A RECEIVER DIVERSITY BASED CODE-TIMING ESTIMATOR FOR ASYNCHRONOUS DS-CDMA SYSTEMS

Zheng-She Liu *Jian Li* *Scott L. Miller*

Department of Electrical and Computer Engineering, University of Florida, Gainesville, FL 32611, USA

ABSTRACT

We propose a receiver diversity based code-timing estimator for DS-CDMA systems. The systems are assumed to work in a flat fading and near-far environment, where an arbitrary antenna array is used at the receiver of the system to achieve the spatial diversity. The algorithm is derived by modeling the known training sequence as the desired signal and all other signals including the multiuser interfering signals and the additive noise as unknown colored Gaussian noise so that the knowledge of the number of active users is not required. We show that by utilizing the information collected via multiple antenna sensors, the length of the training sequences can be greatly reduced. We also show that the algorithm is an asymptotic maximum likelihood estimator. As a result, the mean-squared error of the code-timing estimates obtained by the algorithm approaches the Cramér-Rao lower bound (CRB) as the length of the training sequence increases. Moreover, the algorithm does not require the search over a parameter space and the code-timing is obtained by rooting a second-order polynomial, which is computationally very efficient. Simulation results show that the algorithm is quite robust against the near-far problem and requires a much shorter training sequence than the existing estimators.

1. INTRODUCTION

The ability to achieve code synchronization in a near-far DS-CDMA (direct-sequence code division multiple access) environment has been determined to limit the capacity of communication systems [1]. As a result, code-timing estimation has received much attention in recent years. Several estimators have been proposed in the literature [2]. However, all of these estimators are developed based on a single antenna sensor. The problem of estimating the code-timing of a desired user for a receiver diversity DS-CDMA system that uses multiple antenna sensors at the receiver has not been well studied. In [3], we have proposed a code-timing estimation algorithm for receiver diversity DS-CDMA systems. The algorithm was developed by using the information collected by an arbitrary antenna array consisting of multiple antenna sensors and is referred to as *MASE* (*Multiple Antenna Sensors based Estimator*).

The MASE algorithm is designed for the system where the number of antenna sensors is relatively small. Typically, a few sensors are used for a system with 20 to 30 active users. The performance of MASE cannot be significantly improved by further increasing the number of antenna sensors when, for fair comparisons with a single antenna based methods, we assume that the noise variance is proportional to the number of antenna sensors used in the receiver. In this paper, we propose another code-timing estimator when a relatively large number of antenna sensors is used in the receiver. This new algorithm takes further advantage of the spatial diversity and is referred to as REDIVE (REceiver DIVersity based Estimator). Both MASE and REDIVE are asymptotic maximum likelihood estimators and are derived by modeling the known training sequence as the desired signal and all other signals as unknown colored Gaussian noise. Also, both algorithms do not require the search over the parameter space. The code-timing estimates are obtained by rooting a second-order polynomial. However, the specifics of the data model used in REDIVE are different form those in MASE. Simulation results show that the amount of computations required by REDIVE is about the same as that required by MASE. The length of training sequences required by REDIVE is significantly shorter than that required by MASE, but at a cost of more antenna sensors.

2. PROBLEM FORMULATION

Consider an asynchronous BPSK (binary phase shift keying) DS-CDMA system. The kth user transmits a signal of the form

$$\tilde{x}_k(t) = \sqrt{2P_k}\tilde{s}_k(t)\cos(\omega_c t + \bar{\theta}_k), \tag{1}$$

where P_k is the user's transmitted power, ω_c is the carrier frequency, $\bar{\theta}_k$ is a random carrier phase uniformly distributed between 0 and 2π, and $\tilde{s}_k(t) = \sum_{m=0}^{M-1} d_k(m)\tilde{c}_k(t-mT_b)$ with M being the number of the data bits considered, T_b denoting the data bit duration, $d_k(m) \in \{-1,+1\}$ denoting the value of the mth data bit, and $\tilde{c}_k(t) = \sum_{n=0}^{N-1} c_k(n)\Pi_{T_c}(t-nT_c)$ being the spreading waveform in which $c_k(n) \in \{-1,+1\}$, $N = T_b/T_c$, and $\Pi_{T_c}(t)$ denoting a unit rectangular pulse over the chip period $[0, \quad T_c)$.

