Adaptive Detection for DS-CDMA

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A review of adaptive detection techniques for direct-sequence code division multiple access (CDMA) signals is given. The goal is to improve CDMA system performance and capacity by reducing interference between users. The techniques considered are implementations of multiuser receivers, for which background material is given. Adaptive algorithms improve the feasibility of such receivers. Three main forms of receivers are considered. The minimum mean square error (MMSE) receiver is described and its performance illustrated. Numerous adaptive algorithms can be used to implement the MMSE receiver, including blind techniques, which eliminate the need for training sequences. The adaptive decorrelator can be used to eliminate interference from known interferers, though it is prone to noise enhancement. Multistage and successive interference cancellation techniques reduce interference by cancellation of one detected signal from another. Practical problems and some open research topics are mentioned. These typically relate to the convergence rate and tracking performance of the adaptive algorithm.

Keywords*—Adaptive equalizers, adaptive signal detection, code division multiaccess, decorrelation, interference suppression, lattice filters, least mean square methods, least squares methods, multiaccess communication, Wiener filtering.*

I. INTRODUCTION

Direct-sequence code division multiple access (DS-CDMA) is an important component of numerous recent communications systems, proposed and implemented. Applications include terrestrial cellular, wireless multimedia systems, and personal satellite mobile systems. To achieve increased data throughput and user capacities, it is important to optimize channel utilization. This paper will describe how adaptive detection algorithms can be applied to achieve this goal. A review of major techniques will be presented. Increasing CDMA channel utilization is rooted in multiuser communications research, so a brief background of this field will be given. For a detailed discussion of multiuser receivers, the reader is referred to [1]. All adaptive detectors to be described in this paper are approximate realizations of multiuser receiver structures.

Conventional asynchronous DS-CDMA systems allow each user to transmit and receive independently. Each receiver performs a simple correlation between the received baseband signal and the corresponding user's spreading sequence. In an additive white Gaussian noise (AWGN) channel with orthogonal spreading sequences, this approach would be optimal. Due to the asynchronicity of users and the need to support numerous users, such orthogonality is impossible, even on a hypothetical AWGN channel. Thus, the residual cross correlations are treated like AWGN in the classical analysis of these systems. This is acceptable as a first-order approximation due to the wide-band quasiwhite spectra of the spreading sequences typically used. However, this approach ignores the highly structured, cyclostationary statistics of the interference. System performance is rendered multiple-access interference (MAI) limited, and channel utilization is correspondingly low. The recently adopted CDMA terrestrial cellular standard IS-95 [2] is based on the conventional CDMA receiver but uses a RAKE[1] front-end and powerful, yet complex, error-control coding in an effort to alleviate this problem.

Due to the nonorthogonality of practical spreading sequences, the conventional correlator receiver suffers from the near–far problem. This implies that the cross correlation between the spreading sequence of the user of interest and the signal from a strong interferer can be larger than the correlation with the signal from the desired user. Detection is rendered unreliable. The classical way to deal with this is power control, whereby all users' transmit powers are controlled so that the powers received from all users are equal. This adds complexity to the system, and inaccuracies in power control have a detrimental impact on performance.

The optimal multiuser receiver of Verdú [3] demonstrated that DS-CDMA is not fundamentally MAI limited and can be near–far resistant. The optimal receiver comprises a bank of matched filters (MF's), one for each user, followed by a Viterbi algorithm for maximum likelihood sequence estimation (MLSE). Significantly, it was demonstrated that the output from the bank of matched filters provided a sufficient statistic for optimum detection. Use of such a receiver allows a tradeoff between complexity of signal selection and receiver complexity in a multiuser environment. The requirement to select spreading sequences

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[1] A tapped delay line receiver structure designed to collect energy from multipath signal components. Its form and function resemble a garden rake.

with good correlation properties is relaxed at a cost of increased receiver complexity. The practical application of this approach is limited by two significant issues. Due to the number of states required, the Viterbi algorithm is exponentially complex in the number of active users; thus, with large user populations, the problem becomes intractable. Less obvious is the complexity hidden in the matched filter bank. Although formulated in the context of an AWGN channel, the optimum multiuser receiver can be applied to practical intersymbol interference (ISI) or time-varying channels by combining the instantaneous channel impulse responses with the spreading codes [4], [5]. To realize the matched filter bank in such a case assumes much knowledge about every user in the system. It is necessary to know of the activity, time and phase synchronization, spreading sequence, power, and channel conditions for each user. With such information, a bank of matched filters can be synthesized. Much of this information is also required for the Viterbi algorithm within the receiver. Numerous simplified algorithms have been proposed to replace the Viterbi algorithm [6]–[8] in an attempt to make this approach less computationally demanding.

An important class of suboptimal receivers is the linear receiver described by Lupas and Verdú [9]. This includes the decorrelating receiver proposed earlier by Schneider [10]. These receivers perform a linear transform on the output of the matched filter bank. Symbol decisions are made on the output of the linear transform. The decorrelating linear receiver removes all cross correlations between users by selecting the transform as the inverse of the spreading sequence correlation matrix. Chen and Roy [11] showed how the decorrelating receiver could be realized adaptively. It was demonstrated that the decorrelating receiver has optimum near–far resistance. This means that performance is not sensitive to disparities in user signal power and relaxes the requirement to know all user powers. Using a simple inverse transform introduces potential problems. In some cases, the correlation matrix may be singular, in which case a generalized inverse may be substituted [9]. This was shown to also be optimally near–far resistant. In a manner analogous to zero-forcing equalization, noise enhancement may be a problem. Lupas generalized the decorrelator to the optimum linear receiver [9], in which a different linear transform is applied to the matched filter bank output. A means of calculating the transform based upon maximizing asymptotic efficiency [3] was described. In some cases, computing the optimum linear detector is still exponentially complex in the number of users. This presents a problem in nonstationary environments, as the calculation must be performed repeatedly. A large amount of information about all active users is still required.

An alternative is to select a transform to reduce the total mean square error (MSE) at the receiver output, thus alleviating the problem of noise enhancement. This has led to the development of the minimum mean square error (MMSE) receiver for CDMA [4], [12], which has also been shown to be near–far resistant [13], [14]. Under low noise conditions, the MMSE receiver becomes equivalent to the decorrelation detector, so both receivers exhibit the same asymptotic efficiency [9].

Multistage receivers [sometimes called parallel interference cancellation (PIC)] and successive interference cancellation (SIC) are alternative techniques involving the explicit detection and cancellation of each user's signal from the other users [15]–[20]. Such techniques also require accurate knowledge of channel parameters and may incur excessive complexity.

The above approaches all assumed a bank of well-synchronized matched filters. Numerous authors have approached this as a channel estimation problem [21]–[24]. With accurate channel estimation and user parameters, it is feasible that a bank of matched filters may be synthesized. Nevertheless, simultaneously and accurately estimating all user parameters, especially in nonstationary environments, remains a daunting task. Accurate amplitude estimates are critical to the performance of multistage and SIC schemes. With incorrect ordering of user powers, a successive interference canceler can lead to degraded performance [25]. It is important to consider the impact of imperfect parameter estimation [26]. In a cellular environment, a base station receiver may only have information about its own cell users, i.e., the in-cell interferers. Information about intercell interferers may be unavailable, or at best inaccurate and incomplete. The only protection against such interferers is their decreased power due to propagation loss and the spreading gain. Multiuser receiver performance can be very sensitive to having an incomplete set of interferer statistics [27]. Adaptive techniques are certain to play a role in channel estimation for multiuser receivers, but this approach will not be explored further in this paper.

The adaptive MMSE receiver [13], [28]–[32] may solve the assumed knowledge and complexity problems simultaneously. As matched filtering is a linear operation, it can be shown that an equivalent MMSE structure can be formulated by directly processing samples of the received signal. The matched filter bank can be eliminated. In practice, the receiver span must be made finite by truncating the response of the ideal MMSE filter. This can usually be done with negligible impact on performance. The number of coefficients in the MMSE receiver is thus related to the spreading gain rather than the number of active users. Directly processing samples of the received signal at chip (or subchip) intervals, the adaptive MMSE receiver operates like an adaptive equalizer. It implicitly realizes a filter that both is matched to the desired user's channel-affected signal and suppresses interference from other users. This is achieved by minimizing an MSE cost criterion adaptively. The minimization may be performed over all users or for each user individually. It can easily be shown [33] that these approaches are equivalent. The components of the MSE to be minimized include the effects of MAI, ISI, AWGN, and possibly narrow-band interference (NBI). Furthermore, with adequate filter span, the adaptive MMSE receiver acts as a RAKE receiver [34], [35]. It can combine energy from all multipath components of a user's signal without the extra complexity of separate synchronization and tracking

Table 1 Assumed Knowledge for Multiuser and Adaptive Receiver Structures

	Signature of desired user	Signatures of interferers	Timing of desired user	Timing of interferers	Relative Amplitudes	Training Sequence
Matched Filter	Y	N	Y	N	Y [a]	N
Optimum Multiuser	Y	Y	Y	Y	Y	N
Optimum Linear Receiver	Y	Y	Y	Y	Y	N
Decorrelator	Y	Y	Y	Y	N	N
SIC & Multistage	Y	Y [b]	Y	Y	Y	N
Adaptive MMSE	N	N	Y [c]	N	N	Y
Blind MMSE	Y	N	Y	N	N	N

[a]Strict power control required for adequate performance
[b]Adequate performance with information about most powerful interferers only
[c]Symbol timing only may be adequate

stages for each multipath. Thus, the approach is very flexible for the elimination of many forms of distortion present in the received signal. The idea was suggested for cross-coupled wire lines [5] for which decision feedback equalizers (DFE's) and linear equalizers were shown to suppress cyclostationary interference. At the time, generalization to other applications was also suggested. As interference in DS-CDMA is clearly cyclostationary (for a stationary channel, and approximately so for a fading channel with long coherence time), MMSE equalization is ideally suited. The only knowledge required by the receiver is a training sequence for the user of interest. As no knowledge of other users is required, the MMSE receiver can be considered a *single-user receiver* structure capable of *multiuser interference suppression*. Reception can be decentralized, which is an important practical advantage. Synchronization is required to within approximately one symbol interval, depending upon the receive filter time span. The imposition of a training sequence implies some system overhead, but it is likely that this would be incurred by pilot tones, preamble or midamble sequences in an approach utilizing channel estimation. Some authors [36] have explored blind techniques to eliminate the training sequence. This was proven feasible, given some constraints on the degree of distortion introduced by the channel. Furthermore, the technique has been shown to be effective for the elimination of NBI [37], [38] while concurrently suppressing MAI [39], [40].

The use of subchip sampled input is attractive, as this further reduces the synchronization requirements. In analogy with the fractionally spaced equalizer, the sampling instants within each chip interval are no longer critical. Increased quantity of taps in the filter implies increased complexity and potentially impaired convergence speed [41]. In addition, there is the possibility of poorly constrained coefficient adaption, though this may be overcome using a tap-leakage algorithm [42].

Each receiver structure considered in this paper requires different knowledge about the user of interest and the interfering users. This is summarized in Table 1.

Section II will define a mathematical framework for the system description. Common performance measures for multiuser CDMA receivers will be defined in Section III. The measures for the conventional CDMA receiver and the optimal receiver will be given to facilitate comparison with other structures. The generic linear receiver will be described in Section IV. The MMSE receiver will be described in Section V, including a catalog of adaptive techniques that may be used to realize this important class of receiver. Blind algorithms are considered in this section. Adaptive decorrelating receivers are treated in Section VI. Adaptive forms of multistage and successive interference cancellation are discussed in Section VII. Some comparisons will be made based upon numerical studies in Section VIII before conclusions are drawn.

II. System Model

A discrete baseband equivalent DS-CDMA signal model is used. A stationary channel and chip-matched filtering are assumed. The standard baseband model for a set of asynchronous DS-CDMA transmitters over stationary distorting channels is shown in Fig. 1. The equivalent form of Fig. 2 is more general and leads to easier analysis. The vector of samples at the output of the chip-matched filter that are used to detect the ith transmitted symbol can be written [13]

$$\mathbf{r}(i) = \sum_{j=1}^{L} \sqrt{E_j} b_j(i) \mathbf{p_j} + \mathbf{n}(i) \tag{1}$$

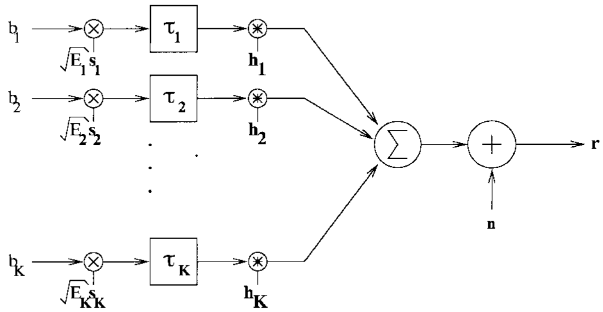


Fig. 1. DS-CDMA transmitter and channel. Equivalent baseband representation. For a synchronous system, all time offsets τ_i are equal. Vectors $\mathbf{h_i}$ represent channel impulse responses.

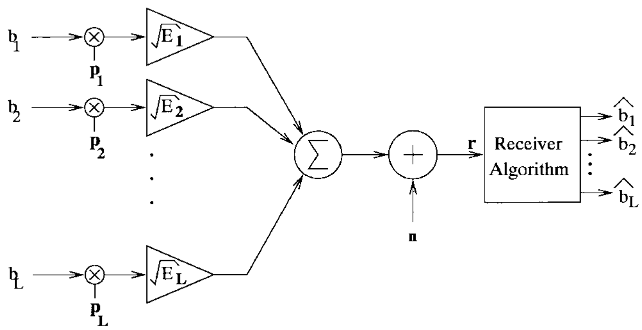


Fig. 2. Generic baseband representation of DS-CDMA system with symbols $\{b_i\}$ spread by vectors $\{\mathbf{p_i}\}$. One or more of the symbol estimates $\hat{b}_i$ may be formed.

where $\mathbf{r}(i) \in \Re^M$, $\Re^M$ is the M-dimensional real number field, and M is the receive filter length. Since the MMSE filter is time invariant, the dependence on symbol interval i will be omitted. Attention is limited to a finite observation time, though optimal detection would in general require an infinite observation interval. $\{\mathbf{p_j}\}$ is the set of unit-energy vectors which are modulated by the users' data symbols $\{b_j\} \in \{-1, 1\}$. The restriction to binary phase shift keying (BPSK) implied by the last statement is not a necessity, though it simplifies analysis. For higher level quadrature modulation, $\mathbf{r}$ can be defined over $\mathcal{C}^M$, the complex number field. The scalar E_j is the received energy corresponding to symbol b_j. This baseband model is general enough to facilitate analysis of both synchronous and asynchronous DS-CDMA systems over ideal and linear time-invariant channels. An asynchronous system can be treated as a synchronous system with additional users. Note that the effects of channel distortion, pulse shaping, sampling instant, and phase rotation can be included in the definition of vectors $\mathbf{p_j}$. Vector $\mathbf{n} \in \Re^M$ comprises noise samples. L is the number of bits contributing to the received signal in the time interval of interest.

