A LINEAR SMOOTHING METHOD FOR ENHANCING NEAR-FAR RESISTANCE OF CDMA DETECTORS

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ABSTRACT

The near-far problem in a multiuser setting places fundamental limitations on the performance of CDMA communication systems. In the past, significant effort has focused on designing practical, and hence suboptimum, detectors to combat multiple access interference (MAI). However, the optimality in near-far resistance is generally lost with the suboptimum detectors. In this paper, one method which can enhance the near-far resistance of the suboptimum detectors under multipath channels is presented. The proposed method is able to overcome the shortcomings of existing methods. Computer simulations confirm the theoretical findings.

1. INTRODUCTION

Direct sequence code division multiple access (DS-CDMA) systems are among the most promising multiplexing technologies for the next generation wireless communications systems. In the DS-CDMA framework, all users transmit data at the same time and in the same frequency band but use distinct signature waveforms to allow signal separation at the receiver. Because of the non-orthogonal signature waveforms among the active mobile users, DS-CDMA suffer from cochannel interference, which results in the near-far problem. Significant effort has been focused in the last two decades on designing multiuser receivers in order to combat multiple access interference (MAI) and the near-far problem. By jointly detecting all users' signals, optimum multiuser detection for DS-CDMA systems is near-far resistant and can achieve significant performance improvement over the conventional single-user detection. The near-far resistance of the optimum detector was derived in [1] for single-path AWGN channels. Because of its nonlinear nature, the computational complexity of the optimum detector increases exponentially when the number of active users increase. As a result, many suboptimum receivers have been developed [2]-[4]. However, it has been shown [5] that the optimum near-far resistance i.e., the near-far resistance achieved by the optimum detector is generally lost with the suboptimum detectors. Then, how can we enhance the near-far resistance performance of those suboptimum detectors, especially when power control is difficult to implement? By examining the structural differences of the channel matrix between the optimum and suboptimum detectors, a method was proposed in [6] to almost restore the near-far resistance of the suboptimum detectors under multipath fading channel situation to that of the optimum one, at least theoretically. However, that method has some disadvantages and is thus not practical.

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In this paper, a linear smoothing method is proposed which is able to overcome all disadvantages of the method of [6]. Computer simulations are performed to verify the theoretical findings.

2. SIGNAL MODELS

Consider an asynchronous DS-CDMA system with J users and L_c chips per symbol with the jth user's spreading code denoted by $\mathbf{c}_j = [c_j(0), \cdots, c_j(L_c-1)]^T$. Then, the jth user's transmitted signal at the chip rate in a baseband discrete-time model representation is given by [2] $s_j(k) = \sum_n b_j(n)\, c_j(k - n\, L_c)$, where $b_j(n)$ is the jth user's nth symbol and at the symbol rate $1/T_s$, $c_j(k)$ and $s_j(k)$ are at the chip rate $1/T_c$, $T_s = L_c T_c$. In the presence of a linear multipath channel where the receiver collects one sample per chip, the received discrete-time sampled signal due to the user j is $x_j(n) = \sum_i \sum_k b_j(k)\, c_j(i - k\, L_c)\, g_j(n - i - d_j)$, where $g_j(n)$ is the effective channel impulse response sampled at the chip interval and d_j is the transmission delay (mod L_c) of user j in chip periods. It is straightforward to show that the above equation is equivalent to $x_j(n) = \sum_k b_j(k)\, h_j(n - k\, L_c - d_j)$, where $h_j(n) \triangleq \sum_{i=0}^{L_c-1} c_j(i)\, g_j(n-i)$. $h_j(n)$ represents the effective signature waveform of user j, i.e., code $c_j(n)$ is "distorted" due to the multipath effect. The total received signal at the chip rate is the superposition of contributions of all users observed in additive white Gaussian noise $v(n)$ as $x(n) = \sum_{j=1}^{J} x_j(n) + v(n)$. Stack up L_c samples of $x(n)$ into $\mathbf{x}(n) = [x(n\, L_c), \cdots, x(n\, L_c + L_c - 1)]^T$ to obtain, at the symbol rate, the MIMO model

