

# Blind Linear MMSE Receivers for MC-CDMA Systems

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**Abstract**—This paper studies blind constrained minimum output energy (CMOE)-based and subspace-based linear minimum mean-squared-error (LMMSE) detectors for multi-carrier code division multiple access (MC-CDMA) systems. By imposing quadratic weight constraint, the CMOE detector is made more robust against signature waveform mismatch, and a better performance over the standard CMOE detector is obtained. Because of separation of signal and noise subspaces, the more complicated subspace-based LMMSE detector has better performance than the CMOE detector. The recursive subspace tracking algorithms are also investigated for the subspace-based MMSE receiver. Numerical results show that the steady-state performance of the robust CMOE detector is close to the subspace-based MMSE method. The blind mode decision-directed LMMSE detection is studied where the blind detectors are used for initial adaptation. Numerical simulations illustrate that the blind mode decision-directed MMSE detection substantially improves the system performance when the frequency-selective channel is slowly-varying.

**Index Terms**—Adaptive signal processing, channel estimation, multiuser detection, wireless communications.

## I. INTRODUCTION

MC-CDMA has recently been proposed as an efficient multicarrier transmission scheme for supporting multiple access communications [1], which combines CDMA and orthogonal frequency division multiplexing (OFDM) techniques. It has received considerable attention because of its advantages in frequency diversity, multipath fading resilience, etc. [2]–[5]. Similar to conventional CDMA systems, MC-CDMA is an interference-limited system. It is rather sensitive to multiple-access interference (MAI), which arises from the sharing of the same frequency band by the users simultaneously. LMMSE multiuser detectors [6]–[8] have been proposed as effective and relatively simple techniques to mitigate MAI in CDMA systems. A typical operation of the LMMSE detector uses decision-directed mode, where a training sequence is sent for initial adaptation. However, the training mode decision-directed detector reduces the data rate and channel efficiency. Blind MMSE receivers with the performance equal or close to that of the exact Wiener solution are hence highly desirable. The subspace-based MMSE detector [9], [10] is one effective blind algorithm exploiting subspace structures of the observation. The subspace-based method has high computational

complexity due to estimation of the signal and noise subspaces. In [11], Honig *et al.* proposed a simpler blind LMMSE receiver, called the CMOE detector, for MAI suppression in CDMA systems. Under ideal conditions, the CMOE detector maximizes the signal-to-interference-plus-noise ratio (SINR), and achieves performance close to that of the optimal LMMSE receiver [12].

Due to the advantages mentioned earlier for MC-CDMA systems, the extension of these blind LMMSE receivers to the MC-CDMA context is of great interest. We first formulate a CMOE-based blind detector and channel estimator for MC-CDMA systems. It is based on the recursive least squares (RLS) updating of the correlation matrix, and the channel can be estimated blindly by solving the minimum eigenvector of a data sub-matrix. It is found that the performance of the CMOE detector will degrade considerably in presence of channel and data correlation matrix estimation errors. This has been observed in adaptive beamforming [13]–[15] and direct sequence (DS)-CDMA multiuser detection [16]. A robust CMOE detector with quadratic constraint is then proposed, where quadratic constraint on the weight vector of the detector is imposed. This technique is a simple and effective method for improving the robustness of the detector with respect to signal modeling errors. In order to reduce the complexity in computing the minimum eigenvector associated with the channel information, the inverse iteration method [17] is employed to recursively estimate the minimum eigenvector.

Adaptive robust CMOE detectors with quadratic constraint have been developed in DS-CDMA either in the direct form or with the partitioned linear interference cancellation (PLIC) structure [16]. The blocking matrix in DS-CDMA is constant and can be computed off line. However, in MC-CDMA systems, the effective signature waveform is the multiplication (element wise) of the spreading code and the channel coefficients. The blocking matrix in MC-CDMA is time variant and should be updated for each time interval in time-varying wireless channels. The PLIC in MC-CDMA thus has high computational complexity due to the real-time updating of the blocking matrix. Moreover, the direct form of the robust CMOE detector in [16] cannot be applied to MC-CDMA for its assumption that the blocking matrix is constant. In this paper, an adaptive algorithm of the robust CMOE detector for MC-CDMA is presented. By imposing quadratic weight constraint, the robust CMOE detector outperforms the standard CMOE detector.

In the case of white Gaussian noise, the subspace-based MMSE detector performs better than the standard CMOE receiver. Recently, there has been a lot of research on the subspace-based blind receivers for MC-CDMA. A subspace-based

Manuscript received November 10, 2004; revised May 10, 2005, October 17, 2005, and May 25, 2006. This paper was recommended by Associate Editor M. Chakraborty.

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Digital Object Identifier 10.1109/TCSI.2006.887595

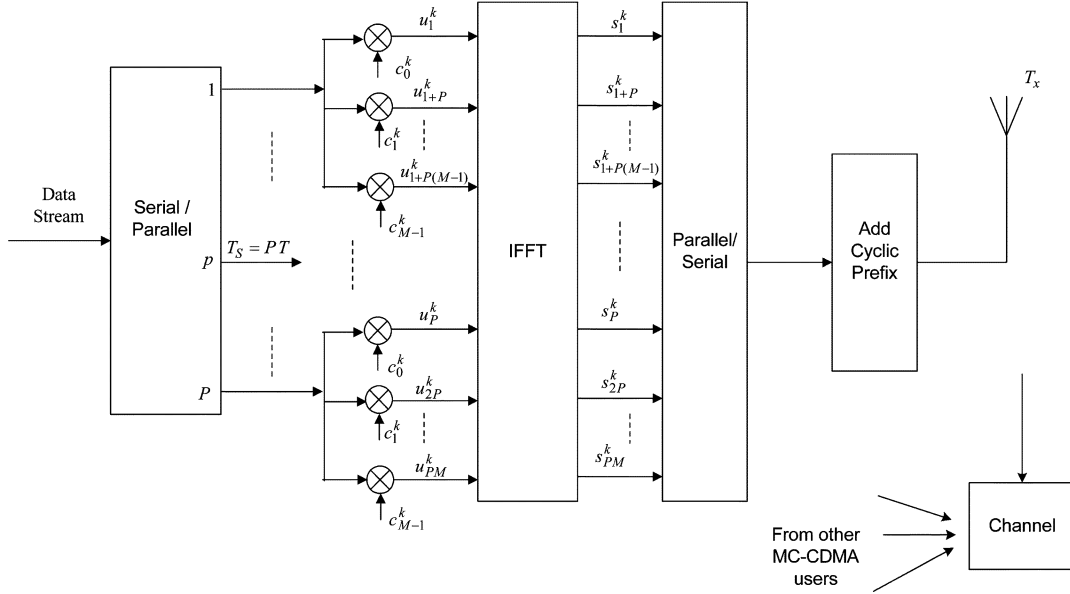


Fig. 1. Block diagram of a MC-CDMA transmitter.

MMSE detector for quasi-synchronous MC-CDMA systems was proposed in [18] without exact knowledge of the channel order. In [19], a subspace-based MMSE detector was proposed for MC-CDMA without cyclic prefix. The subspace-based blind detector was extended to coded MC-CDMA systems [20], [21]. In this paper, we paid special attention to the adaptive subspace-based MMSE receivers using efficient subspace tracking algorithms. In particular, the projection approximation subspace tracking with deflation (PASTd) [22] and the bi-iteration square-root singular value decomposition (Bi-SVD) [23] algorithms are used for signal subspace tracking; while the square-root QR inverse iteration method [24] is adopted for noise subspace tracking. The steady-state performances of the subspace-based MMSE detector and the robust CMOE detector are found to be similar.

By steady-state SINR analysis, the adaptive training LMMSE detector performs much better than the adaptive blind MMSE detectors. Therefore, the blind mode decision-directed LMMSE detector is proposed, where the blind methods are used for initial adaptation. Numerical simulations show that the blind mode decision-directed LMMSE receivers using the robust CMOE and subspace-based detectors present similar MSE performance at medium signal-to-noise ratio (SNR).

The rest of the paper is organized as follows. Section II briefly describes the principle of MC-CDMA systems and the system model under consideration. Section III is devoted to the blind CMOE, robust CMOE and subspace-based LMMSE receivers. The theoretical steady-state SINR analysis of the adaptive blind CMOE and the adaptive training LMMSE detection is derived in Section IV. Section V presents numerical examples, and conclusion is drawn in Section VI.