We use an arbitrary antenna array consisting of L antenna sensors at the receiver of the system. We consider the case of flat fading, where for each user, the time-delay differences due to multipath are negligible. For this case, we model the signal received by the lth sensor as

$$\tilde{y}_l(t) = \sum_{k=1}^{K} \tilde{a}_{l,k}\tilde{x}_k(t-\tau_k) + \tilde{n}_l(t), \quad l = 1, 2, \cdots, L, \tag{2}$$

where K is the number of users, $\tilde{a}_{l,k}$ is the fading coefficient, τ_k is the propagation delay, and $\tilde{n}_l(t)$ denotes the channel noise. Given sufficient physical separation among the constituent antennas, the fading coefficients $\{\tilde{a}_{l,k}\}$ can be modeled as mutually independent random variables [4].

We assume that $\{\tilde{a}_{k,l}\}$ are also independent of the random carrier phase $\left\{\bar{\theta}_k\right\}$ and the channel noise $\{\tilde{n}_l(t)\}$. In addition, we assume that the transmitter and receiver have aligned their clocks to roughly within a bit interval. This could be done, for example, on a side "signalling channel", where a call is initially set up. Hence, we consider only the relative propagation delay, that is, $\tau_k \in [0 \quad T_b)$.

Assume that the receiver front-end consists of an IQ-mixer followed by an integrate-and-dump filter with integration time T_c. The equivalent received complex sequence of the lth sensor, $y_l(i)$, is described as

$$y_l(i) = \sum_{k=1}^{K} a_{l,k}\sqrt{P_k}e^{j\theta_k}\frac{1}{T_c}\int_{(i-1)T_c}^{iT_c}\tilde{s}_k(t-\tau_k)dt + n_l(i), \quad (3)$$

where $\theta_k = \bar{\theta}_k - \omega_c\tau_k$, $n_l(i)$ denotes the noise term assumed to be zero-mean complex white Gaussian with variance σ_n^2, and $a_{l,k}$ is the fading coefficient assumed to be zero-mean complex Gaussian with variance σ_a^2.

Let $\tau_k = p_kT_c + \delta_k$, where $p_k \in \{\ 0, \quad 1, \quad \cdots, \quad N-1\ \}$ and $\delta_k \in [0, T_c)$. The integration in the right-hand side of (3) is then given by

$$\begin{aligned} r_k(i) &\triangleq \frac{1}{T_c}\int_{(i-1)T_c}^{iT_c}\tilde{s}_k(t-\tau_k)dt \\ &= (1-\delta_k/T_c)\, c_k(i-m_1N-p_k-1)d_k(m_1) \\ &\quad +(\delta_k/T_c)c_k(i-m_2N-p_k-2)d_k(m_2), \end{aligned} \quad (4)$$

where m_1 and m_2 are integers such that $0 \le i - m_1N - p_k - 1 \le N-1$ and $0 \le i - m_2N - p_k - 2 \le N-1$. Let

$$\mathbf{c}_k = [\ c_k(N-1) \quad c_k(N-2) \quad \cdots \quad c_k(0)\ ]^T \quad (5)$$

and

$$\mathbf{r}_k(m) = [\ r_k(mN+N) \quad \cdots \quad r_k(mN+1)\ ]^T \quad (6)$$

where $(\cdot)^T$ denotes the transpose. We then have

$$\mathbf{r}_k(m) = [\ \mathbf{a}_1(\tau_k) \quad \mathbf{a}_2(\tau_k)\ ]\,\mathbf{z}_k(m) \triangleq \mathbf{A}(\tau_k)\mathbf{z}_k(m), \quad (7)$$

where

$$\begin{aligned} \mathbf{z}_k(m) &\triangleq \left[\ z_k^{(1)}(m) \quad z_k^{(2)}(m)\ \right]^T \\ &\triangleq \left[\ \tfrac{d_k(m)+d_k(m-1)}{2} \quad \tfrac{d_k(m)-d_k(m-1)}{2}\ \right]^T, \end{aligned} \quad (8)$$

$$\mathbf{a}_1(\tau_k) = \left[\left(1-\frac{\delta_k}{T_c}\right)\mathbf{J}_{+1}^{(p_k)} + \frac{\delta_k}{T_c}\mathbf{J}_{+1}^{(p_k+1)}\right]\mathbf{c}_k, \quad (9)$$

