Blind Code-Timing Estimation for CDMA Systems With Bandlimited Chip Waveforms in Multipath Fading Channels

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***Abstract*—In this paper, we present a blind code-timing estimator for asynchronous code-division multiple-access (CDMA) systems that use bandlimited chip waveforms. The proposed estimator first converts the received signal to the frequency domain, followed by a frequency deconvolution to remove the convolving chip waveform, and then calculates the code-timing estimate from the output of a narrowband filter with a sweeping center frequency, which is designed to suppress the overall interference in the frequency domain. The proposed estimator is near–far resistant, and can deal with time- and frequency-selective channel fading. It uses only the spreading code of the desired user, and can be adaptively implemented for both code acquisition and tracking. We also derive an unconditional Cramér–Rao bound (CRB) that is not conditioned on the fading coefficients or the information symbols. It is a more suitable lower bound than a conditional CRB for blind code-timing estimators which do not assume knowledge of the channel or information symbols. We present numerical examples to evaluate and compare the proposed and several other code-timing estimators for bandlimited CDMA systems.**

***Index Terms*—Code-division multiple access (CDMA), code-timing estimation, Cramér–Rao bound (CRB), interference suppression, time-varying multipath fading.**

I. Introduction

CODE-DIVISION multiple access (CDMA) is a promising air interface scheme for future wireless mobile communications [1]. In CDMA systems, all user transmissions overlap in time and frequency, and are differentiated from one another by assigning a unique spreading code to each user. In order to successfully recover the information of each transmission, the local spreading code generator has to be synchronized to the code timing of the desired transmission.

Traditional approaches to code acquisition are based on matched-filter (MF) estimation [2, Ch. 5]. They are often referred to as single-user-based techniques, since the multiaccess interference (MAI) is modeled as an additive white noise, without taking into account any inherent structure. Multiuser code-timing estimation or acquisition, which parallels the well-acknowledged research on multiuser detection [3], has been receiving increasing interest recently. A variety of multiuser-based code-acquisition schemes have been proposed by exploiting the structure of the MAI. They offer significantly improved performance in near–far environments, and are able to support more user transmissions without enforcing stringent power control. These schemes are usually classified into two categories: *training-assisted* and *blind* techniques. Examples of the former include the minimum mean-squared error (MMSE) [4], large-sample maximum-likelihood (LSML) [5], [6], exact ML [7], and decoupled multiuser acquisition (DEMA) [8] synchronization schemes. A sample list of blind code-synchronization algorithms include MUSIC [9], [10] and the variants [11], [12], and the minimum variance-based schemes [13]–[15]. While most multiuser-based acquisition schemes are, in general, computationally more involved than the single-user-based techniques, there are a few exceptions, including the so-called *differentially coherent (DC)* estimation algorithms that were investigated in several recent studies [16]–[19]. It has been found that the DC-based algorithms incur similar complexity as the MF, and yet are quite effective in dealing with the MAI and multipath fading.

Depite significant advances, most of the aforementioned code-timing estimation schemes implicitly assume *rectangular* chip waveforms which are not bandlimited. Meanwhile, real CDMA systems use *bandlimited* chip waveforms, such as a square-root raised-cosine (SRRC) pulse [20]. Only limited studies are available on code synchronization for CDMA systems with bandlimited chip waveforms. In [21], the MUSIC code-timing estimator was extended by incorporating the knowledge of the chip pulse function. The resulting algorithm involves iterative nonlinear optimization that is computationally intensive and subject to local convergence. Another scheme that considers bandlimited chip waveforms was recently introduced in [22]. It exploits various shift invariances in the frequency domain to isolate the subspace of interest, from which an ESPRIT [23]-like procedure is invoked to derive the code-timing estimates. Unlike the extended MUSIC estimator [21], the shift-invariance-based algorithm is noniterative, yielding a closed-form solution. It works quite well in time-invariant (or slow fading) channels [22]. When the channel is both time- and frequency-selective, however, the algorithm suffers from significant degradation (see Section V).

We present herein an alternative blind code-timing estimation scheme for CDMA systems with bandlimited chip waveforms.

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Similar to the shift-invariance-based algorithm in [22], the proposed scheme is *noniterative*. Unlike the former, however, the proposed scheme can deal with both *time- and frequency-selective* channel fading. The key idea is to first Fourier transform the received signal to the frequency domain, followed by a frequency deconvolution to remove the convolving chip waveform, and finally to estimate the code timing from the output of a narrowband filter with a sweeping center frequency, which is designed to suppress the overall interference, including the MAI, intersymbol interference (ISI), and possibly other unmodeled interference. The proposed scheme requires only the spreading code of the desired user, and thus facilitates a decentralized implementation. It can be readily implemented using standard adaptive schemes, making it appealing for not only code acquisition, but tracking, as well. Also derived in this paper is an unconditional Cramér–Rao bound (CRB) for the blind code-timing estimation problem. The CRB is not conditioned on the fading coefficients or the information symbols, and therefore is a more appropriate lower bound for blind code-synchronization algorithms than a conditional CRB conditioned on the channel and symbols. The conditional CRB is apparently more suitable for training-based synchronization schemes.

While delay estimation via frequency-domain processing is well known in radar and sonar systems (e.g., [24], [25], and references therein), there are several challenging issues in a CDMA mobile network which require special attention. Specifically, the overall interference encountered in CDMA may overwhelm the desired transmission in a near–far environment. The interference in the frequency domain is, in general, correlated (due to asynchronism) with unknown correlation, which renders widely used frequency estimators, such as MUSIC [26], ESPRIT [23], etc., not directly applicable. Moreover, when high-speed transmission and high mobility are involved, the received signal is impaired by both *time- and frequency-selective* channel fading. In the following, we will take all these issues into account, in order to arrive at a code-timing estimation scheme that is not only near–far resistant, but robust against time-varying multipath channel fading, as well.

The rest of the paper is organized as follows. In Section II, we introduce the data model and formulate the problem of interest. The proposed scheme is presented and discussed in Section III. The unconditional CRB is derived in Section IV. Numerical examples are presented in Section V. Finally, we draw conclusions in Section VI.

Notation: Vectors (matrices) are denoted by boldface lower (upper) case letters; all vectors are column vectors; superscripts $(\cdot)^T$, $(\cdot)^*$, and $(\cdot)^H$ denote the transpose, conjugate, and conjugate transpose, respectively; $\mathbf{I}_N$ denotes the $N \times N$ identity matrix; $\mathbf{0}_{M\times N}$ denotes the $M \times N$ matrix with all zero elements; $\text{diag}\{\mathbf{g}\}$ is a diagonal matrix with the elements of $\mathbf{g}$ placed on the diagonal; $E\{\cdot\}$ denotes the statistical expectation; $\lceil\cdot\rceil$ denotes the smallest integer no less than the argument; $\star$ denotes the linear convolution; and finally, $\otimes$ denotes the matrix Kronecker product.

II. Problem Formulation

The system under investigation is an asynchronous K-user CDMA system with periodic spreading codes of length (processing gain) N. The code waveform for user k is

$$\psi_k(t) = \sum_{n=0}^{N-1} c_k(n) p(t - nT_c) \tag{1}$$

where $\{c_k(n)\}_{n=0}^{N-1}$ denotes the spreading code for user k, $p(t)$ the chip waveform assumed to be bandlimited and identical for all users, and T_c the chip duration. The transmitted signal $s_k(t)$ for user k is formed by multiplying $\psi_k(t)$ by the mth transmitted data symbol $d_k(m)$, i.e.,

$$s_k(t) = \sum_{m=0}^{M-1} d_k(m)\psi_k(t - mT_s)$$

where M denotes the number of symbols used for code acquisition, and $T_s = NT_c$ denotes the symbol duration.

