A BLMS Adaptive Receiver for Direct-Sequence Code Division Multiple Access Systems

Walaa Hamouda and Peter J. McLane

Abstract: **We propose an efficient block least-mean-square (BLMS) adaptive algorithm, in conjunction with error control coding, for direct-sequence code division multiple access (DS-CDMA) systems. The proposed adaptive receiver incorporates decision feedback detection and channel encoding in order to improve the performance of the standard LMS algorithm in convolutionally coded systems. The BLMS algorithm involves two modes of operation: (i) The training mode where an uncoded training sequence is used for initial filter tap-weights adaptation, and (ii) the decision-directed where the filter weights are adapted, using the BLMS algorithm, after decoding/encoding operation. It is shown that the proposed adaptive receiver structure is able to compensate for the signal-to-noise ratio (SNR) loss incurred due to the switching from uncoded training mode to coded decision-directed mode. Our results show that by using the proposed adaptive receiver (with decision feedback block adaptation) one can achieve a much better performance than both the coded LMS with no decision feedback employed. The convergence behavior of the proposed BLMS receiver is simulated and compared to the standard LMS with and without channel coding. We also examine the steady-state bit-error rate (BER) performance of the proposed adaptive BLMS and standard LMS, both with convolutional coding, where we show that the former is more superior than the latter especially at large SNRs (SNR $\geq$ 9 dB).**

Index Terms: **Adaptive filtering, block least-mean-square (BLMS) adaptation, code division multiple access (CDMA), convolutional coding, interference cancellation.**

I. INTRODUCTION

The large capacity requirements of future wireless applications have created a great demand for more sophisticated receivers. With code division multiple access (CDMA) being one of the dominant standards for these future wireless systems, many multiuser receiver structures have been proposed to overcome the inherent limitations of the second-generation matched-filter receiver (see [1] for an excellent review on multiuser detection techniques). Even though most of these multiuser receivers achieve optimum or near optimum performance, their application is only limited to the reverse link of the wireless channel where complexity is easily justified at the receiver base station. Furthermore, the majority of these multiuser receivers assume complete information on all users' parameters which in turn increases the receiver complexity.

Motivated by the above, researchers have recently focused on simple adaptive implementations of multiuser receivers (e.g., [2]–[4]). In this quest, adaptive minimum mean-square-error (MMSE) implementations have received most of the attention [5]. This attention is mainly due to their great potential to achieving a performance close to the multiuser-based receivers. Recent studies of adaptive MMSE receivers over both flat and frequency-selective fading channels have been considered in [6]–[10]. Simply put, these adaptive MMSE receivers are single-user detectors where only the desired user bit stream is demodulated. In this case, the detection process is performed on a bit-by-bit basis where a decision is made by observing one bit interval of the received signal. Two practical realizations of the adaptive MMSE receiver are the LMS algorithm and the recursive-least-square (RLS) algorithm. In this paper, we only consider the application of the LMS algorithm and its extension to the block least-mean-square (BLMS) adaptation. Another class of adaptive multiuser detectors is known as blind adaptive detectors. The performance of these blind adaptive detectors has been discussed for different channel models in [11]–[18]. In these blind algorithms, the receiver does not require a training sequence prior to data detection (i.e., the same as the conventional matched filter). Even though most of these blind techniques prove to be bandwidth efficient, they still require large computational complexity relative to trained algorithms.

So far, most of the work on adaptive MMSE detection in CDMA systems only focuses on the performance of uncoded systems. Since error control coding is an integral part of any communication system, one needs to investigate the performance of these adaptive detection techniques in conjunction with channel coding. Motivated by this, we introduce an adaptive forward-error-correction (FEC)-aided BLMS algorithm to improve the performance of the standard LMS algorithm when both systems employ convolutional coding. Our proposed receiver employs decision feedback from a concatenation of the Viterbi decoder and a convolutional encoder to fine tune the filter tap-weights in a block LMS manner. It is important to mention that, the receiver operation is the same as the standard LMS algorithm during filter training where an uncoded training sequence is sent for initial filter tap-weights adaptation. Note that the block implementation of the LMS used here stems from the fact that the decoder decisions are made at the end of every received codeword and hence, the block size is a function of the code rate used. Moreover, the proposed receiver structure can be simply applied to systems that employ block codes as opposed to convolutional coding.

