Adaptive Linear Minimum BER Reduced-Rank Interference Suppression Algorithms Based on Joint and Iterative Optimization of Filters

Yunlong Cai and Rodrigo C. de Lamare

***Abstract*—In this letter, we propose a novel adaptive reduced-rank strategy based on joint iterative optimization (JIO) of filters according to the minimization of the bit error rate (BER) cost function. The proposed optimization technique adjusts the weights of a subspace projection matrix and a reduced-rank filter jointly. We develop stochastic gradient (SG) algorithms for their adaptive implementation and introduce a novel automatic rank selection method based on the BER criterion. Simulation results for direct-sequence code-division-multiple-access (DS-CDMA) systems show that the proposed adaptive algorithms significantly outperform the existing schemes.**

***Index Terms*– reduced-rank techniques, adaptive algorithms, BER cost function, multiuser detection.**

I. Introduction

Detecting a desired user in a DS-CDMA system requires processing the received signal in order to mitigate different types of interference. In the scenario of interest of this work, the receive filters are large, the interference is strong and time-varying, and the training data provided to the receiver is limited. In this context, reduced-rank signal processing has received significant attention in the past several years, since it provides faster convergence speed, better tracking performance and an increased robustness against interference as compared to full-rank schemes operating with a large number of parameters. A number of reduced-rank techniques have been developed to design the subspace projection matrix and the reduced-rank filter [1]-[8]. Among the first schemes are the eigendecomposition-based (EIG) algorithms [1], [2], the multistage Wiener filter (MWF) investigated in [3] and [4], and the auxiliary vector filtering (AVF) algorithm considered in [5]. EIG, MWF and AVF have faster convergence speed compared to the full rank adaptive algorithms with a much smaller filter size, but their computational complexity is high. A strategy based on the joint and iterative optimization (JIO) of a subspace projection matrix and a reduced-rank filter has been reported in [6], [7], whereas algorithms with switching mechanisms have been considered in [8] for DS-CDMA systems.

Most of the contributions to date are either based on the minimization of the mean square error (MSE) and/or the minimum variance criteria [1]-[8]. However, since the measurement of transmission reliability is bit error rate (BER) not MSE, they are not the most appropriate metric from a performance viewpoint in digital communications. Design approaches that can minimize the BER have been reported in [9], [10], [11], [12] and are termed adaptive minimum bit error rate (MBER) techniques. The work in [11] appears to be the first approach to combine a reduced-rank algorithm with the BER criterion. However, the scheme is a hybrid between an EIG or an MWF approach, and a BER scheme in which only the reduced-rank filter is adjusted in an MBER fashion.

In this letter, we propose adaptive reduced-rank techniques based on a novel JIO strategy that minimizes the BER cost function. The proposed strategy adjusts the weights of both the rank-reduction matrix and the reduced-rank filter jointly in order to minimize the BER. By using multiple cycles over the recursions, we develop stochastic gradient (SG) algorithms for an adaptive implementation and introduce a novel automatic rank selection method with the BER as a metric. Simulation results for DS-CDMA systems show that the proposed algorithms significantly outperform existing schemes.

II. DS-CDMA System Model

Let us consider the uplink of an uncoded synchronous binary phase-shift keying (BPSK) DS-CDMA system with K users, N chips per symbol and L_p propagation paths. The delays are multiples of the chip duration and the receiver is synchronized with the main path. The M-dimensional received vector is given by

$$\mathbf{r}(i) = \sum_{k=1}^{K} A_k b_k(i) \widetilde{\mathbf{p}}_k(i) + \boldsymbol{\eta}_k(i) + \mathbf{n}(i), \qquad (1)$$

where $M = N + L_p - 1$, $b_k(i) \in \{\pm 1\}$ is the i-th symbol for user k, and the amplitude of user k is A_k. The $M \times 1$ vector $\widetilde{\mathbf{p}}_k(i) = \mathbf{C}_k \mathbf{h}_k(i)$ is the effective signature sequence for user k, the $M \times L_p$ convolution matrix $\mathbf{C}_k$ contains one-chip shifted versions of the spreading code of user k:

