EURASIP Journal on Wireless Communications and Networking 2005:2, 206–215
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Blind Multiuser Detection for Long-Code CDMA Systems with Transmission-Induced Cyclostationarity

Tongtong Li
Department of Electrical and Computer Engineering, Michigan State University, East Lansing, MI 48824, USA
Email: tongli@egr.msu.edu

Weiguo Liang
Department of Electrical and Computer Engineering, Michigan State University, East Lansing, MI 48824, USA
Email: liangwg@egr.msu.edu

Zhi Ding
Department of Electrical and Computer Engineering, University of California, Davis, CA 95616, USA
Email: zding@ece.ucdavis.edu

Jitendra K. Tugnait
Department of Electrical and Computer Engineering, Auburn University, Auburn, AL 36849, USA
Email: tugnajk@eng.auburn.edu

Received 30 April 2004; Revised 5 August 2004

We consider blind channel identification and signal separation in long-code CDMA systems. First, by modeling the received signals as cyclostationary processes with modulation-induced cyclostationarity, long-code CDMA system is characterized using a time-invariant system model. Secondly, based on the time-invariant model, multistep linear prediction method is used to reduce the intersymbol interference introduced by multipath propagation, and channel estimation then follows by utilizing the nonconstant modulus precoding technique with or without the matrix-pencil approach. The channel estimation algorithm without the matrix-pencil approach relies on the Fourier transform and requires additional constraint on the code sequences other than being a nonconstant modulus. It is found that by introducing a random linear transform, the matrix-pencil approach can remove (with probability one) the extra constraint on the code sequences. Thirdly, after channel estimation, equalization is carried out using a cyclic Wiener filter. Finally, since chip-level equalization is performed, the proposed approach can readily be extended to multirate cases, either with multicode or variable spreading factor. Simulation results show that compared with the approach using the Fourier transform, the matrix-pencil-based approach can significantly improve the accuracy of channel estimation, therefore the overall system performance.

Keywords and phrases: long-code CDMA, multiuser detection, cyclostationarity.

1. INTRODUCTION

In addition to intersymbol and interchip interference, one of the key obstacles to signal detection and separation in CDMA systems is the detrimental effect of multiuser interference (MUI) on the performance of the receivers and the overall communication system. Compared to the conventional single-user detectors where interfering users are modeled as noise, significant improvement can be obtained with multiuser detectors where MUI is explicitly part of the signal model [1].

In literature [2], if the spreading sequences are periodic and repeat every information symbol, the system is referred to as short-code CDMA, and if the spreading sequences are aperiodic or essentially pseudorandom, it is known as long-code CDMA. Since multiuser detection relies on the cyclostationarity of the received signal, which is significantly complicated by the time-varying nature of the long-code system, research on multiuser detection has largely been limited to short-code CDMA for some time, see, for

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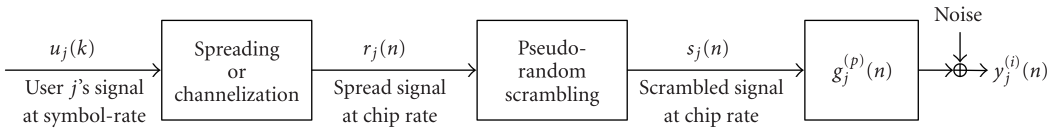

Figure 1: Block diagram of a long-code DS-CDMA system.

example, [3, 4, 5, 6, 7] and the references therein. On the other hand, due to its robustness and performance stability in frequency fading environment [2], long code is widely used in virtually all operational and commercially proposed CDMA systems, as shown in Figure 1. Actually, each user's signal is first spread using a code sequence spanning over just one symbol or multiple symbols. The spread signal is then further scrambled using a long-periodicity pseudorandom sequence. This is equivalent to the use of an aperiodic (long) coding sequence as in *long-code CDMA system*, and the chip-rate sampled signal and MUIs are generally modeled as time-varying vector processes [8]. The time-varying nature of the received signal model in the long-code case severely complicates the equalizer development approaches, since consistent estimation of the needed signal statistics cannot be achieved by time-averaging over the received data record.

More recently, both training-based (e.g., [9, 10, 11]) and blind (e.g., [8, 12, 13, 14, 15, 16, 17, 18, 19]) multiuser detection methods targeted at the long-code CDMA systems have been proposed. In this paper, we will focus on blind channel estimation and user separation for long-code CDMA systems. Based on the channel model, most existing blind algorithms can roughly be divided into three classes.

(i) *Symbol-by-symbol approaches.* As in long-code systems, each user's spreading code changes for every information symbol, symbol-by-symbol approaches (see [8, 17, 18, 19], e.g.) process each received symbol individually based on the assumption that channel is invariant in each symbol. In [8, 17, 18], channel estimation and equalization is carried out for each individual received symbol by taking instantaneous estimates of signal statistics based on the sample values of each symbol. In [19], based on the BCJR algorithm, an iterative turbo multiuser detector was proposed.

(ii) *Frame-by-frame approaches.* Algorithms in this category (see [15, 20], e.g.) stack the total received signal corresponding to a whole frame or slot into a long vector, and formulate a deterministic channel model. In [15], computational complexity is reduced by breaking the big matrix into small blocks and implementing the inversion "locally." As can be seen, the "localization" is similar to the process of the symbol-by-symbol approach. And the work is extended to fast fading channels in [20].

(iii) *Chip-level equalization.* By taking chip-rate information as input, the time-varying effect of the pseudorandom sequence is absorbed into the input sequence. With the observation that channels remain approximately stationary over each time slot, the underlying channel, therefore, can be modelled as a time-invariant system, and at the receiver, chip-level equalization is performed. Please refer to [14, 21, 22, 23] and the references therein.

In all these three categories, one way or another, the time-varying channel is "converted" or "decomposed" into *time-invariant* channels.

