user k. ρ_k is the normalized signal power and N the length of the PN codes. L_f is the number of fading paths. $\alpha_l(t)$ and τ_l are the fading parameter and time delay, respectively. $m_l := \lfloor \tau_l/T_c \rfloor$ and $\tau_l' := \tau_l - m_l T_c$. T_c is the chip interval and is set to 1 in the following. $B_j^{(k)}$ is the data bit, set to $b_{n+\lfloor j/N \rfloor}^{(k)}$. Here, $b_n^{(k)}$ is the n-th transmitted binary bit. $a_i^{(k)} = a_i^{(k),I} + j a_i^{(k),Q}$ is the complex-valued PN assigned to user k [7]. $\eta_{n,j}$ is the zero-mean Gaussian with unit variance.

It can be easily shown that (1) can be written as

$$V_{n,j} = \sum_{k=1}^{K} A_k \sum_{l=0}^{L_o-1} \beta_l B_{j-l}^{(k)} a_{j-l}^{(k)} + \eta_{n,j} \tag{2}$$

where $[\beta_0, \beta_1, ..., \beta_{L_o-1}]^T = \mathcal{F} \cdot [\alpha_1, \alpha_2, ..., \alpha_{L_f}]^T$. L_o is the maximum value of $m_l + 2$ over $l = 1, 2, ..., L_f$. $\mathcal{F}$ is an $L_o \times L_f$ transformation matrix which is constructed as follows. Letting $\mathcal{F}_{i,j}$ ($i = 0, 1, ..., L_o - 1$, $j = 1, 2, ..., L_f$) denote the ij-th entry of the matrix $\mathcal{F}$, we set $\mathcal{F}_{m_l,l} = T_c - \tau_l'$ and $\mathcal{F}_{m_l+1,l} = \tau_l'$ for all $l = 1, 2, ..., L_f$. The other elements in $\mathcal{F}$ are set to zero.

As indicated by (2), in the slowly time-varying environment, the original multipath fading model with arbitrary time delays $\{\tau_l\}$ can be approximated by a tapped delay line model with chip spacing. Such approximation may simplify the design of the receiver in the sense that the receiver needs not to resolve L_f paths of α_l with possibly arbitrary time spacing but to resolve L_o paths with pre-fixed time spacing (T_c). In the following, we will study the detector using the model of (2).

Using (2) and rewriting all $\{V_{n,j}, V_{n+1,j}\}$ that contain the data bit $b_n^{(1)}$ into a vector notation, we have

$$V(n) = \sum_{k=1}^{K} A_k b_n^{(k)} \ddot{S}_k + I(n) + \eta(n) \tag{3}$$

$$\ddot{S}_k = \sum_{l=0}^{L_o-1} \beta_l S_{k,l} \tag{4}$$

where $V(n)$ is the received signal vector. Due to the multipath propagation, $V(n)$ may contain the $(n-1)$-th, n-th, and $(n+1)$-th data bits for all users. $\ddot{S}_k$ is the composite PN code vector for user k [3], in which $S_{k,l}$ is the PN code vector in the l-th path. $I(n)$ denotes the intersymbol interference (ISI) part which consists of all the $(n-1)$-th and $(n+1)$-th data bits involved in $V(n)$, and $\eta(n)$ is the noise vector. We have

$$V(n) = [V_{n,0}, ..., V_{n,N-1}, \underbrace{V_{n+1,0}, ..., V_{n+1,L_o-2}}_{L_o-1}]^T \tag{5}$$

$$S_{k,l} = [\underbrace{0, ..., 0}_{l}, a_1^{(k)}, a_2^{(k)}, ..., a_N^{(k)}, \underbrace{0, 0, ..., 0}_{L_o-1-l}]^T \tag{6}$$

$$\eta(n) = [\eta_{n,0}, ..., \eta_{n,N-1}, \underbrace{\eta_{n+1,0}, ..., \eta_{n+1,L_o-2}}_{L_o-1}]^T \tag{7}$$

From the received signal vector $V(n)$, we now wish to design a receiver to determine the n-th transmitted data bit. In the literature, the MMSE [1] and blind detectors [2, 3] have been proposed. Besides, a multistage interference cancellation (MIC) scheme with diversity reception is also discussed in [7]. In this paper, however, we will focus on the blind minimum output energy (MOE) with the SGD [2] due to its low complexity. We will study the techniques to improve its performance in time-varying fading channels.

