Improved Blind Multipath Estimation for Long Code DS-CDMA

Qian Yu, Guoan Bi, and Gaonan Zhang

Abstract: **This paper proposes a blind channel estimation scheme for long code direct sequence code division multiple access (DS-CDMA) systems with multipath fading channels. This scheme combines the advantages of Toeplitz displacement and correlation matching methods to achieve improved performance. The basic idea is to remove the effects of noise and interferences with Toeplitz displacement operation and then estimate the multipath channel parameters with the correlation matching method. Simulation results are presented to show that the proposed scheme provides better MSE performance and robustness against the near-far problem.**

Index Terms: **Blind channel estimation, correlation matching, long code, Toeplitz displacement.**

I. INTRODUCTION

Direct sequence code division multiple access (DS-CDMA) technique is of increasing importance due to its many desirable properties. The use of long spreading codes will be a main option for the third generation DS-CDMA based wireless networks [1]. Long codes guarantee that all users achieve about the same performance on average, but with a period much longer than that of a data symbol. Because long sequences destroy the bit-interval cyclo-stationarity properties of the signals [2], most estimation algorithms based on short codes cannot be directly applied to long code systems. A few algorithms were reported for long-code CDMA systems [3]–[8]. Based on subspace algorithm in [3], both blind and pilot-assisted channel estimation procedures were presented for synchronous CDMA systems. Blind channel estimation procedures based on array observations were reported in [4]. The least-square criterion algorithms were proposed in [5] for systems with frequency-selective fading channels. The correlation-matching technique was used to blindly estimate multipath parameters in [6]. The channel acquisition problem in the scenario of single-rate reverse link was considered in [7]. A Toeplitz displacement method based on subspace algorithm was developed for multipath channel estimation in [8].

In this paper, a new blind channel estimation method is developed by combining the advantages from both Toeplitz displacement and correlation matching methods. The conventional correlation matching estimation method was developed in [6] to explore the output covariance matrix to match the approximations based on the received data. Compared to the subspace-based approach, the correlation matching estimation offers a better performance for loaded systems with only some mild assumptions. The basic idea of the proposed method is to remove the effects of the channel noise and other user's interferences by applying the Toeplitz displacement operation before the estimation of multipath channel is performed with the correlation matching method. Simulation results are presented to compare the performances of the proposed and other reported methods based on correlation matching and the subspace Toeplitz estimation. The comparison shows that the proposed method offers better MSE performance and near-far resistance.

Manuscript received August 19, 2003; approved for publication by Kwang Bok Lee, Division II Editor, January 25,2005.

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II. SIGNAL MODEL

Consider a coherent synchronized DS-CDMA system over a multipath channel with K active users. To apply the Toeplitz displacement method, we refer to the signal model described in [8]. The baseband representation of the received signal after coherent reception is given by

$$x(t) = \sum_{n=-\infty}^{\infty} \sum_{k=1}^{K} A_k \tilde{c}_k^n(t - nT - \tau_k) b_k(n) + w(t) \tag{1}$$

where $w(t)$ is the additive and circularly symmetric Gaussian noise process with variance σ_w^2 and A_k and b_k are, respectively, the amplitude of the signal and the transmitted bit for user k. The amplitude of each user's signal is modeled as a fixed, but unknown quantity. For randomized long code DS-CDMA, the spreading waveform $\tilde{c}_k^n(t)$ in (1) denotes the effective spreading waveform for user k. The effective spreading waveform is constructed by the convolution of the original spreading waveform with the channel response, that is $\tilde{c}_k^n(t) = c_k^n(t) * h_k(t)$, where $h_k(t)$ is the channel impulse response for user k and the spreading waveform is formed by

$$c_k^n(t) = \sum_{l=1}^{N} c_k^n(l) \psi(t - lT_c) \tag{2}$$

where $\psi(t)$ is the shape of the chip with a duration T_c. In our case, the rectangular pulse is assumed for simplicity. The spreading waveform $c_k^n(l)$ for user k changes from symbol to symbol and takes values of $(\pm 1/\sqrt{N})$ with equal probability, where N is the spreading gain or the number of chips per symbol, i.e., the symbol duration $T = NT_c$. The delay τ_k in (1) for user k is assumed to be the integral multiples of a chip duration. The fractional parts of the delays are incorporated into the effective channel impulse response $h_k(t)$.

It is assumed that signals and the noise are mutually independent, the channel length for each user is the same as M ($M < N$) chips, and the multipath delay spread is less than a symbol interval. It is also assumed that the fading coefficients remain constant over the entire data collection block. The techniques to be explored in this paper require the knowledge of the desired user's channel length. The received signal is sampled at the chip rate and chip-matched by a filtering process. An observation vector $\mathbf{x}(n)$ is formed by concatenating $aN + M - 1$ samples, where a represents the number of symbols contained in the observation vector, which will be explained further shortly. The filtered and sampled complex channel impulse response is denoted by $\mathbf{h}_k = [h_k(0), \cdots, h_k(M-1)]^T$.