and

$$\mathbf{a}_2(\tau_k) = \left[\left(1-\frac{\delta_k}{T_c}\right)\mathbf{J}_{-1}^{(p_k)} + \frac{\delta_k}{T_c}\mathbf{J}_{-1}^{(p_k+1)}\right]\mathbf{c}_k, \quad (10)$$

with

$$\mathbf{J}_s^{(p)} = \begin{bmatrix} \mathbf{0} & \mathbf{I}_{N-p} \\ s\mathbf{I}_p & \mathbf{0} \end{bmatrix}, \quad s = \pm 1, \quad (11)$$

in which $\mathbf{I}_p$ denotes the $p \times p$ identity matrix. Let

$$\mathbf{y}_l(m) = [\ y_l(mN+N) \quad \cdots \quad y_l(mN+1)\ ]^T \quad (12)$$

and

$$\mathbf{n}_l(m) = [\ n_l(mN+N) \quad \cdots \quad n_l(mN+1)\ ]^T. \quad (13)$$

Without loss of generality, assuming that the first user is the desired user, we can rewrite (3) as

$$\mathbf{y}_l(m) = a_{l,1}\sqrt{P_1}e^{j\theta_1}\mathbf{r}_1(m) + \mathbf{e}_l(m), \quad (14)$$

where

$$\mathbf{e}_l(m) = \sum_{k=2}^{K} a_{l,k}\sqrt{P_k}e^{j\theta_k}\mathbf{r}_k(m) + \mathbf{n}_l(m) \quad (15)$$

denotes the sum of the MAI and the additive noise. Let

$$\beta_l = a_{l,1}\sqrt{P_1}e^{j\theta_1}. \quad (16)$$

We then have

$$\mathbf{y}_l(m) = \beta_l\mathbf{A}(\tau_1)\mathbf{z}_1(m) + \mathbf{e}_l(m), \quad l = 1, 2, \cdots, L. \quad (17)$$

The problem of interest herein is to estimate τ_1 from $\left\{\{\mathbf{y}_l(m)\}_{m=1}^{M}\right\}_{l=1}^{L}$ assuming that $\{c_1(n)\}_{n=0}^{N-1}$ and $\{d_1(m)\}_{m=0}^{M-1}$ are known. Since the integer p_1 has only N possible values $\{0, 1, \cdots, N-1\}$, which can be obtained by trying these values one by one, the problem becomes to estimate $\mu \triangleq \delta_1/T_c$ with p_1 being given.

3. THE REDIVE ALGORITHM

To utilize the receiver diversity, we arrange the output samples as follows:

$$\mathbf{Y} = \begin{bmatrix} \mathbf{y}_1^T(1) & \mathbf{y}_1^T(2) & \cdots & \mathbf{y}_1^T(M) \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{y}_L^T(1) & \mathbf{y}_L^T(2) & \cdots & \mathbf{y}_L^T(M) \end{bmatrix}, \quad L \times (MN). \quad (18)$$

Let

$$\mathbf{Z}_1 = [\ \mathbf{z}_1(0) \quad \mathbf{z}_1(1) \quad \cdots \quad \mathbf{z}_1(M-1)\ ], \quad 2 \times M, \quad (19)$$

and $\mathbf{E}$ be defined similarly to $\mathbf{Y}$. We have

$$\mathbf{Y} = \beta\,\mathrm{vec}^T\{\mathbf{A}(\tau_1)\mathbf{Z}_1\} + \mathbf{E}, \quad (20)$$

where $\beta = [\ \beta_1 \quad \beta_2 \quad \cdots \quad \beta_L\ ]^T$ and $\mathrm{vec}(\mathbf{X}) = [\ \mathbf{x}_1^T \quad \mathbf{x}_2^T \cdots \quad \mathbf{x}_N^T\ ]^T$ with $\{\mathbf{x}_n\}_{n=1}^{N}$ being the columns of matrix $\mathbf{X}$. Let $\mathbf{u} = [1-\mu \quad \mu]^T$. Then (20) can be written as

$$\mathbf{Y} = \beta\mathbf{u}^T\mathbf{X} + \mathbf{E}, \quad (21)$$

where

$$\mathbf{X} = \begin{bmatrix} \mathbf{J}_{+1}^{(p_1)}\mathbf{c}_1 & \mathbf{J}_{+1}^{(p_1+1)}\mathbf{c}_1 \\ \mathbf{J}_{-1}^{(p_1)}\mathbf{c}_1 & \mathbf{J}_{-1}^{(p_1+1)}\mathbf{c}_1 \end{bmatrix}^T (\mathbf{Z}_1 \otimes \mathbf{I}_N). \quad (22)$$