*Notation:* Vectors/matrices are denoted by lowercase/uppercase boldfaces; superscripts  $(\cdot)^*$ ,  $(\cdot)^T$  and  $(\cdot)^H$  denote the complex conjugate, transpose, and conjugate transpose, respectively;  $E\{\cdot\}$  denotes the statistical expectation;  $\text{tr}\{\cdot\}$  denotes the trace of a matrix.

## II. SYSTEM MODEL

Consider a  $K$ -user synchronous MC-CDMA system for up-link transmission from the terminal users to the base station. Fig. 1 shows the diagram of an MC-CDMA transmitter. The original data stream of the  $k$ th user is first converted into  $P$  parallel data sequences  $\mathbf{b}_k(i) = [b_{k,0}(i), b_{k,1}(i), \dots, b_{k,P-1}(i)]$  at the  $i$ th time. Let  $T$  and  $T_s$  be the symbol duration before and after the serial/parallel (S/P) conversion, respectively. It has  $T_s = PT$ . When the symbol duration  $T_s$  at the subcarrier is large relative to the channel's multipath delay spread, each subcarrier approximately experiences flat fading. Each S/P converted output spreads with the user's spreading code  $\mathbf{c}_k = [c_{k,0}, \dots, c_{k,M-1}]^T$ ,  $k = 0, \dots, K-1$ . The data chips after spreading are S/P converted into  $M$  subcarriers. The frequency separation between the successive subcarriers is  $\Delta f = 1/T_s$ . To achieve the maximum frequency diversity, the data bit  $b_{k,p}$  are transmitted on subcarriers with frequencies  $f_1 + (p+mP) \cdot \Delta f$ ,  $m = 0, \dots, M-1$ . The resulting chips,  $N = PM$  in total, is  $\mathbf{u}_k(i) = [b_{k,0}(i)c_{k,0}, \dots, b_{k,P-1}(i)c_{k,0}, \dots, b_{k,0}(i)c_{k,M-1}, \dots, b_{k,P-1}(i)c_{k,M-1}]^T$ . The  $N \times 1$  data vector  $\mathbf{u}_k(i)$  is then modulated by an inverse fast Fourier transform (IFFT). The data samples after IFFT modulation of user  $k$  at the  $i$ th time is given as

$$\mathbf{s}_k(i) = \mathbf{F}_1 \mathbf{u}_k(i) \quad (1)$$

where  $\mathbf{F}_1 \in \mathbb{C}^{N \times N}$  is the Fourier matrix performing the IDFT, whose  $(u, v)$ th element is  $\exp(j2\pi uv/N)/N$ .

The user signal propagates through a frequency-selective channel with  $L$  received paths. The channel is represented by a  $(L-1)$ th-order finite-impulse response (FIR) filter [21]

$$h_k(t) = \sum_{l=0}^{L-1} g_{k,l}(t) \delta(t - \tau_{k,l}) \quad (2)$$

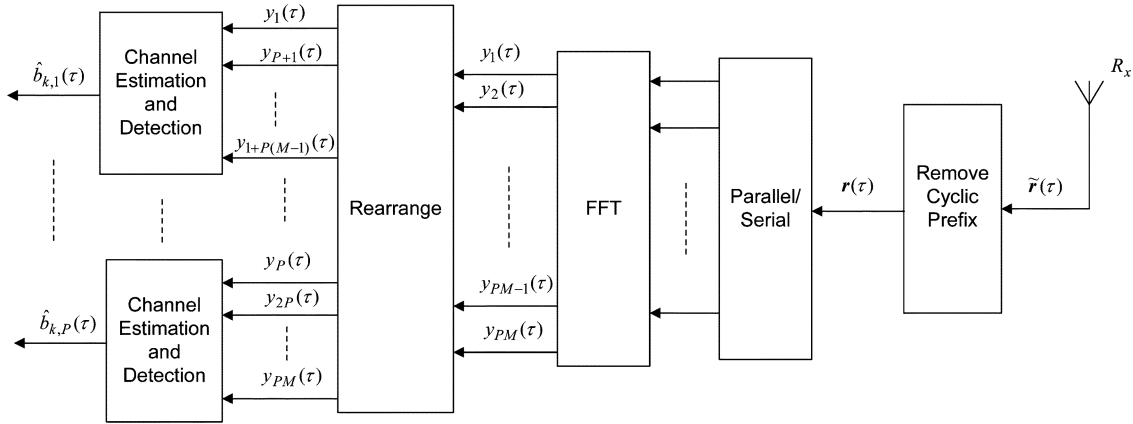


Fig. 2. Block diagram of a MC-CDMA receiver.

where  $k$  is the user index,  $g_{k,l}(t)$  is the  $l$ th path gain which is independent zero mean, complex Gaussian random process with variance  $\sigma_{k,l}^2$ , and  $\tau_{k,l}$  is the propagation delay for the  $l$ th path, respectively. The ensemble  $\sigma_{k,l}^2$  ( $l = 0, \dots, L-1$ ) is the power delay profile.

To combat intersymbol interference (ISI) caused by multipath fading, a cyclic prefix (CP) of  $N_g$  samples is added to an MC-CDMA symbol. When  $N_g \geq L-1$ , the effect of ISI can be eliminated. Fig. 2 illustrates a configuration of an MC-CDMA receiver. Assume the communication channel remains constant during one MC-CDMA symbol. At the receiver, the signal is sampled at a rate  $(N + N_g)/T_s$ . The baseband received signal at the  $\tau$ th sample is hence given by

$$\hat{\mathbf{r}}(\tau) = \sum_{k=0}^{K-1} \sum_{l=0}^{L-1} \sqrt{P_k} g_{k,l}(\tau) \hat{\mathbf{s}}_k(\tau - l) + \hat{\boldsymbol{\eta}}(\tau) \quad (3)$$

where  $g_{k,l}(\tau)$  accounts for the complex envelop at the  $l$ th path,  $\hat{\mathbf{s}}_k(\tau) \in \mathbf{C}^{N_{\text{tot}} \times 1}$  ( $N_{\text{tot}} = N + N_g$ ) is the transmitted signal vector,  $P_k$  is the chip energy of the  $k$ th user, respectively, and  $\hat{\boldsymbol{\eta}}(\tau)$  denotes additive white Gaussian noise vector with zero mean and variance  $\sigma_v^2$ .

Assume that time and frequency synchronization has been achieved at the receiver, and ISI does not occur under the condition  $N_g \geq L-1$ . The samples corresponding to the CP are then discarded. The synchronized  $\tau$ th MC-CDMA symbol after removal of the cyclic prefix is then given as

$$\mathbf{r}(\tau) = \sum_{k=0}^{K-1} \sqrt{P_k} \mathbf{G}_k(\tau) \mathbf{s}_k(\tau) + \boldsymbol{\eta}(\tau) \quad (4)$$

where  $\mathbf{s}_k(\tau) = [\hat{\mathbf{s}}_k(\tau N_{\text{tot}} + N_g), \dots, \hat{\mathbf{s}}_k(\tau N_{\text{tot}} + N_{\text{tot}} - 1)]^T$ ,  $\boldsymbol{\eta}(\tau) = [\hat{\boldsymbol{\eta}}(\tau N_{\text{tot}} + N_g), \dots, \hat{\boldsymbol{\eta}}(\tau N_{\text{tot}} + N_{\text{tot}} - 1)]^T$ , and  $\mathbf{G}_k$  is a Toeplitz matrix with the form

$$\mathbf{G}_k = \begin{bmatrix} g_{k,0} & 0 & 0 & \cdots & g_{k,1} \\ g_{k,1} & g_{k,0} & 0 & \cdots & g_{k,2} \\ g_{k,2} & g_{k,1} & g_{k,0} & \cdots & g_{k,3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & g_{k,0} \end{bmatrix}.$$

Finally, a fast Fourier transform (FFT) of size  $N$  is performed at the receiver. Let  $\mathbf{F} \in \mathbf{C}^{N \times N}$  be the Fourier matrix, the  $(u, v)$ th element of which is  $\exp(-j2\pi uv/N)$ . The baseband MC-CDMA signal in the frequency-domain can then be obtained in matrix notation as

$$\begin{aligned} \mathbf{y}(\tau) &= \mathbf{F} \mathbf{r}(\tau) \\ &= \mathbf{F} \left[ \sum_{k=0}^{K-1} \sqrt{P_k} \mathbf{G}_k(\tau) \mathbf{s}_k(\tau) + \boldsymbol{\eta}(\tau) \right] \\ &= \sum_{k=0}^{K-1} \sqrt{P_k} \mathbf{H}_k(\tau) \mathbf{u}_k(\tau) + \mathbf{n}(\tau) \end{aligned} \quad (5)$$

where  $\mathbf{H}_k(\tau) = \text{diag}\{h_{k,0}(\tau), \dots, h_{k,N-1}(\tau)\}$  represents the channel matrix, whose diagonal elements are the channel frequency response of the user  $k$ , given by  $h_{k,n}(\tau) = \sum_{l=0}^{L-1} g_{k,l}(\tau) \exp(-j2\pi(nl)/N)$ ,  $n = 0, \dots, N-1$ , and  $\mathbf{n}(\tau)$  is the complex white Gaussian with zero mean and variance  $\sigma_n^2$ .