Consider the expression of the observation vector for a synchronized system ($\tau_k = 0, \forall k$). An observation vector is formed to contain a symbols and $M - 1$ bits which belong to a fraction of a symbol. The existence of the fractional part of the symbol is due to the effects of intersymbol interference. The observation vector of $aN + M - 1$ samples at the chip rate is given by

$$\mathbf{x}(n) = \sum_{k=1}^{K} A_k \mathbf{C}_k(n)\mathbf{H}_k\mathbf{b}_k(n) + \mathbf{w}(n) \quad (3)$$

where $\mathbf{x}(n) = [x(n), \cdots, x(n + aN + M - 2)]^T$ and $\mathbf{w}(n) = [w(n), \cdots, w(n + aN + M - 2)]^T$ are vectors of the received samples and noise samples of size $(aN + M - 1) \times 1$, and $\mathbf{b}(n) = [b(\lfloor n/N \rfloor - 1), \cdots, b(\lfloor n/N \rfloor + a)]^T$ is a $(a + 2) \times 1$ vector of data bits. The operator $\lfloor \cdot \rfloor$ returns the largest integer smaller than its argument. The channel matrix $\mathbf{H}_k$ for user k is given by $\mathbf{H}_k = \mathbf{I}_{a+2} \otimes \mathbf{h}_k$, and $\mathbf{C}_k(n)$ is the spreading code matrix for user k with dimension $(aN + M - 1) \times (a + 2)M$.

To derive the spreading code matrix, an $(N + M - 1) \times M$ matrix $\mathbf{C}(\mathbf{c}_k(n), M)$ is defined as [8]

$$\begin{bmatrix} c_k(n) & 0 & \cdots & 0 \\ c_k(n+1) & c_k(n) & \ddots & \vdots \\ \vdots & & \ddots & 0 \\ c_k(n+M-1) & \cdots & \cdots & c_k(n) \\ \vdots & & & \vdots \\ c_k(n+N-1) & \cdots & \cdots & c_k(n+N-M) \\ 0 & c_k(n+N-1) & & \vdots \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & c_k(n+N-1) \end{bmatrix}.$$

If $\mathbf{C}^1_{k,M}(n)$ is defined to be the first N rows of $\mathbf{C}(\mathbf{c}_k(n), M)$ and $\mathbf{C}^2_{k,M}(n)$ to be the last $M - 1$ rows of $\mathbf{C}(\mathbf{c}_k(n), M)$, the spreading code matrix for user k, $\mathbf{C}_k(n)$ is given by

$$\begin{bmatrix} \mathbf{C}^2_{k,M}(n)\, \mathbf{C}^1_{k,M}(n+N) & & & \mathbf{0} \\ & \mathbf{C}^2_{k,M}(n+N)\, \mathbf{C}^1_{k,M}(n+2N) & & \\ \mathbf{0} & & \ddots \quad \ddots & \\ & & & \mathbf{C}^2_{k,M}(n+aN)\, \tilde{\mathbf{C}}^1_{k,M}(n+(a+1)N) \end{bmatrix}$$

where $\tilde{\mathbf{C}}^1_{k,M}(n)$ is composed of the first $M - 1$ rows of $\mathbf{C}^1_{k,M}(n)$.

We use M matched filters per received symbol to fully exploit the properties of the received signals. Without loss of generality, user 1 is assumed to be the desired user. The $aM \times 1$ observation vector $\mathbf{y}(n)$ is given by

$$\begin{aligned} \mathbf{y}(n) &= \mathbf{S}_1(n)\mathbf{x}(n) \quad (4) \\ &= \mathbf{S}_1(n)\left(\sum_{k=1}^{K} A_k\mathbf{C}_k(n)\mathbf{H}_k\mathbf{b}_k(n)\right) + \mathbf{S}_1(n)\mathbf{w}(n) \end{aligned}$$

where the matched filtering matrix $\mathbf{S}_1(n)$ is given by

$$\mathbf{S}_1^T(n) = \begin{bmatrix} \mathbf{C}^1_{1,M}(n+N) & & & \\ \mathbf{C}^2_{1,M}(n+N) & \cdots & & \mathbf{0} \\ & \ddots & \ddots & \\ & \mathbf{0} & & \mathbf{C}^1_{1,M}(n+aN) \\ & & & \mathbf{C}^2_{1,M}(n+aN) \end{bmatrix}. \quad (5)$$

The matrices $\mathbf{S}_1^T(n)$ and $\mathbf{C}_1(n)$ are related by

$$\mathbf{C}_1(n) = \begin{bmatrix} \mathbf{C}^2_{1,M}(n) & \vdots & \mathbf{0} \\ \mathbf{0} & \mathbf{S}_1^T(n) & \mathbf{0} \\ \mathbf{0} & \vdots & \tilde{\mathbf{C}}^1_{1,M}(n+(a+1)N) \end{bmatrix}$$

That is, $\mathbf{C}_1(n)$ is formed by augmenting $\mathbf{S}_1^T(n)$ by $2M$ appropriate columns.