$$\mathbf{x}(n) = \sum_{j=1}^{J} \sum_{i=0}^{L_j-1} b_j(n-i) \begin{bmatrix} h_j(i\, L_c) \\ \vdots \\ h_j(i\, L_c + L_c - 1) \end{bmatrix} + \bar{\mathbf{v}}(n) = \sum_{j=1}^{J} \sum_{i=0}^{L_j-1} b_j(n-i)\mathbf{h}_j(i) + \bar{\mathbf{v}}(n) = \sum_{i=0}^{L_h-1} \mathbf{H}(i)\bar{\mathbf{b}}(n-i) + \bar{\mathbf{v}}(n),$$

where L_j is the length of the jth user's channel impulse response and is related to the length of $g_j(k)$ and the delay d_j. $L_h \triangleq \max_{1 \le j \le J} L_j$, $\mathbf{h}_j(i) = \begin{bmatrix} h_j(i\, L_c) & \cdots & h_j(i\, L_c + L_c - 1) \end{bmatrix}^T$, $\mathbf{H}(l) \triangleq [\mathbf{h}_1(l), \cdots, \mathbf{h}_J(l)]$, $\bar{\mathbf{b}}(l) \triangleq [b_1(l), \cdots, b_J(l)]^T$, and $\bar{\mathbf{v}}(n)$ is the noise vector and defined in a manner similar to $\mathbf{x}(n)$.

Furthermore, by stacking up N successive $\mathbf{x}(n)$ vectors of the received data (where N is called the smoothing factor), the discrete time MIMO model for the dispersive CDMA channel can be represented as follows

$$\chi_N(n) = \mathcal{H}\mathbf{b}(n) + \mathbf{v}(n) \tag{1}$$

where

$$\begin{aligned}
\chi_N^H(n) &= \begin{bmatrix} \mathbf{x}^H(n) & \cdots & \mathbf{x}^H(n+N-1) \end{bmatrix} \\
\mathcal{H} &= \begin{bmatrix} \mathbf{H}(L_h-1) & \cdots & \mathbf{H}(0) & \cdots & \mathbf{0} \\ \vdots & \ddots & & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{H}(L_h-1) & \cdots & \mathbf{H}(0) \end{bmatrix} \\
\mathbf{b}^H(n) &= \begin{bmatrix} \bar{\mathbf{b}}^H(n-L_h+1) & \cdots & \bar{\mathbf{b}}^H(n+N-1) \end{bmatrix} \\
\mathbf{v}^H(n) &= \begin{bmatrix} \bar{\mathbf{v}}^H(n) & \cdots & \bar{\mathbf{v}}^H(n+N-1) \end{bmatrix}
\end{aligned}$$

The following assumptions will be made throughout this paper.

1. The symbols $b_j(n)$ are uncorrelated in time, with variance A_j, for each j. $b_i(n)$ and $b_j(n)$, $i \neq j$ are also uncorrelated.
2. The channel matrix $\mathcal{H}$ in (1) is of full column rank (known as the identifiability condition in the blind multiuser detection/equalization literature [2]-[4]).

3. NEAR-FAR RESISTANT DETECTORS

In order to make expressions more clear, some relevant results of [5]-[7] are reviewed here. The optimum detector processes one entire transmission block (a packet) at a time. Since the transmission before and after a particular block is zero, following (1) the channel matrix $\tilde{\mathcal{H}}$ for the optimum detector is

$$\tilde{\mathcal{H}} = \begin{bmatrix} \mathbf{H}(0) & & \bigcirc \\ \vdots & \ddots & \\ \mathbf{H}(L_h-1) & & \mathbf{H}(0) \\ & \ddots & \vdots \\ \bigcirc & & \mathbf{H}(L_h-1) \end{bmatrix} \tag{2}$$

Note that this matrix is of dimension $(L+L_h-1)\,L_c \times JL$ where L is the number of symbols in a packet (each symbol is sampled L_c times). $\mathcal{H}$ of (1) has a resemblance to $\tilde{\mathcal{H}}$ of (2). If the left and right L_h-1 block columns are cut out, $\mathcal{H}$ would have the same structure as $\tilde{\mathcal{H}}$. However, the dimension of $\tilde{\mathcal{H}}$ is much larger than that of the resulting $\mathcal{H}$ ($L >> N$).