The rest of the paper is organized as follows. In Section II,

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the discrete model for the DS-CDMA system is introduced. The proposed feedback-aided adaptive algorithm is discussed in Section III. In Section IV, simulation results along with discussions are given. Finally, conclusions are drawn in Section V.

II. SYSTEM MODEL

In what follows, we consider a synchronous DS-CDMA system model [19], [20]. This model can be easily generalized to the asynchronous model given the fact that any K-user asynchronous system is equivalent to a synchronous one with $2K-1$ users [10], [21]. Based on this model, user data is detected on a bit-by-bit basis (i.e., single shot detection).

Starting at the transmitter side, each user signal is first encoded using a convolutional encoder followed by signal spreading where the spreading waveform is given by

$$c_k(t) = \sum_{i=1}^{L} b_k[i] P_c(t - iT_c) \tag{1}$$

where $b_k[i]$ denotes the i-th chip of the k-th user code sequence and $P_c(t)$ is the chip pulse waveform defined over the interval $[0, T_c)$ with T_c being the chip duration related to the bit duration through the processing gain $L = T/T_c$. Using (1), the transmitted signal for the k-th user can be written as

$$s_k(t) = \sqrt{E_k} a_k(t) c_k(t) \cos(2\pi f_c t + \theta_k) \tag{2}$$

where E_k is the coded bit signal energy and is related to the uncoded bit energy through $E_k = R_c E_b$ where $R_c = M/N$ is code rate, $a_k(t) \in \{-1, +1\}$ is the k-th user data bit, f_c and θ_k represent the carrier frequency and phase, respectively.

At the receiver side, the received multiuser signal is given in the baseband form by

$$r(t) = \sum_{k=1}^{K} \sqrt{E_k} \alpha_k(t) a_k c_k(t - \tau_k) + n(t) \tag{3}$$

where τ_k is the channel delay associated with the k-th user signal (equal to zero for the synchronous case), $n(t)$ is the Gaussian noise with zero mean and variance $\sigma^2 = N_o/2$, and $\alpha_k(t)$ is the complex fading coefficient for user k. Without loss of generality, in this paper, we consider an AWGN channel with no fading effects (i.e., $\alpha_k(t)$=1 for all k). Similar to the conventional adaptive LMS algorithms, the proposed algorithm can still be applicable in channels with multipath fading provided that the fading variables are known at each user's receiver. For details on the performance of adaptive LMS algorithms in fading channels, the reader is referred to [3], [6].

As shown in Fig. 1, the adaptive receiver is modeled as a finite impulse response (FIR) filter with a tap delay spaced at a multiple of chip duration and total time span equal to the transmitted bit duration. At the input of this adaptive filter, the received signal is sampled at the chip rate and the adaptation is performed at the end of each uncoded bit duration.

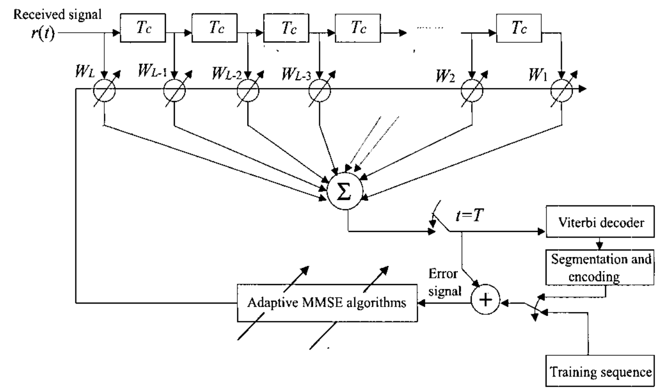

Fig. 1. Receiver structure.