III. Minimum Output Energy Approach

The MOE approach tries to minimize, under a certain constraint, the output energy of the detector [2]. Specifically, suppose that the first user is the user of interest and its decision variable can be written as $< V(n), C_1 >$, where C_1 is the weight coefficients vector and $< \cdot, \cdot >$ denotes the inner product of two vectors. The vector C_1 can be expressed in the canonical form, i.e., $C_1 := \ddot{S}_1 + X_1$. Here the composite PN vector $\ddot{S}_1$ as defined in (4) is a basis vector and the component X_1 is orthogonal to $\ddot{S}_1$. Although [2] considered solely the real-valued signals and the single-path channel, the MOE criterion is also applicable to the complex-valued signals and the multipath channel. Here, by defining $C_1 := \ddot{S}_1^* + X_1^*$ ($*$ denotes the complex conjugate), the MOE criterion is [6]

$$minE\left[\left(< V(n), (\ddot{S}_1 + X_1)^* >\right)^2\right] \tag{8}$$

For the MOE detector, the information of $\ddot{S}_1$, or equivalently, the knowledge of the channel parameters, is required. Here, we assume that the receiver can resolve L ($L \leq L_o$) paths and define the estimate of $\ddot{S}_1$ as

$$\tilde{S}_1 = \sum_{l=0}^{L-1} \tilde{\beta}_l S_{1,l} \tag{9}$$

where $\tilde{\beta}_l$ is the estimate of the channel parameter β_l.

Two adaptation algorithms, namely the recursive least square (RLS) and stochastic gradient descent (SGD) can be used to adjust X_1. Although the MOE with the RLS has a fast convergence rate, its complexity is usually high. Hence, we will focus on the low complexity SGD.

A. MOE with complex-valued SGD (MOE-SGD)

The SGD adaptation for the real-valued signals is given by [2]. For the complex-valued signals, the resulting adaptation is

$$X_1(n+1) = (1-v)X_1(n) - \mu Z^*(n)(V(n) - Z_{MF}(n)\tilde{S}_1) \tag{10}$$

where v is a small leaky stepsize for the stability consideration, μ is the stepsize, $(V(n) - Z_{MF}(n)\tilde{S}_1)$ is the projection of $V(n)$ into $\tilde{S}_1$, and

$$Z_{MF}(n) = < V(n), \tilde{S}_1^* > /||\tilde{S}_1||^2$$

$$Z(n) = < V(n), \tilde{S}_1^* + X_1^*(n) > /||\tilde{S}_1||^2 \tag{11}$$

In the above, $||\tilde{S}_1||^2$ is the norm of the vector $\tilde{S}_1$. The normalization with respect to $||\tilde{S}_1||^2$ is equivalent to normalize $\tilde{S}_1$ so that it has a unit energy ($||\tilde{S}_1|| = 1$) [2, 6].

By using the above adaptation, the corresponding optimum solution for $C_1 (= \tilde{S}_1^* + X_1^*)$ can be given by [2]

$$C_1 = \xi_{min}\mathbf{M}^{-1}\tilde{S}_1^*, \qquad \xi_{min} = ||\tilde{S}_1||^2/(\tilde{S}_1^T\mathbf{M}^{-1}\tilde{S}_1^*) \tag{12}$$

where $\mathbf{M}$ is the autocorrelation matrix of $V(n)$ and ξ_{min} is a normalization factor so that $< \tilde{S}_1, C_1 >$ is $||\tilde{S}_1||^2$.

The MOE-SGD can work quite well in the multipath channel when the channel is time-invariant. Also, the information replicas over the L paths are combined for detection similarly as in the Rake combining (see (9)). However, the calculation of $||\tilde{S}_1||$ for the normalization operation in (11) is required whenever the channel varies and this increases the computational cost. Furthermore, once the channel is time-varying, the optimum solution will be time-varying due to the fact that the composite PN vector $\tilde{S}_1$ in (12) contains the channel parameters. Accordingly, when the MOE-SGD cannot track the time-varying channel well and quickly, the performance will be seriously deteriorated. On the other hand, although the MOE-RLS can provide an improved performance over the blind MOE-SGD in the time-invariant channel [2], it cannot work well when the channel is time-varying. This phenomenon can be shown later in the simulation. To overcome the weakness, we propose a modified MOE-SGD detector, namely, the MOE with Rake combining.