The baseband signal received at the base station is

$$r(t) = \sum_{k=1}^{K}\sum_{l=1}^{L_k} \alpha_{k,l}(t) s_k(t - \tau_{k,l}) + n_r(t) \tag{2}$$

where L_k, $\alpha_{k,l}(t)$, and $\tau_{k,l}$ denote the number of propagation paths, the lth path's gain, and the lth path's delay for user k, respectively, and $n_r(t)$ lumps the channel noise and possibly unmodeled interference. In what follows, we assume that the time-varying fading coefficient $\alpha_{k,l}(t)$ is a stationary random process, while the number of paths L_k and path delay $\tau_{k,l}$ remain (approximately) fixed during code acquisition. The receiver front-end is a chip-matched filter that outputs

$$y(t) = r(t) \star p(T_c - t) = \sum_{k=1}^{K}\sum_{m=1}^{M} d_k(m) h_k(m;t) + n(t) \tag{3}$$

where $h_k(m;t)$ denotes the time-varying impulse response of the overall channel that includes the transmitter/receiver filters and the physical wireless channel

$$h_k(m;t) = \sum_{l=1}^{L_k} \alpha_{k,l}(t) g_k(t - mT_s - \tau_{k,l}) \tag{4}$$

$$g_k(t) = \psi_k(t) \star p(T_c - t),$$
$$n(t) = n_r(t) \star p(T_c - t). \tag{5}$$

We assume herein that the maximum path delay is less than T_s, which may be achieved through a side signaling channel for call setup [4], [27]. To facilitate digital signal processing (DSP) implementation, it is customary to truncate $p(t)$ such that it spans only a few chips [21], [28]. Under these conditions, we may assume that $h_k(m;t)$ has a finite support [21], [28]

$$h_k(m;t) = 0, \text{ for } t \notin [mT_s, (m+2)T_s]. \tag{6}$$

Without loss of generality, let user k be the desired user. The problem of interest is to estimate the code timing $\{\tau_{k,l}\}_{l=1}^{L_k}$ from the chip-matched filter output $y(t)$, while assuming no knowledge of the transmitted symbols $\{d_k(m)\}$ or the channel $\{\alpha_{k,l}(t)\}$.

III. Proposed Code-Timing Estimation Scheme

For DSP processing, the output of the chip-matched filter $y(t)$ is sampled with a sampling interval $T_i = T_c/Q$, where the integer $Q \geq 1$ denotes the oversampling factor

$$y(i) = y(t)|_{t=iT_i}, \quad i = 0, 1, \ldots, (M+1)NQ - 1.$$

Note that because of delay spread, the observation interval that covers M symbols is $(M+1)T_s$. We form M overlapping data blocks of $2NQ$ samples, each block consisting of data samples within two adjacent symbol intervals

$$\mathbf{y}(m) = [y(mNQ), \ldots, y(mNQ + 2NQ - 1)]^T, \quad m = 0, 1, \ldots, M-1. \tag{7}$$

Due to asynchronous transmission and the assumption on channel duration [i.e., (6)], $\mathbf{y}(m)$ is contributed by three consecutive symbols. Let $h_k(m;i) = h_k(m;t)|_{t=iT_i}$. The $2NQ \times 1$ signature vectors, which take into account the spreading, transmitter/receiver filters, and physical channel corresponding to the three adjacent symbols $d_k(m-1)$, $d_k(m)$, and $d_k(m+1)$, have the following forms:

$$\begin{aligned}\mathbf{h}^-_{\boldsymbol{\tau}_k}(m-1) &\triangleq [h_k(m-1; mNQ), \ldots, \\ &\qquad h_k(m-1; (m+1)NQ - 1), \mathbf{0}_{1\times NQ}]^T \\ \mathbf{h}_{\boldsymbol{\tau}_k}(m) &\triangleq [h_k(m; mNQ), \ldots, \\ &\qquad h_k(m; (m+2)NQ - 1)]^T \\ \mathbf{h}^+_{\boldsymbol{\tau}_k}(m+1) &\triangleq [\mathbf{0}_{1\times NQ}, h_k(m+1; (m+1)NQ), \ldots, \\ &\qquad h_k(m+1; (m+2)NQ - 1)]^T\end{aligned}$$

where the subscript $\boldsymbol{\tau}_k \triangleq [\tau_{k,1}, \ldots, \tau_{k,L_k}]^T$ signifies the dependence of these vectors on the path delays [e.g., (4)]. With these definitions, $\mathbf{y}(m)$ can be expressed as [cf. (3) and (4)]

$$\begin{aligned}\mathbf{y}(m) = \sum_{k=1}^{K} \big[& d_k(m-1)\mathbf{h}^-_{\boldsymbol{\tau}_k}(m-1) + d_k(m)\mathbf{h}_{\boldsymbol{\tau}_k}(m) \\ & + d_k(m+1)\mathbf{h}^+_{\boldsymbol{\tau}_k}(m+1)\big] + \mathbf{n}(m)\end{aligned} \tag{8}$$

where $\mathbf{n}(m)$ denotes the $2NQ \times 1$ vectors formed from the noise/interference samples $n(i)$ of $n(t)$.

Given that user k is of interest, we rewrite (8) as

$$\mathbf{y}(m) \triangleq d_k(m)\mathbf{h}_{\boldsymbol{\tau}_k}(m) + \mathbf{e}(m) \tag{9}$$

where $\mathbf{e}(m)$ lumps the channel noise and overall interference, including the MAI, ISI [i.e., the previous and the following symbols $d_k(m-1)$ and $d_k(m+1)$], and any unmodeled interference

$$\begin{aligned}\mathbf{e}(m) \triangleq \sum_{j \neq k} \Big[& d_j(m-1)\mathbf{h}^-_{\boldsymbol{\tau}_j}(m-1) + d_j(m)\mathbf{h}_{\boldsymbol{\tau}_j}(m) \\ & + d_j(m+1)\mathbf{h}^+_{\boldsymbol{\tau}_j}(m+1)\Big] \\ & + d_k(m-1)\mathbf{h}^-_{\boldsymbol{\tau}_k}(m-1) \\ & + d_k(m+1)\mathbf{h}^+_{\boldsymbol{\tau}_k}(m+1) + \mathbf{n}(m).\end{aligned}$$

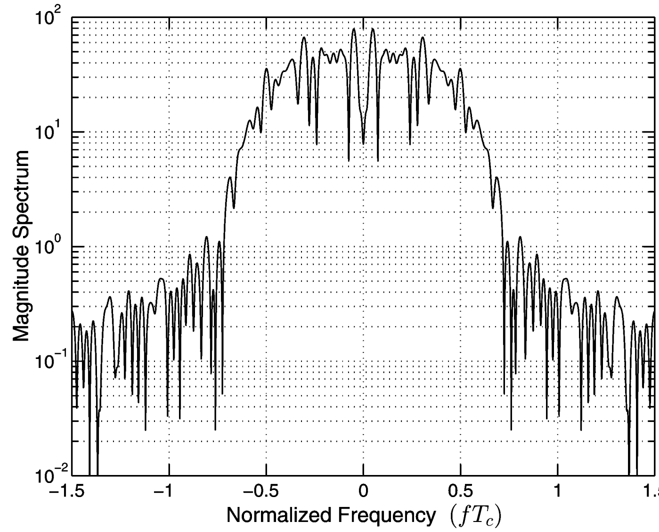

Fig. 1. Magnitude spectrum of a typical spreading waveform $g_k(t)$.