$$\mathbf{C}_k = \begin{pmatrix} a_k(1) & & \mathbf{0} \\ \vdots & \ddots & a_k(1) \\ a_k(N) & & \vdots \\ \mathbf{0} & \ddots & a_k(N) \end{pmatrix},$$

where $a_k(m) \in \{\pm 1/\sqrt{N}\}$, $m = 1, \ldots, N$. The channel vector of user k is $\mathbf{h}_k(i) = [h_{k,0}(i) \ldots h_{k,L_p-1}(i)]^T$, $\boldsymbol{\eta}_k(i)$ is the inter-symbol interference (ISI), $\mathbf{n}(i) = [n_0(i) \ldots n_{M-1}(i)]^T$ is the complex Gaussian noise vector with zero mean and $E[\mathbf{n}(i)\mathbf{n}^H(i)] = \sigma^2 \mathbf{I}$, where σ^2 is the noise variance, $(.)^T$ and $(.)^H$ denote transpose and Hermitian transpose, respectively.

Y. Cai is with Department of Information Science and Electronic Engineering, Zhejiang University, Hangzhou 310027, China (e-mail: ylcai@zju.edu.cn). R. C. de Lamare is with the Communications Research Group, Department of Electronics, University of York, YO10 5DD York, U.K. (e-mail: rcdl500@ohm.york.ac.uk). This work is supported in part by the NSF of China under grant 61101103.

III. Design of MBER Reduced-Rank Schemes

In this section, we detail the design of reduced-rank schemes which minimize the BER. In a reduced-rank algorithm, an $M \times D$ subspace projection matrix $\mathbf{S}_D$ is applied to the received data to extract the most important information of the data by performing dimensionality reduction, where $1 \leq D \leq M$. A $D \times 1$ projected received vector is obtained as follows

$$\bar{\mathbf{r}}(i) = \mathbf{S}_D^H \mathbf{r}(i), \quad (2)$$

where it is the input to a $D \times 1$ filter $\bar{\mathbf{w}}_k = [\bar{w}_1, \bar{w}_2, \ldots, \bar{w}_D]^T$. The filter output is given by $\bar{x}_k(i) = \bar{\mathbf{w}}_k^H \bar{\mathbf{r}}(i) = \bar{\mathbf{w}}_k^H \mathbf{S}_D^H \mathbf{r}(i)$. The estimated symbol of user k is given by $\hat{b}_k(i) = \text{sign}\{\Re[\bar{\mathbf{w}}_k^H \bar{\mathbf{r}}(i)]\}$, where the operator $\Re[.]$ retains the real part of the argument and sign$\{.\}$ is the signum function. The probability of error for user k is given by

$$\begin{aligned} P_e = P(\tilde{x}_k < 0) &= \int_{-\infty}^{0} f(\tilde{x}_k) d\tilde{x}_k \\ &= Q\left(\frac{\text{sign}\{b_k(i)\}\Re[\bar{x}_k(i)]}{\rho(\bar{\mathbf{w}}_k^H \mathbf{S}_D^H \mathbf{S}_D \bar{\mathbf{w}}_k)^{\frac{1}{2}}}\right), \end{aligned} \quad (3)$$

where $\tilde{x}_k = \text{sign}\{b_k(i)\}\Re[\bar{x}_k(i)]$ denotes a random variable, $f(\tilde{x}_k)$ is the single point kernel density estimate [9] which is given by

$$\begin{aligned} f(\tilde{x}_k) = &\frac{1}{\rho\sqrt{2\pi \bar{\mathbf{w}}_k^H \mathbf{S}_D^H \mathbf{S}_D \bar{\mathbf{w}}_k}} \\ &\times \exp\left(\frac{-(\tilde{x}_k - \text{sign}\{b_k(i)\}\Re[\bar{x}_k(i)])^2}{2\bar{\mathbf{w}}_k^H \mathbf{S}_D^H \mathbf{S}_D \bar{\mathbf{w}}_k \rho^2}\right), \end{aligned} \quad (4)$$

