Combined Adaptive Multiuser Detection for DS-CDMA Systems

YISHU GUO

A Thesis

In

The Department

Of

Electrical an Computer Engineering

Presented in Partial Fulfillment of the Requirements

for the Degree of Master of Applied Science at

Concordia University

Montreal, Quebec, Canada

October 2003

Your file Votre référence
ISBN: 0-612-91037-7
Our file Notre référence
ISBN: 0-612-91037-7

Abstract

Combined Adaptive Multiuser Detection for DS-CDMA Systems

YISHU GUO

The inadequacy of the conventional Code Division Multiple Access (CDMA) receivers in a multiple access interference-limited mobile radio environment has spurred research on advanced receiver technologies. This research investigates the use of adaptive receivers for multi-user detection to overcome some of the deficiencies of a conventional receiver and, hence, suppress the multiple access interference (MAI) and narrow band interference (NBI) in DS/CDMA wireless systems. The MAI is a major factor influencing the communication quality and the capacity in CDMA wireless systems. Hence, suppression of MAI and NBI are essential for an efficient performance of a CDMA wireless system and to enhance the system capacity. Analysis of the conventional detector and minimum mean-squared error (MMSE) detector is carried out to provide a better understanding of the effect of the channel parameters on the performance of the detectors and to explain the near-far resilience of the receiver. The performance of these detectors are compared and analyzed. The derivation of the relationship between the minimum mean-squared error detector and minimum output energy (MOE) detector is developed in order to provide an adaptive implementation of the later.

The limitation of the existing RLS blind algorithms for MMSE detector in AWGN channels is analyzed. In order to improve the performance of the existing schemes and to eliminate the requirement of training sequences, a scheme combining the blind adaptation and MAI cancellation is proposed. The performance of this algorithm is analyzed and compared with the existing schemes. Extensive simulations have been carried out to demonstrate that the proposed scheme is more reliable and it provides an effective resilience to the environment changes.

Acknowledgments

I wish to express my profound gratitude to Dr. M.O. Ahmad; he has always motivated me to excel in research. I am greatly thankful to him for his guidance to this thesis work and for his continuous support throughout the period as his graduate student. His insight and motivation are invaluable. His inspiration and support made this work possible.

I would also like to express my appreciation to the members of the examination committee, Professors V. Latinovic, W-P. Zhu, and M.N.S. Swamy, for their comments and suggestions on this thesis.

Finally, I dedicate this work to my husband, Qingshui, and my parents, for their love, support, and encouragement throughout my graduate studies.

Contents

List of Figures

List of Tables

List of Symbols

$y(t)$	Input signal to receiver
A_k	Received amplitude of the k^{th} user
b_k	Input bit symbol of the k^{th} user
$n(t)$	Additive White Gaussian noise
$s_k(t)$	Signature waveform of the k^{th}
T	Bit period
T_c	Chip interval
a_k	Normalized spreading sequence
$p(t)$	Rectangular pulse of duration T_c.
ρ_{ij}	Cross-correlation of the signature sequences
N	Length of the signature sequence
R	Cross-correlation matrix
$\hat{b}_k$	Detected bit symbol of k^{th} user
$\mathrm{w}(n)$	Filter tap weight vector
E	Statistical expectation operator
K	Number of users
G	Processing gain
$d\ (t)$	Output linear multiuser detector
$d_k(t)$	Output of a MMSE detector for user k
sgn( )	Signum function
$r(t)$	Received baseband signal during one symbol
$I(t)$	Narrow-band interference signal

$N(t)$	Ambient channel noise
P_k	Received power of the k th user
σ_n	Standard derivation of the noise samples
∇	Derivative operation

List of Acronyms

AR	Auto Regressive
FDMA	Frequency Division Multiple Access
TDMA	Time Division Multiple Access
CDMA	Code Division Multiple Access
DS/SS	Direct Sequence/Spread Spectrum
MAI	Multiple Access Interference
DS-CDMA	Direct Sequence CDMA
AWGN	Additive White Gaussian Noise
MUD	Multiuser Detection
MMSE	Minimum Mean square Error
PCS	Personal Communications Systems
NBI	Narrow-band Interference
SNR	Signal to Noise Ratio
SIR	Signal to Interference Ratio
iid	Independently and Identically Distributed
MAP	Maximum a Posteriori
BER	Bit Error Rate
ISI	Inter Symbol Interference
MOE	Mean output Energy
MSE	Mean Square Error
RLS	Recursive least squares algorithm

Chapter 1

Introduction

1.1 General

The tremendous strides achieved in wireless communications over the past decade have been spurred by an equally huge increase in the demand for wireless connectivity. The path from the wireless telegraphy to the third-generation personal communications has been a long one, and the stretch spanning the last decade has seen the most rapid progress with no indications of the pace reducing in the near future. The rapid developments are primarily due to the growth in very large scale integration (VLSI), which has led to the availability of greater computational capabilities for lower costs, thus making the implementation of novel technologies feasible.

The industry has increasingly supported the development of new technologies that improve the quality of wireless communications. Due to the finite amount of allocated radio spectrum and the evolution of several wireless communication applications in recent years, the wireless industry is seeking new ways to meet the demands of mobile radio subscribers. Since the ultimate objective of the industry is to establish ubiquitous wireless mobility , there is greater cooperation between industries and research institutions to achieve this goal. The competition between industries has further spurred this progress. Thus, it has been possible for novel and ingenious technologies to be realized commercially. The research presented here was motivated by this perspective of the industry and is a contribution to the cycle of supply and demand in mobile wireless communications. The objective of this research is to propose new techniques for interference suppression in direct sequence code division multiple access communications systems and to analyze these and the existing techniques.

Evaluation of techniques is achieved through both mathematical analysis and computer simulation.

1.2 Multiple Access Techniques

In any wireless communication system, there are many users who need to communicate simultaneously. Therefore, the available radio frequency (RF) resources must be distributed among these users in a way that allows them to access the communication system. In a coordinated system, such as a cellular network, the allocation of these resources requires extensive planning.

Perhaps the most natural and fundamental way for multiple users to communicate simultaneously is to allocate a different subband of the RF spectrum to each user. A simple bandpass filter at the receiver would then select the bandwidth of interest. This method, frequency division multiple access (FDMA), is the oldest method for multiple access, dating back to the invention of broadcast radio. Different channels in a FDMA system are simply assigned different frequency bands that do not overlap, as illustrated in Figure 1.1. One of the main features of FDMA is that each channel is narrowband, allowing either an analog or digital modulation scheme.

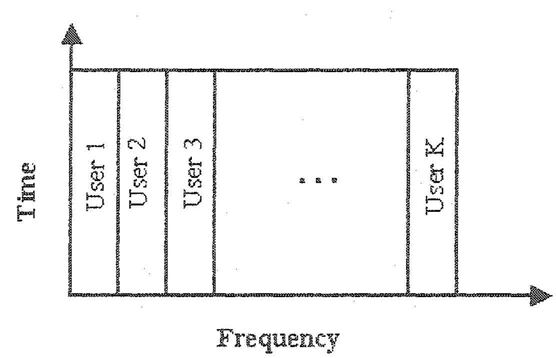

Figure 1.1: Frequency division multiple access

Instead of splitting the RF spectrum into subbands for each user, multiple non-overlapping time slots can be created and assigned to each user. The receiver synchronizes to the correct time slot to recover the user's information. Figure 1.2 shows resource allocation in a time division multiple access (TDMA) system, which is somewhat more complex technology. Since all users occupy the entire RF bandwidth, TDMA channels have much wider bandwidths compared with FDMA channels, usually necessitating equalization to overcome degradation due to multipath. One key source of complexity is the multiple levels of synchronization necessary to recover the information for each user. Due to the nature of TDMA, digital modulation schemes must be used.

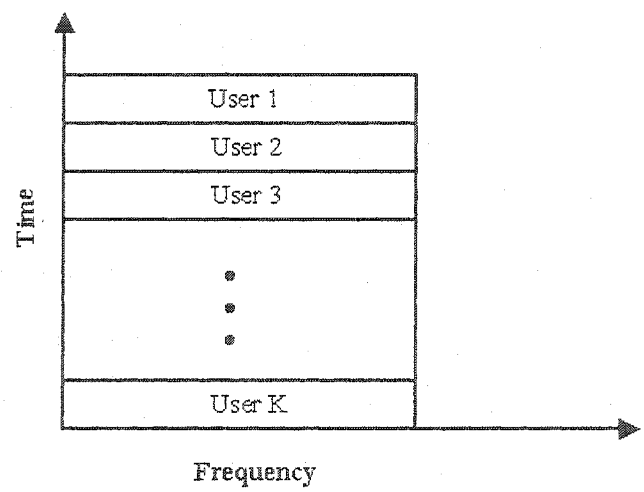

Figure 1.2: Time division multiple access

The most recent multiple access technology is code division multiple access (CDMA), based on direct sequence spread spectrum (DS/SS) communications. Unlike TDMA and FDMA, CDMA users occupy the entire bandwidth all the time. Users are distinguished from each other through the spreading codes assigned to them (Figure 1.3). The spreading code acts as a signature for the user and allows the user's receiver to extract the desired signal from all of the multiple access interference (MAI). Thus, the codes must be sufficiently different, i.e., they must have good crosscorrelation properties, to reduce the interference. Section 2.2 explains the impact of MAI.

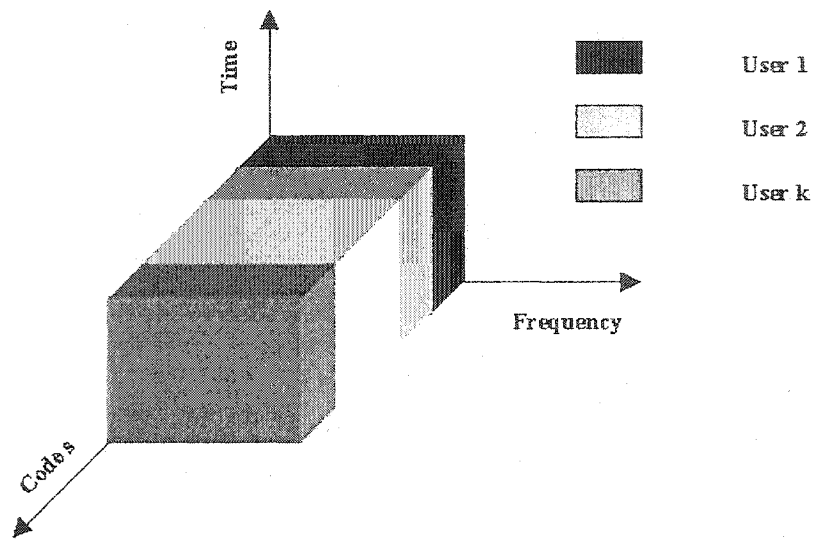

Figure 1.3 Code division multiple access

In a system employing CDMA, all the users within a cell concurrently share the same bandwidth. The most common CDMA flavor is called *direct sequence* CDMA (DS-CDMA). In DS-CDMA, the signal from each user is multiplied by a unique *signature waveform* prior to transmission, a process known as *spreading*. Since the signature waveform has a much larger bandwidth than the information bearing signal from the user, the CDMA signal constitutes a *spread spectrum* signal.

At the receiver, the sum of all the transmitted broadband signals is received. Conventionally, the signals from different users are extracted by cross-correlation with the respective signature sequences. Under ideal conditions, the spread spectrum signals corresponding to different users are orthogonal at the receiver. The output of each correlator is then the transmitted signal of the desired user. This correlation receiver is known as the *conventional receiver*.

In practice, the spread spectrum signals corresponding to different users are non-orthogonal at the receiver, and the outputs of all correlators have contributions from all the transmitted signals. This interference is known as *multiple access interference (MAI)* in the CDMA literature. Still, the conventional receiver works well under the following two conditions:

1) The correlation between the signature sequences is small.
2) The signals from different users are received with approximately the same power.

The first condition can be fulfilled by a careful design of the signature waveforms The second condition can be fulfilled by accurate *power control*, which implies that the receiver measures the received power and instructs the transmitter to adjust its output power to obtain the desired performance. Without power control, the powers of the received signals may differ significantly. This is the so-called *near-far problem*: A strong signal, typically originating near the receiver, will outpower a weak (far) signal.

Wideband CDMA technology has been proposed for the third-generation wireless personal communications [1] - [4]. A wide range of services will be provided by these systems, with the key being a unified radio infrastructure. Third-generation systems will improve the technology and services provided by second generation systems. Furthermore, a great deal of flexibility is being provided to allow for the evolution of technology. One of the special attributes of the proposals for wideband CDMA is the provision for advanced receivers. The novel aspects of wideband CDMA allow for the implementation of interference suppression and cancellation schemes. It will be seen in Chapter 4 that adaptive receivers may be employed in DS-CDMA systems to perform interference suppression and to improve the system performance. More extensive discussions of multiple access technologies can be found in [5] and [6]. Some recent developments in multiple access technologies have been presented in [7].

1.3 Cellular Communications

In the last decade of the 19th century, the world was brought into the era of wireless communications. In 1901, messages had been able to be transmitted across the Atlantic successfully. In 1909, radio transmitters had already been installed on ships all over the world. The wireless telegraph was a blessing for the maritime fleet: for the first time, it was possible to send distress calls irrespective of the weather conditions. It also became possible to receive weather reports and other messages from shore.

During the next few decades, radio transceivers found their way into more and more areas. In 1946, the world's first public mobile telephone system [8] was introduced in St Louis. The idea with this system was to supply the same services to mobile terminals that were available in the fixed telephone network. Within a year, 25 other American cities had mobile networks in operation. Each city had one *base station*, which was designed to cover as large area as possible. Every mobile in this area communicated with the base station, which relayed the calls through its connection with the fixed network.

With this system, the number of simultaneous calls that can be handled is limited by the available spectrum. Another disadvantage is that the transmitter power of the mobile terminals must be rather high to reach the base station. Already in 1947, a solution to these two problem was devised: the cellular system.

The cellular concept

The starting point was this: How do we provide private wireless communication services to mobile customers within a certain area? The original solution with a single powerful base station transmitter is depicted in Figure 1.4. The system has access to N frequencies, which can be used to communicate with the mobiles in its coverage area. Half of these frequencies are used for transmission from the base station to the mobiles, and the remaining frequencies are used for transmission from the mobiles to the base station. The former link is known as the *downlink* or *forward link*, and the latter is called the *uplink* or *reverse link*. In total, the system can accommodate $N/2$ users.

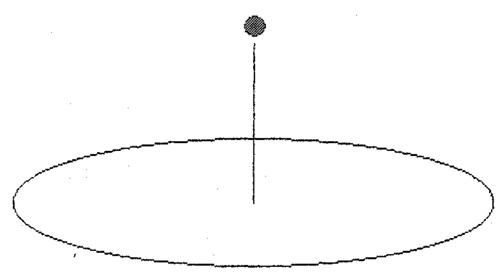

Figure 1.4: A cellular system with a single cell

Another solution is to build several base stations within the area, as depicted in Figure 1.5. Each of the base stations can now use $N/6$ frequencies to set up communication with at most $N/12$ mobiles in its coverage area. The system as a whole can thus still handle (at most) $6 \times N/12 = N/2$ simultaneous calls.

However, since each base station covers only a smaller area, it is possible to reduce the antenna height and the transmitter power so that the range of the base stations is reduced. This leads to reduced interference from neighboring transmissions, making it possible to *reuse* the frequencies. Taking the network in Figure 1.5 as an example, base stations A and F may use the same frequencies, and so may base stations C and D. The available frequencies can then be divided into only four groups with $N/4$ frequencies in each. The system can then handle $6 \times N/8 = 3N/4$ simultaneous calls. By building additional base stations, we have thus increased the system capacity. As a bonus, the mobiles can lower their transmit powers, and hence, their power consumption, which extends the battery life time.

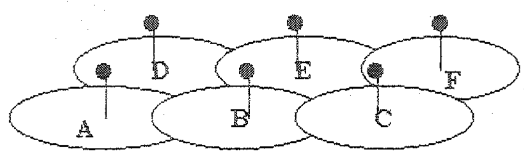

Figure 1.5: A cellular system with 6 cells

This is the *cellular concept*. A geographical area, which can be arbitrarily large, is divided into a number of *cells*. With each cell, we associate one base station, which provides wireless access to all mobiles in the cell. The base station is equipped with a transmitter and a receiver and is connected to a fixed network. The frequencies used by the base station for transmission and reception are reused by a base station some distance away. The smaller the reuse distance, the larger the system capacity.

When a mobile moves across a cell boundary, control of the call must be transferred from one base station to another. This process is known as *handover* or *hand off*. Making a handover without interrupting the telephone call was one of the major problems that delayed the introduction of a fully automatic commercial cellular system until the early 1980s.

In the system we have described so far, the users are granted exclusive access to a communication channel by assigning to each user a different frequency. We have noted this method in Section 1.2 as *frequency division multiple-access (FDMA)*, and was used in the so-called first generation systems. These systems used analog technology and frequency modulation. Examples of such systems are the Nordic standard NMT6, the British standard TACS7 and the North American standard AMPS8.

Modern cellular systems are digital and use a combination of FDMA and *TDMA/CDMA*. Examples of cellular systems which use TDMA are GSM9, the North American standards IS-54 and IS-136 which are sometimes collectively labeled as D-AMPS10 and the Japanese standard PDC11. All these systems belong to the second generation of cellular systems. All major operational CDMA based cellular networks are based on the IS-95 standard [9]. For the upcoming third generation of cellular systems, CDMA is the multiple-access method chosen for most proposals.

1.4 Advantages of Cellular CDMA over FDMA and TDMA

In a single cell scenario in an additive white Gaussian noise (AWGN) channel, the capacities of FDMA, TDMA, and deterministic CDMA, where the spreading waveforms are assumed orthogonal [10], are equal [10] - [12]. However, the potential advantages of CDMA are fully realized in a multi-cell system in the presence of fading multipath radio propagation channels.

The advantages of CDMA are primarily a result of spread spectrum technology [10] - [13]. Spread spectrum provides resistance to frequency selective fading due to multipath through spectral diversity, and robustness to MAI. The variance of the signal-to-noise ratio (SNR) at the receiver is lower for CDMA than for narrowband FDMA when operating in frequency-selective fading channels [11]. This applies to most practical CDMA systems where the signal bandwidth is significantly larger than the channel coherence bandwidth. CDMA is less susceptible to degradation due to inter-symbol interference than is TDMA [11].

One of the principal factors that influence the increase in the system capacity in CDMA systems is universal frequency reuse [14], [15], which means that the same spectrum can be used in all cells, i.e., the reuse factor is 1. This also eliminates the need for frequency planning. The higher the reuse factor, the lower the system capacity. A typical reuse factor used in TDMA and FDMA cellular systems is 7. Furthermore, the impact of cochannel interference, which results from other cells using the same frequency, is greater for TDMA and FDMA systems than for CDMA systems with accurate power control. Power control in TDMA and FDMA systems helps reduce interference. However, power control is a more serious problem in CDMA systems. In the absence of fast and accurate power control, the near-far problem can cause much stronger signals received from users closer to the basestation to jam weaker signals received from mobiles at the edge of the cell. The processing gain of the spread spectrum signal slightly mitigates the impact of interference.

CDMA allows for the exploitation of multipath energy with a Rake receiver [16]. The Rake receiver provides a means of constructive combining of multipath. Distinguishing multipath components is possible because the coherence bandwidth of the channel is much lower than the signal bandwidth or, equivalently, the delays of the components are much larger than a chip duration.

To improve the capacity, CDMA may take advantage of the low voice-activity of normal speech. Humans speak only about 35-40% of the time during a conversation and listen for the rest of the time. If transmission is blocked during the periods of silence, then the interference can be reduced, thus increasing the capacity [15].

When a user moves from one cell to a neighboring one, the signal must also move from one base station to another via handoff. The Rake receiver can be used to monitor the signal powers from two (or more) base stations carrying the same user's information. The gradual transition to another serving base station is carried out through a process known as soft handoff [5], [17]. Soft handoff usually allows for fewer dropped calls and a more consistent coverage area [18].

Another attribute of CDMA is its soft capacity limit, which results in a "soft blocking" of calls and a graceful degradation in performance. TDMA and FDMA place a hard limit on the number of users in a cell, resulting in "hard blocking". With CDMA, however, there is a graceful degradation in voice quality when the number of users exceeds a certain limit.

1.5 Concept of Multiuser Detection

Multiuser detection (MUD) is a technique that can be employed to improve the capacity and coverage in a CDMA systems. In theory, MUD can provide an improvement in capacity by a factor of almost three in additive white Gaussian noise channels, but in practice the improvement depends strongly on the detection scheme, channel estimation and delay estimation. It has been shown that MUD is able to exploit the structure contained in a multi-access interference signal and in that way can be near-far resistant. Hence, a practical system design could be undertaken without depending on high precision power control.

Research in the area of multiuser detection started in the late 1970s and followed along a path typical to numerous other techniques. In the early stages, optimal solutions with best possible performance in Gaussian noise channels were investigated and developed. Unfortunately, the complexity of these schemes increases exponentially with the number of users, which is not suitable for practical applications. This problem has been tackled subsequently and resulted in less complex sub-optimal multi-user detection algorithms such as the decorrelating detector, the multistage detector, the decision-feedback multi-user detector and other sub-optimal detectors.

1.6 Scope and Organization of the Thesis

With CDMA rapidly establishing itself as the multiple-access technology of choice, the need for improving the technology has arisen. This is especially important given the strong backing for CDMA in the third generation personal communications systems (PCS). The objective of this research work is to provide a thorough analysis of this new and the existing interference suppression techniques under the conditions of a practical radio environment and develop a new adaptive multiuser receiver for suppressing both the MAI and NBI in DS-CDMA systems. It is well known that the multiuser receiver improves the capacity of CDMA systems and provides some resistance to the near-far problem. This work unifies different approaches of multiuser detection within the same system model and exploits this model to improve the performance of an existing interference suppression technique. The numerical and simulation analyses are carried out to demonstrate the superiority of the MMSE detection, which leads to an adaptive implementation, over other techniques. The review of the canonical representation of MMSE linear detector paves the way to present the blind RLS adaptive version of multiuser detection. This work provides a crucial information necessary for the practical implementation of interference suppression under a realistic environment.

Chapter 2 provides overview of CDMA systems and its encoding process. Interference suppression concepts are also introduced. The limitations of a conventional receiver are explained and the minimum mean-squared error (MMSE) receiver is introduced for overcoming the limitations. The relative merits of multiuser and single user receivers are discussed, motivating the investigation of the adaptive multiuser receivers.

Multiuser detection (MUD) has been widely discussed in the literature. Chapter 3 provides a discussion on the different approaches to linear multiuser detection of CDMA signals in additive white Gaussian noise channels. Linear MUDs are detectors that operate linearly on the received signal statistic i.e., they perform only linear transformations on the received statistic. Expressions for the different detectors in additive white Gaussian noise channels are derived in terms of the cross-correlations between the spreading codes of the users, the interference-to-signal power ratios, and the signal-to-noise ratio of the desired signal. Simulations on these detectors are carried out and the analysis of the simulation results is presented to provide a comparison between the various detectors. Finally, it concluded that only minimum mean squared error detection can lead to an adaptive implementation of the interference suppression. The adaptation is achieved through a training sequence of data symbols.

Minimum mean-squared error receivers are implemented in practice by allowing an adaptive filter to learn the characteristics of the radio environment and to converge to the optimal solution. Adaptation algorithms, which aim at reducing the need for a training sequence to implement the adaptive MMSE receiver, are discussed in Chapter 4. This chapter also presents an adaptive code-aided technique for the simultaneous suppression of narrow-band interference (NBI) and multi-access interference (MAI) in DS/CDMA systems. This technique is based on the blind RLS version of the MMSE algorithm for multiuser detection. The steady-state performance of this algorithm in terms of signal-to-Interference ratio (SIR) is also reviewed. The limitation of this technique is discussed. In order to further improve the performance of blind RLS MUD in a more practical environment, a new combined adaptive MUD scheme is introduced in this chapter. The derivation of the proposed interference suppression scheme and then further cancellation of remaining MAI are presented. The performance in terms of steady state SIR and convergence of the proposed interference suppression and cancellation scheme are investigated, to show the superior features of the scheme over those of the existing schemes.

Chapter 5 provides extensive simulation results to demonstrate the performance of the new proposed scheme in terms of the steady state output SIR, system convergence, tracking capability, resilience to interference, and system stability. Comparisons between the new proposed technique and the scheme given in [66] are presented as well.

Chapter 6 provides a summary of the investigation undertaken in this thesis and offers some important conclusions of this research. Some suggestions are also made for the future research in this area.

Chapter 2

Adaptive Receivers for CDMA Systems

2.1 Overview of DS/CDMA System

Code division multiple access is a spread spectrum technique that uses neither frequency channels nor time slots. In CDMA, the narrow band message (typically digitized voice data) is multiplied by a large bandwidth signal which is a pseudo random noise (PN) code. All users in a CDMA system use the same frequency band and transmit simultaneously. The transmitted signal is recovered by correlating the received signal with the PN code used by the transmitter.

CDMA technology was originally developed by the military during World War II. Researches were spurred into looking at ways of communicating that would be secure and work in the presence of jamming. Some of the properties that have made CDMA useful are:

- Signal hiding and non-interference with existing systems
- Anti-jam and interference rejection
- Information security
- Accurate ranging
- Multiple user access
- Multipath tolerance

2.1.1 General Structure

In contrast with TDMA and FDMA, where time or frequency is partitioned among users, in CDMA all users occupy the same frequency band simultaneously. Each user is assigned a distinct signature sequence (or waveform) with which the user employs to modulate and spread the information-bearing signal. The signature sequences also allow the receiver to demodulate the message transmitted by multiple users of the channel.

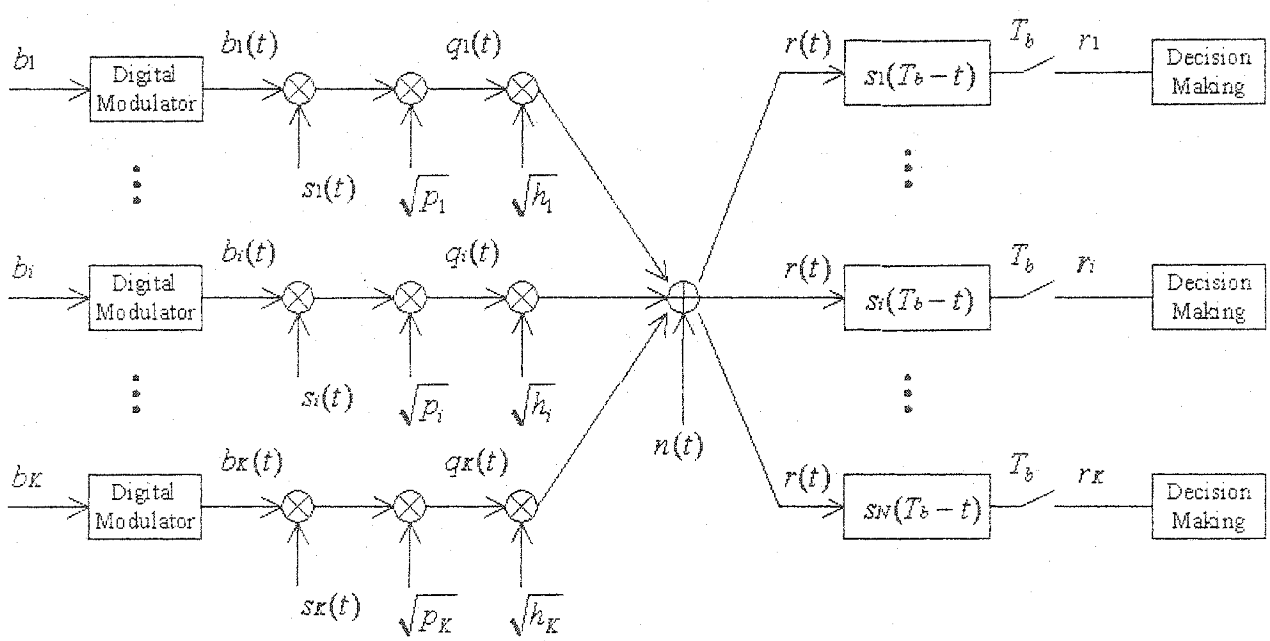

Figure 2.1: General structure of a CDMA system

Figure 2.1 gives a block diagram of the general structure of a CDMA system. In this figure, b_i and $b_i(t)$ are the binary information bit of user i and the corresponding digital waveform at the output of the digital modulator; $s_i(t)$, p_i, h_i are the signature waveform, the transmitted power and the channel gain between the transmitter and receiver of user i; $n(t)$ is an additive white Gaussian noise; T_b is the bit duration of the transmitted information bit;

and K is the number of users in the system. A binary baseband DS/SS signal is derived by multiplying a binary level (± 1) information signal with a binary level spreading sequence, that is signature waveform. The spreading signal $s(t)$ exhibits the constant modulus property given by

$$|s(t)| = 1 \tag{2.1}$$

where $|.|$ denotes the absolute value.