In this paper, the long-code CDMA system is characterized as a time-invariant MIMO system as in [14, 23]. Actually, the received signals and MUIs can be modeled as cyclostationary processes with modulation-induced cyclostationarity, and we consider blind channel estimation and signal separation for long-code CDMA systems using multistep linear predictors. Linear prediction-based approach for MIMO model was first proposed by Slock in [24], and developed by others in [25, 26, 27, 28]. It has been reported [26, 28] that compared with subspace methods, linear prediction methods can deliver more accurate channel estimates and are more robust to overmodeling in channel order estimate. In this paper, multistep linear prediction method is used to separate the intersymbol interference introduced by multipath channel, and channel estimation is then performed using nonconstant modulus precoding technique both with and without the matrix-pencil approach [29, 30]. The channel estimation algorithm without the matrix-pencil approach relies on the Fourier transform, and requires additional constraint on the code sequences other than being nonconstant modulus. It is found that by introducing a random linear transform, the matrix-pencil approach can remove (with probability one) the extra constraint on the code sequences. After channel estimation, equalization is carried out using a cyclic Wiener filter. Finally, since chip-level equalization is performed, the proposed approach can readily be extended to multirate cases, either with multicode or variable spreading factor. Simulation results show that compared with the approach using the Fourier transform, the matrix-pencil-based approach can significantly improve the accuracy of channel estimation, therefore the overall system performance.

2. SYSTEM MODEL

Consider a DS-CDMA system with M users and K receive antennas, as shown in Figure 2. Assume the processing gain is N, that is, there are N chips per symbol. Let $u_j(k)$ $(j = 1, \dots, M)$ denote user j's kth symbol. Assume that the code sequence extends over L_c symbols. Let $\mathbf{c}_j =$

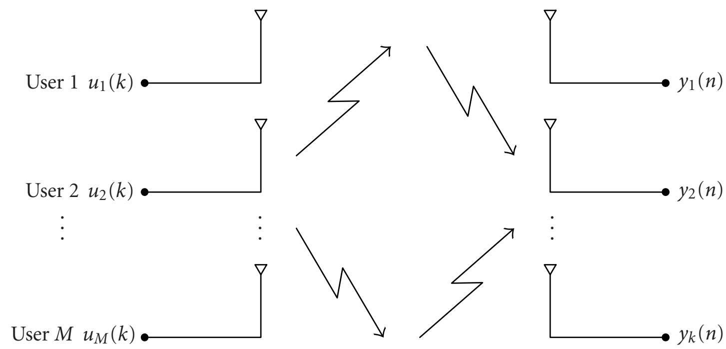

FIGURE 2: Block diagram of a MIMO system.

$[c_j(0), c_j(1), \ldots, c_j(N-1), c_j(N), \ldots, c_j(L_cN-1)]$ denote user j's spreading code sequence. For notations used for each individual user, please refer to Figure 1. When k is a multiple of L_c, the spread signal (at chip rate) with respect to the signal block $[u_j(k), \ldots, u_j(k+L_c-1)]$ is

$$\begin{aligned}&[r_j(kN), \ldots, r_j((k+L_c)N-1)]\\&\quad= [u_j(k)c_j(0), \ldots, u_j(k)c_j(N-1), \ldots,\\&\qquad u_j(k+L_c-1)c_j((L_c-1)N), \ldots,\\&\qquad u_j(k+L_c-1)c_j(L_cN-1)].\end{aligned} \tag{1}$$

The successive scrambling process is achieved by

$$\begin{aligned}&[s_j(kN), \ldots, s_j((k+L_c)N-1)]\\&\quad= [r_j(kN), \ldots, r_j((k+L_c)N-1)]\\&\qquad .*[d_j(kN), d_j(kN+1), \ldots, d_j((k+L_c)N-1)],\end{aligned} \tag{2}$$

where ".*" stands for point-wise multiplication, and $[d_j(kN), d_j(kN+1), \ldots, d_j(kN+N-1)]$ denotes the chip-rate scrambling sequence with respect to symbol $u_j(k)$. Defining

$$\begin{aligned}&[v_j(kN), \ldots, v_j((k+L_c)N-1)]\\&\quad\triangleq [u_j(k)d_j(kN), \ldots, u_j(k)d_j(kN+N-1), \ldots,\\&\qquad u_j(k+L_c-1)d_j((k+L_c-1)N), \ldots,\\&\qquad u_j(k+L_c-1)d_j((k+L_c)N-1)],\end{aligned} \tag{3}$$

we get

$$\begin{aligned}&[s_j(kN), s_j(kN+1), \ldots, s_j((k+L_c)N-1)]\\&\quad= [v_j(kN), v_j(kN+1), \ldots, v_j((k+L_c)N-1)]\\&\qquad .*\,[c_j(0), c_j(1), \ldots, c_j(L_cN-1)].\end{aligned} \tag{4}$$

If we regard the chip rate $v_j(n)$ as the input signal of user j, then $s_j(n)$ is the precoded transmit signal corresponding to the jth user and

$$s_j(n) = v_j(n)c_j(n), \quad n \in Z,\ j = 1, 2, \ldots, M, \tag{5}$$

where $c_j(n) = c_j(n+L_cN)$ serves as a periodic precoding sequence with period L_cN. We note that this form of periodic precoding has been suggested by Serpedin and Giannakis in [31] to introduce cyclostationarity in the transmit signal, thereby making blind channel identification based on second-order statistics in symbol-rate-sampled single-carrier system possible. More general idea of transmitter-induced cyclostationarity has been suggested previously in [32, 33]. In [34], nonconstant precoding technique has been applied to blind channel identification and equalization in OFDM-based multiantenna systems.