Without loss of generality, the  $p$ th data stream transmitted by each user is considered. The  $M \times 1$  data vector  $\mathbf{y}_p(\tau) = [y_p(\tau), y_{P+p}(\tau), \dots, y_{P(M-1)+p}(\tau)]^T$  corresponding to the symbol  $b_{k,p}$  is then represented as

$$\begin{aligned} \mathbf{y}_p(\tau) &= \sum_{k=0}^{K-1} \sqrt{P_k} \mathbf{C}_k \mathbf{h}_{k,p}(\tau) b_{k,p}(\tau) + \mathbf{n}_p(\tau) \\ &= \sum_{k=0}^{K-1} \sqrt{P_k} \mathbf{d}_{k,p}(\tau) b_{k,p}(\tau) + \mathbf{n}_p(\tau) \end{aligned} \quad (6)$$

where  $\mathbf{h}_{k,p}(\tau) = [h_{k,p}(\tau), h_{k,P+p}(\tau), \dots, h_{k,P(M-1)+p}(\tau)]^T$  is the channel coefficients at the  $(Pm + p)$ th subcarriers,  $\mathbf{C}_k = \text{diag}\{c_{k,0}, c_{k,1}, \dots, c_{k,M-1}\}$  denotes the code matrix,  $\mathbf{d}_{k,p}(\tau) = \mathbf{C}_k \mathbf{h}_{k,p}(\tau)$  represents the effective signature of the  $k$ th user, respectively, and  $\mathbf{n}_p(\tau)$  is the complex white Gaussian noise with zero mean and variance  $\sigma_n^2$ .

### III. BLIND LINEAR MMSE DETECTION

In this section, the blind CMOE, robust CMOE, and subspace-based LMMSE detectors will be formulated for MC-CDMA systems, respectively.

### A. CMOE Detection and Channel Estimation

The basic idea of the CMOE detector is to minimize the overall variance of the receiver output, while preserving the desired signals with unit-gain. For convenience, the subscript  $p$  will be dropped from the signal model in (6). Assume the zeroth user is the desired user. The CMOE detector can be formulated by a constrained optimization problem as [12]

$$\min_{\mathbf{w}} \sum_{i=1}^n \lambda^{n-i} |\mathbf{w}^H(n) \mathbf{y}(i)|^2, \quad \text{s.t. } \mathbf{w}^H(n) \mathbf{d}_0(n) = 1 \quad (7)$$

where  $0 < \lambda < 1$  is the forgetting factor,  $\mathbf{w}(n)$  is the weight vector at the  $n$ th time, and  $\mathbf{d}_0(n) = \mathbf{C}_0 \mathbf{h}_0(n)$  is the effective signature waveform of the desired user.

The solution to the constrained optimization problem in (7) is given by [11]

$$\mathbf{w}_o = (\mathbf{d}_0^H(n) \mathbf{R}_y^{-1}(n) \mathbf{d}_0(n))^{-1} \mathbf{R}_y^{-1}(n) \mathbf{d}_0(n) \quad (8)$$

where  $\mathbf{R}_y(n)$  is the covariance matrix obtained as

$$\mathbf{R}_y(n) = \lambda \mathbf{R}_y(n-1) + \mathbf{y}(n) \mathbf{y}^H(n).$$

Using (8), the minimum output variance of the detector can be given as [12]

$$P_{\min} = \mathbf{w}_o^H \mathbf{R}_y(n) \mathbf{w}_o = (\mathbf{d}_0^H(n) \mathbf{R}_y^{-1}(n) \mathbf{d}_0(n))^{-1}. \quad (9)$$

To estimate the effective signature waveform  $\mathbf{d}_0(n)$ , we can maximize (9) with respect to  $\mathbf{d}_0(n)$  such that the signal components at the receiver output are maximized after interference suppression. Maximization of (9) is equivalent to minimization of its reciprocal

$$\hat{\mathbf{d}}_0(n) = \arg \min_{\mathbf{d}_0(n)} \mathbf{d}_0^H(n) \mathbf{R}_y^{-1}(n) \mathbf{d}_0(n). \quad (10)$$

Let  $\mathbf{g}_0(n)$  denote the channel impulse response of the zeroth user with  $L$  paths. It has  $\mathbf{h}_0(n) = \mathbf{F}_m \mathbf{g}_0(n)$ , where  $\mathbf{F}_m$  is an  $M \times L$  matrix with entries,  $[\mathbf{F}_m]_{m,l} = \exp(-j2\pi((Pm+p)l)/(M))$ ,  $m = 0, \dots, M-1$ ,  $l = 0, \dots, L-1$ . Hence, minimizing (10) with respect to  $\mathbf{g}_0(n)$  yields

$$\hat{\mathbf{g}}_0(n) = \arg \min_{\mathbf{g}_0(n) \in \mathcal{C}^{L \times 1}} \mathbf{g}_0^H(n) \underbrace{[\mathbf{F}_m^H \mathbf{C}_0^H \mathbf{R}_y^{-1}(n) \mathbf{C}_0 \mathbf{F}_m]}_{\mathbf{\Omega}} \mathbf{g}_0(n). \quad (11)$$

The channel estimate  $\hat{\mathbf{g}}_0(n)$  is the eigenvector associated with the smallest eigenvalue of  $\mathbf{\Omega} \in \mathcal{C}^{L \times L}$ .

Conventional methods, such as SVD or eigenvalue decomposition (ED), are computationally expensive to keep track of the desired eigenvector of  $\mathbf{\Omega}$ . To further simplify the algorithm, iterative techniques, such as conjugate gradient, inverse iteration, and steepest decent can be developed to seek for the desired eigenvector. The steepest decent method is computationally simplest. However, it is very sensitive to the step size. In

the paper, the inverse iteration algorithm is used because of its reasonable complexity and good tracking performance [17]. The inverse iteration method for computing the minimum eigenvector of the matrix  $\mathbf{\Omega}$ , is given as

$$\begin{aligned} &\text{Initialization: } \hat{\mathbf{g}}(0); \\ &\mathbf{\Omega}(n) \mathbf{a}(n) = \hat{\mathbf{g}}(n-1): \text{LU decomposition to get } \mathbf{a}(n); \\ &\hat{\mathbf{g}}(n) = \mathbf{a}(n) / \|\mathbf{a}^H(n) \mathbf{a}(n)\|^{1/2}: \text{normalization.} \end{aligned} \quad (12)$$

### B. Robust CMOE Detector

In practical applications, the optimal solution given in (8) is rarely achieved. First, the estimated effective signature waveform  $\tilde{\mathbf{d}}_0(n)$  generally contains errors, i.e.,  $\tilde{\mathbf{d}}_0(n) \neq \mathbf{d}_0(n)$ . Secondly, the estimated covariance matrix  $\tilde{\mathbf{R}}_y(n)$  is obtained from a finite number of the observed data. Thus, the adaptive weight vector in practical applications is

$$\mathbf{w} = (\tilde{\mathbf{d}}_0^H(n) \tilde{\mathbf{R}}_y^{-1}(n) \tilde{\mathbf{d}}_0(n))^{-1} \tilde{\mathbf{R}}_y^{-1}(n) \tilde{\mathbf{d}}_0(n). \quad (13)$$

As a result, the performance of the CMOE detector will degrade greatly due to these two adverse factors. Robust CMOE detectors are thus desirable to overcome signal modeling errors. One simple and efficient method is to impose quadratic constraints on the norm of the weight vector  $\mathbf{w}$

$$\mathbf{w}^H \mathbf{w} \leq T_0. \quad (14)$$

The basic idea is to avoid  $\|\mathbf{w}\|$  from being too large so that the desired signal is severely attenuated due to model errors. This method has the same effect to add diagonal loading of the data covariance matrix  $\mathbf{R}_y$  [13]

$$\mathbf{w} = [\mathbf{d}_0^H (\mathbf{R}_y + \beta \mathbf{I}_{M \times M})^{-1} \mathbf{d}_0]^{-1} (\mathbf{R}_y + \beta \mathbf{I}_{M \times M})^{-1} \mathbf{d}_0. \quad (15)$$

