Combined Multiuser Detection and Adaptive Blind Array Processing for DS-CDMA Systems

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A Thesis

in

The Department

of

Electrical and Computer Engineering

Presented in Partial Fulfillment of the Requirements

for the Degree of Master of Applied Science at

Concordia University

Montréal, Québec, Canada

December 2002

0-612-77687-5

ABSTRACT

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There is an increasing interest in the exploitation of both interference cancellation techniques and antenna arrays to enhance the capacity of wireless communication systems. The focus of this thesis is on a study of advanced digital signal processing techniques for multiuser interference cancellation in direct-sequence code-division multiple access mobile communications. We investigate how multiuser detection techniques can be combined with antenna arrays to enhance the performance and capacity of the system. Emphasis is placed on the development of the receiver structures that exploit blind algorithms for beamforming in conjunction with multiuser signal detection.

The work begins with a study of several most frequently referred to sub-optimal multiuser receivers. The four structures of interest are the decorrelator, the minimum mean square error receiver, the multistage parallel interference cancellation receiver, and the successive interference cancellation receiver. The performance of the receiver structures is compared through simulation studies on the basis of bit error rate in additive white Gaussian noise, and near-far channels.

In the second part of this research, array processing techniques are investigated as a means for improving the performance. We evaluate the system performance of some of the existing adaptive blind array schemes for CDMA receivers, and a new adaptive blind algorithm is derived. The knowledge of the desired user's signature

sequence is exploited to design the blind receiver, where no training sequence needs to be transmitted. The blind algorithm is formulated using a constrained energy minimization criterion, and adaptation is carried out by using the LMS algorithm combined with the gradient-projection algorithm to incorporate the quadratic constraint.

The multiple access interference coming from the directions other than that of the desired user can be significantly suppressed by using spatial filtering property of antenna arrays. However, an antenna array cannot suppress a high-level interfering signal from an undesired user with the same direction of arrival as that of the desired user. We propose a new combination scheme which employs adaptive blind arrays and multiuser detection. The interference rejection capability of the proposed receiver is examined in situations where a single interferer dominates the received power. It is shown that this combination can significantly improve the system performance and outperform all existing multiuser detectors as well as smart antenna systems.

Finally, we present a new structure combining two-dimensional RAKE receiver and the multiuser detection for further enhancement of the system performance in multipath fading channels. We analyze the interference rejection capability of the proposed receiver in a frequency-selective slow fading channel.

Dedicated to my wife Farzaneh, and my beautiful daughter Ayda

ACKNOWLEDGEMENTS

The completion of this research project would have been impossible without the support of many people. First of all, I would like to express my thanks to the Lord for His blessings and for providing me with the spiritual support to complete this project. Next, I would like to express my sincere appreciation to my advisors, Dr. M.O. Ahmad, and Dr. W.-P Zhu for their invaluable advice, encouragement, and financial support throughout my master's studies. It has been a great pleasure working under their supervision and I am looking forward to maintaining a continued friendship with them. I would also like to thank Dr. M.N.S Swamy for his active participation in this research, and for his support and advice throughout the course of this work.

I am also grateful to all my friends and colleagues at the Center for Signal Processing and Communications and Concordia university. Their support has helped me to go through the difficult times and meet the challenges encountered in completing this work.

Most of all, I would like to thank my wife for her love and understanding. I could not have completed my degree without her continuous and immeasureable support.

Finally, I would like to thank my parents for their endless love and encouragement throughout my life.

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LIST OF ABBREVIATIONS AND SYMBOLS

2D-RAKE	Two-Dimensional RAKE
AAA	Adaptive Antenna Arrays
APIC	Adaptive Parallel Interference Cancellation
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BPSK	Binary Phase-Shift Keying
CDMA	Code-Division Multiple Access
CM	Constant Modulus
CMF	Chip Matched Filter
CPIC	Conventional Parallel Interference Cancellation
DD	Decision Directed
DMI	Direct Matrix Inversion
DOA	Direction Of Arrivals
DS	Direct-Sequence
FDMA	Frequency-Division Multiple Access
FFT	Fast Fourier Transform
HOS	Higher-Order Statistics
IC	Interference Cancellation
ISI	Inter-Symbol Interference
LES	Linear Equally Spaced
LMS	Least Mean Square
LS	Least Squares
MAI	Multiple Access Interference
MMSE	Minimum Mean-Squared Error
MSE	Mean-Squared Error
MVDR	Minimum Variance Distortionless Response

PIC	Parallel Interference Cancellation
PN	Pseudo-Noise
PPIC	Partial Parallel Interference Cancellation
RLS	Recursive Least Square
SCORE	Spectral self-COherence REstoral
SIC	Successive Interference Cancellation
SINR	Signal-to-Interference-plus-Noise-Ratio
SMI	Sample Matrix Inversion
SNOI	Signal-Not-Of-Interest
SNR	Signal-to-Noise-Ratio
SOI	Signal-Of-Interest
SSMA	Spread-Spectrum Multiple Access
STC	Space-Time Coding
TDMA	Time-Division Multiple Access
WCDMA	Wideband Code-Division Multiple Access

r	The total received signal from K user.
e_k	The power of the k^{th} user signal.
b_k	The information symbol of the k^{th} user.
$\mathbf{s}_k$	The signature code waveform of the k^{th} user.
$\mathbf{n}$	The additive white Gauusian noise vector.
T_b	The bit interval.
T_c	The chip interval.
f_b	The bit rate.
f_c	The chip rate.
y_k	The output of the k^{th} user's correlator.
ρ_{ik}	The correlation between i^{th} and k^{th} user's codes.
$\mathbf{R}$	The correlation matrix containing the cross-correlations between codes.
$\mathbf{E}$	A diagonal matrix containing the K user received amplitudes.
$\mathbf{b}$	A vector containing the K user data symbols.
$\widehat{y}$	The soft estimate of the output of the detector.
$\mathbf{a}_k$	The array response vector of the k^{th} user.
a_{mk}	The complex gain from user k to the m^{th} antenna element.
L_m	The distance between the first and the m^{th} antenna element.
θ_k	The arrival angle of the signal from the k^{th} user.
λ_k	The free space wavelength.
c	The speed of the light.
f	The carrier frequency.
$\mathbf{x}$	The total received signal from M antenna elements and K user.
N	The processing gain.
τ_k	The relative delay of the k^{th} user to the array reference element.
ρ^s_{kl}	The cross-correlation between the signature waveforms l and k.

ρ^a_{kl}	The cross-correlation between the array response vectors l and k.
σ^2	Variance of the noise.
$\widehat{b}_1$	Estimation of the transmitted bit by the first user.
$\mathbf{w}$	The weight vector in adaptive antenna array.
$\mathbf{R}_s$	The covariance matrix of the signal after match filtering.
$\mathbf{R}_I$	The covariance matrix of the multiple access interference plus noise.
$\mathbf{R}_s$	The covariance matrix at the array output.
$\mathbf{w}_{opt}$	The optimum weight vector.
λ_{min}	The minimum eigenvalue.
λ_{max}	The maximum eigenvalue.
μ	Step size in each iteration of the adaptive algorithm.
$\mathbf{F}_w$	The cost function which should be minimized with respect to $\mathbf{w}$.
$\nabla\mathbf{F}_w$	The gradient of the cost function.
$\widehat{\mathbf{R}}_s$	The instantaneous estimate of the covariance matrix $\mathbf{R}_s$.
$\widehat{\mathbf{R}}$	The instantaneous estimate of the covariance matrix $\mathbf{R}$.
$\theta_{k,l}$	The arrival angle of the signal from the k^{th} user and the l^{th} path .
$c_{k,l}$	The complex fading coefficient for the l^{th} path of the k^{th} user.
a_{mk}	The complex gain from the l^{th} path of the k^{th} user to the m^{th} antenna.
$\tau_{k,l}$	The relative delay of the received signal from the k^{th} user on the l^{th} path.

Chapter 1

Introduction

The area of wireless communications for mobile telephone and data transmission is currently undergoing very rapid development. Many of the emerging wireless systems will incorporate considerable signal processing intelligence in order to provide advanced services such as multimedia transmission. Since bandwidth is a valuable resource, the problem of interest is to be able to accommodate as many users as can be reliably demodulated for a given bandwidth. In order to make an optimal use of available bandwidth and to provide maximal flexibility, many wireless systems operate as multiple-access systems, in which channel bandwidth is shared by many users on a random-access basis.

Code-division multiple access (CDMA) is one of the several methods of multiplexing wireless users that has become very popular in recent years. In CDMA, users are multiplexed by distinct codes rather than by orthogonal frequency bands, as in frequency-division multiple access (FDMA), or by orthogonal time slots, as in time-division multiple access (TDMA). In CDMA, all users can transmit at the same time, each being allocated the entire available frequency spectrum. Hence, CDMA is also known as spread-spectrum multiple access (SSMA), or simply spread spectrum communications. CDMA is a promising technology for wireless environments with multiple simultaneous transmissions because of several features: asynchronous multiple access, robustness to frequency selective fading, and multipath combining.

Three major factors that limit the performance of CDMA systems in the uplink cellular channel are multiple access interference (MAI), the near-far effect, and multipath fading. In direct-sequence CDMA (DS-CDMA) communications, the users are multiplexed by distinct code waveforms and MAI is caused by non-orthogonal code sequences. Considering cellular mobile systems, mobile units transmit independently so that their signals arrive asynchronously at the base station. Since their relative time delays are randomly distributed, the cross-correlation between the received signals coming from different users is nonzero.

To achieve a low level of interference, the assigned signatures need to have low cross-correlation for all relative time delays. A low cross-correlation between signatures is obtained by designing a set of orthogonal sequences. However, there is no known set of code sequences that is completely orthogonal when used in an asynchronous system. The non-orthogonal components of signals of other users will appear in the demodulated desired signal as interference. If the matched-filtering receiver is used, in such a system, the number of users is limited by the interference coming from other users. In conclusion, the capacity of DS-CDMA systems is interference-limited, as opposed to other multiple access schemes which are bandwidth limited, and the system performance for all users considerably degrades as the number of active users increases.

The MAI in turn is due not only to the non-perfect orthogonality of the spreading sequences, but also to the multipath channel. The multipath structure of the channel also causes signal fading, and may result in important power imbalances between the arriving signals of different users. Moreover, CDMA systems are particularly susceptible to the near-far problem. A near-far situation is one in which a user or a group of users closer to the base-station are likely to be received with significantly more power than those close to the cell boundary. The near-far effect is due to both multipath fading and to signal power loss as a function of distance from the base-station. At the present time, sophisticated power control techniques are the primary means for combating the near-far problem in CDMA systems. In this thesis, we are interested in the application of interference cancellation techniques to the reverse link of the DS-CDMA systems.

1.1 Previous Work

Many advanced signal processing techniques have been proposed to combat interference and multhipath channel distortion, and these techniques fall largely into two categories: *multiuser detection* [1] and *space-time processing* [6]. It has been well established that multiuser detection techniques can substantially enhance the receiver performance and increase the capacity of CDMA communication systems. Multiuser detection techniques exploit the underlying structure induced by the spreading waveforms of the DS-CDMA user signals for interference suppression. Various linear and nonlinear multiuser detectors have been developed over the past decade. For example, the multiuser detection introduced by Verdu in [2] achieves an optimal performance with respect to probability of error. However, in order to achieve this performance, knowledge of every user's code and the associated timing is required. Unfortunately, this knowledge is not always available and estimating the necessary parameters leads to a complexity that is exponential with the number of users. Other, simpler receivers have been proposed including the conventional receiver. While the conventional receiver requires only the knowledge of the desired user's code and timing, its performance in the presence of large number of users or in a near-far situation is unacceptable. Varanasi and Aazahang [22] developed a suboptimal multistage detector based on successive multiple access interference cancellation. The performance of their receiver approaches that of the optimal detector. However, in order to achieve this performance, several stages are necessary, leading to an increased complexity. Optimal and suboptimal multiuser detectors, depending on their level of complexity, provide full or partial immunity to the near-far effect. An overview of multiuser detection theory can be found in [3].

More recently, adaptive multiuser detection has received considerable attention. Adaptivity not only allows multiuser detection to be applied without additional protocol overhead with respect to that required by the conventional methods, but it also allows the multiuser detectors to operate in the dynamic environments found in mobile communications applications. A review of adaptive multiuser detection techniques is given in [4]. In a DS-CDMA system, the training signal, which consists of symbols known to the intended receiver, can be used to update the filter coefficients in implementation of adaptive algorithms. It is a useful method because it does not require knowledge of the spreading sequences, user powers, or channel estimates. However, the bandwidth and the power, which should be utilized in an efficient way, would be consumed for the training sequence. Blind reception [5] is among the recent developments in interference suppression that does not need any training signal. Blind adaptive receivers require a minimal amount of information about the desired signal.

Another approach to interference suppression in wireless systems is through space-time processing using an antenna array at the receiver [6]. In this approach, the signal structure induced by multiple receiving antennas, i.e., spatial signature, is exploited for interference suppression. Using the spatio-temporal samples of the received signals, the users' signal can now be matched in both temporal and spatial domains. Potential improvements in the uplink performance of different CDMA receivers using spatial processing have been shown in [7].

It is desirable for a multiple antenna receiver to be able to track and follow the array response vectors in an adaptive fashion due to the dynamic nature of cellular communications and severe fading conditions. Adaptive antenna arrays provide an alternative means to cope with the near-far problem. By steering beams toward the desired user and decreasing the total MAI's power level, system near-far resistance, i.e., immunity of the desired user's performance to power variations of the others, can be considerably enhanced. Other benefits of adaptive antennas include advances in operational parameters such as coverage range, power consumption, security, etc. A number of adaptive beamforming techniques have been developed and are well documented in the literature [8]. In a CDMA environment, the knowledge of the desired user's signature sequence can be exploited to design a blind adaptive antenna array receiver, where no training sequence needs to be transmitted [9].

Whereas the above types of techniques have been typically proposed one at a time, it is only recently that the potential of joint methods that utilize all the above remedies has begun to be realized. In fact, antenna arrays can be used to filter out the interfering users that are spatially separated from the desired user, thereby reducing the amount of interference seen by the desired user. However, if there is a high-level interfering signal from an undesired user with the same arrival angle as that of a desired user, an antenna array cannot suppress it. One approach to reduce the in-beam interference is to use a multiuser detector in conjunction with antenna arrays.