III. CHANNEL ESTIMATION

In this section, a method of correlation-matching channel estimation is developed to achieve improvements on estimation performance and robustness to the variations of the system environments. The conventional correlation-matching channel estimation is proposed in [6]. Compared with the subspace-based approaches, this method requires only mild identifiability assumptions and offers better performance for loaded systems. The basic idea is to match the output covariance matrix (parameterized by the unknown channel vectors) with the instantaneous approximations based on the received data. This method is briefly described as follows.

Let us consider the $aM \times 1$ matched filter output vector $\mathbf{y}(n)$ given in (4). The covariance matrix of this observation vector is obtained as

$$\begin{aligned} \mathbf{R}_y(n) &= \mathbb{E}[\mathbf{y}(n)\mathbf{y}^H(n)] \\ &= \sigma_1^2\mathbf{S}_1(n)\mathbf{C}_1(n)\mathbf{H}_1\mathbf{H}_1^H\mathbf{C}_1^H(n)\mathbf{S}_1^T(n) \\ &\quad + \mathbf{R}_I(n) + \mathbf{R}_w(n) \quad (6) \end{aligned}$$

where $\sigma_1^2 = A_1^2\mathbb{E}[b_1^2(n)]$ and $\mathbf{R}_w(n) = \sigma_w^2\mathbf{S}_1(n)\mathbf{S}_1^T(n)$ is noise autocorrelation matrix. The contribution of other users' interferences is

$$\mathbf{R}_I(n) = \sum_{k=2}^{K} \sigma_k^2\mathbf{S}_1(n)\mathbf{C}_k(n)\mathbf{H}_k\mathbf{H}_k^H\mathbf{C}_k^H(n)\mathbf{S}_1^T(n). \quad (7)$$

Let $\hat{\mathbf{R}}_y(n)$ denote some estimator of $\mathbf{R}_y(n)$, and

$$\mathbf{E}(n) = \mathbf{R}_y(n) - \hat{\mathbf{R}}_y(n) \quad (8)$$

be the estimation error matrix. The cost function is defined as

$$\mathbf{J} = \frac{1}{N_s}\sum_{n=1}^{N_s}\mathbf{J}(n) = \frac{1}{N_s}\sum_{n=1}^{N_s}\|\mathbf{E}(n)\|_F^2 \quad (9)$$

where N_s is the number of transmitted symbols. By minimizing this cost function, all channel parameters can be obtained. These are the general framework of the correlation-matching technique.

Now, improvement is to be made on the conventional correlation-matching channel estimation. Before operating the autocorrelation of the observation vector, the Toeplitz displacement is applied to remove the effects of the channel noise and other users' interferences from the observation vector. Let us define

$$\overline{\mathbf{SC}}_1 = \frac{1}{N_s}\sum_{n=1}^{N_s}\mathbf{S}_1(n)\mathbf{C}_1(n) \quad (10)$$

and

$$\overline{\mathbf{SC}}_k = \frac{1}{N_s}\sum_{n=1}^{N_s}\mathbf{S}_1(n)\mathbf{C}_k(n), k = 2,\cdots,K. \quad (11)$$

It is noted that the asymptotic approximation below follows from key assumptions made about the randomized spreading codes. That is, the components of the code sequence are independently and identically distributed, and are stationary at the chip rate. Therefore we have $\mathbf{S}_1(n)\mathbf{C}_1(n) = \mathbf{SC}_1 + \mathbf{A}(n)$, and $\mathbf{S}_1(n)\mathbf{C}_k(n) = \mathbf{SC}_k + \mathbf{B}_k(n), k = 2,\cdots,K$, where $\mathbf{A}(n)$ and $\mathbf{B}_k(n)$ are, respectively, time varying perturbation matrices, $\mathbf{SC}_1 = \lim_{N_s\to\infty}\overline{\mathbf{SC}}_1 = [\mathbf{0}\ \mathbf{I}_{aM}\ \mathbf{0}]$ and $\mathbf{SC}_k = \lim_{N_s\to\infty}\overline{\mathbf{SC}}_k = [\mathbf{0}\ \mathbf{0}_{aM}\ \mathbf{0}]$. As N increases, the perturbations $\mathbf{A}(n)$ and $\mathbf{B}_k(n)$ decrease. When $N\to\infty$, the effects of the perturbations can be negligible and the effects of the imperfect spreading auto-correlation are captured in $\overline{\mathbf{SC}}_1$. Hence,