Assume that all the users in the system are synchronous. We can express the transmitted signal of user i in one information bit interval as

$$q_i(t) = \sqrt{p_i} b_i(t) s_i(t) \tag{2.2}$$

As mentioned above, BPSK modulation scheme and rectangular waveform are used for digital modulation. Then $b_i(t)$ is a rectangular waveform with amplitude +1 or -1. Therefore, (2.2) is equivalent to

$$q_i(t) = \sqrt{p_i} b_i s_i(t) \tag{2.3}$$

At the receiver side, the received signal can be expressed as

$$r(t) = \sum_{i=1}^{N} \sqrt{p_i}\sqrt{h_i}\; b_i s_i(t) + n(t) \tag{2.4}$$

which is then demodulated with the matched filters of the users. At the output of the matched filter of user i, we obtain

$$r_i = \int_{T_b} r(t) s_i(t) dt = \sqrt{p_i}\sqrt{h_i} b_i \rho_{ii} + \sum_{j \neq i} \sqrt{p_i}\sqrt{h_i}\; b_i \rho_{ij} + n_i \tag{2.5}$$

where $\rho_{ij} = \int_{T_b} s_i(t)s_j(t)dt$ is the cross correlation between the signature waveforms of user i and user j, and $n_i = \int_{T_b} n(t)s_i(t)dt$ is a Gaussian random variable. In (2.5), $\sqrt{p_i}\sqrt{h_i}b_i\rho_{ii}$ represents the signal component of the desired user, $\sum_{j \neq i}\sqrt{p_i}\sqrt{h_i}\ b_i\rho_{ij}$ represents the interference caused by other users to the desired user and is called *multiple access interference* (MAI), and n_i represents the interference caused by AWGN. We will see later that MAI has an important effect on the performance of a multiuser CDMA wireless system.

If the signature waveforms satisfy orthogonality, i.e.,

$$\rho_{ij} = \int_{T_b} s_i(t)s_j(t)dt = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases} \tag{2.6}$$

then (2.5) reduces to

$$r_i = \sqrt{p_i}\sqrt{h_i}b_i + n_i \tag{2.7}$$

In (2.7), the interference due to other users or the multiple access interference, is completely eliminated. Thus, with a careful design of the signature waveforms, a multiuser CDMA system can achieve the performance of a single user system.

One of the most important concepts required to understand the spread spectrum techniques is the idea of processing gain. The processing gain of a system indicates the gain or signal to noise improvement exhibited by a spread spectrum system by the nature of the spreading and despreading process. The processing gain of a system is equal to the ratio of the spread spectrum bandwidth used, to the original data bit rate. Thus, the **processing** gain can be written as

$$G_p = \frac{BW_{RF}}{BW_{\inf o}} \tag{2.8}$$

where BW_{RF} is the transmitted bandwidth after the data is spread, and $BW_{\inf o}$ is the bandwidth of the information data being sent.

2.1.2 CDMA Forward Link Encoding

For the forward link, from the base station to the mobile, a CDMA system can use a special orthogonal signature wave sequence, also called the pseudo random noise sequence (PN codes). One such popular sequence is Walsh code, which separats the multiple users on the same channel. This code is based on a Walsh matrix, which is a square matrix with binary elements and dimension which is a power of two. It is generated from the basis that

$$\text{Walsh}(1) = W_1 = 0 \tag{2.9}$$

and

$$W_{2n} = \begin{bmatrix} W_n & W_n \\ W_n & \overline{W_n} \end{bmatrix} \tag{2.10}$$

where W_n is the Walsh matrix of dimension n. For example, W_2 and W_4 can be obtained as

$$W_2 = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \tag{2.11}$$

$$W_4 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 \end{bmatrix} \tag{2.12}$$

Walsh codes are orthogonal, which means that the dot product of any two rows is zero. This is due to the fact that for any two rows exactly half the number of bits match and the half do not.

Each row of a Walsh matrix can be used as the PN code of a user in a CDMA system. By doing so the signals from each user is orthogonal to every other user, resulting in no interference between the signals. However, orthogonality is lost when all users are not synchronized to a single time base. This results in inter-user interference. For the forward link, signals for all the users originate from the base station, thus allowing the signals to be easily synchronized.

2.1.3 CDMA Reverse Link Encoding

The reverse link is different from the forward link in that the signals from each user do not originate from the same source as in the forward link. The transmission from each user arrives at a different time due to the propagation delay and synchronization errors. Due to the unavoidable timing errors between the users, there is little point in using Walsh codes as they will no longer be orthogonal. For this reason simple pseudo random sequence, which are uncorrelated but not orthogonal, are used for the PN codes of each user.

The generation of PN sequences for the reverse link is a topic that has received considerable attention in the technical literature. By far the most widely known PN sequence is m-sequence, which is a maximum-length shift-register sequence, has a length of $n = 2^m - 1$ bits and is generated by an m-stage shift register with a linear feedback.

Ideally, the PN sequences among the users should be mutually orthogonal. However, the PN sequence used in practice exhibit some correlation. As for m-sequence, its cross-correlation peak values will increase to an undesirable level when the number of sequences in the selected set increases. Although it is possible to select a small subset, the number of sequences in the set is usually too small for CDMA applications. Gold code has been proposed by Gold (1967, 1968) and Kasami (1966), which is derived from m sequences and exhibits better periodic cross-correlation properties. Throughout this thesis, Gold codes are used in all the relevant simulations as the spreading sequence for the above reason.

Because of the differences in modulation, the capacity is different for the forward and reverse links. The fact that the reverse link is not orthogonal, results in a significant inter-user interference. For this reason, the reverse channel sets the capacity of the system.

2.2 Interference Suppression in DS/CDMA wireless System

2.2.1 MAI suppression

In CDMA wireless systems, mobile users transmit information bits which are modulated by the signature waveforms of the users. The base stations then demodulate the received signal with the same signature waveform for each user. Due to the effect of channel distortion in a wireless environment, no matter how carefully we design the signature waveforms, the orthogonality condition in (2.6) does not hold in most cases. Thus, at the receiver side (base station), the MAI term of the matched filter output in (2.5) always exists. This non-zero MAI term has asignificant impact on the performance of the system.

Consider the case in which the desired user is far away from its assigned base station while the interfering users are close to that base station. Since the channel gain is proportional to the inverse of the α^{th} power (α is the path loss exponent) of the distance between the transmitter and the receiver, the received powers of the nearby interfering users can be much greater than that of the desired user far away. Thus, due to the non-zero MAI, at the output of the matched filter receiver, the nearby interfering users can dominate the desired user in terms of received power. This can make a reliable detection of the information bits of the desired user almost impossible. This phenomenon is called the *near-far problem* of CDMA wireless system.

In a CDMA system, all the users occupy the same frequency band all the time. There is no absolute allocation of resources (time slots or frequency bands) among the users in the system. Thus, the capacity of a CDMA system depends directly on the average interference levels, rather than on the number of time slots in the TDMA system or the number of frequency subbands in the FDMA system. However, as seen above, the non-zero MAI can cause undesirable interference and result in the near-far problem. Suppression of the MAI is, therefore, essential to the performance of a CDMA wireless system. It can not only improve the communication quality, but also increase the capacity of the system.

In conventional CDMA systems where matched filters are used as receivers, the MAI term as seen from (1.4), is $\sum_{j \neq i} \sqrt{p_i}\sqrt{h_i}\, b_i \rho_{ij}$. Since the receiver (matched filter) structure is fixed after the signature sequences are assigned to the users, ρ_{ij} cannot be changed. Since h_j and b_j are independent of the system design, the only way for us to mitigate the MAI is to reduce p_j, the transmitter powers of the interfering users, as much as possible while at the same time maintain a certain QoS (quality of service) requirement for each user in the system. This MAI suppression approach is called the *power control*.

In practice, the power control is implemented in the form of a feedback control. The base station receives signals and estimates the transmitter powers of the users in the system. Based on the estimation, it then calculates the optimal transmitter power needed by each user and send power update commands back to the users through the forward-link wireless channel. Upon receiving the power update commands from the base station, mobile users update their transmitter powers to their respective optimal levels. For matched filter receivers, power control is an efficient and the only approach to MAI suppression. It has been proved feasible in practical CDMA systems such as IS95.

2.2.2 NBI Suppression

Code-division multiple-access implemented with direct-sequence spread spectrum signaling is among the most promising multiplexing technologies for cellular telecommunications services, such as personal communications, mobile telephony, and indoor wireless networks [13], [19] - [22]. The advantages of the direct-sequence spread spectrum for these services include superior operation in multipath environments, flexibility in the allocation of channels, the ability to operate asynchronously, privacy, and increased capacity in fading channels. Also among the attractive features of spread spectrum CDMA is the ability of the spread spectrum systems to share bandwidth with narrowband communication systems without undue degradation of either system's performance. In particular, the ability of the spread spectrum to provide a reliable performance in severe signal-to-noise (SNR) environments and its low energy profile make the sharing of the frequency bands by multiple and disparate users a real possibility. This ability provides a means by which to alleviate the overcrowding in the radio frequency spectrum, as well as to allow more user flexibility in the choice of the modulation format.

In a direct-sequence spread spectrum system, a data signal is modulated with a binary pseudonoise (PN) signal having a nearly flat spectrum before transmission, so that the transmission bandwidth is much greater than the message bandwidth. At the receiver, the incoming signal is "despread" by correlating it with the PN signal. This process is illustrated in Fig. 2.2. The binary pulses comprising the PN signal are known as chips to distinguish them from the binary bits of the data signal. The number of chips per data bit, G, is the spreading ratio or processing gain of the system given in (2.8). The noise immunity improves with increasing G. Each user in a spread spectrum CDMA system has a distinct PN code that allows the receiver to distinguish it from the other users in the system. Again, increasing the processing gain (and hence, the transmitted bandwidth) allows for the accommodation of more users, since it results in lower cross-correlations between the PN signals of the multiple users [23]. For the demodulation of CDMA signals, the despread data signal can be processed via one of several multiuser receiver algorithms, including simple sign extraction [24], [25], decorrelation [24], [25] or maximum-likelihood sequence detection [26].

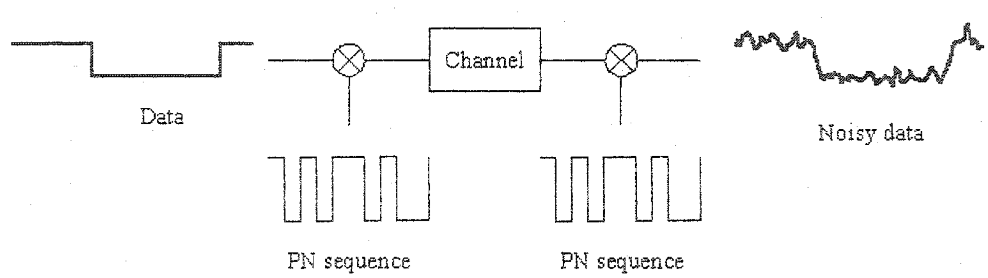

Figure 2.2: Spreading/despreading procedure

As noted above, the spreading of the data signal's energy over a sufficiently wide bandwidth allows it to co-exist with narrowband signals with only a minimum of interference for either signal. Obviously, the low spectral density of the spread spectrum signal assures that it will cause little damage to the narrowband signal beyond that already caused by the ambient wideband noise in the channel. On the other hand, although the narrowband signal has a very high spectral density, this energy is concentrated near one frequency and is of very narrow bandwidth. The despreading operation of the spread spectrum receiver has the effect of spreading this narrowband energy over a wide bandwidth, while at the same time it collapses the energy of the originally spread data signal down to the original data bandwidth. Thus, after despreading, the situation is reversed between the original narrowband interferer (which is now wideband), and the original data signal (which is now narrowband). A bandpass filter can be employed so that only the interferer power that falls in the bandwidth of the despread signal causes any interference. This will be only a fraction, 1/G, of the original narrowband interference that could have occupied that same bandwidth before despreading. This process is illustrated in Fig. 2.3.

Thus, spread spectrum communications is inherently resistant to the narrowband interference (NBI) caused by the co-existence with the conventional communications. However, it has been demonstrated that the performance of spread spectrum systems in the presence of narrowband signals can be enhanced significantly through the use of an active NBI suppression prior to despreading [27] - [29]. Not only does the active suppression improves the error-rate performance [30], but it also leads to increased CDMA cellular system capacity [3] and an improved acquisition capability [31].

2.3 Adaptive Receivers

Since the origin of DS/SS technology, the classical technique of matched filtering has been used for the detection of DS/SS signals. The principal assumption that the background noise

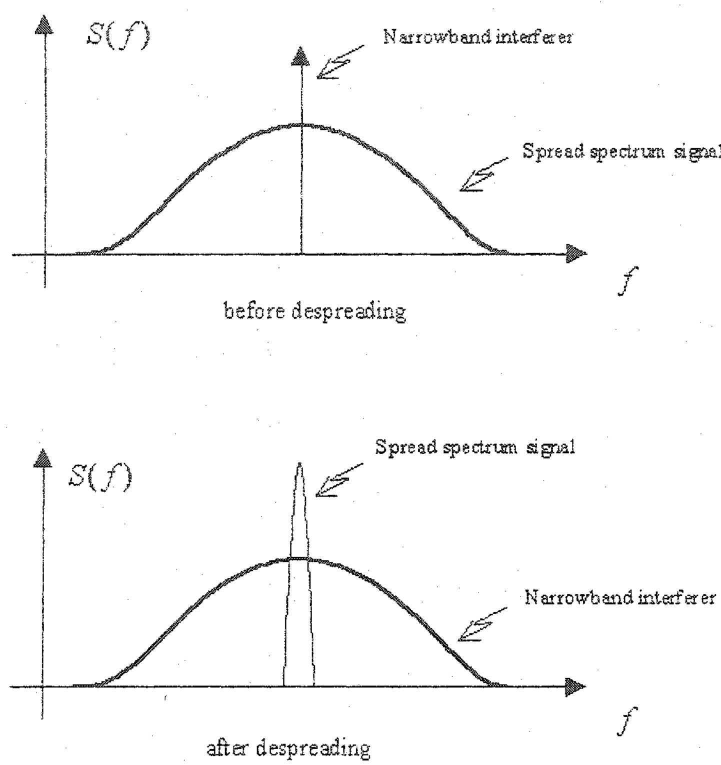

Figure 2.3: Spectral effect

is white makes the matched filter the optimum receiver in the sense that it maximizes the SNR assuming perfect synchronization. Furthermore, when the noise is Gaussian, the matched filter is also the maximum a posteriori (MAP) detector. Thus, no receiver can provide a lower probability of bit error, or bit error rate (BER), than a matched filter based receiver when detecting a DS/SS signal in AWGN [16], [22]. The correlation receiver is merely a realization of the matched filter. In practical DS/SS CDMA systems, the assumption that the desired signal is received with only AWGN is not true and thus there exist better receivers than the matched filter. Understanding the operation of the conventional receiver is helpful in explaining the need for adaptive receivers.

2.3.1 Multiuser Receiver

Since the conventional receiver is far from optimum, a question naturally arises: "what is the optimum receiver?" One approach to obtaining the optimal or near optimal receiver is to demodulate the signals of all of the users in the system. The receivers belonging to this class are known as multiuser receivers. A vast amount of research work exists in this area. Verdu [33] has shown that a maximum likelihood sequence detection approach minimizing the probability of sequence error can provide a solution to this problem. Minimum probability of bit error can be achieved by implementing the optimum receiver as a backward-forward dynamic programming algorithm [34]. It turns out that the structure of the multiuser receiver consists of a bank of matched filters followed by the Viterbi algorithm [16], [35]. The computational complexity of the optimum receiver grows exponentially as the number of users increases and is prohibitive for practical implementation.

From a practical standpoint, a sub-optimum receiver with a much lower complexity is desirable. The decorrelating detector [36] is a relatively low complexity linear receiver. The decision statistics are obtained by a linear transformation of the vector formed by the outputs of the bank of matched filters. The transformation matrix is the inverse of the crosscorrelation matrix. The complexity of this receiver is linear in the number of users. The decorrelating detector outperforms the conventional receiver in most cases of interest and is near-far resistant [37]. The detector has a higher complexity for an asynchronous channel than for a synchronous one and an accurate knowledge of the signal delays is essential. Furthermore, recomputation of the crosscorrelation matrix and its inverse is required whenever a user leaves or enters the system. Finally, there can be problems with matrix inversion with fixed-point arithmetic.

There are also nonlinear sub-optimum multiuser receivers. One such receiver performs successive interference cancellation and uses decision feedback [38]. In this receiver, the signals from all of the users are ranked according to their powers (based on their detected amplitudes). The strongest user is detected by a conventional receiver and the corresponding spread signal regenerated, the strongest interference signal is subtracted out of the received signal, and the process is repeated for progressively weaker signals for all of the signals. Multistage receivers differ from this receiver in that the decisions made at the outputs of the initial matched filters are tentative, and the users' signal estimates are made in parallel rather than in succession [39] - [41]. A multistage Rake receiver [42] can cancel the interference as well as combine the multipath. These schemes also exhibit near-far resistance [43], [44] and their complexities are linear in the number of users, but they again require accurate knowledge of the spreading codes of all of the users, their phases, and their delays. A detailed discussion of multiuser receivers can be found in [44] and [45], and the performance comparison of various multiuser receivers is addressed in [43] and [44].

2.3.2 Classification of Adaptive Receivers for CDMA Systems

CDMA receivers may be categorized broadly into multiuser receivers and single-user receivers. This classification is based on the receiver structure, i.e., based on whether the receiver demodulates a single user or jointly demodulates some or all of the active users in the system. In the literature, receivers which we call "single user" receivers are often classified under multiuser receivers when a number of them are used in parallel to separately demodulate the multiple users. Here, the term "multiuser receivers" is used to describe strictly those receivers that need to demodulate the multiple users even if only one user is of interest. Buehrer [44] and Duel-Hallen et al. [45] discuss the classification of multiuser receivers in detail. Figure 2.4 shows the general classification of multiuser receivers.

During the late 80s and early 90s, a significant amount of research addressed the problem of reducing the computational complexity of multiuser detection. A key approach to this problem is to restrict the optimal detector to be of the form of a linear multiuser detector, in which the data is demodulated by a scalar quantization of a linear mapping on the crosscorrelation matrix of the spreading sequences. This type of detector comprises a linear filter applied to the received waveform, followed by a scalar quantizer. Two types of linear detectors of interests are the decorrelation detector (or decorrelator), which chooses the linear filter to have a zero output MAI [49], and the minimum mean squared error detector, which chooses the linear filter to have minimum output energy within the constraints that the response of the filter to $s_k(t - iT - \tau_k)$ is fixed [50]. Such detectors can be shown to satisfy other optimality criteria as well. Although such detectors fall short of optimal (maximum-likelihood) detection in terms of the error-probability, they are still far superior to the conventional detection in terms of the error-probability performance in interference limited environments.

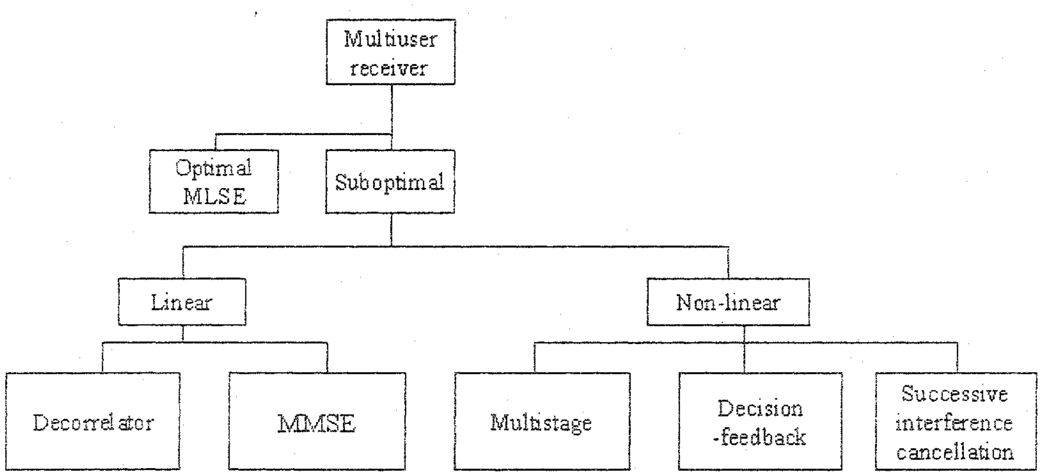

Figure 2.4: Classification of multiuser receivers for CDMA systems

The major challenges for MUD systems are as follows:

- The high DSP load in the receiver which increases rapidly with the number of users

- The need for an accurate channel information and timing for each incoming user

Currently, there are a number of schemes and implementation methods for MUD; these include maximum-likelihood [48], decorrelator [49], MMSE [50], multistage detectors [51], decision feedback detectors [52], and successive interference cancellers [53]. Since they all require a large signal processing overhead, suboptimal solutions must be considered.

2.4 Summary

The objective of this research is to develop adaptive multiuser detection algorithms for wideband CDMA systems that can cope with non-stationary, non-ideal conditions in a mobile radio environment. This chapter has provided a motivation and an overview of DS/CDMA system and adaptive receivers. It has been shown that the conventional matched filter receiver is not optimal when a signal is received in multiple access interference. The near far problem in cellular CDMA systems occurs when a strong multiple access interference completely jams a weak desired signal. Multiuser receivers, which simultaneously demodulate signals from multiple users, are able to alleviate the problems arising from multiple access interference and are near-far resistant. Adaptive receivers, can perform interference rejection with reasonable complexity. A classification of adaptive receivers has also been provided. The details of the commonly used multiuser receiver structures are presented in the next chapter.

Chapter 3

Multiuser Detection

In direct-sequence code division multiple access (DS/CDMA) systems all the users concurrently share the same bandwidth. The users are distinguished by assigning to each user a unique code or signature sequence, whose bandwidth is much larger than that of the transmitted information. This code sequence is used to modulate the data stream.

Conventionally, the transmitted information is retrieved at the receiver by crosscorrelation with the signature sequence, followed by a symbol rate sampling. This matched filter or conventional receiver is optimum in the single-user case or when all the signature sequences are orthogonal at the receiver. The first case is obviously of no interest, and the second one is practically impossible to achieve.

In practice, the detection is adversely affected by multiple-access interference. When the powers of the received signals from different users are approximately equal, the detrimental effect of MAI is relatively small. However, the conventional receiver is unable to detect weak signals, typically originating far from the receiver, in the presence of strong (near) interferers. This is the so-called near-far problem.

In Chapter 2, we have seen that the power control alleviates the MAI and the near-far problem by using a fixed matched filter receiver structure. However, the matched filter receiver is optimal only when the signature sequences of the users in the system are orthogonal to each other, which is normally not the case in wireless communication. To further suppress the MAI, we must use a more complex receiver structure, namely multiuser detector, to demodulate the received signals.

Multiuser Detection is a scheme of estimation/demodulation of transmitted bits in the presence of MAI. MAI occurs in multi-access communication systems (CDMA/ TDMA/ FDMA) where simultaneously occurring digital streams of information interfere with each other. Conventional detectors based on the matched filter treat the MAI just as an additive white gaussian noise (AWGN). However, unlike AWGN, MAI has a nice correlative structure that is quantified by the cross-correlation matrix of the signature sequences. Hence, detectors that take into account this correlation would perform better than the conventional matched filter-bank. MUD is basically the design of signal processing algorithms that run in the black box shown in Figure 3.1. These algorithms take into account the correlative structure of the MAI.

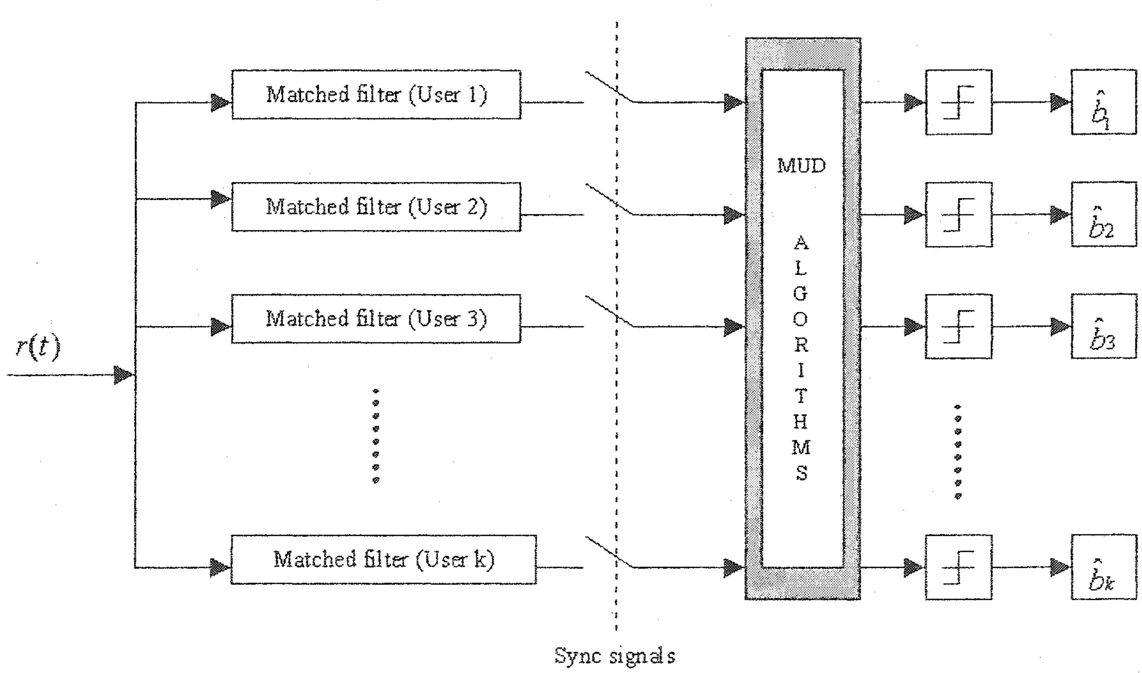

Figure 3.1: A typical multiuser detector

In this chapter, multiuser detection approach to MAI suppression will be discussed. We will first review the matched filter bank detector, which is the conventional and simplest way of demodulating the CDMA signals (or any other set of mutually interfering digital streams). The multiuser detector is a term that is used generically for any receiver that attempts to exploit the structure of a MAI. This term includes the receivers that are interested in a reliable demodulation of a single user. In this chapter, the decorrelating detector takes the matched filter one step further by taking into account the correlative structure of the MAI. The minimum mean square error (MMSE) linear detector is then studied which is a compromise between the matched filter approach and the decorrelating detector.