Since the near-far resistance is calculated by the channel matrix [7], it was shown in [6] that if one can in this way make the channel matrix $\mathcal{H}$ of the suboptimum detector to have the same form as the optimum detector $\tilde{\mathcal{H}}$ (2), the near-far resistance of the suboptimum detector can almost achieve the optimum near-far resistance (ideally) regardless of the dimension difference between these two matrices. Therefore, the key to enhance near-far resistance of those suboptimum detectors is to change $\mathcal{H}$ of (1) to be of the same form as $\tilde{\mathcal{H}}$ of (2). [6] presented a simple method which can achieve this goal. The basic idea of [6] is summarized as follows. From (1), in the absence of the noise, the received signal vector can be rewritten as

$$\begin{aligned}
\chi_N(n) &= \begin{bmatrix} \mathcal{H}_1 & \mathcal{H}_0 & \mathcal{H}_2 \end{bmatrix} \begin{bmatrix} \mathbf{b}_1(n) \\ \mathbf{b}_0(n) \\ \mathbf{b}_2(n) \end{bmatrix} \\
&= \mathcal{H}_0\mathbf{b}_0(n) + \begin{bmatrix} \mathcal{H}_1 & \mathcal{H}_2 \end{bmatrix} \begin{bmatrix} \mathbf{b}_1(n) \\ \mathbf{b}_2(n) \end{bmatrix}
\end{aligned} \tag{3}$$

where $\mathcal{H}_0$ has the same structure as $\tilde{\mathcal{H}}$ in (2) but with a much lower dimension, and $\mathcal{H}_1$ is a block Toeplitz matrix with its first row and first column as $[\mathbf{H}(L_h-1), \cdots, \mathbf{H}(1)]$ and $\left[\mathbf{H}^T(L_h-1), \mathbf{0}, \cdots, \mathbf{0}\right]^T$ respectively. $\mathcal{H}_2$ is also a block Toeplitz matrix with its first row and first column as $[\mathbf{0}, \cdots, \mathbf{0}]$ and $\left[\mathbf{0}, \cdots, \mathbf{0}, \mathbf{H}^T(0), \cdots, \mathbf{H}^T(L_h-2)\right]^T$ respectively. As mentioned before, in order to enhance the near-far resistance, (3) should be made to

$$\chi_N(n) = \mathcal{H}_0\mathbf{b}_0(n) \tag{4}$$

One simplest way to achieve (4) is to let $\mathbf{b}_1(n)$ and $\mathbf{b}_2(n)$ be zero. This is equivalent to zero bit insertion (or isolation) at both ends of each small block of symbols. However, any performance gain on the near-far resistance using the zero bit insertion is accompanied by three disadvantages: i) the new transmission requires partial synchronization of all transmitters; ii) the bit rate of all information sequences is reduced. iii) each information symbol in a detection block needs its own detector. Thus the computational complexity to estimate all the detectors could be high, especially when the number of information bits in one detection block is large. A method which can eliminate these three disadvantages is presented next.

4. LINEAR SMOOTHING METHOD

Another approach to achieve (4) is to use the linear smoothing method (also known as the two-sided linear prediction method). In the absence of noise , construct a data vector

$$\mathcal{Y}(n) = \begin{bmatrix} \chi_{M_1}(n-M_1) \\ \chi_N(n) \\ \chi_{M_2}(n+N) \end{bmatrix} = \bar{\mathcal{H}} \begin{bmatrix} \tilde{\mathbf{b}}_1(n) \\ \mathbf{b}_0(n) \\ \tilde{\mathbf{b}}_2(n) \end{bmatrix} \triangleq \bar{\mathcal{H}}\tilde{\mathbf{b}}(n) \tag{5}$$

where $\chi_{M_i}(n)$ is defined in the same way as (1), and $\bar{\mathcal{H}}$ is shown at the top of the next page. Decompose $\bar{\mathcal{H}}$ as follows

$$\bar{\mathcal{H}} = \left[\mathbf{Q}_1^T \mathbf{Q}_0^T \mathbf{Q}_2^T\right]^T \tag{6}$$

where $\mathbf{Q}_0$, $\mathbf{Q}_1$ and $\mathbf{Q}_2$ have NL_c, M_1L_c and M_2L_c rows respectively. Due to the structure of (6), the matrix $\left[\mathbf{Q}_1^T \mathbf{Q}_2^T\right]^T$ has $(N-L_h+1)\,J$ zero columns in the middle. Striking those zero columns out, it is straightforward to show that the full column rank of the matrix $\left[\mathbf{Q}_1^T \mathbf{Q}_2^T\right]^T$ is guaranteed since $\mathcal{H}$ in (1) has full column rank. This property will be needed in the following linear smoothing step.