$$\begin{aligned}\mathbf{R}_y(n) &= \sigma_1^2\mathbf{S}_1(n)\mathbf{C}_1(n)\mathbf{H}_1\mathbf{H}_1^H\mathbf{C}_1^H(n)\mathbf{S}_1^T(n) + \mathbf{R}_I(n) + \mathbf{R}_w(n)\\ &\approx|_{N\to\infty}\sigma_1^2\,\mathbf{SC}_1\mathbf{H}_1\,\mathbf{H}_1^H\,\mathbf{SC}_1^H\\ &\qquad + \sum_{k=2}^{K}\sigma_k^2\,\mathbf{SC}_k\,\mathbf{H}_k\,\mathbf{H}_k^H\,\mathbf{SC}_k^H + \sigma_w^2\mathbf{I}\\ &\approx|_{N_s\to\infty}\sigma_1^2\,\overline{\mathbf{SC}}_1\,\mathbf{H}_1\,\mathbf{H}_1^H\,\overline{\mathbf{SC}}_1^H + \sigma_w^2\mathbf{I}. \end{aligned} \quad (12)$$

Then, the Toeplitz displacement is performed on the covariance matrix of the observation vector.

$$\begin{aligned}\mathbf{R}_h(n) &= \mathbf{R}_y(n)(2:aM,2:aM) - \mathbf{R}_y(n)(1:aM-1,1:aM-1)\\ &= \mathbf{R}_y^+(n) - \mathbf{R}_y^-(n)\\ &= \sigma_1^2\mathbf{SC}_1^+\mathbf{H}_1\mathbf{H}_1^H\mathbf{SC}_1^{+H} - \sigma_1^2\mathbf{SC}_1^-\mathbf{H}_1\mathbf{H}_1^H\mathbf{SC}_1^{-H} \end{aligned} \quad (13)$$

where the matrix notation $B(i:j,k:l)$ denotes the sub-matrix formed by truncating rows from i to j and columns from k to l from matrix B, and $\mathbf{SC}_1^+$ and $\mathbf{SC}_1^-$ are formed by removing the first row and the last row of $\mathbf{SC}_1$, respectively. The displacement in (13) holds because the components of the code sequences are assumed to be independently distributed and stationary at the chip rate. The details about this Toeplitz displacement procedure can be found in [8]. Then the updated observation vector in (13) contains only the information of the desired user and the contributions from $\mathbf{R}_I$ and $\mathbf{R}_w$ are removed.

Now, the result of Toeplitz displacement is applied for the correlation matching estimation method. Let $\hat{\mathbf{R}}_y(n)$ denote some estimator of $\mathbf{R}_y(n)$ and $\hat{\mathbf{R}}_h(n)$ be the corresponding estimator of $\mathbf{R}_h(n)$, then

$$\begin{aligned}\hat{\mathbf{R}}_h(n) &= \hat{\mathbf{R}}_y^+(n) - \hat{\mathbf{R}}_y^-(n)\\ &= \hat{\mathbf{R}}_y(n)(2:aM,2:aM) - \hat{\mathbf{R}}_y(n)(1:aM-1,1:aM-1).\end{aligned}$$

The estimation error matrix becomes

$$\begin{aligned}\mathbf{E}_h(n) &= \mathbf{R}_h(n) - \hat{\mathbf{R}}_h(n)\\ &= \sigma_1^2\,\mathbf{SC}_1^+\,\mathbf{H}_1\,\mathbf{H}_1^H\,\mathbf{SC}_1^{+H}\\ &\qquad -\sigma_1^2\,\mathbf{SC}_1^-\,\mathbf{H}_1\,\mathbf{H}_1^H\,\mathbf{SC}_1^{-H} - \hat{\mathbf{R}}_h(n). \end{aligned} \quad (14)$$

The new estimation error can be defined with the squared Frobenius norm of $\mathbf{E}_h$

$$\mathbf{J}_h(n) = \|\mathbf{E}_h(n)\|_F^2 = tr[\mathbf{E}_h(n)\mathbf{E}_h^H(n)]. \quad (15)$$

The cost function (15) can be built as the cumulative error

$$\begin{aligned}\mathbf{J}_h &= \frac{1}{N_s}\sum_{n=1}^{N_s}\mathbf{J}_h(n) = \frac{1}{N_s}\sum_{n=1}^{N_s}tr[\mathbf{E}_h(n)\mathbf{E}_h^H(n)]\\ &= \frac{1}{N_s}\sum_{n=1}^{N_s}vec^H[\mathbf{E}_h(n)]vec[\mathbf{E}_h(n)]. \end{aligned} \quad (16)$$