where ρ is the radius parameter of the kernel density estimate, $Q(.)$ is the Gaussian error function. The parameters of $\mathbf{S}_D$ and $\bar{\mathbf{w}}_k$ are designed to minimize the probability of error. By taking the gradient of (3) with respect to $\bar{\mathbf{w}}_k^*$ and after further mathematical manipulations we obtain

$$\begin{aligned} \frac{\partial P_e}{\partial \bar{\mathbf{w}}_k^*} = &\frac{-\exp\left(\frac{-|\Re[\bar{x}_k(i)]|^2}{2\rho^2 \bar{\mathbf{w}}_k^H \mathbf{S}_D^H \mathbf{S}_D \bar{\mathbf{w}}_k}\right)\text{sign}\{b_k(i)\}}{2\sqrt{2\pi}\rho} \\ &\times \left(\frac{\mathbf{S}_D^H \mathbf{r}}{(\bar{\mathbf{w}}_k^H \mathbf{S}_D^H \mathbf{S}_D \bar{\mathbf{w}}_k)^{\frac{1}{2}}} - \frac{\Re[\bar{x}_k(i)]\mathbf{S}_D^H \mathbf{S}_D \bar{\mathbf{w}}_k}{(\bar{\mathbf{w}}_k^H \mathbf{S}_D^H \mathbf{S}_D \bar{\mathbf{w}}_k)^{\frac{3}{2}}}\right). \end{aligned} \quad (5)$$

By taking the gradient of (3) with respect to $\mathbf{S}_D^*$ and following the same approach we have

$$\begin{aligned} \frac{\partial P_e}{\partial \mathbf{S}_D^*} = &\frac{-\exp\left(\frac{-|\Re[\bar{x}_k(i)]|^2}{2\rho^2 \bar{\mathbf{w}}_k^H \mathbf{S}_D^H \mathbf{S}_D \bar{\mathbf{w}}_k}\right)\text{sign}\{b_k(i)\}}{2\sqrt{2\pi}\rho} \\ &\times \left(\frac{\mathbf{r}\bar{\mathbf{w}}_k^H}{(\bar{\mathbf{w}}_k^H \mathbf{S}_D^H \mathbf{S}_D \bar{\mathbf{w}}_k)^{\frac{1}{2}}} - \frac{\mathbf{S}_D \bar{\mathbf{w}}_k \bar{\mathbf{w}}_k^H \Re[\bar{x}_k(i)]}{(\bar{\mathbf{w}}_k^H \mathbf{S}_D^H \mathbf{S}_D \bar{\mathbf{w}}_k)^{\frac{3}{2}}}\right). \end{aligned} \quad (6)$$

IV. Proposed MBER Adaptive Algorithms

In this section, we firstly describe the proposed scheme and MBER adaptive SG algorithms to adjust the weights of $\mathbf{S}_D(i)$ and $\bar{\mathbf{w}}(i)$ based on the minimization of the BER criterion. Then, a method for automatically selecting the rank of the algorithm using the BER criterion is presented.