There is no closed-form expression for the optimal loading level  $\beta$  [16]. Inspired by the approach presented in [14], we propose an adaptive algorithm to compute the diagonal loading  $\beta$  given a quadratic constraint  $T_0$ . To ensure that the constraint  $\mathbf{w}^H(n) \mathbf{d}_0(n) = 1$  is met,  $\mathbf{w}_q(n)$  is defined as

$$\mathbf{w}_q(n) = \mathbf{d}_0(n) (\mathbf{d}_0^H(n) \mathbf{d}_0(n))^{-1}. \quad (16)$$

This vector  $\mathbf{w}_q(n)$  projects the received signal vector onto the constraint subspace. A reasonable constraint value is  $T_0 = 1.5 \|\mathbf{w}_q\|^2$ . Equation (15) can be rewritten as

$$\mathbf{w} = [(\mathbf{I} + \beta \mathbf{R}_y^{-1})^{-1} \mathbf{R}_y^{-1} \mathbf{d}_0]^{-1} \mathbf{d}_0^H (\mathbf{I} + \beta \mathbf{R}_y^{-1})^{-1} \mathbf{R}_y^{-1} \mathbf{d}_0. \quad (17)$$

For small  $\beta$ , the term  $(\mathbf{I} + \beta \mathbf{R}_y^{-1})^{-1}$  can be approximated using the first two terms of its Taylor series expansion. Let  $\mathbf{g}(\beta) = (\mathbf{I} + \beta \mathbf{R}_y^{-1})^{-1}$ . Then, its first-order derivative is

$$\mathbf{g}'(\beta) = -(\mathbf{I} + \beta \mathbf{R}_y^{-1})^{-1} \mathbf{R}_y^{-1} (\mathbf{I} + \beta \mathbf{R}_y^{-1})^{-1}. \quad (18)$$

By Taylor series expansion,  $\mathbf{g}(\beta) \approx \mathbf{g}(0) + \beta \mathbf{g}'(0)$ , that is

$$(\mathbf{I} + \beta \mathbf{R}_{\mathbf{y}}^{-1})^{-1} \approx \mathbf{I} - \beta \mathbf{R}_{\mathbf{y}}^{-1}. \quad (19)$$

With this approximation, (17) becomes

$$\mathbf{w} \approx \frac{(\mathbf{R}_{\mathbf{y}}^{-1} \mathbf{d}_0 - \beta \mathbf{R}_{\mathbf{y}}^{-1} \mathbf{R}_{\mathbf{y}}^{-1} \mathbf{d}_0)}{\mathbf{d}_0^H \mathbf{R}_{\mathbf{y}}^{-1} \mathbf{d}_0 - \beta \mathbf{d}_0^H \mathbf{R}_{\mathbf{y}}^{-1} \mathbf{R}_{\mathbf{y}}^{-1} \mathbf{d}_0}. \quad (20)$$

Denote  $r = \mathbf{d}_0^H \mathbf{R}_{\mathbf{y}}^{-1} \mathbf{d}_0$ ,  $\mathbf{v} = \mathbf{R}_{\mathbf{y}}^{-1} \mathbf{R}_{\mathbf{y}}^{-1} \mathbf{d}_0 / r = \mathbf{R}_{\mathbf{y}}^{-1} \tilde{\mathbf{w}}$ , and  $\tilde{\mathbf{w}} = (\mathbf{R}_{\mathbf{y}}^{-1} \mathbf{d}_0) / r$ , we get

$$\mathbf{w} \approx (\tilde{\mathbf{w}} - \beta \mathbf{v}) / (1 - r\beta \cdot \tilde{\mathbf{w}}^H \tilde{\mathbf{w}}). \quad (21)$$

Hence, when  $\tilde{\mathbf{w}}$  does not satisfy the norm constraint, we can substitute (21) into (14) and solve the equality for  $\beta$

$$\mathbf{w}^H \mathbf{w} - T_0 = a\beta^2 + b\beta + c = 0 \quad (22)$$

where  $a = \|\mathbf{v}\|^2 - T_0 r^2 \|\tilde{\mathbf{w}}\|^4$ ,  $b = 2[-\Re e(\tilde{\mathbf{w}}^H \mathbf{v}) + r T_0 \|\tilde{\mathbf{w}}\|^2]$ , and  $c = \|\tilde{\mathbf{w}}\|^2 - T_0$ .

The solution  $\beta$  is an approximation to the optimal loading level and should be a real, non-negative value. The covariance matrix  $\mathbf{R}_{\mathbf{y}}$  can be decomposed in term of its eigenvectors  $\mathbf{u}_i$  and eigenvalues  $\Lambda_i (i = 1, \dots, M)$

$$\mathbf{R}_{\mathbf{y}} = \sum_{i=1}^M \Lambda_i \mathbf{u}_i \mathbf{u}_i^H. \quad (23)$$

The term  $(\mathbf{R}_{\mathbf{y}} + \beta \mathbf{I}_{M \times M})^{-1}$  is then decomposed as follows:

$$(\mathbf{R}_{\mathbf{y}} + \beta \mathbf{I}_{M \times M})^{-1} = \sum_{i=1}^M \mathbf{u}_i \mathbf{u}_i^H / (\Lambda_i + \beta). \quad (24)$$

The eigenvalues  $\Lambda_i$  are positive since  $\mathbf{R}_{\mathbf{y}}$  is positive definite. To ensure the stability of the algorithm,  $\beta$  should be real and non-negative. In numerical simulations, we found that the value of  $a$  was negative and the value of  $b$  was positive. More details of choosing the value of  $\beta$  from (22) are presented in [14]. With these properties mentioned above, an appropriate solution of (22) is given by

$$\beta = \frac{-b - \Re e(\sqrt{b^2 - 4ac})}{2a}. \quad (25)$$

An RLS algorithm for updating the weight vector  $\mathbf{w}(n)$  in (14) is summarized in Table I, where  $\mathbf{I}_{M \times M}$  is an identity matrix, and  $\delta$  is a positive small constant. It is seen that this algorithm serves as a convenient adaptive implementation of the robust CMOE detector. The update procedure of  $\mathbf{w}(n)$  to satisfy the norm constraint has a complexity of  $O(M)$ . The complexity of the robust CMOE is hence determined by the RLS updating, and has a complexity of  $O(M^2)$ .

TABLE I  
RLS ALGORITHM FOR THE ROBUST CMOE DETECTOR

<i>Initiation</i> : $\mathbf{w}(0) = \mathbf{0}$ , $\mathbf{P}[0] = \delta^{-1} \mathbf{I}_{M \times M}$ ,
<i>Udata</i> : $\mathbf{K}[n] = \frac{\mathbf{P}[n-1] \mathbf{y}[n]}{\lambda + \mathbf{y}^H[n] \mathbf{P}[n-1] \mathbf{y}[n]}$ ,
$\mathbf{P}[n] = \frac{1}{\lambda} (\mathbf{P}[n-1] - \mathbf{K}[n] \mathbf{y}^H[n] \mathbf{P}[n-1])$ ,
$\mathbf{w}[n] = (\mathbf{d}_0^H[n] \mathbf{P}[n] \mathbf{d}_0[n])^{-1} \mathbf{P}[n] \mathbf{d}_0[n]$ ;
$\mathbf{w}_q[n] = \mathbf{d}_0[n] (\mathbf{d}_0^H[n] \mathbf{d}_0[n])^{-1}$ , $T_0 = \ \mathbf{w}_q[n]\ ^2$ ,
if $\ \mathbf{w}[n]\ ^2 > T_0$ ,
$r = (\mathbf{d}_0^H[n] \mathbf{P}[n] \mathbf{d}_0[n])$ , $\mathbf{v}[n] = r \mathbf{P}[n] \mathbf{w}[n]$ ,
$a = \ \mathbf{v}[n]\ ^2 - T_0 r^2 \ \mathbf{w}[n]\ ^4$ ,
$b = 2[-\Re e(\mathbf{w}[n]^H \mathbf{v}[n]) + r T_0 \ \mathbf{w}[n]\ ^2]$ , $c = \ \mathbf{w}[n]\ ^2 - T_0$ ,
$\beta = [-b - \Re e(\sqrt{b^2 - 4ac})] / (2a)$ ,
$\mathbf{w}[n] = (\mathbf{w}[n] - \beta \mathbf{v}[n]) / (1 - r\beta \cdot \mathbf{w}[n]^H \mathbf{w}[n])$ .