Note that for a given p_1, $\mathbf{X}$ is completely known. Let $\mathbf{y}_i$, $\mathbf{x}_i$, and $\mathbf{e}_i$ denote the ith columns of $\mathbf{Y}$, $\mathbf{X}$, and $\mathbf{E}$, respectively. Then

$$\mathbf{y}_i = \left(\beta\mathbf{u}^T\right)\mathbf{x}_i + \mathbf{e}_i, \quad i = 1, 2, \cdots, (NM), \quad (23)$$

where $\{\mathbf{x}_i\}_{i=1}^{NM}$ are known for a given p_1. Due to the central limit theorem, we assume that $\mathbf{e}_i$ is independent of the desired signal and is a circularly symmetric complex Gaussian random vector with zero-mean and arbitrary covariance matrix $\mathbf{Q}_s$ that satisfies

$$\mathrm{E}\left\{\mathbf{e}_i\mathbf{e}_j^H\right\} = \mathbf{Q}_s\delta_{i,j}, \quad (24)$$

where the unknown covariance matrix $\mathbf{Q}_s$ models both thermal noise and all other interference signals including MAI. It follows that the log-likelihood function is proportional to:

$$C = -\ln|\mathbf{Q}_s| - \mathrm{tr}\left\{\mathbf{Q}_s^{-1}\frac{1}{NM}\sum_{i=1}^{NM}[\mathbf{y}_i - \mathbf{C}\mathbf{x}_i][\mathbf{y}_i - \mathbf{C}\mathbf{x}_i]^H\right\}, \tag{25}$$

Minimizing (25) with respect to $\mathbf{Q}_s$ yields the ML estimate $\hat{\mathbf{Q}}_s$ of $\mathbf{Q}_s$

$$\hat{\mathbf{Q}}_s = \frac{1}{NM}\sum_{i=1}^{NM}[\mathbf{y}_i - \mathbf{C}\mathbf{x}_i][\mathbf{y}_i - \mathbf{C}\mathbf{x}_i]^H. \tag{26}$$

Inserting $\hat{\mathbf{Q}}_s$ in (26) into (25), we note that the estimate $\hat{\mathbf{C}}$ of $\mathbf{C}$ is determined by minimizing the following cost function

$$C_1 = \left|\frac{1}{NM}\sum_{i=1}^{NM}[\mathbf{y}_i - \mathbf{C}\mathbf{x}_i][\mathbf{y}_i - \mathbf{C}\mathbf{x}_i]^H\right|. \tag{27}$$

Let

$$\hat{\mathbf{R}}_{xx} = \frac{1}{NM}\sum_{i=1}^{NM}\mathbf{x}_i\mathbf{x}_i^H, \tag{28}$$

$$\hat{\mathbf{R}}_{xy} = \frac{1}{NM}\sum_{i=1}^{NM}\mathbf{x}_i\mathbf{y}_i^H, \tag{29}$$

$$\hat{\mathbf{R}}_{yy} = \frac{1}{NM}\sum_{i=1}^{NM}\mathbf{y}_i\mathbf{y}_i^H. \tag{30}$$

The matrix in the right-hand side of (27) can be described as

$$\begin{aligned}\mathbf{F} &\triangleq \frac{1}{NM}\sum_{i=1}^{NM}[\mathbf{y}_i - \mathbf{C}\mathbf{x}_i][\mathbf{y}_i - \mathbf{C}\mathbf{x}_i]^H && (31)\\ &= \left[\mathbf{C} - \hat{\mathbf{R}}_{xy}^H\hat{\mathbf{R}}_{xx}^{-1}\right]\hat{\mathbf{R}}_{xx}\left[\mathbf{C} - \hat{\mathbf{R}}_{xy}^H\hat{\mathbf{R}}_{xx}^{-1}\right]^H \\ &\quad + \hat{\mathbf{R}}_{yy} - \hat{\mathbf{R}}_{xy}^H\hat{\mathbf{R}}_{xx}^{-1}\hat{\mathbf{R}}_{xy}. && (32)\end{aligned}$$