The channel parameters can be obtained by minimizing this cost function. In practice, the average correlation matrix $\hat{\mathbf{R}}_y$ is sampled and formed by

$$\hat{\mathbf{R}}_y = \frac{1}{N_s}\sum_{n=1}^{N_s}\hat{\mathbf{R}}_y(n) = \frac{1}{N_s}\sum_{n=1}^{N_s}\mathbf{y}(n)\mathbf{y}^H(n). \quad (17)$$

The estimated $\hat{\mathbf{R}}_h$ can be similarly formed. We define new unknowns by

$$\mathbf{D}_1 = \sigma_1^2\mathbf{H}_1\mathbf{H}_1^H. \quad (18)$$

The error matrix (14) becomes

$$\mathbf{E}_h(n) = \mathbf{SC}_1^+\mathbf{D}_1\mathbf{SC}_1^{+H} - \mathbf{SC}_1^-\mathbf{D}_1\mathbf{SC}_1^{-H} - \hat{\mathbf{R}}_h(n) \quad (19)$$

and

$$\begin{aligned}vec(\mathbf{E}_h(n)) = (\mathbf{SC}_1^{+*}\otimes\mathbf{SC}_1^+ - \mathbf{SC}_1^{-*}\otimes\mathbf{SC}_1^-)vec(\mathbf{D}_1)\\ -vec(\hat{\mathbf{R}}_h(n)). \end{aligned} \quad (20)$$

Then let

$$\mathbf{d}_1 = vec(\mathbf{D}_1), \quad (21)$$

$$\mathbf{Q} = \mathbf{SC}_1^{+*}\otimes\mathbf{SC}_1^+ - \mathbf{SC}_1^{-*}\otimes\mathbf{SC}_1^-. \quad (22)$$

We have

$$\mathbf{J}_h(n) = \{\mathbf{Q}\mathbf{d}_1 - vec(\hat{\mathbf{R}}_h(n))\}^H\{\mathbf{Q}\mathbf{d}_1 - vec(\hat{\mathbf{R}}_h(n))\}. \quad (23)$$

Therefore, the cost function becomes

$$\mathbf{J}_h = \frac{1}{N_s}\sum_{n=1}^{N_s}\{\mathbf{Q}\mathbf{d}_1 - vec(\hat{\mathbf{R}}_h(n))\}^H\{\mathbf{Q}\mathbf{d}_1 - vec(\hat{\mathbf{R}}_h(n))\}. \quad (24)$$

Thus, a quadratic cost function of new unknowns is obtained by over-parameterizing the problem given in (21).

Let us now consider the estimate of (24). Based on the cost function, an adaptive algorithm is to be derived by considering $\mathbf{J}_h(n)$ at time n. The least mean square (LMS) recursion can be formulated for $\mathbf{d}_1$ with step size μ

$$\mathbf{d}_1^{(n+1)} = \mathbf{d}_1^{(n)} - \mu\nabla_{\mathbf{d}_1^H}\mathbf{J}_h(n) \quad (25)$$

where $\mu\nabla_{\mathbf{d}_1^H}\mathbf{J}_h(n)$ is a function of $\mathbf{d}_1^{(n)}$ and computed by

$$\mu\nabla_{\mathbf{d}_1^H}\mathbf{J}_h(n) = \mathbf{Q}^H\mathbf{Q}\mathbf{d}_1^{(n)} - \mathbf{Q}^H vec[\hat{\mathbf{R}}_h(n)]. \quad (26)$$

Here, $\mathbf{Q}$ is approximately approached by

$$\hat{\mathbf{Q}} = \hat{\mathbf{SC}}_1^{+*} \otimes \hat{\mathbf{SC}}_1^{+} - \hat{\mathbf{SC}}_1^{-*} \otimes \hat{\mathbf{SC}}_1^{-} \quad (27)$$

where $\hat{\mathbf{SC}}_1^{+}$ and $\hat{\mathbf{SC}}_1^{-}$ are formed by removing the first and the last rows of $\hat{\mathbf{SC}}_1$, respectively.

$$\hat{\mathbf{SC}}_1 = \frac{1}{N_s}\sum_{n=1}^{N_s}\mathbf{S}_1(n)\mathbf{C}_1(n). \quad (28)$$

Based on (25) and (26), $\mathbf{d}_1$ can be updated by

$$\mathbf{d}_1^{(n+1)} = \mathbf{d}_1^{(n)} - \mu\hat{\mathbf{Q}}^H\hat{\mathbf{Q}}\mathbf{d}_1^{(n)} + \mu\hat{\mathbf{Q}}^H vec[\hat{\mathbf{R}}_h(n)] \quad (29)$$

and consequently, $\mathbf{D}_1^{(n+1)}$ can be reconstructed from $\mathbf{d}_1^{(n+1)}$. Once $\mathbf{D}_1$ is found by the adaptive implementation, singular value decomposition (SVD) on $\mathbf{D}_1$ can be performed to obtain its eigenvector corresponding to the unique maximum eigenvalue, which is the estimated and normalized channel vector for desired user within a phase ambiguity.