III. BLMS ADAPTIVE RECEIVER STRUCTURE

In this section, we introduce the steps involved in the operation of the adaptive filter shown in Fig. 1. Starting with the training mode, the receiver adapts its coefficients using the LMS algorithm. After this initial adaptation, the receiver switches to the decision directed mode where the BLMS algorithm is used for filter tap-weights adaptation using blocks of re-encoded data. In what follows, we discuss these two modes of operation in more detail. The application of the BLMS introduced here can be easily generalized to fading channels, provided that the channel coefficients of each user are perfectly known (i.e., estimated) at the receiver side.

A. Training Mode and Adaptive LMS

Let $\mathbf{w}(n)$ be an L length coefficient vector representing the adaptive filter weights[1] given by

$$\mathbf{w}(n) = [\ w_1(n) \quad w_2(n) \quad \cdots \quad w_L(n)\ ]^T \tag{4}$$

and let $\mathbf{r}(n)$ be an L vector representing the input chips during one bit interval

$$\mathbf{r}(n) = [\ r(n) \quad r(n-1) \quad \cdots \quad r(n-L+1)\ ]^T \tag{5}$$

where the subscript n denotes the discrete time index. Using (4) and (5), the discrete output signal $y(n)$ can be written as

$$y(n) = \mathbf{w}^T(n)\mathbf{r}(n). \tag{6}$$

Given the filter output $y(n)$, the receiver forms an error signal

$$e(n) = d(n) - y(n) \tag{7}$$

where $d(n)$ is the desired user filter output given by the uncoded training sequence, and is equal to a_k for the k-th user. Finally, the LMS algorithm is used to adjust the filter weights according to the recursion

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 2\mu e(n)\mathbf{r}(n) \tag{8}$$

where μ is the adaptation step size chosen to optimize both the convergence rate and the mean-squared error. It is important to mention that during filter's training, we assume that the

[1] In the paper, vectors will be referred to by bold letters, while scalar quantities will be referred to by italic letters.

transmitted training sequence is uncoded and hence independent from the error control code used in the decision-directed mode where actual encoded data is sent.

B. Decision Directed Mode and Adaptive BLMS

Once the adaptive LMS reaches steady-state, the receiver switches to the decision directed mode where actual encoded data is used for filter tap-weights adaptation. As mentioned earlier, this switching from uncoded training sequence to coded decision directed mode results in a sudden increase in the achieved MSE. To overcome this problem, we use the data estimates at the Viterbi decoder output after encoding to generate an estimate of the desired user's coded data. This estimate is then used to fine tune the filter tap-weights using the BLMS algorithm. It is worth mentioning that, both the decoding and the subsequent encoding operations at the receiver are performed on large data blocks. Without loss of generality and for illustration purposes, we segment the encoder output into smaller blocks which are then fed back to the BLMS algorithm for tap-weights adjustment.

In what follows, we describe the operation of the BLMS algorithm. Starting with the gradient vector for each received codeword of length N, the BLMS algorithm forms [22]

$$\nabla e_B^2 = -2\sum_{i=0}^{N-1} e(nN+i)\mathbf{r}(nN+i) \tag{9}$$

where e_B is gradient vector used to update the filter tap weights. Now similar to the LMS algorithm, the block auto correlation matrix $\mathcal{R}$ and the cross correlation vector $\mathcal{P}$, are defined as follows

$$\begin{aligned} \mathcal{R} &= E\left[\underline{\mathbf{r}}^T(n)\underline{\mathbf{r}}(n)\right] && (10a)\\ \mathcal{P} &= E\left[\underline{\mathbf{r}}^T(n)\mathbf{a}(n)\right] && (10b)\end{aligned}$$

where

$$\begin{aligned}\underline{\mathbf{r}}(n) &= [\ \mathbf{r}(nN)\quad \mathbf{r}(nN+1)\quad \cdots\quad \mathbf{r}(nN+N-1)\ ]^T\\ \mathbf{a}(n) &= [\ a(nN)\quad a(nN+1)\quad \cdots\quad a(nN+N-1)\ ]^T\end{aligned} \tag{11}$$

and $E[\cdot]$ denotes statistical expectation. Then, the BLMS algorithm adjusts the filter tap weights according to the recursion