For synchronous CDMA in an AWGN channel with a receiver filter spanning exactly one symbol, the $\mathbf{p_j}$ represent the baseband-sampled received spreading codes, and $L = K$ the number of active users. Hence, for coherent reception over an AWGN channel

$$\mathbf{p_j} = \mathbf{s_j} \tag{2}$$

the normalized spreading sequence used for the transmission of symbol b_j.

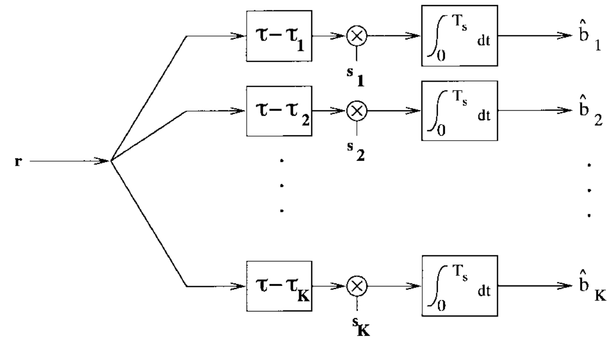


Fig. 3. Conventional asynchronous DS-CDMA receiver bank. Equivalent discrete baseband representation. For a synchronous system, all time offsets τ_i are equal.

Define matrices

$$\mathbf{P} = [\mathbf{p_1 p_2} \cdots \mathbf{p_K}] \tag{3}$$

$$\mathbf{E} = \text{diag}(E_1, E_2, \cdots, E_K) \tag{4}$$

and the vector of symbols transmitted during the time interval of interest

$$\mathbf{b} = (b_1 b_2 \cdots b_K)^T. \tag{5}$$

Hence, the received signal can be written

$$\mathbf{r} = \mathbf{P}\sqrt{\mathbf{E}}\mathbf{b} + \mathbf{n}. \tag{6}$$

The output of a bank of synchronized MF's, in the conventional receiver of Fig. 3, is a vector of K components given by

$$\mathbf{y} = \mathbf{P}^H\mathbf{r} \tag{7}$$

$$= \mathbf{H}\sqrt{\mathbf{E}}\mathbf{b} + \tilde{\mathbf{n}} \tag{8}$$

where $\tilde{\mathbf{n}}$ is a vector of colored noise samples. The Hermitian transpose operator[2] is denoted $(.)^H$. Matrix $\mathbf{H}$ comprises the normalized spreading sequence auto and cross-correlation values

$$\mathbf{H} = \mathbf{P}^H\mathbf{P}. \tag{9}$$

Similarly, define

$$\mathbf{G} = \sqrt{\mathbf{E}}\mathbf{H}\sqrt{\mathbf{E}} \tag{10}$$

as the matrix of unnormalized sequence correlations.

The conventional detector makes decisions

$$\hat{\mathbf{b}} = \text{sgn}(\mathbf{y}). \tag{11}$$

Many multiuser receiver structures use $\mathbf{y}$ as an input to subsequent signal-processing stages. Verdú showed that $\mathbf{y}$ formed a sufficient statistic for optimal detection [3].

If a receiver was designed to span $\mathcal{M}$ symbols, then the number of bits affecting the received signal at any given time is $L = \mathcal{M}K$. For example, with $\mathcal{M} = 3$, the matrix of data spreading vectors is

$$\mathbf{P} = \begin{bmatrix} \mathbf{s_1} & \mathbf{s_2} & \cdots & \mathbf{s_K} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{s_1} & \cdots & \mathbf{s_K} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{s_1} & \cdots & \mathbf{s_k} \end{bmatrix} \tag{12}$$

and

$$\mathbf{E} = \text{diag}(E_1, E_2, \cdots, E_K, E_1, \cdots, E_K, E_1, \cdots, E_K) \tag{13}$$

[2] Complex conjugate transpose $\mathbf{A}^H = (\mathbf{A}^*)^T$.

$$\mathbf{b} = (b_{1,-1} b_{2,-1}, \cdots, b_{K,-1}, b_{1,0}, \cdots, b_{K,0}, b_{1,1}, \cdots, b_{K,1}) \tag{14}$$

where $b_{k,i}$ represents the bit from user k with relative time offset i. $\mathbf{0}$ is a zero vector with the same length as $\mathbf{s_i}$. The general vector representation of (6) still applies.

In practice, spanning multiple symbol intervals would only be of benefit to control ISI. In that case, the $\mathbf{s_i}$ should be substituted by the vector representations of the channel-distorted spreading sequences. We will still refer to $\mathbf{p_i}$ as the spreading vectors to indicate that an equivalent system as in Fig. 2 could be constructed using these sequences in the transmitters with transmission occurring over a simple AWGN channel. Hence

$$\mathbf{p_i} = \mathbf{s_i} * \mathbf{h_i} \tag{15}$$

where the $*$ operator represents convolution and $\mathbf{h_i}$ is a discrete baseband representation of the channel response for symbol i.

In an asynchronous DS-CDMA system, each interfering user may contribute interference from multiple bits, so that $L > K$. In an AWGN channel, $L \leq 2K - 1$ if the receiver filter is chosen to span one symbol and is perfectly synchronized to the symbol from the user of interest.

For the asynchronous case, a matrix $\mathbf{P}$ similar to (12) can be defined, except that the structure will not be as regular. For example, a two-user system with a spreading gain of seven and with the second user offset by three chips relative to the first may have

$$\mathbf{P}^T = \begin{bmatrix} \mathbf{s_1}_1 & \mathbf{s_1}_2 & \mathbf{s_1}_3 & \mathbf{s_1}_4 & \mathbf{s_1}_5 & \mathbf{s_1}_6 & \mathbf{s_1}_7 \\ \mathbf{s_2}_4 & \mathbf{s_2}_5 & \mathbf{s_2}_6 & \mathbf{s_2}_7 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \mathbf{s_2}_1 & \mathbf{s_2}_2 & \mathbf{s_2}_3 \end{bmatrix} \tag{16}$$

where $\mathbf{s_k}_j$ are the elements of the spreading sequence for user k after appropriate scaling to ensure that $\mathbf{p_k}$ are unit energy vectors.[3] Received signal and MF output representations (1), (6), and (8) still apply.

It will be assumed throughout that it is required to form an estimate $\hat{b}_1$ of b_1. A single-user linear CDMA receiver can form this estimate via

$$\hat{b}_1 = \text{sgn}(\mathbf{c}^H \mathbf{r}) \tag{17}$$

where $\mathbf{c}$ is a vector of filter coefficients. The conventional CDMA receiver sets $\mathbf{c}$ equal to the spreading code. The decorrelating receiver selects $\mathbf{c}$ to eliminate multiple-access interference, and the MMSE receiver selects $\mathbf{c}$ to minimize the total mean squared error.

Let $\mathbf{Q} = \mathbf{PEP}^H$. Then the covariance matrix of the received vector is

$$\mathbf{R} = E[\mathbf{rr}^H] \tag{18}$$

$$= \sum_{l=1}^{L} E_l \mathbf{p}_l \mathbf{p}_l^H + \sigma_n^2 \mathbf{I}_M \tag{19}$$

$$= \mathbf{Q} + \sigma_n^2 \mathbf{I}_M \tag{20}$$

[3] In practice, carriers would not be coherent, so the effect of carrier phase would have to be applied to each spreading vector.

where σ_n^2 is the noise variance in the sampled received signal and $\mathbf{I}_M$ is the $M * M$ identity matrix. Independent data symbols have been assumed. Note that due to the cyclostationary character of the received signal, $\mathbf{R}$ is Hermitian, but it is *not* Toeplitz. This has important implications when considering fast adaptive algorithms to process the received signal. Many such algorithms rely upon the unit time-shifting property of the received signal manifested by a Toeplitz correlation matrix. That is, they depend upon the stationarity of the signal statistics. A DS-CDMA signal is cyclostationary in character. If the receiver is designed to span $\mathcal{M}$ symbol periods, then the correlation matrix will be block Toeplitz [43], i.e.,

$$\mathbf{R} = \begin{bmatrix} \mathbf{R}(0) & \mathbf{R}(1) & \cdots & \mathbf{R}(\mathcal{M}-1) \\ \mathbf{R}(1)^H & \mathbf{R}(0) & \cdots & \mathbf{R}(\mathcal{M}-2) \\ \vdots & & \ddots & \vdots \\ \mathbf{R}(\mathcal{M}-1)^H & \mathbf{R}(\mathcal{M}-2)^H & \cdots & \mathbf{R}(0) \end{bmatrix} \tag{21}$$

where $\mathbf{R}(j)$ are square Hermitian matrices of size equal to the number of samples per symbol.

III. Performance Measures

To compare the various forms of CDMA receivers, three important performance measures will be defined.

A. *Asymptotic Efficiency*

Asymptotic efficiency is a measure of the influence interfering users have on the bit error rate (BER) of the user of interest. A single user with energy E_k on an AWGN channel using BPSK modulation with noise variance σ^2 has a probability of bit error

$$P_{k_{SU}} = Q\left(\sqrt{\frac{E_k}{\sigma^2}}\right) \tag{22}$$

where $Q(x) = 1/(\sqrt{2\pi}) \int_x^\infty e^{-u^2/2}\, du$, the unit Gaussian tail probability.

With interfering users, the probability of error may increase. Define the *effective energy* $e_k(\sigma)$ as the energy that would be required for a single user in AWGN to achieve the BER that is observed in the presence of other users. Thus, the efficiency is given by the ratio of the energy required in the single-user system to the energy required in the multiple-user system for the same BER performance

$$\eta_k(\sigma) = \frac{e_k(\sigma)}{E_k}. \tag{23}$$

The asymptotic efficiency is defined as the limit in the high signal-to-noise-ratio (SNR) region

$$\eta_k = \lim_{\sigma \to 0} \frac{e_k(\sigma)}{E_k}. \tag{24}$$

η_k lies between zero and one, with a value of one indicating that the user of interest is not affected at all by the presence of other users.

The asymptotic efficiency of a synchronous DS-CDMA system with a conventional receiver is [1]

$$\eta_k = \max^2\left\{0,\, 1 - \sum_{j\neq k}\sqrt{\frac{E_j}{E_k}}\,|H_{jk}|\right\} \tag{25}$$

where H_{jk} is the element from matrix $\mathbf{H}$ representing the normalized cross correlation between spreading vectors for bits j and k. The asymptotic efficiency of Verdú's optimal multiuser receiver is given by [1]

$$\eta_k = \frac{d_{k,\min}^2}{\sqrt{E_k}} \tag{26}$$

where $d_{k,\min}$ is half of the minimum energy of the difference between two modulated signals that differ in the bit for user k (with the other bits unconstrained). For a two-user system, this becomes

$$\eta_1 = \min\left\{1,\, 1 + \frac{E_2}{E_1} - 2|H_{12}|\sqrt{\frac{E_2}{E_1}}\right\}. \tag{27}$$

B. Near–Far Resistance

The near–far resistance quantifies the robustness against unequal user powers. Power inequality can cause a near–far effect whereby a weak user is swamped by interference from a strong user. The near–far resistance is defined as the worst case asymptotic efficiency measured over all relative user energies

$$\overline{\eta}_k = \inf_{\substack{E_j>0\\ j\neq k}} \eta_k. \tag{28}$$

The near–far resistance of the conventional receiver in a synchronous channel is

$$\overline{\eta}_k = \begin{cases} 1 & \text{if } H_{jk} = 0,\, j\neq k \\ 0 & \text{otherwise.}\end{cases} \tag{29}$$

That is, the conventional receiver is not near–far resistant unless the spreading sequences are orthogonal. This is intuitive, as with finite cross correlation between sequences, the response due to an interferer in the correlator of the user of interest may be made arbitrarily large by increasing the interferer power.

The near–far resistance of the optimum multiuser receiver is

$$\overline{\eta}_k = \begin{cases} \dfrac{1}{\mathbf{H}_{kk}^{+}} & \text{if } k\text{th user signal is independent} \\ 0 & \text{if } k\text{th user signal is in subspace spanned by other signals}\end{cases} \tag{30}$$

where $\mathbf{H}^{+}$ is the Moore–Penrose generalized inverse of $\mathbf{H}$ [9], equal to the inverse if $\mathbf{H}$ is nonsingular. In the two-user case

$$\overline{\eta}_k = 1 - \mathbf{H}_{12}^2 \tag{31}$$

implying that the receiver is near–far resistant unless the spreading sequences are linearly dependent.

C. Probability of Bit Error

The ultimate goal in most communications systems is to decrease the probability of bit error. For a conventional synchronous system, the BER can be expressed

$$P_k = 2^{1-K} \sum_{\substack{\mathbf{b}\in\{-1,1\}^K\\ b_k=-1}} Q\left(\frac{\sqrt{E_k} - \sum_{j\neq k}\sqrt{E_j}H_{kj}b_j}{\sigma_n}\right). \tag{32}$$

There is no simple closed-form expression for the optimum detector. Bounds on BER performance were given in [1] and [3]. The simplest bound is the single-user bound.

IV. Linear Receiver

Many adaptive DS-CDMA detectors are based on the linear multiuser receiver. The symbol decisions are made using

$$\hat{\mathbf{b}} = \text{sgn}(\mathbf{z}) \tag{33}$$

where

$$\mathbf{z} = \mathbf{T}\mathbf{y} \tag{34}$$

$\mathbf{y}$ is the output from the matched filter bank and $\mathbf{T}$ is a matrix representing a linear transformation. This is given in a multiuser form. It is also possible to define a single user form for user k

$$\hat{b}_k = \text{sgn}(\mathbf{z}_k) \tag{35}$$

where

$$\begin{aligned} \mathbf{z}_k &= \mathbf{t}_\mathbf{k}^H\mathbf{y} && (36)\\ &= \mathbf{c}_\mathbf{k}^H\mathbf{r} && (37)\end{aligned}$$

recognizing that $\mathbf{y}$ is a linear transform of the input from (8) and so the matched filtering and the transform $\mathbf{T}$ can be combined. Vector $\mathbf{t}_\mathbf{k}^H$ is row k of matrix $\mathbf{T}$. $\mathbf{c}_\mathbf{k}$ represents the coefficients of an equivalent filter operating directly on the received signal.

Selection of $\mathbf{T}$ or $\mathbf{c}_\mathbf{k}$ is made by minimizing some cost criterion. The minimization can be made over all users for (34) or by just considering one user using (36).

The form given by (34) is convenient, as it can represent many linear receivers, as follows.

1) $\mathbf{T} = \mathbf{I}_K$: The conventional DS-CDMA receiver.
2) $\mathbf{T} = \mathbf{H}^{-1}$: The decorrelating receiver, so that

$$\begin{aligned} \hat{\mathbf{b}} &= \text{sgn}(\mathbf{T}\mathbf{y}) && (38)\\ &= \text{sgn}\left(\sqrt{\mathbf{E}}\mathbf{b} + \mathbf{P}^{-1}\mathbf{n}\right). && (39)\end{aligned}$$

It is clear that this detector has decoupled all users' signals and is near–far resistant. The detector of [11] is an adaptive approximation of this receiver.

3) $\mathbf{T} = (\mathbf{G} + \sigma_n^2\mathbf{I}_K)^{-1}$: The MMSE receiver that minimizes $E[(\mathbf{z}-\mathbf{b})^H(\mathbf{z}-\mathbf{b})]$. The MMSE receivers proposed in [13], [28], and [31] are adaptive forms of this receiver.