Hence, the unstructured ML estimate of $\mathbf{C}$, which does not use the structure of $\mathbf{C}$, is given by

$$\hat{\mathbf{C}} = \hat{\mathbf{R}}_{xy}^H\hat{\mathbf{R}}_{xx}^{-1}. \tag{33}$$

Using the $\hat{\mathbf{C}}$ in (33), we obtain the unstructured estimate $\hat{\mathbf{Q}}_s$ of $\mathbf{Q}_s$:

$$\hat{\mathbf{Q}}_s = \hat{\mathbf{R}}_{yy} - \hat{\mathbf{R}}_{xy}^H\hat{\mathbf{R}}_{xx}^{-1}\hat{\mathbf{R}}_{xy}. \tag{34}$$

Consider now the structure of $\mathbf{C}$. The C_1 in (27) can be rewritten as

$$\begin{aligned}C_1 &= \left|(\mathbf{C} - \hat{\mathbf{C}})\hat{\mathbf{R}}_{xx}(\mathbf{C} - \hat{\mathbf{C}})^H + \hat{\mathbf{Q}}_s\right| \\ &= \left|\hat{\mathbf{Q}}_s\right|\left|\mathbf{I}_N + \hat{\mathbf{Q}}_s^{-1}(\mathbf{C} - \hat{\mathbf{C}})\hat{\mathbf{R}}_{xx}(\mathbf{C} - \hat{\mathbf{C}})^H\right|. && (35)\end{aligned}$$

Minimizing C_1 in (35) with respect to the unknown parameters in $\mathbf{C}$ requires a multidimensional search over the parameter space, which is computationally prohibitive. Hence, instead of determining the exact ML estimates of the unknown parameters, we determine the large sample approximate ML estimates as follows. By neglecting the second- and higher-order terms in the Taylor expansion of the gradient of $\ln(C_1)$ with respect to the unknowns, we can show that minimizing $\ln(C_1)$ is asymptotically (for large NM) equivalent to minimizing [5]

$$C_2 = \mathrm{tr}\left[\hat{\mathbf{R}}_{xx}(\beta\mathbf{u}^T - \hat{\mathbf{C}})^H\hat{\mathbf{Q}}_s^{-1}(\beta\mathbf{u}^T - \hat{\mathbf{C}})\right]. \tag{36}$$

Note that the number of known samples here is NM, which is easily much larger than L for a moderate M when L is about the same as N.

Let

$$\bar{\mathbf{u}} = \hat{\mathbf{R}}_{xx}^{\frac{1}{2}}\mathbf{u} \triangleq [\ \bar{\mu}_1 \quad \bar{\mu}_2\ ]^T, \tag{37}$$

and

$$\hat{\bar{\mathbf{C}}} = \hat{\mathbf{C}}\hat{\mathbf{R}}_{xx}^{\frac{1}{2}} \triangleq [\ \hat{\bar{\mathbf{c}}}_1 \quad \hat{\bar{\mathbf{c}}}_2\ ]. \tag{38}$$

Then (36) can be written as

$$\begin{aligned}C_2 &= \left(\beta - \hat{\bar{\mathbf{C}}}\bar{\mathbf{u}}/\|\bar{\mathbf{u}}\|^2\right)^H\|\bar{\mathbf{u}}\|^2\,\hat{\mathbf{Q}}_s^{-1}\left(\beta - \hat{\bar{\mathbf{C}}}\bar{\mathbf{u}}/\|\bar{\mathbf{u}}\|^2\right) \\ &\quad - \left(\hat{\bar{\mathbf{C}}}\bar{\mathbf{u}}\right)^H\hat{\mathbf{Q}}_s^{-1}\left(\hat{\bar{\mathbf{C}}}\bar{\mathbf{u}}\right)/\|\bar{\mathbf{u}}\|^2 + \text{constant}, && (39)\end{aligned}$$

where $(\cdot)^*$ denotes the complex conjugate. The minimization of C_2 is achieved when

$$\hat{\beta} = \frac{\hat{\bar{\mathbf{C}}}\bar{\mathbf{u}}}{\|\bar{\mathbf{u}}\|^2} = \frac{\hat{\mathbf{C}}\hat{\mathbf{R}}_{xx}\mathbf{u}}{\mathbf{u}^T\hat{\mathbf{R}}_{xx}\mathbf{u}}, \tag{40}$$