B. MOE with Rake Combining (MOE-RAKE)

In order to design a receiver whose optimum weight coefficients are slightly or not affected by the channel parameters, we modify the MOE-SGD by letting the original PN vectors $\{S_{1,l}\}$ instead of the previously used $\tilde{S}_1$ as the basis vectors for the MOEs and then combining the outputs of a bank of those MOE detectors with different basis vectors in the Rake diversity. The resulting detector is henceforth to be referred to as the MOE-RAKE to reflect the explicit Rake combining. To avoid confusion, we point out that the MOE-SGD is also with the Rake combining because the composite PN vector $\tilde{S}_1$ in (9) has included the L PN vectors $\{S_{1,l}\}$. In the MOE-RAKE, the final decision variable is given by

$$Y(n) = \sum_{i=0}^{L-1} \tilde{\beta}_i^* Z_i(n) \tag{13}$$

where $Z_i(n)$ is the output of the i-th MOE detector. Similarly as in (10) and (11), we have

$$\begin{aligned} Z_i(n) &= < V(n), S_{1,i}^* + X_{1,i}^*(n) > /2N \\ Z_{MF_i}(n) &= < V(n), S_{1,i}^* > /2N \\ X_{1,i}(n+1) &= (1-v)X_{1,i}(n) - \mu Z_i^*(n)\,(V(n) - \\ &\quad Z_{MF_i}(n)S_{1,i}) \end{aligned} \tag{14}$$

In the above, the basis vector is $S_{1,i}$ and $||S_{1,i}||^2 = 2N$ for all i. In addition, note that the large $V(n)$ may raise up the *gradient noise amplification* problem [4] in the blind SGD adaptation as in the LMS. To ease the problem, the *normalized* SGD is developed by replacing μ with $\mu/(\epsilon + ||(V(n)||^2)$ in (14). The resulting adaptation is given by

$$\begin{aligned} X_{1,i}(n+1) = \quad & (1-v)X_{1,i}(n) - \tfrac{\mu}{\epsilon + ||V(n)||^2} \quad \cdot \\ & Z_i^*(n)(V(n) - Z_{MF_i}(n)S_{1,i}) \end{aligned} \tag{15}$$

where $||V(n)||^2$ is the norm of $V(n)$ and ϵ is a tiny positive number inserted to avoid the numerical difficulty [4].

In the MOE-RAKE, we set the initial value of $X_{1,i}(n)$ to zero. Besides, noting that the PN vector $S_{1,i}$ has zero components (see $S_{k,l}$ in (6)), we also set the corresponding components of the $X_{1,i}$ to zero during each adaptation to avoid their values being unlimited. Accordingly, in the practical MOE-RAKE, we may reduce the dimension of $V(n)$, $S_{1,i}$, and $X_{1,i}(n)$ from $N + L_o - 1$ to N by excluding the operations on those 0 components in both $S_{1,i}$ and $X_{1,i}(n)$. As a result, in each MOE detector, say the i-th MOE, the corresponding optimum solution for $C_{1,i} := S_{1,i}^* + X_{1,i}^*$ can be written in the same form as in (12) but with the PN vector $S_{1,i}$, i.e.,

$$C_{1,i} = \xi_{min,i}\mathbf{M}^{-1}S_{1,i}^*, \qquad \xi_{min,i} = \frac{2N}{(S_{1,i}^T\mathbf{M}^{-1}S_{1,1}^*)}$$

where $\xi_{min,i}$ is the normalization factor in the i-th MOE.