As will be shown next, bandlimited chip waveforms can be dealt with in the frequency domain via a frequency deconvolution. We will therefore need to take the Fourier transform, or the discrete Fourier transform (DFT) in particular, of the observed data. Before proceeding, we note that the spectrum of $g_k(t)$ in (5) usually tapers off at the end frequencies. To see this, Fig. 1 depicts the DFT (magnitude) of a typical $g_k(t)$ using an SRRC chip waveform $p(t)$ [see (1) and (5)] and a Gold spreading code with processing gain $N = 31$. In the presence of channel noise, the end frequencies have a lower signal-to-noise ratio (SNR) than the middle frequencies. Hence, we should skip the end frequencies to avoid noise amplification caused by the frequency deconvolution [28]. In view of that, we will only use the 100η percent of the total DFT (frequency) grids that correspond to the high-SNR middle frequencies, and discard the low-SNR end DFT grids. Here and henceforth, $\eta \in (0, 1]$ denotes the DFT grid-selection parameter (we will defer the discussion of the choice of η to Section V). Put more exactly, we will use a truncated DFT matrix $\boldsymbol{\mathcal{F}} \in \mathbb{C}^{2N_s \times 2NQ}$ to convert $\mathbf{y}(m)$ into the frequency domain. The truncated DFT matrix $\boldsymbol{\mathcal{F}}$ is formed by the $2N_s$ rows that correspond to the selected DFT grids of the $2NQ \times 2NQ$ full DFT matrix, where $N_s = \lceil \eta NQ \rceil$. That is

$$\boldsymbol{\mathcal{F}} = \begin{bmatrix} 1 & \phi^{-N_s} & \ldots & \phi^{-(2NQ-1)N_s} \\ 1 & \phi^{-(N_s-1)} & \ldots & \phi^{-(2NQ-1)(N_s-1)} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \phi^{N_s-1} & \ldots & \phi^{(2NQ-1)(N_s-1)} \end{bmatrix}$$

where $\phi \triangleq e^{-j(2\pi/2NQ)}$. Multiplying both sides of (9) by $\boldsymbol{\mathcal{F}}$ yields[1]

$$\bar{\mathbf{y}}(m) \triangleq \boldsymbol{\mathcal{F}}\mathbf{y}(m) = d_k(m)\boldsymbol{\mathcal{F}}\mathbf{h}_{\boldsymbol{\tau}_k}(m) + \bar{\mathbf{e}}(m) \tag{10}$$

where $\bar{\mathbf{e}}(m) \triangleq \boldsymbol{\mathcal{F}}\mathbf{e}(m)$. To facilitate our derivation, we assume here that the fading process $\alpha_{k,l}(t)$ [see (2)] is slowly changing, relative to T_s, such that it remains approximately unchanged

[1]Henceforth, $\bar{(\cdot)}$ is used to denote quantities in the frequency domain.

within $2T_s$.[2] It follows that $\mathbf{h}_{\boldsymbol{\tau}_k}$ can be expressed as [cf. (4) and (5)]

$$\mathbf{h}_{\boldsymbol{\tau}_k}(m) = \sum_{l=1}^{L_k} \alpha_{k,l}(m)\mathbf{g}_{k,l} \tag{11}$$

where $\alpha_{k,l}(m) \triangleq \alpha_{k,l}(t)|_{t=mT_s}$ and

$$\mathbf{g}_{k,l} \triangleq [g_k(-\tau_{k,l}), \ldots, g_k((2NQ-1)T_i - \tau_{k,l})]^T. \tag{12}$$

Using the time-shifting property of the Fourier transform [29], we have

$$\boldsymbol{\mathcal{F}}\mathbf{h}_{\boldsymbol{\tau}_k} \approx \mathrm{diag}\,(\bar{\mathbf{g}}_k)\boldsymbol{\Phi}_k\boldsymbol{\alpha}_k(m) \tag{13}$$

where

$$\boldsymbol{\Phi}_k \triangleq \begin{bmatrix} \phi^{-N_s\tau_{k,1}} & \ldots & \phi^{-N_s\tau_{k,L_k}} \\ \phi^{-(N_s-1)\tau_{k,1}} & \ldots & \phi^{-(N_s-1)\tau_{k,L_k}} \\ \vdots & \vdots & \vdots \\ \phi^{(N_s-1)\tau_{k,1}} & \ldots & \phi^{(N_s-1)\tau_{k,L_k}} \end{bmatrix} \tag{14}$$

$$\boldsymbol{\alpha}_k(m) \triangleq [\alpha_{k,1}(m), \ldots, \alpha_{k,L_k}(m)]^T \tag{15}$$

$$\bar{\mathbf{g}}_k \triangleq \boldsymbol{\mathcal{F}}[g_k(0), \ldots, g_k((2NQ-1)T_i)]^T. \tag{16}$$

Equation (13) holds only approximately because of the aliasing caused by the truncation of $p(t)$ (see Section II). The truncation widens the spectrum of $g_k(t)$ a little bit, and sampling at a rate $1/T_i$ introduces some small aliasing due to spectral folding, which will eventually lead to a small bias in the code-timing estimate. The aliasing, however, can be neglected, compared with the noise/interference-induced estimation error [28].

Substituting (13) into (10) yields

$$\bar{\mathbf{y}}(m) \approx d_k(m)\mathrm{diag}(\bar{\mathbf{g}}_k)\boldsymbol{\Phi}_k\boldsymbol{\alpha}_k(m) + \bar{\mathbf{e}}(m). \tag{17}$$

Note that the spectral nulls (i.e., end frequencies of the DFT) of $g_k(t)$ are avoided by selecting appropriate DFT grids (as explained before). Thus, we can perform a frequency deconvolution without undue noise amplification, as follows:

$$\begin{aligned} \bar{\mathbf{x}}_k(m) &\triangleq \mathrm{diag}^{-1}(\bar{\mathbf{g}}_k)\bar{\mathbf{y}}(m) \\ &\approx d_k(m)\boldsymbol{\Phi}_k\boldsymbol{\alpha}_k(m) + \mathrm{diag}^{-1}(\bar{\mathbf{g}}_k)\bar{\mathbf{e}}(m) \\ &\triangleq \boldsymbol{\Phi}_k\boldsymbol{\beta}_k(m) + \bar{\mathbf{v}}_k(m) \end{aligned} \tag{18}$$

where $\bar{\mathbf{v}}_k(m) \triangleq \mathrm{diag}^{-1}(\bar{\mathbf{g}}_k)\bar{\mathbf{e}}(m)$ and $\boldsymbol{\beta}_k(m) \triangleq d_k(m)\boldsymbol{\alpha}_k(m)$. In scalar form, we can express (18) as

$$\bar{x}_k(m,n) \approx \sum_{l=1}^{L_k} \beta_{k,l}(m)e^{j2\pi f_{k,l}n} + \bar{v}_k(m,n), \quad m = 0, \ldots, M-1; \quad n = -N_s, \ldots, N_s - 1 \tag{19}$$

where $\bar{x}_k(m,n)$ and $\bar{v}_k(m,n)$ are the nth element of $\bar{\mathbf{x}}_k(m)$ and $\bar{\mathbf{v}}_k(m)$, respectively, $\beta_{k,l}(m)$ is the lth element of $\boldsymbol{\beta}_k(m)$, and

$$f_{k,l} \triangleq -\frac{\tau_{k,l}}{2NQ}. \tag{20}$$

For fixed m in (19), $\bar{x}_k(m,n)$ consists of a sum of L_k sinusoids with complex amplitude $\beta_{k,l}(m)$ at frequency $f_{k,l}$. Hence, the delay-estimation problem reduces to a frequency-estimation problem.

It should be noted that the interference/noise term $\bar{v}_k(m,n)$ is, in general, correlated (colored) with *unknown* correlation. This makes several popular frequency-estimation algorithms, such as MUSIC [26], ESPRIT [23], etc., not directly applicable. While nonlinear least squares (NLS) or ML frequency estimators (e.g., [30]) can deal with unknown interference/noise, these iterative-search-based estimators have a high computational complexity. In what follows, we consider a filterbank-based frequency estimator (also see [31]) that can handle colored noise/interference with unknown correlation, and yet, is computationally much simpler than the NLS and ML estimators [31].