Based on Figures 1 and 2, the received chip-rate signal at the pth antenna ($p = 1, 2, \ldots, K$) can be expressed as

$$y_p(n) = \sum_{j=1}^{M}\sum_{l=0}^{L-1} g_j^{(p)}(l)s_j(n-l) + w_p(n), \tag{6}$$

where $L-1$ is the maximum multipath delay spread in chips, $\{g_j^{(p)}(l)\}_{l=0}^{L-1}$ denotes the channel impulse response from jth transmit antenna to pth receive antenna, and $w_p(n)$ is the pth antenna additive white noise. Let $\mathbf{s}(n) = [s_1(n), s_2(n), \ldots, s_M(n)]^T$ be the precoded signal vector. Collect the samples at each receive antenna and stack them into a $K \times 1$ vector, we get the following *time-invariant* MIMO system model:

$$\mathbf{y}(n) = [y_1(n), y_2(n), \ldots, y_K(n)]^T = \sum_{l=0}^{L-1}\mathbf{H}(l)\mathbf{s}(n-l) + \mathbf{w}(n), \tag{7}$$

where

$$\mathbf{H}(l) = \begin{bmatrix} g_1^{(1)}(l) & g_2^{(1)}(l) & \cdots & g_M^{(1)}(l)\\ g_1^{(2)}(l) & g_2^{(2)}(l) & \cdots & g_M^{(2)}(l)\\ \vdots & \vdots & \ddots & \vdots\\ g_1^{(K)}(l) & g_2^{(K)}(l) & \cdots & g_M^{(K)}(l)\end{bmatrix}_{K\times M} \tag{8}$$

and $\mathbf{w}(n) = [w_1(n), w_2(n), \ldots, w_K(n)]^T$.

Defining $\mathcal{H}(z) = \sum_{l=0}^{L-1} \mathbf{H}(l)z^{-l}$, it then follows that

$$\mathbf{y}(n) = \mathcal{H}(z)\mathbf{s}(n) + \mathbf{w}(n) \triangleq \mathbf{y}_s(n) + \mathbf{w}(n). \tag{9}$$

In the following section, channels are estimated based on the desired user's code sequence and the following assumptions.

(A1) The multiuser sequences $\{u_j(k)\}_{j=1}^{M}$ are zero mean, mutually independent, and i.i.d. Take $E\{|u_j(k)|^2\} = 1$ by absorbing any nonidentity variance of $u_j(k)$ into the channel.

(A2) The scrambling sequences $\{d_j(k)\}_{j=1}^{M}$ are mutually independent i.i.d. BPSK sequences, independent of the information sequences.

(A3) The noise is zero mean Gaussian, independent of the information sequences, with $E\{\mathbf{w}(k+l)\mathbf{w}^H(k)\} = \sigma_w^2 \mathbf{I}_K \delta(l)$ where $\mathbf{I}_K$ is the $K \times K$ identity matrix.

(A4) $\mathcal{H}(z)$ is irreducible when regarded as a polynomial matrix of z^{-1}, that is, $\text{Rank}\{\mathcal{H}(z)\} = M$ for all complex z except $z = 0$.

3. BLIND CHANNEL IDENTIFICATION BASED ON MULTISTEP LINEAR PREDICTORS

In this section, first, multistep linear prediction method is used to resolve the intersymbol interference introduced by multipath channel. Secondly, based on the ISI-free MIMO model, two channel estimation approaches are proposed by exploiting the advantage of nonconstant modulus precoding: one uses the Fourier analysis, and the other is based on the matrix-pencil technique.

3.1. ISI reduction and separation based on multistep linear predictors

Based on the results in [6, 28, 35], it can be shown that under (A1), (A2), (A3), and (A4), finite length predictors exist for the noise-free channel observations

$$\mathbf{y}_s(n) = \mathcal{H}(z)\mathbf{s}(n) = \sum_{l=0}^{L-1} \mathbf{H}(l)\mathbf{s}(n-l) \tag{10}$$

such that it has the following canonical representation:

$$\mathbf{y}_s(n) = \sum_{i=l}^{L_l} A_{n,i}^{(l)} \mathbf{y}_s(n-i) + \mathbf{e}(n|n-l), \quad l = 1, 2, \ldots, \tag{11}$$

for some $L_l \le M(L-1) + l - 1$, where the l-step ahead linear prediction error $\mathbf{e}(n|n-l)$ is given by

$$\mathbf{e}(n|n-l) = \sum_{i=0}^{l-1} \mathbf{H}(i)\mathbf{s}(n-i) \tag{12}$$

satisfying

$$E\{\mathbf{e}(n|n-l)\mathbf{y}_s^H(n-m)\} = 0 \quad \forall m \ge l. \tag{13}$$

Therefore, based on (11) and (13), the coefficient matrices $A_{n,i}^{(l)}$'s can be determined from

$$E\{\mathbf{y}_s(n)\mathbf{y}_s^H(n-m)\} = \sum_{i=l}^{L_l} A_{n,i}^{(l)} E\{\mathbf{y}_s(n-i)\mathbf{y}_s^H(n-m)\} \quad \forall m \ge l. \tag{14}$$

Actually, consider

$$\begin{aligned} \mathbf{R}_s(n,k) &\triangleq E\{\mathbf{s}(n)\mathbf{s}^H(n-k)\} \\ &= \text{diag}\left[\,|c_1(n)|^2, \ldots, |c_M(n)|^2\right]\delta(k). \end{aligned} \tag{15}$$

It follows that $\mathbf{R}_s(n,k)$ is periodic with respect to n:

$$\mathbf{R}_s(n,k) = \mathbf{R}_s(n + L_c N, k) \tag{16}$$

(where N is the processing gain) since $c_j(n) = c_j(n + L_c N)$ for $j = 1, 2, \ldots, M$. Note that $\mathbf{R}_s(n,k) = 0$ for any $k \ne 0$. Defining $\mathbf{R}_s(n) \triangleq \mathbf{R}_s(n, 0)$, then

$$\mathbf{R}_s(n) = \mathbf{R}_s(n + L_c N). \tag{17}$$

It follows that the $K \times K$ autocorrelation matrix of the noise-free channel output

$$\begin{aligned} \mathbf{R}_{y_s}(n,k) &\triangleq E\{\mathbf{y}_s(n){\mathbf{y}_s}^H(n-k)\} \\ &= \sum_{l=0}^{L-1} \mathbf{H}(l)\mathbf{R}_s(n-l)\mathbf{H}^H(l-k) \end{aligned} \tag{18}$$

is also periodic with period $L_c N$ in this circumstance. In (14), letting $m = l, l+1, \ldots, L_l$, we have