By using the spatial filtering property of antenna array, the existing optimum as well as suboptimal multiuser detectors can be implemented with much lower computational complexity. In addition, substantial performance improvements can also be achieved as a result of the capability of beamforming to suppress MAIs. The idea of combining interference cancellation with multiple antennas was first suggested by Kohno *et al.* in [10]. The integration of antenna array signal processing and multiuser detection has also been studied for AWGN channels with known parameters in [11]. The optimal receiver structure in that case consists of a beamforming network that performs spatial processing, followed by a bank of matched filters and a multiuser detection algorithm that performs temporal processing.

In wireless systems, diversity reception is one of the most powerful techniques to combat the fading effects of the channel. Besides explicit antenna diversity, CDMA systems exploit the diversity inherent in multipath propagation by using a RAKE receiver [41]. The RAKE receiver combats MAI by cross-correlating with the desired user code and multipath fading by performing maximal ratio combining of its multipath channel components. This detector is optimal only in the case of perfectly orthogonal arriving signals and white additive Gaussian noise. The technique of joint antenna diversity and linear multiuser signal detection for coherent CDMA systems over the flat fading channels is addressed in [12] and [13].

The first generation of space-time detectors have used array processing with either RAKE detection [15] or with multiuser detection [11]. Later, in space-time CDMA detectors, all the three processing techniques (space, time, and multiuser techniques) were combined together. A maximum-likelihood approach was proposed in [14]. In [33], the CDMA code-filtering approach of beamforming together with decorrelating multiuser detection was proposed on both single and multipath fading channels. The performance of a joint beamforming-RAKE and decorrelating multiuser detector using Matrix Levinson Polynomials in a multipath fading CDMA channel has been analyzed in [36]. Major contribution of the later work is laid on the development of the decorrelating process without involving the direct matrix inversion (DMI) with low computational complexity, and the verification of its deployment on the spatial-temporal decorrelator. Combining beamforming and parallel interference cancellation has been addressed in [34] and [35]. In [34], a fast adaptation algorithm, the conjugate gradient, was suggested to find the optimum beamforming weights. In [35], an FFT beamformer which is capable of forming M orthogonal antenna patterns is used. With the use of the FFT beamformer, less fingers are needed to achieve a good overall performance. Minimum mean-squared error (MMSE) multiuser multi-antenna detectors for multipath channels are developed in [37] and [38]. More recently, a successive interference canceler combined with a blind adaptive array has been proposed in [16].

1.2 Scope and Organization of the Thesis

Although each of the different combinations of multiuser detection and beamforming techniques have been the subject of much of the recent literature, there is little published work considering the severe near-far situation. Driven by the need to develop simple and flexible yet efficent detectors, we investigate the technique of combining interference cancellation with adaptive blind arrays. The motivation behind a blind implementation approach is avoiding the need for training sequences for adaptive interference cancellation. The knowledge of spreading waveform and propagation channel of the desired user is exploited to design the blind algorithm which is formulated using a constrained optimization criterion. We also analyze the case where CDMA signals are subject to the frequency-selective fading channel. In particular, we investigate the integration of multiuser detection with spatial processing along with temporal diversity over the frequency selective slow-fading wireless channels. The implementation structure combines multiuser detection with an adaptive blind 2D-RAKE receiver incorprates antenna array in the conventional RAKE receiver.

This dissertation consists of six chapters. A brief overview of multiuser receivers is presented in Chapter 2 along with a comparison of some of the most commonly investigated multiuser detectors, such as the decorrelator, the minimum mean square error (MMSE) receiver, the multistage parallel interference cancellation receiver, and the successive interference cancellation receiver. Comparisons are based on simulation results, examining bit error rate (BER) performance in AWGN channel. In addition, we also try to compare the receiver structures on the basis of computational complexity and present a trade off between computational complexity and performance of different receiver structures. Chapters 3, 4, and 5 make up the main body of the dissertation.

In Chapter 3, we discuss three methods for interference suppression using antenna arrays that are applicable to DS-CDMA systems [44][46]. This chapter also includes a short overview of the fundamentals of antenna arrays. The major concern in this chapter is to design adaptive blind algorithms to adaptively form beams toward the desired user and to cancel the interference coming from other directions in a blind fashion. The performances of these schemes are compared, and the extent of the performance improvement achieved by employing antenna arrays in contrast to with their single-element counterpart is examined. A structure that combines the advantages of multiuser detectors and the adaptive antenna arrays is presented in Chapter 4 [43][44]. The detector implements adaptive blind arrays as the first stage of a multistage parallel interference canceler to cancel out the MAI coming from directions other than the desired one. Then, an adaptive parallel interference canceler is employed as the second stage to suppress the remaining interference from the previous stage. Chapter 5 is also focused on combined interference cancellation and adaptive blind array processing. In this chapter, an adaptive blind 2D-RAKE scheme is introduced over frequency-selective slow fading channels [45][46]. The performance of the detector is examined over the multipath Rayleigh fading channels. Chapter 6 concludes the thesis along with providing some future research directions.

Chapter 2

Multiuser Detection

2.1 Introduction

Direct-sequence CDMA is the most popular of CDMA techniques. The DS-CDMA transmitter multiplies each user's signal by a distinct code waveform. The detector receives a signal composed of the sum of all users' signals, which overlap in time and frequency. In a conventional DS-CDMA system, a particular user's signal is detected by correlating the entire received signal with that user's code waveform.

Multiple access interference (MAI) is a factor which limits the capacity and performance of DS-CDMA systems. MAI refers to the interference between direct-sequence users. This interference is the result of the random time offsets between signals, which makes it impossible to design the code waveforms to be completely orthogonal. Although the MAI caused by individual user is generally small, as the number of interferers or their power increases, MAI becomes substantial. Even if the number of users is not very large, some users may be received at such high signal levels that a lower power user may be overwhelmed by stronger users. This is known as the near-far effect: users near the receiver are received at higher powers than those far away, and thus users far away from receiver suffer from a degradation in performance. Even if users are at the same distance, there can be effective near-far effect because some users may be received during a deep fade. The conventional detector does not take into account the existence of MAI and also it is not near-far resistant. It follows a single-user detection strategy in which each user is detected separately without regard for other users.

Because of the interference among users, however, a better detection strategy is one of multiuser detection (also referred to as joint detection or interference cancellation). Here, information about multiple users is used jointly for detection of each active user in the system. The utilization of multiuser detection algorithm has the potential to provide significant additional benefits for DS-CDMA systems.

The next Section contains a description of signal model followed by a short review of the conventional DS-CDMA receiver in Section 2.3. In Section 2.4, we present the two main linear multiuser detectors. We then discuss interference cancellation multiuser detectors in Section 2.5.

2.2 Signal model

We begin with a mathematical description of a synchronous DS-CDMA channel. Assuming K direct-sequence users in a single-path BPSK real channel, the received baseband signal can be expressed as:

$$r(t) = \sum_{k=1}^{K} \sqrt{e_k(t)} b_k(t) s_k(t) + n(t) \tag{2.1}$$

where $e_k(t)$, $b_k(t)$, and $s_k(t)$ are, respectively, the power, the modulated symbol, and the signature code waveform, of the k^{th} user, and $n(t)$ is the additive white Gaussian noise (AWGN) with a two-sided power spectral density of $N_o/2$ W/Hz. The amplitude of the k^{th} signal is equal to the square root of its power, which is assumed to be constant over a bit interval. The modulation consists of rectangular

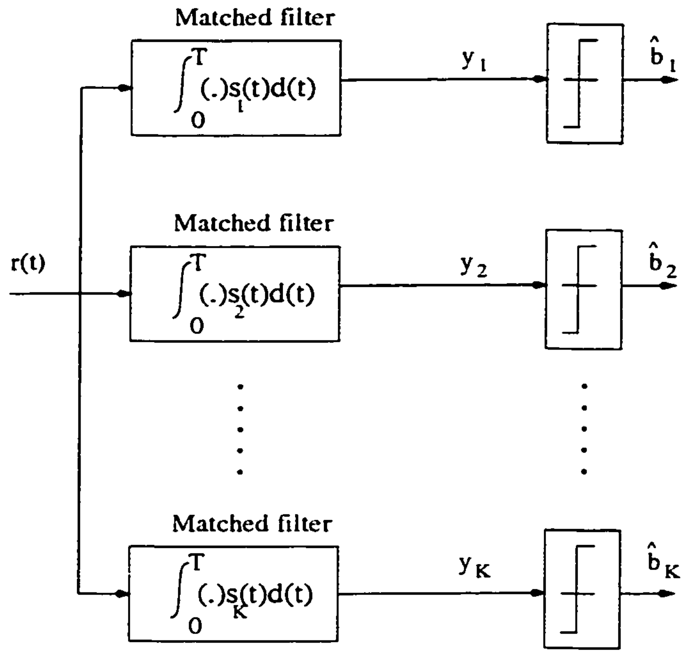


Figure 2.1: Block diagram of the conventional receiver.

pulses of duration T_b (bit interval), which take on $d_k = \pm 1$ values corresponding to the transmitted data.The code waveform consists of rectangular pulses of duration T_c (chip interval), which pseudo-randomly take on ± 1 values, corresponding to some binary "pseudo-noise" (PN) code sequence.

The rate of the code waveform, $f_c = 1/T_c$ (chip rate), is much greater than the bit rate, $f_b = 1/T_b$. Thus, multiplying the BPSK signal at the transmitter by $s_k(t)$ has the effect of spreading it out in frequency by a factor of f_c/f_b , (hence, the codes are sometimes referred to as "the spreading codes.") The frequency spread factor of a direct-sequence system is referred to as the processing gain.

2.3 Conventional Receiver

The conventional receiver corresponds to a bank of matched filters, where each filter is matched to the signature of the desired user as shown in Figure 2.1.

Here, each code waveform is generated and correlated with the received signal in a separate detector branch. The outputs of the correlators (or matched filters) are sampled at the bit times, which yields "soft" estimates of the transmitted data. The final ± 1 "hard" data decisions are made according to the signs of the soft estimates.

The success of this detector depends on the properties of the correlation between codes. We require the correlation between the same code waveforms (i.e., the autocorrelations) to be much larger than the correlations between different codes (i.e., the cross-correlations). The correlation value is defined as:

$$\rho_{ik} = \frac{1}{T_b} \int_0^{T_b} s_i(t) s_k(t) dt \tag{2.2}$$

Here, if $i = k$, $\rho_{kk} = 1$, (i.e., the integrand must equal one since $s_k = \pm 1$, and if $i \neq k$, $0 \leq \rho_{ik} \leq 1$. The output of the k^{th} user's correlator for a particular bit interval is

$$y_k = \frac{1}{T_b} \int_0^{T_b} r(t) s_k(t)$$

$$= \sqrt{e_k(t)} b_k(t) + \sum_{i=1, i \neq k}^{K} \sqrt{e_k(t)} b_k(t) \rho_{ik} + \frac{1}{T_b} \int_0^{T_b} n(t) s_k(t) dt \tag{2.3}$$

$$= \sqrt{e_k(t)} b_k(t) + MAI_k + z$$

$$= Desired\ Signal + MAI + noise$$

It is convenient to introduce a matrix-vector system model to describe the output of the conventional detector.

$$\mathbf{y} = \mathbf{REb} + \mathbf{z} \tag{2.4}$$

For a K user system, the vectors $\mathbf{b}$, $\mathbf{z}$, and $\mathbf{y}$, are K-vectors that hold the data, noise, and matched filter outputs of all K users, respectively; the matrix $\mathbf{E}$ is a diagonal matrix containing the corresponding received amplitudes; the matrix $\mathbf{R}$ is a $K \times K$ correlation matrix, whose entries contain the values of the correlations between every pair of codes. Note that since $\rho_{ki=\rho_{ik}}$, the matrix $\mathbf{R}$ is clearly symmetric.

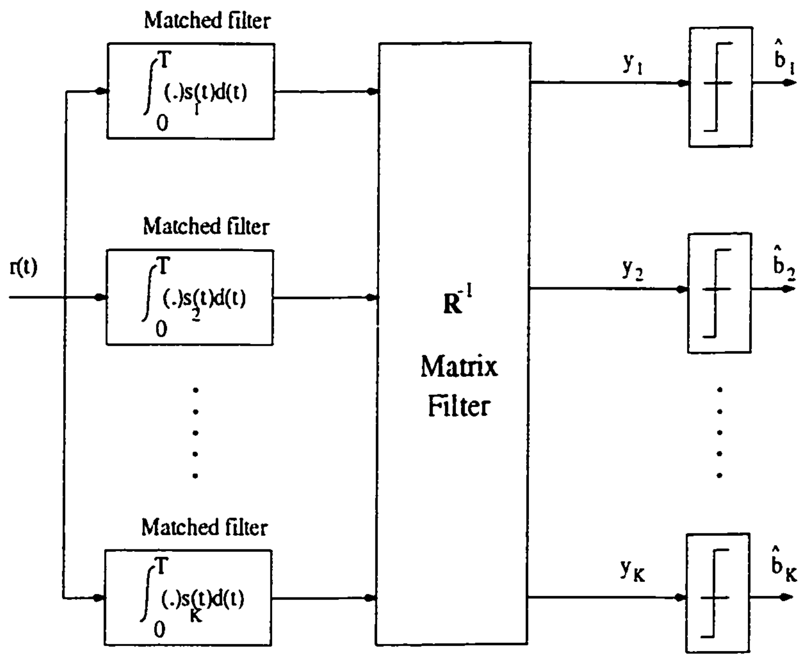


Figure 2.2: Block diagram of the decorrelating detector.