By using (13), the output $Y(n)$ of the MOE-RAKE can also be expressed as a linear transformation of the received signal vector $V(n)$. The corresponding optimum weight coefficients vector C_1 for transforming $V(n)$ to $Y(n)$ is

$$C_1 := \sum_{i=0}^{L-1} \xi_{min,i}\mathbf{M}^{-1}\tilde{\beta}_i^* S_{1,i}^* \tag{16}$$

Comparing (16) with (12), we note that if the normalization factors $\{\xi_{min,i}\}$ were the same for all i, the above C_1 would be a scalared vector of that in (12), and it implies the identical performance of the MOE-RAKE and MOE-SGD. Practically, $\{\xi_{min,i}\}$ might be unbalanced and a slight performance degradation may occur to the MOE-RAKE. However, the MOE-RAKE with the separated MOEs has two advantages. Firstly, unlike the MOE-SGD, where the frequent calculation of $||\tilde{S}_1||^2$ is required in (11) whenever the channel is time varying, the MOE-RAKE has the same normalization of $||S_{1,i}||^2$ for all i, which is free from the channel parameters, so that there is no need to frequently calculate the value. Secondly, due to the fact that for each MOE, the corresponding optimum $C_{1,i}$ mainly depends on $\mathbf{M}$ and $S_{1,i}$ rather than the channel parameters $\{\tilde{\beta}_i\}$, the MOE-RAKE is less affected by the time-varying of the channel parameters than the previously mentioned MOE-SGD. In this sense, the MOE-RAKE may have a good performance particularly in the time-varying environment.

IV. Illustrative Results

In simulation, we consider the forward link channel and assume that all active users are experiencing the same multipath fading channel. The channel parameters $\{\alpha_l\}$ are different for l and they are assumed statistically independent. The total average power of the channel coefficients is normalized to 1. The equivalent fading parameters $\{\beta_l\}$ in the tap delay model with T_c spacing are obtained as in (2). Gold codes with N=31 are considered as spreading sequences. For user k, $SNR = 2E_k/N_o$. For all detectors, we allow 10^4 symbols period for training and then conduct 3×10^6 trials to estimate the average BER.

The channel simulation is based on the 6-tap ($L_f = 6$ in (1)) typical urban GSM model [8]. The time-varying rate is determined by $f_d T_b$, where f_d is the maximum Doppler frequency shift and T_b is the bit interval. Here, we assume that $f_d T_b$ is very small so that within one bit interval, the fading parameter β_l can be treated as a constant, while from bit to bit, it is time-varying and is denoted by $\beta_l(n)$. As an illustration, we consider $1/T_c =$ 1.2288 MHz, $T_b = 31T_c$, and $f_d T_b = 10^{-4}$. The time-varying $\beta_l(n)$ in an 8-path fading channel is plotted in Fig. 1, where we take one sample every $50T_b$ and plot the amplitudes of $\beta_l(n)$ over the 4 dominant paths while those over other fading paths are very small and hence not plotted.

For all detectors, we assume that the estimates of the fading parameters are given by

$$\tilde{\beta}_l(n) = \beta_l(n-1) + e_l(n), \qquad l = 0, 1, ..., L-1 \quad (17)$$

where e_l is the estimation noise, assumed to be independent and identically distributed (i.i.d.) Gaussian with zero mean and variance σ_e^2.

In the following, we consider equal-power users, $L_o = 8$, $f_d T_b = 10^{-4}$, and $\sigma_e^2 = 0.001$. The number of the resolvable paths is set to $L = 3$ for all detectors except for the MMSE detector which can inherently combine the fading replicas over all fading paths.

A. Blind Subspace detectors

In the PASTd algorithm for the blind subspace detectors [3], the forgetting factor β is used as if there is a sliding window to cover the recent data for the tracking consideration. The effective window length (N_w) is approximately equal to $1/(1-\beta)$ [5]. Fig. 2 plots the BERs of the BS-MMSE and BS-DECO with $\beta = 0.9, 0.96, 0.99,$ 0.999 (corresponding $N_w = 10, 25, 100, 1000$) in a multiuser system with SNR=23dB over an 8-path time-varying fading channel.

The figure clearly shows that choosing an appropriate β can significantly affect the performance. In particular, by using the weighting factor $\beta = 0.99$ ($N_w = 100$), the BS-MMSE and BS-DECO can track the channel well and give good performance. In contrast, choosing a larger forgetting factor ($\beta = 0.999$) or smaller one ($\beta = 0.9$) cannot improve but worsen the performance. This can be explained as follows. With β being close to 1, the effective window length is very large and many data samples are taken into consideration. As a result, the solution given by the detector is for all these data samples and it cannot reflect the time-varying characteristic of the channel.