3.1 System Model

In this chapter, the basic K-user discrete time synchronous model is used for a CDMA system. BPSK modulation is applied to modulate the user information. The Gold code is chosen as the pseudo-random signature sequence. For the system simulation, a small spreading sequence of length 31 was used. In all the simulations, a perfect power control is assumed (i.e, the received amplitudes of all the users are assumed to be the same). The signal at the receiver is given by

$$r(t) = \sum_{k=1}^{K} A_k\, b_k s_k(t) + n(t) \qquad t \in [0, T] \tag{3.1}$$

where, $b_k \in \{-1,1\}$ is the input bit of the k^{th} user, A_k is the received amplitude of the k^{th} user, $n(t)$ is additive white gaussian noise with PSD N_0. And $s_k(t)$ is the signature waveform of the k^{th} user (s_k is normalized to have a unit energy i.e., $< s_k, s_k > =1$). For BPSK spreading with a Gold-code of length 31, the signature waveform is defined as

$$s_k(t) = \sum_{k=1}^{31} a_k p_T(t - kT_c), \tag{3.2}$$

where, T is bit period, T_c is chip interval, a_k represents the normalized spreading sequence, and $p(t)$ is a rectangular pulse of duration T_c.

For the sake of simplicity, a perfect synchronous CDMA system is considered. It is assumed that the receiver has some means of achieving a perfect chip synchronization. The cross-correlation of the signature sequence is defined as

$$\rho_{ij} = < s_i s_j > = \sum_{k=1}^{G} s_i(t) s_j(t) \tag{3.3}$$

where G is the length of the signature sequence (31 in this case). The cross-correlation matrix is then defined as

$$\mathbf{R} = \{ \rho_{ij} \} = \begin{bmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1K} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2K} \\ \vdots & \vdots & \cdots & \vdots \\ \rho_{K1} & \rho_{K2} & \cdots & \rho_{KK} \end{bmatrix} \tag{3.4}$$

$\mathbf{R}$ is a symmetric, non-negative definite, toeplitz matrix.

3.2 The Matched-filter Bank

This section introduces and analyzes the matched filter bank detector that is the conventional and simplest way of demodulating CDMA signals (or any other set of mutually interfering digital streams). The matched filter also forms the front-end in most MUDs, and hence, an understanding of its operation is crucial in appreciating the evolution of the MUD technology.

3.2.1 Receiver Operation

In the conventional single-user digital communication systems, the matched filter is used to generate sufficient statistics for signal detection. In the case of a multi-user system, the detector consists of a bank of matched filters (each matched to the signature waveform of a user in the case of CDMA). This is shown in Figure 3.2. This type of detector is referred to as the conventional detector in the MUD literature. It is worth mentioning that we need the exact knowledge of the users signature sequences and the signal timing of the desired users in order to implement this detector.

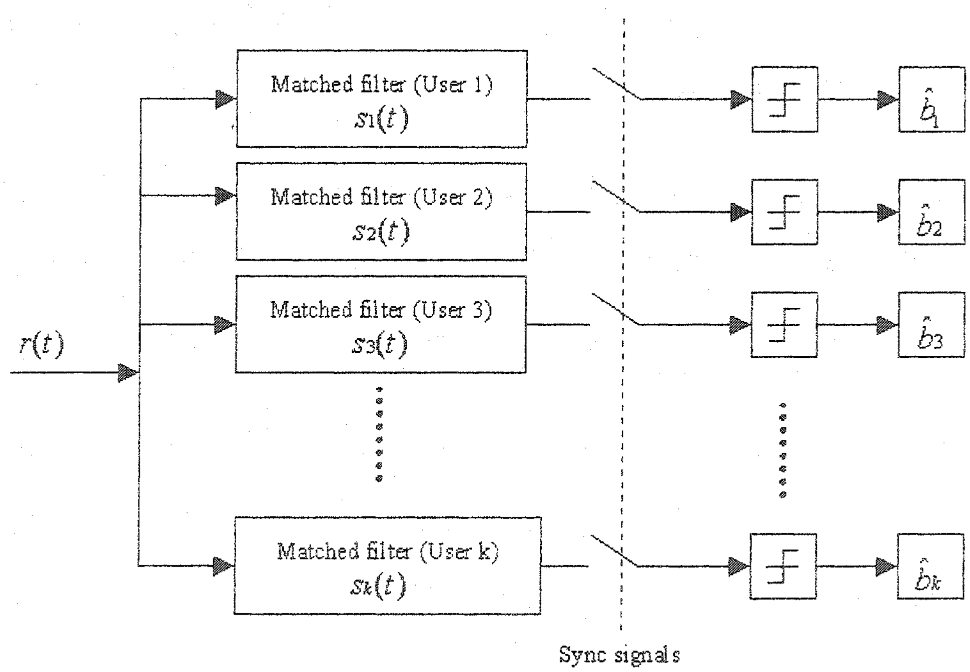

Figure 3.2: A matched filter bank receiver

The decision statistic at the output of the kth matched filter is given by

$$r_k = \int_0^T y(t)s_k(t)dt \tag{3.5}$$

where $r(t)$ and $s_k(t)$ is given by (3.1) and (3.2). Expanding (3.5), we have

$$\begin{aligned} r_k &= \int_0^T \{\sum_{k=1}^{K} A_k\, b_k s_k(t) + n(t)\} s_k(t)dt \\ &= \sum_{j=1}^{K} A_j\, b_j \rho_{jk} + n_k \end{aligned} \tag{3.6}$$

where

$$n_k = \int_0^T n(t)s_k(t)dt \tag{3.7}$$

Since $\rho_{11} = 1$, (3.6) simplifies to

$$r_k = A_k b_k + \sum_{\substack{j=1 \\ j \neq k}}^{K} A_j\, b_j \rho_{jk} + n_k \tag{3.8}$$

The second term in (3.8) is the MAI, which is caused by the cross-talk between users. The matched filter treats the MAI just as a white noise. The noise variance at the output of the matched filter is given by

$$\begin{aligned} E(n_k^2) &= E\left[\int_0^T n(t)s_k(t)dt \int_0^T n(w)s_k(w)dw\right] \\ &= \int_0^T \int_0^T E[n(t)n(w)] s_k(t)s_k(w)dtdw \\ &= \int_0^T \int_0^T N_0 \delta(t-w) s_k(t)s_k(w)dtdw \end{aligned}$$

$$= \int_0^T N_0 s_k^2(t)dt$$

$$= N_0 \tag{3.9}$$

Similarly, the noise covariance can be shown to be

$$E(n_i n_j) = N_0 \rho_{ij} \tag{3.10}$$

Hence, the noise covariance matrix can be defined as

$$E[\mathbf{nn}^T] = \{N_0 \rho_{ij}\}_{ij} = N_o \mathbf{R} \tag{3.11}$$

where $\mathbf{R}$ is given by (3.4) and $\mathbf{n} = [n_1, n_2, .., n_k]^T$. Stacking up (3.8) for all the users we get

$$\begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_k \end{bmatrix} = \begin{bmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1K} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2K} \\ \vdots & \vdots & \cdots & \vdots \\ \rho_{K1} & \rho_{K2} & \cdots & \rho_{KK} \end{bmatrix} \begin{bmatrix} A_1 & 0 & \cdots & 0 \\ 0 & A_2 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & A_K \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_k \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \\ \vdots \\ n_k \end{bmatrix} \tag{3.12}$$

Thus, in matrix notation we have,

$$\mathbf{r} = \mathbf{RAb} + \mathbf{n} \tag{3.13}$$

3.2.2 Simulation Results for a Matched Filter Bank Receiver

To be consistent with other approaches to linear multiuser detection, the system model will be the same as the one presented in 3.1 in all the simulation throughout this chapter. Figure

3.3 shows the BER **(bit error rate)** performance for the matched filter bank receiver. In this example, a CDMA system with perfect synchronization is considered. The plots of BER versus SNR (signal to noise ratio) illustrates the performance of the same system with different users. The spreading gain is 31. The spreading codes are Gold code, which were generated using two m-sequences, and found to have Gold-like properties.

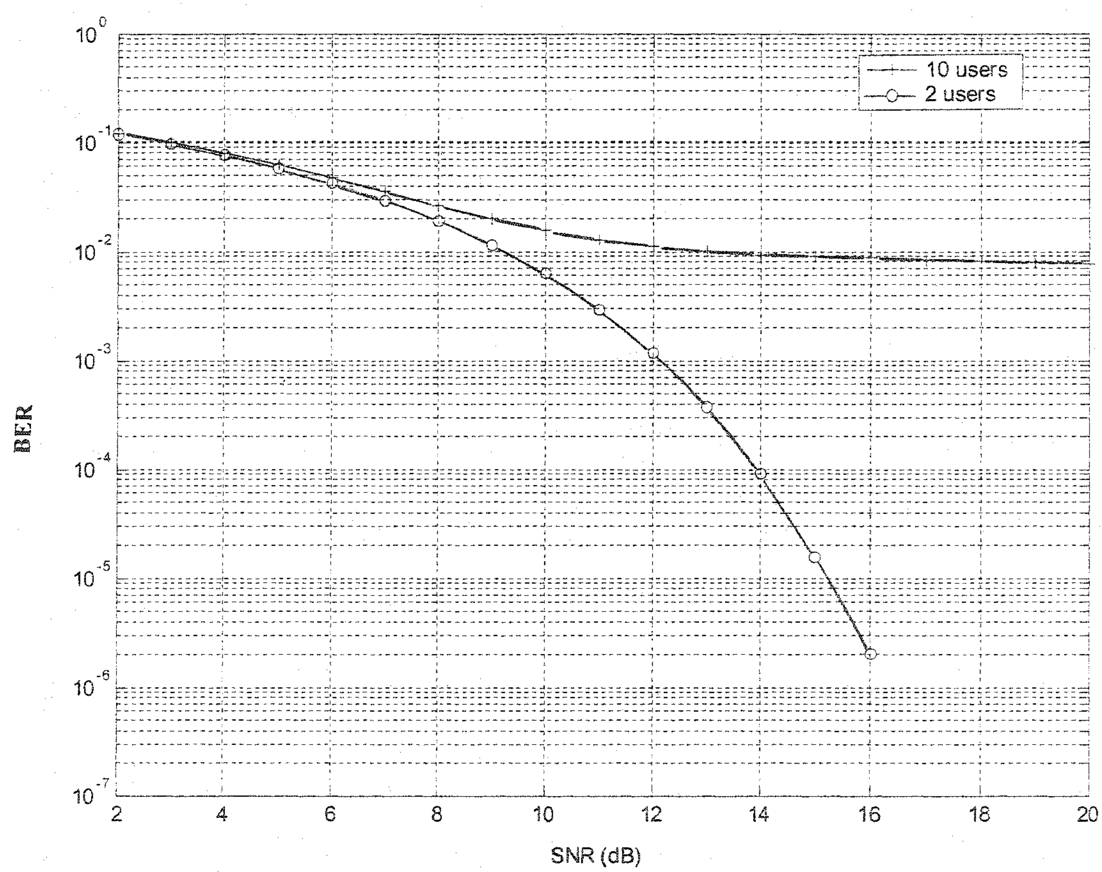

Figure 3.3: BER performance of the matched–filter bank detector

It is observed that the MF receiver performance is tolerable when there are only two users. In such a case, the BER degrades dramatically as the signal power increases. As the number of user increases up to 10, the performance is extremely poor with the BER remaining 10^{-2}, no matter how much the signal power is increased. This is because the detector ignores the cross-talk (that is the MAI) between the users as white noise. Thus, it is severely limited by the near-far problem even in the presence of a perfect power control. Good MUDs, as described in the following sections, take into account the correlative property of the cross-talk.

3.2.3 Limitations of The Conventional Detector

As we have seen in the previous subsections, the conventional detector makes the wrong assumption that r_k is a sufficient statistic for detecting b_k by ignoring the MAI as background noise. This is one reason for the poor performance of the matched filter bank when the number of users is large.

Another serious limitation of the conventional detector is that it is seriously affected by the near-far problem. This causes a significant degradation in the system performance even when the number of users is very small. This fact will now be illustrated with an example. This example adapts (3.8) to the 2 users scenario. We assume that the user 1 is the user of interesting.

$$r_1 = A_1 b_1 + A_2 b_2 \rho_{12} + n_1 \tag{3.14}$$

It is now obvious that the bit error probability for user 1 is given by

$$P_{s1} = \frac{1}{2}\left\{Q\left(\frac{A_1 + A_2\rho_{12}}{N_0}\right) + Q\left(\frac{A_1 - A_2\rho_{12}}{N_0}\right)\right\} \tag{3.15}$$

The probability of bit error is then readily bounded as

$$P_{s1} \leq \frac{1}{2} Q\left(\frac{A_1 - A_2|\rho_{12}|}{N_0}\right) \tag{3.16}$$

The fact that Q is a monotonically decreasing function has been used to get this upper bound. If the interferer is not dominant i.e., $A_2\rho_{12} < A_1$, the bit error probability is less than one-half. But, if the interferer is dominant (near-far problem), i.e., $A_2\rho_{12} > A_1$, the bound becomes greater than one-half. Consider the case when there is no noise in the system (i.e., $N_0 = 0$) and the interferer is dominant, then (3.16) gives $P_{s1} = 1/2$. This is because the output of the matched filter outputs is now governed by b_2 rather than b_1. Hence, we see that in the absence of noise, though highly hypothetical, the matched filter receiver reduces to flipping a coin and deciding the output bits. This is an undesirable feature of the conventional detector. As a matter of fact, the conventional detector may perform better in the presence than in the absence of noise.

3.2.4 The Conventional Detector as a Front End to MUDs

The front end of any MUD has a section to convert the received continuous-time signal to its discrete-time version. This is usually done by sampling, it can also be done using the matched filter bank. As seen earlier, the conventional detector takes the received signal $r(t)$ and outputs the statistic $\{r_1, \ r_2, \ \ldots, \ r_k\}^T$. It has been proved [55] that the matched filter bank sacrifices no information relevant to the demodulation. Hence, $r(t)$ can be replaced by r without any loss in system performance. Most MUDs, therefore, have the matched filter as the front end.

With the matched filter at front end, the objective of MUD can be stated as follows: *Given the statistic* $\{r_1, \ r_2, \ \ldots, \ r_k\}$ *at the output of the matched filter, find an estimate for the* *transmitted bits* $\{b_1, \ b_2, \ \ldots, \ b_k\}$ *that minimize the probability of the error.* The probability of the error is chosen as the optimization criterion, since it is the most important criterion for measuring the efficiency of a digital communication system.

3.3 The Decorrelating Detector

We have seen in Section 3.2 that due to the vulnerability to the near-far problem of the simple matched filter receivers, it is impossible to completely suppress the MAI with matched filter receivers in wireless communications.

It was noted that the matched filter bank may provide erroneous detection even in the absence of background AWGN. This is not a very attractive property for any receiver. An optimal receiver must be capable of decoding the bits error-free when the noise power is zero. In this section the decorrelating detector is investigated. This detector makes use of the structure of MAI to improve the performance of the matched filter bank. The decorrelating detector falls into the category of linear multiuser detectors, which has a linear computational complexity but does not exhibit the vulnerability to other user interferences. This fact is substantiated as this section progresses.

3.3.1 Receiver Operation

As shown in Figure 3.4, the decorrelating detector operates by processing the output of the matched filter bank with the $\mathbf{R}^{-1}$ operator where $\mathbf{R}$ is the cross-correlation matrix as defined in Section 3.1. Again a synchronous CDMA system is considered.

The received signal vector $\mathbf{r}$ that represents the output of the K matched filters is described by

$$\mathbf{r} = \mathbf{RAb} + \mathbf{n} \tag{3.17}$$

The noise vector has a covariance given by

$$E[\mathbf{nn}^T] = \frac{N_0}{2}\mathbf{R} \tag{3.18}$$

Since the noise is Gaussian, $\mathbf{r}$ is described by a K-dimensional Gaussian pdf with a mean of **RAb** and covariance of **R.** Thus, the probability of error is

$$p(\mathbf{r} \mid \mathbf{b}) = \frac{1}{\sqrt{(N_0\pi)^k \det \mathbf{R}}} \exp\left[-\frac{1}{N_0}(\mathbf{r} - \mathbf{RAb})^T \mathbf{R}^{-1}(\mathbf{r} - \mathbf{RAb})\right] \tag{3.19}$$

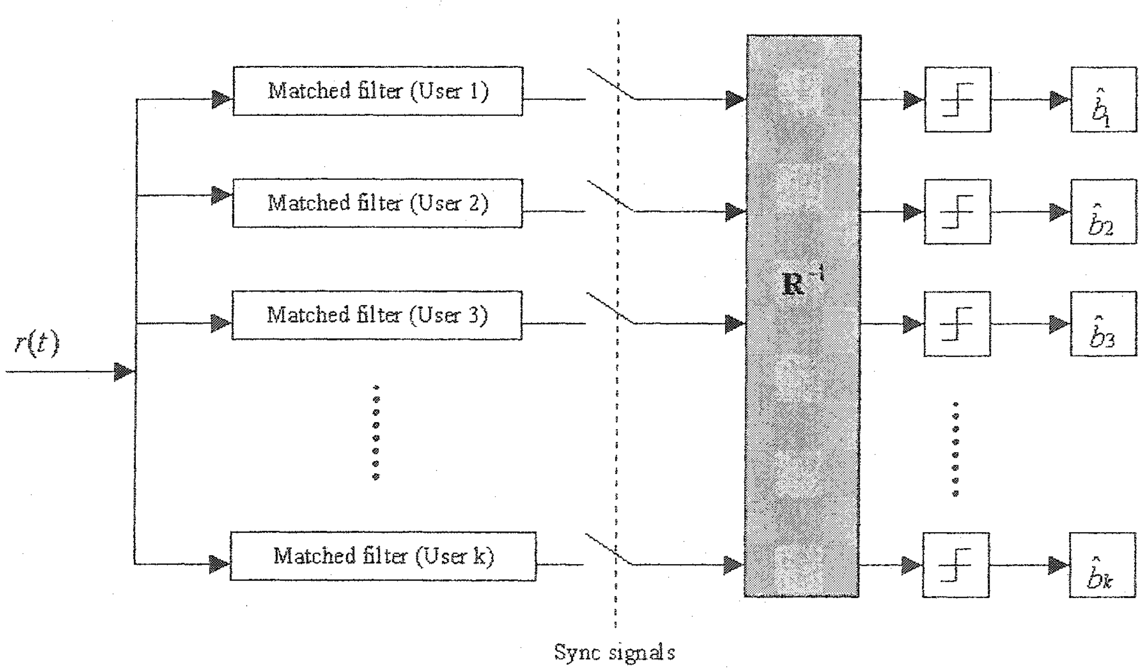

Figure 3.4: Decorrelating detector

The best linear estimation of $\mathbf{b}$ is the value of $\mathbf{b}$ that minimizes the likelihood function given by

$$\Lambda(\mathbf{b}) = (\mathbf{r} - \mathbf{RAb})^T \mathbf{R}^{-1}(\mathbf{r} - \mathbf{RAb}) \tag{3.20}$$

The result of this minimization yields

$$\mathbf{b}^0 = \mathbf{R}^{-1}\mathbf{r} \tag{3.21}$$

The detected symbols are then obtained by taking the sign of each element of $\mathbf{b}^0$, that is,

$$\hat{\mathbf{b}} = \mathrm{sgn}(\mathbf{b}^0) \tag{3.22}$$

By substituting (3.21) into (3.22), the output of the decorrelating detector is given by

$$\begin{aligned}\hat{\mathbf{b}} &= \mathrm{sgn}(\mathbf{b}^0)\\ &= \mathrm{sgn}(\ \mathbf{R}^{-1}(\mathbf{RAb} + \mathbf{n}))\\ &= \mathrm{sgn}(\ \mathbf{Ab} + \mathbf{R}^{-1}\mathbf{n})\end{aligned} \tag{3.23}$$

When the background noise is absent, i.e., $N_0 = 0$,

$$\hat{\mathbf{b}} = \mathrm{sgn}(\ \mathbf{Ab}) = \mathbf{b} \tag{3.24}$$

Hence, we observe that in the absence of a background noise the decorrelating detector, unlike the matched filter bank, achieves a perfect demodulation. One advantage of the decorrelating detector is that it does not require the knowledge of the amplitudes of the received signal.

For the case of K=2,

$$\mathbf{R} = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}, \tag{3.25}$$

where ρ is the cross-correlation between the normalized signature waveforms of user 1 and user 2. Thus, we have

$$\mathbf{R}^{-1} = \frac{1}{1-\rho^2}\begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \tag{3.26}$$

The received signal is given by

$$\mathbf{y} = \begin{bmatrix} A_1 b_1 + \rho A_2 b_2 + n_1 \\ \rho A_1 b_1 + A_2 b_2 + n_2 \end{bmatrix} \tag{3.27}$$

After some manipulation, we have

$$\mathbf{b}^0 = \mathbf{R}^{-1}\mathbf{r}$$

$$= \frac{1}{1-\rho^2}\begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\begin{bmatrix} A_1 b_1 + \rho A_2 b_2 + n_1 \\ \rho A_1 b_1 + A_2 b_2 + n_2 \end{bmatrix}$$

$$= \begin{bmatrix} A_1 b_1 + (n_1 - \rho n_2)/(1-\rho^2) \\ A_2 b_2 + (n_2 - \rho n_1)/(1-\rho^2) \end{bmatrix} \tag{3.28}$$

From (3.28), it is clear that the interference components between the two users are eliminated by performing a linear transformation on the vector of the correlator outputs. Thus, the computational complexity is linear in K.

We see that the decorrelating receiver performs only linear operations on the received statistic $\mathbf{r}$, and hence, it is indeed a linear detector. The decorrelating detector is proved to be optimal under 3 different criteria: least squares, near-far resistance and maximum-likelihood [54].

It is also interesting to note that the result similar to the one given by (3.28) is obtained if we correlate $\mathbf{r}$ with the two modified signature waveforms given by

$$s_1'(t) = s_1(t) - \rho s_2(t) \tag{3.29}$$

$$s_2'(t) = s_2(t) - \rho s_1(t) \tag{3.30}$$

This means that, by correlating the received signal with the modified signature waveforms, we have decorrelated the multiuser interference. Hence, the detector based on (3.21) is called a decorrlator detector.

3.3.2 Simulation Results

Consider a CDMA system presented in Section 3.1. For simplicity, we assume that the channel is synchronous. The BER versus SNR plots have been obtained for the cases of 2 and 10 users and are shown in Figure 3.5. The simulation scenario is as described in Section 3.1. Comparing Figure 3.3 and Figure 3.5, we note that for the case of 10 users, as the SNR increases, the performance of the decorrelating detector gets better, since the linear transformation has been performed on the vector of correlator outputs and eliminated the

MAI. This makes the MAI suppression possible in decorrelating detector. It is observed that at low SNRs, the matched filter performs better. Hence, the decorrelating detector is only an sub-optimal detector [16].

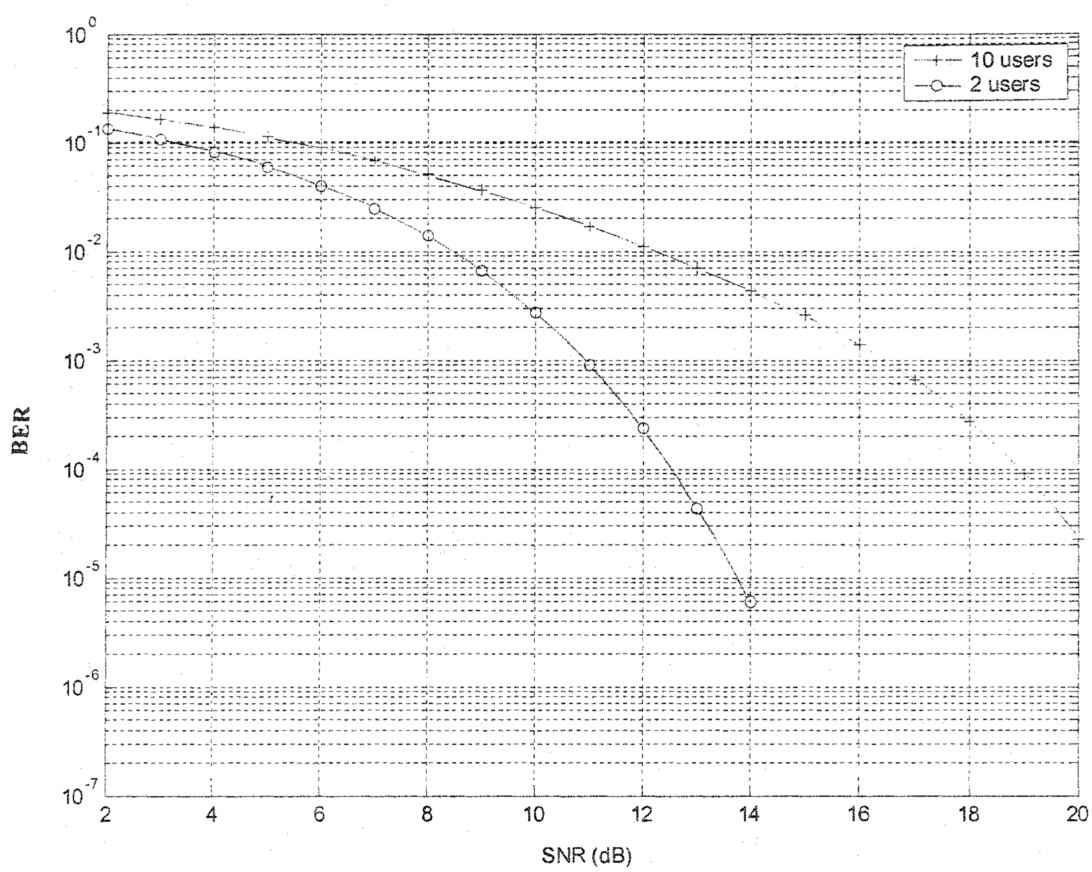

Figure 3.5: BER performance of the decorrelating detector.

From the simulation results given above, it is noted that the decorrelating detector (modified matched filter orthogonal to the multiaccess interference) is sufficient in order to achieve optimum resistance against the near-far problem (for high SNR).

3.4 The MMSE Linear Detector

In Section 3.3, we noted that the only information required by the decorrelating detector was the cross-correlation matrix **R** of the spreading sequences. At low SNRs, the matched filter bank performs better than the decorrelating detector as observed from Figures 3.3 and 3.5. Hence, it might be possible to improve the performance by incorporating some interference information in the MUD algorithms. In this section, one such approach is investigated, where the mean squared error between the output and data is minimized. The detector resulting from the minimum mean square error (MMSE) criterion is a linear detector.