2.4 Linear receivers

2.4.1 Decorrelator

This approach, first proposed in [17] and analyzed in [18], operates to eliminate the MAI in a manner analogous to the way a zero forcing equalizer eliminates Inter Symbol Interference (ISI). A linear transformation $\mathbf{L}_{dec} = \mathbf{R}^{-1}$ that corresponds to the inverse of the correlation matrix is applied to the matched filter bank outputs y in an attempt to cancel interference resulting from cross-correlations among the signature sequences. Then, the soft estimate of this detector is:

$$\widehat{b}_{dec} = sgn\left[\widehat{y}\right] \tag{2.5}$$

where

$$\widehat{y} = \mathbf{R}^{-1}\mathbf{y} = \mathbf{E}\mathbf{b} + \mathbf{R}^{-1}\mathbf{z} \tag{2.6}$$

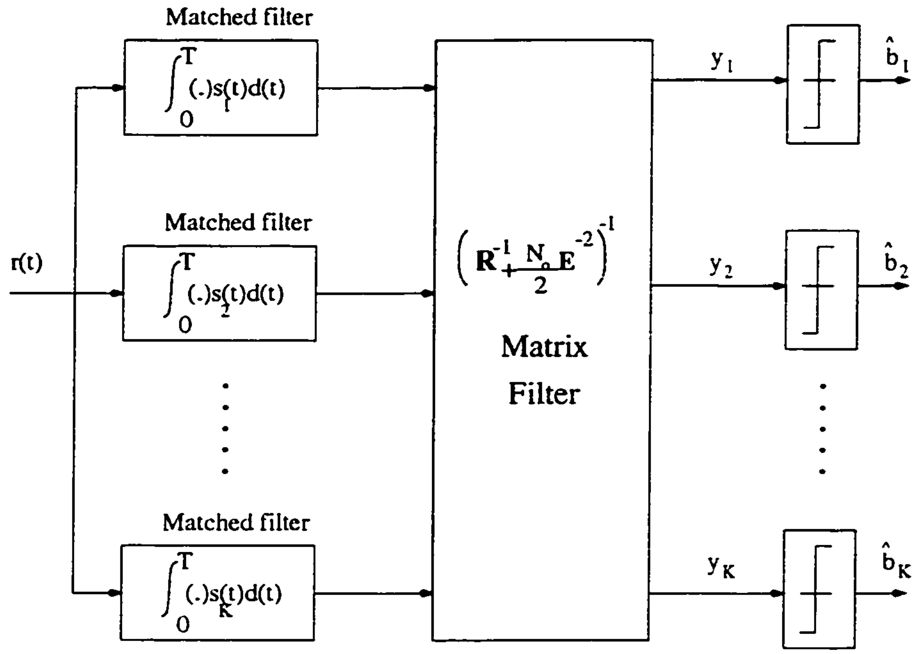


Figure 2.3: Block diagram of the MMSE detector.

From these equations we can see that the noise term is enhanced. Despite this drawback, the decorrelating detector generally provides significant improvement over conventional detector. Figure 2.2 shows a block diagram of the decorrelator.

The decorrelator has a very desirable feature that it does not require knowledge of the users' received energies. Another important characteristic of the decorrelator is that it can be viewed as decentralized. Demodulation of each user can be performed independently and thus can be viewed as matched filter detection with a modified filter bank.

2.4.2 Linear Minimum Mean-Square Error (MMSE) Receiver

The minimum mean-squared error detector [19] is a linear detector which takes into account the background noise and utilizes knowledge of the received signal powers. This detector implements the linear mapping which minimizes $\{||\mathbf{b} - \mathbf{L}_{MMSE}\mathbf{y}||^2\}$, the mean-squared error between the actual data and the soft output of the conventional detector. The solution to this minimization problem is given by

$$\mathbf{L}_{MMSE} = \left(\mathbf{R} + (N_o/2)\,\mathbf{E}^{-2}\right)^{-1} \tag{2.7}$$

Thus, the soft estimate of the MMSE detector is simply

$$\mathbf{L}_{MMSE}\mathbf{y} = \widehat{y} \tag{2.8}$$

As can be seen, the MMSE detector implements a partial or modified inverse of the correlation matrix. Because it takes the background noise into account, the MMSE detector generally provides better probability of error performance than the decorrelating detector. However, as the background noise goes to zero, the MMSE detector converges in performance to the decorrelating detector. The operation of the MMSE detector can be viewed as offering a balance between interference cancellation and noise enhancement. Another advantage of the MMSE receiver is that the linear transformation $\mathbf{L}_{MMSE}$ always exists even when $\mathbf{R}^{-1}$ is singular.

A main disadvantage of this detector is that, unlike the decorrelating detector, it requires estimation of the received amplitudes. Another disadvantage is that its performance depends on the powers of the interfering users. Therefore, there is some loss in resistance to the near-far problem as compared to the decorrelating detector. Figure 2.3 illustrates a block diagram of the MMSE detector.

2.5 Interference Cancellation methods

In interference cancellation (IC), the multiuser interference is estimated from each user's received signal and removed from the total received signal before making data decisions. In principle, the IC schemes considered in the literature fall into two categories, namely, *successive interference cancellation (SIC)* and *parallel interference cancellation(PIC)*.

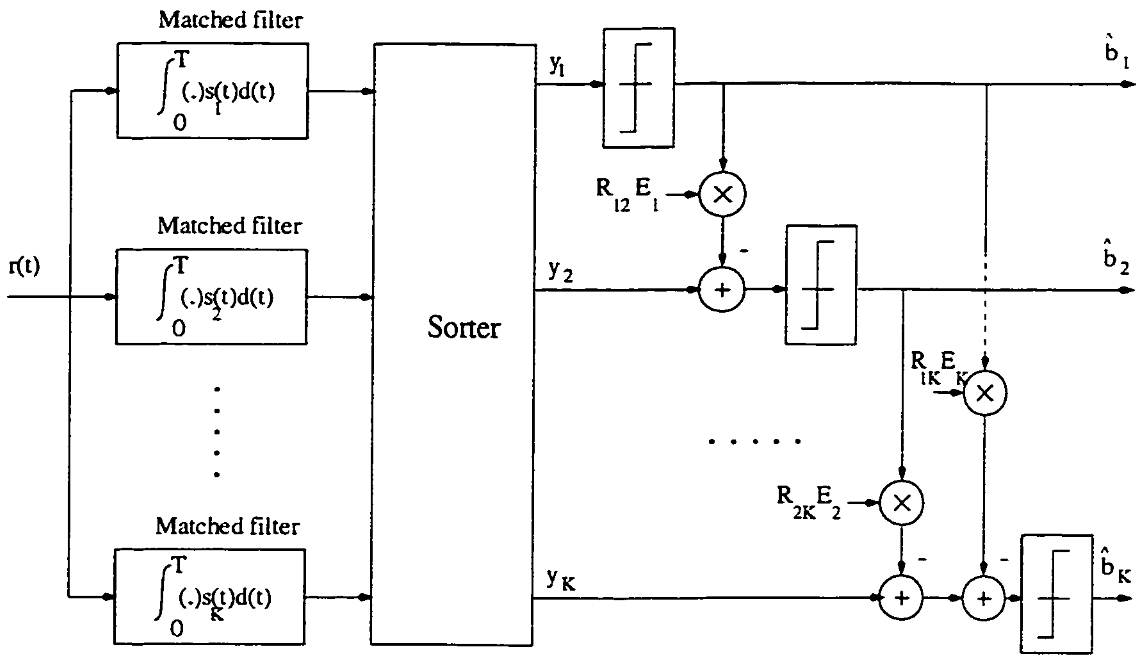


Figure 2.4: Block diagram of the successive interference cancellation receiver.

2.5.1 Successive Interference Cancellation (SIC)

This approach was first suggested by Viterbi [20] (see also Patel and Holtzman [21]). He considered coordinated processing of the received signal with a successive interference cancellation scheme in which the interference caused by the remaining users is removed from each user in succession. One disadvantage of this scheme is the fact that a specific geometric power distribution must be assigned to the users in order that each sees the same signal power to background plus interference noise ratio. This comes about because of the fact that with successive cancellation the first user to be processed sees all of the interference from the remaining M-1 users, whereas each user downstream sees less and less interference as the cancellation progresses. Another disadvantage of this scheme has to do with the delay required to fully accomplish the IC for all users in the system. Since the IC proceeds serially, a delay on the order of M computation stages is required to complete the job. Nevertheless, Viterbi showed that the SIC scheme could approach channel capacity for the aggregate Gaussian noise channel. As such, the scheme does not become multiuser interference limited.

In practice, users are first ranked successively according to their received powers, and then estimated and cancelled in the order from strongest to weakest. This cancellation approach has two advantages. First, the strongest users cause the most interference. Thus it is more beneficial to eliminate these interferers first. Second, the strongest users provide the most reliable estimates and thus cause the least error in cancellation. The result is that each user is estimated and only cancelled once. In this approach, the relative performance of the successive scheme improves as the user powers get more widely distributed. Figure 2.4 illustrates a block diagram of the SIC.

2.5.2 Multistage Parallel Interference Cancellation (PIC)

Recently, multistage parallel interference cancellation (PIC) has received considerable attention due to the fact that it has much simpler structure than the linear multiuser detectors and involves less decision delay as compared to SIC. Multistage receivers have multiple stages of interference estimation and cancellation. Although any receiver can be used at each stage (particularly the first stage) this approach is most often used in conjunction with PIC. In the conventional PIC (CPIC) [22], a conventional receiver is used in the first stage to estimate the channel gain and data symbol. These estimates along with independent delay estimates are used to remove the interference of the other users by subtracting the estimate of each interferer from the desired users' signals. Ideally, this would allow elimination of all interfering signals from the desired user. However, due to the inaccuracy of the estimates, this interference will be subtracted imperfectly. Thus to overcome this, the entire process can be repeated in several stages. Nevertheless, when the number of active users becomes large, CPIC fails to guarantee performance improvements with more stages, due to improper interference estimates in cancellation.

In [23], Divsalar *et al.* proposed a partial PIC (PPIC) scheme, which alleviates the above-mentioned problem by introducing a weight in each stage to reduce the cost of wrong estimation. They proved that when the interference estimate is poor (as in the early stages of IC), it is preferable not to cancel the entire amount of estimated MAI. In this approach, the decision statistic at the current stage is a weighted sum of the previous decision statistic and the statistic resulting from MAI cancellation. To some extent, this iterative manner is based on the likelihood concept. As the IC operation progresses, the estimates of the MAI improve and, thus, in the later stages of the iterative scheme, it becomes desirable to increase the weight of the interference being removed.

Even though PPIC has better performance than CPIC, the weights determining the amount of cancellation of the MAI estimate are given stage by stage and initially set as fixed values. Besides, at a heavy system load, the update of likelihood information becomes unreliable and may degrade the system performance significantly.

An adaptive multistage structure based on PPIC is investigated in [24] which is named as adaptive PIC (APIC). In this structure, unlike the PPIC, a set of weights are introduced for all users. The weights are obtained by minimizing the mean-square error between the received signal and its estimate through a least mean square (LMS) algorithm. It is shown that this scheme can outperform some of the existing interference cancellation methods in both additive white Gaussian noise (AWGN) and the multipath fading channels. One of the major advantages of APIC is that the imperfect power estimation only has a little impact on the performance of the receiver. Moreover, the LMS-based APIC scheme can provide a considerable performance improvement over the RLS decorrelating method [25] with much lower complexity. A block diagram of the PIC is depicted in Figure 2.5.

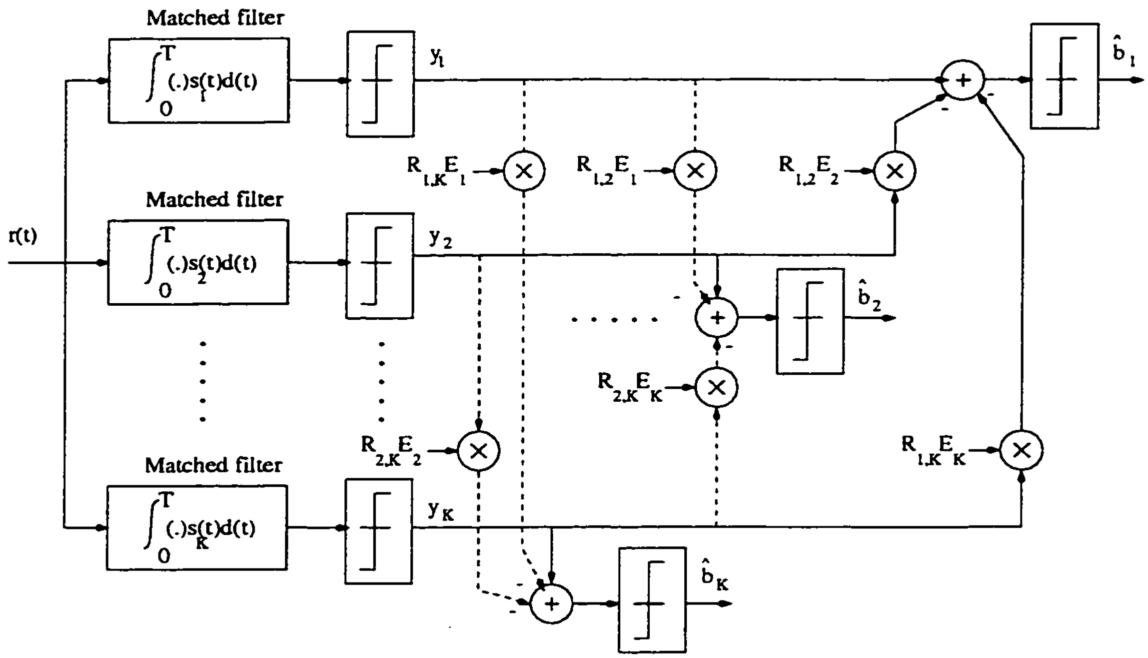


Figure 2.5: Block diagram of the parallel interference cancellation receiver.

2.6 Comparison of Alternative Techniques

All of the simulations for this thesis were performed on UNIX based SUN workstations with the use of MATLAB.