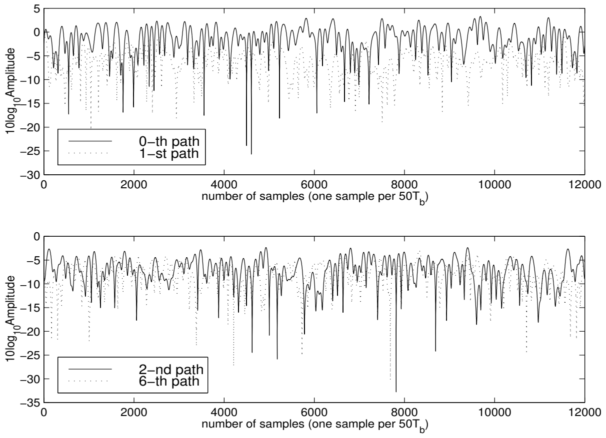

Fig. 1. Amplitudes of 4 dominant paths in an 8-path time-varying channel with $f_d T_b = 10^{-4}$.

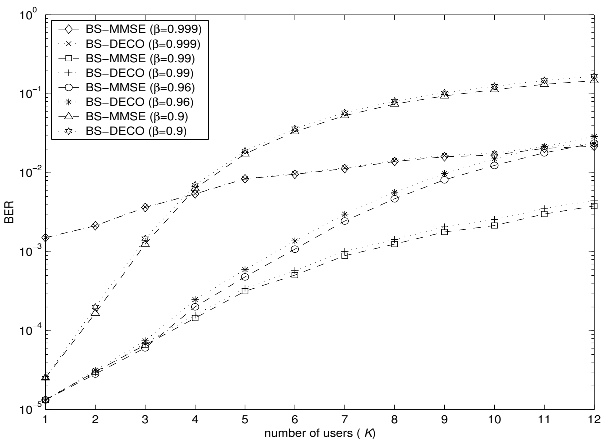

Fig. 2. Effect of β on the BER of the BS-MMSE and BS-DECO in a multiuser system with SNR=23dB.

On the other hand, with small $\beta = 0.9$, the detector considers only a few of data samples which are not enough to ease the background noise. From Fig. 2, it can also be seen that the performance of the BS-MMSE is better than that of the BS-DECO. This is due to the fact that the MMSE-type approach makes a compromise between suppressing the MAI and enhancing the ambient noise while the zero-forcing DECO-type one may enhance the noise [3]. In the following, we will use the BS-MMSE for further comparison.

B. RLS-type detectors

Similarly as in the PASTd based blind subspace detectors, the forgetting factor ω will also play a crucial role on the performance of the RLS-type detectors. In Fig. 3, the BERs of the MMSE-RLS and MOE-RLS with $\omega = 0.9, 0.96, 0.99, 0.999$ over an 8-path time-varying channel are plotted versus the number of users. We can notice a large performance gap between the MMSE-RLS with $\omega = 0.999$ and that with $\omega = 0.99$. This is also due to the fact that with large $\omega = 0.999$, too many data samples are considered to reach a solution for weight coefficients over all these samples and thus the tracking capability of the MMSE-RLS is weakened. Furthermore, due to the use of the decision as a reference signal for

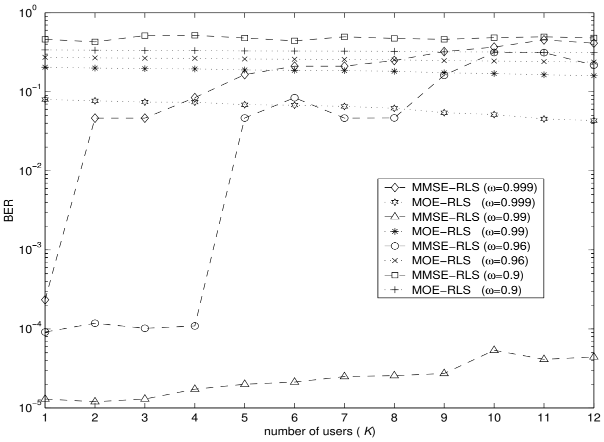

Fig. 3. Effect of ω on the BER of the MMSE-RLS and MOE-RLS in a multiuser system with SNR=23dB.