We first rewrite (18) as

$$\bar{\mathbf{x}}_k(m) = \sum_{l=1}^{L_k} \beta_{k,l}(m)\boldsymbol{\phi}(f_{k,l}) + \bar{\mathbf{v}}_k(m) \tag{21}$$

where $\boldsymbol{\phi}(f_{k,l}) \triangleq [e^{-j2\pi f_{k,l}N_s}, \ldots, e^{j2\pi f_{k,l}(N_s-1)}]^T$ denotes the lth column of $\boldsymbol{\Phi}_k$ in (14). The idea is to estimate the frequencies $\{f_{k,l}\}_{l=1}^{L_k}$ first and then use (20) to derive the code-timing estimates. In order to find estimates of $\{f_{k,l}\}_{l=1}^{L_k}$, we design a narrowband filter $\mathbf{w}_k(f) \in \mathbb{C}^{2N_s\times 1}$ with the center frequency f varying through the entire frequency interval of interest, i.e., $f \in [-1/2, 0]$ (note from (20) that $f_{k,l} \leq 0$). At each frequency f, $\mathbf{w}_k(f)$ is designed to pass the current frequency component with no distortion (unit gain), meanwhile minimizing the average filter output power so that the overall interference is suppressed by the filter. This amounts to the following filter-design criterion:

$$\mathbf{w}_k(f) = \arg \min_{\mathbf{w}_k(f)\in\mathbb{C}^{2N_s\times 1}} \frac{1}{M}\sum_{m=0}^{M-1} \left|\mathbf{w}_k^H(f)\bar{\mathbf{x}}_k(m)\right|^2, \quad \text{subject to } \mathbf{w}_k^H(f)\boldsymbol{\phi}(f) = 1. \tag{22}$$

The solution to the constrained minimization problem is well known (e.g., [31])

$$\mathbf{w}_k(f) = \left[\boldsymbol{\phi}^H(f)\hat{\mathbf{R}}_{\bar{\mathbf{x}}}^{-1}\boldsymbol{\phi}(f)\right]^{-1}\hat{\mathbf{R}}_{\bar{\mathbf{x}}}^{-1}\boldsymbol{\phi}(f) \tag{23}$$

where

$$\hat{\mathbf{R}}_{\bar{\mathbf{x}}} \triangleq \frac{1}{M}\sum_{m=0}^{M-1} \bar{\mathbf{x}}_k(m)\bar{\mathbf{x}}_k^H(m) \tag{24}$$

denotes the sample covariance matrix, and we assume $\hat{\mathbf{R}}_{\bar{\mathbf{x}}}^{-1}$ exists, implying that the number of symbols required for code acquisition should satisfy $M \geq 2N_s$. Substituting (23) into the cost function of (22) yields

$$V_k(f) \triangleq \left[\boldsymbol{\phi}^H(f)\hat{\mathbf{R}}_{\bar{\mathbf{x}}}^{-1}\boldsymbol{\phi}(f)\right]^{-1}. \tag{25}$$

It can be seen that as f sweeps through the frequency interval of interest, a peak of the cost function $V_k(f)$ is attained whenever f hits one of the sinusoidal frequencies $\{f_{k,l}\}_{l=1}^{L_k}$ [recall that $\bar{\mathbf{x}}_k(m)$ consists of a sum of L_k sinusoids contaminated by noise/interference; see (19)]. Thus, these L_k frequencies, or equivalently, the L_k delay parameters [cf. (20)], can be estimated by a 1-D search for the L_k largest peaks of $V_k(f)$ over all possible frequencies, i.e., $\forall f \in [-1/2, 0]$.

An alternative approach that avoids the 1-D search is to use polynomial rooting [31, p. 158], a procedure that is usually more efficient and reliable. Specifically, let

$$V_k^{-1}(z) \triangleq \boldsymbol{\phi}^T(z^{-1})\mathbf{R}_{\bar{\mathbf{x}}}^{-1}\boldsymbol{\phi}(z) \tag{26}$$

[2] We will relax this assumption and allow continuously varying $\alpha_{k,l}(t)$ in our simulations; see Section V.

$\boldsymbol{\phi}(z) \triangleq [z^{-N_s}, z^{-(N_s-1)}, \ldots, z^{(N_s-1)}]^T$. One can see that $V_k^{-1}(z)$ is a $2(2N_s-1)$st-order polynomial with a total of $(2N_s-1)$ pairs of reciprocal zeros [31, p. 159]. The L_k frequencies can be estimated as the phase angles of the L_k (pairs of reciprocal) zeros that are located on the lower half of the z-plane and that are closest to the unit circle. Once we have the L_k frequency estimates $\{\hat{f}_{k,l}\}_{l=1}^{L_k}$, we can obtain the path-delay estimates $\{\hat{\tau}_{k,l}\}_{l=1}^{L_k}$ from (20). It should be noted that $V_k^{-1}(z)$ is a $2(2N_s-1)$st-order polynomial with $(2N_s-1)$ pairs of reciprocal zeros. Hence, we can first factorize it into a minimum-phase and a maximum-phase subpolynomial of order $2N_s-1$, and then root either of the two subpolynomials. This can lead to considerable computational saving, since efficient spectral factorization algorithms exist (e.g., [31]), and only a $(2N_s-1)$st-order (halved) polynomial rooting is required,

To summarize, the proposed blind code-timing estimation scheme consists of the following steps.

1) Form $2NQ \times 1$ vectors $\{\mathbf{y}(m)\}$ as in (7) from the chip-matched filter output samples $\{y(i)\}$. Compute the DFT or fast Fourier transform (FFT) $\{\bar{\mathbf{y}}(m)\}$ of $\{\mathbf{y}(m)\}$ with the selected DFT grids by using (10).
2) Perform the frequency deconvolution and compute $\bar{\mathbf{x}}_k(m)$ by using (18). Compute the sample covariance $\hat{\mathbf{R}}_{\bar{\mathbf{x}}}$ by using (24).
3) Identify the L_k largest peaks, which are frequency estimates $\{\hat{f}_{k,l}\}_{l=1}^{L_k}$ of (25) via polynomial rooting. Finally, compute the code-timing estimates $\{\hat{\tau}_{k,l}\}_{l=1}^{L_k}$ from $\{\hat{f}_{k,l}\}_{l=1}^{L_k}$ by using (20).

We stress that the proposed scheme does not impose any assumption on the statistics of the noise/interference term $\bar{\mathbf{v}}_k(m)$ in (21). As the average filter output power is minimized, the overall interference, including the MAI, ISI, and other unmodeled interferences, is suppressed. On the other hand, the constraint in (22) ensures that the signal of interest is preserved without distortion.

For code-tracking applications, the proposed code-timing estimation scheme can be adaptively implemented with recursive least squares (RLS) adaptation, by invoking the matrix inversion lemma to calculate $\hat{\mathbf{R}}_{\bar{\mathbf{x}}}^{-1}$ recursively. Least mean squared (LMS) adaptive implementations of the proposed scheme are also possible, which, in general, entails a lower complexity but a slower convergence, as well. We will not pursue such adaptive implementations here, since they can be readily modified from standard adaptive algorithms in, e.g., [32].

IV. Cramér–Rao Bound

In this section, we derive a CRB for the blind estimation problem posed in Section II. The CRB is not conditioned on the fading coefficients or the information symbols, which makes it a more appropriate lower bound for blind code-timing estimation algorithms than a conditional CRB. We note that an unconditional CRB was also derived in [33]. That derivation, however, assumes a time-invariant, frequency-flat channel model. The CRB derived in the following is based on a more general channel model that allows both time and frequency selectivity.