### C. Subspace-Based LMMSE Detector

Assume that the data stream for each user is independent, that is,  $E\{b_i(t)b_j^*(t)\} = 0$ , and the ambient noise is white Gaussian. The correlation matrix  $\mathbf{R}_{\mathbf{y}}$  can be given by

$$\mathbf{R}_{\mathbf{y}} = E\{\mathbf{y}(n)\mathbf{y}^H(n)\} = \sum_{k=0}^{K-1} P_k \mathbf{d}_k \mathbf{d}_k^H + \sigma_n^2 \mathbf{I}_{M \times M} \quad (26)$$

Following the eigenvalue decomposition,  $\mathbf{R}_{\mathbf{y}}$  is given as

$$\begin{aligned} \mathbf{R}_{\mathbf{y}} &= [\mathbf{U}_s \quad \mathbf{U}_n] \begin{bmatrix} \Lambda_s & \mathbf{0} \\ \mathbf{0} & \Lambda_n \end{bmatrix} \begin{bmatrix} \mathbf{U}_s^H \\ \mathbf{U}_n^H \end{bmatrix} \\ &= \mathbf{U}_s \Lambda_s \mathbf{U}_s^H + \mathbf{U}_n \Lambda_n \mathbf{U}_n^H \end{aligned} \quad (27)$$

where  $\Lambda_s = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_K)$  contains  $K$  largest eigenvalues,  $\mathbf{U}_s \in \mathbf{C}^{M \times K}$  contains  $K$  signal eigenvectors which span the signal subspace, and  $\mathbf{U}_n \in \mathbf{C}^{M \times (M-K)}$  contains  $M-K$  noise eigenvectors which span the noise subspace.

The subspace-based LMMSE detector for the zeroth user is formulated as the following constrained optimization problem

$$\begin{aligned} J(\mathbf{w}) &= \min_{\mathbf{w}} E\{|\sqrt{P_0} b_0(n) - \mathbf{w}^H \mathbf{y}(n)|^2\}, \\ &\text{s.t. } \mathbf{w}^H \mathbf{d}_0 = 1. \end{aligned} \quad (28)$$

By the method of Lagrange multipliers, the solution of (28) can be written as [9]

$$\mathbf{w} = (\mathbf{U}_s \Lambda_s^{-1} \mathbf{U}_s^H \mathbf{d}_0) / (\mathbf{d}_0^H \mathbf{U}_s \Lambda_s^{-1} \mathbf{U}_s^H \mathbf{d}_0). \quad (29)$$

The orthogonality between the noise and signal subspace implies  $\mathbf{U}_n^H \mathbf{d}_0 = \mathbf{U}_n^H \mathbf{C}_0 \mathbf{F}_m \mathbf{g}_0 = 0$ . Therefore, the channel vector  $\mathbf{g}_0$  can be estimated by the least-squares approach

$$\hat{\mathbf{g}}_0 = \arg \min_{\mathbf{g}_0 \in \mathbf{C}^{L \times 1}} \mathbf{g}_0^H \underbrace{\{\mathbf{F}_m^H \mathbf{C}_0^H \mathbf{U}_n \mathbf{U}_n^H \mathbf{C}_0 \mathbf{F}_m\}}_{\Omega_0} \mathbf{g}_0. \quad (30)$$

The channel estimate  $\hat{\mathbf{g}}_0$  is the eigenvector associated with the minimum eigenvalue of the matrix  $\mathbf{\Omega}_0$ . As  $\text{SNR} \rightarrow \infty$  and  $n \rightarrow \infty$ , the CMOE-based channel estimate asymptotically converges to the subspace-based channel estimate [12].

The computational complexity of the detectors employing recursive implementation depends on the subspace tracking algorithms. In the paper, the PASTd algorithm [22] with a complexity of  $O(MK)$ , and the Bi-SVD algorithm [23] with a complexity of  $O(MK^2)$  are used for signal subspace tracking. The square-root QR inverse iteration method [24] with a complexity of  $O(M(M-K)^2)$  is adopted for noise subspace tracking. In the numerical simulations, we found that the convergence of the PASTd algorithm is quite slow especially when the rank of signal subspace is large and SNR is high. Whereas, the Bi-SVD algorithm has a close performance to the exact SVD solution. When Bi-SVD/(square-root QR inverse iteration) is used for signal/noise subspace tracking, the subspace-based LMMSE detector has a computational complexity of  $\max\{O(MK^2), O(M(M-K)^2)\}$ .

The desired user's data bit is demodulated according to

$$\hat{b}_0 = \text{sgn}(z) = \text{sgn}\{\Re\{e^{\mathbf{w}^H \mathbf{y}}\}\}. \quad (31)$$

The proposed blind CMOE and subspace-based MMSE receivers for synchronous MC-CDMA systems in uplink channels can be directly extended to quasi-synchronous MC-CDMA systems uplink. The required timing of the desired user can be estimated by training or blind methods [27], [28].

#### IV. SINR ANALYSIS

The efficiency of linear detectors to suppress MAI is evaluated by the output SINR. Assume that the users' transmitting symbols are independently and identically distributed (i.i.d.) sequences. The correlation matrix  $\mathbf{R}_y$  is hence given in (24), and can be rewritten as

$$\mathbf{R}_y = P_0 \mathbf{d}_0 \mathbf{d}_0^H + \left( \sum_{k=1}^{K-1} P_k \mathbf{d}_k \mathbf{d}_k^H + \sigma_n^2 \mathbf{I} \right) = \mathbf{R}_s + \mathbf{R}_{in}. \quad (32)$$

The SINR is defined as  $\text{SINR} = E\{(\mathbf{w}^H \mathbf{R}_s \mathbf{w}) / (\mathbf{w}^H \mathbf{R}_{in} \mathbf{w})\}$ . The ideal CMOE detector maximizes the output SINR, and the optimal value is given as  $\text{SINR}_{\text{opt}} = P_0 (\mathbf{d}_0^H \mathbf{R}_{in}^{-1} \mathbf{d}_0)$ .

*Steady-State SINR for RLS Adaptive Blind CMOE Detector:* The mean value  $E\{\mathbf{w}^H(n) \mathbf{R}_s \mathbf{w}(n)\}$  is given as

$$E \left\{ \left| \mathbf{w}^H(n) \sqrt{P_0} \mathbf{d}_0 b_0(n) \right|^2 \right\} = P_0 E\{\mathbf{w}^H(n) \mathbf{d}_0\} = P_0. \quad (33)$$

Let the optimal weight vector be  $\bar{\mathbf{w}}$ , and  $\zeta(n) = \mathbf{w}(n) - \bar{\mathbf{w}}$ .  $\eta(n) = E\{\mathbf{w}(n)^H \mathbf{R}_y \mathbf{w}(n)\}$  is given by

$$\begin{aligned} \eta(n) &= E \left\{ \left[ \bar{\mathbf{w}}^H + \zeta^H(n-1) \right] \mathbf{y}(n) \mathbf{y}^H(n) \left[ \bar{\mathbf{w}} + \zeta(n-1) \right] \right\} \\ &= \bar{\eta} + \text{tr}[\mathbf{R}_y \mathbf{K}(n-1)] + 2\bar{\mathbf{w}}^H \mathbf{R}_y E\{\zeta(n-1)\} \end{aligned} \quad (34)$$

where  $\bar{\eta} = \bar{\mathbf{w}}^H \mathbf{R}_y \bar{\mathbf{w}} = P_0(1+1/\text{SINR}_{\text{opt}})$ . Since  $E\{\zeta(n)\} \rightarrow 0$  as  $n \rightarrow \infty$  [30], we have  $\eta(n) \approx \bar{\eta} + \eta_{\text{ex}}(n)$ . In [29], it gets

$$\begin{aligned} \eta_{\text{ex}}(n) &= \text{tr}[\mathbf{R}_y \mathbf{K}(n-1)] \\ &= [\lambda^2 + (1-\lambda)^2] \eta_{\text{ex}}(n-1) + (1-\lambda)^2 (M-1) \bar{\eta} \end{aligned} \quad (35)$$

where  $M$  is the length of  $\mathbf{w}$ . Since  $\lambda^2 + (1-\lambda)^2 < 1$  for  $0 < \lambda < 1$ ,  $\eta_{\text{ex}}(n)$  converges, i.e.,  $\eta_{\text{ex}}(\infty) = \lim_{n \rightarrow \infty} \text{tr}[\mathbf{R}_y \mathbf{K}(n)] = \nu \bar{\eta}$ , where  $\nu = (1-\lambda)(M-1)/(2\lambda)$ . The steady-state SINR of the RLS adaptive CMOE detector can then be obtained as

$$\text{SINR}_{\text{moe}}^\infty = \frac{\text{SINR}_{\text{opt}}}{(1+\nu) + \nu \cdot \text{SINR}_{\text{opt}}}. \quad (36)$$