4) The optimum linear multiuser receiver, described by Lupas [9], where $\mathbf{T}$ is chosen to maximize asymptotic efficiency.

V. The Adaptive MMSE Receiver

The linear MMSE receiver defined by

$$\mathbf{T} = (\mathbf{G} + \sigma_n^2 \mathbf{I_K})^{-1} \tag{40}$$

in the previous section would require knowledge of $\mathbf{G}$ and a bank of synchronized matched filters. Thus, it appears to suffer the problem of large assumed knowledge in common with many multiuser receivers. Repeated matrix inversions would be necessary if the channel was nonstationary, so the technique would also be computationally expensive. The advantage of this receiver is that it can be well approximated by an adaptive finite impulse response (FIR) filter. Indeed, it can be treated exactly as an adaptive equalization problem with an MSE criterion [44].

An important feature is that the MSE can be minimized on a user-by-user basis, leading to

$$\hat{b}_k = \mathrm{sgn}\big(\mathbf{c_k}^H \mathbf{r}\big) \tag{41}$$

where

$$\begin{aligned}\mathbf{c_k} &= (\mathbf{Q} + \sigma_n^2 \mathbf{I})^{-1} \sqrt{E_k}\mathbf{p_k} &(42)\\ &= \mathbf{P}[(\mathbf{G} + \sigma_n^2 \mathbf{I_K})^{-1}]_k &(43)\end{aligned}$$

where $[.]_k$ represents the extraction of row k from a matrix. The form of (42) can be derived from straightforward Weiner–Hopf theory [45], with

$$\mathbf{c_k} = \mathbf{R}^{-1} \boldsymbol{\alpha}_\mathbf{k} \tag{44}$$

using the correlation matrix $\mathbf{R}$ from (20) and the cross-correlation vector

$$\begin{aligned}\boldsymbol{\alpha}_\mathbf{k} &= E[\mathbf{r} b_k^*] &(45)\\ &= \sqrt{E_k}\mathbf{p_k} &(46)\end{aligned}$$

for independent noise and user data random processes. Equation (43) comes from a combination of (40) and (8). The equivalence of (42) and (43) can be shown using Woodbury's identity.[4]

The near–far resistance of the MMSE detector, for the first user, is given by [13][5]

$$\overline{\eta} = 1 - \boldsymbol{\rho}^T \mathbf{H_I}^{-1} \boldsymbol{\rho} \tag{47}$$

[4] *Woodbury's identity* (or the *matrix inversion lemma* [45]). For positive definite square matrices $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{D}$ related by $\mathbf{A} = \mathbf{B}^{-1} + \mathbf{C}\mathbf{D}^{-1}\mathbf{C}^H$, the inverse of A is given by $\mathbf{A}^{-1} = \mathbf{B} - \mathbf{B}\mathbf{C}(\mathbf{D} + \mathbf{C}^H\mathbf{B}\mathbf{C})^{-1}\mathbf{C}^H\mathbf{B}$.

[5] A similar expression exists when $\mathbf{H_I}$ is singular [13].

where $\mathbf{H_I}$ is the matrix of correlations between interferers, i.e., $\mathbf{H}$ without the first row and column. Vector $\boldsymbol{\rho}$ contains the correlations between the first user and other users, i.e., the first column of $\mathbf{H}$ without the first entry. The MMSE receiver is near–far resistant provided the spreading vector for the user of interest is not linearly dependent on other spreading vectors.

An expression for the BER performance of the MMSE receiver can be calculated. The filter output is

$$z_k = \mathbf{t_k}^H \mathbf{H} \sqrt{\mathbf{E}}\mathbf{b} + \mathbf{t_k}^H \mathbf{P}^H \mathbf{n} \tag{48}$$

with mean

$$\overline{z}_k = \mathbf{t_k}^H \mathbf{H} \sqrt{\mathbf{E}}\mathbf{b} \tag{49}$$

and variance

$$\sigma_{z_k}^2 = \sigma_n^2 \mathbf{t_k}^H \mathbf{H} \mathbf{t_k}. \tag{50}$$

To find the probability of error, it is necessary to sum the Gaussian tail probability function over all possible data vectors using the above expressions for mean and variance. Thus, see (51) at the bottom of the page. This can be seen as a specific instance of the expression given for the linear receiver described by Lupas [9].

A simpler approximation can be derived by characterizing the distribution for z_k, conditioned on $b_k = 1$. Assuming the user data to be zero-mean, independently distributed, and invoking the central limit theorem, z_k may be considered a Gaussian distributed random variable. The mean filter output is given by

$$\begin{aligned}\overline{z}_k &= E[z_k | b_k = 1] &(52)\\ &= \mathbf{c_k}^H \boldsymbol{\alpha}_\mathbf{k} &(53)\\ &= 1 - J_{\min_k}. &(54)\end{aligned}$$

$J_{\min}$ is the minimum MSE value for user k, given by

$$J_{\min_k} = 1 - \boldsymbol{\alpha}_\mathbf{k}^H \mathbf{R}^{-1} \boldsymbol{\alpha}_\mathbf{k}. \tag{55}$$

The variance of the filter output is

$$\begin{aligned}\sigma_{z_k}^2 &= E\big[(z_k - \overline{z}_k)^2 | b_k = 1\big] &(56)\\ &= \overline{z}_k - \overline{z}_k^2 &(57)\\ &= J_{\min_k}(1 - J_{\min_k}). &(58)\end{aligned}$$

Hence, an approximation to the BER performance for the ideal MMSE receiver of user k is

$$P_k \approx Q\left(\sqrt{\frac{1 - J_{\min_k}}{J_{\min_k}}}\right). \tag{59}$$

Previous publications [31], [46] dealing with asynchronous DS-CDMA systems have used a simpler Gaussian

$$P_k = 2^{1-L} \sum_{\substack{\mathbf{b} \in \{-1,1\}^L \\ b_k = -1}} Q\left(\frac{\sqrt{E_k}\mathbf{t_{k_k}} + \sqrt{E_k}\sum_{j \neq k} \mathbf{t_{k_j}} H_{jk} + \sum_{i \neq k} \sqrt{E_i} b_i \sum_{j=1}^{L} \mathbf{t_{k_j}} H_{ji}}{\sqrt{\sigma_n^2 \mathbf{t_k}^T \mathbf{H} \mathbf{t_k}}}\right). \tag{51}$$

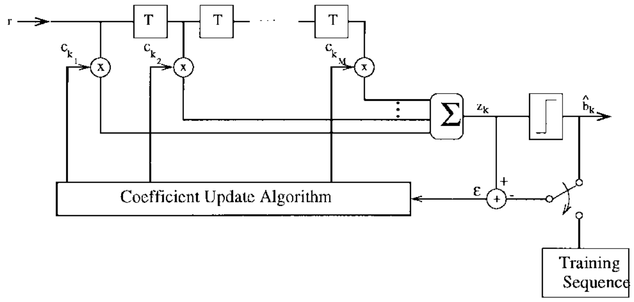


Fig. 4. Single-user adaptive MMSE receiver for user k based on a transversal FIR filter.

assumption, centered on the $b_k \in \{-1, 1\}$ signal points, giving

$$P'_k \approx Q\left(\frac{1}{\sqrt{J_{\min_k}}}\right). \tag{60}$$

It is apparent from (54) that in low SNR cases, the mean of the Gaussian distribution is significantly closer to zero, and hence the BER is higher than given by (60). To evaluate either bound, only $J_{\min_k}$ need be known. From (20), (46), and (55), this requires knowledge of all spreading sequences, powers, and the noise variance.

Decision feedback structures have been proposed for adaptive MMSE receivers. Abdulrahman [29] described a single-user decision feedback structure. This approach was found to be no more effective than a feed-forward filter in suppressing MAI [28], though it is of benefit to counter ISI. Multiuser decision feedback is effective for suppression of MAI, as analyzed by Klein [4] for a fixed filter with optimum coefficients. Due to the causality constraint on the feedback filter, only symbols from previously detected users may be fed back, making the multiuser decision feedback filter conceptually equivalent to successive interference cancellation. Adaptive forms have been considered [35], [47] and will be described in Section VII.

Rapajic [48] showed that the normalized MMSE receive filter coefficients would make a better choice for spreading sequence than the original sequence. Thus, an adaptive transmitter–receiver structure was derived, in which the transmit spreading sequences were adapted in concert with the receiver filter coefficients. This leads to lower MAI and was proven to give decreased MMSE. System capacity is improved, as will be shown in Section VIII.

It is well known [45] that the MMSE filter can be approximated adaptively by many algorithms. The application of some of these algorithms will be described in the following subsections.

A. Least Mean Squares (LMS)

The LMS algorithm approximates the method of steepest descent. It operates by taking small steps on the quadratic error performance surface in the direction of negative gradient. Instantaneous gradient estimates are used. Coefficient updates follow

$$\hat{\mathbf{c}}_{\mathbf{k}}(n+1) = \hat{\mathbf{c}}_{\mathbf{k}}(n) - \mu\nabla\left[|e_k(n)|^2\right] \tag{61}$$

$$= \hat{\mathbf{c}}_{\mathbf{k}}(n) + \mu E[\mathbf{r}_{\mathbf{k}}(n)e_k^*(n)] \tag{62}$$

$$\approx \hat{\mathbf{c}}_{\mathbf{k}}(n) + \mu \mathbf{r}_{\mathbf{k}}(n)e_k^*(n) \tag{63}$$

where the index n indicates the time epoch (and will be omitted where no ambiguity arises). Assuming knowledge of the bit to be detected, the error is defined by

$$e_k(n) = b_k(n) - z_k(n). \tag{64}$$

Scalar μ is a step size, bounded by the conflicting requirements of stable operation and acceptable convergence speed.

Fig. 4 shows the structure of an adaptive MMSE CDMA receiver for a single user, realized by direct processing of the sampled received signal. This highlights that a major advantage of the adaptive MMSE approach is simplicity. Implementation may be by a simple tapped delay line filter with appropriate tap update mechanism. Accurate synchronization and multiuser processing stages are unnecessary.

The adaptive MMSE approach can similarly be applied to a multiuser reception structure, as initially proposed by Xie [12]. Fig. 5 illustrates one implementation of the multiuser MMSE receiver whereby the matched filter bank output is processed by a simple transversal adaptive FIR filter. The multiuser approach has the disadvantage of added complexity, with the requirement of a bank of synchronized correlators. An advantage is that a shorter filter may be used to process the output of the fixed correlator bank. This potentially delivers more rapid filter convergence [41]. By vectorizing the filter coefficients, detection can be centralized for all users, a useful attribute in a base-station receiver.

The use of a finite, nonzero step size in the adaptive algorithm implies that the coefficients wander, so there will always be some filter misadjustment. The mean squared error above the MMSE is termed excess mean squared error J_{ex}. The misadjustment is defined by [45]

$$\mathcal{M} = \frac{J_{ex}(\infty)}{J_{\min}} \tag{65}$$

$$= \sum_{i=1}^{M} \mu\lambda_i/(2-\mu\lambda_i) \tag{66}$$

where $J_{ex}(\infty)$ is the excess MSE after complete convergence and λ_i are the eigenvalues of the autocorrelation matrix $\mathbf{R}$ of size M by M. In a nonstationary environment, tracking lag will also result in excess MSE.

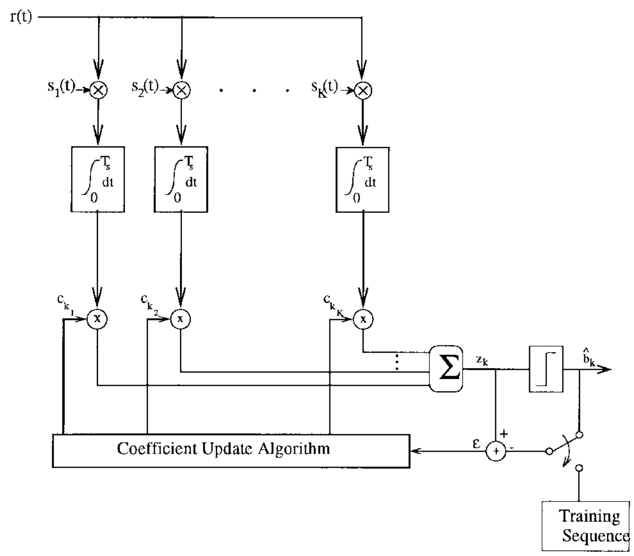


Fig. 5. Multiuser adaptive MMSE receiver for user k based on a transversal FIR.

For nonideal filter coefficients, the MSE at the receiver output is given by

$$J_k = 1 - \mathbf{c}_k^H \boldsymbol{\alpha} - \boldsymbol{\alpha}^H \mathbf{c}_k + \mathbf{c}_k^H \mathbf{R}\mathbf{c} \tag{67}$$

when the desired signal has unit variance [45]. Thus, using (53)

$$\overline{z}_{k,1} = 1 - J_k - \boldsymbol{\alpha}^H \mathbf{c}_k + \mathbf{c}_k^H \mathbf{R}\mathbf{c}. \tag{68}$$

If the misadjustment of $\mathbf{c}_k$ is small so that

$$\boldsymbol{\alpha}^H \mathbf{c}_k \approx \mathbf{c}_k^H \mathbf{R}\mathbf{c}_k \tag{69}$$

then

$$\overline{z}_{k,1} \approx 1 - J_k. \tag{70}$$

Likewise, the variance

$$\sigma_z^2 = \mathbf{c}_k^H \mathbf{R}\mathbf{c}_k - \overline{z}_{k,1}^* \overline{z}_{k,1} \tag{71}$$

and so invoking (69)

$$\sigma_z^2 \approx J_k(1 - J_k). \tag{72}$$

Thus, for small misadjustment, the BER of the adaptive MMSE receiver can be written

$$P_k \approx Q\left(\sqrt{\frac{1-J}{J}}\right). \tag{73}$$

Related expressions were given in [13] and [30]. A very good Gaussian fit to the conditional receiver output probability distributions, using the means and variances derived above, has been confirmed by extensive computer simulations. In an environment with high noise or interference, it is necessary to disable decision-directed operation; otherwise, a reversal can occur in the filter output (the filter trains to the opposite of the desired signal in the bipolar case), and the conditional probability distributions no longer fit the above parameters.

A variation of the LMS algorithm given in (63) is the normalized (N)LMS algorithm, which is attractive in practice. The step size is chosen by the algorithm to be equal to the inverse of the instantaneous input signal power [45]

$$\mu = \frac{\overline{\mu}}{a + \|\mathbf{r}(n)\|^2} \tag{74}$$

where $\overline{\mu}$ is a constant, which can be used to adjust the convergence speed, and a is a small constant to ensure stability when the input signal energy is small. Nominally, $\overline{\mu}$ is chosen equal to unity. This short-term average is an approximation to the optimal step size for quickest convergence.

The filter would normally require an initial training period, during which the error signal used for the update is generated as the difference between the FIR filter output and a stored copy of the known transmitted sequence. After training, the coefficients may be locked, be applicable for a stationary environment, or continue to adapt and track channel variations in a decision-directed manner. In that phase of operation, the error is formed using

$$e_k(n) = \hat{b}_k(n) - \mathbf{c}_{\mathbf{k}}^H \mathbf{r}. \tag{75}$$

Occasionally, retraining may be necessary due to channel perturbations, or changes such as users' arriving or departing. The most significant problem with the adaptive LMS form of the MMSE receiver is inadequate convergence speed and tracking capability. Slow convergence implies long overhead during training and retraining periods, during which time no useful data may be sent. This is an active area of research [30], [49]–[52].