$$\begin{aligned} &\left[A_{n,l}^{(l)}, A_{n,l+1}^{(l)}, \ldots, A_{n,L_l}^{(l)}\right] \\ &\quad = \left[\mathbf{R}_{y_s}(n,l), \ldots, \mathbf{R}_{y_s}(n,L_l)\right]\mathcal{R}^{\#}(n,l,L_l), \end{aligned} \tag{19}$$

where # stands for pseudoinverse and $\mathcal{R}(n,l,L_l)$ is a $(L_l - l + 1)K \times (L_l - l + 1)K$ matrix with its (i,j)th $K \times K$ block element as $\mathbf{R}_{y_s}(n-l-i+1, j-i) = E\{\mathbf{y}_s(n-l-i+1){\mathbf{y}_s}^H(n-l-j+1)\}$ for $i, j = 1, \ldots, L_l - l + 1$. And $\mathbf{R}_{y_s}(n,k)$ can be estimated from

$$\mathbf{R}_y(n,k) \triangleq E\{\mathbf{y}(n)\mathbf{y}^H(n-k)\} = \mathbf{R}_{y_s}(n,k) + \sigma_n^2 \mathbf{I}_K \delta(k) \tag{20}$$

through noise variance estimation, please see [6, 28] for more details.

Now define $\bar{\mathbf{e}}_l(n) \triangleq \mathbf{e}(n|n-l) - \mathbf{e}(n|n-l+1)$ and let

$$\mathbf{E}(n) \triangleq \begin{bmatrix} \bar{\mathbf{e}}_{d+1}(n+d) \\ \bar{\mathbf{e}}_d(n+d-1) \\ \vdots \\ \bar{\mathbf{e}}_2(n+1) \\ \bar{\mathbf{e}}(n|n-1) \end{bmatrix}. \tag{21}$$

It then follows from (12) that

$$\mathbf{E}(n) = \begin{bmatrix} \mathbf{H}(d) \\ \mathbf{H}(d-1) \\ \vdots \\ \mathbf{H}(0) \end{bmatrix} \mathbf{s}(n) \triangleq \widetilde{\mathbf{H}}\mathbf{s}(n), \tag{22}$$

where

$$\widetilde{\mathbf{H}} \triangleq \begin{bmatrix} \mathbf{H}(d) \\ \mathbf{H}(d-1) \\ \vdots \\ \mathbf{H}(0) \end{bmatrix}. \tag{23}$$

Thus, we obtained an ISI-free MIMO model (22).

3.2. Channel estimation through the Fourier analysis

Consider the correlation matrix of $\mathbf{E}(n)$,

$$\begin{aligned} \mathbf{R}_{\mathbf{E}}(n) &\triangleq E\{\mathbf{E}(n)\mathbf{E}^H(n)\} = \widetilde{\mathbf{H}}\mathbf{R}_s(n)\widetilde{\mathbf{H}}^H \\ &= \widetilde{\mathbf{H}}\,\mathrm{diag}\,\{|c_1(n)|^2, |c_2(n)|^2, \dots, |c_M(n)|^2\}\widetilde{\mathbf{H}}^H. \end{aligned} \tag{24}$$

Note that $c_j(n) = c_j(n + L_cN)$, $j = 1, 2, \dots, M$, so $\mathbf{R}_{\mathbf{E}}(n)$ is periodic with period L_cN. The Fourier series of $\mathbf{R}_{\mathbf{E}}(n)$ is

$$\begin{aligned} S_E(m) &= \sum_{n=0}^{L_cN-1} \mathbf{R}_{\mathbf{E}}(n)e^{-i(2\pi mn/L_cN)} \\ &= \widetilde{\mathbf{H}}\mathbf{C}_s(m)\widetilde{\mathbf{H}}^H, \end{aligned} \tag{25}$$

where

$$\begin{aligned} \mathbf{C}_s(m) &\triangleq \mathrm{diag}\left(\sum_{n=0}^{L_cN-1} |c_1(n)|^2 e^{-i(2\pi mn/L_cN)}, \dots, \right. \\ &\qquad \left. \sum_{n=0}^{L_cN-1} |c_M(n)|^2 e^{-i(2\pi mn/L_cN)}\right) \\ &= \mathrm{diag}\,(C_{s_1}(m), \dots, C_{s_M}(m)). \end{aligned} \tag{26}$$

The basic idea of this channel estimation algorithm is to design precoding code sequences $\{c_j(n)\}_{n=0}^{L_cN-1}$ ($j = 1, 2, \dots, M$) such that for a given cycle $m = m_j$, $C_{s_j}(m_j) \neq 0$ and $C_{s_k}(m_j) = 0$ for all $k \neq j$. That is, all but one entries in $\mathbf{C}_s(m)$ are zero. Choosing a different cycle m_j for each user (obviously, we need $L_cN > M$), blind identification of each individual channel can then be achieved through (25).

In fact, if for $m = m_j$, $C_{s_j}(m_j) \neq 0$, but $C_{s_k}(m_j) = 0$, for all $k \neq j$, then

$$S_E(m_j) = \widetilde{\mathbf{H}}\,\mathrm{diag}\,(0, \dots, 0, C_{s_j}(m_j), 0, \dots, 0)\widetilde{\mathbf{H}}^H. \tag{27}$$

It then follows from (8), (23), and (27) that

$$\mathbf{g}_j = \left[g_j^{(1)}(d), \dots, g_j^{(K)}(d), \dots, g_j^{(1)}(0), \dots, g_j^{(K)}(0)\right]^T \tag{28}$$

can be determined up to a complex scalar from the $K(d+1)\times K(d+1)$ Hermitian matrix $\mathbf{g}_j\mathbf{g}_j^H$. In other words, the channel responses from user j to each receive antenna $p = 1, 2, \dots, K$ can be identified up to a complex scalar. This ambiguity can be removed either by using one training symbol or using differential encoding.