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 2\mu_B\underline{\mathbf{r}}^T(n)\mathbf{e}(n) \tag{12}$$

where the definition of μ_B is similar to the step size used for the LMS algorithm. Given the filter tap weights, the filter output can be represented as

$$\mathbf{y}(n) = \underline{\mathbf{r}}(n)\mathbf{w}(n) \tag{13}$$

where

$$\begin{aligned}\mathbf{y}(n) &= [\ y(nN)\quad y(nN+1)\quad \cdots\quad y(nN+N-1)\ ]^T\\ \mathbf{e}(n) &= [\ e(nN)\quad e(nN+1)\quad \cdots\quad e(nN+N-1)\ ]^T.\end{aligned} \tag{14}$$

Now, let us examine the stability limits on the step size μ_B to ensure steady-state convergence. For a fixed excess MSE e_{excess} and filter misadjustment η, a common choice for the LMS step size is given by [23]

$$\mu \approx \frac{\eta}{\text{trace}[\mathbf{R}]} \tag{15}$$

for the conventional LMS, where $\mathbf{R} = \mathbf{E}\left[\mathbf{r^T(n)r(n)}\right]$ is the bit-wise auto correlation matrix and by

$$\mu_B \approx \frac{\eta}{\text{trace}[\mathcal{R}]} \tag{16}$$

for the BLMS algorithm where $\eta = \frac{e_{excess}}{e_{\min}}$. Now, assuming that the BLMS inputs are stationary, it is easy to show that $\text{trace}[\mathbf{R}] = \text{trace}[\mathcal{R}]$. Hence for a fixed filter misadjustment for both the uncoded and coded systems, the step size μ_B should be set equal to μ. Note that this constraint is important since it allows for a fair comparison between the conventional LMS and the proposed BLMS algorithm. Having satisfied this condition, both the LMS and the BLMS algorithms will converge to the same MSE value.

IV. SIMULATION RESULTS

In this section, we present simulation results for the proposed adaptive algorithm and discuss its convergence properties and steady-state BER performance relative to the conventional LMS adaptive algorithm with and without coding. The system parameters used in the simulations are as follows.

- We consider a DS-CDMA system with $K = 8$ users and transmission based on binary-phase-shift-keyed (BPSK) modulation.
- Each user data is encoded using a convolutional code of rate $R_c = 1/2$ and constraint length $\mathcal{K} = 7$, and the decoder used is based on the Viterbi algorithm with 3-bit soft decision decoding.
- The number of filter taps $L = 31$.
- Random code sequences are used throughout the simulations.
- Finally, the ensemble average is taken over 30 independent trials or else mentioned.

A. Convergence

Fig. 2 shows the transient behavior for the proposed BLMS algorithm, with and without decisions feedback, along with the performance of the conventional LMS operating in the training mode. The results are shown for equal power users with signal-to-noise ratio (SNR) of 10 dB. In these results, we use a training sequence of 100 symbols after which the proposed receiver switches to the BLMS where decision feedback is used. For the purpose of this study, the encoder (at the receiver side) operates on large data frames (i.e., $N = 500$) which are then segmented into smaller blocks and fed back to the BLMS for filter adaptation. Later, we study the effect of codeword length on the receiver performance. In Figs. 2 and 3, we consider the case where the block size is equal to two coded symbols and 32 symbols, respectively. As seen from these results, the coded BLMS is shown to suffer from a sudden MSE degradation when the receiver switches from training to decision directed mode.. On the