Define an NL_c dimensional two-sided prediction error or smoothing error vector

$$\varepsilon(n) = \begin{bmatrix} -\mathbf{P}_1 & \mathbf{I} & -\mathbf{P}_2 \end{bmatrix} \mathcal{Y}(n) \tag{7}$$

where $\mathbf{P}_1$, $\mathbf{I}$ and $\mathbf{P}_2$ are $NL_c \times M_1L_c$, $NL_c \times NL_c$ and $NL_c \times M_2L_c$ respectively. Performing least squares minimization on (7) gives the following result

Propostion 1 *The optimal solution to the linear smoothing problem (7) results in*

$$\begin{bmatrix} -\mathbf{P}_1 & \mathbf{I} & -\mathbf{P}_2 \end{bmatrix} \bar{\mathcal{H}} = \begin{bmatrix} \mathbf{0} & \mathcal{H}_0 & \mathbf{0} \end{bmatrix} \tag{8}$$

and the smoothing error is

$$\varepsilon(n) = \mathcal{H}_0\mathbf{b}_0(n) \tag{9}$$

$$\bar{\mathcal{H}} = \begin{bmatrix} \mathbf{H}(L_h-1) & \cdots & \mathbf{H}(0) & \cdots & \mathbf{0} & & & & & & \bigcirc \\ \vdots & \ddots & & \ddots & \vdots & & & & & & \\ \mathbf{0} & \cdots & \mathbf{H}(L_h-1) & \cdots & \mathbf{H}(0) & & & & & & \\ \mathbf{0} & \cdots & \mathbf{0} & & \mathcal{H}_1 & \mathcal{H}_0 & \mathcal{H}_2 & & \mathbf{0} & \cdots & \mathbf{0} \\ & & & & & & \mathbf{H}(L_h-1) & \cdots & \mathbf{H}(0) & \cdots & \mathbf{0} \\ & & & & & & \vdots & \ddots & & \ddots & \vdots \\ \bigcirc & & & & & & \mathbf{0} & \cdots & \mathbf{H}(L_h-1) & \cdots & \mathbf{H}(0) \end{bmatrix}$$

Proof: Using (5) (6) and (7), we have

$$E\left\{\varepsilon(n)\,\varepsilon^H(n)\right\} = \begin{bmatrix} -\mathbf{P}_1 & \mathbf{I} & -\mathbf{P}_2 \end{bmatrix} \begin{bmatrix} \mathbf{Q}_1 \\ \mathbf{Q}_0 \\ \mathbf{Q}_2 \end{bmatrix} \mathbf{A}$$

$$\cdot \begin{bmatrix} \mathbf{Q}_1^H & \mathbf{Q}_0^H & \mathbf{Q}_2^H \end{bmatrix} \begin{bmatrix} -\mathbf{P}_1^H \\ \mathbf{I} \\ -\mathbf{P}_2^H \end{bmatrix}$$

$$= (\mathbf{Q}_0 - \mathbf{P}_1\mathbf{Q}_1 - \mathbf{P}_2\mathbf{Q}_2)\,\mathbf{A}\left(\mathbf{Q}_0^H - \mathbf{Q}_1^H\mathbf{P}_1^H - \mathbf{Q}_2^H\mathbf{P}_2^H\right) \quad (10)$$

where $\mathbf{A}$ is a diagonal matrix with the diagonal elements being the powers of the symbols of the users. Minimizing $E\left\{\varepsilon(n)\,\varepsilon^H(n)\right\}$ over $\mathbf{P}_1$ and $\mathbf{P}_2$ then gives

$$\begin{bmatrix} \mathbf{Q}_1 \\ \mathbf{Q}_2 \end{bmatrix} \mathbf{A} \left(\mathbf{Q}_0 - \begin{bmatrix} \mathbf{P}_1 & \mathbf{P}_2 \end{bmatrix} \begin{bmatrix} \mathbf{Q}_1 \\ \mathbf{Q}_2 \end{bmatrix}\right)^H = \bigcirc \quad (11)$$

and

$$\mathbf{Q}_0 - \begin{bmatrix} \mathbf{P}_1 & \mathbf{P}_2 \end{bmatrix} \begin{bmatrix} \mathbf{Q}_1 \\ \mathbf{Q}_2 \end{bmatrix} = \mathbf{Q}_0 - \begin{bmatrix} \times & \bigcirc & \times \end{bmatrix}$$
$$= \begin{bmatrix} \times & \mathcal{H}_0 & \times \end{bmatrix} \quad (12)$$