and

$$\hat{\mu} = \arg\max_{\mu}\left\{\frac{\mathbf{u}^T\hat{\mathbf{R}}_{xx}\hat{\mathbf{C}}^H\hat{\mathbf{Q}}_s^{-1}\hat{\mathbf{C}}\hat{\mathbf{R}}_{xx}\mathbf{u}}{\mathbf{u}^T\hat{\mathbf{R}}_{xx}\mathbf{u}}\right\}, \tag{41}$$

which is obtained by rooting a second order polynomial.

4. CRB OF THE PARAMETER ESTIMATES

Let

$$\eta = [\ \mu \quad \mathrm{Re}^T(\beta) \quad \mathrm{Im}^T(\beta)\ ]^T, \tag{42}$$

where $\mathrm{Re}(\mathbf{X})$ and $\mathrm{Im}(\mathbf{X})$, respectively, denote the real and imaginary part of $\mathbf{X}$. The CRBs for the parameter estimates of η can be written as

$$\mathrm{CRB}(\eta) = \left(2\mathrm{Re}\left\{\begin{bmatrix} F_{\mu\mu} & \mathbf{F}_{\mu\beta} & j\mathbf{F}_{\mu\beta} \\ \mathbf{F}_{\mu\beta}^H & \mathbf{F}_{\beta\beta} & j\mathbf{F}_{\beta\beta} \\ -j\mathbf{F}_{\mu\beta}^H & -j\mathbf{F}_{\beta\beta} & \mathbf{F}_{\beta\beta}\end{bmatrix}\right\}\right)^{-1}, \tag{43}$$

where

$$F_{\mu\mu} = \left\{\sum_{i=1}^{NM}\mathbf{x}_i^H\begin{bmatrix}1 & -1 \\ -1 & 1\end{bmatrix}\mathbf{x}_i\right\}\beta^H\mathbf{Q}_s^{-1}\beta, \tag{44}$$

$$\begin{aligned}\mathbf{F}_{\mu\beta} &= \left\{\sum_{i=1}^{NM}\mathbf{x}_i^H\begin{bmatrix}-\mu^T \\ \mu^T\end{bmatrix}\mathbf{x}_i\right\} \\ &\quad [\ \beta^H\mathbf{Q}_s^{-1}\mathbf{i}_1 \quad \cdots \quad \beta^H\mathbf{Q}_s^{-1}\mathbf{i}_L\ ], && (45)\end{aligned}$$

and

$$\mathbf{F}_{\beta\beta} = \left\{\sum_{i=1}^{NM}\mathbf{x}_i^H\mu\mu^T\mathbf{x}_i\right\}\mathbf{Q}_s^{-1}. \tag{46}$$

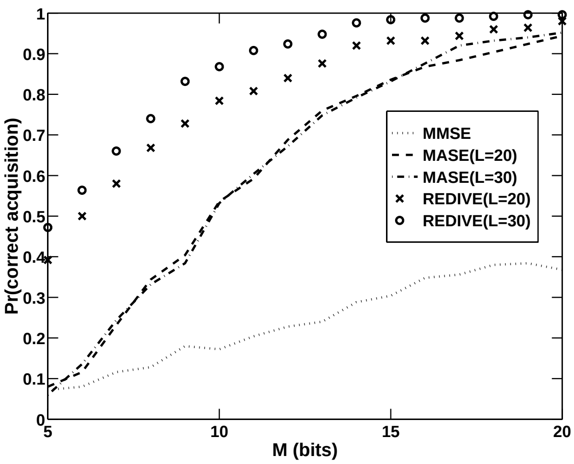

Figure 1. Probability of correct acquisition as a function of M for $K = 20$ users, $N = 31$ chips/bit, $E_b/N_0 = 10$dB, and log-normally distributed interfering powers with a mean 10 dB above the desired signal and a standard deviation of 10 dB.