3.3. Channel estimation using the matrix-pencil approach

Noting that $\mathbf{R}_{\mathbf{E}}(n) = \mathbf{R}_{\mathbf{E}}(n + L_cN)$, we form a matrix pencil $\{S_1, S_2\}$ based on linear combination of $\{\mathbf{R}_{\mathbf{E}}(n)\}_{n=0}^{L_cN-1}$ with random weighting. Let $\alpha_i(n)$ be uniformly distributed in interval (0,1), where $i = 1, 2$. Define

$$\begin{aligned} S_i &= \sum_{n=0}^{L_cN-1} \alpha_i(n)\mathbf{R}_{\mathbf{E}}(n) \\ &= \widetilde{\mathbf{H}}\,\mathrm{diag}\left(\sum_{n=0}^{L_cN-1} \alpha_i(n)|c_1(n)|^2, \dots, \sum_{n=0}^{L_cN-1} \alpha_i(n)|c_M(n)|^2\right)\widetilde{\mathbf{H}}^H \\ &\triangleq \widetilde{\mathbf{H}}\Gamma_i\widetilde{\mathbf{H}}^H \quad \text{for } i = 1, 2. \end{aligned} \tag{29}$$

According to the definition,

$$\begin{aligned} \Gamma_i = \mathrm{diag}&\left(\sum_{n=0}^{L_cN-1} \alpha_i(n)|c_1(n)|^2, \dots, \right. \\ &\left. \sum_{n=0}^{L_cN-1} \alpha_i(n)|c_M(n)|^2\right), \quad i = 1, 2, \end{aligned} \tag{30}$$

are two positively-definited matrices.

Consider the generalized eigenvalue problem

$$S_1\mathbf{x} = \lambda S_2\mathbf{x} \Longleftrightarrow \widetilde{\mathbf{H}}(\Gamma_1 - \lambda\Gamma_2)\widetilde{\mathbf{H}}^H\mathbf{x} = 0. \tag{31}$$

If $\widetilde{\mathbf{H}}$ is of full column rank (which is ensured by assumption (A4)), then (31) reduces to

$$(\Gamma_1 - \lambda\Gamma_2)\widetilde{\mathbf{H}}^H\mathbf{x} = 0. \tag{32}$$

By using random weighting, all the generalized eigenvalues corresponding to (32),

$$\lambda_j = \frac{\sum_{n=0}^{L_cN-1} \alpha_1(n)|c_j(n)|^2}{\sum_{n=0}^{L_cN-1} \alpha_2(n)|c_j(n)|^2}, \quad j = 1, 2, \dots, M, \tag{33}$$

are distinct eigenvalues with probability 1. In this case, since Γ_1 and Γ_2 are both diagonal, the generalized eigenvector $\mathbf{x}_j$ corresponding to λ_j should satisfy

$$\widetilde{\mathbf{H}}^H\mathbf{x}_j = \beta_j I_j, \tag{34}$$

where β_j is an unknown scalar, and $I_j = [0, \dots, 1, \dots, 0]^T$ with 1 in the jth entry is the jth column of the $M\times M$ identity matrix $\mathbf{I}$ [29].

It then follows from (31) and (34) that

$$S_1\mathbf{x}_j = \widetilde{\mathbf{H}}\Gamma_1\widetilde{\mathbf{H}}^H\mathbf{x}_j = \beta_j \sum_{n=0}^{L_cN-1} \alpha_1(n)\left|c_j(n)\right|^2\mathbf{g}_j, \tag{35}$$

where $\mathbf{g}_j$ is as in (28). And $\mathbf{g}_j$ can be determined up to a scalar once the generalized eigenvector $\mathbf{x}_j$ is obtained.

Remark 1. It should be noticed that the channel estimation algorithm based on the Fourier analysis requires an additional condition on the coding sequences, which actually implies that for a given cycle, all antennas, except one, are nulled out. More specifically, this constraint on the code sequences implies that for each user, there exists at least one narrow frequency band over which no other user is transmitting. When using the matrix-pencil approach, on the other hand, random weights, hence a random linear transform, is introduced instead of the Fourier transform, resulting in that the condition on the code sequences can be relaxed to any nonconstant modulus sequences which make λ_j's in (33) be distinct from each other for $j = 1, 2, \ldots, M$.

4. CHANNEL EQUALIZATION USING CYCLIC WIENER FILTER

After the channel estimation, in this section, equalization/desired user extraction is carried out using an MMSE cyclic Wiener filter. Without loss of generality, assume user 1 is the desired user. We want to design a chip-level $K \times 1$ MMSE equalizer $\{\mathbf{f}_d(n,i)\}_{i=0}^{L_e-1}$ of length L_e ($L_e \geq L$) which satisfies

$$\mathbf{f}_d(n,i) = \mathbf{f}_d(n + L_cN, i), \quad i = 0, 1, \ldots, L_e - 1. \tag{36}$$

The equalizer output can be expressed as

$$\hat{v}_1(n-d) = \sum_{i=0}^{L_e-1} \mathbf{f}_d^H(n,i)\mathbf{y}(n-i). \tag{37}$$

With the above equalizer, the MSE between the input signal and the equalizer output is

$$E\left\{\left|e(n)\right|^2\right\} = E\left\{\left|\sum_{i=0}^{L_e-1} \mathbf{f}_d^H(n,i)\mathbf{y}(n-i) - v_1(n-d)\right|^2\right\}. \tag{38}$$

Applying the orthogonality principle, we obtain

$$E\left\{\left[\sum_{i=0}^{L_e-1} \mathbf{f}_d^H(n,i)\mathbf{y}(n-i) - v_1(n-d)\right]\mathbf{y}^H(n-k)\right\} = 0 \tag{39}$$

for $k = 0, 1, \ldots, L_e - 1$.