Due to the full column rank property of the non-zero part of the matrix $\begin{bmatrix} \mathbf{Q}_1 \\ \mathbf{Q}_2 \end{bmatrix}$, in (12) those rows of the matrix $\left(\mathbf{Q}_0 - \begin{bmatrix} \mathbf{P}_1 & \mathbf{P}_2 \end{bmatrix} \begin{bmatrix} \mathbf{Q}_1 \\ \mathbf{Q}_2 \end{bmatrix}\right)^H$ corresponding to the non-zero part of $\begin{bmatrix} \mathbf{Q}_1 \\ \mathbf{Q}_2 \end{bmatrix}$ must be zero. In other words, the corresponding entries in $\times$ of (12) should be all zeros. Thus (8) is obtained. Furthermore,

$$\begin{bmatrix} -\mathbf{P}_1 & \mathbf{I} & -\mathbf{P}_2 \end{bmatrix} \mathcal{Y}(n) = \begin{bmatrix} -\mathbf{P}_1 & \mathbf{I} & -\mathbf{P}_2 \end{bmatrix}$$

$$\cdot \begin{bmatrix} \mathbf{Q}_1 \\ \mathbf{Q}_0 \\ \mathbf{Q}_2 \end{bmatrix} \tilde{\mathbf{b}}(n) = \begin{bmatrix} \bigcirc & \mathcal{H}_0 & \bigcirc \end{bmatrix} \begin{bmatrix} \tilde{\mathbf{b}}_1(n) \\ \mathbf{b}_0(n) \\ \tilde{\mathbf{b}}_2(n) \end{bmatrix} = \mathcal{H}_0\mathbf{b}_0(n) \quad (13)$$

Hence, (9) is obtained. □

Define the data correlation matrix

$$\mathbf{R} = E\left\{\mathcal{Y}(n)\mathcal{Y}^H(n)\right\} = \begin{bmatrix} \mathbf{R}_{11} & \mathbf{R}_{12} & \mathbf{R}_{13} \\ \mathbf{R}_{21} & \mathbf{R}_{22} & \mathbf{R}_{23} \\ \mathbf{R}_{31} & \mathbf{R}_{32} & \mathbf{R}_{33} \end{bmatrix} \quad (14)$$

where $\mathbf{R}_{11}$, $\mathbf{R}_{22}$ and $\mathbf{R}_{33}$ are M_1L_c, NL_c and M_2L_c square matrices respectively. Then, it is well known that the optimal solution for the linear least squares optimization problem (7) is [4]

$$\begin{bmatrix} \mathbf{P}_1 & \mathbf{P}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{R}_{21} & \mathbf{R}_{23} \end{bmatrix} \begin{bmatrix} \mathbf{R}_{11} & \mathbf{R}_{13} \\ \mathbf{R}_{31} & \mathbf{R}_{33} \end{bmatrix}^+ \quad (15)$$

where $(\cdot)^+$ denotes pseudoinverse.

This linear smoothing step is used as a pre-processing stage. Once the smoothing error (9) is obtained, it is then used as the new data in any subsequent suboptimum detector. Clearly, neither information rate reduction nor partial synchronization is needed.

5. SIMULATIONS

Simulation examples are presented to illustrate our arguments. In all of the simulations, the channel response of each user is randomly generated by [8] $g(t) = \sum_{q=1}^{L_d} \alpha_q\, p\,(t - \tau_q)$ where L_d is the total number of multipaths; τ_q is the associated delay of the qth path; α_q is the attenuation of the qth path; $p(t)$ is the raised-cosine pulse function with a roll-off factor of 0.5. $g(t)$ is then sampled and truncated to length L_g. The user delay d_i, the multipath delay τ_q, and the number of multipath components L_d are uniformly distributed within [0 , $L_c - 1$], [0 , $(L_c - 1)T_c$], and [1 , 30], respectively. α_q is generated according to the Gaussian distribution with zero mean and unit variance. Gold sequence of length $L_c = 31$ is used. All input symbols are drawn from a BPSK constellation and then multiplied by various magnitude factors to generate the near-far situations. The first user is the desired user. The near-far ratio is defined as $10\log_{10} A_i/A_1$ for $i \neq 1$, where A_1 is the desired user's power, and all other users have the same power A_i. L_g is 30 chips in all simulations. Two methods (Subspace method [2] and linear-prediction method [3]) are implemented for comparison. For the signal subspace in [2], the rank was determined by taking empirically selected thresholds. All results are based on 100 Monte Carlo runs unless specified. The user codes, channel and user delays are randomly generated in each Monte Carlo run. The optimum near-far resistance is calculated according to [6].