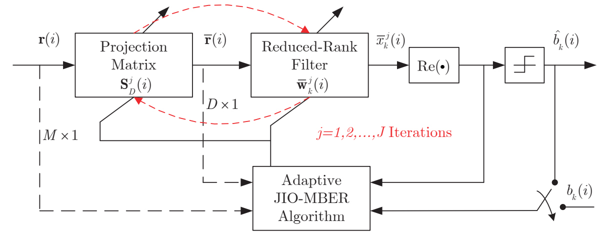

Fig. 1. Structure of the proposed reduced-rank scheme

A. Adaptive Estimation of Projection Matrix and Receiver

The proposed scheme is depicted in Fig. 1, the projection matrix $\mathbf{S}_D(i)$ and the reduced-rank filter $\bar{\mathbf{w}}_k(i)$ are jointly optimized according to the BER criterion. The algorithm has been devised to start its operation in the training (TR) mode, and then to switch to the decision-directed (DD) mode. The proposed SG algorithm is obtained by substituting the gradient terms (5) and (6) in the expressions $\bar{\mathbf{w}}_k(i+1) = \bar{\mathbf{w}}_k(i) - \mu_w \frac{\partial P_e}{\partial \bar{\mathbf{w}}_k^*}$ and $\mathbf{S}_D(i+1) = \mathbf{S}_D(i) - \mu_{S_D} \frac{\partial P_e}{\partial \mathbf{S}_D^*}$ [14] subject to the constraint of $\bar{\mathbf{w}}_k^H(i)\mathbf{S}_D^H(i)\mathbf{S}_D(i)\bar{\mathbf{w}}_k(i) = 1$. Unlike prior JIO schemes, the proposed JIO-MBER algorithm employs multiple cycles over the recursions for $\bar{\mathbf{w}}_k$ and $\mathbf{S}_D$. At each time instant, the weights of the two quantities are updated in an alternating way by using the following equations

$$\begin{aligned} \bar{\mathbf{w}}_k^{j+1}(i) = \bar{\mathbf{w}}_k^j(i) + \mu_w &\frac{\exp\left(\frac{-|\Re[\bar{x}_k^j(i)]|^2}{2\rho^2}\right)\text{sign}\{b_k(i)\}}{2\sqrt{2\pi}\rho} \\ &\times \left(\mathbf{S}_D^{jH}(i)\mathbf{r}(i) - \Re[\bar{x}_k^j(i)]\mathbf{S}_D^{jH}(i)\mathbf{S}_D^j(i)\bar{\mathbf{w}}_k^j(i)\right) \end{aligned} \quad (7)$$

$$\begin{aligned} \mathbf{S}_D^{j+1}(i) = \mathbf{S}_D^j(i) + \mu_{S_D} &\frac{\exp\left(\frac{-|\Re[\bar{x}_k^j(i)]|^2}{2\rho^2}\right)\text{sign}\{b_k(i)\}}{2\sqrt{2\pi}\rho} \\ &\times \left(\mathbf{r}(i)\bar{\mathbf{w}}_k^{jH}(i) - \mathbf{S}_D^j(i)\bar{\mathbf{w}}_k^j(i)\bar{\mathbf{w}}_k^{jH}(i)\Re[\bar{x}_k^j(i)]\right) \end{aligned} \quad (8)$$

where μ_w and μ_{S_D} are the step-size values, the superscript j denotes the j-th iteration at the time instant, $j = 1, \ldots, J$, and J is the maximum number of iterations. Expressions (7) and (8) need initial values, $\bar{\mathbf{w}}_k^1(0)$ and $\mathbf{S}_D^1(0)$, and we scale the reduced-rank filter by $\bar{\mathbf{w}}_k^j \leftarrow \frac{\bar{\mathbf{w}}_k^j}{\sqrt{\bar{\mathbf{w}}_k^{jH}\mathbf{S}_D^{jH}\mathbf{S}_D^j\bar{\mathbf{w}}_k^j}}$ at each iteration. The scaling has an equivalent performance to using a constrained optimization with Lagrange multipliers although it is computationally simpler. The updated filters for the next time instant are given by $\bar{\mathbf{w}}_k^1(i+1) \leftarrow \bar{\mathbf{w}}_k^J(i)$ and $\mathbf{S}_D^1(i+1) \leftarrow \mathbf{S}_D^J(i)$. The proposed adaptive JIO-MBER algorithm is summarized in table I.

Since the BER is employed as a design criterion, there is no guarantee that the algorithms proposed will obtain the global minimum solution [9]. The proposed JIO-MBER technique and the other existing BER-driven algorithms can only have their convergence guaranteed to a local minimum. In [15], the work provides a general proof for the convergence of alternating optimization algorithm. By extending the work in [15], we can obtain local minimum solutions for the projection matrix and the reduced-rank filter of the proposed JIO-MBER algorithms.