Let $\mathbf{r}(m) \triangleq [y(mNQ), \ldots, y((m+1)NQ-1)]^T$ be formed from the NQ adjacent samples covering *one* symbol period [cf. $\mathbf{y}(m)$ in (7)]. Due to asynchronousness, we will find it convenient to collect several adjacent $\mathbf{r}(m)$ together

$$\mathbf{r}_J(n) \triangleq \left[\mathbf{r}^T(Jn), \ldots, \mathbf{r}^T(J(n+1)-1)\right]_{JNQ\times 1}^T, \quad n = 0, \ldots, M_r - 1$$

where $M_r \triangleq \lceil (M+1)/J \rceil$, and J denotes the number of symbol intervals grouped in $\mathbf{r}_J(n)$. Next, we stack all measurements together and define $\mathfrak{r} = [\mathbf{r}_J^T(0), \ldots, \mathbf{r}_J^T(M_r-1)]_{JM_rNQ\times 1}^T$. For sufficiently large J, the correlation between $\mathbf{r}_J(n_1)$ and $\mathbf{r}_J(n_2)$, for $n_1 \neq n_2$, can be ignored [33]. In that case, we have

$$\mathbf{R}_{\mathfrak{r}} = \mathbf{I}_{M_r} \otimes \mathbf{R}_{\mathbf{r}_J} \tag{27}$$

where $\mathbf{R}_{\mathfrak{r}} \triangleq E\{\mathfrak{r}\mathfrak{r}^H\}$ and $\mathbf{R}_{\mathbf{r}_J} \triangleq E\{\mathbf{r}_J(n)\mathbf{r}_J^H(n)\}$.

Let $\boldsymbol{\theta}$ contain all unknown parameters: $\boldsymbol{\theta} \triangleq [\sigma^2, \boldsymbol{\theta}_P^T, \boldsymbol{\tau}^T]_{(2L+1)\times 1}^T$, where $\boldsymbol{\tau} \triangleq [\boldsymbol{\tau}_1^T, \ldots, \boldsymbol{\tau}_K^T]_{L\times 1}^T$, $\boldsymbol{\theta}_P \triangleq [P_{1,1}, \ldots, P_{1,L_1}, \ldots, P_{K,1}, \ldots, P_{K,L_K}]_{L\times 1}^T$ and $L \triangleq \sum_{k=1}^K L_k$. Here, we assume that the noise samples $n(i)$ are spectrally white with zero mean and variance σ^2, and $P_{k,l} \triangleq E\{|\alpha_{k,l}(m)|^2\}$, which is the average received power associated with the lth path of user k. By the Slepian–Bangs formula, the CRB matrix is given by (see, e.g., [31])

$$\begin{aligned}\left[\mathrm{CRB}^{-1}(\boldsymbol{\theta})\right]_{i,j} &= \mathrm{tr}\left[\mathbf{R}_{\mathfrak{r}}^{-1}\frac{\partial \mathbf{R}_{\mathfrak{r}}}{\partial[\boldsymbol{\theta}]_i}\mathbf{R}_{\mathfrak{r}}^{-1}\frac{\partial \mathbf{R}_{\mathfrak{r}}}{\partial[\boldsymbol{\theta}]_j}\right] \\ &= M_r \mathrm{tr}\left[\mathbf{R}_{\mathbf{r}_J}^{-1}\frac{\partial \mathbf{R}_{\mathbf{r}_J}}{\partial[\boldsymbol{\theta}]_i}\mathbf{R}_{\mathbf{r}_J}^{-1}\frac{\partial \mathbf{R}_{\mathbf{r}_J}}{\partial[\boldsymbol{\theta}]_j}\right]\end{aligned} \tag{28}$$

where $[\mathrm{CRB}^{-1}(\boldsymbol{\theta})]_{i,j}$ denotes the (i,j)th element of the CRB matrix, $[\boldsymbol{\theta}]_i$ the ith element of $\boldsymbol{\theta}$, and the second equality is due to the block diagonal structure of the covariance matrix (27).

To compute the CRB, we need to determine $\mathbf{R}_{\mathbf{r}_J}$ and its derivatives with respect to (w.r.t.) the individual unknown parameters. To that end, we first express $\mathbf{r}(m)$ as follows [observing that two adjacent symbols contribute to $\mathbf{r}(m)$]:

$$\begin{aligned}\mathbf{r}(m) = \sum_{k=1}^{K}\sum_{l=1}^{L_k}\Big[&d_k(m-1)\alpha_{k,l}(m)\mathbf{g}_{k,l}^{(2)} \\ &+ d_k(m)\alpha_{k,l}(m)\mathbf{g}_{k,l}^{(1)}\Big] + \mathbf{n}_r(m)\end{aligned} \tag{29}$$

where $\mathbf{g}_{k,l}^{(1)}$ and $\mathbf{g}_{k,l}^{(2)}$ are $NQ \times 1$ vectors defined as [cf. $\mathbf{g}_{k,l}$ in (12)]

$$\left[\mathbf{g}_{k,l}^{(1)T}, \mathbf{g}_{k,l}^{(2)T}\right]^T \triangleq \mathbf{g}_{k,l}$$

and $\mathbf{n}_r(m) \triangleq [n(mNQ), \ldots, n((m+1)NQ-1)]^T$ collects noise samples within one symbol interval.

Recall the constraint that the delay spread is within one symbol period (see Section II). We can see that $\mathbf{r}(m_1)$ and $\mathbf{r}(m_2)$ are correlated only for $|m_1 - m_2| \le 1$. Hence, $\mathbf{R}_{\mathbf{r}_J}$ has the following block tridiagonal structure:

$$\mathbf{R}_{\mathbf{r}_J} = \begin{bmatrix} \mathbf{R_r}(0) & \mathbf{R_r}(1) & & \mathbf{0} \\ \mathbf{R_r}^H(1) & \mathbf{R_r}(0) & \ddots & \\ & \ddots & \ddots & \mathbf{R_r}(1) \\ \mathbf{0} & & \mathbf{R_r}^H(1) & \mathbf{R_r}(0) \end{bmatrix} \tag{30}$$

where $\mathbf{R_r}(0) \triangleq E\{\mathbf{r}(m)\mathbf{r}^H(m)\}$ and $\mathbf{R_r}(1) \triangleq E\{\mathbf{r}(m)\mathbf{r}^H(m+1)\}$. Assume that the information symbols $\{d_k(m)\}$ are identically independently distributed (i.i.d.) with zero mean and drawn from some unit-energy constellation, $\{\alpha_{k,l}(m)\}$ are also i.i.d., and that the symbols, fading coefficients, and noise samples are independent of each other. Then, one can easily verify

$$\mathbf{R_r}(0) = \sum_{k=1}^{K}\sum_{l=1}^{L_k} P_{k,l}\left[\mathbf{g}_{k,l}^{(1)}\mathbf{g}_{k,l}^{(1)H} + \mathbf{g}_{k,l}^{(2)}\mathbf{g}_{k,l}^{(2)H}\right] + \sigma^2\mathbf{I}_{NQ}$$

$$\mathbf{R_r}(1) = \sum_{k=1}^{K}\sum_{l=1}^{L_k} P_{k,l}\mathbf{g}_{k,l}^{(1)}\mathbf{g}_{k,l}^{(2)H}.$$