Example 1: Performance in near-far resistance

The simulations are set in a 10 user channel case with $0\,dB$ and $10\,dB$ near-far ratios. The detector length N is 5, and $M_1 = M_2 = 2$. 1000 symbols were used to estimate various detectors. According to [6], the practical near-far resistance of the desired user in all simulated algorithms is calculated as $\eta = \frac{\|\mathbf{f}^H\mathbf{H}_d\|^2}{\mathbf{f}^H\mathbf{f}}$ in the noise free situation, where $\mathbf{f}$ is the suboptimum detector and $\mathbf{H}_d$ is one column in the channel matrix $\mathcal{H}$ corresponding to the desired symbol. The results are presented in Figure 1. It can be seen that the linear smoothing method has a performance gain on the near far resistance. Furthermore, it can also be seen that when more symbols were used to estimate the detector, the performance on near-far resistance becomes better in all simulated algorithms.

Example 2: Performance in output SINR

In this example we present the output signal to interference plus noise ratio (SINR) of the proposed linear smoothing method under various input signal to noise ratio (SNR). The definitions of SNR and SINR can be found in [3]. The simulations' environments are the same as those of Example 1. After calculating the suboptimum

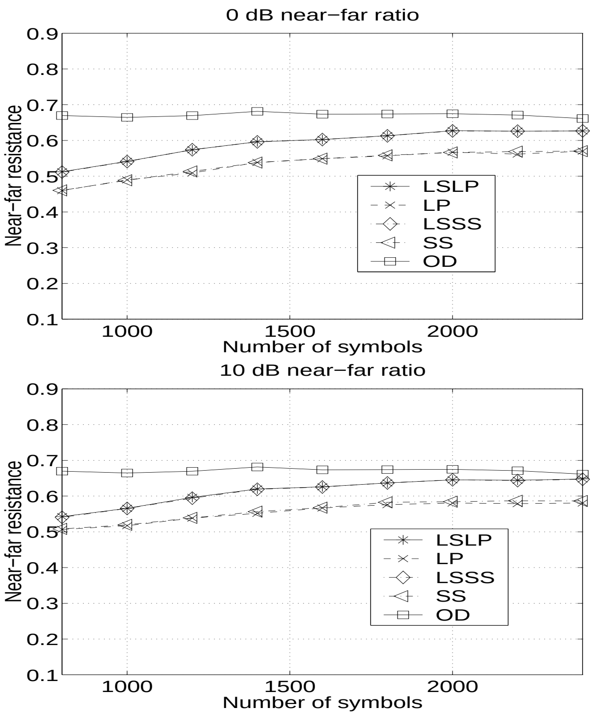

Fig. 1. Near-far resistance vs different symbol length under different near-far ratio, random channels. □: Optimum [6]; $*$: Linear prediction using smoothing error (LSLP); $\times$: Linear prediction (LP); ⋄: Subspace method using smoothing error (LSSS); ◁: Subspace method (SS).