In mobile CDMA systems, the knowledge about the transmitted data of the user of interest and interference signals is hardly available. An adaptive solution of detection problem that requires a minimal information about the user of interest and the interference signals is highly desirable. As we will see in the following chapters, a major advantage of MMSE schemes, relative to other previously proposed interference suppression schemes, is that an explicit knowledge of interference parameters is not required, since filter parameters can be adapted to achieve the MMSE solution. This feature will lead to a blind adaptive implementations of a CDMA system. Also, the complexity of these schemes, measured in terms of number of filter coefficients, can be adjusted to achieve a given level of performance.

In this section, we will study the characteristics and the performance of the linear MMSE detector, which will pave the way for a blind adaptive implementation of MUD for a CDMA system. The MMSE linear detector for a pulse-amplitude modulated data signal, in the presence of interfering data signals, consists of sampling the channel output at the chip rate and using a K-tap adaptive FIR filter to minimize the mean squared error (MSE) between the transmitted and detected symbols, where K is the processing gain [55].

3.4.1 MMSE Linear Detector in an AWGN Channel

In the previous discussion, an estimate was derived by performing a linear transformation on the output of the bank of correlators or matched filters. If we seek the linear transformation $\mathbf{b}^0 = \mathbf{W}\mathbf{r}$, another solution can be obtained, in which the $K \times K$ matrix $\mathbf{W}$ is to be determined to minimize the mean squared error (MSE) given by

$$\begin{aligned} J(\mathbf{b}) &= E[(\mathbf{b}-\mathbf{b}^0)^T(\mathbf{b}-\mathbf{b}^0)] \\ &= E[(\mathbf{b}-\mathbf{W}\mathbf{r})^T(\mathbf{b}-\mathbf{W}\mathbf{r})] \end{aligned} \tag{3.31}$$

Assuming that user 1 is the user of interest, the objective function (the mean square error) for this user is defined as

$$E[(b_1 - \sum_{i=1}^{K} w_i r_i)^2] \tag{3.32}$$

which can also be expressed in a compact form, using convenient matrix notations, as

$$\Psi(\mathbf{w}) = E[(b_1 - \mathbf{w}^T\mathbf{r})^2] \tag{3.33}$$

where, $\mathbf{r} = \{r_1, r_2, \ldots, r_K\}^T$ is the output of the matched filter bank sampling at the symbol rate, and $\mathbf{w} = \{w_1, w_2, \ldots, w_K\}^T$ is a vector consisting of K weights that minimize the MSE defined in (3.32), and operate on the received statistic $\mathbf{r}$.

Using the linearity of the expectation operator, we have

$$\Psi(\mathbf{w}) = E(b_1^2) - E(2b_1\mathbf{w}^T\mathbf{r}) + E\left\{(\mathbf{w}^T\mathbf{r})(\mathbf{w}^T\mathbf{r})^T\right\} \tag{3.34}$$

Since the bits of user 1 are i.i.d, $E(b_1^2)=1$. Therefore, we have

$$\begin{aligned}\Psi(\mathbf{w}) &= 1-2\mathbf{w}^T E(b_1\mathbf{r}) + E\left\{\mathbf{w}^T\mathbf{r}\mathbf{r}^T\mathbf{w}\right\} \\ &= 1-2\mathbf{w}^T E(b_1\mathbf{r}) + \mathbf{w}^T E\left\{\mathbf{r}\mathbf{r}^T\right\}\mathbf{w}\end{aligned} \tag{3.35}$$

From (3.13), we have

$$\mathbf{r} = \mathbf{RAb}+\mathbf{n}$$

Now, consider

$$\begin{aligned}E(b_1\mathbf{r}) &= E(b_1\mathbf{RAb}+b_1\mathbf{n}) \\ &= \mathbf{RA}E\left(b_1\begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_K\end{bmatrix}\right) + E(b_1\mathbf{n}) \\ &= \mathbf{RA}\begin{bmatrix} E(b_1^2) \\ E(b_1\, b_2) \\ \vdots \\ E(b_1 b_K)\end{bmatrix} + b_1 E(\mathbf{n})\end{aligned} \tag{3.36}$$

Since the transmitted bits of any user are i.i.d and are uncorrelated with the bits of other users, we have

$$E(b_i b_k) = \begin{cases} 0, & i \neq j \\ 1, & i = j \end{cases} \tag{3.37}$$

Using (3.37) and the fact that the noise $\mathbf{n}$ has a zero mean i.e., E($\mathbf{n}$)=0 in (3.36), we have

$$E(b_1\mathbf{r}) = \mathbf{RA}[1 \quad 0 \quad 0 \quad \cdots \quad 0] \tag{3.38}$$

Using the definitions of **A** and **R** from (3.4) and (3.12) yields

$$E(b_1\mathbf{r}) = \begin{bmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1K} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2K} \\ \vdots & \vdots & \cdots & \vdots \\ \rho_{K1} & \rho_{K2} & \cdots & \rho_{KK} \end{bmatrix} \begin{bmatrix} A_1 & 0 & \cdots & 0 \\ 0 & A_2 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & A_K \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} \rho_{11}A_1 \\ \rho_{211} \\ \vdots \\ \rho_{K1}A_1 \end{bmatrix} \tag{3.39}$$

Now, consider the part of the second expectation term in (3.35) as given by

$$\begin{aligned} E\{\mathbf{r}\mathbf{r}^T\} &= E\{(\mathbf{RAb})(\mathbf{RAb})^T\} + E(\mathbf{nn}^T) \\ &= E\{\mathbf{RAbb}^T\mathbf{A}^T\mathbf{R}^T\} + E(\mathbf{nn}^T) \end{aligned} \tag{3.40}$$

Using the fact that **A** and **R** are symmetric matrices, we get

$$\begin{aligned} E\{\mathbf{r}\mathbf{r}^T\} &= \mathbf{RAE}\{\mathbf{bb}^T\}\mathbf{AR} + N_0\mathbf{R} \\ &= \mathbf{RA}^2\mathbf{R} + N_0\mathbf{R} \end{aligned} \tag{3.41}$$

Substituting (3.39) and (3.41) in (3.35), we have

$$\Psi(\mathbf{w}) = 1 - 2\mathbf{w}^T[\rho_{11}A_1 \quad \rho_{21}A_1 \quad \cdots \quad \rho_{K1}A_1]^T + \mathbf{w}^T[\mathbf{RA}^2\mathbf{R} + N_0\mathbf{R}]\mathbf{w} \tag{3.42}$$

Equation (3.42) gives the objective function that should be minimized according to the MMSE criterion. Performing a matrix derivative operation on (3.42), we get

$$\nabla_w \Psi(\mathbf{w}) = -2[\rho_{11}A_1 \quad \rho_{21}A_1 \quad \cdots \quad \rho_{K1}A_1]^T + 2[\mathbf{R}\mathbf{A}^2\mathbf{R} + N_0\mathbf{R}]\mathbf{w} \tag{3.43}$$

We have used the fact that $[\mathbf{R}\mathbf{A}^2\mathbf{R} + N_0\mathbf{R}]$ is a symmetric matrix to get (3.43). The optimum weights that minimize the MSE can be obtained by setting $\nabla_w \Psi(\mathbf{w})$ to zero. Hence, we have

$$-2[\rho_{11}A_1 \quad \rho_{21}A_1 \quad \cdots \quad \rho_{K1}A_1]^T + 2[\mathbf{R}\mathbf{A}^2\mathbf{R} + N_0\mathbf{R}]\mathbf{w}_{mmse} = 0 \tag{3.44}$$

Solving (3.44), the optimal weights are obtained as

$$\mathbf{w}_{mmse} = [\mathbf{R}\mathbf{A}^2\mathbf{R} + N_0\mathbf{R}]^{-1}[\rho_{11}A_1 \quad \rho_{21}A_1 \quad \cdots \quad \rho_{K1}A_1]^T \tag{3.45}$$

To calculate the optimal weights for user m, we can just replace ρ_{i1} by ρ_{im} for all i and replace A_1 by A_m in (3.45). Equation (3.45) can be written in a more general and compact form as

$$\mathbf{W}_{mmse} = [\mathbf{R} + N_0\mathbf{A}^{-2}]^{-1} \tag{3.46}$$

where, $\mathbf{W}_{mmse}$ is a $K \times K$ matrix, whose k^{th} column is the MMSE solution for the k^{th} user as shown in (3.45), and

$$N_0\mathbf{A}^{-2} = diag\left\{\frac{N_0}{A_1^2}, \frac{N_0}{A_2^2}, \ldots, \frac{N_0}{A_K^2}\right\} \tag{3.47}$$

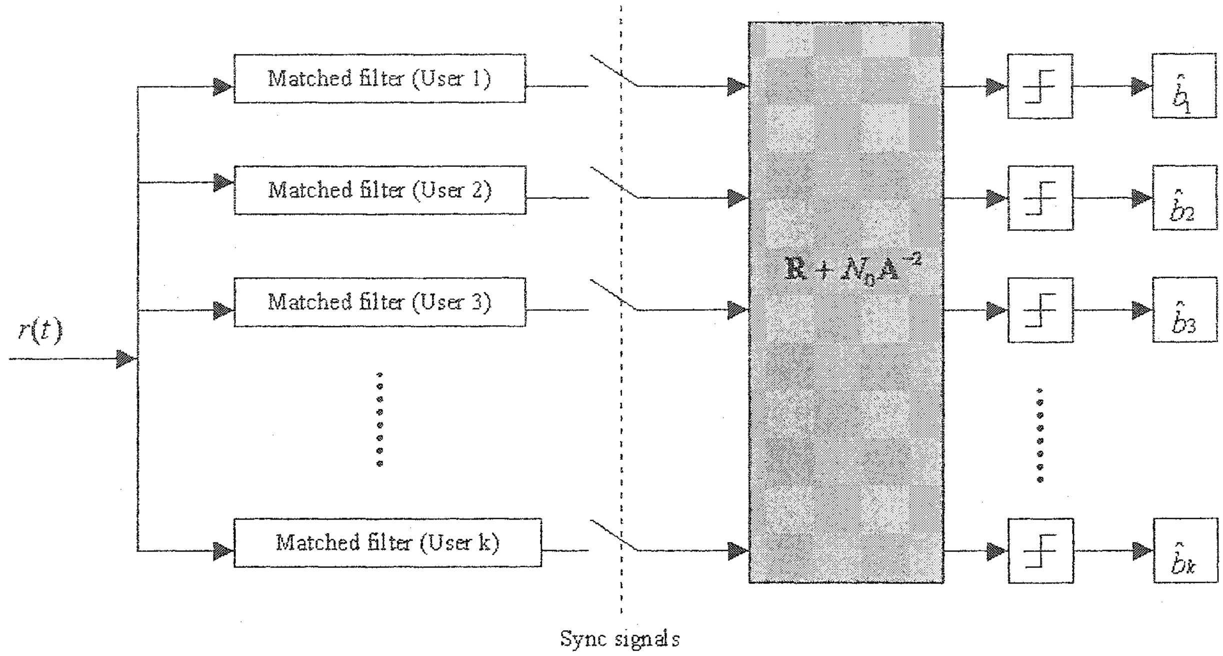

Figure 3.6: MMSE linear detector

Equation (3.46) explains the operation of the receiver. The receiver simply weights the received statistic with $\mathbf{W}_{mmse}$ and makes a decision as shown in Figure 3.1. This leads to the receiver architecture shown in Figure 3.6.

Equation (3.46) reveals the dependency of the optimum solution of MMSE detector on the cross-correlation matrix $\mathbf{R}$ defined in (3.4) and diagonal matrix $\mathbf{A}$. In order to obtain the optimum $\mathbf{W}_{mmse}$, we need the information about the signature sequences and amplitudes from all the users. Furthermore, for practical implementations of the MMSE detector, the algorithm employed, whether LMS or RLS algorithm, requires a reference signal to update the weight vector and produce the optimum $\mathbf{W}_{mmse}$. Obviously the best choice for the reference signal is the data symbol transmitted, which is practically unavailable. In many cases the use of a training sequence is a relatively simple solution. But in a constantly changing mobile environment, the system performance and stability may not be ideal by applying a training sequence. The knowledge of the signature sequence and amplitude of active users in the system is available only at the cost of additional complexity. We are seeking a possible solution of MMSE interference suppression, which is achievable in practice while keeping the additional complexity as low as possible. Such a solution will be presented in the next chapter.

It has been shown in [55] that the MMSE receiver maximizes the output SIR. As we know, the conventional matched filter receiver is optimized to fight the background white noise exclusively, whereas the decorrelating detector eliminates the multiuser interference disregarding the background noise. In contrast, the MMSE linear detector can be seen as a compromise solution that takes into account the relative importance of each interfering user and the background noise. In fact, both the conventional receiver and the decorrelating receiver are the limiting cases of the MMSE linear detector. If we hold A_1 fixed and let $A_{2,} \ \ldots, \ A_k \rightarrow \infty$, the first row of $[\mathbf{R} + N_0\mathbf{A}^{-2}]^{-1}$ tends to

$$\left[\frac{A_1^2}{A_1^2 + \sigma^2}, \quad 0, \quad \cdots, \quad 0 \right]$$

which corresponds to the matched filter for user 1. As σ grows, $[\mathbf{R} + N_0\mathbf{A}^{-2}]^{-1}$ becomes a strongly diagonal matrix, and the MMSE detector approaches the conventional detector as $\sigma \rightarrow \infty$.

If we hold all the amplitudes fixed and let $\sigma \rightarrow 0$, then

$$[\mathbf{R} + N_0\mathbf{A}^{-2}]^{-1} \rightarrow \mathbf{R}^{-1} \qquad (3.48)$$

Therefore, as the signal-to-noise ratio goes to infinity, the MMSE linear detector converges to the decorrelating detector. This fact implies that the MMSE linear detector has the same asymptotic efficiency and near-far resistance as the decorrelating detector.

3.4.2 Simulation Results

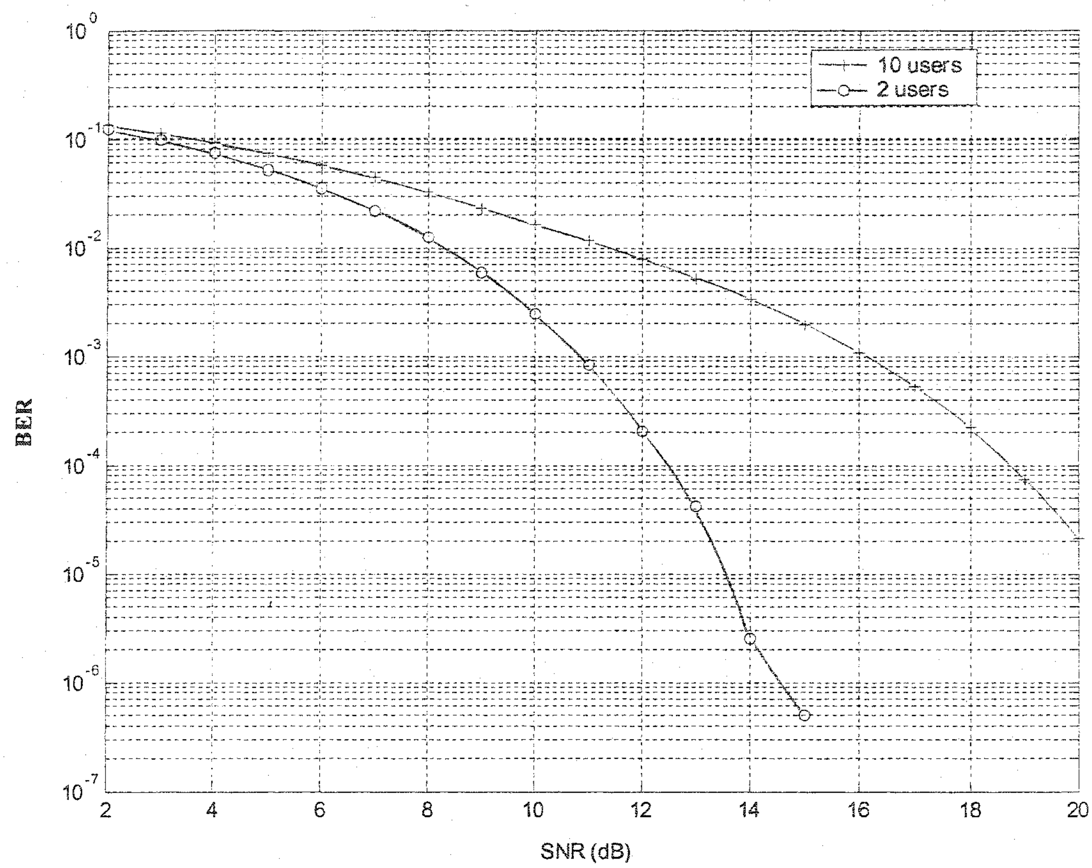

Figure 3.7: BER performance of MMSE linear detector

Figure 3.7 shows the BER performance of the MMSE linear detector in an AWGN channel with K=2 and K=10. The simulation scenario is identical to the one used in section 3.3.2

Figures 3.8 and 3.9 show the probability of the error achieved by the MMSE detector, the matched filter bank and the decorrelating detector for K=2 and K=10, respectively, with identical crosscorrelations and perfect power control. The direct-sequence signature waveforms with G=31 are randomly chosen.

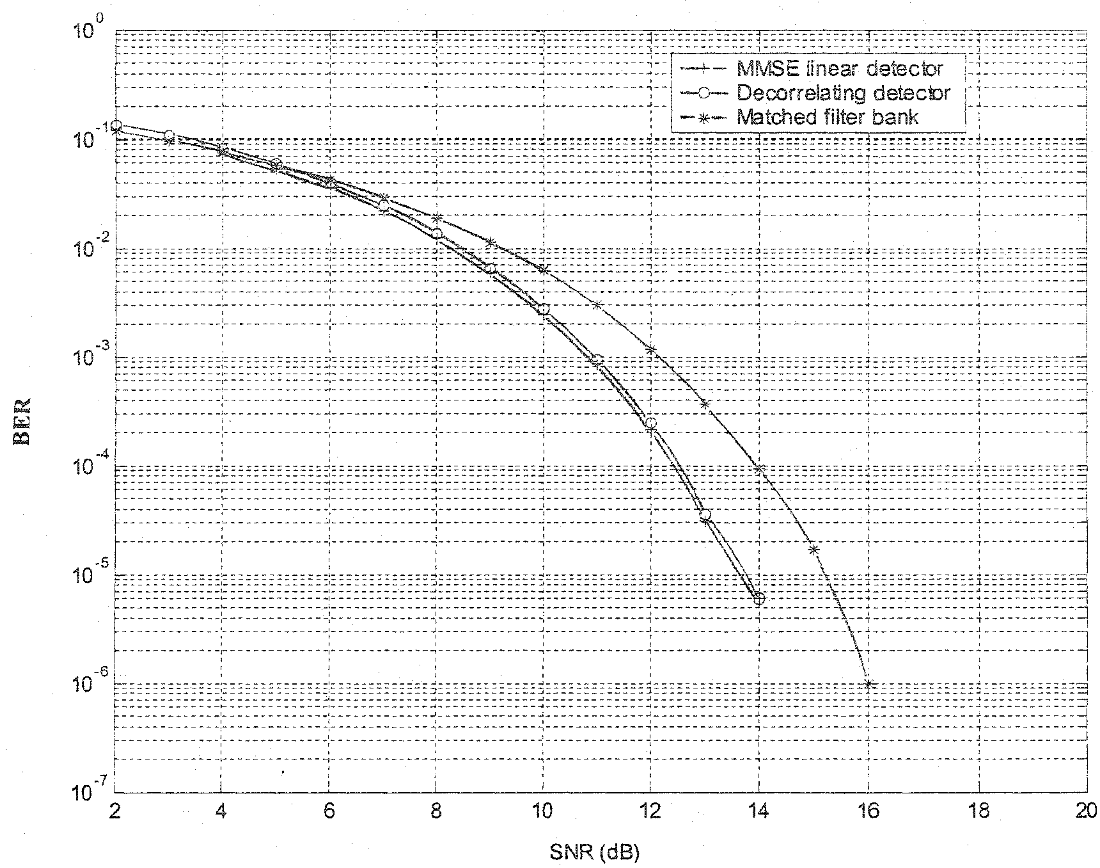

Figure 3.8: BER performance comparison for K = 2

For K=2, as shown in Figure 3.8, the matched filter bank receiver has a tolerable BER performance. As the number of users increases, the matched filter bank converges slowly. But the MMSE detector and the decorrelating detector converge faster as $K \to \infty$. Also, a large gap in the performances between the MMSE detector and the matched filter bank is noted even when K is small. Figures 3.8 and 3.9 also show that the bit-error rate of the MMSE detector is better than that of the decorrelator for various levels of background Gaussian noise, the number of users, and the crosscorrelations.

Figure 3.10 is a zoomed version of the BER plot of Figure 3.9. From 3.10 and 3.9, it is clear that the performance of the matched filter receiver is better than that of the decorrelator for sufficiently low signal-to-noise ratios. The MMSE detector also makes the performance improvement at low SNR, and it is truely a compromise solution that takes into account the relative importance of each interfering user and the background noise.

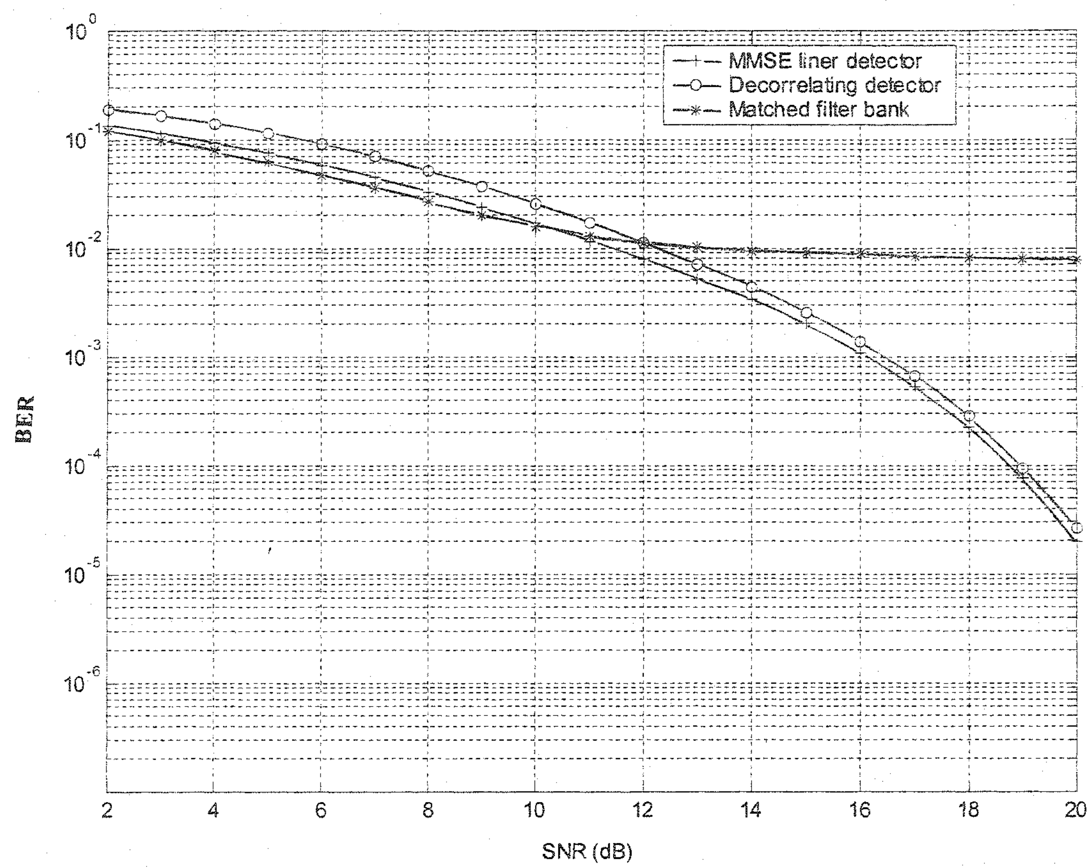

Figure 3.9: BER performance for K = 10

3.5 Summary

Although the matched filter bank, decorrelation detector, and MMSE receiver have been investigated in the literature, there is a need to study the relationship between them and their capabilities for the interference suppression. Moreover, the investigation of the dependence of the MMSE detection on the crosscorrelations between the spreading codes of the users in the system will pave the way for deriving the adaptive MMSE solutions.

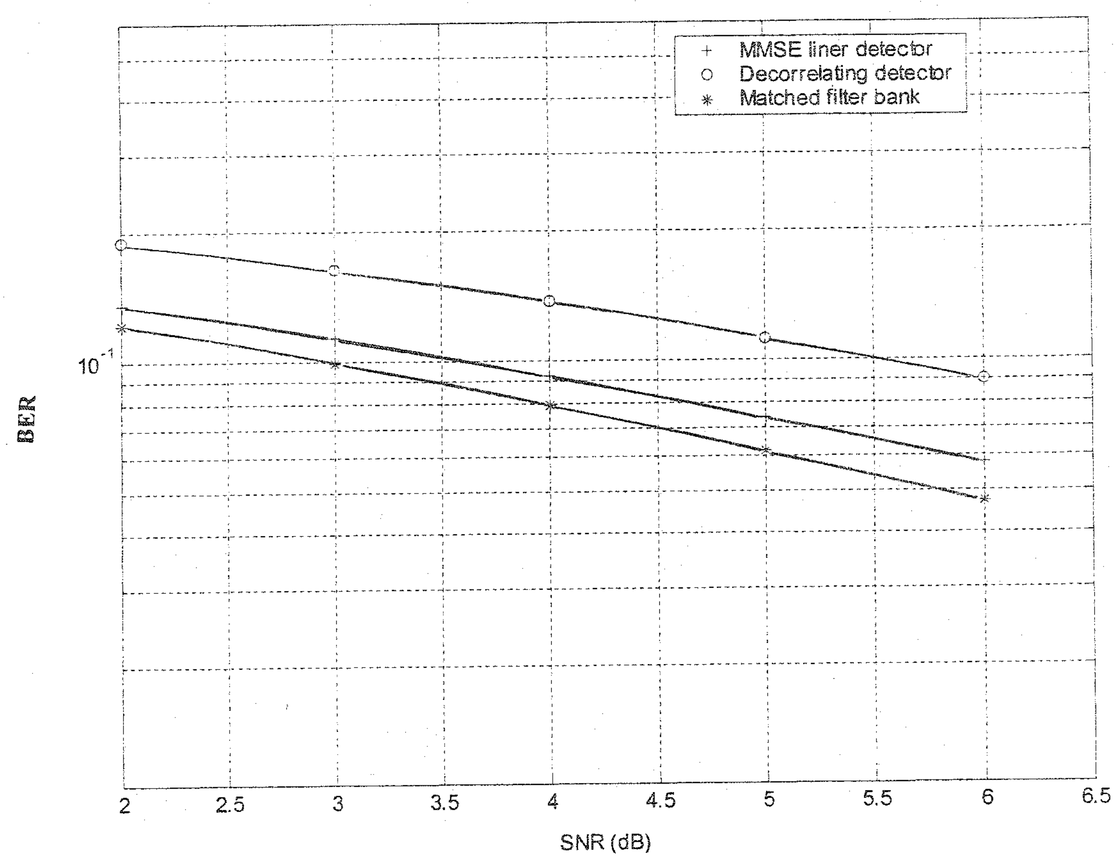

Figure 3.10: Zoomed version of Figure 3.9

The matched filter bank receiver treats other users signals as noise (self noise). This self noise limits the systems capacity and can jam communications in the presence of the strong nearby signals. It has been shown that the matched filter bank may carry out the detection erroneously even in the absence of background AWGN. However, operating on the output of the matched filter bank has some advantages. The sampled signal constitutes a sufficient statistics of the received continuous-time signal. This feature makes the matched filter to form the front end in most MUDs. Also, it is observed that, with a few users active in the system, the matched filter bank reduces the number of measurement signals considerably, resulting in lower complexity.