With $\mathbf{R}_{\mathbf{r}_J}$ determined as in the above, we next compute the partial derivatives of $\mathbf{R}_{\mathbf{r}_J}$, or equivalently, $\mathbf{R_r}(0)$ and $\mathbf{R_r}(1)$, w.r.t. the unknown parameters

$$\frac{\partial \mathbf{R}_{\mathbf{r}_J}}{\partial \sigma^2} = \mathbf{I}_{JNQ} \tag{31}$$

$$\frac{\partial \mathbf{R_r}(0)}{\partial P_{k,l}} = \mathbf{g}_{k,l}^{(1)}\mathbf{g}_{k,l}^{(1)H} + \mathbf{g}_{k,l}^{(2)}\mathbf{g}_{k,l}^{(2)H} \tag{32}$$

$$\frac{\partial \mathbf{R_r}(1)}{\partial P_{k,l}} = \mathbf{g}_{k,l}^{(1)}\mathbf{g}_{k,l}^{(2)H} \tag{33}$$

$$\frac{\partial \mathbf{R_r}(0)}{\partial \tau_{k,l}} = 2P_{k,l}\Re\left[\frac{\partial \mathbf{g}_{k,l}^{(1)}}{\partial \tau_{k,l}}\mathbf{g}_{k,l}^{(1)H} + \frac{\partial \mathbf{g}_{k,l}^{(2)}}{\partial \tau_{k,l}}\mathbf{g}_{k,l}^{(2)H}\right] \tag{34}$$

$$\frac{\partial \mathbf{R_r}(1)}{\partial \tau_{k,l}} = P_{k,l}\left[\frac{\partial \mathbf{g}_{k,l}^{(1)}}{\partial \tau_{k,l}}\mathbf{g}_{k,l}^{(2)H} + \mathbf{g}_{k,l}^{(1)H}\frac{\partial \mathbf{g}_{k,l}^{(2)}}{\partial \tau_{k,l}}\right] \tag{35}$$

where $\Re[\cdot]$ takes the real part of the argument. The partial derivatives $\partial \mathbf{g}_{k,l}^{(1)}/\partial\tau_{k,l}$ and $\partial \mathbf{g}_{k,l}^{(2)}/\partial\tau_{k,l}$ need the evaluation of $\partial g_k(t)/\partial t$. Since [see (1) and (5)] $g_k(t) = \sum_{n=0}^{N-1} c_k(n)q(t-nT_c)$, where $q(t) = p(t) \star p(t)$, we have

$$\frac{\partial g_k(t)}{\partial t} = \sum_{n=0}^{N-1} c_k(n)\frac{\partial q(t-nT_c)}{\partial t}. \tag{36}$$

Using (30)–(36) in (28), the CRB can be readily computed.

Finally, we note that the calculation of $\partial q(t)/\partial t$ requires an explicit pulse function form. Consider, for example, that $p(t)$ is an SRRC pulse (which is used in our simulations next). Accordingly, $q(t)$ is a raised-cosine function [20]

$$q(t) = \frac{\sin\left(\frac{\pi t}{T_c}\right)}{\frac{\pi t}{T_c}}\frac{\cos\left(\frac{\pi\rho t}{T_c}\right)}{1-\frac{4\rho^2t^2}{T_c^2}}$$

where ρ denotes the rolloff (excess bandwidth) parameter. We can easily obtain

$$\frac{\partial q(t)}{\partial t} = \frac{t\cos\left(\frac{\pi t}{T_c}\right) - \frac{T_c}{\pi}\sin\left(\frac{\pi t}{T_c}\right)}{t^2} \times \frac{\cos\left(\frac{\pi\rho t}{T_c}\right)}{1-\frac{4\rho^2t^2}{T_c^2}} + \frac{\sin\left(\frac{\pi t}{T_c}\right)}{\frac{\pi t}{T_c}}\left[\frac{-\frac{\pi\rho}{T_c}\sin\left(\frac{\pi\rho t}{T_c}\right)}{1-\frac{4\rho^2t^2}{T_c^2}} + \frac{\frac{8\rho^2 t}{T_c^2}\cos\left(\frac{\pi\rho t}{T_c}\right)}{\left(1-\frac{4\rho^2t^2}{T_c^2}\right)^2}\right].$$

V. Numerical Results

We consider a K-user asynchronous CDMA system using a unit-energy binary phase-shift keying (BPSK) constellation and bandlimited chip waveform. Each user is assigned a Gold code of $N = 31$. We consider a near–far environment whereby the transmitted power P_1 for the desired user is scaled so that $P_1 = 1$, whereas the power for the $K-1$ interfering users in *all* simulations follows a log normal distribution $P_k/P_1 = 10^{0.1P}, P \sim N(10, 100)$, for $k = 2, \ldots, K$. Note that all the interfering users transmit at a mean power level 10 dB higher than that of the desired user, i.e., the near–far ratio (NFR) is 10 dB for all examples. The bandlimited chip waveform is a SRRC pulse with rolloff factor $\rho = 0.52$, truncated to have a duration of $4T_c$. In *all* examples, we consider a time-varying fading channel model whereby the fading $\alpha_{k,l}(t)$ is parameterized by the normalized Doppler rate f_DT_s, with f_D denoting the maximum Doppler rate. In the following, we use $f_DT_s = 0.01$, which corresponds to the case when the carrier frequency is 900 MHz, the symbol rate is $1/T_s = 10$ kHz, and the mobile speed is 75 mph. The fading process is generated by the Jakes' model [34] and is updated continuously every T_i (recall $T_i = T_c/Q$); hence, it is not fixed within two symbol intervals, even though the derivation of the proposed scheme in Section III assumed so for mathematical tractability.

In the following, we compare the proposed scheme with the modified MUSIC [21] and the shift-invariance-based (SIB) [22] estimators. We note again that the SIB and the proposed estimators are in closed form, whereas the extended MUSIC estimator requires nonlinear optimization, which is implemented using the Matlab `fminsearch` function initialized by the original MUSIC estimator [11] that assumes rectangular chip waveforms. We consider two performance measures. One is the probability of correct acquisition, which is defined as the probability of the event $|\hat{\tau} - \tau| < T_c/2$, where $\hat{\tau}$ denotes an estimate of the code-timing τ. The other measure is the root mean-squared error (RMSE) normalized by T_c, given correct acquisition. Unless otherwise specified, the delays, fading coefficients, powers, information symbols, and channel noise are changed randomly from one trial to another. All results are averaged over 400 independent trials.

We first examine numerically the choice of η, the DFT grid selection parameter (see Section III), for the proposed scheme. For SIB, $\eta = 0.5$ is suggested in [22]. Fig. 2 depicts the probability of correct acquisition and RMSE of the proposed scheme in time-varying frequency-flat ($K = 14$) and two-path ($K = 6$) Rayleigh fading channels when $M = 150$, NFR = 10 dB, SNR = 20 dB, and $f_DT_s = 0.01$. It is seen that as η increases, the performance of the proposed scheme improves; when η is too large (i.e., close to one), however, the estimation accuracy suffers slightly (cf. lower half of Fig. 2), due to the inclusion of noisy end DFT grids. We also note that for $Q = 1$, a choice of $\eta \geq 0.7$ is necessary to achieve the best possible performance; on the other hand, with $Q = 2$, the performance is less sensitive to the choice of η. In what follows, we use $\eta = 0.7$ whenever $Q = 2$.

We next examine the user capacity, i.e., the number of users that can be supported by these schemes. Fig. 3 depicts the per-

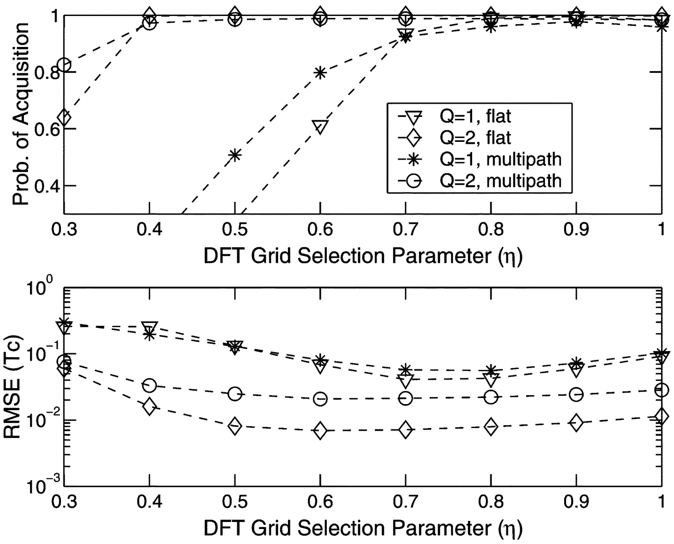

Fig. 2. Probability of correct acquisition (upper) and RMSE (lower) versus the DFT grid selection parameter η in time-varying frequency-flat ($K = 14$) and multipath ($K = 6$) Rayleigh fading channels when $M = 150$, NFR $= 10$ dB, SNR $= 20$ dB, and $f_D T_s = 0.01$.