Recall that (see (5)) if we define

$$\begin{aligned}\mathbf{C}(n) &\triangleq \operatorname{diag}\{c_1(n), c_2(n), \ldots, c_M(n)\},\\ \mathbf{v}(n) &\triangleq \left[v_1(n), v_2(n), \ldots, v_M(n)\right]^T,\end{aligned} \tag{40}$$

then

$$\mathbf{s}(n) = \left[s_1(n), s_2(n), \ldots, s_M(n)\right]^T = \mathbf{C}(n)\mathbf{v}(n). \tag{41}$$

It then follows from (7) that

$$\mathbf{y}(n) = \sum_{l=0}^{L-1} \mathbf{H}(l)\mathbf{C}(n-l)\mathbf{v}(n-l) + \mathbf{w}(n). \tag{42}$$

Stacking L_e successive $\mathbf{y}(n)$ together to form the $KL_e \times 1$ vector

$$Y(n) = \begin{bmatrix} \mathbf{y}(n) \\ \mathbf{y}(n-1) \\ \vdots \\ \mathbf{y}(n-L_e+1) \end{bmatrix} \triangleq \mathcal{H}_{C,n}V(n) + W(n), \tag{43}$$

where

$$\mathcal{H}_{C,n} = \begin{bmatrix} \mathbf{H}(0)\mathbf{C}(n) & \cdots & \mathbf{H}(L-1)\mathbf{C}(n-L+1) & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & \mathbf{H}(0)\mathbf{C}(n-L_e+1) & \cdots & \mathbf{H}(L-1)\mathbf{C}(n-L_e-L+2) \end{bmatrix} \tag{44}$$

is a $KL_e \times [(L + L_e - 1)M]$ matrix, $V(n) = [\mathbf{v}^T(n), \mathbf{v}^T(n-1), \ldots, \mathbf{v}^T(n - L_e - L + 2)]^T$ and $W(n)$ is defined in the same manner as $Y(n)$. It follows from (A1), (A2), and (A3) that

$$\begin{aligned}\mathbf{R}_Y(n) &\triangleq E\{Y(n)Y^H(n)\} = \mathcal{H}_{C,n}\mathcal{H}_{C,n}^H + \sigma_w^2\mathbf{I}_{KL_e},\\ \mathbf{R}_{v_1Y}(n,d) &\triangleq E\{v_1(n-d)Y^H(n)\} = I_d^H\mathcal{H}_{C,n}^H,\end{aligned} \tag{45}$$

where $I_d = [\mathbf{0}, \ldots, \mathbf{0}, \underbrace{1, 0, \ldots, 0}_{(d+1)'s\,M\times 1\text{ block}}, \ldots, \mathbf{0}]^H$ is the $(Md+1)$th column of the $M(L+L_e-1) \times M(L+L_e-1)$ identity matrix.

Define

$$\tilde{\mathbf{f}}_d(n) \triangleq \left[\mathbf{f}_d^H(n,0), \mathbf{f}_d^H(n,1), \ldots, \mathbf{f}_d^H(n, L_e-1)\right]^H \tag{46}$$

as the $KL_e \times 1$ equalizer coefficients vector. Then (39) can be rewritten as

$$\mathbf{R}_Y(n)\,\widetilde{\mathbf{f}}_d(n) = \mathcal{H}_{C,n} I_d. \tag{47}$$

It then follows that for $n = 0, \ldots, L_c N - 1$,

$$\widetilde{\mathbf{f}}_d(n) = \mathbf{R}_Y^{\#}(n)\mathcal{H}_{C,n} I_d, \tag{48}$$

where # denotes pseudoinverse.

5. EXTENSION TO MULTIRATE CDMA SYSTEMS

To support multimedia services with different quality of services requirements, multirate scheme is implemented in 3G CDMA systems by using *multicode* (MC) or *variable spreading factor* (VSF). In MC systems, the symbols of a high-rate user are subsampled to obtain several symbol streams, and each stream is regarded as the signal from a low-rate virtual user and is spread using a specific signature sequence. In VSF systems, users requiring different rates are assigned signature sequences of different lengths. Thus in the same period, more symbols of high-rate users can be transmitted.

Since chip-level channel modeling and equalization are performed, the proposed approach can readily be extended to multirate case. As an MC system with high-rate users is equivalent to a single-rate system with more users, extension of the proposed approaches to MC multirate CDMA systems is therefore trivial. For VSF systems, let N be the smallest processing gain and let $L_{c,j}N$ denote the length of the jth user's spreading code. Defining

$$L_c = LCM(L_{c,1}, \ldots, L_{c,M}) \tag{49}$$

as the least common multiple of $\{L_{c,1}, \ldots, L_{c,M}\}$, the generalization of the proposed algorithm to VSF systems is then straightforward.

6. SIMULATION EXAMPLES

We consider the case of two users and four receive antennas. Each user transmits QPSK signals. The spreading gain is chosen to be $N = 8$ or $N = 16$, and three cases are considered. (1) Both users have spreading gain $N = 8$. (2) Both users have spreading gain $N = 16$. (3) Two users have different data rates, the spreading gain for the low-rate user is $N = 16$, and for the high-rate user is $N = 8$.

The nonconstant modulus channelization codes spread over 32 chips (i.e., 2 to 4 symbols depending on the user's spreading gain). Both randomly generated codes which are uniformly distributed within the interval $[0.8, 1.2]$ and codes that satisfy the additional constraint (as described in Section 3.2) are considered. In the simulation, "codes with constraint" are chosen to be

$$\begin{aligned}
\mathbf{c}_1 = [&0.6857, 0.7145, 0.6356, 0.6849, 0.8433, 0.8036, 0.7597,\\
&0.5856, 0.7488, 0.5641, 0.7300, 0.7542, 0.7482, 0.5870,\\
&0.7902, 0.6172, 0.5409, 0.5474, 0.6425, 0.7834, 0.7520,\\
&0.6743, 0.6904, 0.8114, 0.5829, 0.6913, 0.5939, 0.7339,\\
&0.8608, 0.6380, 0.8207, 0.8808],\\
\mathbf{c}_2 = [&0.6670, 0.7275, 0.8540, 0.6100, 0.7518, 0.6363, 0.5545,\\
&0.6887, 0.7092, 0.6143, 0.6313, 0.7625, 0.5210, 0.8036,\\
&0.7582, 0.6979, 0.8136, 0.6944, 0.6902, 0.6660, 0.6536,\\
&0.6908, 0.6010, 0.8078, 0.7622, 0.5486, 0.6005, 0.6395,\\
&0.6176, 0.8070, 0.6382, 0.8265].
\end{aligned} \tag{50}$$