By exploiting the structures of MAI, the decorrelation detector provides a considerable performance gain at high SNR. But, when the SNR is at lower level, its performance is not as good as that of the matched filter bank in terms of BER. This is due to the result of ignoring the existence of the background noise.

The MMSE detector exploits the MAI structures and also takes into account the existence of background noise. It can be seen as a compromise solution between the matched filter and decorrelation detector. It improves the performance both at low and high SNR, and provides the significant performance gain over the conventional matched filter detection.

The theoretical analysis has shown that the MMSE solution allows an adaptive implementation of the multiuser detector. This multiuser detector operates directly on the received signal, sampled during each chip period. However, adaptive receivers that employ the MMSE algorithm require a training sequence and the signature waveforms of all users in the system. Though the training sequence technique is used in many cases of practical implementation today, the frequent uses of training sequence cause the system unstable. Thus, an adaptive MMSE mutiuser detection that alleviates the need for training sequences is highly desirable. In the next chapter, we will present two implementations of MMSE detection, one requiring training sequence and the other only the signature waveform of active users.

Chapter 4

A New Adaptive MMSE Detector

Various existing multiuser detection approaches were discussed in the previous chapters. It is clear from these discussions that the demodulation of CDMA signals by the conventional matched filter receiver suffers from the near-far problem: because of the non-zero crosscorrelaiton between the signature sequences for different transmissions, any sufficiently powerful interferer can severely degrade the demodulation of the desired signal. In the DS/CDMA format, the MAI represents a wide-band form of interference. Over the past decade, a significant amount of research has been directed to address the problem of multiuser detection. Recently, the MMSE linear multiuser detector has been considered in the context of suppressing the MAI in CDMA networks [55], [58] - [60].

One of the main advantages of the spread-spectrum communications system is that the wide-band signals can share a channel with narrow-band communication signals, without one unduly interfering the other. As noted in Chapter 1, the spread-spectrum communications is inherently resistant to the NBI caused by coexistence with conventional communications, but substantial performance gains can be achieved through the use of active NBI suppression prior to the despreading and demodulating.

Adaptive interference suppression is currently receiving particularly intense scrutiny because of the key practical role it plays in the emerging vision of "anywhere, anytime" communications promised by the systems such as personal communications, digital cellular telephony, and mobile computing. The adaptive receivers applying interference suppression mechanisms have been proposed by a number of authors at approximately the same time [55], [58], [59], which are all based on the linear MMSE criterion. As noted in Chapter 3, The MMSE detector requires an exact knowledge of the signature sequences and that of the amplitude of the received signals of all the users in the system to detect the information bits of the user of interest. However, the conventional matched filter receiver requires only the knowledge of the signature sequence of the desired user to complete the detection in a synchronous system. If we can eliminate the need for the knowledge of other users in the MMSE detection, it will make the MMSE detection more valuable in practical implementations.

In [55], an adaptive MMSE multiuser detector was proposed, which replaces the need of a priori knowledge of all other users by using a training data sequence for each user in the system. The operation of the adaptive MMSE detector requires that each user at the beginning transmits a training sequence that is used by the receiver detector for initial adaptation. After the training phase ends, adaptation for actual data transmission is realized by making use of the transmitted data. However, at any time when there is a dramatic change in the interfering environment, which is not unusual in wireless communications, the adaptation based on the transmitted data becomes unreliable, and data transmission must be temporarily suspended, requiring a new training sequence. The frequent use of training sequences is certainly a waste of channel bandwidth.

The foregoing observations suggest that the need for a blind adaptive receiver is even more desirable in multiaccess channels than in single-user channels which is subjected to intersymbol interferrence. Therefore, it is of great value if the need for training sequences can eliminated. The goal of this chapter is to derive an adaptive receiver, which does not require a training sequence and uses only the signature waveforms of active users in the system.

In the following sections, a blind adaptive MMSE detection in terms of canonical representation that requires the same received data knowledge as that of a matched filter receiver to demodulate the information bits will be reviewed. Then, an adaptive implementation of a DS/CDMA system using a blind RLS adaptation rule to suppress both

MAI and NBI will be studied. The limitation of the blind RLS adaptation algorithm presented. Next, a new combined adaptive interference suppression scheme is proposed to deal with the limitation of blind RLS adaptation algorithm in a more practical situation.

4.1 Blind Adaptive Multiuser Detection

In Chapter 3, the MMSE detector was derived. An attractive feature of the MMSE detector is that it can be implemented in a decentralized fashion where only the user or users of interest need to be demodulated. It also paves the way for an adaptive or even blind adaptive implementation. To develop the blind adaptive detector, we first need to introduce the canonical representation of a linear multiuser detector.

4.1.1 System Model

To be consistent with the discussion in Chapter 2, we use the same system model as given in Chapter 3, where the BPSK modulation scheme is implemented, The received signal through a synchronous CDMA system in one information bit interval is given by

$$r(t) = \sum_{k=1}^{K} A_k b_k s_k(t) + n(t) \qquad t \in [0, T] \tag{4.1}$$

where, $s_k(t)$ is the signature waveform of the k^{th} user and is normalized to unit energy, i.e., $\int_0^T s_k(t) = 1$, and is given by

$$s_k(t) = \sum_{j=0}^{G-1} s_k[j] \mathrm{H}(t - kT_c) \tag{4.2}$$

where, $\mathrm{H}(t)$ is a normalized chip waveform of duration $T_c = T / G$, G is the processing gain, $\{s[j]\}_{k=0}^{G-1}$ is the signature sequence of user k, $s_k[j] \in \{+1,-1\}$, T is bit period, T_c is chip interval, a_k represents the normalized spreading sequence, K is the number of users, b_k is the input bit of the k_{th} user, $b_k \in \{-1,1\}$ with equal probability, A_k is the received amplitude of the k_{th} user, and $n(t)$ is additive white Gaussian noise with zero mean and σ^2 variance.

Note that $\{ \mathrm{H}(t-kT_c)\}_{k=0}^{G-1}$ forms a basis for the signal space. Therefore, we can express the signature waveforms with G-dimension vectors. Let $\mathbf{s}_j = [s_j[0], \; s_j[1], \; \ldots, \; s_j[G-1]]^T$ denote the vector of the signature sequence of user j. In terms of the signal vectors, the received signal can then be written as

$$\mathbf{r} = \sum_{k=1}^{K} A_k \, b_k \mathbf{s}_k + \mathbf{n} \tag{4.3}$$

where $\mathbf{n}$ is a Gaussian random vector with $E(\mathbf{n}\mathbf{n}^T) = \sigma^2 \mathbf{I}$.

In the following, we will discuss the multiuser detection problem in the framework of the system model given by (4.1) and (4.3).

4.1.2 Canonical Representation of Linear Detectors

This Canonical approach is based on the decomposition of the linear multiuser detector as the sum of two orthogonal components. One of the components is equal to the signature waveform of the desired user which is assumed to be known and fixed.

For convenience, we assume that user 1 is the user of interest. An arbitrary linear multiuser detector $d_1(t) \in L_2[0,T]$ can be represented as

$$d_1(t) = \beta[s_1(t) + x_1(t)] \tag{4.4}$$

where $\beta > 0$ is a scalar, $s_1(t)$ is the signature waveform of user 1, $x_1(t)$ is the component of $d_1(t)$ orthogonal to $s_1(t)$, i.e.,

$$< s_1, x_1 > = \int_0^T s_1(t)x_1(t)dt = 0 \tag{4.5}$$

Note that in situations where users are to be demodulated simultaneously, it is equivalent to consider a linear multiuser detector as a multidimensional linear transformation or as a bank of single-user detectors.

The system given by (4.4) and (4.5) is a canonical representation for the MMSE detector of user 1. Since the decision making at the linear detector output is invariant to β, without loss of generality, we restrict our attention to linear multiuser detectors whose inner product with the signature waveform of the desired user is normalized to 1, i.e., $\beta = 1$. It has been shown in [50] that any linear multiuser detector can be represented in its canonical form.

As it was noted in Chapter 3, the MMSE detector is a linear detector that minimizes the mean square error between the decision statistics and the transmitted information bits. But the adaptive implementation of the MMSE detector requires a training sequence. Using the canonical representation, we will have a linear detector that is equivalent to the MMSE detector, which is more convenient for obtaining a blind implementation.

4.1.3 Minimum Output-Energy Linear Detector

In this subsection, we will use the canonical representation of a linear detector to show that the linear detector that minimizes the mean output energy of the detector is the MMSE detector. Let $d_1(t)$ be an arbitrary linear detector of user 1. From the discussion in the previous subsection, we know that $d_1(t)$ can be expressed in canonical representation as $d_1(t) = s_1(t) + x_1(t)$. At the receiver's side, $r(t)$, the received signal given in (4.1), is correlated by linear detector $d_1(t)$. We define the mean output energy of the detector as

$$MOE(x_1) = E[(< r, s_1 + x_1 >)^2] \tag{4.6}$$

Let $d_k(t) \in L_2[0, T]$ denote the MMSE detector of user k. The received signal $r(t)$ is correlated by $d_k(t)$ to generate the decision statistics. The output of the MMSE detector of user k is thus given by

$$< r, d_k > = \int_0^T r(t) d_k(t) dt \tag{4.7}$$

Thus, we can express the MMSE detector as

$$d_k(t) = \underset{d_k \in L_2[0,T]}{\arg\min} E[(A_k b_k - < r, d_k >)^2] \tag{4.8}$$

Correspondingly, the decision on the information bit of user k is given by

$$\hat{b}_k = \mathrm{sgn}(< r, d_k >) = \mathrm{sgn}\left(\int_0^T r(t) d_k(t) dt \right) \tag{4.9}$$

It is clear that when $d_k(t) = s_k(t)$, (4.8) becomes the conventional matched filter detector.

As described by (4.8), the mean square error of the detector for user 1 can be written as

$$MSE(x_1) = E[(A_1 b_1 - < r, s_1 + x_1 >)^2] \tag{4.10}$$

Since the transmitted information bits of the users are independent to each other, it is adequate to assume that the signals of the interfering users are uncorrelated with the signal of the desired user. Therefore, we can express (4.10) as

$$MSE(x_1) = A_1^2 + MOE(x_1) - 2A_1^2 < s_1, s_1 + x_1 > \tag{4.11}$$

From (4.10), we obtain that

$$MSE(x_1) = MOE(x_1) - A_1^2 \tag{4.12}$$

From the structure of (4.12), we find that in an canonical representation the MSE function and the MOE function of the linear detector differ only by a constant, and the arguments that minimize both the functions are the same. Therefore, the linear multiuser detector with minimum output energy is, in fact, the MMSE detector. Thus, the MMSE detector in (4.1.7) reduces to the minimum output-energy linear detector, which is defined as

$$d_1(t) = s_1(t) + x_1(t) \tag{4.13}$$

$$x_1(t) = \arg\min_{x_1 \in L_2[0,T]} MOE(x_1)$$

$$= \arg\min_{x_1 \in L_2[0,T]} E[(< r, s_1 + x_1 >)^2]$$

The simple observation that the mean-square-error and the mean output energy differ by a constant in terms of the canonical representation of the linear detector has the consequence for its adaptive implementation. The arguments that minimize both the functions are the same. This means that (in contrast to the MMSE criterion) it is not necessary to know the data transmitted in order to implement a gradient descent algorithm for the minimization of mean-square-error. This sidesteps the use of training sequences and leads to the blind adaptation rule presented in the next section.

4.2 Adaptive Implementation of Blind MMSE MUD

As noted previously, the linear MMSE mutiuser detector has the capability of simultaneously suppressing both NBI and MAI, and it allows a blind adaptive implementation. Therefore, this technique is well suited for practical use in mobile communication applications. The recursive least-squares (RLS) adaptive algorithms are known to converge extremely fast, and have excellent tracking capabilities in a time-varying environment. In this section, we review the RLS blind adaptive version of the linear MMSE multiuser detection algorithm for the simultaneous suppression of NBI and MAI. Optimum performance of such receiver requires a perfect synchronization of the spreading or pseudonoise (PN) code. Synchronization includes both the initial code acquisition as well as the code tracking. This alone is a vast and important research area. To limit this research to a reasonable scope, it is assumed in the rest of this thesis that a perfect synchronization is achievable. References [62] - [64] provide excellent overviews of the techniques for code acquisition and tracking.

4.2.1 System Model

Consider a synchronous K-user binary communication system signaling through an additive white Gaussian noise channel. The received baseband signal during one symbol interval in such a channel can be modeled as

$$r(t)=\sum_{k=1}^{K}A_k b_k s_k(t)+I(t)+N(t), \qquad t\in[0,T] \tag{4.14}$$

where $I(t)$ represents the narrow-band interference signal. Which NBI signal is added to the system model to show how the blind adaptive MMSE detectors cope with the mobile environment with NBI and MAI, $N(t)$ represents the ambient channel noise, K is the number of users, T is the symbol interval, $\{A_k\}$ denotes the amplitude of the received signal of the kth user, $\{b_k\}$ denotes data bit of the kth user, $\{s_k(t);0\le t\le T\}$ denotes normalized signaling waveform of the kth user. It is assumed that $s_k(t)$ is supported only in the interval [0, T] and has a unit energy, and $\{b_k\}$ is a collection of independent equiprobable ± 1 random variables.

By passing through a chip-matched filter, followed by a chip-rate sampler, the received signal $r(t), t\in[0,T]$ is converted to a vector of G samples of chip-matched filter outputs within a symble interval T, where G is the processing gain. The received signal $\mathbf{r}$ is given by

$$\mathbf{r}=\sum_{k=1}^{K}\sqrt{p_k}\,b_k\mathbf{s}_k+\mathbf{i}+\sigma_n\mathbf{n} \tag{4.15}$$

where, $\mathbf{s}_k$ is the normalized signature sequence vector of the kth user, i.e., $\mathbf{s}_k{}^T\mathbf{s}_k=1$, $P_k=A_k^2$ is the received power of the kth user, $\mathbf{i}$ is the NBI signal sample vector, which is assumed to be wide-sense stationary with a zero mean and covariance matrix $\mathbf{R}_i$, σ_n is the variance of the noise samples, and $\mathbf{n}$ is a white Gaussian sample vector with a zero mean and covariance matrix $\mathbf{I}$, where $\mathbf{I}$ is $G\times G$ indentity matrix. It is assumed that $\{b_k\}$, $\mathbf{i}$, and $\mathbf{n}$ are mutually independent.

4.2.2 Linear MMSE Detector and RLS Blind Adaptation Rule

We assume that user 1 is the user of interest, and we will use the notations $P = P_1, \mathbf{s} = \mathbf{s}_1$, and $\mathbf{b} = \mathbf{b}_1$, corresponding to user 1.

The linear MMSE detector has the form $\hat{b} = \mathrm{sgn}(\bar{\mathbf{c}}^T \mathbf{r})$, where $\bar{\mathbf{c}}$ is given by

$$\bar{\mathbf{c}} = \frac{1}{\mathbf{s}^T \mathbf{R}^{-1} \mathbf{s}} \mathbf{R}^{-1} \mathbf{s} \tag{4.16}$$

In (4.16), $\mathbf{R}$ represents the autocorrelation matrix of the received discrete signal $\mathbf{r}$, as given by

$$\mathbf{R} = E\{\mathbf{r}\mathbf{r}\} = \sum_{k=1}^{K} P_k \mathbf{s}_k \mathbf{s}_k^T + \mathbf{R}_i + \sigma_n^2 \mathbf{I} \tag{4.17}$$

The signal-to-interference ratio is a performance measure which is defined to be the ratio of the energy in the decision statistic due to the desired signal to the energy due to the interfering users plus the background Gaussian noise. The output signal-to-interference ratio (SIR) of $\bar{\mathbf{c}}$ is given by [65]

$$\mathbf{SIR}^* = \frac{E^2\{\bar{\mathbf{c}}^{\mathrm{T}} \mathbf{r}\}}{\mathrm{var}\{\bar{\mathbf{c}}^{\mathrm{T}} \mathbf{r}\}} = P\,[\mathbf{s}^{\mathrm{T}} \mathbf{Z}^{-1} \mathbf{s}] \tag{4.18}$$

where

$$\mathbf{Z} = \mathbf{R} - P\mathbf{s}\mathbf{s}^T = \sum_{k=2}^{K} P_k \mathbf{s}_k \mathbf{s}_k^T + \mathbf{R}_i + \sigma_n^2 \mathbf{I} \tag{4.19}$$

As we noted earlier, the mean-square-error and the mean output energy differ only by constant in a canonical representation of the linear detector. The arguments that minimize the both functions are the same. This implies that we can solve the problem by seeking a minimum mean-output-energy detector instead of a minimum mean-square detector.

The mean output energy (MOE) of $\bar{\mathbf{c}}$, defined as the mean-square output value, is

$$\bar{\xi} = E\{(\bar{\mathbf{c}}^T \mathbf{r})^2\} = \bar{\mathbf{c}}^T \mathbf{R} \bar{\mathbf{c}} = \frac{1}{\mathbf{s}^T \mathbf{R}^{-1} \mathbf{s}} = P + \frac{1}{\mathbf{s}^T \mathbf{Z}^{-1} \mathbf{s}} \tag{4.20}$$

The mean-square error at the output of $\bar{\mathbf{c}}$ is given by

$$\bar{\varepsilon} = E\{(\sqrt{P}b - \bar{\mathbf{c}}^T \mathbf{r})^2\}$$

$$= P + \bar{\xi} - 2P(\bar{\mathbf{c}}^T \mathbf{s}) = \bar{\xi} - P = \frac{1}{\mathbf{s}^T \mathbf{Z}^{-1} \mathbf{s}} \tag{4.21}$$

Next, an RLS adaptation rule for adapting the weight vector $\bar{\mathbf{c}}$ is considered. The exponentially windowed RLS algorithm selects the weight vector $\mathbf{c}(n)$ to minimize the sum of exponentially weighted output energy as

Minimize $\quad \sum_{i=1}^{n} \lambda^{n-i} [\mathbf{c}^T(n) \mathbf{r}(n)]^2$

Subject to $\quad \mathbf{s}^T \mathbf{c}(n) = 1$

where $0 < \lambda < 1$ is the forgetting factor, and $1-\lambda << 1$, which ensures that the data in the distant past are forgotten in order to provide the tracking capability in a nonstationary environment. The solution to this constrained optimization problem is given by

$$\mathbf{c}(n) = \frac{1}{\mathbf{s}^T \mathbf{R}^{-1}(n)\mathbf{s}} \mathbf{R}^{-1}(n)\mathbf{s} \tag{4.22}$$

where

$$\mathbf{R}(n) = \sum_{i=1}^{n} \lambda^{n-i} \mathbf{r}(i)\mathbf{r}^T(i) \tag{4.23}$$

A recursive procedure with complexity $O(N^2)$ for updating $\mathbf{c}(n)$ are obtained as follows:

$$\mathbf{k}(n) = \frac{\mathbf{R}^{-1}(n-1)\mathbf{r}(n)}{\lambda + \mathbf{r}^T(n)\mathbf{R}^{-1}(n-1)\mathbf{r}(n)} \tag{4.24}$$

$$\mathbf{h}(n) = \mathbf{R}^{-1}(n)\mathbf{s} = \frac{1}{\lambda}[\mathbf{h}(n-1) - \mathbf{k}(n)\mathbf{r}^T(n)\mathbf{h}(n-1)] \tag{4.25}$$

$$\mathbf{c}(n) = \frac{1}{\mathbf{s}^T \mathbf{h}(n)} \mathbf{h}(n) \tag{4.26}$$

$$\mathbf{R}^{-1}(n) = \frac{1}{\lambda}[\mathbf{R}^{-1}(n-1) - \mathbf{k}(n)\mathbf{r}^T(n)\mathbf{R}^{-1}(n-1)] \tag{4.27}$$

In contrast to the conventional RLS algorithm, the adaptation rule defined by (4.22) – (4.27) requires no reference signal, and therefore, result in a blind RLS adaptation.

4.2.3 Steady-State SIR of Blind RLS Adaptation

Based on the work in [66] the steady-state output SIR of the RLS blind adaptive algorithm is given by

$$SIR^{\infty} = \lim_{n\to\infty} \frac{E^2\{\mathbf{r}^T(n)\mathbf{c}(n-1)\}}{\operatorname{var}\{\mathbf{r}^T(n)\mathbf{c}(n-1)\}}$$

$$= \frac{SIR^*}{(1+d)+d\cdot SIR^*} \tag{4.28}$$

where $d = \frac{1-\lambda}{2\lambda}(G-1)$, and SIR^* is the optimum SIR value given in (4.18). Usually, the RLS algorithm operates in a range such that $d \ll 1$. Equation (4.28) shows a severe degradation of the steady-state SIR for the blind adaptive algorithm from the optimum value SIR^*, especially when $SIR^* \gg 1$.

In [66], a solution has been suggested to address this dilemma. By using decision feedback, the system would be able to take the advantage of the conventional RLS algorithm to have the steady-state SIR much closer to the optimum value, after the initial blind adaptation converges. During the stage of using the conventional RLS adaptation rule, the data symbols $\mathbf{b}(n)$ are assumed to be known to the receiver.

4.2.4 Steady-State SIR of Conventional RLS with Known Data Symbols

The RLS algorithm is a mature subject, extensively applied in diversity displines [67]. Using the system model described in Section 4.2.1, the conventional RLS adaptation rule can be found in as follows:

$$\mathbf{k}(n) = \frac{\mathbf{R}^{-1}(n-1)\mathbf{r}(n)}{\lambda + \mathbf{r}^T(n)\mathbf{R}^{-1}(n-1)\mathbf{r}(n)} \tag{4.29}$$

$$e_p(n) = \sqrt{P}b(n) - \mathbf{c}^T(n)\mathbf{r}(n) \tag{4.30}$$

$$\mathbf{c}(n) = \mathbf{c}(n-1) + e_p(n)\mathbf{k}(n) \tag{4.31}$$

$$\mathbf{R}^{-1}(n) = \frac{1}{\lambda}[\mathbf{R}^{-1}(n-1) - \mathbf{k}(n)\mathbf{r}^T(n)\mathbf{R}^{-1}(n-1)] \tag{4.32}$$

where $e_p(n)$ is the prediction error at time n, and $\mathbf{k}(n)$ is the Kalman gain vector [67]. The adaptation rule given above is used to choose the weight vector $\mathbf{c}(n)$ to minimize the cost function given by

$$\sum_{i=1}^{n} \lambda^{n-i}[\sqrt{P}b(i) - \mathbf{c}^T(n)\mathbf{r}(n)]^2 \tag{4.33}$$

From [66], the output SIR in the steady-state can be expressed as

$$SIR^{\infty} = \lim_{n\to\infty} \frac{E^2\{\mathbf{r}^T(n)\mathbf{c}(n-1)\}}{\mathrm{var}\{\mathbf{r}^T(n)\mathbf{c}(n-1)\}}$$

$$= \frac{SIR^*}{(1+d) + d / SIR^*} \tag{4.34}$$

where $d = \frac{1-\lambda}{2\lambda}(G-1)$.

It is seen from (4.34) that, in the extreme case of having the perfect estimation of data symbols $\mathbf{b}(n)$ from the first stage using the blind RLS adaptation, the steady state output SIR is close to its optimum value.

4.2.5 Limitations of the Blind Adaptive Interference Suppression in [66]

The main purpose of the blind adaptive scheme presented in [66], and discussed above was to apply the RLS blind adaptive algorithm in linear MMSE interference suppression for DS-CDMA systems. From the above discussion, it can be seen that MMSE multiuser detection to suppress both MAI and NBI is able to be implemented in the RLS blind adaptive version. This implementation reduces the requirements for a training sequence and the signature waveforms and amplitudes of other users in the system as the interference. In other words, it reduces the dependence of the MMSE solution on the training sequence technique and the crosscorrelations between the spreading codes of the users in the system. It takes the linear MMSE interference suppression one more step further towards the practical implementations.

However, the derivation of its steady-state SIR reveals a drawback of this implementation. Let us look again of the steady-state value of SIR, which is given by

$$SIR^{\infty} = \frac{SIR^*}{(1+d)+d\cdot SIR^*} \tag{4.35}$$

where $d = \dfrac{1-\lambda}{2\lambda}(G-1)$, and SIR^* is the optimum value of SIR. Usually, the RLS algorithm operates in the range such that $d << 1$. When $SIR^* >> 1$, especially when $1/d << SIR^*$, the steady state value of SIR is far less than its optimum value SIR^*, and is upper bounded by

$1/d$. In other words, the performance of the blind adaptive algorithm suffers form severe degradation of the optimum value SIR^*.

In Section 4.2.4, a solution was given in [66] to overcome this problem by switching to the conventional RLS algorithm that uses decision-directed adaptation after the initial blind adaptation converges. To realize the implementation of the conventional RLS algorithm, [66] an assumption was made that the data symbols $b(n)$ were to be known to the receiver, and this condition could be achieved by using a training sequence.

As we have discussed earlier in this chapter, MMSE linear detection admits adaptive implementation by using a training sequence in the beginning of the transmission. However, in the frequently changing mobile environment, adaptation based on the transmitted training sequence may become unreliable. Therefore, data transmission must be temporarily suspended, requiring a new training sequence. The frequent use of training sequences is certainly a waste of channel bandwidth.

The scheme presented in [66] is the blind adaptive version of MMSE detection, which overcomes the drawback of using training sequence. To improve the systems, steady state value SIR^∞, it switches to the decision-directed adaptation at the second stage, which uses a training sequence. It seems to have less practical meaning by doing so. Furthermore, when the received signal changes, it has to switch back to the first stage to use blind adaptation, since the second stage adaptation require the data symbol to be known. At this moment, the steady state value SIR^∞ drops down again. The frequent switches between the two stages may cause the system to become unstable. The conventional RLS adaptation in the second stage depends on an assumption that the data symbols are known at the receiver. No matter which estimation scheme applied, this condition cannot be realized in practice.

We are seeking a solution to the MMSE interference problem that will improve the system performance with more practical meaning. In the next section, a new combined adaptive scheme is proposed, which does not depends on the condition of having data symbol known at the receiver, and no training sequence is required. The new scheme improves the steady-state value of SIR significantly. It pays some prices to require the knowledge of the signature waveforms of the other active users, however, it does not require the use of a training sequence in a dynamic mobile environment

4.3 Proposed Combined Blind and Conventional RLS Adaptation Scheme

It is noted from the discussions of the previous section that blind adaptive scheme has the steady state SIR degraded from its optimum value. In other words, there are certain amount of interference still remaining after the detection. As we have studied in Chapter 3, MMSE multiuser detector has the ability to suppress the NBI and background noise. In this section we focus on the cancellation of some of the remaining MAI to achieve further improvement on the estimation.