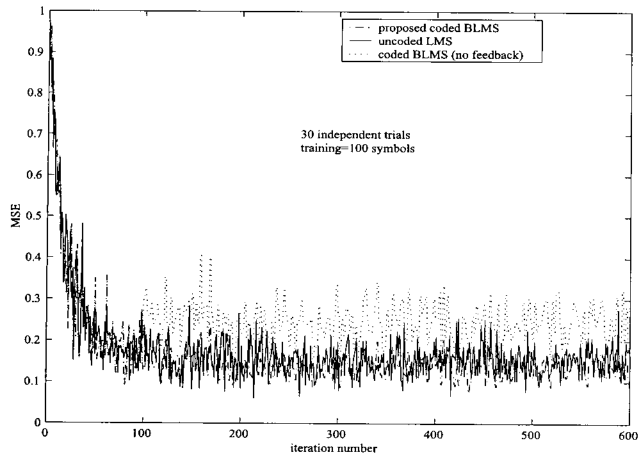

Fig. 2. Convergence using 100-symbol training sequence for the FEC-aided BLMS, the uncoded LMS, and the coded BLMS algorithms for an 8-user DS-CDMA system and $N = 2$.

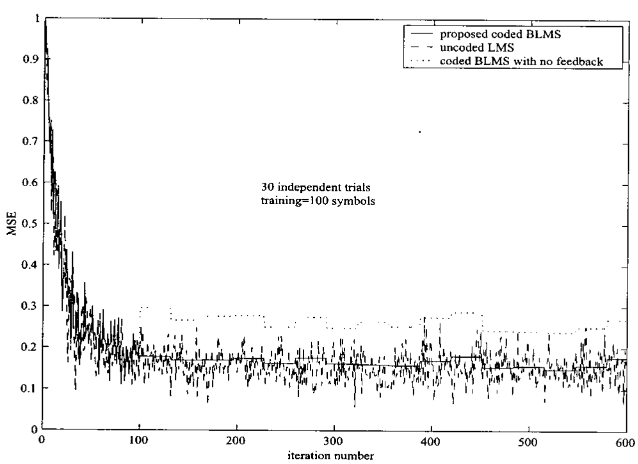

Fig. 3. Convergence using 100-symbol training sequence for the FEC-aided BLMS, the uncoded LMS, and the coded BLMS algorithms for an 8-user DS-CDMA system $N = 32$.

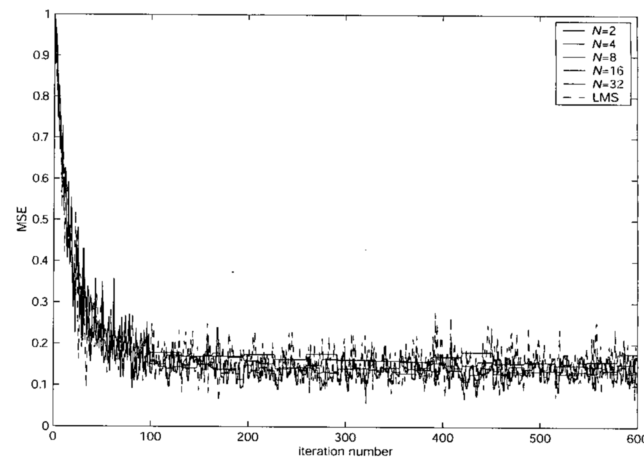

Fig. 4. Convergence behavior for different block sizes and using 100 symbols training sequence.