*Steady-State SINR for RLS Adaptive Training MMSE Detector:* In this case, the exponentially windowed algorithm chooses  $\mathbf{w}(n)$  to minimize the cost function

$$\sum_{i=1}^n \lambda^{n-i} |\sqrt{P_0} b_0(i) - \mathbf{w}^H(n) \mathbf{y}(i)|^2. \quad (37)$$

Denote the optimal solution  $\bar{\mathbf{w}}$  and  $\bar{\zeta}(n) = \mathbf{w}(n) - \bar{\mathbf{w}}$ . Then  $\eta_s = E\{\mathbf{w}^H(n) \mathbf{R}_s \mathbf{w}(n)\}$  is given as

$$\begin{aligned} \eta_s &= E\{[\bar{\mathbf{w}}^H + \bar{\zeta}^H(n-1)] P_0 \mathbf{d}_0 \mathbf{d}_0^H [\bar{\mathbf{w}} + \bar{\zeta}(n-1)]\} \\ &= \bar{\mathbf{w}}^H \mathbf{R}_s \bar{\mathbf{w}} + \text{tr}[\mathbf{R}_s \mathbf{K}(n-1)] + 2\bar{\mathbf{w}}^H \mathbf{R}_s E\{\bar{\zeta}(n-1)\}, \end{aligned} \quad (38)$$

where  $E\{\bar{\zeta}(n)\} \rightarrow 0$  as  $n \rightarrow \infty$ . The weight error correlation matrix  $\mathbf{K}(n)$  is given as [29]

$$\mathbf{K}(n) = E\{\bar{\zeta}(n) \bar{\zeta}^H(n)\} \approx \lambda^2 \mathbf{K}(n-1) + (1-\lambda)^2 \mathbf{R}_y^{-1} \bar{\varepsilon} \quad (39)$$

where  $\bar{\varepsilon} = P_0/(1 + \text{SINR}_{\text{opt}})$  is the MSE of the optimum filter  $\bar{\mathbf{w}}$ . Pre-multiplying both sides of (39) by  $\mathbf{R}_s$ , then taking the trace, it yields

$$\text{tr}[\mathbf{R}_s \mathbf{K}(n)] \approx \lambda^2 \text{tr}[\mathbf{R}_s \mathbf{K}(n-1)] + (1-\lambda)^2 P_0 \times (\mathbf{d}_0^H \mathbf{R}_y^{-1} \mathbf{d}_0) \bar{\varepsilon}. \quad (40)$$

Hence,  $\text{tr}[\mathbf{R}_s \mathbf{K}(n)]$  converges for  $0 \leq \lambda \leq 1$ , and it has

$$\begin{aligned} \bar{\eta}_{\text{ex}}(\infty) &= \lim_{n \rightarrow \infty} \text{tr}[\mathbf{R}_s \mathbf{K}(n)] \\ &= P_0 \cdot \frac{1-\lambda}{1+\lambda} \cdot \frac{\text{SINR}_{\text{opt}}}{(1 + \text{SINR}_{\text{opt}})^2}. \end{aligned} \quad (41)$$

In practical applications,  $\lambda$  is around 0.9. Therefore, with reasonably high SNR, it has  $\bar{\eta}_{\text{ex}}(\infty) \rightarrow 0$ , and  $\eta_s = E\{\mathbf{w}^H(n) \mathbf{R}_s \mathbf{w}(n)\}$  can be approximated by  $\bar{\mathbf{w}}^H \mathbf{R}_s \bar{\mathbf{w}} = P_0 \cdot \text{SINR}_{\text{opt}}^2 / (1 + \text{SINR}_{\text{opt}})^2$ . It is shown that [26]

$$\eta(n) = E\{\mathbf{w}^H(n) \mathbf{R}_y \mathbf{w}(n)\} = P_0 \frac{\nu + \text{SINR}_{\text{opt}}}{1 + \text{SINR}_{\text{opt}}}. \quad (42)$$

Therefore, the output SINR of the RLS adaptive training LMMSE detector is given by

$$\text{SINR}_{\text{mmse}}^{\infty} = \frac{\text{SINR}_{\text{opt}}}{(1 + \nu) + \nu/\text{SINR}_{\text{opt}}}. \quad (43)$$

It is seen that the SINR performance of the adaptive blind CMOE detector is inferior to that of the adaptive training LMMSE detector, due to the absence of training.

V. NUMERICAL RESULTS

In this section, numerical results are presented to illustrate the performance of the proposed blind LMMSE receivers and the blind mode decision-directed LMMSE detectors. Consider a synchronous MC-CDMA system in uplink channels with random spreading sequence of length  $M$ . The quadratic constraint is set as  $T_0 = 1.5\|\mathbf{w}_q\|^2$ . The SNR is defined to be the average received bit energy to noise ratio  $P_k/\sigma_n^2$ . A frequency-selective channel is considered with  $L = 6$  paths. The total channel power of the  $k$ th user is normalized to 1. In the simulations, the inherent scalar ambiguity of the blind channel estimators is compensated with a complex constant, which makes the first element of the estimation  $\hat{\mathbf{h}}_{0,p}$  and that of the true channel vector  $\mathbf{h}_{0,p}$  identical. Referred to the design scheme for MC-CDMA in [3], we set  $M = 16, P = 8$ . Consequently, the original data sequence is first S/P converted into 8 parallel data streams, then each data symbol after S/P spreads with a random spreading code of length  $M = 16$ . An additional guard tones  $N_g = 8$  is added to prevent ISI. There are 8 simultaneous users in the channel, and assume the zeroth user is the desired user. The interference-signal ratio (ISR) of the multiple access interferers (MAI's) is 10-dB higher than the desired user, i.e.,  $P_k/P_0 = 10$ .

*Static Channels:* First, the steady-state performance of the detectors is investigated. Following the Rayleigh fading assumption, the channel coefficients are randomly generated according to a complex Gaussian distribution. The simulation results are averaged over 400 Monte Carlo trials. Fig. 3(a) and (b) shows the normalized channel estimation error of the CMOE-based and subspace-based channel estimators versus data samples and SNR, respectively. The normalized channel estimation error is measured by  $\|\mathbf{h}_{0,p} - \hat{\mathbf{h}}_{0,p}\|/\|\mathbf{h}_{0,p}\|$ . The square-root QR inverse iteration subspace tracker is adopted in the subspace-based channel estimator. It is shown that, at high SNR, the CMOE-based channel estimator has a similar performance to the subspace-based channel estimator. Fig. 4 illustrates the output SINR of the blind CMOE and subspace-based LMMSE receivers versus snapshots. The PASTd and the Bi-SVD algorithms were employed for signal subspace tracking in the subspace-based detection. We found that the convergence of the PASTd algorithm is very slow. However, the Bi-SVD algorithm presents similar convergence property as that of the exact SVD solution. It can also be seen that the output steady-state SINR of the proposed robust CMOE detector is much better than the standard CMOE, and it is close to that of the subspace-based LMMSE detector. Fig. 5(a) and (b) shows the SINR and MSE for different LMMSE detectors versus the SNR. The robust CMOE performs better than the

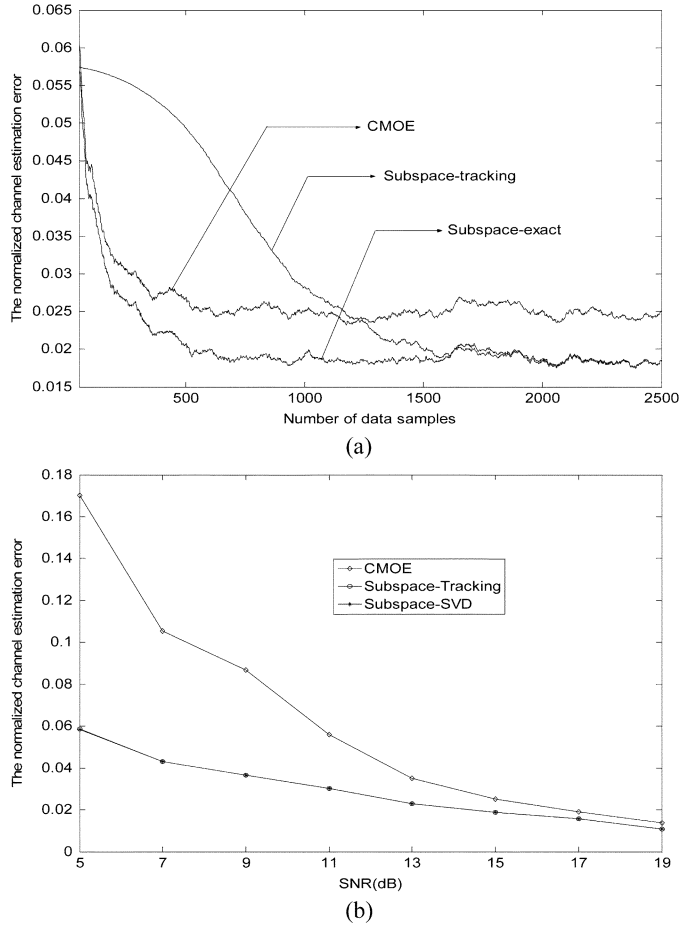


Fig. 3. (a) Normalized channel estimation error versus the data samples at SNR = 15 dB. (b) Normalized channel estimation error versus the SNR. When  $M = 16, P = 8, K = 8, \text{ISR} = 10 \text{ dB}, \lambda = 0.995, \delta = 0.1$ .