In order to compare the capabilities of different multiuser structures, we have conducted a simulation study based on Monte Carlo method for AWGN channels, using a common set of parameters. We have considered BPSK modulation and Gold codes with the length of 31. We also assume five active users in the system. The BER performance versus E_b/N_o for the aforementioned multiuser detectors along with single user bound and conventional receiver is given in Figure 2.6. For the perfect power control case we find that a significant performance improvement has been achieved by employing multiuser detection techniques, while the successive interference canceler provides a small improvement in comparison to other sub-optimum detectors. As we can see the decorrelator, MMSE, and parallel canceler all provide roughly similar performance, with the parallel interference canceler providing better

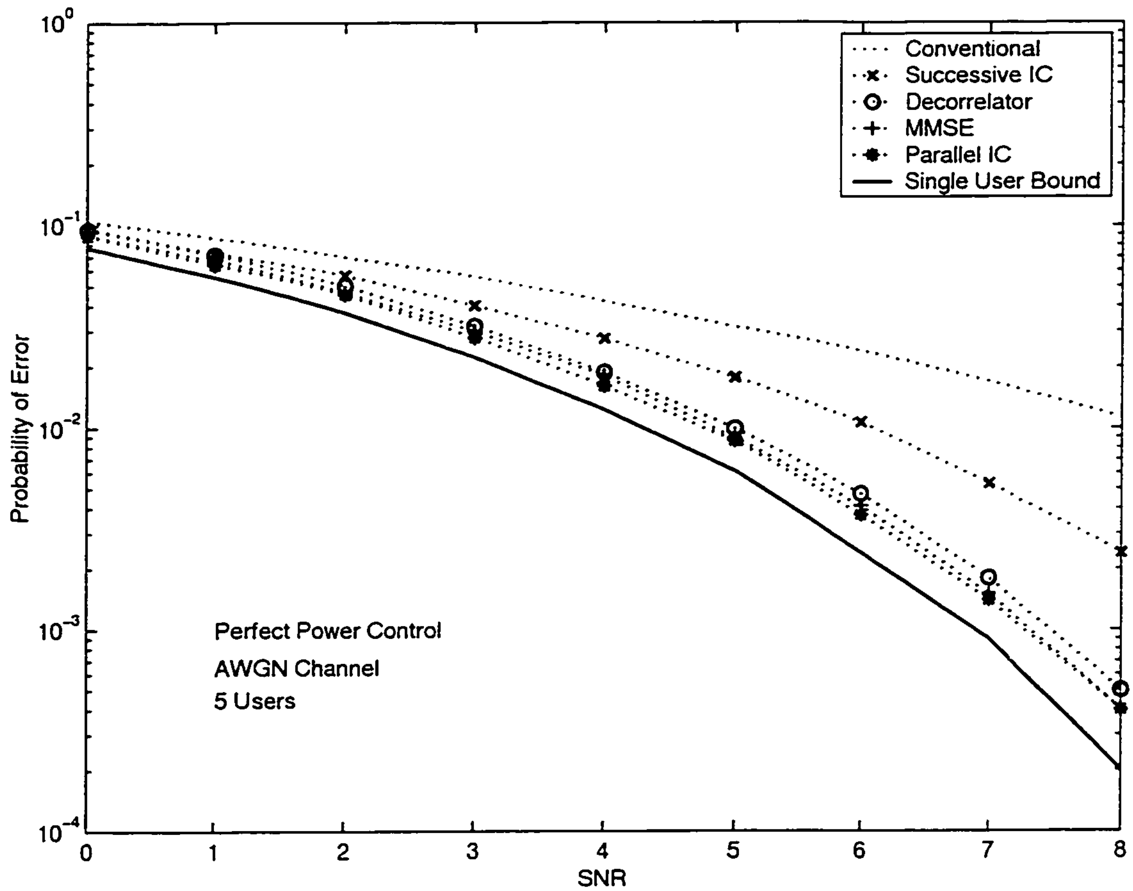


Figure 2.6: BER versus E_b/N_o with Perfect Power Control for various multiuser detectors.

performance than the linear detectors. More precisely, the MMSE performance is upper bounded by the decorrelator, while the parallel canceler outperforms both of them. The performance of the successive canceler is significantly poorer due to the lack of the variance in the received powers. Since the successive canceler orders cancellation based on average powers and average powers are the same, the performance of signals detected early in the cancellation process suffers. In fact, the performance of the first user is equivalent to that of the conventional receiver.

The second set of results are capacity curves for SNR=8 dB for all users. Assuming perfect power control, the simulation results are shown in Fig. 2.7. The results show that the MMSE is upper bounded by the decorrelator, while parallel

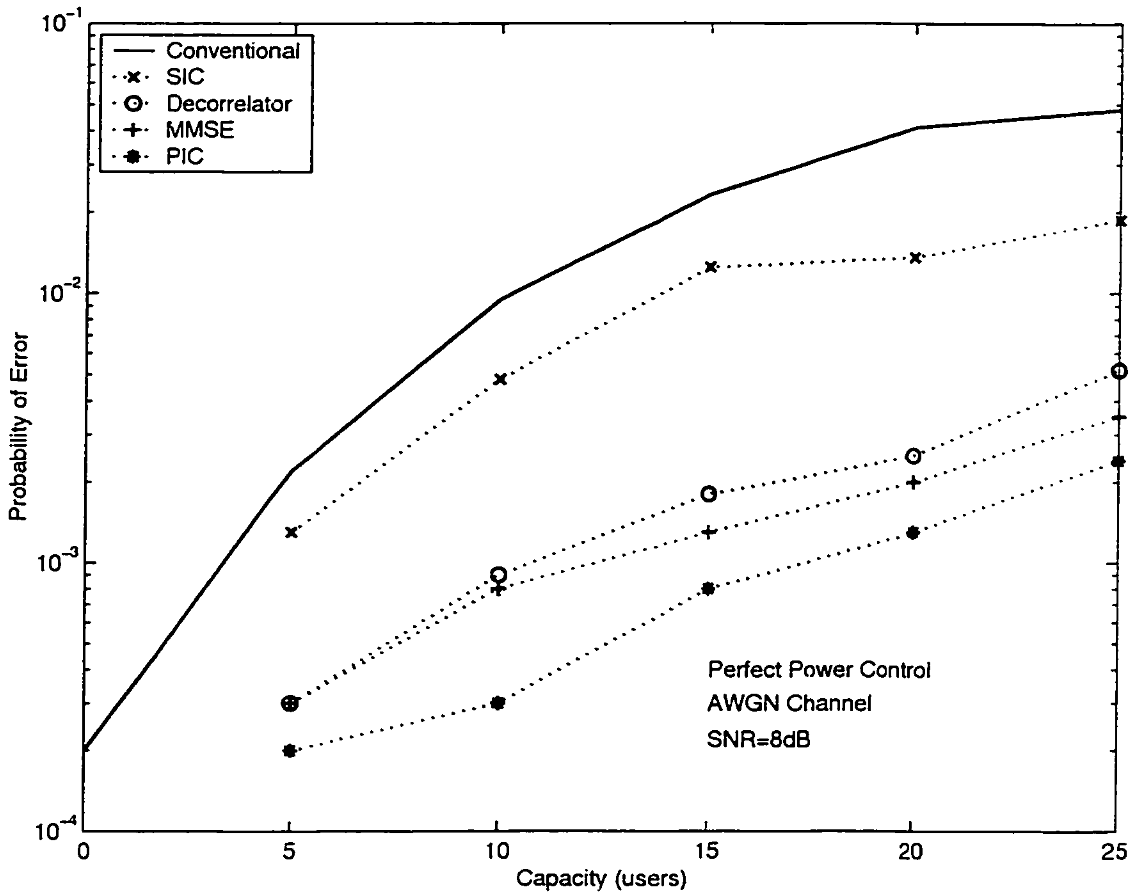


Figure 2.7: Capacity curves for perfect power control for various multiuser detectors.

canceler shows more increase in capacity than the other detectors. As we expected the SIC is not able to provide a considerable capacity improvement. Thus, in AWGN channels the decorrelator, MMSE, and PIC provide superior performance which results in a significant capacity improvement in the system although the difference is minor at low loading levels. So far, we have examined the possible improvement in BER performance by utilizing multiuser structures in perfect power control. However, as mentioned earlier, one of the drawbacks of the conventional receiver is its subjection to the near-far problem. Thus we wish to examine the performance of each of the receiver structures in situations where a single interferer dominates the received power. Fig. 2.8 presents the performance of the receivers in the presence

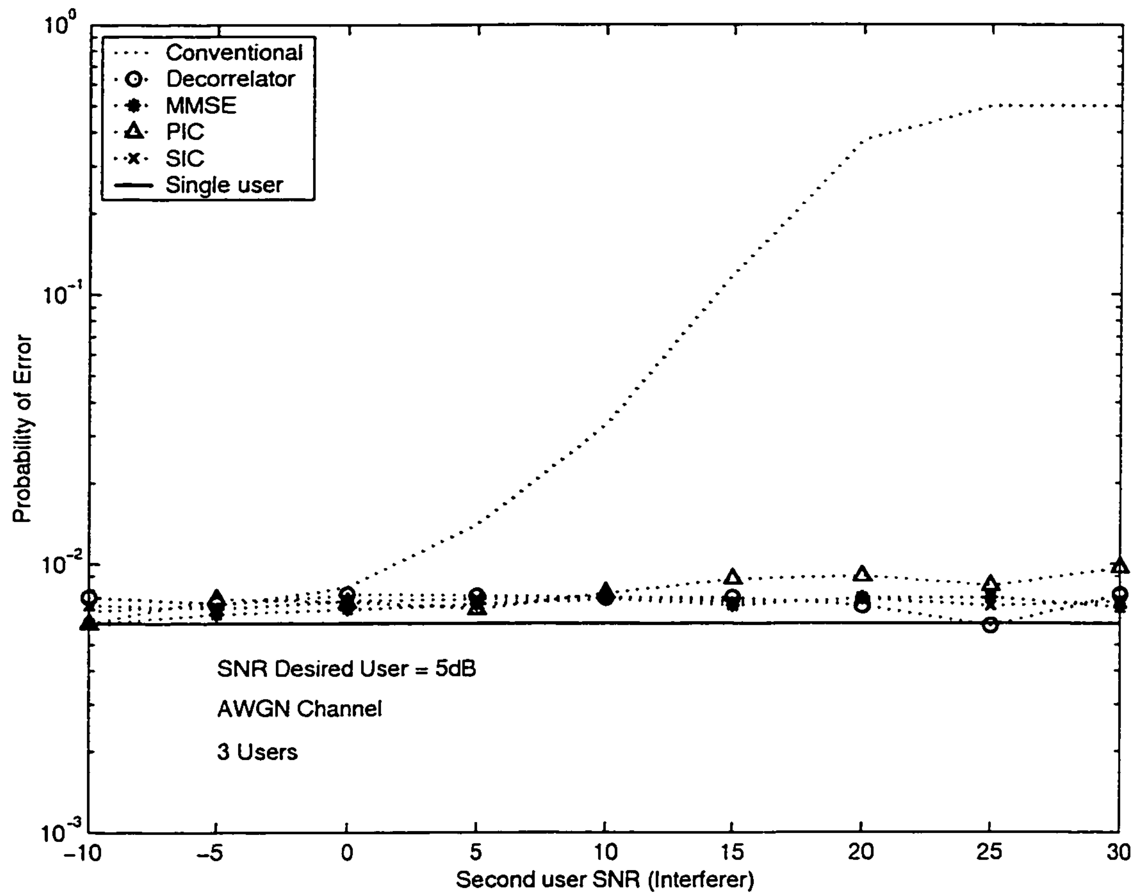


Figure 2.8: Performance degradation in near-far channels.

of two interferers, one with the same power as the desired signal which is 5 dB, and one with a power which varies from -10 to 30 dB. As expected, the conventional receiver degrades quickly in the presence of strong interference. The successive canceler which benefits from diverse powers is found to be robust to strong interferers, as is the decorrelator which has a performance that is independent of user energies. The MMSE also has a near-far resistance identical to the decorrelator. The parallel canceler is not as robust and shows slow degradation. The parallel canceler suffers due to the fact that cancellation of the weak user is inaccurate because of the dominating interference.

These results show that with perfect or imperfect power control multiuser receivers provide significant gains over the conventional matched filter. We also conclude that the parallel interference cancellation, decorrelator, and MMSE receivers significantly outperform the successive cancellation approach.

2.7 Conclusions

In this chapter, a number of multiuser detection techniques have been studied. The results show, when compared with classical CDMA receivers, the improvement in performance is dramatic at the expense of a practically feasible increase in complexity. We also conclude that among the multiuser detection techniques, a tradeoff between performance and computational complexity can be obtained by employing parallel interference cancellation. In Chapter 4, the integration of APIC and adaptive antenna arrays for CDMA systems will be investigated.

Chapter 3

Adaptive Blind Arrays for DS-CDMA Systems

3.1 Introduction

An application of antenna arrays has been suggested in recent years for mobile communications systems to overcome the problem of limited channel bandwidth, thereby satisfying an evergrowing demand for a large number of mobiles on communications channels. It has been shown by many studies that the deployment of antenna arrays in a mobile communications system can improve the system performance by increasing channel capacity and spectrum efficiency (the amount of traffic a given system with certain spectrum allocation could handle), extending range coverage, and steering multiple beams to track many mobiles. The use of antenna arrays also reduces the effect of multipath fading, cochannel interferences, system complexity cost, BER, and outage probability (the probability that a user would not be able to communicate via the mobile communications system).

An array of antennas may be used in a variety of ways to improve the performance of a communications system. Perhaps most important is its capability to cancel cochannel interferences in the receiver. An array works on the premise

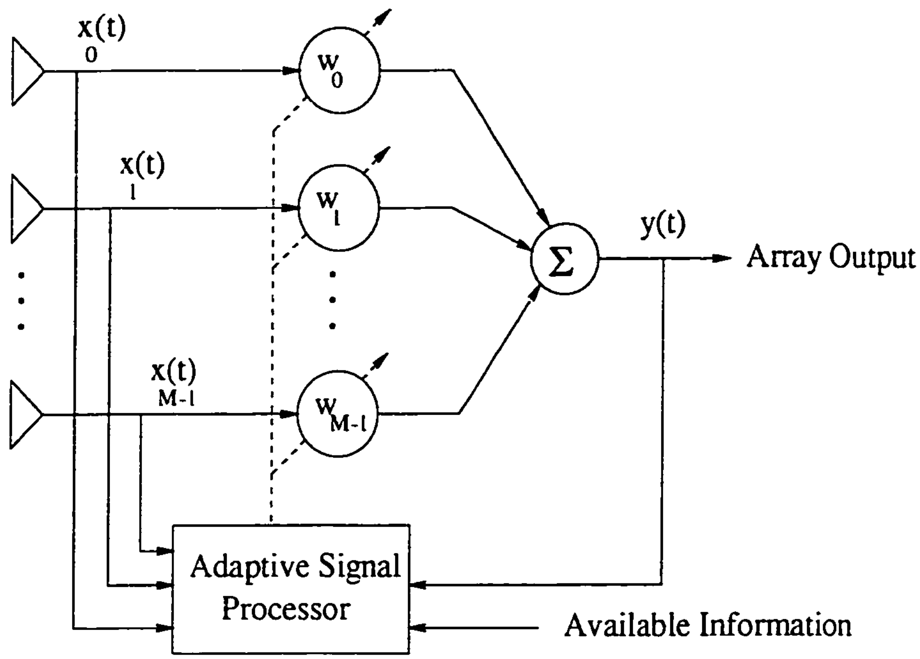


Figure 3.1: Block diagram of an adaptive array system

that the desired signal and unwanted cochannel interferences arrive from different directions. The beam pattern of the array is adjusted to suit the requirements by combining signals from different antennas with appropriate weighting. The scheme needs to differentiate the desired signal from the cochannel interferences and normally requires either the knowledge of a reference signal, a training signal, or the direction of the the desired signal source to achieve its desired objectives. There exists a range of schemes to estimate the direction of sources with different levels of accuracy and processing power. Similarly, there are many methods to update the array weights, each with its speed of convergence and required processing time. Algorithms also exist that exploit properties of signals to eliminate the need of training signals in some circumstances.