The major influences on the convergence speed of the LMS filter are the filter length [41] and the eigenvalue spread of the input correlation matrix

$$\rho = \frac{\lambda_{\max}}{\overline{\lambda}_{\text{eff}}} \tag{76}$$

where $\lambda_{\max}$ is the maximum eigenvalue of $\mathbf{R}$ and $\overline{\lambda}_{\text{eff}}$ is the effective mean eigenvalue (allowing for fractionally spaced structures, where insignificant eigenvalues need not be considered [44]).

With large spreading gains, receive filters may become very long. Various authors have proposed ways to overcome this, included the cyclically shifted filter bank of Madhow [13] and the dimensionality reduction schemes of Ström [53]. Oppermann [54] considered parallel adaption of multiple filters with differing step sizes and repeated filter training over the same data. These measures were shown to improve the stability, convergence speed, and tracking ability of a system employing the LMS algorithm.

Rapajic [28] proposed a fractionally chip-spaced structure. This has the advantage of simplifying synchronization. The sampling instant within chip periods is no longer important. A major disadvantage of this approach is increased filter length, and thus increased complexity and potentially slower convergence. The synchronization requirements of the single-user MMSE receiver are regardless much less stringent than most multiuser receivers, as only one user needs to be synchronized and tracked, so the motivation to use a fractionally spaced structure may be diminished.

The main benefits of the LMS algorithm are its simplicity and its robustness to noise. The algorithm complexity is $\mathcal{O}(M)$, where the "big O" notation is used to indicate that the algorithm complexity is proportional to M, the length of the tapped delay line. Considering the expression for complexity in more detail, let $M = \mathcal{M}p$, where $\mathcal{M}$ is the symbol span of the filter and p is the number of samples per symbol. The complexity can now be written $\mathcal{O}(\mathcal{M}p)$.

B. Recursive Least Squares

Application of the recursive least squares (RLS) algorithm to the linear MMSE CDMA receiver has been considered by numerous authors [31], [55], [56]. It minimizes the cost function based upon the sum of squares

$$J_{\text{LS}} = \sum_{i=1}^{n} \lambda^{n-i} |e(i)|^2 \tag{77}$$

and typically provides much more rapid convergence than the LMS algorithm. Furthermore, the convergence rate is independent of the eigenvalue spread of the correlation matrix.

A major impediment to using the RLS algorithm is its computational complexity, $\mathcal{O}(\mathcal{M}^2 p^2)$. There have been numerous "fast" RLS algorithms proposed [45], [57] for use in system identification and equalization applications. These algorithms are termed "fast" because in conventional applications they implement the RLS algorithm with much lower complexity. As the receiver is grossly fractionally spaced relative to the data symbols, these algorithms provide no computational advantage [31], [49]. The fast algorithms typically exploit the case when only a small amount of new data is introduced into the receiver at each symbol interval, which is clearly not the case for DS-CDMA, when each new symbol is represented by many sample values. The complexity becomes $\mathcal{O}(\mathcal{M}p^3)$ [58], with p typically much larger than $\mathcal{M}$.

It is well documented [45] that the standard RLS algorithm is prone to numerical instability and divergence problems. This is of particular concern in the DS-CDMA system with low background noise, as the number of significant eigenvalues of the correlation matrix can be much less than the filter dimension. The insignificant eigenvalues lie near the noise floor and so may cause the correlation matrix to be ill conditioned [59].

Due to the quicker convergence of the RLS algorithm, it would be attractive to believe that it could also be more effective in tracking nonstationary channel conditions. It is known [45], [60] that this is not necessarily the case. The simpler, standard LMS algorithm may be just as effective, depending upon the exact environment under consideration. The tracking behavior of these algorithms will be compared with an example later in this paper.

Yoshida [34] demonstrated improved performance in fast flat fading channels by using differential coding of the user data symbols. This reduces the adaptive algorithm's requirement to track the channel phase variations. The error fed back to update the MMSE filter coefficients is computed after the differential decoder, so that phase changes significantly slower than the symbol rate do not have to be tracked. The filter coefficients can thus adapt more effectively to achieve interference cancellation. Honig [52] proposed a differential least squares (DLS) algorithm to cope with flat fading channels. A similar approach by Zhu and Madhow [50] further relaxes the channel amplitude tracking requirement. Systems with differential encoding were shown by simulation to be much more effective in tracking fading channels compared to the standard RLS algorithm. Further investigations considering performance over frequency-selective channels are anticipated.

C. Transform Domain LMS (TRLMS)

The potential problems with the RLS and standard LMS algorithms motivate the search for alternative adaptive algorithms for this application. The goal of TRLMS techniques is to orthogonalize the receiver input signal, thus increasing the LMS algorithm convergence speed [61]–[63].

A fixed transform, represented by matrix $\mathbf{X}$, is applied to the input signal

$$\mathbf{r_n} \rightarrow \mathbf{X}\mathbf{r_n} \tag{78}$$

in an attempt to diagonalize the correlation matrix $\mathbf{R}$

$$\mathbf{R_X} = \mathbf{X}\mathbf{R}\mathbf{X}^H \tag{79}$$

$$\approx \text{diag}[\lambda_1,\, \lambda_1,\, \cdots,\, \lambda_M] \tag{80}$$

where λ_i are the eigenvalues of $\mathbf{R}$. The equality is exact if $\mathbf{X}$ is the Karhunen–Lôeve Transform. With an approximately diagonal correlation matrix, the LMS algorithm can use multiple, optimal step sizes, one for each filter tap

$$c_{n+1} = c_n + \mu \begin{bmatrix} \hat{\lambda}_1 & 0 & \cdots & 0 \\ 0 & \hat{\lambda}_2 & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & \hat{\lambda}_M \end{bmatrix}^{-1} \epsilon_n^* \mathbf{r_n} \tag{81}$$

where $\hat{\lambda}_j$ is an estimate of the eigenvalue j of $\mathbf{R_X}$ made by a sliding average of the energy at filter tap j. This is a form of the Newton–Gauss update algorithm [60], [63], [64]. The convergence of the algorithm is now dictated by eigenvalue spread of the matrix

$$\text{diag}[\hat{\lambda}_1, \cdots, \hat{\lambda}_M]^{-1}\mathbf{R_X} = \hat{\mathbf{R}}_{\mathbf{X}}^{-1}\mathbf{R_X} \tag{82}$$

$$\approx \mathbf{I_M}. \tag{83}$$

Ideally, the eigenvalue spread is now unity, so convergence can be expected to be much more rapid. The time constants for each mode of convergence have been optimized.

The principle problem with using the TRLMS technique is choosing a suitable fixed transform that will give significant convergence improvement to justify the increased complexity. This is especially the case on nonstationary channels. Generic transforms such as the discrete Fourier transform and discrete cosine transform can be considered [61], [63], [65], though in practice, these have been found to give little or no benefit for this application [66]. Additionally, due to the fractional nature of the filter, the numerous small eigenvalues can cause numerical divergence when inverted in update (81). A mechanism to disable updates on taps corresponding to such eigenvalues may be employed. While preventing algorithm divergence, such an approach may impair convergence speed.

Transforms can be used for dimensionality reduction. The high dimensionality of the received signal and filter may be a significant impairment to algorithm convergence speed. Typically, there will be a large number of small eigenvalues near the noise floor, indicating modes for which convergence may be slow. Transform matrix $\mathbf{X}$ is selected of size $\mathcal{L} * M$, where $\mathcal{L} < M$ is the reduced dimension. Ström [53] derived conditions for the optimum transform. It was shown that the transform was not unique. It requires knowledge of all user spreading sequences and delays. By using the Cramér–Rao bound, it was shown that no decrease in performance can be expected from using the optimum dimensionality reduction [67]. In practice, the optimum transform is complex to compute, so suboptimal approaches have been proposed. Another approach is to project the received vector onto a lower dimensional subspace spanned by the eigenvectors of the received correlation matrix corresponding to the largest eigenvalues. These correspond to the principle, or highest power, components of the received signal. This approach was shown to give superior performance to the cyclically shifted filter bank of [13].

Lee [59] presented an adaptive orthogonalization technique based on the structure of Fig. 6. The coefficients are derived from the Cholesky factorization of the correlation matrix. The result is the set of backward prediction errors that are well known to form an orthogonal set. Lee demonstrated that with such prefiltering, convergence of an LMS MMSE filter for CDMA was rendered insensitive to eigenvalue spread.

D. Lattice Algorithms

Lattice preprocessing provides an adaptive way of realizing the orthogonalization attempted by the TRLMS technique, thus improving convergence of the final transversal stage at a cost of having to adapt extra coefficients within the lattice. A lattice with appropriate reflection coefficients performs a Gram–Schmidt orthogonalization of its input signal [45], [60], [68].

An adaptive lattice filter was employed by Jitsukawa and Kohno [69], [70] with multiuser MMSE receivers. This was extended to spatial and temporal filtering for DS-CDMA [71], [72].

This approach promises to give improved convergence speed with good numerical stability [73], [74]. The generic structure of one form of the lattice receiver, a multichannel joint process estimator, is given in Fig. 7. The function of the lattice section, in the upper half of Fig. 7(a), is to generate mutually orthogonal backward prediction errors $\mathbf{e_b(m)}$, which are used as inputs to a multiple regression filter [45]. Due to its decorrelated input, good convergence speed for the lower section of Fig. 7(a) can be achieved even with a simple LMS update algorithm. The lattice reflection coefficients are $p * p$ matrices, where p is the number of channels, i.e., samples per symbol. The multiple regression filter coefficients are vectors of p elements.

The optimum values for the lattice reflection coefficients can be computed using a multichannel form of the well-known Levinson–Durbin algorithm [60], [68]. However, this requires knowledge of the received signal's autocorrelation properties.

In practice, the correlation parameters are not known, so the filter coefficients must be estimated adaptively. Either an MSE or least squares (LS) cost criterion can be used to derive such an algorithm. A multichannel gradient adaptive lattice (GAL) algorithm using an MSE criterion was proposed [73], as this should result in lower complexity and similar performance to the LS approach. Updates can be computed using an error feedback approach or by the correlation quotient method. The latter method is conceptually easier, as updates of prediction error autocorrelations and cross correlations are formed using weighted-sum averaging, and a new estimate of the lattice coefficient is made at each iteration by taking the quotient. Nevertheless, this method is more prone to numerical difficulties [60], so an asymmetric form of the error feedback form may be used. Furthermore, *a priori* error values must be used to derive the feedback during decision-directed operation, as the desired response is unknown until after the filter has produced a data estimate. The multichannel lattice algorithm described has been shown to give good performance and numerical qualities [73]. The corresponding cost is high computational complexity of $\mathcal{O}(\mathcal{M}p^3)$.

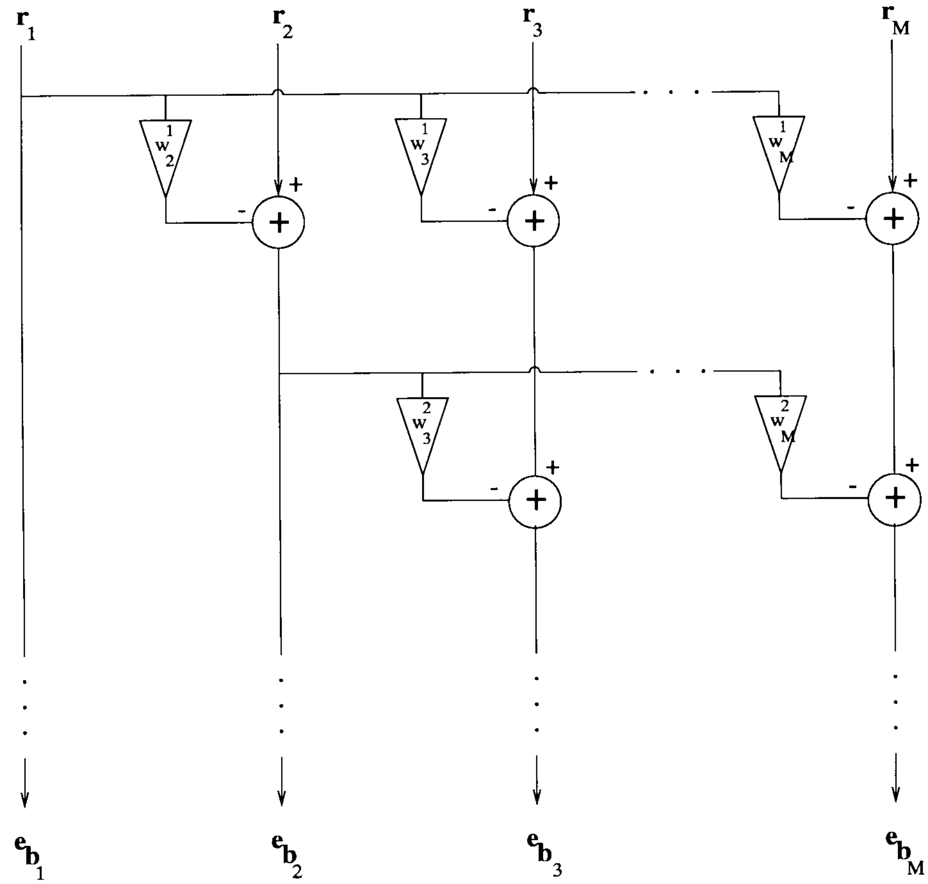


Fig. 6. Structure for adaptive Gram–Schmidt orthogonalization of received signal [59].

E. Blind Adaptive MMSE Receivers

A major impediment to the use of the adaptive MMSE receiver is the requirement for a training sequence. This implies extra coordination between the receiver and transmitters as well as system overhead. Time is spent training the receiver rather than sending useful data. Blind adaptive techniques can eliminate the need for a training sequence [75]. The method proposed by Honig *et al.* [36] requires the receiver to know the spreading sequence and timing of the user of interest. The adaptive receiver's impulse response is decomposed into two orthogonal components. For user k, the vector representing the receive filter coefficients is

$$\mathbf{c_k} = \mathbf{s_k} + \mathbf{x_k}. \tag{84}$$

The first component, $\mathbf{s_k}$, is the spreading sequence used for user k and is nonadaptive. This provides an anchor for the receive filter updates. The second component, $\mathbf{x_k}$, is adaptive. Updates are constrained to be orthogonal to the anchor vector. The optimization criterion is to minimize output energy (MOE). It is shown that this converges to the MMSE filter coefficients.

The above approach assumes that the spreading sequence for the user of interest is known exactly at the receiver. In practice, an estimate $\hat{\mathbf{s}}_\mathbf{k}$ of the actual received spreading vector $\mathbf{s_k}$ is used as a filter anchor. In the event of a mismatch, as would be the case in the presence of channel distortion, further constraints on $\mathbf{x_k}$ must be imposed. The receive filter's excess energy, defined by $\chi = ||\mathbf{x_k}||^2$, must be allowed to grow large enough to effectively cancel interference, yet is bounded so as to prevent complete cancellation in the direction of $\mathbf{s_k}$. It is required that the estimate $\hat{\mathbf{s}}_\mathbf{k}$ be closer to the $\mathbf{s_k}$ than to the space spanned by the interferers [36]. If this is not the case, no suitable range for χ can be found.