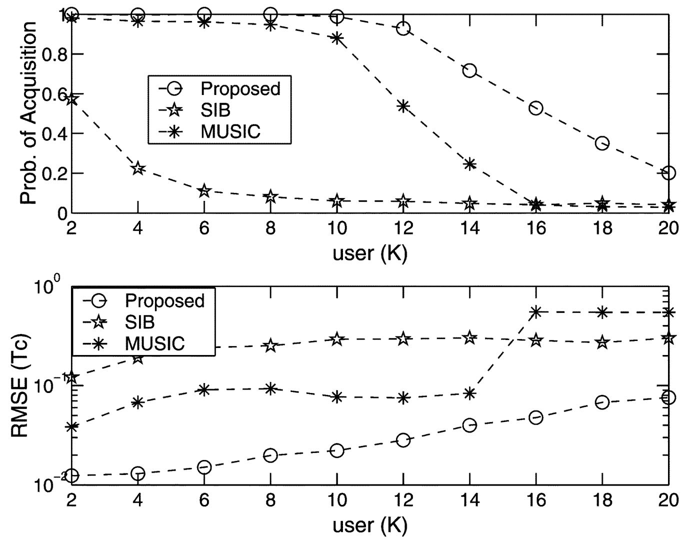

Fig. 4. Probability of correct acquisition (upper) and RMSE (lower) versus user number K in time-varying multipath Rayleigh fading channels when $Q = 2$, $M = 150$, NFR $= 10$ dB, SNR $= 20$ dB, and $f_D T_s = 0.01$.

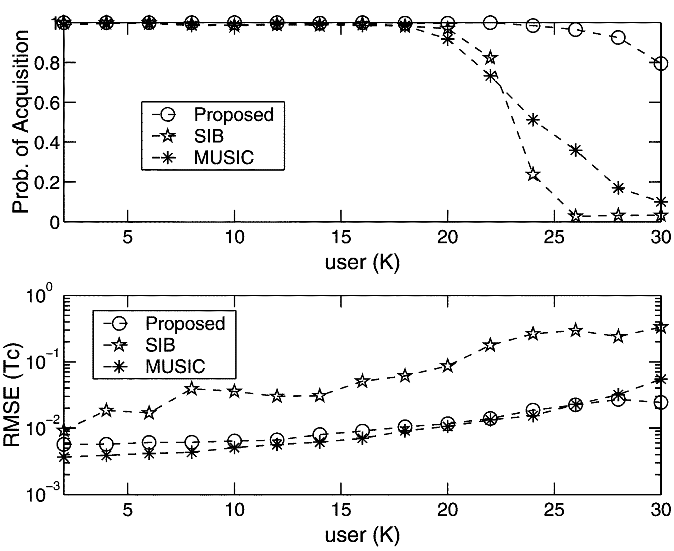

Fig. 3. Probability of correct acquisition (upper) and RMSE (lower) versus user number K in time-varying frequency-flat fading channels when $Q = 2$, $M = 150$, NFR $= 10$ dB, SNR $= 20$ dB, and $f_D T_s = 0.01$.

formance of the three synchronization algorithms as a function of user number K in time-varying frequency-flat Rayleigh fading channels when $Q = 2$, $M = 150$, SNR $= 20$ dB, NFR $= 10$ dB, and $f_D T_s = 0.01$, whereas Fig. 4 shows the corresponding results in time-varying two-path Rayleigh fading channels for a similar setup. We note that in both cases, the proposed scheme achieves the largest user capacity and, overall, the best performance in terms of both acquisition and RMSE. The only exception is that MUSIC yields slightly smaller RMSE than the proposed scheme when K is small and the channel is frequency-flat (cf. lower half of Fig. 3). As shown in Fig. 4, the performance of SIB is very poor when both time and frequency selectivity occur. It should be noted that SIB was originally proposed for time-invariant (or slow fading) channels, and works excellently in those environments. We also observe the reasonably good performance of SIB in time-varying frequency-flat channels (cf. Fig. 3). This is because with only a single path, the time-varying channel coefficient can be absorbed by the information symbols, and therefore, $\mathbf{h}_k$ in [22, eq. (1)] can be made time-invariant. That is, the time-varying channel is equivalent to a time-invariant channel with modified symbols that lump together the original information symbols and the channel fading. Consequently, SIB can be applied with no modification to yield reasonable performance. With multipath, however, $\mathbf{h}_k$ are time-varying. Direct application of SIB leads to incorrect acquisition most of the time. How to extend SIB to the general case of time-varying multipath channels remains an interesting future problem.

Finally, Fig. 5 depicts the performance of the three methods as a function of the SNR in time-varying two-path Rayleigh fading channels when $Q = 2$, $M = 150$, $K = 6$, NFR $= 10$ dB, and $f_D T_s = 0.01$. Also shown in Fig. 5 is the unconditional CRB derived in Section IV. Since the CRB depends on the propagation delays, in this example, they are randomly generated and then fixed through the simulation, whereas the other parameters are changed randomly from one trial to another. In terms of acquisition, it is seen that the proposed scheme has the smallest SNR threshold. Fig. 5 indicates that the proposed scheme is also more consistent than the others. That is, the estimation error of the former decreases consistently as the SNR increases, whereas the other two exhibit irreducible error floors. It is seen that none of the three estimators achieve the CRB. For the proposed scheme, this is not surprising, since the MAI and ISI are lumped into an unstructured term. Better estimation accuracy may be achieved if the structure of the interference is accounted for in the estimation process. This, however, may increase the complexity and trade off the robustness of the proposed scheme.

VI. Conclusions

We have presented an interference- and fading-resistant blind code-timing estimation algorithm for CDMA systems with bandlimited chip waveforms. This estimator is noniterative, requiring

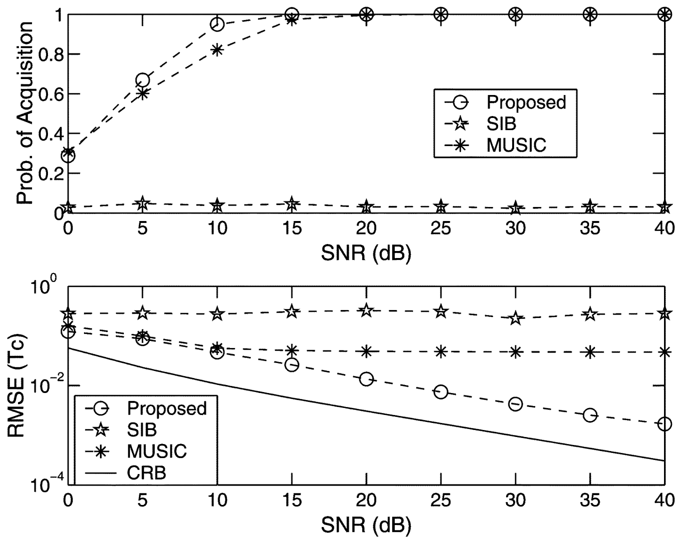

Fig. 5. Probability of correct acquisition (upper) and RMSE (lower) versus SNR in time-varying multipath Rayleigh fading channels when $Q = 2, M = 150, K = 6$, NFR $= 10$ dB, and $f_D T_s = 0.01$.

only the knowledge of the spreading code of the desired user. It can be adaptively implemented and can thus be used for not only code acquisition, but also code tracking. We have shown numerically that the proposed estimator outperforms the extended MUSIC and the SIB estimators in time-varying multipath fading channels. As a benchmark for various blind code-synchronization schemes, we have derived an unconditional CRB that is averaged over the information symbols and channel fading coefficients. It has been observed that the proposed scheme, albeit unable to achieve the CRB, is statistically more consistent than the MUSIC and SIB estimators as the SNR increases. It has been inferred that improved estimation accuracy may be achieved by exploiting the inherent structure of the interference, at the cost of increased complexity and some loss of robustness. This will be investigated in the future.