TABLE I

PROPOSED ADAPTIVE JIO-MBER ALGORITHMS

Initialize $\bar{\mathbf{w}}_k^1(0)$ and $\mathbf{S}_D^1(0)$.
Set step-size values μ_w and μ_{S_D} and the no. of iterations J.
for each time instant i do
    for j from 1 to J do
        Compute $\bar{\mathbf{w}}_k^{j+1}(i)$ and $\mathbf{S}_D^{j+1}(i)$ using (7) and (8).
        Scale the $\bar{\mathbf{w}}_k^j$ using $\bar{\mathbf{w}}_k^j \leftarrow \frac{\bar{\mathbf{w}}_k^j}{\sqrt{\bar{\mathbf{w}}_k^{jH}\mathbf{S}_D^{jH}\mathbf{S}_D^j\bar{\mathbf{w}}_k^j}}$.
    end cycles
After the J cycles, obtain $\bar{\mathbf{w}}_k^1(i+1) \leftarrow \bar{\mathbf{w}}_k^J(i)$
and $\mathbf{S}_D^1(i+1) \leftarrow \mathbf{S}_D^J(i)$ for the next time instant.

B. Computational Complexity of Algorithms and Delay Issues

We describe the computational complexity of the proposed JIO-MBER adaptive algorithm in DS-CDMA systems. In Table II, we compute the number of additions and multiplications to compare the complexity of the proposed JIO-MBER algorithm with the conventional adaptive reduced-rank algorithms, the adaptive least mean squares (LMS) full-rank algorithm based on the MSE criterion [14] and the SG full-rank algorithm based on the BER criterion [9]. Note that the MWF-MBER algorithm corresponds to the use of the procedure in [3] to construct $\mathbf{S}_D[i]$ and (7) with $J = 1$ to compute $\bar{\mathbf{w}}[i]$. In particular, for a configuration with $N = 31$, $D = 6$ and $L_p = 3$, the number of multiplications for the MWF-MBER and the proposed JIO-MBER algorithms are 8377 and 1262, respectively. The number of additions for them are 5920 and 962, respectively. Compared to the MWF-MBER algorithm, the JIO-MBER algorithm reduces the computational complexity significantly.

TABLE II

COMPUTATIONAL COMPLEXITY OF ALGORITHMS.

Algorithm	Number of operations per symbol	
	Multiplications	Additions
Full-Rank-LMS	$2M+1$	$2M$
Full-Rank-MBER	$4M+1$	$4M-1$
MWF-LMS [4]	DM^2-M^2 $+2DM+4D+1$	DM^2-M^2 $+3D-2$
EIG [2]	$O(M^3)$	$O(M^3)$
JIO-LMS [6]	$3DM+M$ $+3D+6$	$2DM+M$ $+4D-2$
MWF-MBER [11]	$(D+1)M^2$ $+(3D+1)M+3D$ $+ML_p+10$	$(D-1)M^2$ $+(2D-1)M+2D$ $+ML_p+1$
JIO-MBER	$6MDJ+5DJ$ $+MJ+11J$	$5MDJ+DJ$ $-MJ-J$

Note that generally the delay associated with receive processing of filters is quite small as compared to the delay of channel decoding used in some systems such as maximum a posteriori (MAP), sum-product algorithm (SPA) and others for turbo and LDPC codes. We can find that the delay introduced by the receive filter is much lower than that of the channel decoder in [16]. We can see that the decoder has a much bigger impact on the delay and actually dominates the delay in the receiver [17]. For example, in the case of 64 kbit/s UMTS transmission, the encoded broadcast service requires more than 5 s system delay, and the uncoded systems such as conferencing and telephony require 150 ms delay.

C. Automatic Rank Selection

The performance of reduced-rank algorithms depends on the rank D, which motivates automatic rank selection schemes to choose the best rank at each time instant [3], [7], [8]. Unlike prior methods for rank selection, we develop a rank selection algorithm based on the probability of error, which is given by

$$P_D(i) = Q\left(\frac{\text{sign}\{b_k(i)\}\Re[\bar{x}_k^D(i)]}{\rho}\right) \quad (9)$$