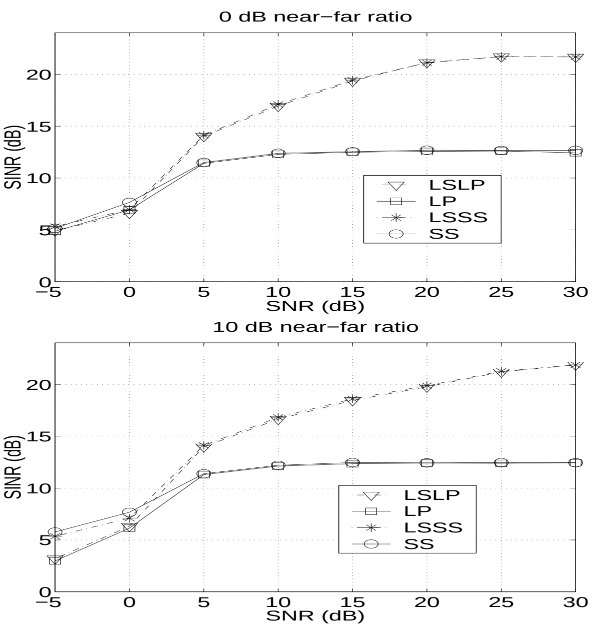

Fig. 2. Output SINR vs input SNR under different near-far ratio for random channels. □: Linear prediction (LP); ∘: Subspace method (SS); ▽: Linear prediction using smoothing error (LSLP); $*$: Subspace method using smoothing error (LSSS).

detectors based on the given data record (1000 symbols in our simulations), the obtained suboptimum detectors were then applied to calculate the output SINR. The results are presented in Figure 2. Performance gains using the linear smoothing method is clear.

Example 3: Performance in BER

In this example we present the bit error rate (BER) of the proposed linear smoothing method under various input SNR. The simulations' environments are the same as those of Example 1. MMSE detectors were used for comparison. After calculating the detectors based on the given data record (500 symbols), the obtained detectors were then applied to an independent record of length 2000 symbols to calculate the BER. The averaged BER is based on 500 independent Monte Carlo runs. The results are presented in Figure 3. It is clear that the linear smoothing method significantly improves the BER performance for medium and high SNR situations (>3 dB SNR).

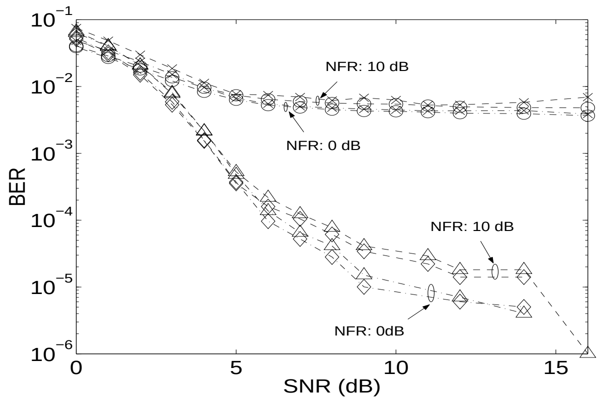

Fig. 3. Bit error rate vs input SNR under different near-far ratio (NFR) for random channels. $\times$: Linear prediction (LP); ∘: Subspace method (SS); △: Linear prediction using smoothing error (LSLP); ⋄: Subspace method using smoothing error (LSSS).

References

[1] S. Verdú, *Multiuser detection.* Cambridge University Press, 1998.

[2] X. Wang and H. V. Poor, "Blind equalization and multiuser detection in dispersive CDMA channels, " *IEEE Trans. Commun.*, Vol. 46, pp. 91-103, Jan.

[3] X. Li and H. H. Fan, "Direct blind multiuser detection for CDMA in multipath without channel estimation," *IEEE Trans. Signal processing*, vol. 49, pp. 63-73, Jan. 2001.

[4] H. Fan and X. Li, "Linear prediction approach for joint blind equalization and blind multiuser detection in CDMA systems," *IEEE Trans. Signal processing*, vol. 48, pp. 3134-3145, Nov. 2000.

[5] X. Yue and H. Fan, "Near-far resistance under multipath: Optimum and suboptimum detectors," *Proc. of the 35th Asilomar Conference on Signals, Systems, and Computers*, Vol. 3, pp. 2601-2604, Pacific Grove, CA, Nov. 2001.

[6] X. Yue, H. Fan, Enhancing near-far resistance for linear CDMA detectors, To appear in *IEEE Military Communications Conference, Anaheim*, CA, 7-10 Oct. 2002.

[7] X. Yue and H. Fan, "Optimum and Suboptimum CDMA Detectors: Near-Far Resistance under Multipath," *Proc. of the International conference on Acoustics, Speech and Signal Processing*, Vol. 2, pp. 1723-1727, Orlando, FL, May 2002.

[8] M. Torlak and G. Xu, "Blind multiuser channel estimation in asynchronous CDMA systems," *IEEE Trans. Signal processing*, vol. 45, pp. 137-147, Jan. 1997.