Adaptive spatial filtering was introduced as a way for the array to track mobile units as they move and account for time variability in the radio channel. An adaptive array system consists of an array of spatially distributed antennas and an adaptive signal processor that generates a weight vector for combining the array output. Fig. 3.1 shows a block diagram of an adaptive array system. There are a number of adaptive algorithms which were developed explicitly for CDMA systems. These algorithms can be classified as 1) conventional algorithms 2) blind adaptive algorithms 3) channel estimation algorithms. Conventional algorithms use the knowledge of the desired or training signal and the received signal to adapt its weights. Among the most popular techniques in this category, we can mention Least Mean Square (LMS), Recursive Least Square (RLS), and Sample Matrix Inversion (SMI). On the other hand, blind adaptive array algorithms do not require any training signal. Instead, they use the properties of the signals such as constant modulus, cyclostationarity, or knowledge of the code to adapt the weights. These algorithms compared to conventional techniques, can save bandwidth, because of the overhead reduction in transmission and can offer more flexibility to the networking protocols. Channel estimation techniques use the knowledge of the special code properties of the spread spectrum signal to obtain estimates of channel parameters. In this research, only the blind adaptive array algorithms to adapt the antenna weights will be considered.

3.2 Adaptive Blind Algorithms

Due to mobility of the users and the constantly changing environment surrounding them, the transmitted signals from the users go through variable, independent patterns of scattering and fading, making it very difficult for the receiver to know the direction of the received signal from any user at a given time. Therefore, it is highly desirable to develop a technique to combine the received signals at different antenna elements adaptively and in blind fashion, requiring neither the knowledge of the array manifold nor a training sequence for the user of interest. Considerable research efforts have been made on the blind detection problem. A number of different blind

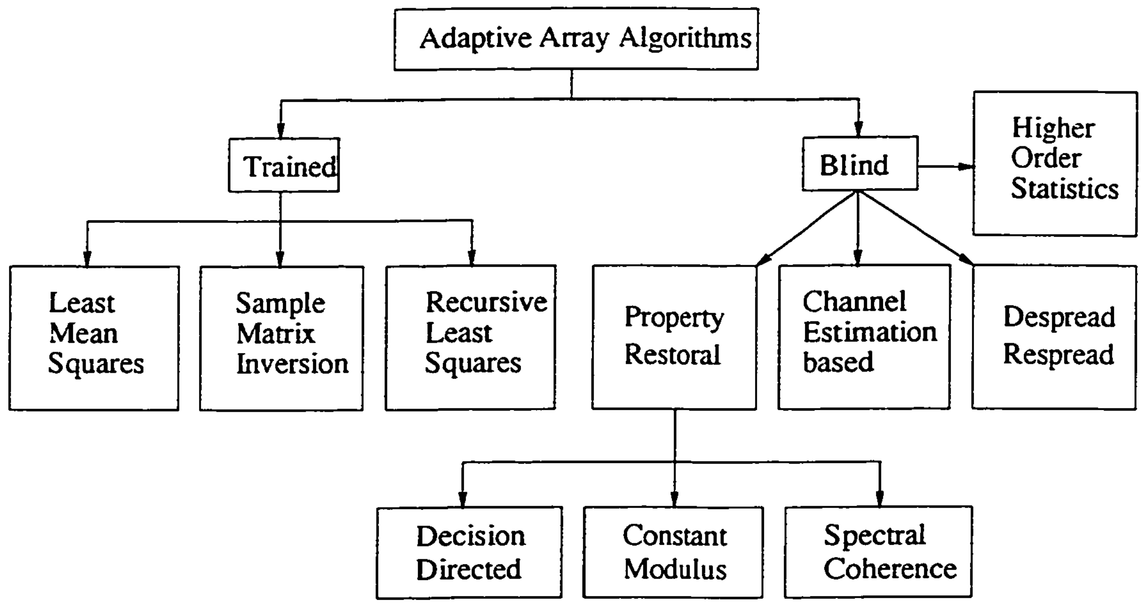


Figure 3.2: Classification of adaptive array algorithms.

receiver design methods have been developed by employing constrained optimization, subspace methods, and higher-order statistics (HOS), etc. Blind algorithms developed specifically for adaptive array applications can be classified as property restoral algorithms [26], channel estimation algorithms [7], despread and respread algorithms [29], and HOS-based algorithms. Property restoral algorithms restore certain properties of the desired signal and hence enhance the SINR. The property that is being restored may be the modulus or the spectral coherence. Blind property restoral algorithms can be classified as Constant Modulus (CM) algorithm [26], Spectral self-COherence REstoral (SCORE) algorithms [27], and decision directed (DD) algorithms [28]. The classification of adaptive array algorithms is depicted in Fig. 3.2.

The CM algorithm [26] is applicable to constant modulus signals and the algorithm tries to undo the distortion introduced by the channel and the interference by forcing the output magnitude of the array to be constant, but preserving the phase of the input signal. The CM algorithms can use steepest-descent approach or least-squares based approach to minimize the CM cost function. CM algorithms using the LS adaptation converges very fast and its performance is very similar to a trained algorithm. The only disadvantage of using a CM type algorithm is that it lacks the property of signal-selectivity, i.e., the algorithm cannot distinguish one constant modulus signal from the other. The CM algorithm always has a tendency to capture the strongest signal.

SCORE algorithm [27] exploit the property of cyclostaionarity, which most digital and some analog signals exhibit. A signal with cyclostationarity has the statistical property of correlating with either a frequency-shift or a complex-conjugate version of itself. By restoring this property at a known value of frequency separation, it is possible to favor the desired signal and to discriminate against the interference and noise. In addition, adaptive beamforming can suppress Gaussian and non-Gaussian interferers as well by utilizing the signal cyclostationarity.

Decision directed algorithm [28] demodulates the array output followed by a binary decision which can be regarded as an estimate of the desired samples. Then, these decisions are fed back as the reference signal. However, when errors occur at the demodulator, the reconstructed estimate of the desired signal is poor, and adaptive algorithms that use this estimate can lead to an incorrect weight solution, further degrading the quality of the demodulated signal.

Channel estimation techniques [[7], [15], [31]] use the knowledge of the special code properties of the spread spectrum signals to obtain estimates of channel parameters. These techniques first estimate channel parameters and then use them to form beams in the direction of the desired signals. These techniques are applicable only for CDMA signals.

Despread-respread technique [29] for CDMA work on the principle of despreading signal at the output of the desired user and then making a bit decision. Then the desired user PN code respreads the data bit. Then the error between the respread data and the output of the array is minimized using a least-squares or a steepest descent approach. The assumption behind the despread-respread based adaptation is

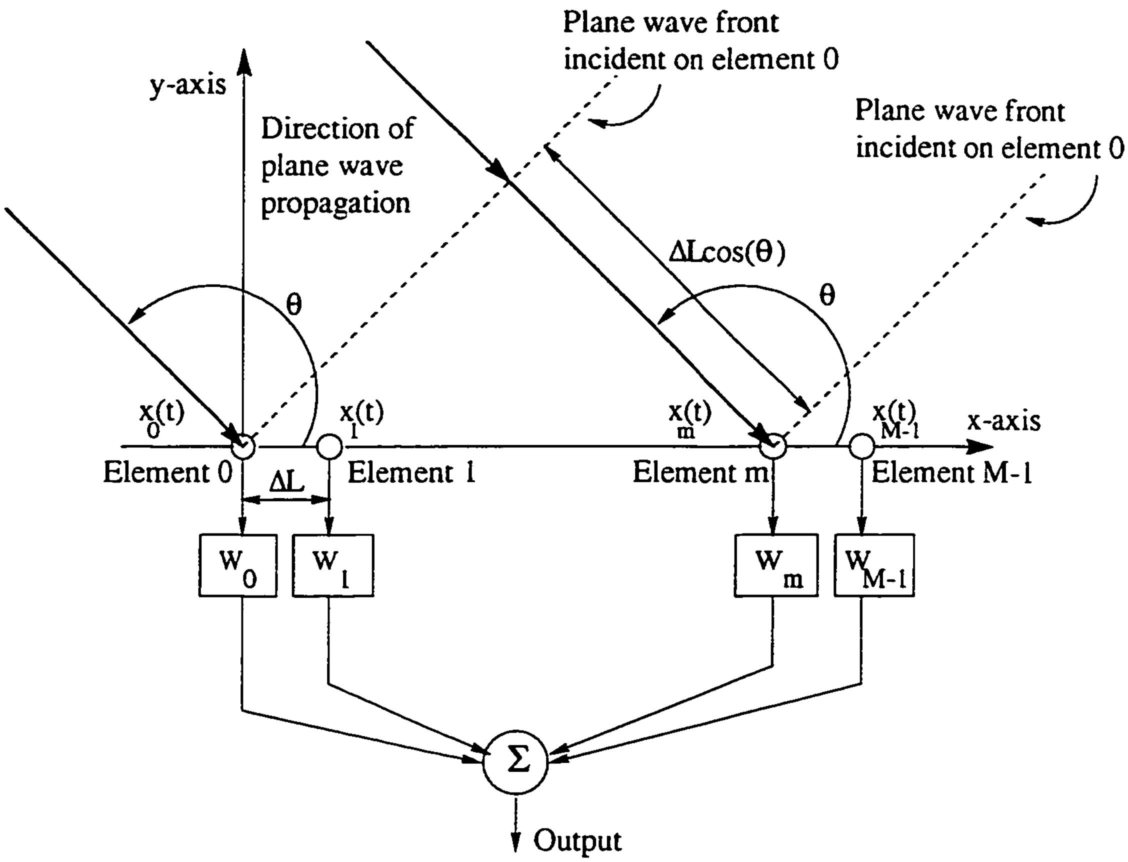


Figure 3.3: Illustration of plane wave incident from an angle of θ on an uniform linear array with inter-element spacing of ΔL.

that the synchronization has been achieved prior to beamforming, since despreading requires synchronization.

In the following section, several adaptive blind algorithms which are based on the despread-respread technique will be developed. We utilize the spreading signal of each user in a CDMA system to adapt the weight vectors of the beamformer.

3.2.1 Signal model

An arbitrary array of elements is shown in Fig. 3.3. The spacing between array elements is assumed to be small that there is no amplitude variation between the signals received at different elements. We also assume that there is no mutual coupling between elements. In addition, the propagation delay between antenna elements is assumed to be small relative to the inverse of the transmission bandwidth (i.e., the bandwidth of the signal incident on the array is small compared to the carrier frequency) so the received signals at the M baseband array outputs are identical to within a complex constant, essentially assuming a narrowband model for the received signal.

The array is implemented as a M-element *linear equally spaced* (LES) antenna array, oriented along the x-axis, with an element spacing of ΔL, and θ is the azimuth angle of a plane wave incident on the array. A complex quantity a_m is defined as the ratio of the signal received at the antenna element m to the signal received at the reference element when a plane wave is incident on the array. Assuming a CDMA system where K users are transmitting signals, the *array response vector* for the k^{th} user can be written as

$$\mathbf{a}_k = [a_{1k}, a_{2k}, \ldots, a_{Mk}]^T \tag{3.1}$$

where a_{mk} is the complex gain from user k to the m^{th} antenna element, given by

$$a_{mk} = e^{-j\beta L_m sin(\theta_k)} \tag{3.2}$$

where $\beta = 2\pi/\lambda$ is the *phase propagation factor*, $L_m = m\Delta L$ the distance between the first and the m^{th} antenna element, θ_k the arrival angle of the signal from the k^{th} user, and λ denotes the free-space wave length, given by c/f, where c is the speed of light, $3 \times 10^8 m/s$, and f is the carrier frequency in Hz. To simplify the analysis, the array response vectors are normalized so that

$$|a_{1k}| = 1 \qquad\qquad k = 1, \ldots, K. \tag{3.3}$$

By this assumption when the channel bandwidth is large enough, the intersymbol interference can be ignored. In a direct sequence CDMA system, where K users transmit asynchronous over a passband channel, the lowpass equivalent of the received signal at the antenna array can be modeled as:

$$\mathbf{x}(t) = \sum_{i=0}^{I}\sum_{k=1}^{K} \sqrt{e_k}\mathbf{a}_k b_k(i) s_k(t - \tau_k - iT_b) + \sigma\mathbf{n}(t) \tag{3.4}$$

where

$$\mathbf{x}(t) = [x_1(t), x_2(t), \ldots, x_M(t)]^T \tag{3.5}$$

is the vector of the signals received at M antenna elements.