The multipath channels have three rays and the multipath amplitudes are Gaussian with zero mean and identical variance. The transmission delays are uniformly spread over 6 chip intervals. Complex zero mean white Gaussian noise was added to the received signals. The normalized mean-square-error of channel estimation (CHMSE) for the desired user is defined as

$$\text{CHMSE} = \frac{1}{KIL}\sum_{i=1}^{I}\sum_{p=1}^{K}\frac{\left\|\hat{\mathbf{g}}_1^{(p)} - \mathbf{g}_1^{(p)}\right\|^2}{\left\|\mathbf{g}_1^{(p)}\right\|^2}, \tag{51}$$

where I stands for the number of Monte-Carlo runs, and K is the number of receive antennas. And SNR refers to the signal-to-noise ratio with respect to the desired user and is chosen to be the same at each receiver. The result is averaged over $I = 100$ Monte-Carlo runs. The channel is generated randomly in each run, and is estimated based on a record of 256 symbols. In the case of multirate, we mean 256 lower-rate symbols. The equalizer with length $L_e = 6$ is constructed according to the estimated channel, and is applied to a set of 1024 independent symbols in order to calculate the symbol MSE and BER for each Monte-Carlo run. Blind channel estimation based on nonconstant modulus precoding is carried out both with and without the matrix-pencil approach. Without the matrix-pencil approach, channel estimation is obtained directly through the second-order statistics of $\mathbf{E}(n)$ (see (22)) based on the nonconstant precoding technique and the Fourier transform, as presented in Section 3.2. Simulation results show that by introducing a random linear transform, the matrix-pencil approach delivers significantly better results for both single-rate and multirate systems. Figures 3 and 4 correspond to the single-rate cases, where both users have spreading gain $N = 8$ or $N = 16$, and the codes in (50) are used. In the figures, "MP" stands for "matrix pencil". Figures 5 and 6 compare the performances of the matrix-pencil-based approach when different codes are used. In the figures, "codes with constraint" denote the codes in (50), and we choose $N = 8$ for the high-rate user and $N = 16$ for the low rate user. Optimal spreading code design and random linear transform design will be investigated in future work.

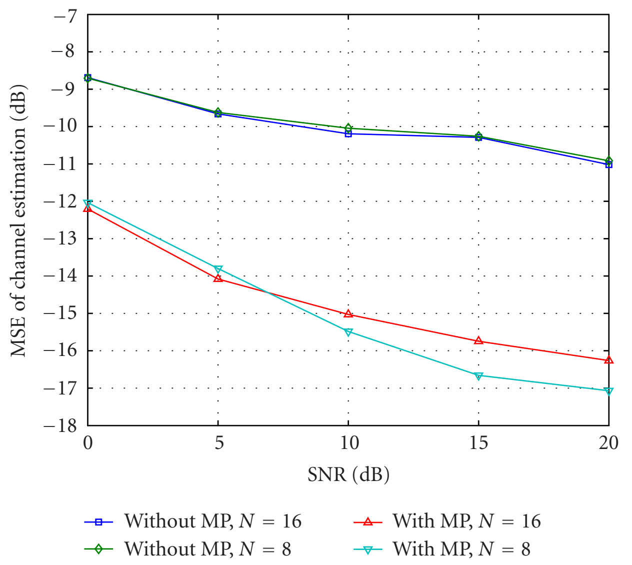

FIGURE 3: Normalized MSE of channel estimation versus SNR, single-rate cases with $N = 8$ and $N = 16$, respectively.

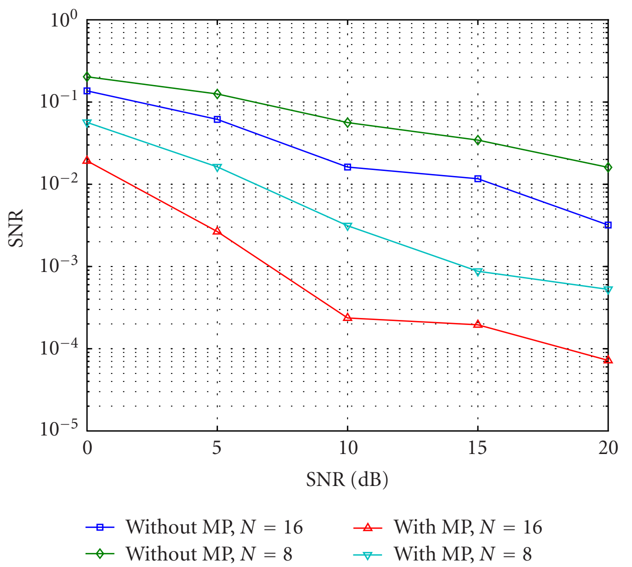

FIGURE 4: Comparison of BER versus SNR, single-rate cases with $N = 8$ and $N = 16$, respectively.

7. CONCLUSIONS

In this paper, blind channel identification and signal separation for long-code CDMA systems are revisited. Long-code CDMA system is characterized using a time-invariant system model by modeling the received signals and MUIs as cyclostationary processes with modulation-induced cyclostationarity. Then, multistep linear prediction method is used to reduce the intersymbol interference introduced by multipath propagation, and channel estimation is performed by exploiting the nonconstant modulus precoding technique with