In the new proposed scheme, we take advantage of the blind RLS adaptation rule in the first stage. In the second stage, we add another conventional RLS adaptation mechanism in an attempt to remove of the remaining MAI from other users' in the received signals before making data decision. The conventional RLS adaptation introduces a weight vector to minimize the squared Euclidean distance between the received signal and the weighted sum of the estimates of all users' signals during a bit interval with respect to the weights. The estimates of all users' signals come from the estimation of the first stage. Using the weight vector from the RLS adaptation, the maximum amount of MAI can be reconstructed. By reducing the reconstructed MAI from the received signal, the desired signal with the less interfered signals produced, and a more reliable decision is then made based on it. Neither a training sequence nor decision feedback is needed. Also, no assumption is made on the transmitted symbol.

4.3.1 System Model

To be consistent with the previous discussion, we have the same system model as presented in Section 4.2.1, where a synchronous K-user binary communication system signaling through an additive white Gaussian noise channel is given by

$$r(t) = \sum_{k=1}^{K} A_k b_k s_k(t) + I(t) + N(t), \qquad t \in [0, T] \tag{4.36}$$

In the above equation, $I(t)$ represents the narrow-band interference signal, $N(t)$ the ambient channel noise, K the number of users, T the symbol interval, $\{A_k\}$ the amplitude of the received signal of the kth user, $\{b_k\}$ data bit of the kth user, and $\{s_k(t); 0 \le t \le T\}$ normalized signaling waveform of the kth user, It is assumed that $s_k(t)$ is supported only in the interval [0, T] and has a unit energy, and $\{b_k\}$ is a collection of independent equiprobable ± 1 random variables.

By passing through a chip-matched filter, followed by a chip-rate sampler, the received signal $r(t)$, $t \in [0, T]$ is converted to a vector of G samples of chip-matched filter output within a symbol interval T, where G is the processing gain. The received signal $\mathbf{r}$ is given by

$$\mathbf{r} = \sum_{k=1}^{K} \sqrt{p_k} b_k \mathbf{s}_k + \mathbf{i} + \sigma_n \mathbf{n} \tag{4.37}$$

where, $\mathbf{s}_k$ is the normalized signature sequence vector of the kth user, i.e., $\mathbf{s}_k^T \mathbf{s}_k = 1$, $P_k = A_k^2$ is the received power of the kth user, $\mathbf{i}$ is the NBI signal sample vector, which is assumed to be wide-sense stationary with a zero mean and covariance matrix $\mathbf{R}_i$, σ_n is the variance of the noise samples, and $\mathbf{n}$ is a white Gaussian sample vector with a zero mean and covariance matrix $\mathbf{I}$, where $\mathbf{I}$ is $G \times G$ indentity matrix. It is assumed that $\{b_k\}$, $\mathbf{i}$, and $\mathbf{n}$ are mutually independent.

As we have mentioned before, here we are focusing on the MAI cancellation. To simplify the notation, the received signal can be expressed as

$$\mathbf{r} = \sum_{k=1}^{K} \sqrt{p_k} b_k \mathbf{s}_\mathbf{k} \tag{4.38}$$

which is actually $\mathbf{r}_{MAI}$, the received signal containing only MAI. The m^{th} chip-bit of the G samples of the received signal $\mathbf{r}_{MAI}$ within one bit interval can be written as

$$r(m) = \sum_{k=1}^{K} \sqrt{p_k} b_k s_k(m) \tag{4.39}$$

4.3.2 Adaptation Rules and Decision Making

We assume that user 1 is the user of interest, and we will use the notations $P = P_1$, $\mathbf{s} = \mathbf{s}_1$, and $\mathbf{b} = \mathbf{b}_1$, corresponding to user 1.

For the first stage, the blind RLS adaptation is applied to produce the estimate for the second stage. Therefore, adaptation rule given in Section 4.2 are applied:

$$\mathbf{k}(n) = \frac{\mathbf{R}^{-1}(n-1)\mathbf{r}(n)}{\lambda + \mathbf{r}^T(n)\mathbf{R}^{-1}(n-1)\mathbf{r}(n)} \tag{4.40}$$

$$\mathbf{h}(n) = \mathbf{R}^{-1}(n)\mathbf{s} = \frac{1}{\lambda}[\mathbf{h}(n-1) - \mathbf{k}(n)\mathbf{r}^T(n)\mathbf{h}(n-1)] \tag{4.41}$$

$$\mathbf{c}(n) = \frac{1}{\mathbf{s}^T\mathbf{h}(n)}\mathbf{h}(n) \tag{4.42}$$

$$\mathbf{R}^{-1}(n) = \frac{1}{\lambda}[\mathbf{R}^{-1}(n-1) - \mathbf{k}(n)\mathbf{r}^T(n)\mathbf{R}^{-1}(n-1)] \tag{4.43}$$

where $0 < \lambda < 1$ is the forgetting factor $(1-\lambda \ll 1)$.

In the second stage, the conventional RLS algorithm is applied to minimize the cost function as

$$\underset{\mathrm{w}}{\text{minimize}}\ E[|\, r(m) - \mathbf{w}^T(m)\hat{\mathbf{r}}(m)\,|^2] \tag{4.44}$$

where, $\mathbf{w} = (w_1,\ w_2,\ \dots\ w_K)^T$ is the weight vector. $\hat{\mathbf{r}}(m)$ the m^{th} chip-bit vector of the estimate of the received signal, which is defined as

$$\hat{\mathbf{r}}(m) = \sqrt{p_k}\,\hat{b}_k\mathbf{s}_k(m) \tag{4.45}$$

where, $\hat{b}_k$ is the estimate of data symbol b_k from the first stage. The adaptation rules are given

$$\mathbf{k}(m) = \frac{\mathbf{R}^{-1}(m-1)\hat{\mathbf{r}}(m)}{\lambda + \hat{\mathbf{r}}^T(m)\mathbf{R}^{-1}(m-1)\hat{\mathbf{r}}(m)} \tag{4.46}$$

$$e_p(m) = r(m) - \mathbf{w}^T(m)\hat{\mathbf{r}}(m) \tag{4.47}$$

$$\mathbf{w}(m) = \mathbf{w}(m-1) + e_p(m)\mathbf{k}(m) \tag{4.48}$$

$$\mathbf{R}^{-1}(m) = \frac{1}{\lambda}[\mathbf{R}^{-1}(m-1) - \mathbf{k}(m)\hat{\mathbf{r}}^T(m)\mathbf{R}^{-1}(m-1)] \tag{4.49}$$

where $\mathbf{w}(m)$ is the weight vector for the conventional RLS adaptation, $e_p(m)$ the prediction error at time n, $\mathbf{k}(m)$ is the Kalman gain vector [69], $\hat{\mathbf{r}}(m)$ is the input vector of the RLS algorithm at m^{th} chip-bit interval, for k^{th} user is defined in (4.45). $\mathbf{R}(m)$, correlation matrix of input vector $\hat{\mathbf{r}}(m)$ is defined by

$$\mathbf{R}(m) = \sum_{i=1}^{m} \lambda^{m-i}\hat{\mathbf{r}}(i)\,\hat{\mathbf{r}}^T(i) \tag{4.50}$$

Using the results from [69], we conclude that the mean weight vector $\mathbf{w}(m)$ converges to its optimum value $\mathbf{w}^*$, i.e., $E\{\mathbf{w}(m)\} \to \mathbf{w}^*$, as $n \to \infty$. This $\mathbf{w}^*$ is used as the weight in the MAI cancellation. For user 1 as the user of intereste, at m^{th} chip-bit interval, the MAI cancellation is carried out as

$$r_{desired}(m) = r(m) - \sum_{j=2}^{K} w_j(m)\hat{r}_j(m) \tag{4.51}$$

where $w_j(m)$ is used to construct the maximum amount of MAI for the user 1. By subtracting this amount from the received signal, the remaining $r_{desired}(m)$ will be the less interfered signal, which produces a more reliable decision on the transmitted data symbol as

$$\hat{b}_{tr} = \mathrm{sgn}[\ \sum_{m=0}^{G-1} r_{desired}(m)s(m)\ ] \tag{4.52}$$

where $\hat{b}_{tr}$ is the estimate of transmitted data symbol, and $\mathbf{s}$ is the signature sequence for user 1.

It is clear that the new scheme includes a blind RLS adaptation in the first stage to produce estimate for each desired user and the conventional RLS adaptation in the second stage to reduce the remaining MAI and to produce a less interfered received signal for each user of interest. A more reliable decision of the data symbol for the desired user is made based on the detected received signal. Since the reliability of the data estimation from stage 1 varies from one user to another and from bit to bit depends on the MAI levels, different weight vectors are obtained for each user, instead of a single weight vectors for all the users.

We noted from (4.51), the power of transmitted signals is assumed to be unity. This assumption can be achieved by employing a power control at the transmitter which is a common technique used in cellular radio systems today. It is also observed that the signature waveforms of other users in the system are required to further reduce remaining MAI. This is the compromise to be made between canceling the MAI to have better performance and having a lower cost scheme to have a less accurate estimate. The knowledge of the signature waveform of other users can be achieved at the cost of additional complexity.

The new scheme at the second stage requires more knowledge of users in the system than the first stage does where only signature waveform and amplitude of desired user are needed.

Obviously, the new scheme is no longer blind adaptation. Instead, it is a combination of the blind and conventional RLS adaptation, it is also a combination of interference suppression and cancellation. It reduces the need of a training sequence from the adaptive implementation of MMSE detector, which we discussed in Chapter 3. It also reduces the need for training sequence and assumption of having data symbol to be known in the scheme given in [66], which we studied in Section 4.2. Furthermore, since the second stage cancels the remaining MAI, it makes a significant performance improvement than the blind MMSE interference suppression scheme. The scheme proposed in [66] uses decision–directed adaptation to improve the performance. However, decision-directed adaptation is subject to a catastrophic error propagation in the case of a sudden change in the environment. The new scheme proposed here is not affected by any training sequence, it takes advantage of the fast convergence and tracking ability of conventional RLS algorithm to produce the optimum weight, and to reduce the remaining MAI. Therefore, it provides a better resistance to a changing environment.

4.3.3 Convergence Analysis of the Combined RLS Adaptation

The combined RLS adaptation consists of two stages of adaptation rules, namely blind RLS and conventional RLS adaptation. For the first stage, only blind RLS algorithm is applied. The recursive relationship between the weight vectors $\mathbf{c}(n)$ and $\mathbf{c}(n-1)$ is given by [66]

$$\mathbf{c}(n) = \mathbf{c}(n-1) - e(n)\mathbf{k}(n) + \lambda\beta(n)e(n)\mathbf{h}(n) \tag{4.53}$$

where

$$e(n) = \mathbf{r}^T(n)\mathbf{c}(n-1) = \alpha(n-1)\mathbf{r}^T(n)\mathbf{h}(n-1) \tag{4.54}$$

is the *a priori* least-square (LS) estimation at time n.

Let $\theta(n)$ be the weight error vector between the weight vector $\mathbf{c}(n)$ at time n and the optimal weight vector $\overline{\mathbf{c}}$, that is,

$$\boldsymbol{\theta}(n) = \mathbf{c}(n) - \overline{\mathbf{c}}. \tag{4.55}$$

After some manipulation, (4.55) becomes

$$\boldsymbol{\theta}(n) \cong [\lambda\mathbf{I} + \overline{\mathbf{c}}\mathbf{s}^T\mathbf{k}(n)\mathbf{r}^T(n)]\boldsymbol{\theta}(n-1) + (\overline{\mathbf{c}}\mathbf{s}^T - \mathbf{I})\mathbf{k}(n)\mathbf{r}^T(n)\overline{\mathbf{c}} \tag{4.56}$$

Equation (4.56) is the recursive equation that the weight error vector $\boldsymbol{\theta}(n)$ satisfies for large n.

Taking the expectation of both sides of (4.56), we have

$$\begin{aligned} E\{\boldsymbol{\theta}(n)\} &\cong \lambda E\{\boldsymbol{\theta}(n-1))\} + \overline{\mathbf{c}}\mathbf{s}^T E\{\mathbf{k}(n)\mathbf{r}^T(n)\} \cdot E\{\boldsymbol{\theta}(n-1))\} \\ &\quad + (\overline{\mathbf{c}}\mathbf{s}^T - \mathbf{I})E\{\mathbf{k}(n)\mathbf{r}^T(n)\}\overline{\mathbf{c}} \\ &= \lambda E\{\boldsymbol{\theta}(n-1)\} \end{aligned} \tag{4.57}$$

Therefore, the expected weight error vector always converges to zero. That is to say, the weight vector $\mathbf{c}(n)$ always converges to the optimal weight vector $\overline{\mathbf{c}}$, and this convergence is independent of the eigenvalue distribution.

At the second stage, the conventional RLS adaptation is enforced. The convergence analysis of the conventional RLS algorithm is given by S. Haykin in [67]. Applying it in this system model, the prediction error is given by

$$e_p(m) = r(m) - \mathbf{w}^{*T}(m)\hat{\mathbf{r}}(m) \tag{4.58}$$

where $\mathbf{w}^{*T}$ is the optimum regression parameter vector. The expected value of $\mathbf{w}(m)$ can be expressed as

$$E[\mathbf{w}(m)] = \mathbf{w}^*, \qquad m \geq K \tag{4.59}$$

Equation (4.59) states that the RLS algorithm is convergent in the mean value for $n \geq K$, where K is the number of taps in the adaptive transversal filter.

4.3.4 Steady-State SIR

Since the new scheme takes advantage of the blind RLS algorithm described in Section 4.2.2 for the first stage, we have analysis of steady-state SIR similar to that in Section 4.2.3. An expression for the steady-state SIR of the blind RLS adaptation in terms of the optimum value SIR^* is given by

$$SIR^{\infty} = \frac{SIR^*}{(1+d) + d \cdot SIR^*} \tag{4.60}$$

We have already analyzed the disadvantage of a severe degradation from the optimum value of the system having such steady-state SIR, especially when $SIR^* >> 1$.

As we have seen in Section 4.3.2, the conventional RLS produces a weight vector, which is employed to further cancel MAI components. It results in reducing the interference power has been reduced from the estimate in the first stage. Therefore, the steady-state SIR of the second stage is improved over the first stage. Equation (4.60) provides the lower boundary for the steady-state SIR in the proposed scheme.

4.4 Summary

As seen from the discussion in the Chapter 3, the adaptive MMSE detector requires a training sequence to achieve the interference suppression. To eliminate the requirement for the training sequence, several approaches of adaptive detector are exploited. In this chapter, the canonical representation of linear detector in the designed system model has been derived. The minimum output energy linear detector in this system model has been discussed. The impulse response of the linear receiver has been decomposed into the signature waveform component of the desired user and the orthogonal adaptive component. By using the canonical form of linear detector, it has been shown that the linear detector that minimizes the mean output energy of the detector is the MMSE detector. Although, the theory for this kind of detector already exists, the analysis of the system model carried out in this chapter provides a new insight into the blind MMSE solution for multisuer detection, justifying the use of a linear MMSE detector for blind adaptation.

The fact that the mean-square-error and the mean output energy of the linear detector differ by a constant in terms of the canonical representation of the detector leads to a blind adaptive implementation of the MMSE detector for the CDMA system. A blind RLS version of the MMSE multiuser receiver to suppress both MAI and NBI has also been reviewed, which reduces the need of a training sequence. The steady state performance of this algorithm in terms of the signal-to-interference ratio has been studied.

It has been seen that this algorithm has a fast convergence and good tracking abilities, but it suffers from a severe steady-state SIR degradation in that this value is significantly smaller than the optimum value when the optimum value is greater than unity. One solution to address this deficiency, which applies a decision-directed adaptation mode after the initial blind adaptation converges has been reviewed [66]. This solution has a condition that the data symbol is assumed to be known at the receiver by using a training sequence. The use of a training sequence in a rapidly changing mobile environment, causes the system to be unreliable and an inefficient use of the channel bandwidth. It is difficult to meet the estimation demand of a mobile environment by applying training sequence at this stage. Moreover, the decision-directed adaptation is subject to catastrophic error propagation in the case of sudden change in the environment. The system applying decision-directed adaptation is not suitable to the mobile communications. Also, a perfect estimation cannot be achieved to produce the detected symbol as accurate as the data symbol. In other words, the assumption that the data symbols are known at the receiver is not realistic.

In this chapter, a new scheme consisting of a combination of blind RLS algorithm and conventional RLS algorithm, which provides an adaptive MMSE solution to the detection problem and results in a improved steady-state value of SIR without assuming the knowledge of the data symbols, has been proposed.

The proposed scheme consists of two stages. The first stage takes the blind RLS adaptation, which realizes the adaptive MMSE implementation in CDMA systems to suppress both MAI and NBI and provides an estimate on data symbol for the second stage. The second stage employs the conventional RLS adaptation to produce an optimum weight vector to further cancel the remaining MAI. In the second stage, a less interfered received signal is yielded, which is the base of making more reliable estimate on the data symbol.

Unlike the scheme presented in [66], the new scheme combines both interference suppression and cancellation using blind and conventional RLS adaptation to detect the desired signal, instead of having a blind RLS adaptation first and then assuming that the data symbols are known as the reference signal for the conventional RLS algorithm. Consequently, when the received signal changes, the system does not have to suspend the conventional RLS adaptation and goes back only to the blind adaptation stage. It increases the system ability of resilience to sudden changes at the cost of additional complexity to achieve the signature sequence of other users in the system. However, it improves the steady state SIR from the blind adaptation without using a training sequence or making an unachievable assumption about the transmitted data symbol. Furthermore, it solves the problem of decision directed adaptation on the catastrophic error propagation. Therefore, this scheme is better suited for DS-CDMA systems.

Chapter 5

Experimental Results

5.1 Introduction

The increasing interest in CDMA systems for mobile radio has spawned a great deal of research in recent years to exploit multiuser detection to mitigate both MAI and NBI. As it was seen in Chapter 3, the performance of the conventional matched filter receiver is susceptible to degradation caused by near-far effects, since it is not capable of performing any interference mitigation as the number of interference increases. The decorrelation receiver is capable to improve the performance at high SNR level by exploiting the MAI structures, its performance degrades as the SNR level becomes low. This is because of that the decorrelation detector simply neglects the existence of background noise. The use of the MMSE multiuser receiver for CDMA interference suppression has also been investigated. Some of the important results on the MMSE receiver have been provided in [55], in which the authors have discussed the MMSE in terms of code cross-correlation.

As seen in the previous chapters, a multiuser MMSE receiver can reduce the MAI yielding significant performance gains over the conventional receiver. It provides a compromised solution for multiuser detection by taking into account the background noise as well as MAI structure. Furthermore, the important advantage of the MMSE detector is that it admits itself to adaptive implementation. However, the adaptive receiver that employ the MMSE algorithm require a training sequence, which may mot be feasible in a dynamically changing mobile environment.

The purpose of this work has been to follow the existing approaches of the multiuser detection and to derive an adaptive MMSE solution with more practical meanings. In Chapter

4, the relationship between the MMSE detector and MOE detector is revealed in terms of their canonical representations. With this relationship established, it is easy to study the dependency of MMSE adaptive solution on the signature waveforms and amplitude of the user of interest and on the interference in the system. As we have seen, the linear detector that minimizes the mean output value of energy of the detector is the MMSE detector. This observation leads the MMSE detector for the blind adaptation, in which only the signature waveform and amplitude of the desired user are required at the receiver for the implementation of DS/CDMA systems.

The recursive least-squares (RLS) adaptive algorithm is known to converge extremely fast, and has excellent tracking capabilities in a time-varying environment. A blind adaptive linear MMSE multiuser detector based on RLS algorithm has been proposed in [66]. As seen in Chapter 4, the SIR performance of this version exhibits a significantly lower steady-state value of SIR than the optimum value. In [66], a solution to this problem has been provided by switching to the conventional RLS algorithm that uses a decision directed adaptation after the initial blind adaptation converges. As we have seen in Chapter 4, when the adaptive algorithm makes use of the known data symbols $b(n)$, the steady-state output SIR is close to its optimum possible value.

The idea to have the system switched to the conventional RLS algorithm, after the convergence of initial blind RLS is a good one. But the assumption that the transmitted data symbols b(n) is known to the receiver may not be true in reality. Even though the technique to achieve this condition by using a training sequence or using a decision feedback is used in practice, the estimated data symbols $\hat{b}(n)$ are not as accurate as the transmitted symbols b(n).

In Chapter 4, a new scheme of combined blind and conventional RLS algorithms to improve steady-state SIR has been proposed. The new scheme does not simply switch to the conventional RLS adaptation stage. In fact, it uses the blind and conventional RLS together to attain a adaptation of the linear MMSE detector in order to provide a better performance in the steady state.

The new scheme takes advantage of the blind RLS adaptation rule in the first stage, which requires only the signature waveform of the desired user. In the second stage, the system makes another adaptation, which uses the conventional RLS algorithm to produce an optimum weight vector to further cancel the remaining MAI. Thus, the system improves the steady state SIR over the blind RLS adaptation and does not have to switch back to the blind adaptation only when the received signal changes.

Table 5.1: System parameters for Experiment 1

n (Number of iterations)	Adaptation rules	Signal	MAI (Random)	NBI (AR)	SNR (After despreading)	Signature sequence (Desired signal)
0 - 500	Blind RLS	20 dB	Two 10 dB	One 20 dB	20 dB	Gold code
500 - 1000	Conventional RLS of	20 dB	Three 10 dB	One 20 dB	20 dB	Gold code

In this chapter, the experimental results for the combined adaptive RLS scheme are presented and discussed. First, we will see that the steady state SIR of the proposed scheme makes a significant improvement over the blind RLS adaptation without assuming the knowledge of the data symbol, or using a training sequence. Afterwards, the tracking abilities of the proposed scheme are studied. The system resilience to the dynamic changes is also presented. The comparisons with the scheme proposed in [66] are made in terms of the various features.

5.2 Experimental Results for Steady-State SIR

We consider a synchronous DS-CDMA system with processing gain G is set to be 31.

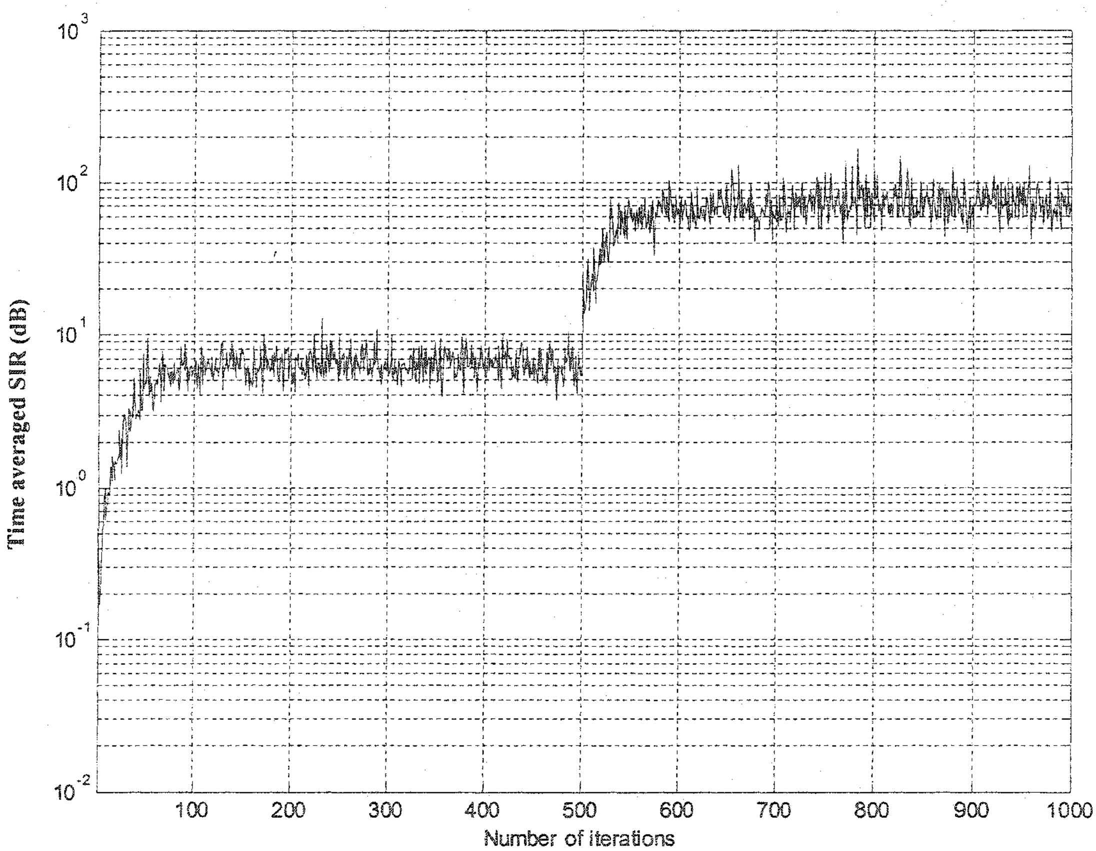

Figure 5.1: Time averaged SIR versus time for the blind adaptation and the conventional RLS adaptation (Three 10-dB MAIs)

Experiment 1

The first set of experimental parameters are given in Table 5.1. There are three 10-dB MAI signals, each with a random signature. In addition, there is a 20-dB NBI signal, which is a second-order AR signal with the both poles at 0.99. The signal power to background noise power is 20- dB. These interference signals form a strong near-far environment. The blind adaptation is used for the first 500 iterations. During the iterations 501 – 1000, the system has the construct presented in [66], which use decision-directed conventional RLS adaptation only and assume the data symbol is known at the receiver. A training sequence or decision feedback is used to achieve this assumption.

Table 5.2: System parameters for Experiment 2

n (Number of iterations)	Adaptation rules	Signal	MAI (Random)	NBI (AR)	SNR (After despreading)	Signature sequence (Desired signal)
0 - 500	Blind RLS	20dB	Three 10 dB	One 20 dB	20 dB	Gold code
500 - 1000	Blind RLS + Conventional RLS for MAI cancellation	20dB	Three 10 dB	One 20 dB	20 dB	Gold code

Figure 5.1 shows the plot of time-averaged out put of SIR versus time for the different adaptation rules. An AWGN channel is chosen in the example, and perfect synchronization is

assumed. From Figure 5.1, we observe for the first 500 iterations, the steady state SIR is about 8 dB, which is far less than its optimum value of MMSE detector, 18 dB in this case. This can be explained by (4.28), the steady state SIR of blind RLS adaptation has the degradation from its optimum value. For the iteration 500 – 1000, the steady state SIR is very closed to the optimum value. This can be explained by (4.34) that the conventional RLS adaptation with the known data symbol as the reference signal has the steady state SIR close to its optimum value.

Experiment 2

The second example we consider in this section has the parameters given in Table 5.2. This example has the same signal parameters with Table 5.1. During the iterations 501 – 1000, the blind adaptation is still active to produce the estimate $\hat{b}_k(n)$, which is the input signal for the conventional RLS to regenerate the estimated MAI signals. At the same time, the MAI cancellation employing conventional RLS adaptation is forced to produce more accurate estimation.

Figure 5.2 shows a plot of time-averaged output of SIR versus time for the different adaptation rules. From Figure 5.2, we observe for the first 500 iterations, the steady state SIR is about 8 dB. For the iteration 500 – 1000, the steady state SIR is improved to 14 dB.

Comparing Figure 5.1 and Figure 5.2, we observe that the conventional RLS adaptation with known data symbols has a higher SIR than the combined remaining MAI cancellation scheme. The difference is about 2 dB. However, the assumption that the data symbol is known at the receiver is not realistic, and decision-directed adaptation can cause catastrophic error propagation when the mobile environment has sudden changes. We will consider such example in the next section.