It was shown that the blind algorithm convergence was quite noisy compared to a training-based approach. This problem is more pronounced when mismatch between $\mathbf{s_k}$ and $\hat{\mathbf{s}}_\mathbf{k}$ is large. It was suggested that initial convergence be accomplished via the blind, constrained MOE algorithm [36]. This can be followed by a decision-directed MMSE algorithm once the signal-to-interference ratio at the receiver output has grown sufficiently large, implying that decision errors are infrequent.

Madhow [76] has extended the idea to allow joint timing acquisition and demodulation of DS-CDMA in a near–far tolerant manner.

Wang [77] developed a blind multiuser receiver based on projection of the received signal onto signal and noise subspaces. The signal subspace is spanned by the user signature sequences. The basis for the noise subspace comprises the eigenvectors of the correlation matrix corresponding to the eigenvalues equal to the noise variance. The decorrelating and MMSE receive filter coefficients were recast in terms of projections onto the signal subspace. As

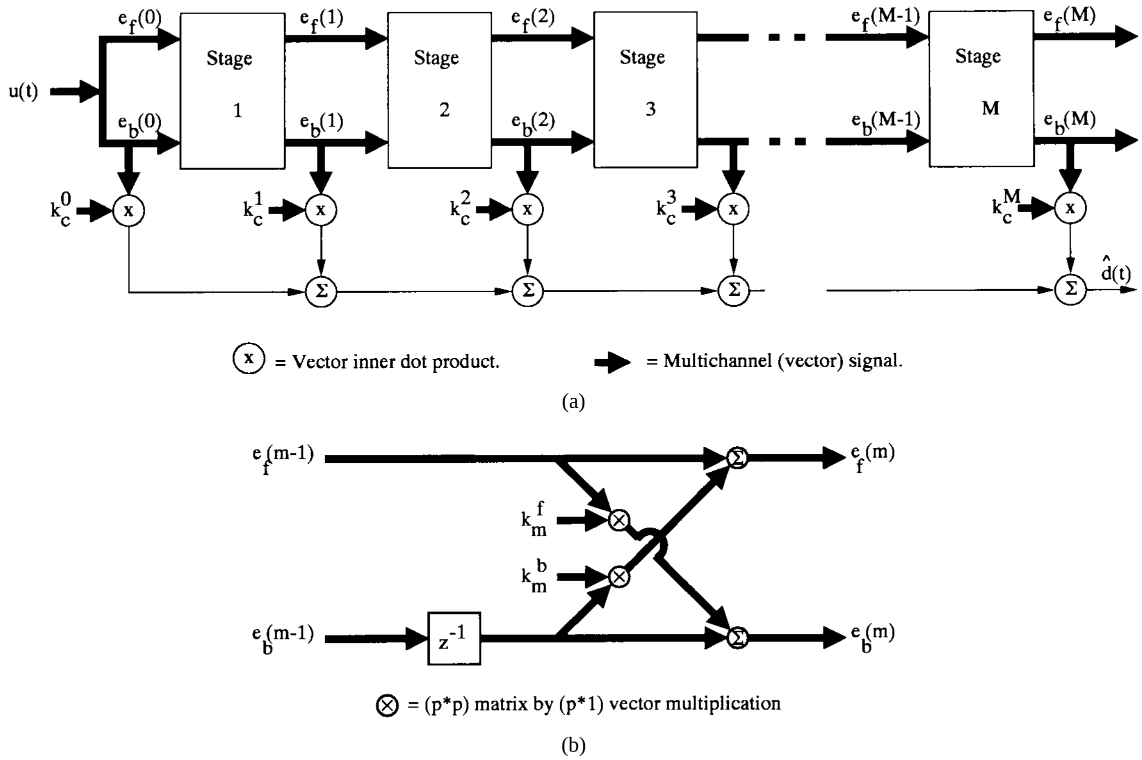


Fig. 7. Multichannel lattice receiver.

only the received signal correlation matrix and the desired user's spreading sequence are required, either receiver can be determined in a blind manner. Subspace estimation and tracking is simplified by using a recursive subspace tracking algorithm. Total complexity is less than the MOE algorithm [36]. Furthermore, the subspace algorithm was shown to perform better under conditions of signature mismatch. Only the component of the mismatch within the signal subspace contributes to performance degradation. An efficient algorithm for joint channel estimation and multiuser detection for multipath channels was presented.

VI. Adaptive Decorrelating Receiver

The multiuser decorrelating receiver structure described in [9] multiplies the output of a bank of unit-energy normalized signature-matched filters by the inverse of the signature cross-correlation matrix

$$\hat{\mathbf{b}}_{\mathbf{k}} = \text{sgn}(\mathbf{H}^{-1}\mathbf{y}). \tag{85}$$

The asymptotic efficiency and near–far resistance of the decorrelator is given by

$$\overline{\eta}_k = \eta_k \begin{cases} \dfrac{1}{\mathbf{H}^{+}_{kk}} & \text{if } k\text{th user signal is independent} \\ 0 & \text{if } k\text{th user signal is in subspace} \\ & \text{spanned by other signals.} \end{cases} \tag{86}$$

Thus, the near–far resistance is identical to the optimal multiuser receiver of Verdú.

Chen [11] proposed the signal reconstruction filter of Fig. 8 to realize the decorrelator adaptively. The approach is to find the vector of coefficients $\mathbf{c}$, which multiply the spreading sequences to form the best estimate of the received signal. An AWGN channel is assumed. At the start of each symbol interval, the filter coefficients are zeroed and then updated once per sample interval. The optimum filter coefficients at iteration n can be computed according to

$$\mathbf{c}(n) = \mathbf{R}^{-1}(n)\boldsymbol{\alpha}(n) \tag{87}$$

where, employing a least squares approach, the sampled correlation matrix can be determined iteratively by

$$\mathbf{R}(n) = \sum_{m=1}^{n} \lambda^{n-m}[\mathbf{S}]_m^H[\mathbf{S}]_m \tag{88}$$

and

$$\boldsymbol{\alpha}(n) = \sum_{m=1}^{n} \lambda^{n-m} r_m[\mathbf{S}]_m^H \tag{89}$$

where λ is a memory decay constant between zero and unity. Setting $\lambda < 1$ allows tracking of nonstationary channels.

The final optimal filter values are

$$\mathbf{c}(M) = \sqrt{\mathbf{E}}\mathbf{b} + \mathbf{R}(M)^{-1}\mathbf{\Gamma} \tag{90}$$

where $\mathbf{\Gamma}$ is a zero-mean Gaussian process and infinite algorithm memory is assumed, in which case $\mathbf{R}(M) = \mathbf{H}$. M samples per symbol have been used. Comparison with (39) confirms that this is an adaptive form of the decorrelating receiver.

Decisions are made according to the signs of the filter taps at the end of the symbol period, i.e.,

$$\hat{\mathbf{b}} = \text{sgn}[\mathbf{c}(M)]. \tag{91}$$

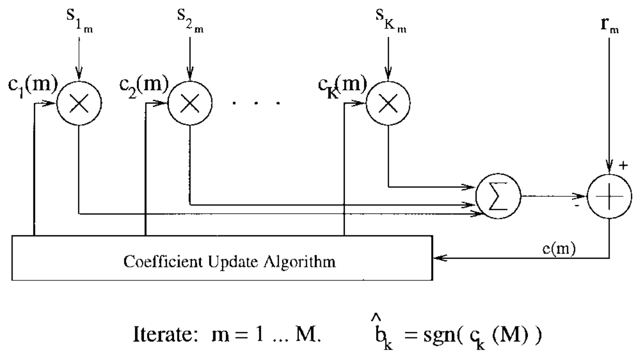


Fig. 8. Adaptive decorrelator receiver for user k [11].

The mean of $\mathbf{c}(M)$ is

$$\overline{\mathbf{c}} = E[\mathbf{c}(M)] = \sqrt{\mathbf{E}}\mathbf{b}. \tag{92}$$

The variance of each coefficient is determined from the diagonal elements of the covariance matrix

$$\sigma_{\mathbf{c}}^{\mathbf{2}} = \left[\sigma_{c_1}^2 \sigma_{c_2}^2 \cdots \sigma_{c_K}^2\right]^H \tag{93}$$
$$= \sigma_n^2 \text{diag}\left(\mathbf{H}^{-1}\right) \tag{94}$$

where $\mathbf{\Gamma} = \mathbf{S}^H \mathbf{n}$ and the assumption of independent noise samples has been used.

Thus, the probability of error for user k using the adaptive decorrelator can be expressed

$$P_k = Q\left(\frac{\sqrt{E_k}}{\sigma_{c_k}}\right). \tag{95}$$

The idea was further extended to multipath fading channels. In this case, the delays of each resolvable multipath component must be found and the amplitudes estimated. This problem was discussed in [23]. In effect, each multipath component is detected in a manner analogous to the AWGN channel case. The size of vector $\mathbf{c}$ is increased to

$$\sum_{k=1}^{K} N_k \tag{96}$$

where N_k is the number of resolvable paths for user k. The results from all the multipath components for each user are combined as for a RAKE receiver. The approach was demonstrated to be effective under the assumption of accurate channel estimation. Complexity is increased markedly as the number of multipaths increases. Each path for each user entails a channel estimation problem as well as a least squares adaption.

An alternative adaptive scheme was proposed by Myers [78] to compute the coefficients of the decorrelating detector without the need for matrix inversions. The technique was based on efficient calculation of a Gram–Schmidt orthogonalization of all the spreading vectors.

VII. Adaptive Successive Interference Cancellation

Multistage [18], [79] and successive interference cancellation [19] rely upon making decisions about the interfering bits and using this information to cancel interference from the bit of interest. This may involve reconstruction of the modulated interfering signal in order to subtract it from the congregate signal. Adaptive algorithms may be utilized to achieve this [16], [80]. Accurate estimations of time offsets and powers must be made. Much of the work published in this field concerns receivers with fixed coefficients, calculated off-line, or those that only utilize adaptive algorithms for channel estimation purposes. This paper will not address these issues.

Alternatively, interference can be removed from the output of a bank of matched filters without regeneration. Siveski proposed an adaptive means of achieving this, as shown in Fig. 9 [81]. A weighted sum of the estimated interferer bits is subtracted from the matched filter output corresponding to the user of interest. This forms the decision variable

$$z_k = y_k - \mathbf{w}_{\mathbf{k}}^T \hat{\mathbf{b}} \tag{97}$$

where y_k is the matched filter output for user k and $\mathbf{w_k}^T = [w_{k,1}, \cdots, w_{k,k-1}, 0, w_{k,k+1}, \cdots, w_{k,K}]$ is a vector of adaptive filter coefficients. The estimated interference bits from the output of the decorrelator are represented by $\hat{\mathbf{b}}^T = [\hat{b}_1, \cdots, \hat{b}_K]$. The final decision is

$$\hat{\hat{b}}_k = \text{sgn}(z_k). \tag{98}$$

A gradient algorithm is proposed to minimize the output energy $E[z_k^2]$. It is important to note that element $w_{k,k}$ in $\mathbf{w_k}$ is equal to zero, so the system is being driven to cancel only the interference. This technique requires no training sequence but does require much knowledge of all the users on the system in order to implement the matched filter bank and form the initial interference estimates in the decorrelator.

Chen and Roy [11] proposed the adaptive decorrelator described in Section VI. They also showed how the decorrelator could be used in each stage of a successive interference cancellation, or decision feedback, structure, as shown in Fig. 10. The first-stage decorrelator is used to estimate the bit for the highest power user. The modulated signal for that user is then regenerated and subtracted from the original received signal. The second-stage decorrelator uses this signal to detect the next strongest user, whose influence is then also subtracted from the congregate signal. Successive cancellation continues in order of decreasing user power until all users are detected. Significant performance improvement was demonstrated over an AWGN channel, assuming good synchronization and knowledge of spreading sequences. With equal power users, performance was close to the single-user bound. Robustness to poor power control was also observed.

Baines [82] proposed a hybrid detector. It used an adaptive multistage receiver [83] to cancel intracell interference, about which a reasonable knowledge of spreading sequences may be assumed. A blind MMSE approach was used to cancel intercell interference for which the multistage receiver has no knowledge and is thus unable to cancel. A

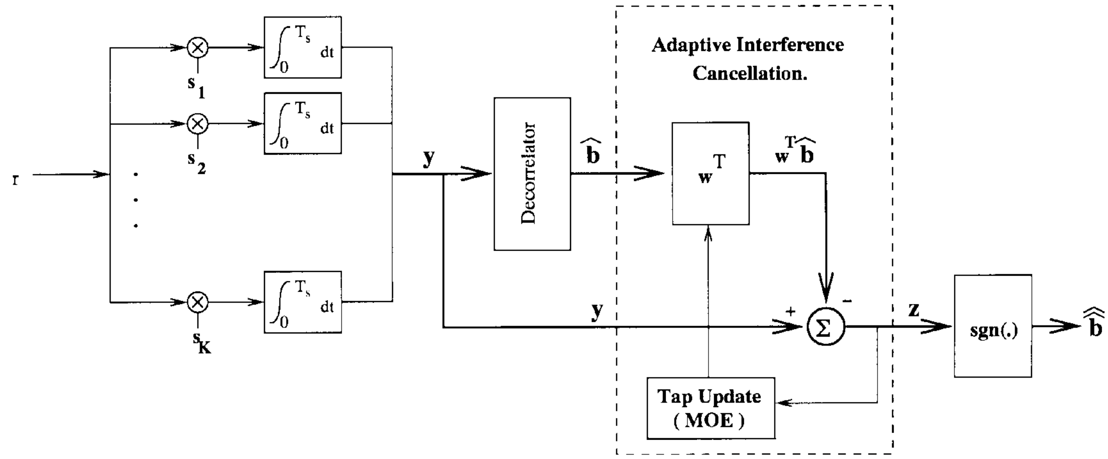


Fig. 9. Adaptive interference cancellation scheme from [81].

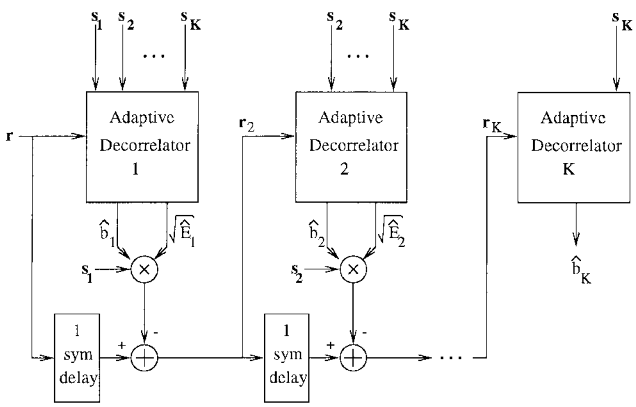


Fig. 10. SIC using adaptive decorrelators at each stage [11]. Users are subscripted one to K from strongest to weakest.