Some issues have to be considered for practical implementation. Normalization of the resulting channel estimate is needed to remove the effect of the scalar ambiguity. To further improve the channel estimate, a cleaning operation is needed for the sample covariance matrix.

The asymptotic behavior of the adaptive algorithm is considered for the step size μ. Let $\Delta\mathbf{d}_1^{(n)} = \mathbb{E}[\mathbf{d}_1^{(n)}] - \mathbf{d}_1$ be the bias at time n. By subtracting $\mathbf{d}_1$ on both sides of (29) and taking expectation, we obtain

$$\begin{aligned}\Delta\mathbf{d}_1^{(n+1)} &= [\mathbf{I} - \mu\mathbb{E}[\hat{\mathbf{Q}}^H\hat{\mathbf{Q}}]]\Delta\mathbf{d}_1^{(n)} + \mu\mathbb{E}[\hat{\mathbf{Q}}^H vec[\hat{\mathbf{R}}_h(n)]] \\ &\quad -\mu\mathbb{E}[\hat{\mathbf{Q}}^H\hat{\mathbf{Q}}]\mathbf{d}_1 \\ &\approx [\mathbf{I} - \mu\mathbb{E}[\hat{\mathbf{Q}}^H\hat{\mathbf{Q}}]]\Delta d_1^{(n)} = (\mathbf{I} - \mu\mathbf{U})\Delta\mathbf{d}_1^{(n)} \quad (30)\end{aligned}$$

where $\mathbf{U}$ is a constant matrix characterized by the given system parameters. This equation implies that the convergence of the proposed adaptive method depends on the eigenvalue of matrix $\mathbf{I} - \mu\mathbf{U}$. The necessary condition on the step size is then $|1 - \mu\lambda_i| < 1 \ \forall\ i$, where λ_i's are the eigenvalues of $\mathbf{U}$. Equivalently, $0 < \mu < 1/\lambda_{\max}$.

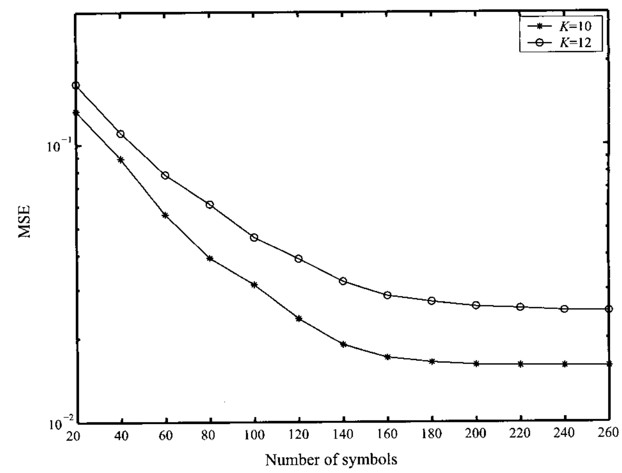


Fig. 1. MSE versus the number of the symbols (SNR = 15 dB).

IV. SIMULATION RESULTS

During the simulations, long spreading codes of transmitted bits of all users are assumed to take values from independent equiprobable random variables $+1$ and -1. The data are regenerated randomly for each run of the simulation and the channel coefficients for all users are also randomly produced from independent complex Gaussian random variables. It is noted that the estimator for channel vector has a complex scalar ambiguity. To simplify the presentation and avoid the norm ambiguity, the following MSE is used as the performance measure.

$$\mathrm{MSE} = \frac{1}{N_r}\sum_{i=1}^{N_r}\left\|\hat{\mathbf{h}}_1^i - (\mathbf{h}_1/\|\mathbf{h}_1\|)\right\|^2 \quad (31)$$

where N_r is the number of runs in the simulation. We select $N_r = 50$ for each simulation in our examples. The true channel is denoted by $\mathbf{h}_1$ and the channel estimate for run i is represented by $\hat{\mathbf{h}}_1^i$. Thus, the channel estimator is normalized, as discussed previously.

Let us first study the convergence of the proposed algorithm. The MSE is plotted as a function of the number of symbols in Fig. 1. The simulations are made for $K = 10$ and 12 and SNR $= 15$ dB, and the spreading gain is chosen as $N = 35$. As illustrated in Fig. 1, convergence is achieved after 200 symbols.

Next let us consider the MSE performance as a function of a which is the number of the whole symbols used in the observation vector. The environment parameters are $K = 8$, SNR $= 12$ dB, spreading gain $N = 35$, and the number of the transmitted symbols is $N_s = 200$. Fig. 2 shows the MSE values versus a for two different channel lengths $M = 4$ and $M = 5$, respectively.