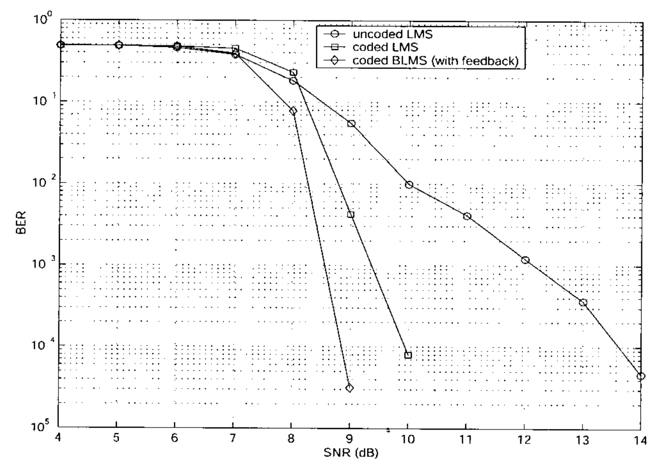

Fig. 5. BER performance of the proposed BLMS algorithm compared to the uncoded LMS and the coded LMS for an 8-user DS-CDMA system.

other hand, the proposed FEC-aided BLMS is shown to offer no loss in performance relative to the uncoded LMS algorithm. The superior performance of the proposed FEC-aided BLMS algorithm is simply due to the decision feedback algorithm used to compensate for the SNR loss incurred during the decision directed mode.

As a second investigation, we examine the convergence behavior of the proposed BLMS algorithm for different block sizes. The results of this investigation are shown in Fig. 4 for a fixed training period of 100 symbols. Also shown, as a bench mark, is the convergence plot for the uncoded LMS algorithm operating in the training mode only. As one can see, the performance of the proposed BLMS algorithm is relatively insensitive to the block size used in the adaptation process.

B. BER Performance

Given the superior convergence properties of the proposed adaptive algorithm, it is of interest to examine its steady-state performance in terms of the system BER. In Fig. 5, we present simulation results for three scenarios: (i) The uncoded LMS algorithm, (ii) the coded LMS algorithm with no feedback applied, and (iii) our FEC-aided BLMS algorithm. In generating these plots, we used a large training period of 1000 symbols to ensure that steady-state has been reached before actual data detection takes place. From these results, one can see that the performance of all three systems is almost the same at relatively medium SNRs and after which the proposed FEC-aided algorithm starts to show a significant improvement relative to the uncoded LMS algorithm. This behavior is expected since the decoder estimates are not reliable enough for filter tap-weights adaptation. Note that as the SNR increases, the re-encoded data estimates become more reliable for filter adaptation and hence a higher gain than the coded LMS algorithm is achieved.

V. CONCLUSIONS

In this paper, we considered the application of an FEC-aided BLMS adaptive algorithm for DS-CDMA systems. We have shown that the use of decision feedback in conjunction with the BLMS algorithm can improve the performance of the coded BLMS algorithm with no feedback applied. Compared with the uncoded standard LMS algorithm, the FEC-aided BLMS proposed adaptive receiver converges to the same MSE value with no loss incurred. Moreover, we examined the steady-state performance of the proposed decision feedback adaptive receiver and showed that it is superior than the standard LMS algorithm when both employ the same channel code.

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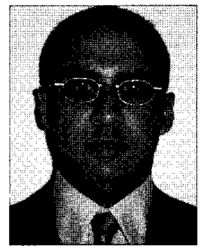
REFERENCES