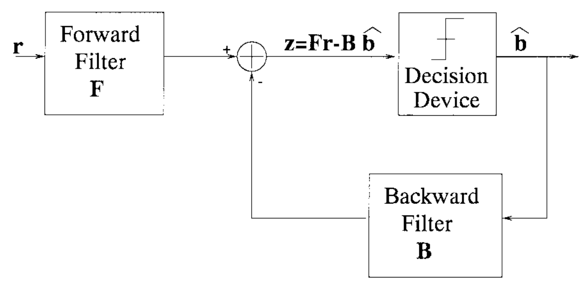


Fig. 11. Multiuser decision feedback receiver. $\mathbf{B}$ is constrained to be strictly lower diagonal, so that the backward filter performs interference cancellation.

significant improvement in receiver convergence speed was demonstrated. Performance was uniformly better than either of the constituent structures alone.

Another hybrid detector was proposed by Cruickshank [84]. A MMSE filter was used to derive the first symbol estimates in a parallel interference receiver. Significant performance improvement was demonstrated compared to a system with a matched filter bank to provide initial symbol estimates.

The adaptive multiuser decision feedback receiver mentioned in Section V [47] is a form of successive interference cancellation for synchronous CDMA systems. It does not require regeneration of a CDMA modulated signal. It is a development of the fixed structures discussed in [4] and [85]. A block diagram is given in Fig. 11. Two matrix filters $\mathbf{F}$ and $\mathbf{B}$ are used. The forward filter operates directly on the received signal samples and outputs preliminary symbol estimates $\mathbf{Fr}$. It may be a fixed matched filter bank [85], though an adaptive MMSE filter was proposed [47]. The backward filter $\mathbf{B}$ is constrained to be lower diagonal. In this way, it operates to successively cancel interference due to already detected symbols. It was shown that in the absence of error propagation, the minimum output MMSE can be written

$$J_{\min_{k(DF)}} = 1 - \mathbf{p}_\mathbf{k}^H \mathbf{R}_\mathbf{U}^{-1} \mathbf{p}_\mathbf{k} \tag{99}$$

where $\mathbf{R}_\mathbf{U}$ is the correlation matrix for $\mathbf{r}$ ignoring the signal components from already detected users. This is very similar to the expression for the linear MMSE receiver given in (55), except that the backward filter has perfectly cancelled interference due to already detected users. A simple gradient approach for the filter coefficient updates was proposed.

VIII. Numerical Results

This section will present results of numerical studies, comparing the various forms of the MMSE receiver and other adaptive receivers discussed above.

Fig. 12 shows the performance of the ideal MMSE, decorrelating, and matched filter receivers for synchronous systems using Gold sequences of length 31 with equal power users. Results were derived both from theory and through Monte Carlo simulations. The equivalence of the single-user and multiuser form of the MMSE receiver is confirmed by the close agreement between the Monte Carlo simulation results. The step when the fourth user is added is due to the relatively poor cross-correlation properties of the second and fourth sequences.

The immunity of the multiuser receivers to the near–far problem is illustrated in Fig. 13. System parameters are

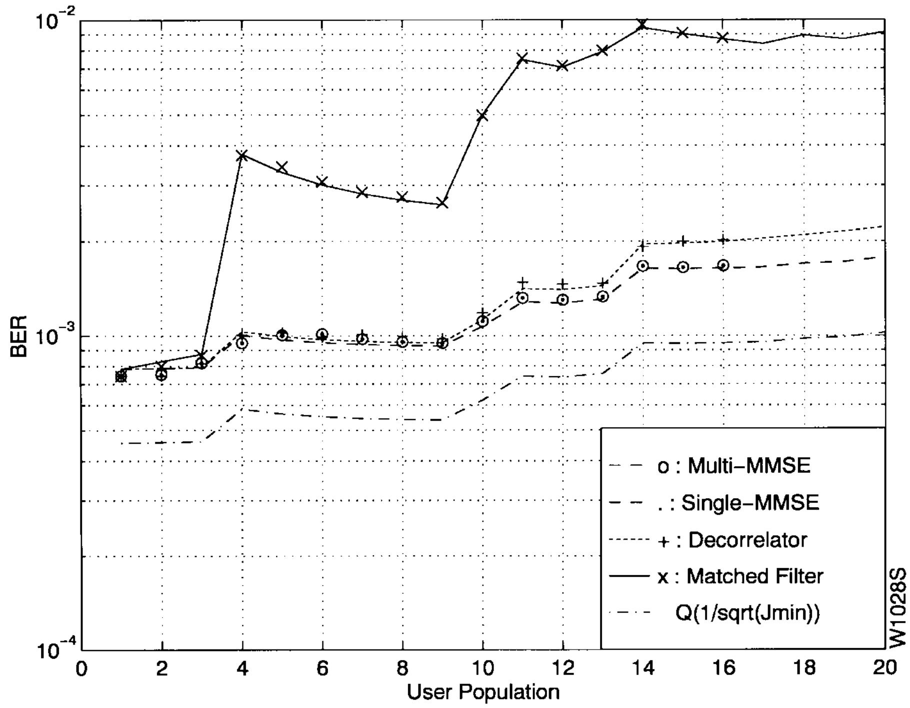


Fig. 12. Receiver performances with $E_b/N_o = 7$ dB for each user. Average over all users. Equal power users spread by Gold sequence of length 31. Lines represent theory and points represent Monte Carlo simulation results.

identical to the previous example, except that the first user's power is increased by 20 dB. Fig. 13 shows that the error performance of the weak users is much worse with the matched filter receiver but not much affected by the stronger interferer when a multiuser receiver is used.

Fig. 14 shows the output SNR of the ideal MMSE and the conventional matched filter receivers as a function of the number of users in the system and the E_b/N_0. An asynchronous system using Gold sequences of length 31 and transmitting over an AWGN is considered. The conventional receiver is clearly interference limited, as observed by the rapid performance degradation as the users are added. The MMSE receiver is noise limited until the user population reaches a certain value, termed the critical number of users (CNU) [28]. At that point, the MMSE filter is not able to suppress additional interference effectively. The improved performance of an ideal combined adaptive transmitter/receiver system [48] is also illustrated in Fig. 14.

Fig. 15 shows the effect of using an adaptive approximation to the MMSE filter with a finite training interval. An asynchronous system with a spreading factor of 31 was investigated. A stationary ISI channel with chip-sampled impulse response

$$\mathbf{h} = [0.25\ 1.00\ 0.25] \tag{100}$$

is assumed. To present results independent of packet size, receive filter coefficients were fixed at the conclusion of the training interval. In practice, decision-directed operation would permit further reduction in MSE. The slow convergence of the NLMS algorithm is evident by its poor performance with a short training length. Thus, it can only support a reduced number of users. The RLS algorithm performs the best of the three proposed algorithms with short training lengths, especially when the noise level is low. When the training length is increased, the GAL and RLS algorithms perform very similarly. In all cases, the performance is more dependent upon the level of interference than the ideal MMSE receiver.

MSE convergence profiles are given in Fig. 16 for a system with spreading ratio of 31, three active transmitters of unit power, and thermal noise variance of 10^{-3} over the spread bandwidth. The ISI channel of (100) is assumed. Three forms of adaptive algorithm are used to approximate the MMSE receiver. The performance of the fixed, optimum MMSE receiver is given for comparison. Each receiver spans three input symbols. It is apparent that the initial convergence speed of the GAL algorithm is better than the NLMS algorithm. Satisfactory MSE convergence is observed in around 30 iterations, compared to about 70 for the NLMS. The RLS algorithm converges more quickly but is prone to numerical problems, as can be seen by the divergence at around 100 symbols. This can be controlled, to some extent, by varying the initialization condition and the LS decay constant used in the algorithm. These parameters affect the conditioning of the correlation matrix, especially during the initial convergence period. The tradeoffs may be decreased initial convergence rate and reduced tracking capability in nonstationary channels.

An important limitation of the LMS-based algorithms is their ability to track nonstationary channels. A system was simulated with the four-path Rayleigh frequency-selective

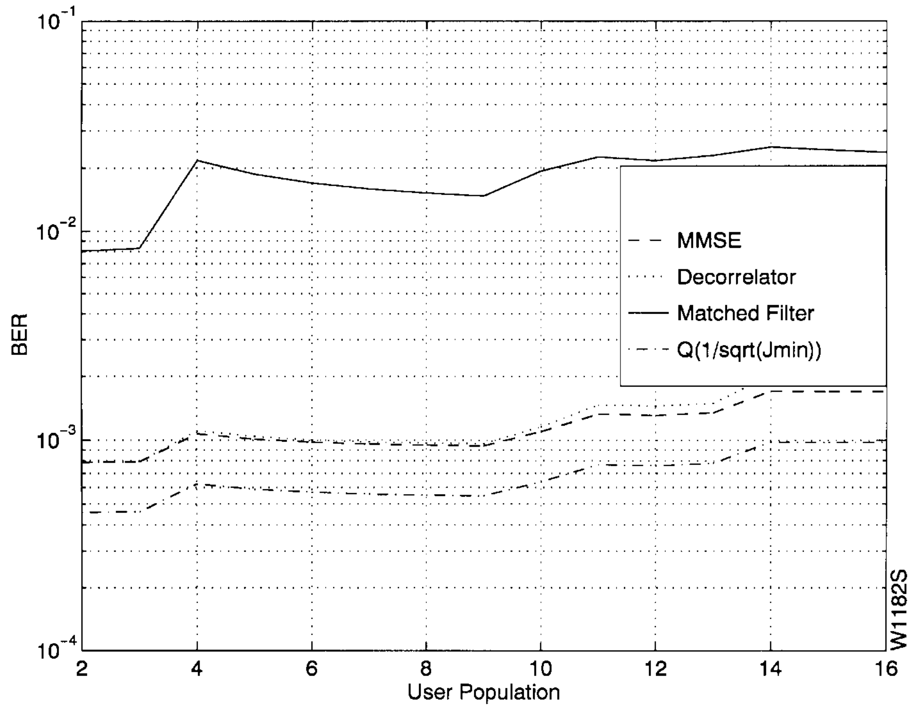


Fig. 13. Receiver performances in presence of near–far problem. $E_b/N_o = 7$ dB for all but the first user. User 1 is 20 dB stronger. BER is averaged over all low power users. Gold sequences of length 31.

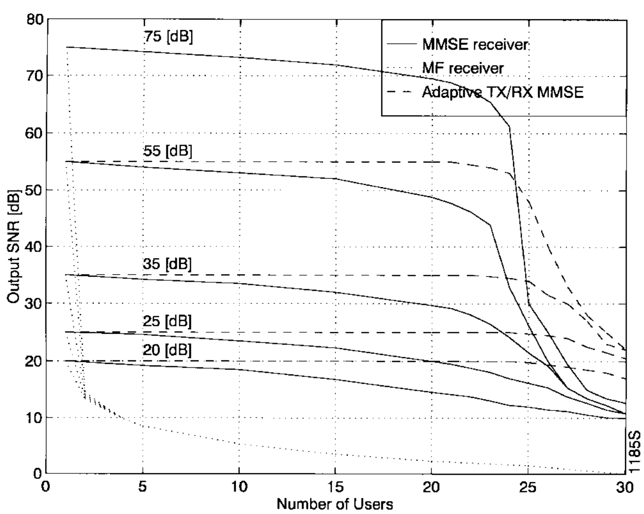
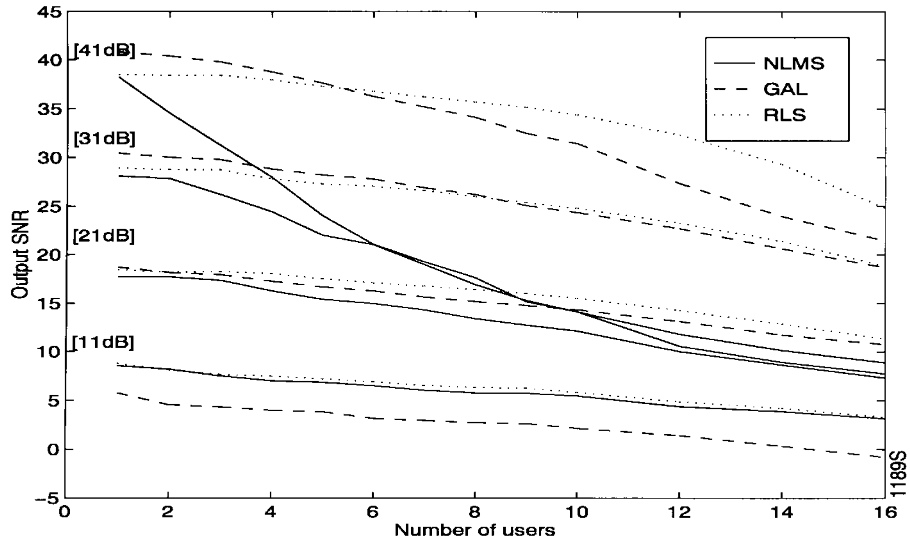


Fig. 14. Receiver output SNR with increasing number of users. Curves are parameterized by E_b/N_0. The conventional MF receiver, optimal MMSE receiver [28], and adaptive MMSE transmitter/receiver system [48] are considered.

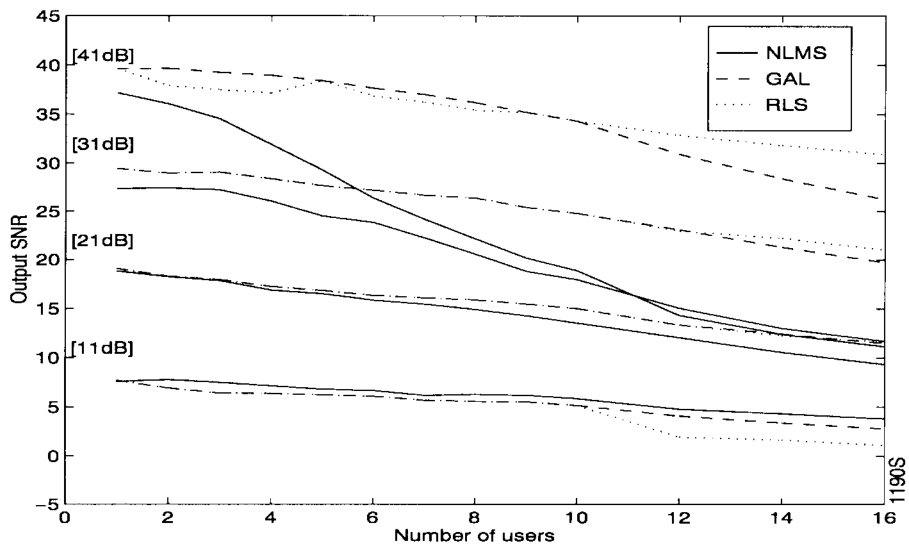
fading channel model shown in Fig. 17. Each path was characterized by a continuous Rayleigh-fading variable generated using Jake's model [86]. The data rate was set at 9600 BPSK symbols per second, an appropriate symbol rate for mobile voice traffic. Fig. 18 shows MSE convergence for a synchronous three-user system with a spreading gain of seven. A maximum Doppler frequency of 10 Hz was used. The NLMS algorithm displays difficulty in tracking the fading environment, with MSE generally no better than 10^{-2}. The GAL and RLS algorithm convergence is roughly 10 dB better, and these algorithms are much better able to track the channel variations. Although the initial RLS convergence is better than the GAL in this case, tracking capability appears equivalent. Further experiments have shown that increasing the fade rate to 50 Hz renders system performance unsatisfactory when the data rate of 9600 bps is retained. Other authors have reported improved performance in flat fading channels with faster fade rates when differential coding is used [50], [52].