It can be seen that the MSE performance is not good enough when one complete symbol is used. However, significant improvements can be achieved after two complete symbols are used in the estimation. Therefore, we choose $a = 2$ as a suitable choice for the following simulations.

We now consider the effects of the spreading factor on the estimation performance. Fig. 3 shows the MSE versus the spreading gain for $K = 10$ and 12 users, which are obtained by the proposed method, the correlation matching (CM) method in [6] and the Toeplitz displacement (TD) method in [8]. Different

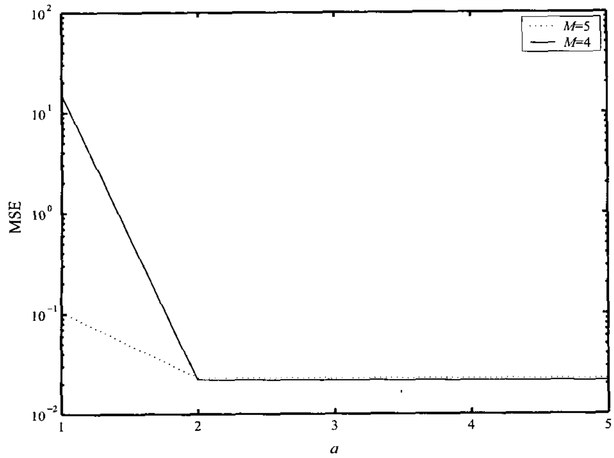


Fig. 2. MSE versus a for $K = 8$ and SNR = 15 dB.

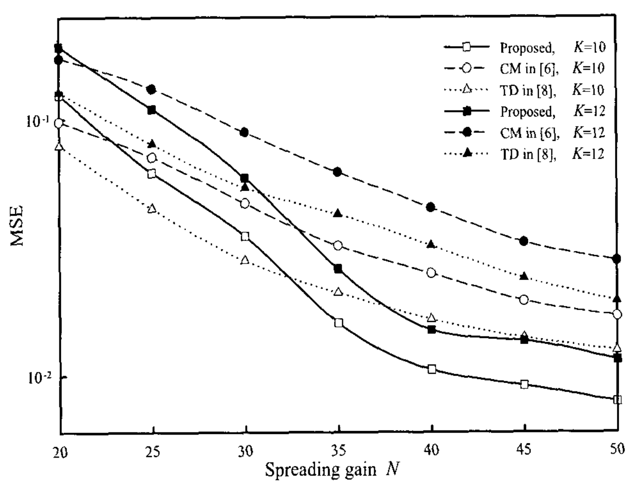


Fig. 3. MSE versus spreading gain for SNR = 15 dB.

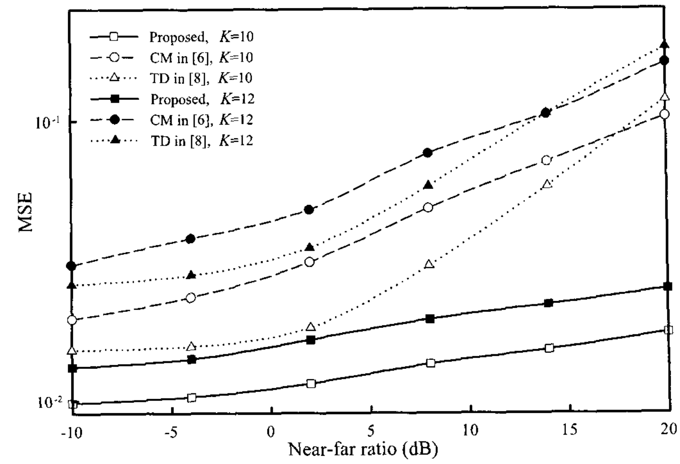


Fig. 4. MSE evolution for a near-far environment.

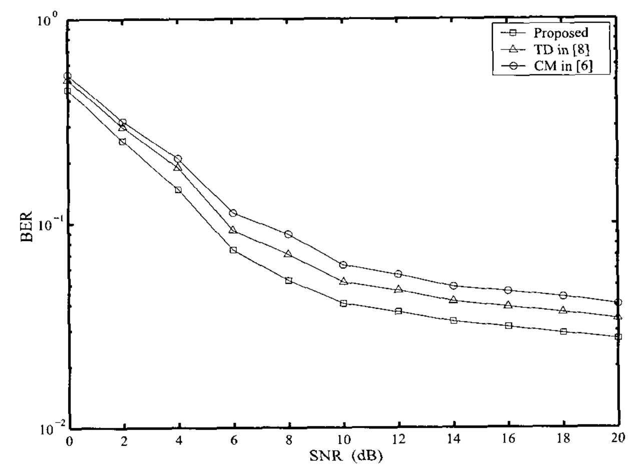


Fig. 5. BER versus SNRs.

random channels with length $M = 5$, SNR = 15 dB, and 200 transmitted symbols for all users are used in the simulation.