where the receiver is subject to $\bar{\mathbf{w}}_k^H\mathbf{S}_D^H\mathbf{S}_D\bar{\mathbf{w}}_k = 1$. For each time instant, we adapt a reduced-rank filter $\tilde{\bar{\mathbf{w}}}_k(i)$ and a projection matrix $\tilde{\mathbf{S}}_D(i)$ with the maximum allowed rank $D_{\max}$, which can be expressed as $\tilde{\bar{\mathbf{w}}}_k(i) = [\tilde{\bar{w}}_1(i), \ldots, \tilde{\bar{w}}_{D_{\min}}(i), \ldots, \tilde{\bar{w}}_{D_{\max}}(i)]^T$ and $\tilde{\mathbf{S}}_D(i) = \begin{bmatrix} \tilde{s}_{1,1}(i) & \ldots & \tilde{s}_{1,D_{\min}}(i) & \ldots & \tilde{s}_{1,D_{\max}}(i) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{s}_{M,1}(i) & \ldots & \tilde{s}_{M,D_{\min}}(i) & \ldots & \tilde{s}_{M,D_{\max}}(i) \end{bmatrix}$ where $D_{\min}$ and $D_{\max}$ are the minimum and maximum ranks allowed for the reduced-rank filter, respectively. For each symbol, we test the value of rank D within the range, namely, $D_{\min} \leq D \leq D_{\max}$. For each tested rank, we substitute the filter $\tilde{\bar{\mathbf{w}}}_k(i) = [\tilde{\bar{w}}_1(i), \ldots, \tilde{\bar{w}}_D(i)]^T$ and the matrix $\tilde{\mathbf{S}}'_D(i) = \begin{bmatrix} \tilde{s}_{1,1}(i) & \ldots & \tilde{s}_{1,D}(i) \\ \vdots & \vdots & \vdots \\ \tilde{s}_{M,1}(i) & \ldots & \tilde{s}_{M,D}(i) \end{bmatrix}$ into (9) to obtain the probability of error $P_D(i)$. The optimum rank can be selected as

$$D_{\text{opt}}(i) = \arg \min_{D \in \{D_{min}, \ldots, D_{max}\}} P_D(i). \quad (10)$$

Note that after we obtain the projection matrix with rank D_{max}, we generate the $M \times D$ projection matrix by grouping the columns which are from the first column to the D-th column. The proposed auto rank selection mechanism only requires a modest increase in the complexity of the JIO-MBER algorithm with a fixed rank. The number of multiplications and additions for the JIO-MBER algorithm with the auto rank mechanism are $(6M+5)D_{max} + M + 11$ and $(5M+1)D_{max} - M - 1$, respectively. In addition, a simple search over the values of $\bar{x}_k^D(i)$ and the selection of the terms corresponding to D_{opt} and $P_{D_{\text{opt}}}(i)$ are performed.

V. SIMULATIONS

In this section, we evaluate the performance of the proposed JIO-MBER reduced-rank algorithms and compare them with existing full-rank and reduced-rank algorithms. Monte-carlo simulations are conducted to verify the effectiveness of the JIO-MBER adaptive reduced-rank SG algorithms. The DS-CDMA system employs Gold sequences as the spreading codes, and the spreading gain is $N = 31$. The sequence of channel coefficients for each path is $h_{k,f}(i) = p_{k,f}\alpha_{k,f}(i)(f = 0, 1, 2)$. All channels have a profile with three paths whose powers are $p_{k,0} = 0$ dB, $p_{k,1} = -7$ dB and $p_{k,2} = -10$ dB, respectively, where $\alpha_{k,f}(i)$ is computed according to the Jakes model. We optimized the parameters for the proposed and conventional algorithms based on simulations. In this work, we focus on the case with fixed step-size values. Note that motivated by the work in [18], a low-complexity variable step-size mechanism with the error probability as a metric can be further developed. The initial full rank and reduced-rank filters are all zero vectors. The initial projection matrix is given by $\mathbf{S}_D^1(0) = [\mathbf{I}_D, \mathbf{0}_{D\times(M-D)}]^T$. The algorithms process 250 symbols in TR and 1500 symbols in DD. We set $\rho = 2\sigma$.