[1] S. Moshavi, "Multi-user detection for DS-CDMA communications," *IEEE Commun. Mag.*, vol. 34, no. 10, pp. 124–137, Oct. 1996.
[2] S. Buzzi, M. Lops, and A. Tulino, "Partially blind adaptive MMSE interference rejection in asynchronous DS-CDMA networks over frequency-selective fading channels," *IEEE Trans. Commun.*, vol. 49, no. 1, pp. 94–108, Jan. 2001.
[3] M. Latva-aho and M. Juntti, "MMSE detection of DS-CDMA systems in fading channels," *IEEE Trans. Commun.*, vol. 48, no. 2, pp. 194–199, Feb. 2000.
[4] W. Hamouda and P. McLane, "A fast adaptive algorithm for MMSE receivers in DS-CDMA systems," *IEEE Signal Processing Lett.*, Feb. 2004.
[5] S. Miller, "An adaptive direct-sequence code-division multiple-access receiver for multi-user interference rejection," *IEEE Trans. Commun.*, vol. 43, no. 4, pp. 1746–1755, Apr. 1995.
[6] S. Miller, M. Honig, and L. Milstein, "Performance analysis of MMSE receivers for DS-CDMA in frequency-selective fading channels," *IEEE Trans. Commun.*, vol. 48, no. 11, pp. 1919–1929, Nov. 2000.
[7] A. Barbosa and S. Miller, "Adaptive detection of DS/CDMA signals in fading channels," *IEEE Trans. Commun.*, vol. 46, no. 1, pp. 115–124, Jan. 1998.
[8] G. Rajappan and M. Honig, "Signature sequence adaptation for DS-CDMA with multipath," *IEEE J. Select. Areas Commun.*, vol. 20, no. 2, pp. 384–395, Feb. 2002.
[9] U. Madhow and M. Honing, "MMSE interference suppression for direct-sequence spread-spectrum CDMA," *IEEE Trans. Commun.*, vol. 42, pp. 3178–3188, Dec. 1994.
[10] P. Rapajic and B. Vucetic, "Adaptive receiver structures for asynchronous CDMA systems," *IEEE J. Select. Areas Commun.*, vol. 12, no. 4, pp. 685–697, May 1994.
[11] M. Honig, U. Madhow, and S. Verdú, "Blind adaptive multiuser detection," *IEEE Trans. Inform. Theory*, vol. 41, no. 4, pp. 944–960, July 1995.
[12] D. Das and M. Varanasi, "Blind adaptive multiuser detection for cellular systems using stochastic approximation with averaging," *IEEE J. Select. Areas Commun.*, vol. 20, no. 2, pp. 310–319, Feb. 2002.
[13] S. Park and J. Doherty, "Generalized projection algorithm for blind interference suppression in DS-CDMA communications," *IEEE Trans. Circuits Syst. II*, vol. 44, pp. 453–460, June 1997.
[14] Z. Xu and M. Tsatsanis, "Blind adaptive algorithms for minimum variance CDMA receivers," *IEEE Trans. Commun.*, vol. 49, no. 1, pp. 180–194, Jan. 2001.
[15] U. Madhow, "Blind adaptive interference suppression for the near-far resistant acquisition and demodulation of direct-sequence CDMA signals," *IEEE Trans. Signal Processing*, vol. 45, no. 1, pp. 124–136, Jan. 1997.
[16] Y. Li and K. Liu, "On blind MIMO channel identification using second-order statistics," in *Proc. Inform. Science and Syst.*, Mar. 1996, pp. 1166–1171.
[17] N. Mangalvedhe and J. Reed, "Blind CDMA interference-rejection in multipath channels," in *Proc. IEEE VTC'97*, Phoenix AZ, May 1997.
[18] R. Gaudenzi, F. Giannetti, and M. Luise, "Blind adaptive interference-rejection linear detectors for CDMA receivers," in *Proc. ISSSTA'96*, Mainz, Germany, Sept. 1996.
[19] S. Verdú, *Multiuser Detection*, Cambridge University Press, U.K., 1998.
[20] H. V. Poor and X. Wang, "Code-aided interference suppression for DS/CDMA communications-part I: Interference suppression capability," *IEEE Trans. Commun.*, vol. 45, pp. 1101–1111, Sept. 1997.
[21] M. J. Juntti, B. Aazhang, and J. O. Lilleberg, "Iterative implementation of linear multiuser detection for dynamic asynchronous CDMA systems," *IEEE Trans. Commun.*, vol. 46, pp. 503–508, Apr. 1998.
[22] S. Haykin, *Adaptive Filter Theory*, 3rd ed., Englewood Cliffs, NJ: Prentice-Hall Inc. PTR, 1996.
[23] B. Farhang-Boroujeny, *Adaptive Filters Theory and Applications*, U.K.: John Wiley & Sons, Inc., 1998.



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