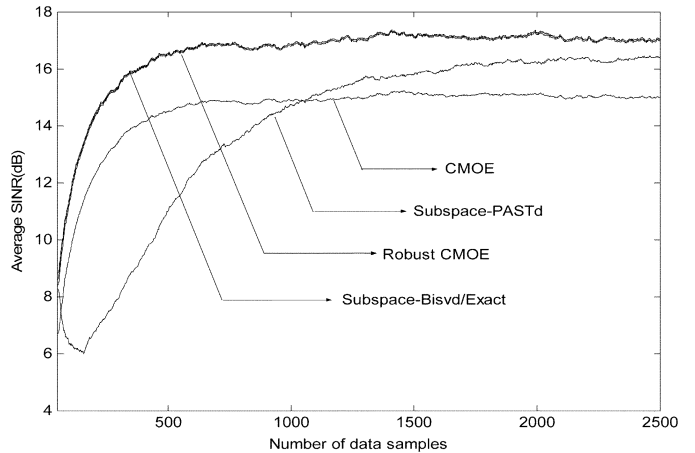


Fig. 4. The averaged SINR versus data samples. When SNR = 15 dB,  $M = 16, P = 8, K = 8, \text{ISR} = 10 \text{ dB}, \lambda = 0.995, \delta = 0.1$ .

conventional CMOE detector, and has similar performance as that of the subspace-based detector at high SNR. It can also be seen that the output SINR and MSE of the adaptive training LMMSE detector is close to the optimal values. Moreover, Fig. 6 shows that the SINR of the blind mode decision-directed LMMSE detectors (after 800 samples) converges to the optimal SINR, which is plotted as the dash line. Therefore, switching to

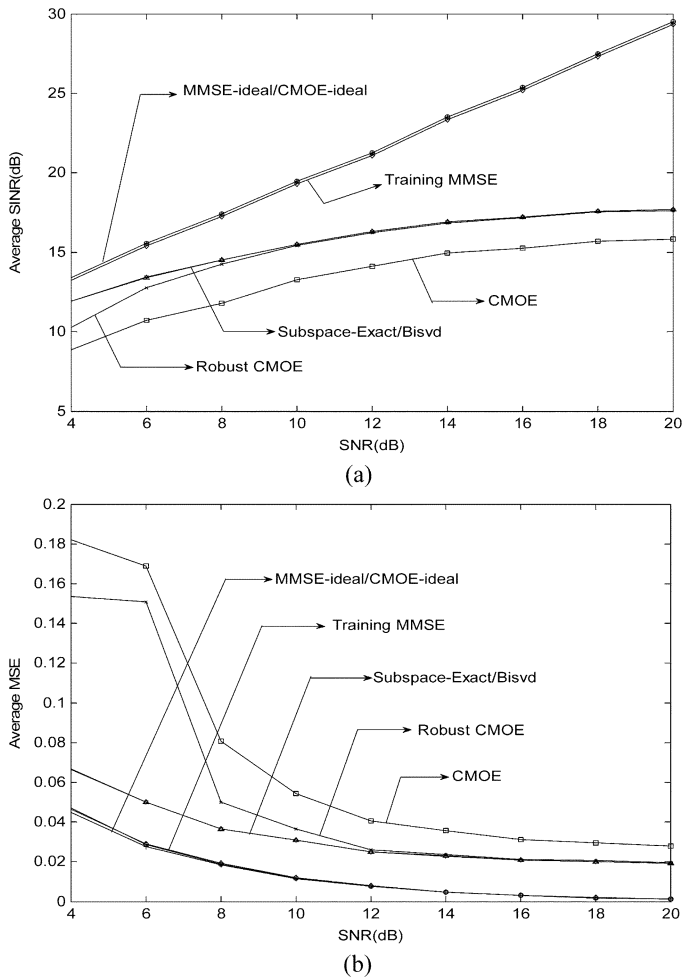


Fig. 5. (a) The averaged SINR versus the SNR. (b). The MSE versus the SNR. When  $M = 16$ ,  $P = 8$ ,  $K = 8$ ,  $ISR = 10$  dB,  $\lambda = 0.995$ ,  $\delta = 0.1$

the decision-directed mode after the blind detectors reach their steady states will greatly improve the system performance. Figs. 4 and 6 show that the SINR learning curves of the robust CMOE and subspace-based MMSE detector have the same convergence property when  $SNR = 15$  dB. Since both RLS updating and Bi-SVD subspace tracking algorithm exploit the one rank update of the correlation matrix, the learning curves present the same convergence property with identical forgetting factor  $\lambda$ .

As mentioned in Section III, the proposed blind CMOE and subspace-based receivers can be directly applied to quasi-synchronous MC-CDMA systems in uplink channels assuming the receivers know the timing of the desired user. Next, we consider the performance of the blind CMOE and subspace-based receivers in quasi-synchronous MC-CDMA systems. We use the same system setting as that in synchronous systems. The users' transmission delays are discrete random variables with equi-probable values  $\{0, 1, 2\}$ . Fig. 7(a) and (b) shows the normalized channel estimation error of the CMOE-based and subspace-based channel estimators. Verde [18] proposed a subspace-based detector to jointly estimate the timing and the channel coefficients. As a comparison, the channel estimation error of the subspace-based channel estimator presented in [18] (labeled as Subspace-Exact-Verde) is also shown in Fig. 7. It is

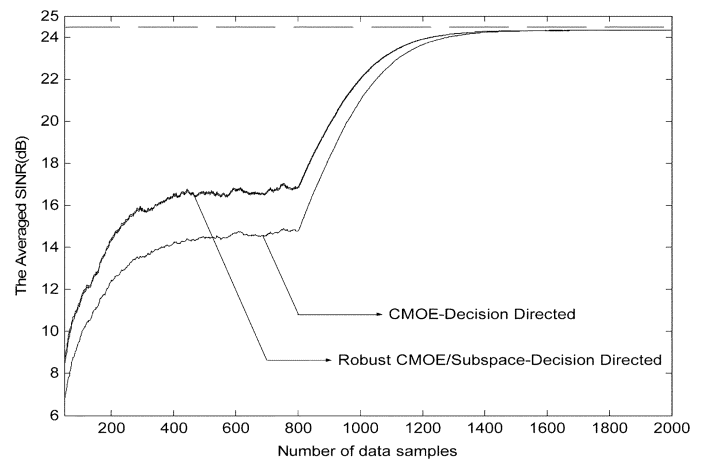


Fig. 6. The averaged SINR versus the data samples in the decision-directed mode. When  $SNR = 15$  dB,  $M = 16$ ,  $P = 8$ ,  $K = 8$ ,  $ISR = 10$  dB,  $\lambda = 0.995$ ,  $\delta = 0.1$ .