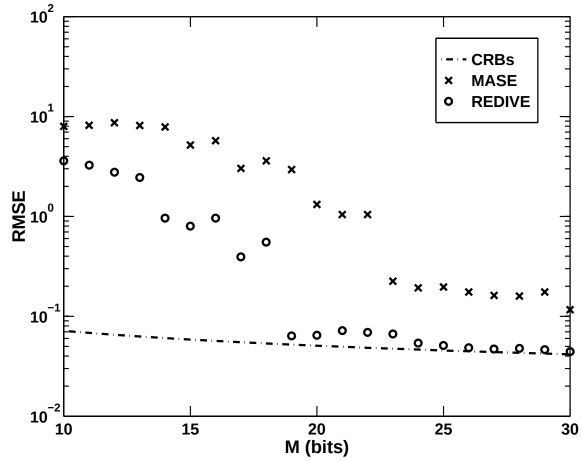

Figure 2. Comparison of RMSEs obtained by MASE and REDIVE with those of the CRBs as a function of M, when $N = 31$ chips/bit, $K = 20$ users, $L = 30$ antenna sensors, $E_b/N_0 = 10$dB, and log-normally distributed interfering powers with a mean 10 dB above the desired signal and a standard deviation of 10 dB.

5. NUMERICAL EXAMPLES

It has been shown in [2] that among the correlator [6], MMSE [7], MUSIC [8], and LSML [2], the performance of the correlator is the worst. Of the other three approaches, the MMSE estimator is the best when M is smaller than N, while when M is larger than N, LSML is the best. Since we study the situation where M is small in this paper, we only compare our estimator with MMSE.

Figure 1 shows the code acquisition probability for MASE and REDIVE with different L along with the MMSE estimator. It is seen that MMSE performs poorly. It is also seen that REDIVE is significantly better than MASE. Yet the average numbers of MATLAB flops required by REDIVE with $L = 20$ and 30, respectively, are about 0.8 and 1.5 times as much as those required by MASE.

In Figure 2, the performance of the REDIVE algorithm is compared with the MASE algorithm and the CRB as a function of M. It is seen that as M increases, the performance of the REDIVE algorithm approaches the CRB. The RMSE (root mean-squared error) of REDIVE is much smaller than that of MASE.

6. CONCLUSIONS

We have proposed a code-timing estimator for receiver diversity DS-CDMA systems. The systems are considered working in a flat fading and near-far environment. The algorithm has been derived by modeling the known training sequence as the desired signal and all other signals including the multiuser interfering signals and the additive noise as unknown colored Gaussian noise so that the knowledge of the number of active users is not required. We have shown that by utilizing the information collected via multiple antenna sensors, the length of training sequences can be greatly reduced. The algorithm is an asymptotic maximum likelihood estimator. As a result, the mean-squared error of the code-timing estimates obtained by the algorithm approaches the Cramér-Rao lower bound as the length of the training sequence increases. Moreover, the algorithm does not require the search over a parameter space and the code-timing is obtained by rooting a second-order polynomial, which is computationally very efficient. Simulation results have shown that the algorithm is quite robust against the near-far problem and requires a much shorter training sequence than the existing estimators.

REFERENCES

[1] U. Madhow and M. Pursley, "Acquisition based capacity of direct-sequence spread-spectrum communication networks," *Proceedings of the Conference of Information Science and Systems*, pp. 1186–1189, March 1991.

[2] D. Zheng, J. Li, S. L. Miller, and E. G. Ström, "An efficient code-timing estimator for DS-CDMA signals," *IEEE Transactions on Signal Processing*, vol. 45, pp. 82–89, January 1997.

[3] Z.-S. Liu, J. Li, and S. L. Miller, "An efficient code-timing estimator for receiver diversity ds-cdma systems," submitted to *IEEE Transactions on Communications*, 1997.

[4] G. W. Wornell and M. D. Trott, "Efficient signal processing techniques for exploiting transmit antenna diversity of fading channels," *IEEE Transactions on Signal Processing*, vol. 45, pp. 191–205, January 1997.

[5] J. Li, B. Halder, P. Stoica, and M. Viberg, "Computationally efficient angle estimation for signals with known waveforms," *IEEE Transactions on Signal Processing*, vol. 43, pp. 2154–2163, September 1995.

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

[7] R. F. Smith and S. L. Miller, "Code timing estimation in a near-far environment for direct-sequence code-division multiple-access," *Proceedings of 1994 IEEE Military Communications Conference*, pp. 47–51, 1994.

[8] 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 Transactions on Communications*, vol. 44, pp. 84–93, January 1996.