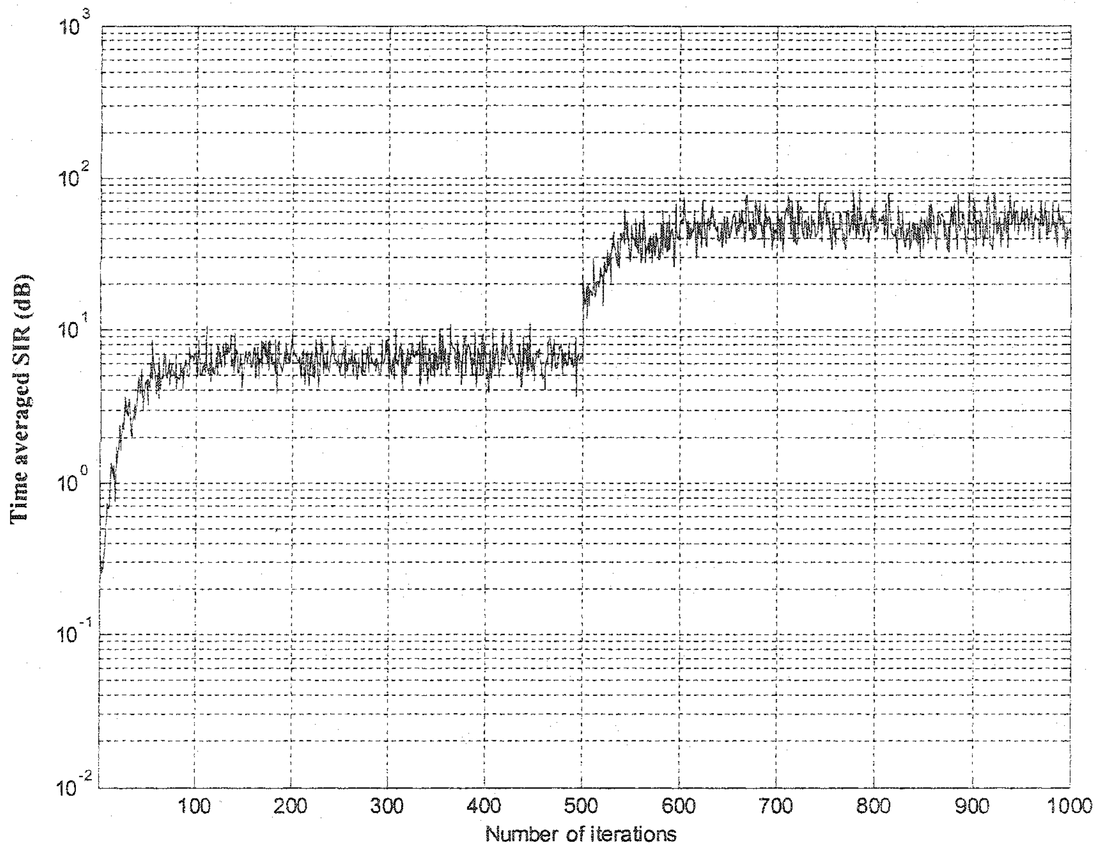

Figure 5.2: Time averaged SIR versus time for the blind adaptation and the combined RLS adaptation (Three 10-dB MAIs)

Experiment 3

The third example we are going to look at has the experimental parameters given in Table 5.3.

Table 5.3: System parameters for Experiment 3

n (Number of iterations)	Adaptation rules	Signal	MAI (Random)	NBI (AR)	SNR (After despreading)	Signature sequence (Desired signal)
0 - 500	Blind RLS	20dB	Two 10 dB One 20 dB	One 20 dB	20 dB	Gold code
500 - 1000	Blind RLS + Conventional RLS for MAI cancellation	20dB	Two 10 dB One 20 dB	One 20 dB	20 dB	Gold code

In this example, we change the number and the power of MAIs. There are two 10-dB MAI signals and one 20-dB MAI signal, each with a random signature. In addition, there is a 20-dB NBI signal which is a second-order AR signal with the both poles at 0.99. The signal power to background noise power is 20 dB. The interference signals components have been changed. The blind adaptation is used for the first 500 iterations. From 501 to 1000, the blind adaptation and conventional RLS are employed to make more reliable decision.

The time-averaged output of SIR versus time is given in Figure 5.3. From Figure 5.3, we observe for the first 500 iterations, the steady state SIR is about 8 dB. For the iteration 500 – 1000, the steady state SIR is improved to 14 dB.

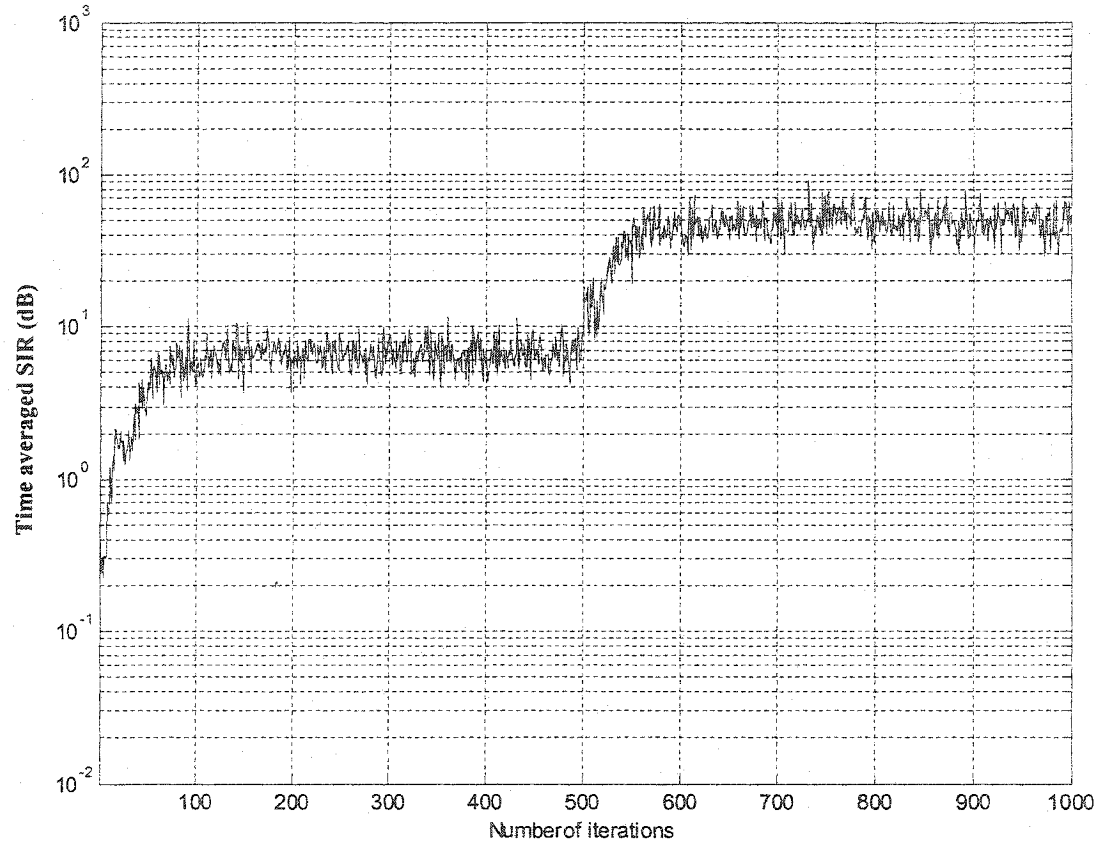

Figure 5.3: Time averaged SIR versus time for the blind adaptation rule and the combined RLS adaptation (two 10-dB MAIs and one 20-dB MAI)

Experiment 4

In this experiment, we investigate the effect of different numbers of MAIs to the proposed system. The parameter set for this experiment is given in Table 5.4. What makes this example different from example in of Figure 5.3 is that it has six MAIs, each with a power of 10 dB.

The result is given in Figure 5.4. From Figure 5.4, we observe for the first 500 iterations, the steady state SIR is about 8 dB. For the iteration 500 – 1000, the steady state SIR is improved to 14 dB.

Table 5.4: System parameters for Experiment 4

n (Number of iterations)	Adaptation rules	Signal	MAI (Random)	NBI (AR)	SNR (After dispreading)	Signature sequence (Desired signal)
0 - 500	Blind RLS	20dB	Six 10 dB	One 20 dB	20 dB	Gold code
500 - 1000	Blind RLS + Conventional RLS for MAI cancellation	20dB	Six 10 dB	One 20 dB	20 dB	Gold code

By comparing Figures 5.2, 5.3 and 5.4, it is observed that the SIR levels during the iteration from 500 to 1000 are at the same level. There is no obvious difference between them. They are all significantly improved over that using the blind RLS adaptation. Thus, different numbers and power of MAIs in the system has very little impact on its performance. Therefore, the proposed system has very good resistance to MAIs.

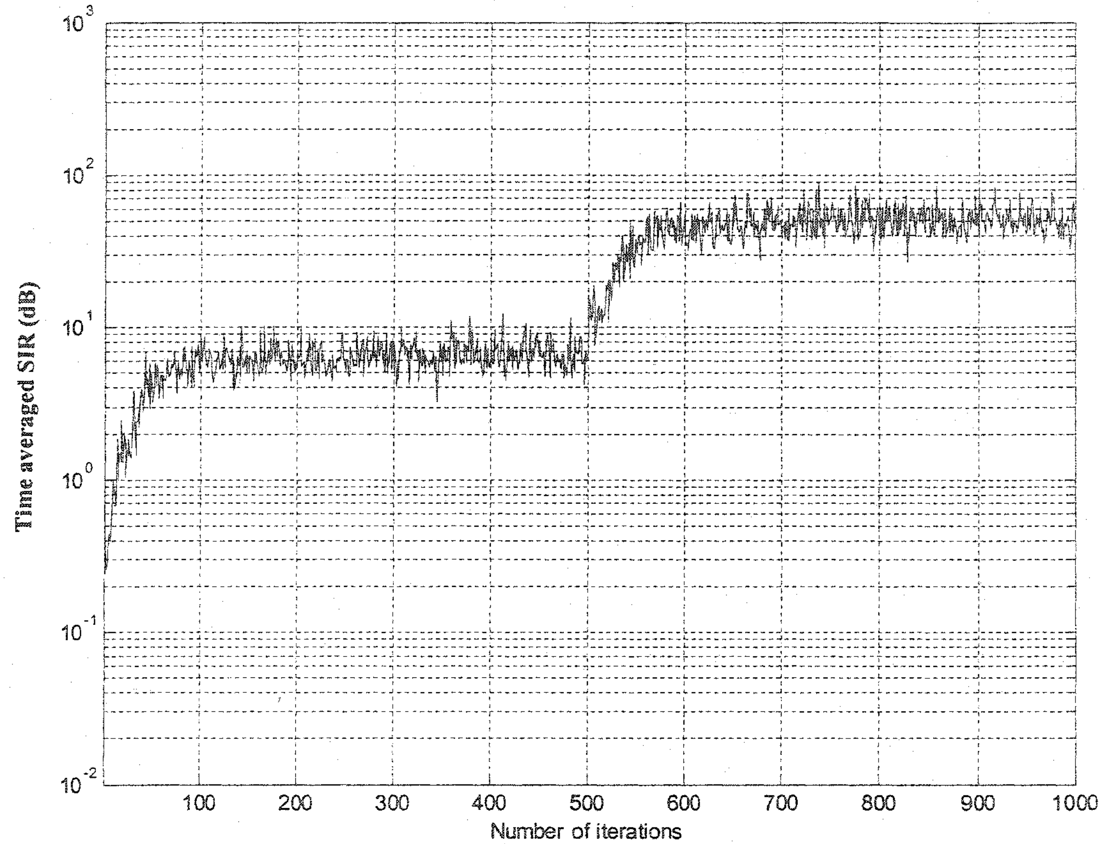

Figure 5.4: Time averaged SIR versus time for the blind adaptation rule and the combined RLS adaptation (six 10-dB MAIs)

5.3 Experimental Results on the Convergence and Tracking Abilities of the Proposed Scheme

In this section, we study the tracking abilities of the proposed scheme. To show the reactions of the system to a dynamically changing mobile environment, different environments, where the number, type and power of interferers vary with time, are simulated.

Table 5.5: Experimental parameters for Experiment 5

n (Number of iterations)	Adaptation rules	Signal	MAI (Random)	NBI (AR)	SNR (After dispreading)	Signature sequence (Desired signal)
0 - 500	Blind RLS	20 dB	Three 10 dB		20 dB	Gold code
500 - 1000	Blind RLS + Conventional RLS for MAI cancellation	20 dB	Three 10 dB		20 dB	Gold code
1001-1500	Blind RLS + Conventional RLS for MAI cancellation	20 dB	Six 10 dB	One 20 dB	20 dB	Gold code
1501-2000	Blind RLS + Conventional RLS for MAI cancellation	20 dB	Three 10 MAI + one 20 dB	One 20 dB	20 dB	Gold code

Experiment 5

Again, we consider a synchronous DS-CDMA system with processing gain G is set to be 31. The first example in this section has the experimental parameters given in Table 5.5.

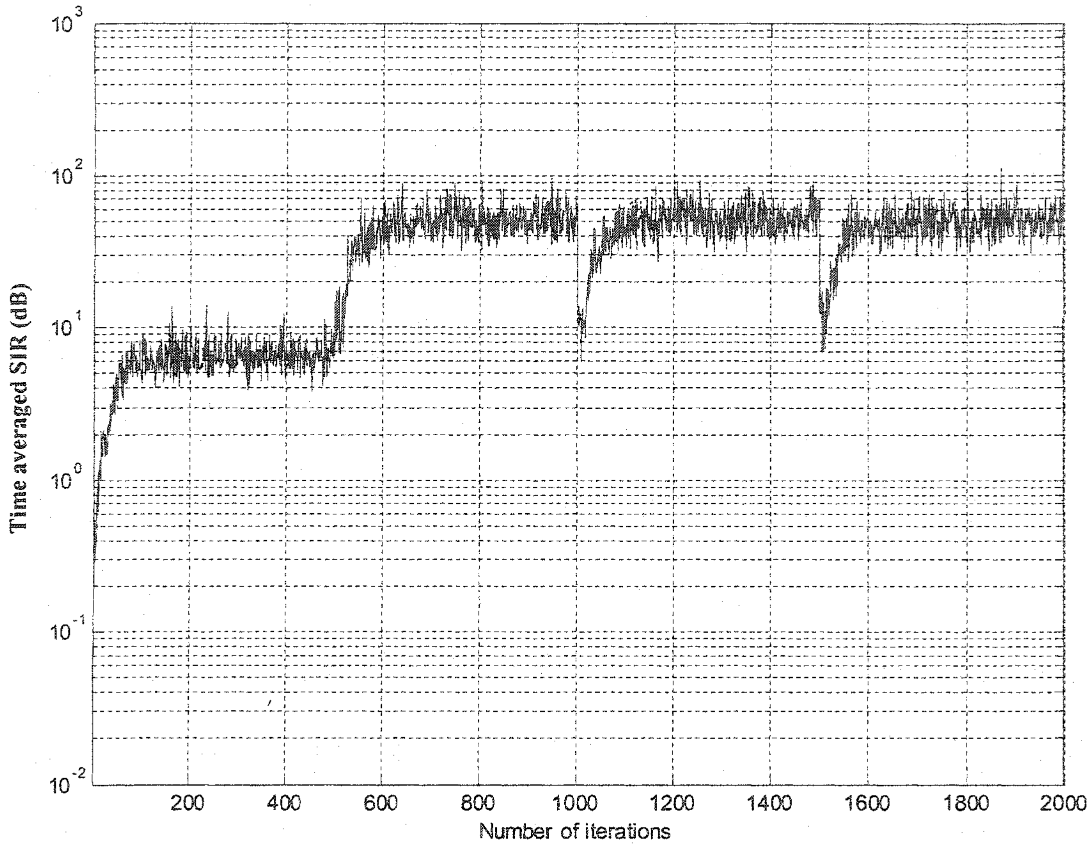

Figure 5.5: Time averaged SIR versus time for the blind adaptation and the combined RLS adaptation

In this example, the signal power to background noise power is 20 dB. At the time instant $n = 0$, the simulation starts with one desired signal and six MAI signals, each of power 10 dB. To compare the performance of blind RLS adaptation and the combined RLS adaptation with MAI cancellation, from time 0 to 500, we use only blind adaptation. After wards, we use proposed combined scheme to detect the data symbols until n = 2000. During the time duration n=500 to 1000, the signal components remain unchanged. At time $n = 1000$, a strong NBI signal of 20 dB is added in the system. At time $n = 1500$, another strong MAI signal of 20 dB is added. The desired user's signature sequence uses Gold code, and the signature sequences of the MAIs are generated randomly. The NBI signal is a second-order AR signal with both the poles at 0.99.

Table 5.6: System parameters for Experiment 6

n (Number of iterations)	Adaptation rules	Signal	MAI (Random)	NBI (AR)	SNR (After dispreading)	Signature sequence (Desired signal)
0 - 500	Blind RLS	20 dB	Six 10 dB		20 dB	Gold code
500 - 1000	Blind RLS	20 dB	Six 10 dB	One 20 dB	20 dB	Gold code
1001-1500	Blind RLS	20 dB	Six 10 dB + One 20 dB	One 20 dB	20 dB	Gold code
1501-2000	Blind RLS	20 dB	Three 10 MAI + One 20 dB	One 20 dB	20 dB	Gold code

Figure 5.5 shows a plot of time averaged output SIR versus time of the blind RLS adaptation and combined scheme. From this figure, it is observed that the proposed combined scheme has very good convergence and tracking ability. In Sections 4.2 and 4.3, we observed the good convergence properties of both the blind and conventional RLS adaptations. Figure 5.5 reflects these features. Since the new proposed scheme employs both the adaptations, the blind adaptation provides the initial estimate and then the conventional one minimizes the remaining MAIs and produces more reliable estimate. There is a time difference between the

derivation of the initial estimate and the final one. In Figure 5.5, there is a delay of about 10 to 20 more iterations for convergence of the combined scheme than in the case of the blind adaptation. The combined scheme has to make additional computation. However, since the RLS algorithm has a fast convergence and tracking property, the delay caused by these computing is still tolerable. The performance enhanced by the proposed scheme is about 7 to 8 dB. It is also noticed that after the convergence of the combined system, the output levels of SIR are all at the same level. This fact indicates that the combined system has the ability to effectively resist the environment changes.

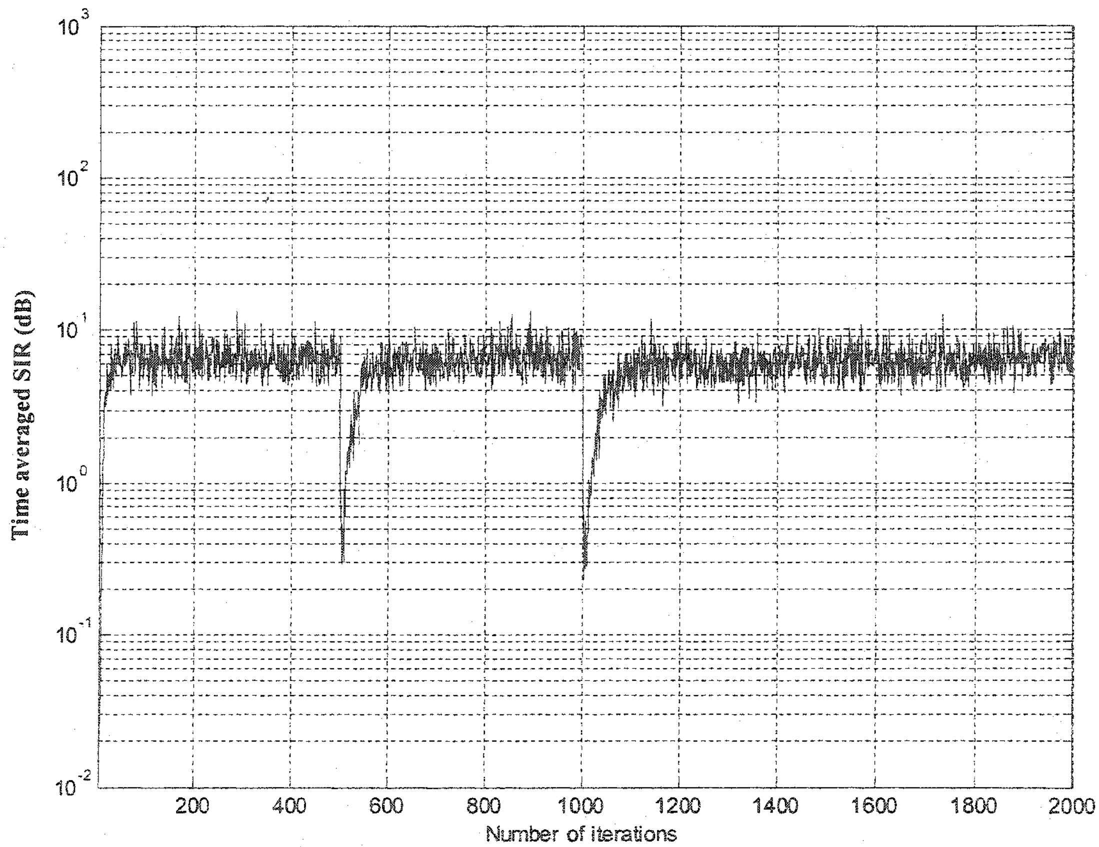

Figure 5.6: Time averaged SIR versus time for the blind adaptation

In Section 4.2.5, we analyzed the limitations of the blind RLS adaptation scheme proposed in [66]. One of them concerns the stability of the system. Since the system employs decision directed adaptation to improve the steady state SIR after the convergence of the blind adaptation, it has to switch back to the blind adaptation once there is a sudden change in the environment. But the frequent sudden changes are not unusual mobile communications. Therefore, the system becomes unstable because of the catastrophic error propagation of the decision directed adaptation with the varying received signal. In the following examples, we will see how the new proposed scheme overcomes this drawback of the conventional scheme.

Experiment 6

The set of parameters for the second example presented in this section is given in Table 5.6. For the system simulated using the parameters given in this table, we apply blind RLS adaptation to estimate the data symbols since the first stage of proposed scheme is based on this adaptation. In this example, the signal power to background noise power is 20 dB. At the time instant $n = 0$, the simulation starts with one desired signal and six MAI signals, each having a power of 10 dB. At $n = 500$, a strong NBI signal of 20 dB is added to the system. At $n = 1000$, another strong MAI signal of 20 dB is added. At $n = 1500$, three of the original 10-dB MAI signals are removed from the system. The desired user's signature sequence uses a Gold code, and the signature sequences of the MAI are generated randomly. The NBI signal is a second-order AR signal with both the poles at 0.99.

Figure 5.6 shows a plot of time averaged output SIR versus time of the blind RLS adaptation and combined scheme. In this figure, we observe that the system applying only the blind RLS adaptation has a fast convergence and a good tracking ability. But it suffers from a low SIR output at steady state. We also note that, at $n = 1500$, the removal of three 10-dB MAIs has almost no effect on the system, which shows the ability of the system to be resistant to MAIs. This is a property providing a good estimate based on further cancellations of the MAIs.

Table 5.7: System parameters for Experiment 7

n (Number of iterations)	Adaptation rules	Signal	MAI (Random)	NBI (AR)	SNR (After dispreading)	Signature sequence (Desired signal)
0 - 250	Blind RLS	20 dB	Six 10 dB		20 dB	Gold code
251 - 500	Conventional RLS decision feedback	20 dB	Six 10 dB		20 dB	Gold code
500 - 750	Blind RLS	20 dB	Six 10 dB	One 20 dB	20 dB	Gold code
751 - 1000	Conventional RLS decision feedback	20 dB	Six 10 dB	One 20 dB	20 dB	Gold code
1001-1250	Blind RLS	20 dB	Six 10 dB + one 20 dB	One 20 dB	20 dB	Gold code
1251 - 1500	Conventional RLS decision feedback	20 dB	Six 10 dB + one 20 dB	One 20 dB	20 dB	Gold code
1501-1750	Blind RLS	20 dB	Three 10 MAI + one 20 dB	One 20 dB	20 dB	Gold code
1751 - 2000	Conventional RLS decision feedback	20 dB	Three 10 MAI + one 20 dB	One 20 dB	20 dB	Gold code

Experiment 7

The Third example presented in this section has the same environment as that of the proceeding example, with the only exception of the adaptation mechanism used, which is presented in [66] and studied in Section 4.2. After convergence of the blind adaptation, system employs the conventional RLS having the decision directed adaptation using a training sequence or a decision feedback to obtain the data symbols. The data symbols are assumed to be known at the receiver.

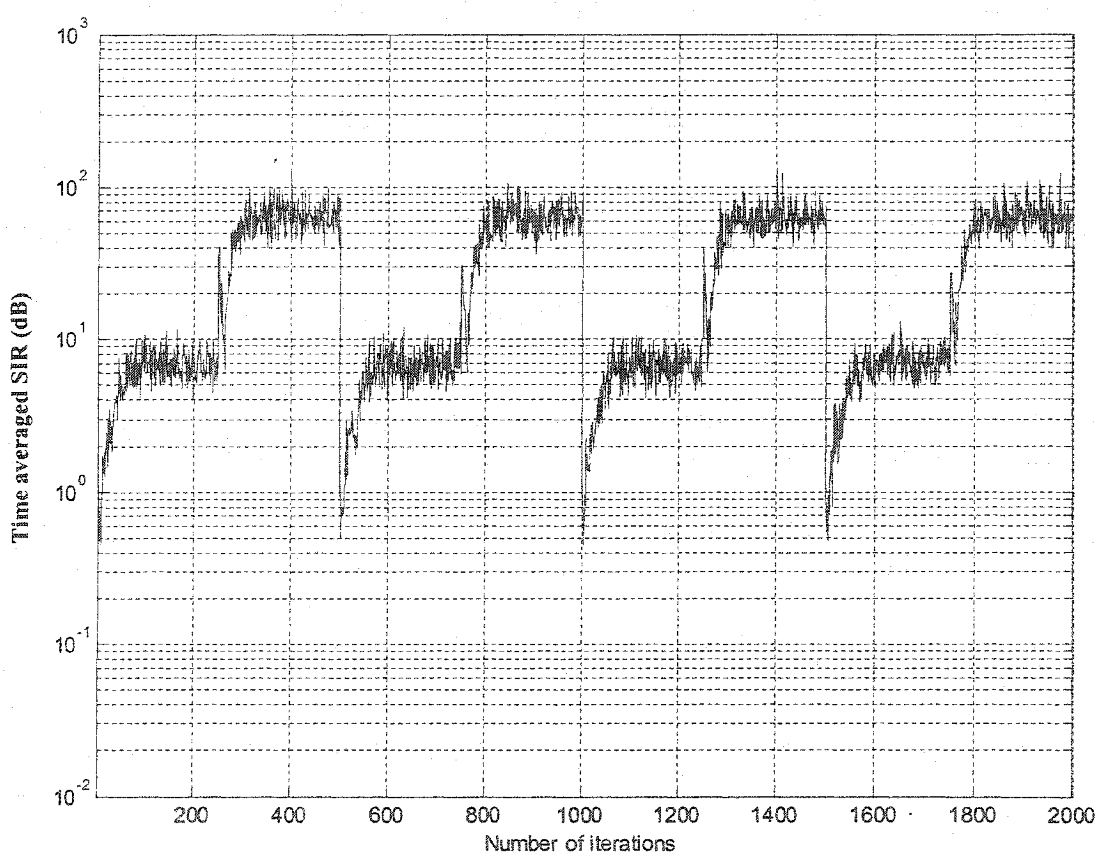

Figure 5.7: Time averaged SIR versus time for the conventional RLS having decision directed adaptation in a dynamically changing mobile environment

Putting aside the implementation feasibility of in the scheme in [66], let us focus on its performance. The sets of experimental parameters are given in Table 5.7. Figure 5.7 shows a plot of time averaged output SIR versus time for the scheme presented in [66] and using the decision directed adaptation. In this figure, one can observe the indentation of output SIR value, caused by the switching between the blind RLS adaptation and the conventional one. The system switches to conventional RLS adaptation after the blind adaptation converges in order to improve the steady state SIR, and then switches back to blind adaptation when there is any changes in the environment. This is done, since the previously trained system is no longer suited to detect the changed signals. The conventional adaptation has to be suspended and to wait until the convergence of the blind adaptation stage is achieved. As we can see, there is a need to check the status of convergence of the blind stage, which increases the complexity. Also, there is a time difference between the switching from blind adaptation to the conventional one, which is difficult to estimate. However, by comparing the time delay of the proposed scheme, which (Figure 5.5) is 10 – 20 iterations, the time delay in checking the convergence status is rather long. Furthermore, the stability of the system and the resilience to environment changes make the system given in [66] unsuitable to mobile environment.