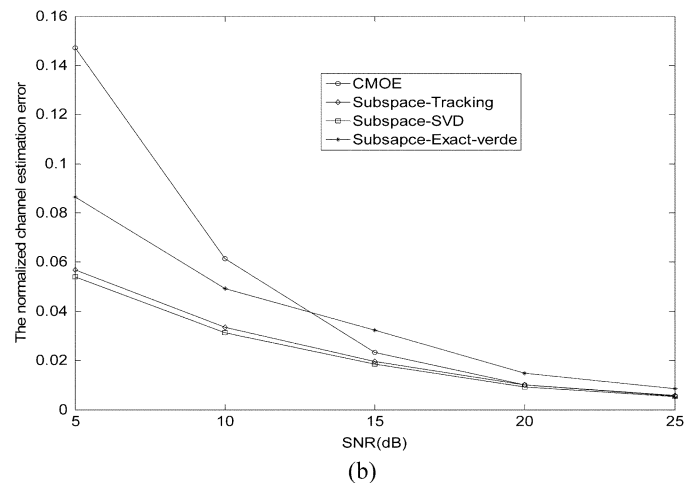
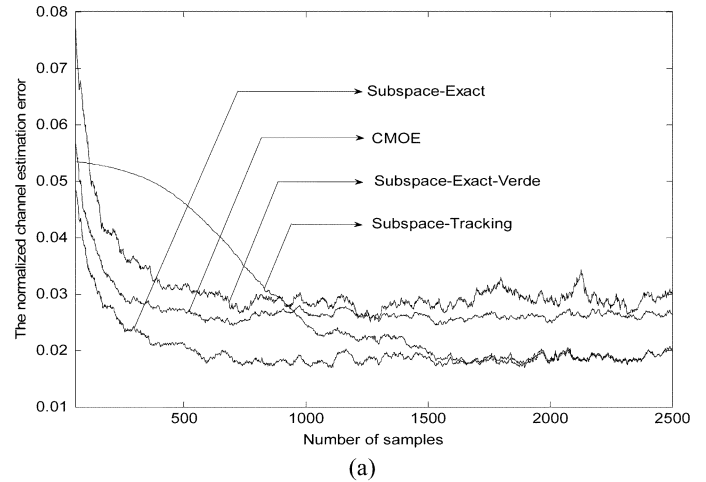


Fig. 7. Normalized channel estimation error for quasi-synchronous MC-CDMA systems. (a) Versus the data samples at  $SNR = 15$  dB. (b) Versus the SNR. When  $M = 16$ ,  $P = 8$ ,  $K = 8$ ,  $ISR = 10$  dB,  $\lambda = 0.995$ ,  $\delta = 0.1$ .

shown that the proposed subspace-based channel estimator with the known timing outperforms the channel estimator in [18], while the latter has better performance than the CMOE-based channel estimator when SNR is low. Fig. 8 depicts the output SINR of the different receivers versus snapshots. It can be seen that the output SINR of the subspace-based detector in [18]



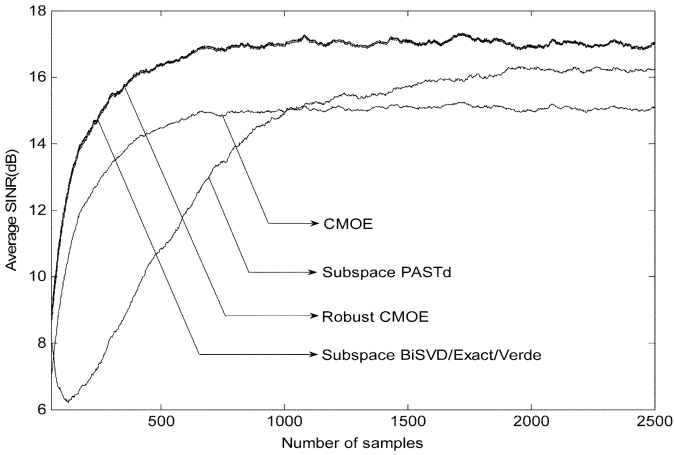


Fig. 8. The averaged SINR versus data samples for quasi-synchronous MC-CDMA systems. When SNR = 15 dB,  $M = 16$ ,  $P = 8$ ,  $K = 8$ , ISR = 10 dB,  $\lambda = 0.995$ ,  $\delta = 0.1$ .

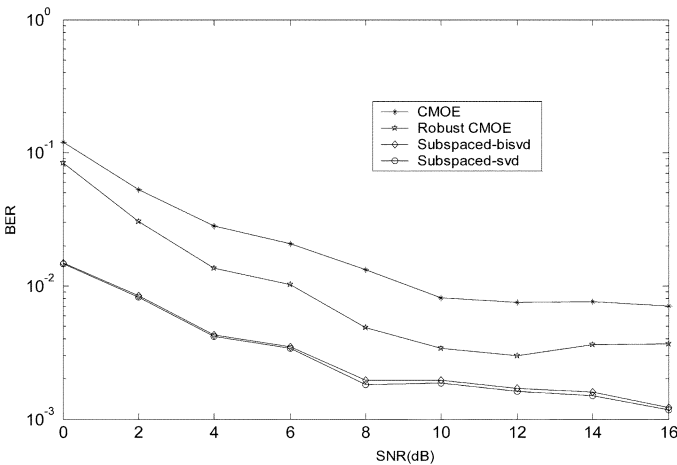


Fig. 9. The BER versus the SNR of the blind LMMSE detection.  $M = 16$ ,  $P = 8$ ,  $K = 8$ , ISR = 10 dB,  $f_D T_s = 1.664 \times 10^{-4}$ ,  $\lambda = 0.97$ ,  $\delta = 0.1$

(labeled as Subspace-Verde) is close to that of the proposed robust CMOE and subspace-based MMSE detectors.

*Indoor Rayleigh Fading Channels:* A slowly time-varying frequency-selective channel with six ( $L = 6$ ) Rayleigh fading paths in indoor environments is considered [31]. The multipath intensity profile decays exponentially. The maximum Doppler frequency ( $f_D$ ) is 52 Hz corresponding to a terminal speed  $v = 3$  m/s with a carrier frequency of 5.2 GHz. The subcarrier spacing ( $\Delta f$ ) is 312.5 KHz, and the time duration at the subcarrier is  $T_s = 3.2 \mu\text{s}$ . The normalized fading rate is  $f_D T_s = 1.664 \times 10^{-4}$ . Fig. 9 compares the BER performance for the blind CMOE, robust CMOE, and subspace-based LMMSE detectors. In the numerical simulations, 500 bits are allowed for the blind detectors to reach a steady state before accumulating errors. The BER is averaged over 600 000 MC-CDMA symbols. It can be seen that the robust CMOE detector performs much better than the standard CMOE detector. The performance of the subspace-based detector using the subspace tracking algorithms is close to that of detectors using an exact SVD, which provides a performance upper bound for all SVD-based subspace tracking algorithms. Fig. 10 shows the MSE performance versus the SNR

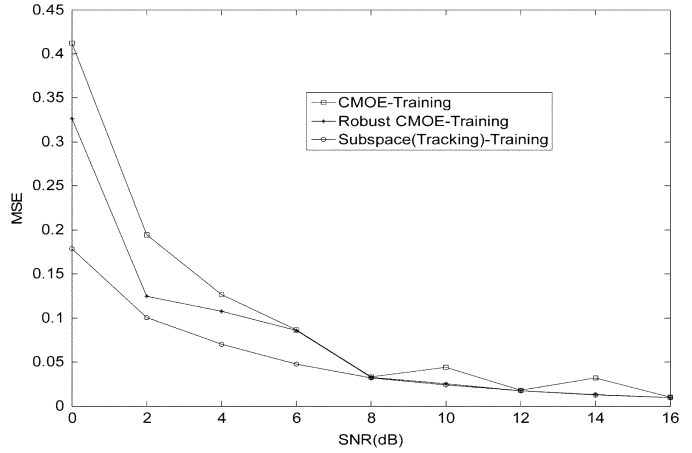


Fig. 10. The MSE versus the SNR of the blind mode decision-directed LMMSE detection. When  $M = 16$ ,  $P = 8$ ,  $K = 8$ , ISR = 10 dB,  $f_D T_s = 1.664 \times 10^{-4}$ ,  $\lambda = 0.97$ ,  $\delta = 0.1$ .

of the proposed blind mode decision-directed LMMSE detector. The blind detectors switch to the decision-directed mode after 500 data samples. It is seen that the blind mode decision-directed LMMSE detector with the subspace-based method performs best at the low SNR. The detector using the robust CMOE for the initial adaptation outperforms the detector using the standard CMOE.

## VI. CONCLUSION

In this paper, the blind CMOE, robust CMOE and subspace-based LMMSE receivers for MC-CDMA systems are studied. By imposing quadratic weight constraints, the CMOE detector is made more robust against signal modeling errors, and a better performance over the standard CMOE detector is obtained. The subspace-based LMMSE receiver has better performance and higher computational complexity than the CMOE method. The performance of subspace-based receiver using subspace tracking algorithms is also studied. The robust CMOE and the subspace-based LMMSE receivers present similar steady-state SINR and MSE performance. The blind mode decision-directed LMMSE detection is proposed to further improve the performance of the blind detection, where the blind detectors are used for initial adaptation. Numerical examples show that the blind mode decision-directed detectors using the robust CMOE and the subspace-based LMMSE detection have the same MSE performance at medium SNR when the channel is slowly-varying.

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