An alternative approach is to combine CDMA with time division multiple access in order to increase the symbol rate. Multiple users can share the spreading sequence by time multiplexing. Each user must then transmit symbols more rapidly, over a short burst of time. Thus, the relative fade rate, defined as the ratio of the channel Doppler frequency to the symbol rate, decreases. This parameter is significant when considering the convergence speed of adaptive algorithms rather than the absolute value of the Doppler frequency. The channel appears to be almost stationary over a larger number of symbols. This approach was investigated in [56] and found to be effective in lifting capacity of a terrestrial cellular mobile system.

These results have shown that the adaptive MMSE receiver is an effective means of increasing system capacity and is suitable for use on stationary and slow fading channels. Applicability to channels with faster fade rates is an active research area. The theoretical BER expressions given in Section V were based on convergence to the optimum MMSE coefficient set. Thus, these expressions form a lower bound on the expected performance of the adaptive MMSE receiver. The bound becomes closer as the adaptive algorithm training length increases.



(a)



(b)

Fig. 15. Effect of finite training length and choice of algorithm for adaptive MMSE receiver. Curves are parameterized by E_b/N_0. (a) Short training length, 64 symbols. (b) Long training length, 128 symbols.

Fig. 19 compares the BER performance of the ideal matched filter receiver, the adaptive decorrelator [11], the ideal linear MMSE receiver, and the multiuser decision feedback MMSE receiver with fixed optimum coefficients. A synchronous CDMA system supporting 25 users with a spreading gain of 31 was considered. Results are averaged over many runs using randomly generated binary spreading sequences. The performance of the first user in the multiuser decision feedback receiver matches the linear MMSE receiver, as this user gains nothing from decision feedback. The final user benefits from interference cancellation of all other users. Almost all of the gain from interference cancellation is achieved by the time the first half of the users are detected. As sequences were chosen at random, with no regard for correlation properties, the decorrelator and matched filter receivers perform poorly. The decorrelator delivers significantly worse performance than the linear MMSE receiver due to noise enhancement when the correlation properties of the spreading sequences are poor. Under such high load conditions, the matched filter fails to deliver satisfactory performance, highlighting the motivation for multiuser reception to maximize capacity of CDMA systems.

IX. Conclusion

The conventional matched filter DS-CDMA receiver offers system capacity well below the channel capacity. In addition, such systems are near–far sensitive, requiring careful power control and spreading sequence design. This has motivated research into multiuser detection algorithms in order to eliminate or reduce the interference between users. Adaptive algorithms provide an attractive and feasible way to implement many of the proposed multiuser receiver

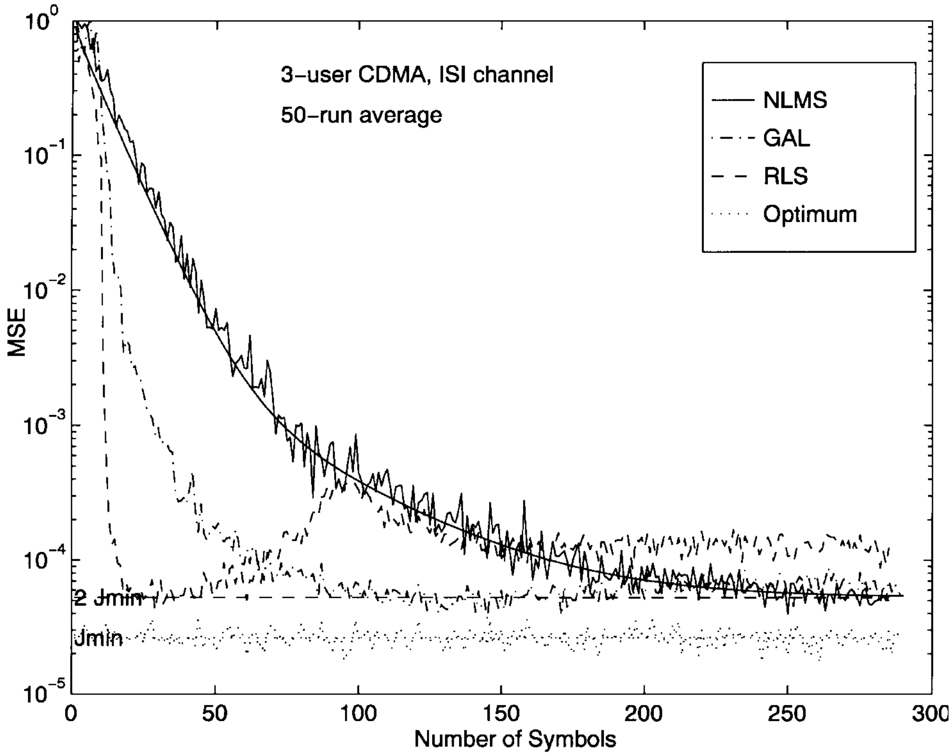


Fig. 16. MSE convergence profiles. Synchronous system with three users and spreading gain of 31.

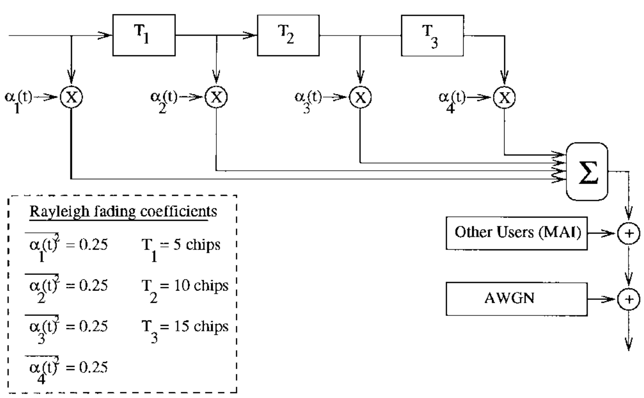


Fig. 17. Four-path Rayleigh-fading channel model.

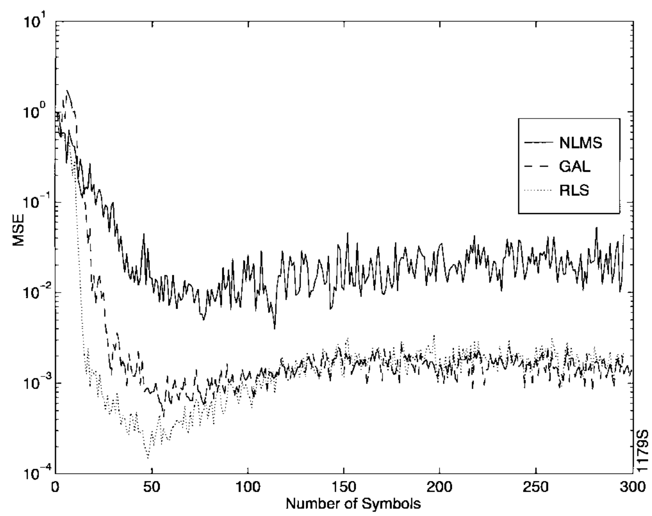


Fig. 18. Convergence and tracking of adaptive receivers in four-path, 10-Hz, Rayleigh-fading channel. Three users with spreading gain of seven. Average over 20 independent runs.

structures. The adaptive MMSE receiver is particularly appealing, as it can be operated as a single-user receiver, requiring no explicit knowledge of the interfering users, and is capable of multiuser interference suppression. Reception can be decentralized, which is often an important practical advantage. The adaptive decorrelator may be attractive for centralized applications where good knowledge of the interferers may be attainable. Performance is impaired slightly compared to the MMSE receiver due to noise enhancement. Adaptive successive interference cancellation could be considered where accurate information about the most significant interferers in a system is available. The decision feedback MMSE receiver combines the advantages of the linear MMSE receiver with those of successive interference cancellation and thus is particularly attractive.

The potential for significant improvement in communication systems capacity through the use of adaptive forms of multiuser receivers has been demonstrated. The selection and implementation of practical CDMA receivers is an area for ongoing research. Outstanding issues include ensuring adequate performance from the adaptive algorithm. Increased convergence rates or improved performance of blind algorithms are desirable to reduce system overheads. Algorithm tracking capability should be improved to enable

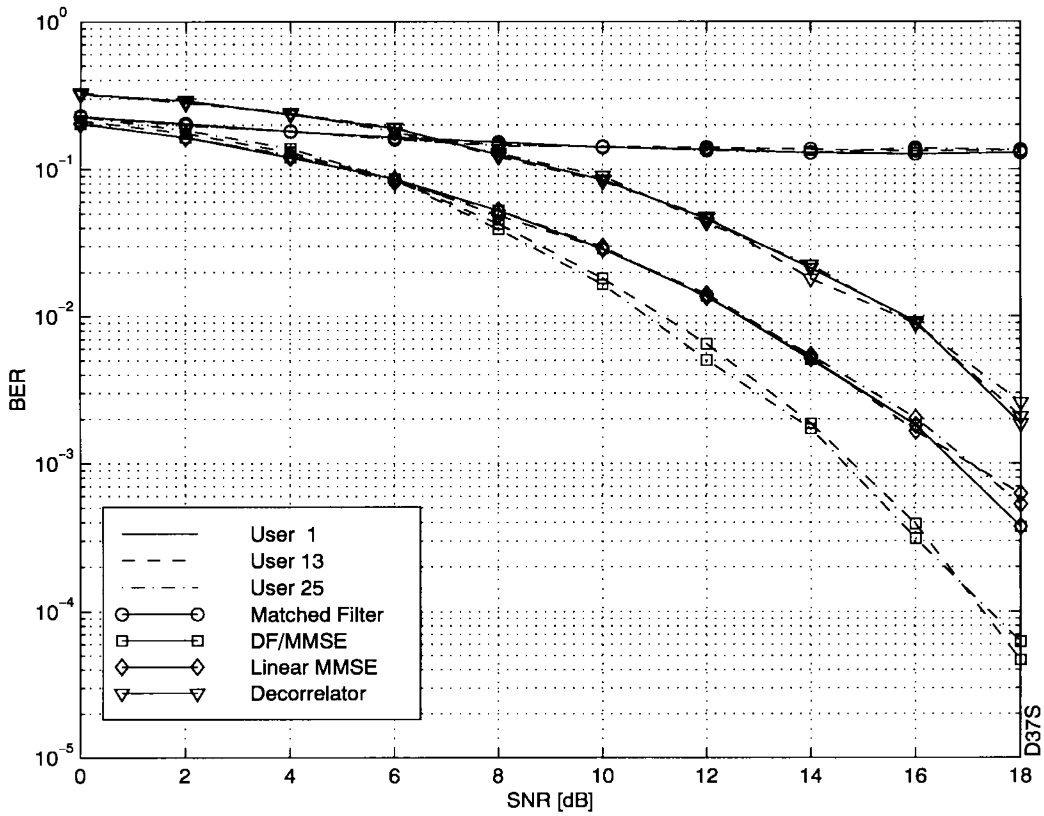


Fig. 19. Receiver BER comparisons. Twenty-five synchronous users with random spreading sequences of length 31. AWGN channel.

operation in rapidly changing channel environments, typical of wireless mobile communication systems. Accurate and reliable system parameter estimation is required for effective and stable implementation of successive interference cancellation and matched-filtering-based approaches. With improved algorithm performance there is typically a cost in increased computational complexity. These issues ensure that adaptive multiuser receivers, and their implementation in real-world environments, continue to be a dynamic and interesting research field.

REFERENCES

[1] S. Verdú, *Multiuser Detection.* Greenwich, CT: JAI Press, 1993, vol. 2, pp. 369–409.

[2] Telecommunications Industry Association, "Mobile station-base station compatibility standard for dual-mode wideband spread spectrum cellular system," Tech. Rep. TIA/EIA/IS-95, Electronic Industries Association, July 1993.

[3] S. Verdú, "Minimum probability of error for asynchronous Gaussian multiple-access channels," *IEEE Trans. Inform. Theory,* vol. IT-32, pp. 85–96, Jan. 1986.

[4] A. Klein, G. K. Kaleh, and P. W. Baier, "Zero forcing and minimum mean-square-error equalization for multiuser detection in code-division multiple-access channels," *IEEE Trans. Veh. Technol.,* vol. 45, pp. 276–287, May 1996.

[5] B. R. Petersen and D. D. Falconer, "Minimum mean square equalization in cyclostationary and stationary interference—Analysis and subscriber line calculations," *IEEE J. Select. Areas Commun.,* vol. 9, pp. 931–940, Aug. 1991.

[6] Z. Xie, C. K. Rushforth, and R. T. Short, "Multiuser signal detection using sequential decoding," *IEEE Trans. Commun.,* vol. 38, pp. 578–583, May 1990.

[7] P. Alexander, L. Rasmussen, and C. Schlegel, "A linear receiver for coded multiuser CDMA," *IEEE Trans. Commun.,* vol. 45, p. 605, May 1997.

[8] L. Wei, L. Rasmussen, and R. Wyrwas, "Near optimum tree-search detection schemes for bit-synchronous multiuser CDMA systems over Gaussian and two-path Rayleigh fading channels," *IEEE Trans. Commun.,* vol. 45, p. 691, June 1997.

[9] R. Lupas and S. Verdú, "Linear multiuser detectors for synchronous code-division multiple-access channels," *IEEE Trans. Inform. Theory,* vol. 35, pp. 123–136, Jan. 1989.

[10] K. S. Schneider, "Optimum detection of code division multiplexed signals," *IEEE Trans. Aerosp. Electron. Syst.,* vol. AES-15, pp. 181–185, Jan. 1979.

[11] D. S. Chen and S. Roy, "An adaptive multiuser receiver for CDMA systems," *IEEE J. Select. Areas Commun.,* vol. 12, pp. 808–816, June 1994.

[12] Z. Xie, R. T. Short, and C. K. Rushforth, "A family of suboptimum detectors for coherent multiuser communications," *IEEE J. Select. Areas Commun.,* vol. 8, pp. 683–690, May 1990.

[13] U. Madhow and M. L. Honig, "MMSE interference suppression for direct-sequence spread spectrum CDMA," *IEEE Trans. Commun.,* vol. 42, pp. 3178–3188, Dec. 1994.

[14] P. Monogioudis, R. Tafazolli, and B. Evans, "Linear adaptive fractionally spaced equalization of CDMA multiple-access interference," *Electron. Lett.,* vol. 29, pp. 1823–1825, Oct. 14, 1993.

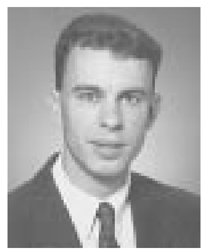
[15] R. Kohno, M. Hatori, and H. Imai, "Cancellation techniques of co-channel interference in asynchronous spread spectrum multiple access systems," *Electron. Commun. Japan,* vol. 66-A, no. 5, pp. 20–29, 1983.

[16] R. Kohno, H. Imai, M. Hatori, and S. Pasupathy, "Combination of an adaptive array antenna and a canceller of interference for direct-sequence spread-spectrum multiple-access system," *IEEE J. Select. Areas Commun.,* vol. 8, pp. 675–682, May 1990.