Experiment 8

In the last example of this section, we present the performance of the proposed system in terms of convergence and stability to a varying environment. For the purpose of comparison the signal component and dynamic environment simulated are the same as given in Table 5.6. The complete set of experimental parameters are given in Table 5.8.

Figure 5.8 shows a plot of time averaged output SIR versus time for the proposed combined scheme. In this figure, it is observed that the system is recovered very fast from signals changing. And there is no output SIR indentation from time to time as in the case appears in Figure 5.7

Table 5.8: System parameters for Experiment 8

n (Number of iterations)	Adaptation rules	Signal	MAI (Random)	NBI (AR)	SNR (After dispreading)	Signature sequence (Desired signal)
0 - 500	Combined scheme	20 dB	Six 10 dB		20 dB	Gold code
500 - 1000	Combined scheme	20 dB	Six 10 dB	One 20 dB	20 dB	Gold code
1001-1500	Combined scheme	20 dB	Six 10 dB + one 20 dB	One 20 dB	20 dB	Gold code
1501-2000	Combined scheme	20 dB	Three 10 MAI + one 20 dB	One 20 dB	20 dB	Gold code

Comparing Figure 5.8 with Figure 5.6, it is observed that the proposed combined scheme yields a performance gain of about 7 dB over that of the blind adaptation. The convergence of proposed scheme is fast to the varying environment. The output steady state SIR remains at the same level after the convergence, which indicates a good resilience to different interferences. It is also noticed from Figure 5.8 that there is a fast convergence to the steady state after the removal of three 10 dB MAI signals at $n = 1500$. In the proposed scheme, the detection of the data symbols using the conventional RLS MAI cancellation can also resume right after the first data symbol is produced by the blind adaptation.

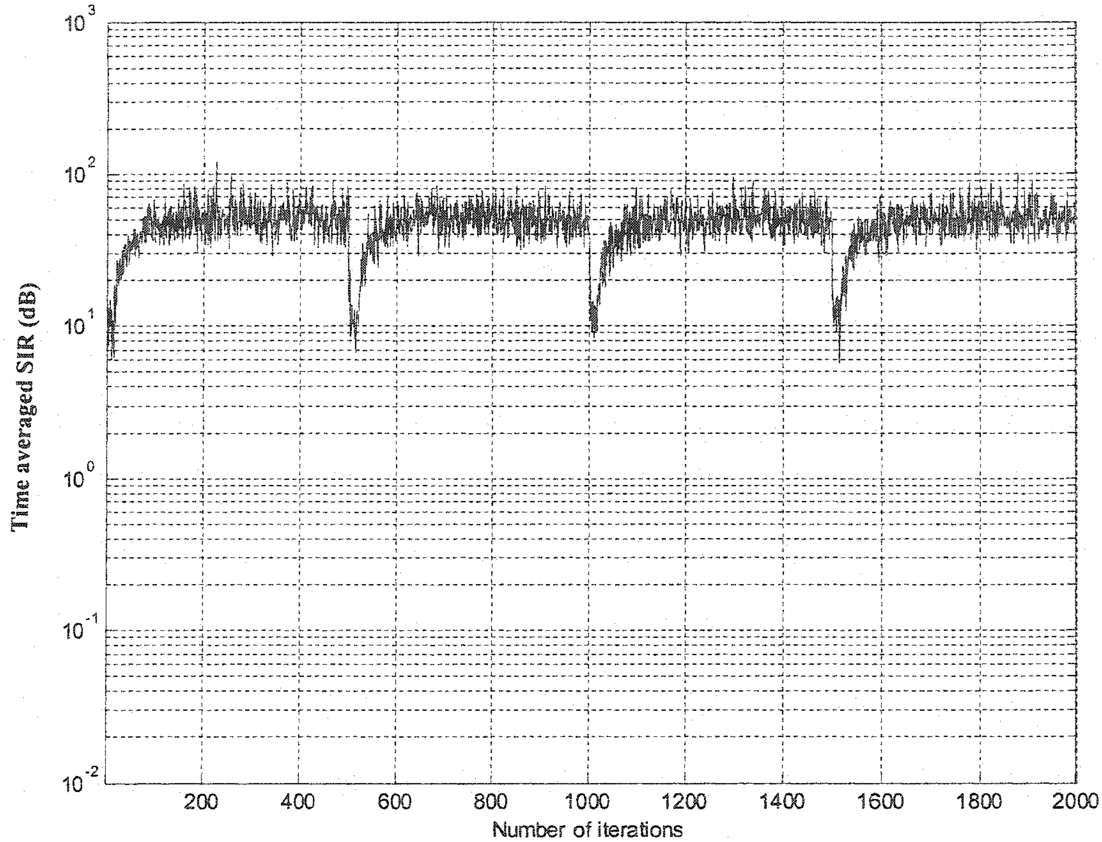

Figure 5.8: Time averaged SIR versus time for the proposed combined scheme

By comparing Figure 5.8 and Figure 5.7, it is even more clear that the system using the combined scheme has superior stability than that of the scheme in [66]. There is no switching required. The second stage is still able to perform well when the environment changes unlike the system of [66], since it does not have to wait for the convergence of the first stage and then be trained to be able to detect the data symbols. The catastrophic error propagation problem is solved by the scheme proposed.

5.4 Summary

In this chapter, an extensive simulation study have been undertaken to demonstrate the superior performance of the proposed combined scheme, which uses the blind RLS adaptation in the first stage to produce the initial estimate and conventional RLS in the second stage to minimize the remaining MAI. Comparisons are also made between the proposed scheme and the one presented in [66] to see the performance improvement in terms of the steady state output SIR, system convergence, tracking ability, resilience to interference, and system stability.

The proposed scheme has been shown to yield a performance gain of about 7 dB over the blind RLS adaptation of [66] in synchronous AWGN channels. This value is 2 dB lower than yielded by the conventional RLS scheme in [66] under an unrealistic assumption that the data symbol is known to the receiver.

The convergence rate of the proposed scheme is fast and the tracking ability is very good in a dynamically changing environment. There is a time delay of about 10 to 20 iterations in the convergence in the proposed scheme in comparison to that using the blind adaptation. If compare the time delay in the scheme presented in [66], where one has to wait for the first stage to converge, use training sequence, switch to the second stage and then to acquire its steady state in order to estimate the data symbols, the time delay of the proposed scheme is only negligible.

The proposed scheme yields a significant improvement in terms of system stability over the one presented in [66]. Because of the poor performance of the decision-directed algorithm in the scheme of [66], the system is subject to catastrophic error propagation with a varying environment. The proposed scheme solves this problem by minimizing the effect of the remaining MAIs, to provide more reliable estimates. The proposed scheme require neither a training sequence nor switch between two sets of adaptation rules.

Overall, it has been seen that the combined adaptive scheme improves the system performance in a practical mobile environment. In contrast to the decision directed scheme, the proposed combined adaptation algorithm has a little lower steady-state SIR, but it does not require the assumption that the data symbols are known to the receiver and provides a better resistance to the environment changes. Therefore, the proposed scheme is better suited for practical applications.

Chapter 6

Conclusions and Future Work

6.1 Contributions of the Thesis and Concluding Remarks

The work reported in this thesis has been undertaken in support of moving the current knowledge of the adaptive CDMA receivers towards making them more relevant to practical wireless systems. The objective has been to analyze the existing techniques in the area of adaptive CDMA receivers and to develop a novel technique. While the new technique presented in this thesis that is more practical to overcome some of the drawbacks of the existing adaptive receivers, the theoretical and experimental analyses of the existing techniques assist in a better understanding of the influence of the radio environment on the performance of adaptive receivers. The following paragraphs summarize the contributions of the thesis and the conclusions drawn from the results presented therein.

The matched filter bank receiver is optimum when the additive noise is Gaussian but it fails to exploit the structure in the MAI, and thus, the system performance degrades when the interference is non-Gaussian. This disadvantage of matched filter bank receiver limits the system capacity and can jam the communication in the presence of strong nearby signals. As a linear receiver, the decorrelation detector is adequate to provide an optimum resistance to the near-far problem caused by the MAI. But, when the SNR is at a lower level, its performance is not as good as the matched filter bank, since it ignores the existence of the background noise. By exploiting the structures of MAI and taking into account the existence of the background noise, the MMSE detector makes improvements with both low and high SNRs, and improves the performance significantly over the matched filter bank receiver. The decorrelation detector can be considered as a special case of the MMSE detector when the background noise level goes to zero. However, the MMSE detector lends itself to adaptive implementation more readily than the decorrelation detector. In Chapter 3, an extensive analytical and experimental study has been undertaken on the similarities and differences among the various multiuser detectors employing the same system model. Although the individual studies on these detection do exists in the literature, the unified investigation carried out in this chapter provides an insight into the dependence of the MMSE detector on the system parameters, and the relative merits that can lead to different possible implementations.

A limitation of the MMSE mutiuser detector is that it requires a training data sequence for every active user to provide an adaptive interference suppression. After the training phase, the receiver can continue to perform in a decision-directed mode. However, in a drastically changing mobile environment, the decision-directed adaptation becomes unreliable. An attempt has been made in [66] to solve this problem by using a blind RLS version of the MMSE multiuser receiver, which does not require training sequences. This algorithm has lower steady-state SIR than its optimum value. A solution to this problem was suggested in [66] by using a decision-directed adaptation after the initial blind adaptation is converged. However, this solution requires the use of a training sequence technique, and, in a drastically changing mobile environment, the frequent switching of the adaptation mechanism makes the system unreliable.

The proposed adaptive scheme in Chapter 4 has been devised to overcome the above weaknesses by combining the blind RLS adaptive interference suppression and the conventional RLS adaptive MAI cancellation. Instead of assuming known data symbols for the second phase, the proposed scheme uses the output of the blind RLS adaptation of the first stage as the initial estimate in order to produce the optimum weight vector by using the conventional RLS adaptation. Then, based on the optimum weight vector, a less interfered received signal is produced, which results in a more reliable decision.

The proposed scheme overcomes the drawback of the existing technique presented in [66], and increases the system reliability in a drastically changing mobile environment.

In Chapter 5, simulation results have been furnished to demonstrate that the proposed scheme is robust against a continuously changing mobile environment. Experimental results for different numbers of MAI and NBI signals have been provided to demonstrate the merits of the proposed algorithm. These results have shown that the combined scheme of blind and conventional RLS adaptive adaptations for the interference suppression has a fast convergence rate and an excellent tracking capability.

6.2 Recommendations for Future Work

For the sake of limiting this research to a reasonable scope, it has been assumed in this thesis that a perfect synchronization is achievable. It would be interesting to extend this work to asynchronous systems. In multiuser detection problems, asynchronous systems in practice use the so called "one-shot" approach, in which a particular transmitted data bit is estimated based only on the received signal within the symbol interval corresponding to that data bit. An asynchronous system of N users can then be equivalently viewed as a synchronous system with 2N - 1 users [56]. Alternatively, an asynchronous CDMA system can be considered as a special case of the more general dispersive CDMA system in which the channel introduces intersymbol interference (ISI), in addition to the presence of MAI [70]. Joint suppression of both MAI and ISI may help to extend the results obtained for synchronous system to asynchronous system [71].

In this thesis, it has been assumed that a given DS-CDMA system has a fixed channel gain during the information bit interval. However, in a dramatically changing mobile environment, channel variations do exist, often with large amplitudes. Future research can explore the impact of imperfect channel estimation on the performance of the proposed algorithm. It is noted that the suppression of ISI deals mainly with the channel distortion recovery. Thus, it would also be challenging to develop a technique that can jointly suppress MAI and ISI in an imperfect channel estimation environment.

For the reason of simplicity, an AWGN channel has been assumed throughout this thesis. It would also be interesting to extend this research to a multipath fading channel, which exploits the correlated nature of the multipath.

References

[1] European Telecommunications Standards Institute, "Universal Mobile Telecommuniations System (UMTS); UMTS Terrestrial Radio Access (UTRA); Concept Evaluation (UMTS 30.06 version 3.0.0): Technical Report," ETSI Secretariat, Valbonne, France, 1997, TR 101 146 V3.0.0 (1997-12).

[2] K. Buchanan et al., "IMT-2000: Service Provider's Perspective," *IEEE Personal Communications*, pp. 8-13, Aug. 1997.

[3] E. Nikula, A. Toskala, E. Dahlman, L. Girard, and A. Klein, "FRAMES Multiple Access for UMTS and IMT-2000," *IEEE Personal Communications*, pp. 16-24, Apr. 1998.

[4] T. Ojanpera and Ramjee Prasad, "An Overview of Third-Generation Wireless Personal Communications: A European Pespective," *IEEE Personal Communications*, pp. 59-65, Dec. 1998.

[5] T. S. Rappaport, Wireless Communications, Principles and Practice, IEEE Press, New York, 1996.

[6] V. K. Garg and J. E. Wilkes, Wireless and Personal Communications Systems, Prentice Hall, Upper Saddle River, New Jersey, 1993.

[7] N. Abramson, Ed., Multiple Access Communications----Foundations for Emerging Technologies, IEEE Press, New York, 1993.

[8] John Meurling and Richard Jeans, *Mobil telefoni*: Informationsf¨orlaget, 1994.

[9] TIA/EIA/IS-95 Interim Standard, Mobile Station-Base Station, Compatibility Standard for Dual-Mode Wideband Spread Spectrum Cellular System, July 1993.

[10] S. Vembu and A. J. Viterbi, "Two Different Philosophies in CDMA ---a Comparison," *Proc. 46th IEEE VTC*, 1996, pp. 869-873.

[11] P. Jung, P. W. Baier, and A. Steil, "Advantages of CDMA and Spread Spectrum Techniques over FDMA and TDMA in Cellular Mobile Radio Applications," *IEEE Trans. Veh. Technol.*, vol. 42, no. 3, pp. 357-364, Aug. 1993.

[12] S. Glisic and B. Vucetic, Spread Spectrum CDMA Systems for Wireless Communications, Artech House, Inc., Boston, 1997.

[13] A. J. Viterbi, "The orthogonal-random waveform dichotomy for digital mobile personal communicationsieee personal," *IEEE Personal Communications*, vol. 1, no. 1, pp. 18-24, 1994.

[14] K. S. Gilhousen, I. M. Jacobs, R. Padovani, and Jr. L. A. Weaver, "Increased Capacity Using CDMA for Mobile Satellite Communication," *IEEE J. Sel. Areas Commun.*, vol. 8, no. 4, pp. 503-514, May 1990.

[15] K. S. Gilhousen, I. M. Jacobs, R. Padovani, A. J. Viterbi, Jr. L. A. Weaver, and C. E. Wheatley III, "On the Capacity of a Cellular CDMA System," *IEEE Trans. Veh. Technol.*, vol. 40, no. 2, pp. 303-312, May 1991.

[16] J. G. Proakis, Digital Communications, McGraw-Hill, New York, third edition, 1995.

[17] W. C. Y. Lee, Mobile Cellular Telecomunications, McGraw-Hill, New York, second edition, 1995.

[18] A. J. Viterbi, A. M. Viterbi, K. S. Gilhousen, and E. Zehavi, "Soft Handoff Extends CDMA Cell Coverage and Increases Reverse Link Capacity," *IEEE J. Sel. Areas Commun.*, vol. 12, no. 8, pp. 1281-1288, Oct. 1994.

[19] D. L. Schilling, R. Pickholz, and L. B. Milstein, "Spread spectrum goes commercial," *IEEE Spectrum*, pp. 41-45, Aug. 1990.

[20] D. L. Schilling, L. B. Milstein, R. Pickholz, M. Kullback, and F. Miller, "Spread spectrum for commercial communica-tions," *IEEE Communications Magazine*, pp. 66-79, Apr. 1991.

[21] R. L. Pickholtz, L. B. Milstein, and D. L. Schilling, "Spread spectrum for mobile communications," *IEEE Transactions on Vehicular Technology*, vol. 40, no. 2, pp. 313-322, 1991.

[22] W. C. Y. Lee, "Overview of cellular CDMA," *IEEE Transactions on Vehicular Technology*, vol. 40, no. 2, pp. 291-302, 1991.

[23] R. J. McEliece, Finite Fields for Computer Scientists and Engineers. Boston: Kluwer Academic, 1987.

[24] R. Lupas and S. Verdu, "Linear multiuser detectors for synchronous code division multiple-access channels," *IEEE Transactions on Information Theory*, vol. IT-35, pp. 123-136, Jan. 1989.

[25] R. Lupas and S. Verdu, "Near-far resistance of multiuser detectors in asynchronous channels," *IEEE Transactions on Communications*, vol. COM-38, pp. 496-508, Apr. 1990.

[26] S. Verdu, "Minimum probability of error for asynchronous Gaussian multiple-access channels," *IEEE Transactions on Information Theory*, vol. IT-32, pp. 85-96, Jan. 1986.

[27] S. M. Sussman and E. J. Ferrari, "The effects of match filters on the correlation properties of pn signals," *IEEE Transactions on Aerospace Electronic Systems*, vol. AES-10, pp. 385-390, May 1974.

[28] L. B. Milstein, D. L. Schilling, R. Pickholz, V. Erceg, M. Kullback, E. G. Kanterakis, D. S. Fishman, W. H. Biederman, and D. C. Salerno, "On the feasibility of a CDMA overlay for personal communications networks," *IEEE Journal on Selected Areas in Communications*, vol. 10, pp. 655-668, May 1992.

[29] L. B. Milstein, "Interference rejection techniques in spread spectrum communications," *Proceedings of the IEEE*, vol. 76, no. 6, pp. 657-671, 1988.

[30] N. J. Bershad, "Error probabilities of ds spread-spectrum systems using an ale for narrow-band interference rejection," *IEEE Transactions on Communications*, vol. 36, no. 5, pp. 587-595, 1988.

[31] L. B. Milstein, "Interference suppression to aid acquisition in direct-sequence spread-spectrum communications," *IEEE Transactions on Communications*, vol. 36, no. 11, pp. 1200-1202, 1988.

[32] R. E. Ziemer and R. L. Peterson, Introduction to Digital Communication, Macmillan Publishing Company, New York, 1992.

[33] S. Verdu, "Minimum Probability of Error for Asynchronous Gaussian Multiple-Access Channels," *IEEE Trans. Info. Theory*, vol. IT-32, pp. 85-96, Jan. 1986.

[34] S. Verdu and H. V. Poor, "Abstract Dynamic Programming Models under Commutativity," *SIAM J. Control and Optimization*, vol. 24, pp. 990-1006, July 1987.

[35] S. Verdu, "Recent Progress in Multiuser Detection," in Advances in Communication and Signal Processing. Springer-Verlag, Berlin-Heidelberg, 1989.

[36] R. Lupas and S. Verdu, "Linear Multiuser Detectors for Synchronous Code-Division Multiple Access Channels," *IEEE Trans. Info. Theory*, vol. 35, no.1, pp. 123-136, Jan. 1989.

[37] R. Lupas and S. Verdu, "Near-Far Resistance of Multiuser Detectors in Asynchronous Channels," *IEEE Trans. Commun.*, vol. 38, no. 14, pp. 496-508, Apr. 1990.

[38] P. Patel and J. Holtzman, "Analysis of a Simple Succesive Interference Cancellation Scheme in a DS/CDMA System," *IEEE J. Sel. Areas Commun.*, vol. 12, no. 5, pp. 796-807, June 1994.

[39] M. K. Varanasi and B. Aazhang, "Multistage Detection in Asynchronous Code-Division Multiple-Access Communications," *IEEE Trans. Commun.*, vol. 38, no.4, pp. 509-519, Apr. 1990.

[40] D. Divsilar and M. K. Simon, "Improved CDMA Performance Using Parallel Interference Cancellation," *Proc. IEEE MILCOM*, Oct. 1994, pp. 911-917.

[41] A. Kaul and B. D. Woerner, "Analytic Limits on the Performace of Adaptive Multistage Interference Cancellation for CDMA," *IEEE Electronics Letters*, vol. 30, no. 25, pp. 2093-2095, Dec. 1994.

[42] S. Striglis, A. Kaul, N. Yang, and B. D. Woerner, "A Multistage RAKE Receiver for Improved Capacity of CDMA Systems," *Proc. 44th IEEE VTC*, 1994, pp. 789-793.

[43] R. M. Buehrer, N. S. Correal, and B. D. Woerner, "A Comparison of Multiuser Receivers for Cellular CDMA," *Proc. IEEE GLOBECOM*, 1996, pp. 1571-1577.

[44] R. M. Buehrer, The Application of Multiuer Detection to Cellular CDMA, Ph.D. Dissertation, Virginia Polytechnic Institute and State University, June 1996.

[45] A. Duel-Hallen, J. Holtzman, and Z. Zvonar, "Multiuser Detection for CDMA Systems," *IEEE Personal Communications*, pp. 46-58, Apr. 1995.

[46] F.-C. Cheng and J. M. Holtzman, "Effect of Tracking Error on DS/CDMA Successive Interference Cancellation," Proc. *IEEE GLOBECOM* -------Communications Theory Mini-Conference, 1994, pp. 166-170.

[47] R. M. Buehrer, A. Kaul, S. Striglis, and B. D. Woerner, "Analysis of DS-CDMA Parallel Interference Cancellation with Phase and Timimg Errors," *IEEE J. Sel. Areas Commun.*, pp. 1522-1535, Oct. 1996.

[48] S. Verdu, "Multi-User Detection", in Advances in Statistical Signal Processing-Vol. 2 Signal Detection, H. V. Poor and J. B. Thomas, eds. JAI Press: Greenwich, Conn., 1993.

[49] R. Lupas and S. Verdu, "Linear Multiuser Detectors for Synchronous Code Division Multiple Access Channel", *IEEE Trans Inform. Theory*, Vol. IT-35, No. 1, pp. 123-136, 1989.

[50] L. M. Honig, U. Madhow and S. Verdu, "Adaptive Blind Multiuser Detection", *IEEE Trans. Inform. Theory*, Vol. IT-41, No. 4, pp. 944-960, 1995.

[51] M. K. Varanasi and B. Aazhang, "Multistage Detection in Asynchronous Code Division Multiple Access Communnications", *IEEE Trans. Comm.* Vol. COM-38, No. 4, pp. 509-519, 1990.

[52] A. Duel-Hallen, "A Family of Multiuser Decision-Feedback Multiuser Detectors for Asynchronous Code Division Multiple Access Channels", *IEEE Trans. Comm.* 1995

[53] J. M. Holtzman, "DS-CDMA Successive Interference Cancellation", *Proc. ISSSTA'94*, Oulu, Finland, July 1994, pp. 69-78.

[54] S. Verdu, *Multiuser Detection*, Cambridge University Press, 1998.

[55] U. Madhow, L. M. Honig, "MMSE Interference Suppression for Direct-Sequence Spread-Sprectrum CDMA", *IEEE Trans. Commun.*, Vol. 42, No. 12, pp. 3178-3188, Dec. 1994.

[56] Stefan Parkvall, Erik Strom, and Bjorn Ottersten, "The impact of timing errors on the performance of linear DS-CDMA receivers," *IEEE Journal on Selected Areas in Communications*, vol. 14, no. 8, pp. 1660–1668, October 1996.

[57] Fu-Chun Zheng and Stephen K. Barton, "On the performance of near-far resistant CDMA detectors in the presence of synchronization errors," *IEEE Transactions on Communications*, vol. 43, no. 12, pp. 3037–3045, December 1995.

[58] M. Abdulrahman, D. D. Falconer, and A. U. H. Sheikh, "Equalization for Interference Cancellation in Spread Spectrum Multiple Access Systems," *Proc. 42nd IEEE VTC*, 1992, pp. 71-74.

[59] Miller, S.L., "An Adaptive Direct-Sequence Code-Division Multiple-Access Receiver for Multiuser Interference Rejection," *IEEE Transactions on Communications*, Vol.43, pp.1746-1755, 1995.

[60] P. B. Rapajic and B. S. Vucetic, "Adaptive Receiver Structures for Asynchronous CDMA Systems," *IEEE J. Sel. Areas Commun.*, vol. 12, no. 4, pp. 685-697, May 1994.

[61] S. Verdú, "Multiuser Detection," *Advances in Statistical Signal Processing*, vol. 2: Signal Detection pp. 369-409, JAI Press: Greenwich, CT , 1993.

[62] S. Glisic and B. Vucetic, Spread Spectrum CDMA Systems for Wireless Communications, Artech House, Inc., Boston, 1997.

[63] R. E. Ziemer and R. L. Peterson, Digital Communications and Spread Spectrum Systems, Macmillan Publishing Company, New York, 1985.

[64] M. K. Simon, J. K. Omura, R. A. Scholtz, and B. K. Levitt, Spread Spectrum Communication Handbook, McGraw-Hill, New York, 1994.

[65] H. V. Poor, Xiaodong Wang, "Code-Aided Interferenc Suppression for DS/CDMA Communications: Interference suppression capabilities," *IEEE Trans. Commun.*, Vol. 45, No. 9, pp. 1101-1111, Sept. 1997.

[66] H. V. Poor, Xiaodong Wang, "Code-Aided Interferenc Suppression for DS/CDMA Communications----Part Π : Parallel Blind Adaptive Implementations", *IEEE Trans. Commun.*, Vol. 45, No. 9, pp. 1112-1122, Sept. 1994.

[67] S. Haykin, Adaptive Filter Theory, Prentice Hall, Englewood Cliffs, NJ, third edition, 1996.

[68] M. L. Honig, U. Madhow, and S. Verdu, "Blind Adaptive Multiuser Detection," *IEEE Trans. Info. Th.*, vol. 41, no. 4, pp. 944-960, July 1995.

[69] E. Eleftheriou and D. D. Falconer, "Tracking properties and steady-state performance of RLS adaptive algorithm", *IEEE Trans. Acoust., Speech, Signal Processing*, Vol. ASSP-34.pp. 1097-1109, Oct. 1986.

[70] Wang, X. and Poor, H.V., "Blind Multiuser Detection: A Subspace Approach," *IEEE Transactions on Information Theory*, Vol.44, No.2, 1998.

[71] Wang, X. and Poor, H.V., "Blind Equalization and Multiuser Detection in Dispersive CDMA Channels," *IEEE Transactions on Communications*, Vol.46, No.1, 1998