Here, the received energy of the k^{th} user at each antenna is denoted by e_k, and $b_{k,i} \in \{-1. +1\}$ is the i^{th} symbol transmitted by user k. The parameter I is used as the number of bits or packet that each user transmits. The signature waveforms $\{s_k(t)\}$ are assumed to be real and normalized:

$$\int_0^{T_b} s_k(t)^2 dt = 1 \tag{3.6}$$

where T_b is the symbol interval. If the received signal is sampled at the chip rate $T_c = \frac{T_b}{N}$, where N is the *spreading gain,* then the linearly independent signature waveforms can be modeled as:

$$s_k(t) = \sum_{n=0}^{N-1} s_{k,n} u(t - nT_c) \tag{3.7}$$

where $\mathbf{s_k} = [s_{k,0}, s_{k,1}, \ldots, s_{k,N-1}]^T$; $s_{k,n} \in \{-1, +1\}$ is the assigned code of user k, and $u(t)$ is the chip pulse waveform. The relative delay of the k^{th} user to the array reference element is denoted by τ_k, and $\mathbf{n}(t)$ is the vector of the additive complex white Gaussian noises at antenna elements which are assumed to be independent, i.e.

$$E\left\{\mathbf{n}(t)\mathbf{n}^H(t)\right\} = I \tag{3.8}$$

and

$$E\left\{Re[n_m(n)]Im[n_{m'}(n')]\right\} = 0 \quad for\ all \quad m,\ n,\ m',\ n'. \tag{3.9}$$

To keep the complexity of analysis and notation manageable, we restrict our model to the synchronous case, in which $\tau_1 = \tau_2 = \ldots = \tau_K = 0$. Using filters matched to the chip pulse at the receiver and sampling at the chip rate, the following $M \times N$ matrix representation can be used for the received signal:

$$\mathbf{X} = \begin{bmatrix} \mathbf{x}_1^T \\ \vdots \\ \mathbf{x}_M^T \end{bmatrix} = \sum_{k=1}^{K} \sqrt{e_k} b_k \mathbf{a}_k \mathbf{s_k}^T + \sigma \mathbf{N} \tag{3.10}$$

The demodulator for user l computes the following decision variable

$$y_l = \frac{\mathbf{a}_l{}^H}{||\mathbf{a}_l||} \mathbf{X} \mathbf{s}_l = \int_0^T \frac{\mathbf{a}_l^H}{||\mathbf{a}_l||} \mathbf{x}(t) s_l(t)\, dt$$

$$= \sqrt{e_l} b_l ||\mathbf{a}_l|| + \sum_{k=1, k\neq l}^{K} \sqrt{e_k} b_k \rho_{kl}^s \rho_{kl}^a ||\mathbf{a}_l|| + \sigma n_l \tag{3.11}$$

where

$$\rho_{kl}^s = \int_0^T s_l(t) s_k(t) dt = \mathbf{s}_l^T \mathbf{s}_k \tag{3.12}$$

is the cross-correlation between the signature waveforms l and k, and

$$\rho_{kl}^a = \frac{\mathbf{a}_l^H \mathbf{a}_k}{||\mathbf{a}_l||\,||\mathbf{a}_k||} \tag{3.13}$$

is the cross-correlation between the array response vectors l and k, and

$$n_l = \frac{\mathbf{a}_l^H}{||\mathbf{a}_l||} \mathbf{N} \mathbf{s}_l \tag{3.14}$$

is a zero mean Gaussian random variable with unit variance. It can be shown that the set of $\{y_l;\, l = 1, \ldots, K\}$ form a set of sufficient statistics for the detection of the corresponding transmitted bits. For the remainder of the thesis, without loss of generality, we assume that the first user is our desired user. The decision variable for user 1 is

$$y_1 = \frac{\mathbf{a}_1^H}{||\mathbf{a}_1||} \mathbf{X}_1 \mathbf{s}_1 = ||\mathbf{a}_1|| e_1 b_1 + i_1$$

where $\mathbf{X}_1$ is the received signal at the receiver from user 1, and

$$i_1 = \sum_{k=2}^{K} \sqrt{e_k} b_k \rho_{1k}^{s} \rho_{1k}^{a} ||\mathbf{a}_k|| + \sigma n_1 \tag{3.15}$$

is the multiple access interference (MAI) at the output of the detector, and

$$n_1 = \frac{\mathbf{a}_1^H}{||\mathbf{a}_1||} N_1 s_1 \tag{3.16}$$

is the filtered noise. The transmitted bit by the desired user is then optimally detected using the decision variable in

$$\widehat{b_1} = sgn[Re(y_1)] \tag{3.17}$$

3.2.2 Blind Algorithms

In this section we derive three blind algorithms based on constrained optimization that compute the weight vectors in order to preserve the desired signal and mitigate the interference [44][46]. The receiver is blind in the sense that only the knowledge of the desired user's code is necessary. The goal is to compute the combining weights in an optimum fashion, so that the output of the receiver attains a maximum SINR. The block diagram of an adaptive multi-element interference canceling receiver is shown in Fig. 3.4. The received signal, $\mathbf{X}$, is combined in space (by $\mathbf{w}$) and despread in time (by $\mathbf{s}$)to form the decision variable for first user, y_1, which is respread again in time, subtracted from array output to provide the error signal, e. Then, this error signal is used to adapt $\mathbf{w}$.

$$y = \mathbf{w}^H \mathbf{X}\mathbf{s} = (\mathbf{w}^H \mathbf{a})\sqrt{e}b + i_1 \tag{3.18}$$

In each method, the beamformer will either steer nulls in the direction of the interfering users, (depending on the relative number of users and antenna elements which basically determines the degrees of freedom for the array) or only beams the adaptive array to the desired user without any interference nulling. To avoid the

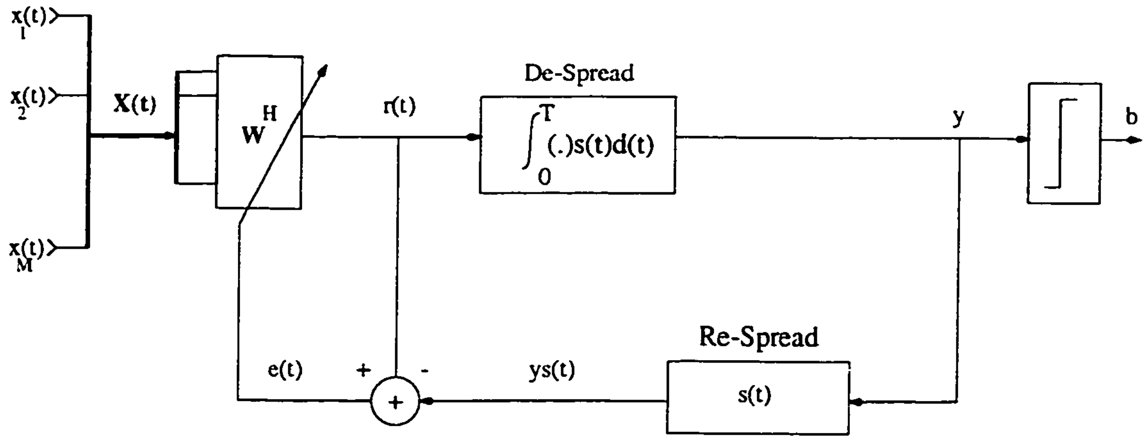


Figure 3.4: Block diagram of an adaptive multi-element interference canceler for CDMA systems.

trivial solution, an additional constraint is required. Here, we assume that the array response vector for the desired user, $\mathbf{a}$, is unknown.

If the array response vector of the desired user is known by the receiver, the optimal solution would be achieved with a constant gain in the direction of the desired user (linear constraint). The goal is to minimize the variance at the output of receiver subject to the constraint that the desired signal remains unaffected. The optimum beamformer is the minimum variance distortionless response (MVDR) solution for the following constrained minimization problem

$$\min_{\mathbf{w}} E[\,|y|^2] = \mathbf{w}^H \mathbf{R}_s \mathbf{w} \quad \textit{subject to} \quad \mathbf{w}^H \mathbf{a} = 1 \tag{3.19}$$

In this formula, $\mathbf{R}_s$ is the covariance matrix of the signal after matched filtering with a matched filter corresponding to the desired user. This covariance matrix is defined as

$$\mathbf{R}_s = E[\,\mathbf{X}\mathbf{s}\mathbf{s}^T\mathbf{X}^H] = \mathbf{A}(\mathbf{EP})^2\mathbf{A}^H + \sigma^2\mathbf{I}_M \tag{3.20}$$

where

$$\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \ldots, \mathbf{a}_K] \tag{3.21}$$

$$\mathbf{E} = diag(\sqrt{e_1}, \sqrt{e_2}, \ldots, \sqrt{e_K}) \tag{3.22}$$

$$\mathbf{P} = diag(\rho_{11}, \rho_{12}, \ldots, \rho_{1K}] \tag{3.23}$$

The method of *Lagrange multipliers* [42] can be used to solve this constrained optimization problem. The solution for the optimum weight vector $\mathbf{w}_{opt}$ is given by

$$\mathbf{w}_{opt} = \frac{\mathbf{R}_s^{-1}\mathbf{a}}{\mathbf{a}^H \mathbf{R}_s^{-1}\mathbf{a}} \tag{3.24}$$

Method I: In this method, the weights of the beamformer are chosen to minimize the error signal energy subject to a constant energy of unity at the output of receiver. Here, we use the output energy of the decision variable for the desired user as the (quadratic) constraint. The optimization rule can be written as

$$\min_{\mathbf{w}} E[\mathbf{e}^H \mathbf{e}] = \mathbf{w}^H(\mathbf{R} - \mathbf{R}_s)\mathbf{w} = \mathbf{w}^H(\mathbf{R}_I)\mathbf{w}$$

$$subject\ to \quad E[|y|^2] = \mathbf{w}^H \mathbf{R}_s \mathbf{w} = 1 \tag{3.25}$$

where $\mathbf{R}$ is the covariance matrix at the array output and can be expressed as

$$\mathbf{R} = E[\mathbf{X}\mathbf{X}^H] = \mathbf{A}\mathbf{E}^2\mathbf{A}^H + N\sigma^2\mathbf{I}_M \tag{3.26}$$

and $\mathbf{R}_I = \mathbf{R} - \mathbf{R}_s$ is the covariance matrix of the multiple access interference plus white Gaussian noise and can be written as

$$\mathbf{R}_I = \mathbf{R} - \mathbf{R}_s = \mathbf{A}_I\mathbf{E}^2(1 - \mathbf{P}^2)\mathbf{A}_I^H + (N-1)\sigma^2\mathbf{I}_M \tag{3.27}$$

Also, from Fig. 1, the error signal that is used to adapt $\mathbf{w}$ can be written as

$$\mathbf{e}^H = \mathbf{w}^H\mathbf{X} - (\mathbf{w}^H\mathbf{X}\mathbf{s})\mathbf{s}^T = \mathbf{w}^H\mathbf{X}(\mathbf{I} - \mathbf{s}\mathbf{s}^T) \tag{3.28}$$

which is the orthogonal projection of the beamformer output on the null space spanned by the signature sequence of the desired user.

This optimization is linked to an eigenvalue problem. We wish to find the weight vector, $\mathbf{w}$, that satisfies the condition

$$\mathbf{R}_I \mathbf{w} = \lambda_{min} \mathbf{R}_s \mathbf{w} \tag{3.29}$$

where λ_{min} is the minimum eigenvalue of the matrix pencil $(\mathbf{R_I}, \mathbf{R}_s)$, and $\mathbf{w}$ is the generalized eigenvector associated with the minimum eigenvalue.

Method II: For this method, a simpler approach is used for the blind adaptation of the beamformer. The optimization rule is to maximize the output energy of the receiver subject to the unit norm constraint for the beamformer weight vector. The optimization rule is given by

$$\max_{\mathbf{w}} E[\,|y|^2] = \mathbf{w}^H \mathbf{R}_s \mathbf{w} \quad \textit{subject to} \quad \mathbf{w}^H \mathbf{w} = 1 \tag{3.30}$$

Assuming the interference plus noise at the matched filter output has Gaussian distribution, this method approximates the conventional beamformer. The solution, which is the eigenvector corresponding to the maximum eigenvalue of $\mathbf{R}_s$ is approximately the array response vector of the desired user. The eigenvalue problem can be written as

$$\mathbf{R}_s \mathbf{w} = \lambda_{max} \mathbf{w} \tag{3.31}$$

Method III: This method is based on minimizing the output power of the array subject to a constant energy of unity at the output of receiver. Accordingly, the optimization rule can be written as follows:

$$\min_{\mathbf{w}} E[\mathbf{r}^H \mathbf{r}] = \mathbf{w}^H \mathbf{R} \mathbf{w} \quad \textit{subject to} \quad E[|y|^2] = 1 \tag{3.32}$$

The solution to this problem is given by the generalized eigenvector corresponding to the minimum eigenvalue of the matrix pencil $(\mathbf{R}, \mathbf{R}_s)$ such that

$$\mathbf{R} \mathbf{w} = \lambda_{min} \mathbf{R}_s \mathbf{w} \tag{3.33}$$

To compare the three methods, it is more intuitive to reformulate them as follows:

$$\textit{Method I}: \qquad \max_{\mathbf{w}} \frac{\mathbf{w}^H \mathbf{R}_s \mathbf{w}}{\mathbf{w}^H (\mathbf{R}_I) \mathbf{w}} \tag{3.34}$$

$$\textit{Method II}: \qquad \max_{\mathbf{w}} \frac{\mathbf{w}^H \mathbf{R}_s \mathbf{w}}{\mathbf{w}^H \mathbf{w}} \tag{3.35}$$

$$\textit{Method III}: \qquad \max_{\mathbf{w}} \frac{\mathbf{w}^H \mathbf{R}_s \mathbf{w}}{\mathbf{w}^H \mathbf{R} \mathbf{w}} \tag{3.36}$$

In comparison, Method I maximizes the ratio of an estimate of the energy of the user of interest to the energy of multiple access interference plus white Gaussian noise, while Method II maximizes the ratio of the estimate of the energy of the user of interest to only the energy of white noise. Method III maximizes the ratio of an estimate of the energy of the user of interest to the energy of signal at the array output. As a result, Methods I and III have the capability of nulling some of the interferers while preserving the desired signal, while Method II only beams the adaptive array to the desired user without any interference nulling. It can be shown that while the solution to Method II is very close to the array response vector of the user of interest, the solution to Methods I and III is close to the optimum solution, where both form a beam to the desired user while placing a null in the direction of the interferers.

In general, the number of antennas is usually much smaller than the number of users ($M \ll$ K). In this situation, the number of interfering users that can be spatially nulled by the antenna array will be very small compared to the total number of interferers. Therefore, the optimum solution to the beamformer will be very close to the array response vector of the desired user, which means that all methods have a very similar performance. The adaptive LMS-based algorithms for the three methods are derived in the following section.

3.2.3 Adaptation Algorithms

Adaptive filters can be implemented in a sequential update algorithm such as Least Mean Square (LMS) and Recursive Least Square (RLS). LMS algorithm adaptation has a low computational complexity but can be slow to converge. The RLS algorithm has a quick convergence but is more computationally complex. Of course, there are methods of implementing the RLS algorithm with reduced complexity, but they were not considered in this work.

Considering the computational complexity, the constrained LMS algorithm, combined with the gradient-projection algorithm to incorporate the quadratic constraint, can be used to determine the adaptation algorithms for $\mathbf{w}$. First, using the results of last section, we can reformulate the three algorithms as follows:

$$\max_{\mathbf{w}} F_{\mathbf{w}} = \mathbf{w}^H \mathbf{R}_s \mathbf{w} \quad \textit{subject to} \left\{ \begin{array}{cr} I & \mathbf{w}^H(\mathbf{R}-\mathbf{R}_s)\mathbf{w} = 1 \\ II & \mathbf{w}^H\mathbf{w} = 1 \\ III & \mathbf{w}^H\mathbf{R}\mathbf{w} = 1 \end{array} \right\} \tag{3.37}$$

All algorithms involve maximizing the output energy subject to different quadratic constraints. Based on the gradient-projection algorithm, the implementation of the adaptive algorithm involves two steps:

1. Update the weight vector by making a change in the direction of the instantaneous estimate of the gradient vector

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu \nabla F_{\mathbf{w}} \tag{3.38}$$

   where μ is the step size.