[17] P. Patel and J. Holtzman, "Analysis of a simple successive interference cancellation scheme in a DS/CDMA system," *IEEE J. Select. Areas Commun.,* vol. 12, pp. 796–806, June 1994.

[18] M. K. Varanasi and B. Aazhang, "Multistage detection in asynchronous code-division multiple-access communications," *IEEE Trans. Commun.*, vol. 38, pp. 509–519, Apr. 1990.
[19] A. Duel-Hallen, "Decorrelating decision-feedback multiuser detector for synchronous code-division multiple-access channel," *IEEE Trans. Commun.*, vol. 41, pp. 285–290, Feb. 1993.
[20] A. Duel-Hallen, J. Holtzman, and Z. Zvonar, "Multiuser detection for CDMA systems," *IEEE Personal Commun. Mag.*, pp. 47–58, Apr. 1995.
[21] B. Steiner and P. Jung, "Uplink channel estimation in synchronous CDMA mobile radio systems with joint detection," in *Proc. Int. Symp. Personal, Indoor and Mobile Radio Communications 1996*, Yokohama, Japan, Sept. 1993, pp. 123–127.
[22] ——, "Optimum and suboptimum channel estimation for the uplink of CDMA mobile radio systems with joint detection," *Eur. Trans. Telecommun. Related Technol.*, vol. 5, pp. 39–50, Jan./Feb. 1994.
[23] T. J. Lim and L. K. Rasmussen, "Adaptive symbol and parameter estimation in asynchronous multiuser CDMA detectors," *IEEE Trans. Commun.*, vol. 45, p. 213, Feb. 1997.
[24] H. Liu, "A subspace method for signature waveform estimation in synchronous CDMA systems," *IEEE Trans. Commun.*, vol. 44, pp. 1346–1354, Oct. 1996.
[25] S. Verdú, "Adaptive multiuser detection," in *Proc. Int. Symp. Spread Spectrum Theory and Applications*, 1994, pp. 43–50.
[26] R. M. Buehrer, A. Kaul, and S. S. B. D. Woerner, "Analysis of DS-CDMA parallel interference cancellation with phase and timing errors," *IEEE J. Select. Areas Commun.*, vol. 14, pp. 1522–1535, Oct. 1996.
[27] E. S. Esteves and R. A. Scholtz, "Bit error probability of linear multiuser detectors in the presence of unknown multiple access interference," in *Proc. GLOBECOM'97*, Phoenix, AZ, Nov. 1997, pp. 599–603.
[28] P. B. Rapajic and B. S. Vucetic, "Adaptive receiver structures for asynchronous CDMA systems," *IEEE J. Select. Areas Commun.*, vol. 12, pp. 685–697, May 1994.
[29] M. Abdulrahman, A. U. H. Sheikh, and D. D. Falconer, "Decision feedback equalization for CDMA in indoor wireless communications," *IEEE J. Select. Areas Commun.*, vol. 12, pp. 698–706, May 1994.
[30] S. L. Miller, "Training analysis of adaptive interference suppression for direct-sequence code-division multiple-access systems," *IEEE Trans. Commun.*, vol. 44, pp. 488–495, Apr. 1996.
[31] ——, "An adaptive direct-sequence code-division multiple-access receiver for multiuser interference rejection," *IEEE Trans. Commun.*, vol. 43, pp. 1746–1755, Feb.–Apr. 1995.
[32] C. N. Pateros, "An adaptive correlator receiver for spread spectrum communication," Ph.D. dissertation, Rensselaer Polytechnic Institute, Troy, NY, Mar. 1993.
[33] T. J. Lim and S. Roy, "Adaptive detectors for multiuser CDMA," in *Wireless Networks*. The Netherlands: Baltzer, to be published.
[34] S. Yoshida and A. Ushirokawa, "Capacity evaluation of CDMA-AIC: CDMA cellular system with adaptive interference cancellation," in *Proc. IEEE Int. Conf. Universal Personal Communications*, Tokyo, Japan, Nov. 6–10, 1995, pp. 148–152.
[35] P. Monogioudis, R. Tafazolli, and B. Evans, "Performance of adaptive nonlinear NEFAR CDMA receiver architecture," *Electron. Lett.*, vol. 30, pp. 192–193, Feb. 3, 1994.
[36] M. Honig, U. Madhow, and S. Verdú, "Blind adaptive multiuser detection," *IEEE Trans. Inform. Theory*, vol. 41, pp. 944–960, July 1995.
[37] L. B. Milstein, "Interference rejection techniques in spread spectrum communications," *Proc. IEEE*, vol. 76, pp. 657–671, June 1988.
[38] C. N. Pateros and G. J. Saulnier, "An adaptive correlator receiver for direct sequence spread spectrum communication," *IEEE Trans. Commun.*, vol. 44, pp. 1543–1552, Nov. 1996.
[39] P. Rapajic and B. Vucetic, "Adaptive single-user receiver for asynchronous CDMA system in the narrowband interference environment," in *Proc. Mobile and Personal Communications Systems*, Adelaide, Australia, Apr. 12–13, 1992, pp. 143–148.
[40] M. Gustavsson, G. Woodward, and B. S. Vucetic, "Adaptive narrowband interference suppression in CDMA overlay systems," in *Proc. ICT'97*, Melbourne, Australia, Apr. 1997, pp. 417–422.
[41] G. Ungerboeck, "Theory on the speed of convergence in adaptive equalizers for digital communication," *IBM J. Res. Develop.*, pp. 546–555, Nov. 1972.
[42] R. D. Gitlin, J. H. C. Meadors, and S. B. Weinstein, "The tap-leakage algorithm: An algorithm for the stable operation of a digitally implemented, fractionally spaced adaptive equalizer," *Bell Syst. Tech. J.*, vol. 61, pp. 1817–1839, Oct. 1982.
[43] N. Kalouptsidis, D. Manolakis, and G. Carayannis, "A family of computationally efficient algorithms for multichannel signal processing—A tutorial review," *Signal Process.*, pp. 5–19, 1983.
[44] S. U. H. Qureshi, "Adaptive equalization," *Proc. IEEE*, vol. 73, pp. 1349–1387, Sept. 1985.
[45] S. Haykin, *Adaptive Filter Theory*, 3rd ed. Englewood Cliffs, NJ: Prentice-Hall, 1996.
[46] I. Oppermann, G. Woodward, and B. S. Vucetic, "BER calculations and the effect of training period on CDMA MMSE receivers," in *Proc. ICT'97*, Melbourne, Australia, Apr. 1997, pp. 345–349.
[47] P. B. Rapajic, M. L. Honig, and G. Woodward, "Multiuser decision-feedback detection: Performance bounds and adaptive algorithms," in *Proc. Int. Symp. Information Theory*, Cambridge, MA, to be published.
[48] P. B. Rapajic and B. S. Vucetic, "Linear adaptive transmitter–receiver structures for asynchronous CDMA systems," *Eur. Trans. Telecommun. Related Technol.*, vol. 6, pp. 21–27, Jan./Feb. 1995.
[49] G. Woodward, P. Rapajic, and B. Vucetic, "Adaptive algorithms for asynchronous DS-CDMA receivers," in *Proc. Int. Symp. Personal, Indoor and Mobile Radio Communications*, Taipei, Taiwan, R.O.C., 1996, pp. 583–587.
[50] L. J. Zhu and U. Madhow, "Adaptive interference suppression for direct sequence CDMA over severely time-varying channels," in Proc. *GLOBECOM'97*, Phoenix, AZ, Nov. 1997, pp. 917–922.
[51] ——, "Adaptive interference suppression for DS-CDMA over a Rayleigh fading channel," in *Proc. Conf. Information Sciences and Systems*, Mar. 1997.
[52] M. L. Honig, M. J. Shensa, S. L. Miller, and L. B. Milstein, "Performance of adaptive linear interference suppression for DS-CDMA in the presence of flat Rayleigh fading," in *Proc. Int. Vehicular Technology Conf.*, 1997, pp. 2191–2195.
[53] E. G. Ström and S. L. Miller, "Optimum complexity reduction of minimum mean square error DS-CDMA receivers," in *Proc. Int. Vehicular Technology Conf.*, 1994, pp. 568–572.
[54] I. Oppermann and M. Latva-aho, "Adaptive LMMSE receiver for wideband CDMA systems," in *Proc. IEEE Global Telecommunications Conf.*, Phoenix, AZ, Nov. 1997, pp. 133–138.
[55] P. B. Rapajic and B. S. Vucetic, "Application of fast adaptive algorithms in asynchronous CDMA systems," in *Proc. Int. Symp. Information Theory and Its Applications*, Sydney, Australia, Nov. 20–24, 1994, pp. 97–102.
[56] G. Woodward, P. Rapajic, and B. Vucetic, "CDMA cellular mobile system capacity improvement by combination with TDMA and adaptive interference suppression," in *Proc. Wireless Communications Systems Symp.*, Long Island, NY, Nov. 1995, pp. 171–177.
[57] D. D. Falconer and L. Ljung, "Application of fast Kalman estimation to adaptive equalization," *IEEE Trans. Commun.*, vol. COM-26, pp. 1439–1446, Oct. 1978.
[58] M. S. Mueller, "Least-squares algorithms for adaptive equalizers," *Bell Syst. Tech. J.*, vol. 60, pp. 1905–1925, Oct. 1981.
[59] E. K. B. Lee, "Rapid converging adaptive interference suppression for direct-sequence code-division multiple-access systems," in *Proc. IEEE Global Telecommunications Conf.*, 1993, pp. 1683–1687.
[60] N. Kalouptsidis and S. Theodoridis, *Adaptive System Identification and Signal Processing Algorithms.* Hertfordshire, UK: Prentice-Hall, 1993.
[61] S. S. Narayan, A. M. Peterson, and M. J. Narasimha, "Transform domain LMS algorithm," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. ASSP-31, pp. 609–615, June 1983.
[62] J. C. Lee and C. K. Un, "Performance of transform-domain LMS digital filters," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. ASSP-34, pp. 499–510, June 1986.
[63] D. F. Marshall, W. K. Jenkins, and J. J. Murphy, "The use of orthogonal transforms for improving performance of adaptive filters," *IEEE Trans. Circuits Syst.*, vol. 36, pp. 474–484, Apr. 1989.
[64] P. S. R. Diniz and L. W. P. Biscainho, "Optimal variable step

size for the LMS/Newton algorithm with application to subband adaptive filtering," *IEEE Trans. Signal Processing,* vol. 40, pp. 2825–2828, Nov. 1992.
[65] J. J. Shynk, "Frequency-domain and multirate adaptive filtering," *IEEE Signal Processing Mag.,* pp. 14–37, Jan. 1992.
[66] T. Lim, personal correspondence, 1997.
[67] E. G. Ström, S. Parkvall, S. L. Miller, and B. E. Ottersten, "Complexity reduction of direct-sequence code division multiple access receivers," in *Proc. Int. Conf. Communications,* 1994, pp. 1643–1647.
[68] M. L. Honig and D. G. Messerschmitt, *Adaptive Filters, Structures, Algorithms and Applications.* Norwell, MA: Kluwer, 1984.
[69] D. Jitsukawa, R. Kohno, and H. Imai, "Multiuser adaptive equalizing scheme for DS/CDMA," *Tech. Rep. IEICE* (in Japanese), vol. SST94-55, pp. 7–12, Oct. 1994.
[70] D. Jitsukawa and R. Kohno, "Adaptive multi-user equalization using multi-dimensional lattice filter for DS/CDMA," *IEICE Trans. Fundamentals,* vol. E79-A, pp. 1464–1470, Sept. 1996.
[71] R. Kohno, P. Rapajic, and B. S. Vucetic, "An overview of adaptive techniques for interference minimization in CDMA systems," *Wireless Personal Commun.* vol. 1, no. 1, pp. 3–21, 1994.
[72] N. Ishii and R. Kohno, "A study of path combining scheme on joint transmitter and receiver system based on array antenna for DS/CDMA," *Tech. Rep. IEICE,* vol. SST96-53, pp. 25–30, Oct. 1996.
[73] G. Woodward, R. Kohno, and B. S. Vucetic, "Comparison of adaptive algorithms for single user MMSE CDMA receivers," in *Proc. Int. Conf. Advances in Communications and Control,* Corfu, Greece, June 1997, pp. 555–564.
[74] G. Woodward and B. S. Vucetic, "Adaptive lattice algorithm for DS-CDMA receivers," in *Proc. Asia-Pacific Conf. Communications,* Sydney, Australia, Dec. 1997, pp. 739–743.
[75] Y. Sato, "A method of self-recovering equalization for multilevel amplitude-modulation systems," *IEEE Trans. Commun.,* vol. COM-23, no. 6, pp. 679–682, 1975.
[76] U. Madhow, "Blind adaptive interference suppression for acquisition and demodulation of direct-sequence CDMA signals," *IEEE Trans. Signal Processing,* vol. 45, pp. 124–136, Jan. 1997.
[77] X. Wang and H. V. Poor, "Blind multiuser detection: A subspace approach," *IEEE Trans. Inform. Theory,* vol. 44, pp. 677–690, Mar. 1998.
[78] T. Myers and M. E. Magana, "An adaptive implementation of the 'one-shot' decorrelating detector for CDMA communications," *IEEE Trans. Circuits Syst. II,* vol. 44, pp. 762–765, Sept. 1997.
[79] M. K. Varanasi and B. Aazhang, "An iterative detector for asynchronous spread-spectrum multiple-access systems," in *Proc. IEEE Global Telecommunications Conf.,* 1988, pp. 556–560.
[80] R. Mowbray, R. Pringle, and P. Grant, "Increased CDMA system capacity through adaptive cochannel interference regeneration and cancellation," *Proc. Inst. Elect. Eng.,* vol. 139, pt. I, pp. 515–524, Oct. 1992.
[81] Z. Siveski, Y. Bar-Ness, and D. W. Chen, "Error performance of synchronous multiuser code division multiple access detector with multidimensional adaptive canceler," *Eur. Trans. Telecommun. Related Technol.,* vol. 5, pp. 73–78, Nov./Dec. 1994.
[82] S. Baines, A. Burr, and T. Tozer, "Adaptive architecture for signal separation and interference suppression in DS-CDMA systems," *Electron. Lett.,* vol. 32, pp. 1057–1058, June 6, 1996.
[83] Y. Bar-Ness and J. Punt, "An improved multi-user CDMA decorrelating detector," in *Proc. Int. Symp. Personal, Indoor and Mobile Radio Communications 1996,* Toronto, Canada, 1995, pp. 975–979.
[84] D. Cruickshank, "Suppression of multiple access interference in a DS-CDMA system using Weiner filtering and parallel cancellation," *Proc. Inst. Elect. Eng. Commun.,* vol. 143, pp. 226–230, Aug. 1996.
[85] A. Duel-Hallen, "A family of multiuser decision-feedback detectors for asynchronous code-division multiple-access channels," *IEEE Trans. Commun.,* vol. 43, pp. 421–434, Feb.–Apr. 1995.
[86] W. Jakes, *Microwave Mobile Communications.* New York: Wiley, 1974.
[87] *Proc. IEEE Global Telecommunications Conference,* Phoenix, AZ, Nov. 1997.
[88] *Proc. Int. Conf. Telecommunications,* Melbourne, Australia, Apr. 1997.



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