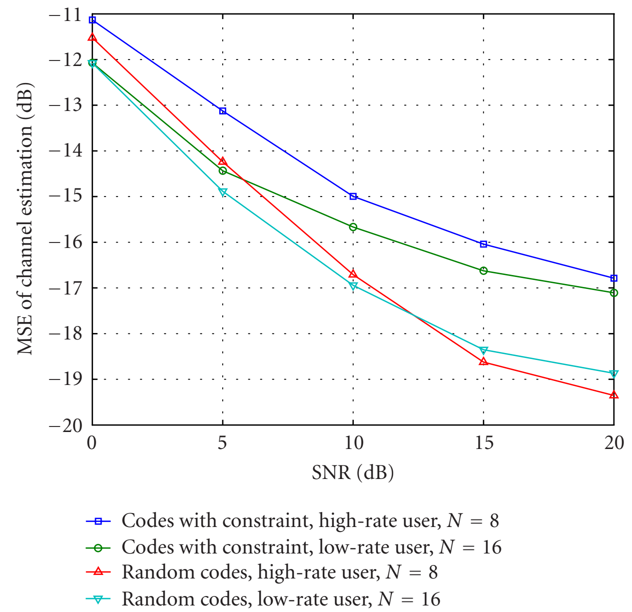

FIGURE 5: Normalized MSE of channel estimation versus SNR for matrix-pencil-based approach with different codes, multirate configuration with $N = 8$ for the high-rate user and $N = 16$ for the low-rate user, respectively.

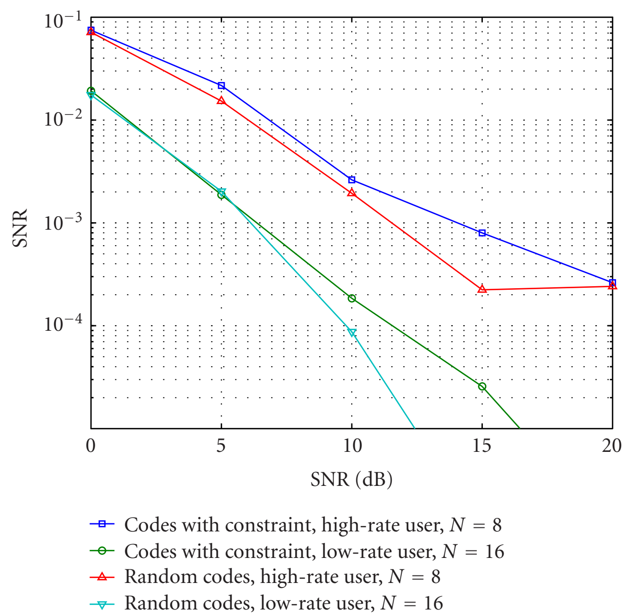

FIGURE 6: Comparison of BER versus SNR for matrix-pencil-based approach with different codes, multirate configuration with $N = 8$ for the high-rate user and $N = 16$ for the low-rate user, respectively.

and without the matrix-pencil approach. It is found that by introducing a random linear transform, the matrix-pencil-based approach delivers a much better result than the one relying on the Fourier transform. As chip-level channel modeling and equalization are performed, the proposed approach can be extended to multirate CDMA systems in a straight forward manner.

ACKNOWLEDGMENT

This paper is supported in part by MSU IRGP 91-4005 and NSF Grants CCR-0196364 and ECS-0121469.

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Tongtong Li received her Ph.D. degree in electrical engineering in 2000 from Auburn University. From 2000 to 2002, she was with Bell Labs, and has been working on the design and implementation of wireless communication systems, including 3GPP UMTS and IEEE 802.11a. She joint the faculty of Michigan State University in 2002, and currently is an Assistant Professor at the Department of ECE. Her research interests fall into the areas of wireless and wirelined communication systems, multiuser detection and separation over time-varying wireless channels, wireless networking and network security, and digital signal processing with applications in wireless communications. She is serving as an Editorial Board Member for EURASIP Journal on Wireless Communications and Networking.

Weiguo Liang was born in Hebei province, China, January 1975. He received the B.E. degree in biomedical engineering from Tsinghua University, Beijing, China, and the M.S. degree in electrical engineering from the Chinese Academy of Sciences, Beijing, China, in 1998 and 2001, respectively. He is currently pursuing the Ph.D. degree at the Department of Electrical and Computer Engineering, Michigan State University, East Lansing, Mich. Since 2001, he has been a Research Assistant at this department. His research interests include blind equalization, multiuser detection, space-time coding, and wireless sensor network.

Zhi Ding is Professor at the University of California, Davis. He received his Ph.D. degree in electrical engineering from Cornell University in 1990. From 1990 to 2000, he was a faculty member of Auburn University and later, University of Iowa. He has held visiting positions in the Australian National University, Hong Kong University of Science and Technology, NASA Lewis Research Center, and USAF Wright Laboratory. He has active collaboration with researchers from several countries including Australia, China, Japan, Canada, Taiwan, Korea, Singapore, and Hong Kong. He is also a Visiting Professor at the Southeast University, Nanjing, China. He is a Fellow of IEEE and has been an active Member of IEEE, serving on technical programs of several workshops and conferences. He was an Associate Editor for IEEE Transactions on Signal Processing from 1994–1997, 2001–2004. He is currently an Associate Editor of the IEEE Signal Processing Letters. He was a member of technical committee on statistical signal and array processing and member of technical committee on signal processing for communications. Currently, he is a member of the CAS technical committee on blind signal processing.

Jitendra K. Tugnait received the B.S. (honors) degree in electronics and electrical communication engineering from the Punjab Engineering College, Chandigarh, India, in 1971, the M.S. and E.E. degrees from Syracuse University, Syracuse, NY, and the Ph.D. degree from the University of Illinois at Urbana-Champaign, in 1973, 1974, and 1978, respectively, all in electrical engineering. From 1978 to 1982 he was an Assistant Professor of electrical and computer engineering at the University of Iowa, Iowa City, Iowa. He was with the Long Range Research Division of the Exxon Production Research Company, Houston, Tex, from June 1982 to September 1989. He joined the Department of Electrical and Computer Engineering, Auburn University, Auburn, Ala, in September 1989 as a Professor. He currently holds the title of James B. Davis and Alumni Professor. His current research interests are in statistical signal processing, wireless and wireline digital communications, and stochastic systems analysis. He is a past Associate Editor of the IEEE Transactions on Automatic Control and of the IEEE Transactions on Signal Processing. He is currently an Editor of the IEEE Transactions on Wireless Communications. He was on elected Fellow of the IEEE in 1994.