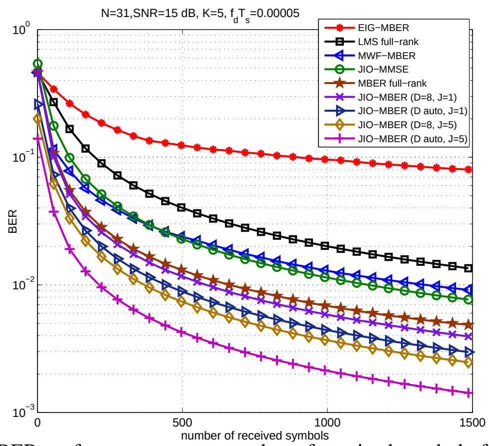

Fig. 2. BER performance versus number of received symbols for the JIO-MBER reduced-rank algorithms and the conventional schemes. JIO-MBER (D=8, J=5): $\mu_w = \mu_{S_D} = 0.005$. JIO-MBER (D auto, J=5): $\mu_w = \mu_{S_D} = 0.005$. JIO-MBER (D=8, J=1): $\mu_w = \mu_{S_D} = 0.105$. JIO-MBER (D auto, J=1): $\mu_w = \mu_{S_D} = 0.16$. EIG-MBER (D=8): $\mu_w = 0.215$. LMS full-rank: $\mu_w = 0.105$. MBER full-rank: $\mu_w = 0.05$. MWF-MBER (D=8): $\mu_w = 0.05$. ($D_{min} = 3$, $D_{max} = 20$)

Fig. 2 shows the bit error rate (BER) performance of the desired user versus the number of received symbols for the JIO-MBER adaptive SG algorithms and the conventional schemes. We set the rank $D = 8$, $K = 5$, $SNR = 15$dB and $f_dT_s = 5 \times 10^{-5}$. We can see that the JIO-MBER reduced-rank algorithms converge much faster than the conventional full rank and reduced-rank algorithms. For the group of JIO-MBER adaptive algorithms, the auto-rank selection algorithms outperform the fixed rank algorithms. Fig. 3 illustrates the BER performance of the desired user versus SNR and number of users K. In particular, the JIO-MBER algorithm using $D = 8$ with $J = 1$ iteration can save up to over 6dB and support up to six more users in comparison with the MWF-MBER algorithm using $D = 8$, at the BER level of 2×10^{-2}.

VI. Conclusions

In this paper, we have proposed a novel adaptive MBER reduced-rank scheme based on joint iterative optimization of filters for DS-CDMA systems. We have developed SG-based algorithms for the adaptive estimation of the reduced-rank filter and the projection matrix, and proposed an automatic rank selection scheme using the BER as a criterion. The simulation results have shown that the proposed JIO-MBER adaptive reduced-rank algorithms significantly outperform the existing full-rank and reduced-rank algorithms at a low cost.

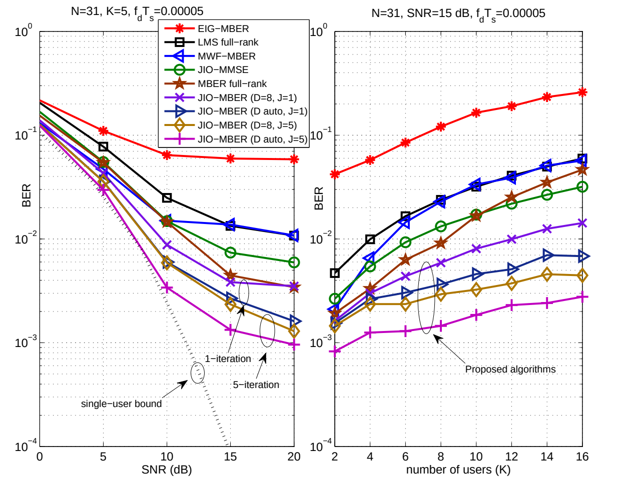

Fig. 3. BER performance versus SNR and number of users for the JIO-MBER reduced-rank algorithms and the conventional schemes. 1500 symbols are transmitted. ($D_{min} = 3$, $D_{max} = 20$)

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