2. Project the updated weight vector onto the constraint boundary.

In Method II, the constraint region is a closed sphere centered at the origin, and therefore projection will be simply equivalent to scaling the weight vector to satisfy the constraint, i.e.

$$\mathbf{w}(n+1) \longleftarrow \frac{\mathbf{w}(n+1)}{|\mathbf{w}(n+1)|} \tag{3.39}$$

For Methods I and III, the constraint region is actually an ellipsoid centered at the origin and scaling does not have the projection property anymore. This problem can be solved by transforming the system into new coordinates, so that the quadratic constraint boundary is spherical again. For this transformation we use the Cholesky factorization of $\mathbf{R}$ in Method III (or $\mathbf{R}_f = \mathbf{R} - \mathbf{R}_s$ for Method I) which can be written as

$$\mathbf{R} = \mathbf{c}^H \mathbf{c} \tag{3.40}$$

The optimization rule can be modified as

$$\max_{\mathbf{v}} F_{\mathbf{v}} = \mathbf{v}^H (\mathbf{c}^H)^{-1} \mathbf{R}_s \mathbf{c}^{-1} \mathbf{v} \textit{subject to} \qquad \mathbf{v}^H \mathbf{v} = 1 \tag{3.41}$$

where $\mathbf{v} = \mathbf{c}\mathbf{w}$ is the new transformed weight vector and equivalently can be written as

$$\mathbf{w} = \mathbf{c}^{-1} \mathbf{v} \tag{3.42}$$

$$\mathbf{w}^H = \mathbf{v}^H (\mathbf{c}^H)^{-1} \tag{3.43}$$

The adaptation rule using the new weight vector is given by

$$\mathbf{v}(n+1) = \mathbf{v}(n) + \mu \nabla F_{\mathbf{v}} \tag{3.44}$$

$$\mathbf{v}(n+1) \longleftarrow \frac{\mathbf{v}(n+1)}{|\mathbf{v}(n+1)|} \tag{3.45}$$

For transforming back to the old coordinates, we first compute gradient vector $\nabla F_{\mathbf{v}}$ in terms of $\nabla F_{\mathbf{w}}$ as follows:

$$\nabla F_{\mathbf{w}} = \widehat{\mathbf{R}}_s \mathbf{w} \tag{3.46}$$

where $\widehat{\mathbf{R}}_s$ is the instantaneous estimate of the covariance matrix $\mathbf{R}_s$ and is defined as

$$\widehat{\mathbf{R}}_s = \mathbf{X}\mathbf{s}\mathbf{s}^T\mathbf{X}^H \tag{3.47}$$

We may now write

$$\nabla F_{\mathbf{v}} = (\mathbf{c}^H)^{-1}\widehat{\mathbf{R}}_s\mathbf{c}^{-1}\mathbf{v} = (\mathbf{c}^H)^{-1}\widehat{\mathbf{R}}_s\mathbf{w} = (\mathbf{c}^H)^{-1}\nabla F_{\mathbf{w}} \tag{3.48}$$

Premultiplying both sides of Eq. (3.44) by $\mathbf{c}^{-1}$ yields,

$$\mathbf{c}^{-1}\mathbf{v}(n+1) = \mathbf{c}^{-1}\mathbf{v}(n) + \mu\mathbf{c}^{-1}\nabla F_{\mathbf{v}} \tag{3.49}$$

Using Eqs. (3.42) and (3.48), we may rewrite Eq. (3.49) as

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\mathbf{c}^{-1}(\mathbf{c}^H)^{-1}\nabla F_{\mathbf{w}} \tag{3.50}$$

For Method III, Eq. (3.40) may be equivalently written as

$$\widehat{\mathbf{R}}^{-1} = \mathbf{c}^{-1}(\mathbf{c}^H)^{-1} \tag{3.51}$$

After substitution of Eqs. (3.51) and (3.47) into Eq. (3.50), we obtain

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu_3\widehat{\mathbf{R}}^{-1}\widehat{\mathbf{R}}_s\mathbf{w} \tag{3.52}$$

The smoothened estimate of the covariance matrix $\mathbf{R}$, is defined as

$$\widehat{\mathbf{R}}(t) = (1-\alpha)\widehat{\mathbf{R}}(t-1) + \alpha\mathbf{X}(t)\mathbf{X}^H(t) \tag{3.53}$$

where α is the smoothing parameter ($0 < \alpha \leq 1$). In the special case of no smoothing (i.e. $\alpha = 1$), we have

$$\widehat{\mathbf{R}} = \mathbf{X}\mathbf{X}^H \tag{3.54}$$

Therefore, we have

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu_3(\mathbf{X}\mathbf{X}^H)^{-1}\mathbf{X}\mathbf{s}\mathbf{s}^T\mathbf{X}^H\mathbf{w} \tag{3.55}$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu_3(\mathbf{X}\mathbf{X}^H)^{-1}\mathbf{X}\mathbf{s}y^\star \tag{3.56}$$

where

$$y^\star = \mathbf{s}^T\mathbf{X}^H\mathbf{w} \tag{3.57}$$

Now, scaling of the weight vector can be performed as follows

$$\mathbf{w}(n+1) \longleftarrow \frac{\mathbf{w}(n+1)}{\mathbf{w}(n+1)\mathbf{R}\mathbf{w}(n+1)} \tag{3.58}$$

Similarly, in Method I, we may write

$$\mathbf{R}_I^{-1} = (\mathbf{R} - \mathbf{R}_s)^{-1} = \mathbf{c}^{-1}(\mathbf{c}^H)^{-1} \tag{3.59}$$

Hence, Eq. (3.50), can be expressed as

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu_1(\widehat{\mathbf{R}} - \widehat{\mathbf{R}}_s)^{-1}\widehat{\mathbf{R}}_s\mathbf{w} \tag{3.60}$$

Therefore, we have

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu_1(\mathbf{X}\mathbf{X}^H - \mathbf{X}\mathbf{s}\mathbf{s}^T\mathbf{X}^H)^{-1}\mathbf{X}\mathbf{s}\mathbf{s}^T\mathbf{X}^H\mathbf{w} \tag{3.61}$$

Finally, we may have the following adaptive equations:

$$I: \quad \mathbf{w}(n+1) = \mathbf{w}(n) + \mu_1\left[\mathbf{X}(n)(\mathbf{I} - \mathbf{s}\mathbf{s}^T)\mathbf{X}^H(n)\right]^{-1}\mathbf{X}(n)\mathbf{s}y^\star \tag{3.62}$$

$$II: \quad \mathbf{w}(n+1) = \mathbf{w}(n) + \mu_2\mathbf{X}(n)\mathbf{s}y^\star \tag{3.63}$$

$$III: \quad \mathbf{w}(n+1) = \mathbf{w}(n) + \mu_3\left[\mathbf{X}(n)\mathbf{X}^H(n)\right]^{-1}\mathbf{X}(n)\mathbf{s}y^\star \tag{3.64}$$

3.3 Simulation Results in AWGN Channel

This section is divided into two parts. The first set of simulation results shows how an antenna array improve the performance of a conventional receiver. In the second part of the simulation, we will demonstrate and analyze the performance of the adaptive blind arrays developed in Section 3.2.

User #	Power (dB)	DOA (deg.)
1	0-8	60
2	10	0
3	10	30
4	10	45
5	10	90

Table 3.1: Signal parameters of five users transmitting signals from different directions

3.3.1 Simulation Assumptions

The system we consider in the simulation is a DS-CDMA system with a processing gain, N, equal to 31. The modulation scheme used in the system is the binary phase-shift keying (BPSK), and the carrier frequency f_c is equal to 2 GHz. An uniform linear array with half wave-length spacing between the elements is used in the base station of the system to perform spatial filtering in the reverse link (from the mobile to the base station). All of the antenna arrays modeled are omni directional arrays which cover 0 to 180 degree region. The direction of arrivals (DOA) of the signal are equally spaced between 0^o and 180^o. We assume that there is no multipath and the radio channel only introduces the *additive white Gaussian noise* (AWGN). The noise is assumed to be independent between the antenna elements; therefore, it is generated separately and independently for each element. To simplify the analysis, we will assume that the interfering signals are uncorrelated with the desired signal. We also assume perfect power control in the base station unless otherwise stated, so all signals impinging on the array have the same power. Almost all of the above mentioned assumptions and conditions will be used in all examples throughout this research.

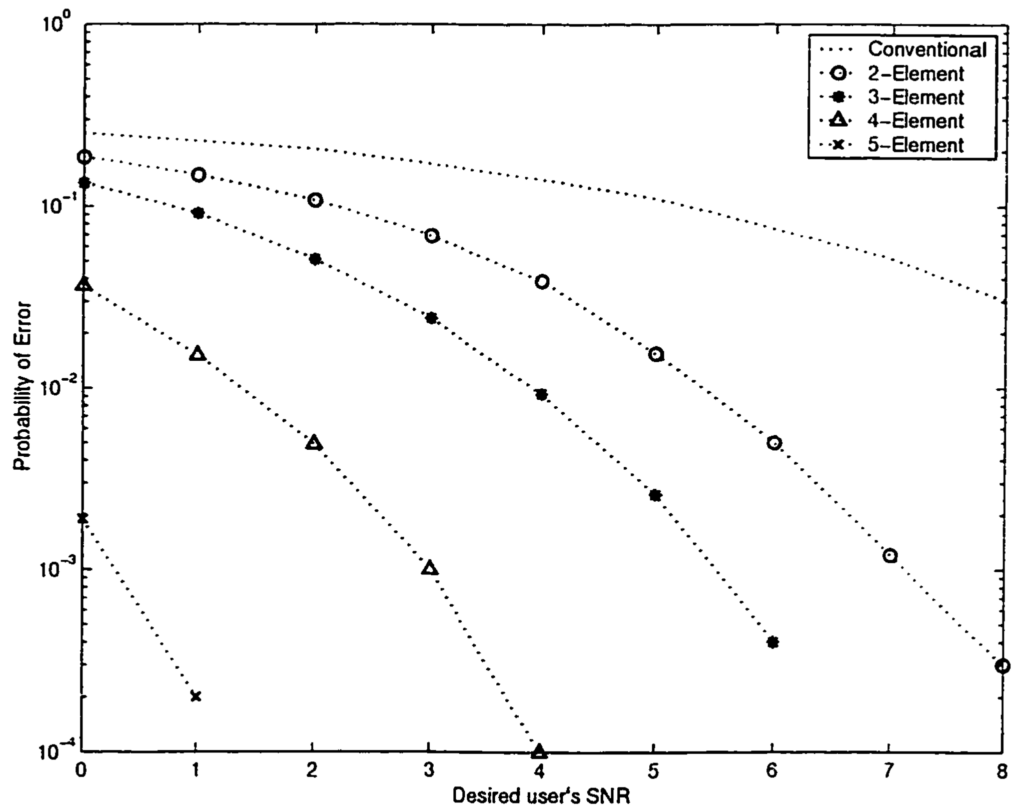


Figure 3.5: BER performance of a conventional beamformer as a function of number of antennas.

3.3.2 BER Performance of an Conventional Beamformer

As the first example, let's compare the performance of a conventional beamformer with a conventional single-element receiver. Besides, we will examine the performance achievable by employing antenna arrays as a function of the number of elements.

We will assume that five users are present in the system, transmitting CDMA signals from different directions. Assuming the first user as the desired one, the input signal to noise ratio per bit (E_b/N_0) for all other users (interferers) is set to 10 dB. Table 3.1 shows the parameters of all the user's signals.The BER performance of the conventional beamformer for different number of antennas has been shown in Fig. 3.5. As we can see, by increasing the number of antenna elements at the receiver the BER performance has been improved dramatically. The reason is that the interferers have a relatively large angle separation from the desired user so there is no interference falling into the main beam of the array which is steered toward the desired signal. As a result, using its spatial filtering property, the antenna array is able to suppress the interference effectively.

3.3.3 Degrees of Freedom for an Adaptive Antenna Array

The more antenna elements in an array, the more degrees of freedom the antenna possesses in combating interference and multipath fading. In general, for an antenna array with N-elements, there would be $N-1$ degrees of freedom and thus it will be able to null out $N-1$ interferers. To illustrate how an adaptive array performs with different number of elements, we will use the following example. Assuming the same system as the previous example with five active users. Table 3.2 shows the power levels and the DOAs of all the user's signal. This time we will perform the experiment by using adaptive antenna arrays. The convergence factor, μ, of 0.001 was selected to control the rate of convergence of the weights. The input signal to

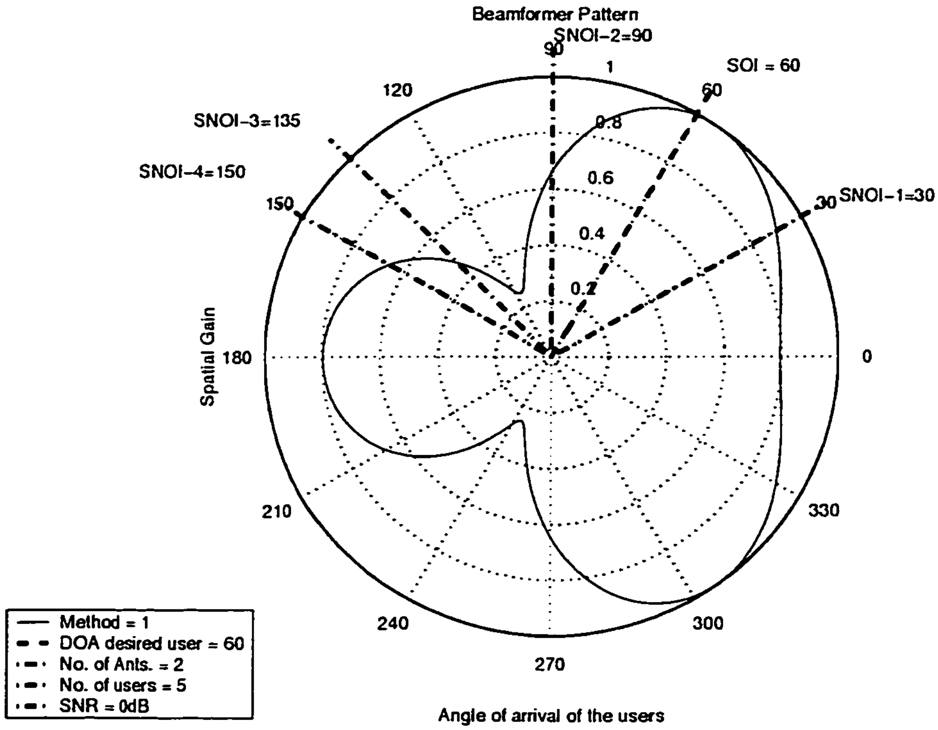
User #	Power (dB)	DOA (deg.)
1	0	60
2	10	30
3	10	90
4	10	135
5	10	150