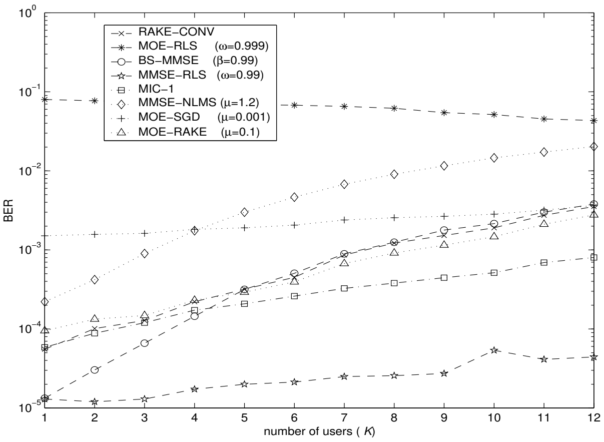

Fig. 4. BER of the RAKE-CONV, MIC-1, blind detectors, MMSE-NLMS, and MMSE-RLS in a multiuser system with SNR=23dB.

adaptation, the performance of the MMSE-RLS may be driven even worse by the wrong decisions if the BER is not small as in the cases of $\omega = 0.999 (K > 1)$ and $\omega = 0.96 (K > 4)$. For the MOE-RLS, however, the performance for all ω is poor. This indicates that the blind MOE-RLS is quite "noisy" in comparison with the MMSE-RLS.

C. Overall performance comparison

An overall comparison of the BERs for the detectors is given in Fig. 4, where the same simulation environment as previously mentioned is considered. Here, the MOE-SGD is also with a normalized SGD as in the MOE-RAKE. We can see that the MMSE-RLS has a best performance and outperforms other detectors while the MOE-RLS seems to have a worst performance and its BER is even higher than that of the conventional RAKE (RAKE-CONV). In addition, the BS-MMSE is shown to be better than the RAKE-CONV, MIC-1, and MOE-RAKE when the number of users is small ($K < 4$). For larger number of users ($K > 5$), the MIC-1 and MOE-RAKE provide better performance than the BS-MMSE.

Further performance comparison in a multiuser synchronous system over an 8-path time-varying fading channel is given in Fig. 5, where the BERs are plotted versus the SNR values. As benchmarks, we let MMSE-RLS (ref) denote the MMSE-RLS with the correct data bit for each adaptation and MMSE-RLS (dd) with the decision-directed one. The figure shows that the MMSE-RLS (ref) can provide a much better performance than the other detectors while the decision-directed one (MMSE-RLS (dd)) may lose tracking by the wrong decisions when the SNR value is less than 20dB. For the MOE-RLS, the performance is worse than the other techniques. Among the blind detectors, the MOE-RAKE still shows its superiority in performance over the others. However, to further improve its performance, the blind adaptation should be switched to the decision-directed one especially in the situation of high SNR values.

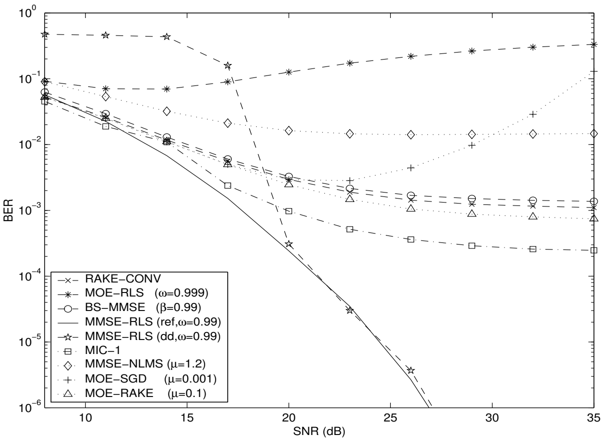

Fig. 5. BER of the RAKE-CONV, MIC-1, blind detectors, and MMSE-RLS versus SNR in a 10-user system.

Acknowledgment

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