Fig. 3 shows that the MSE reduces as N increases. The reason is that the spreading sequences become increasingly orthogonal with each other as the increase of the spreading gain. It is also observed that, for small values of the spreading gain, the proposed algorithm has no superiority to the other methods, but when the spreading gain $N > 35$, it achieves a better MSE performance compared to the methods reported in [6] and [8]. This is because that the displacement is based on the approximation: Spreading gain $N \rightarrow \infty$. When N is small, the approximation is not accurate enough and therefore the performance is not improved. When N is large to achieve more accurate approximation, the proposed method can suppress the effects of channel noise and interference by using the Toeplitz displacement operation and, at the same time, achieve better estimation with the correlation matching method.

The capability of near-far resistance for the three estimation methods is compared as follows. As described in previous sections, the matched filter preprocessing provides multiple access interference suppression and the Toeplitz displacement removes the remaining interference significantly. As a result, the proposed method is expected to improve the near-far resistance.

The near-far ratio is defined as $20\log(A_1/A_k)$ dB, where A_1 is the received amplitude of the desired user and A_k is the received amplitude of other interfering users. Let us fix the power of the desired user and change the power of interfering users. It is assumed that all interfering users have the same power. We test the performance as the function of near-far ratio and compare the results with the methods described in [6] and [8]. The simulated system has $K = 10$ and 12 users, $N = 40$, SNR = 15dB, $a = 2$, $M = 5$, and 200 transmitted symbols.

Fig. 4 shows that as the near-far ratio increases, the proposed method achieves substantially better performance in suppressing the strong interference. Since the MSE changes slowly as the increase of the near-far ratio, the proposed method is very robust against near-far problem.

Finally, the bit error rate (BER) performance is obtained by using the estimated channel for a RAKE receiver with parameters $N = 35$, $M = 5$, and $K = 10$. Fig. 5 compares the BERs obtained by using three estimation methods, which again illustrates that the best BER is achieved by using the proposed estimation method.

V. CONCLUSIONS

This paper presents a method of blind adaptive multipath channel estimation for long code DS-CDMA systems. Because the cross-correlation functions of the random spreading sequences in such systems vary with the time, the use of the asymptotic statistics of such spreading codes is made to deal with this difficult problem. The contribution of channel noise and interference is removed by applying the Toeplitz displacement on the covariance matrix of the output vector before the correlation matching method is explored to obtain the multipath channel estimation. Simulation results show that the proposed technique substantially improves the MSE performance and robustness against the near-far problem.

REFERENCES

[1] E. H. Dinan, B. Jabbari, and G, Mason, "Spreading codes for direct sequence CDMA and wideband CDMA cellular networks," *IEEE Commun. Mag.*, vol. 36, no. 9, pp. 48–54, 1998.

[2] K. Tang, P. H. Siegel, and L. B. Milstein, "A comparison of long code versus short spreading sequences in coded asynchronous DS-CDMA systems," *IEEE J. Select. Areas Commun.*, vol. 19, no. 8, pp. 1614–1624, 2001.

[3] A. J. Weiss and B. Friedlander, "Channel estimation for DS-CDMA downlink with aperiodic spreading codes," *IEEE Trans. Commun.*, vol. 47, no. 10, pp. 1561–1569, 1999.

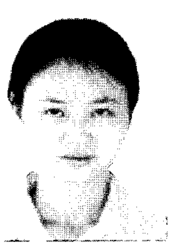
[4] M. Torlak, B. L. Evans, and G. Xu, "Blind estimation of FIR channels in CDMA systems with aperiodic spreading sequences," in *Proc. 31st Asilomar Conf. Signals, Syst., Comput.*, vol. 1, Nov. 1997, pp. 495–499.

[5] S. Buzzi and H. V. Poor, "Channel estimation and multiuser detection in long-code DS/CDMA systems," *IEEE J. Select. Areas Commun.*, vol. 19, no. 8, pp. 1476–1487, 2001.

[6] Z. Xu and M. K. Tsatsanis, "Blind channel estimation for long code multiuser CDMA systems," *IEEE Trans. Signal Processing*, vol. 48, no. 4, pp. 988–1001, 2000.

[7] A. M. V. Tripathi and V. Veeravalli, "Channel acquisition for wideband CDMA signals," *IEEE J. Select. Areas Commun.*, vol. 18, no. 8, pp. 1483–1495, 2000.

[8] C. Escudero, U. Mitra, and D. Slock, "A Toeplitz displacement method for blind multipath estimation for long code DS-CDMA signals," *IEEE Trans. Signal Processing*, vol. 49, no.3, pp. 654–665, 2001.



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