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REFERENCES

[1] R. Prasad and T. Ojanperä, "An overview of CDMA evolution toward wideband CDMA," *IEEE Commun. Lett.*, vol. 1, no. 1, pp. 2–29, Jan. 1998.

[2] R. L. Peterson, R. E. Ziemer, and D. E. Borth, *Introduction to Spread Spectrum Communications*. Englewood Cliffs, NJ: Prentice-Hall, 1995.

[3] S. Verdú, *Multiuser Detection*. Cambridge, U.K.: Cambridge Univ. Press, 1998.

[4] R. F. Smith and S. L. Miller, "Acquisition performance of an adaptive receiver for DS-CDMA," *IEEE Trans. Commun.*, vol. 47, no. 9, pp. 1416–1424, Sep. 1999.

[5] D. Zheng, J. Li, S. L. Miller, and E. G. Ström, "An efficient code-timing estimator for DS-CDMA system," *IEEE Trans. Signal Process.*, vol. 45, no. 1, pp. 82–89, Jan. 1997.

[6] S. E. Bensley and B. Aazhang, "Maximum-likelihood synchronization of a single user for code-division multiple-access communication systems," *IEEE Trans. Commun.*, vol. 46, no. 3, pp. 392–399, Mar. 1998.

[7] E. G. Ström and F. Malmsten, "A maximum likelihood approach for estimating DS-CDMA multipath fading channels," *IEEE J. Sel. Areas Commun.*, vol. 18, no. 1, pp. 132–140, Jan. 2000.

[8] H. Li, J. Li, and S. L. Miller, "Decoupled multiuser code-timing estimation for code-division multiple-access communication systems," *IEEE Trans. Commun.*, vol. 49, no. 8, pp. 1425–1436, Aug. 2001.

[9] E. G. Ström, S. Parkvall, S. L. Miller, and B. E. Ottersten, "Propagation delay estimation in asynchronous direct-sequence code-division multiple access systems," *IEEE Trans. Commun.*, vol. 44, no. 1, pp. 84–93, Jan. 1996.

[10] S. E. Bensley and B. Aazhang, "Subspace-based channel estimation for code division multiple access communications systems," *IEEE Trans. Commun.*, vol. 44, no. 8, pp. 1009–1020, Aug. 1996.

[11] E. G. Ström, S. Parkvall, S. L. Miller, and B. E. Ottersten, "DS-CDMA synchronization in time-varying fading channels," *IEEE J. Sel. Areas Commun.*, vol. 14, no. 10, pp. 1636–1642, Oct. 1996.

[12] T. Östman, S. Parkvall, and B. Ottersten, "An improved MUSIC algorithm for estimation of time delays in asynchronous DS-CDMA systems," *IEEE Trans. Commun.*, vol. 47, no. 11, pp. 1628–1631, Nov. 1999.

[13] U. Madhow, "Blind adaptive interference suppression for the near–far resistant acquisition and demodulation of direct-sequence CDMA signals," *IEEE Trans. Signal Process.*, vol. 45, no. 1, pp. 124–136, Jan. 1997.

[14] M. Latva-aho, J. Lilleberg, J. Iinatti, and M. Juntti, "CDMA downlink code acquisition performance in frequency-selective fading channels," in *Proc. IEEE Int. Symp. Pers., Indoor, Mobile Radio Commun.*, Boston, MA, Sep. 1998, pp. 1476–1479.

[15] H. Li and R. Wang, "Filterbank-based blind code synchronization for DS-CDMA systems in multipath fading channels," *IEEE Trans. Signal Process.*, vol. 51, no. 1, pp. 160–171, Jan. 2003.

[16] C.-D. Chung, "Differentially coherent detection technique for direct-sequence code acquisition in a Rayleigh fading mobile channel," *IEEE Trans. Commun.*, vol. 43, no. 2–4, pp. 1116–1126, Feb.–Apr. 1995.

[17] M. H. Zarrabizadeh and E. S. Sousa, "A differentially coherent PN code acquisition receiver for CDMA systems," *IEEE Trans. Commun.*, vol. 45, no. 11, pp. 1456–1465, Nov. 1997.

[18] J. Iinatti and A. Pouttu, "Differentially coherent code acquisition in jamming and data modulation," in *Proc. IEEE Mil. Commun. Conf.*, Atlantic City, NJ, Oct./Nov. 1999, pp. 579–583.

[19] T. Ristaniemi and J. Joutsensalo, "Code timing acquisition for DS-CDMA in fading channels for differential correlations," *IEEE Trans. Commun.*, vol. 49, no. 5, pp. 899–910, May 2001.

[20] J. G. Proakis, *Digital Communications*, 3 ed. New York: McGraw-Hill, 1995.

[21] T. Östman and B. Ottersten, "Near–far robust time delay estimation for asynchronous DS-CDMA systems with bandlimited pulse shapes," in *Proc. IEEE 48th Veh. Technol. Conf.*, Ottawa, ON, Canada, May 1998, pp. 1650–1654.

[22] N. Petrochilos and A. J. van der Veen, "Blind time delay estimation in asynchronous CDMA via subspace intersection and ESPRIT," in *Proc. 2001 IEEE Int. Conf. Acoust., Speech, Signal Process.*, Salt Lake City, UT, May 2001, pp. 2217–2220.

[23] R. Roy and T. Kailath, "ESPRIT-estimation of signal parameters via rotational invariance techniques," *IEEE Trans. Acoust., Speech, Signal Process.*, vol. 37, no. 7, pp. 984–995, Jul. 1989.

[24] A. L. Swindlehurst, "Time delay and spatial signature estimation using known asynchronous signals," *IEEE Trans. Signal Process.*, vol. 46, no. 2, pp. 449–462, Feb. 1998.

[25] R. Wu and J. Li, "Time delay estimation with multiple looks in colored Gaussian noise," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 35, no. 5, pp. 1354–1361, Oct. 1999.

[26] R. O. Schmidt, "Multiple emitter location and signal parameter estimation," *IEEE Trans. Antennas Propag.*, vol. AP-34, no. 3, pp. 276–280, Mar. 1986.

[27] T. S. Rappaport, *Wireless Communications: Principles and Practice*. Upper Saddle River, NJ: Prentice-Hall, 1996.

[28] A. J. van der Veen, M. C. Vanderveen, and A. Paulraj, "Joint angle and delay estimation using shift-invariance techniques," *IEEE Trans. Signal Process.*, vol. 46, no. 2, pp. 405–418, Feb. 1998.

[29] A. V. Oppenheim and R. W. Schafer, *Discrete-Time Signal Processing*. Englewood Cliffs, NJ: Prentice-Hall, 1989.

[30] J. Li and P. Stoica, "Efficient mixed-spectrum estimation with applications to target feature extraction," *IEEE Trans. Signal Process.*, vol. 44, no. 2, pp. 281–295, Feb. 1996.

[31] P. Stoica and R. L. Moses, *Introduction to Spectral Analysis*. Upper Saddle River, NJ: Prentice-Hall, 1997.

[32] S. Haykin, *Adaptive Filter Theory*, 3rd ed. Upper Saddle River, NJ: Prentice-Hall, 1996.

[33] T. Östman. (1997) On the bounds of performance in parameter estimation in communications systems. Royal Inst. Technol., Sweden. [Online]. Available: ftp://ftp.s3.kth.se/pub/signal/reports/97/IR-S3-SB-9725.ps

[34] W. C. Jakes, Jr., *Microwave Mobile Communications*. New York: Wiley-Interscience, 1974.

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