Table 3.2: Signal parameters of five users transmitting signals from different directions

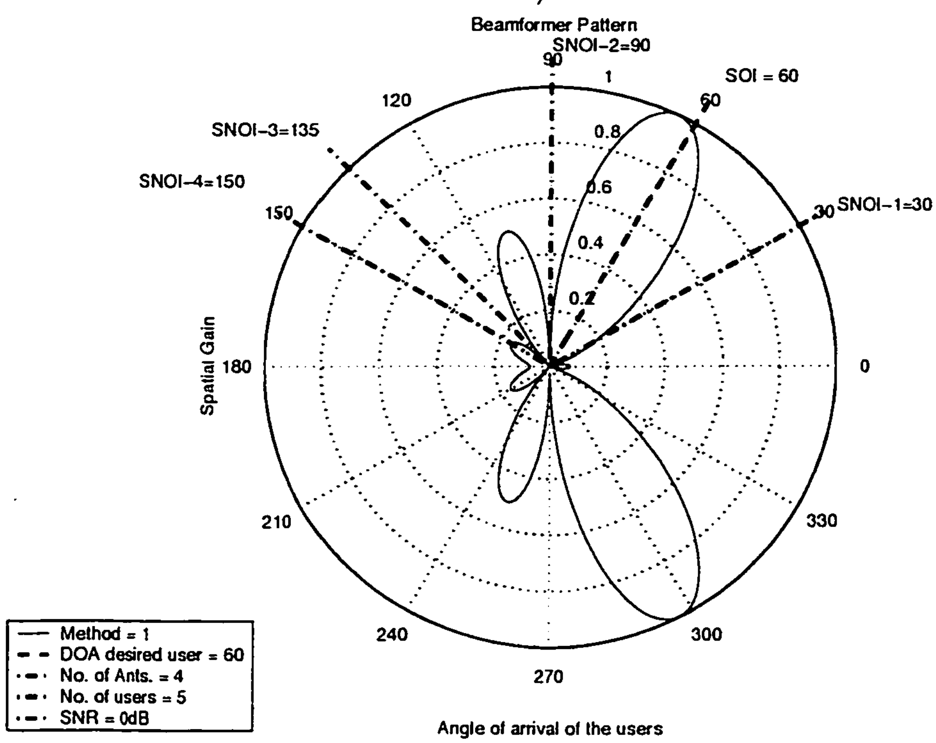
noise ratio per bit (E_b/N_0) is set to 0 dB for the desired signal. We will further assume that interfering signals, signal-not-of-interest (SNOI), are 10 times stronger than the desired signal and uncorrelated. The polar coordinate plots of the desired users' beampattern for arrays with different number of elements are shown in Figs. 3.6 and 3.7. The labels surrounding the diagram are the angles of arrival.

This example demonstrates the ability of a narrowband antenna array to adapt its antenna gain to enhance signals of interest while reducing or completely cancelling signals which are not of interest. A close analysis of the antenna pattern shows that the beam is directed toward the desired user while nulls are placed at the interferers' DOAs. However, the number of nulls in each case, depends on the number of antennas.

Comparing Fig. 3.6(a), (b) and Fig. 3.7, we see that the array with six elements is more effective in nulling the interference compared to the array with 2- or 4-elements. In addition, we can see from Fig. 3.6 (b) that in a 4-element linear array, the antenna only has three degree of freedom, hence it can only put three nulls in the direction of the interferers. If there is more than three interferer, the array will pick the strongest interferer and automatically put a null in that direction. The obvious conclusion is that the more elements the array has, the more effective it will be against the interference because it has more degrees of freedom in terms of controlling the antenna pattern. Nevertheless, a tradeoff between the number of antennas, which, in turn, affects the complexity, and the desirable performance



a)



b)

Figure 3.6: Array gain versus angle of arrival a) 2-element b) 4-element

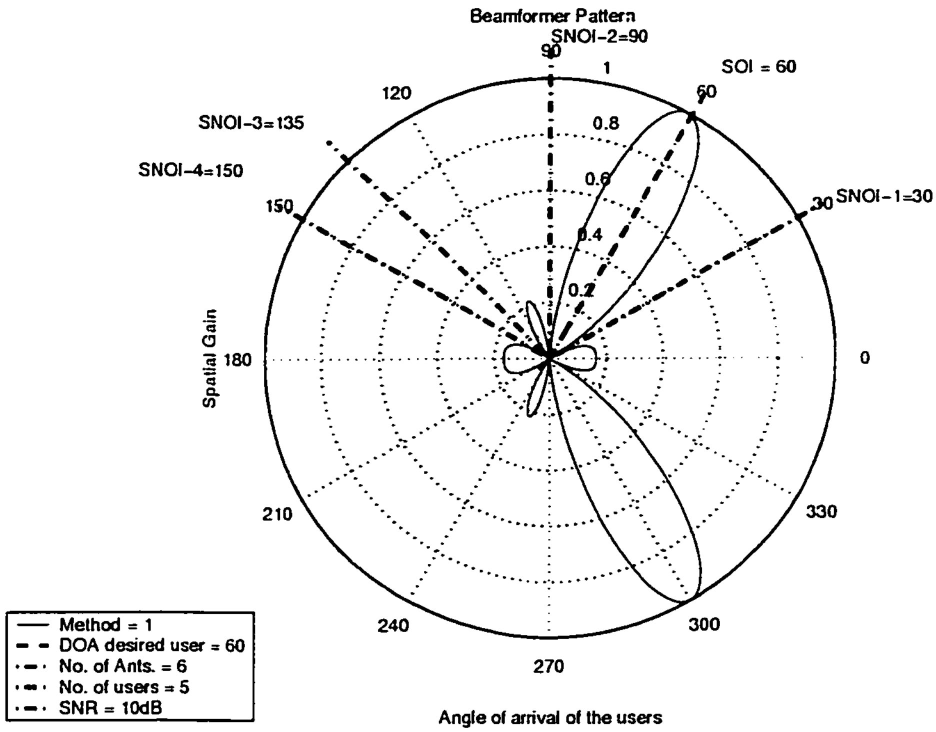


Figure 3.7: Array gain versus angle of arrival for a 8-element array

should be considered. Furthermore, having more elements will cause all the weights to take longer to converge. As a result, a time delay will occur, which cannot be ignored in a real time communication system.

In a wireless communication system, especially in a CDMA system, the number of users in a radio channel is always much greater than the number of array elements, and if the multipaths of each user's signal are taken into account, the total number of signals impinging on the array will far exceed the number of array elements (i. e. over-loaded adaptive array). In this case, the array will continue to form a beam in the direction of the desired user; however, the interference nulling property of the array will be sharply reduced. Hence, the purpose of having a higher degree of freedom is just to form nulls in the directions of the strong interferers instead of nulling out all of the interfering signals.

3.3.4 Performance of Adaptive Blind Arrays

In this section, we analyze and compare the performance of the different adaptive blind algorithms. In each example, the beam-patterns of the detectors will be compared. All the examples correspond to a system with Gold codes of length $N = 31$ and five users $K = 5$.

Example 1 The power levels and the spatial distribution of the 5 users are given in Table 3.2. Figs. 3.8 and 3.9 show the beam-patterns of the desired user, which is assumed to be the first user, using all three adaptive blind algorithms presented in Section 3.2, for 3-element and 5-element linear arrays, respectively. In each beam-pattern, more or less, the array is able to adjust the main lobe and point it toward the DOA of the signal-of-interest (SOI) which is assumed to be 60^o. Among the three methods, with no knowledge of the array response vector, the first and third methods perform very similar to each other and overall better than Method II. It is because of the spatial nulls placed in the direction of the interferers (e.g. In Fig. 3.8 two interferers are $SNOI - 2 = 90^o$ and $SNOI - 4 = 150^o$). However, the other interferers have also been attenuated effectively (e.g. In Fig. 3.8 other two interferers are $SNOI - 1 = 30^o$ and $SNOI - 2 = 135^o$) .

As explained in Section 3.2, in Method I the beamformer is adapted to maximize the ratio of desired user's energy to the energy of interference plus noise, while in Method II, the beamformer maximizes the ratio of desired user's energy to energy of noise. When interference energy dominates the noise energy, the beamofrmer achieves the maximum ratio by placing nulls in the direction of the interferers. However, since the receiver doesn't know the array response vector of the desired user and the numerator of the optimization function is only an approximation of the energy of the desired user, no mechanism is involved to prevent the desired user from being attenuated in the process.

Comparing the performance of Methods I and III, we can see that Method I can generate deeper nulls in the DOAs of the interference than Method III; therefore,

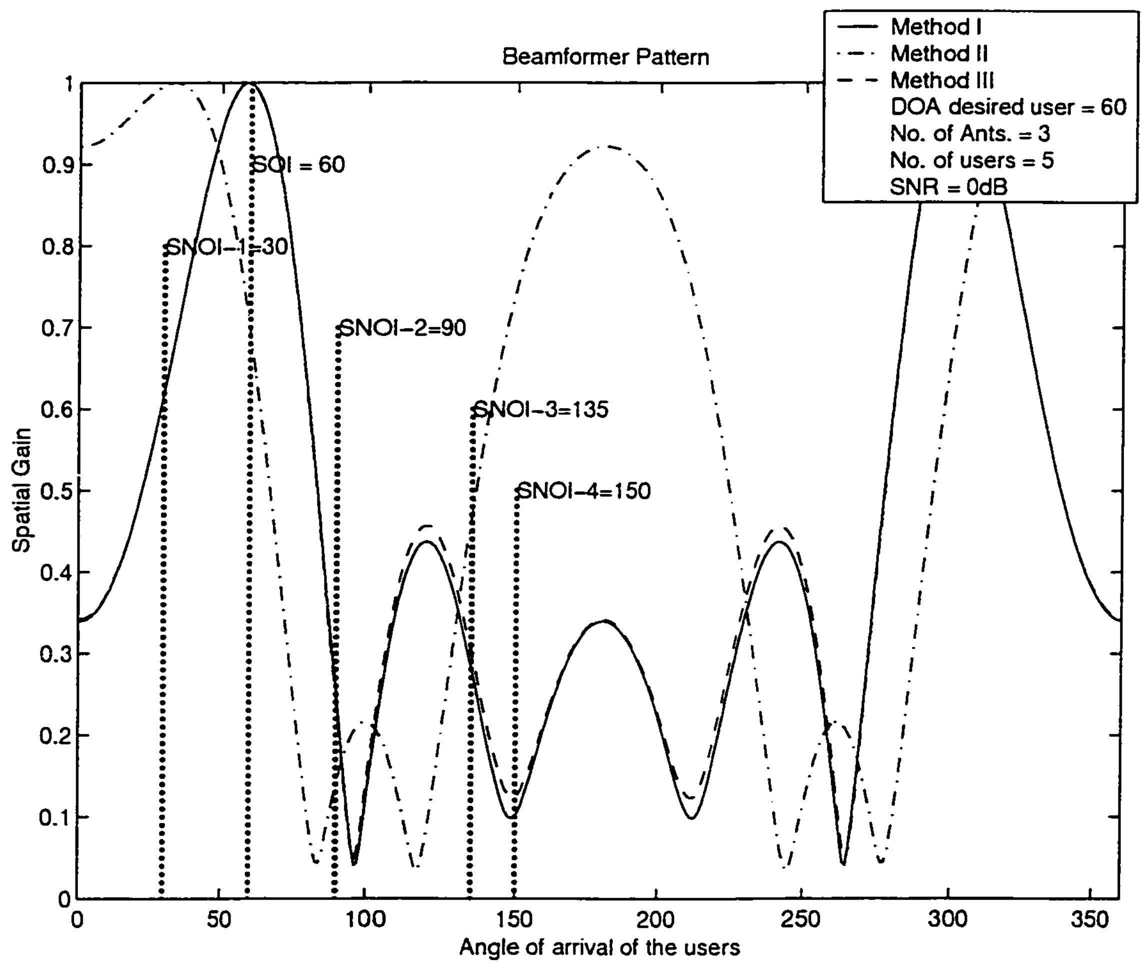


Figure 3.8: Beam-patterns for three adaptive blind algorithms.

Method I can reduce the interference to a lower level. The reason is that in Method I by minimizing the error in our optimization, we have utilized the estimate of the data at the output of the receiver, while in Method III, the output energy of beamformer is used as the cost function.

It should be noted that the improvement of Methods I and III over Method II becomes smaller when the system is over-loaded. This is because under the over-loaded situation, the multiple access interference can be approximately considered to be spatially white, since in average the interfering users cover the space more densely at smaller angular distances from each other. Moreover, the interference falling into the main beam of each output port will dominate the overall interference level.

Example 2 To evaluate the performance of the adaptive blind arrays for different ratio of desired user's energy to energy of noise, we consider a system with the same spatial distribution of the users as in Table 3.1. Assuming 10 dB as the SNR for all four interferers, Fig. 3.10 shows the beampatterns correspoding to the desired signal using Method II discussed in the previous section. In Fig. 3.10(a) and (b), the SNR of the desired signal is assumed to be 0 dB and in Fig 3.10(c) and (d) the SNR is changed to 10 dB. As we can see in Fig. 3.10(a), when the SNR is low, the beamformer is not capable to steer the main beam toward the desired signal source. However, as we increase the number of elements from three to four, a substantial performance improvement can be achieved (Fig. 3.10(b)). In Fig. 3.10(c) and (d), the same simulation conditions apply, but this time we vary the strength of the desired signal (e. g. SNR=10 dB). As the SNR changes, we notice that this time, the beamformer performs much better. This shows that the shape of the beam in Method II is a suction of the desired user' strength. However, it can be seen that adding extra antennas and using the spatial distribution of the users to further discriminate between them always improve the performance of the receiver.

Since Methods I and III are very close in respect to the performance, we have

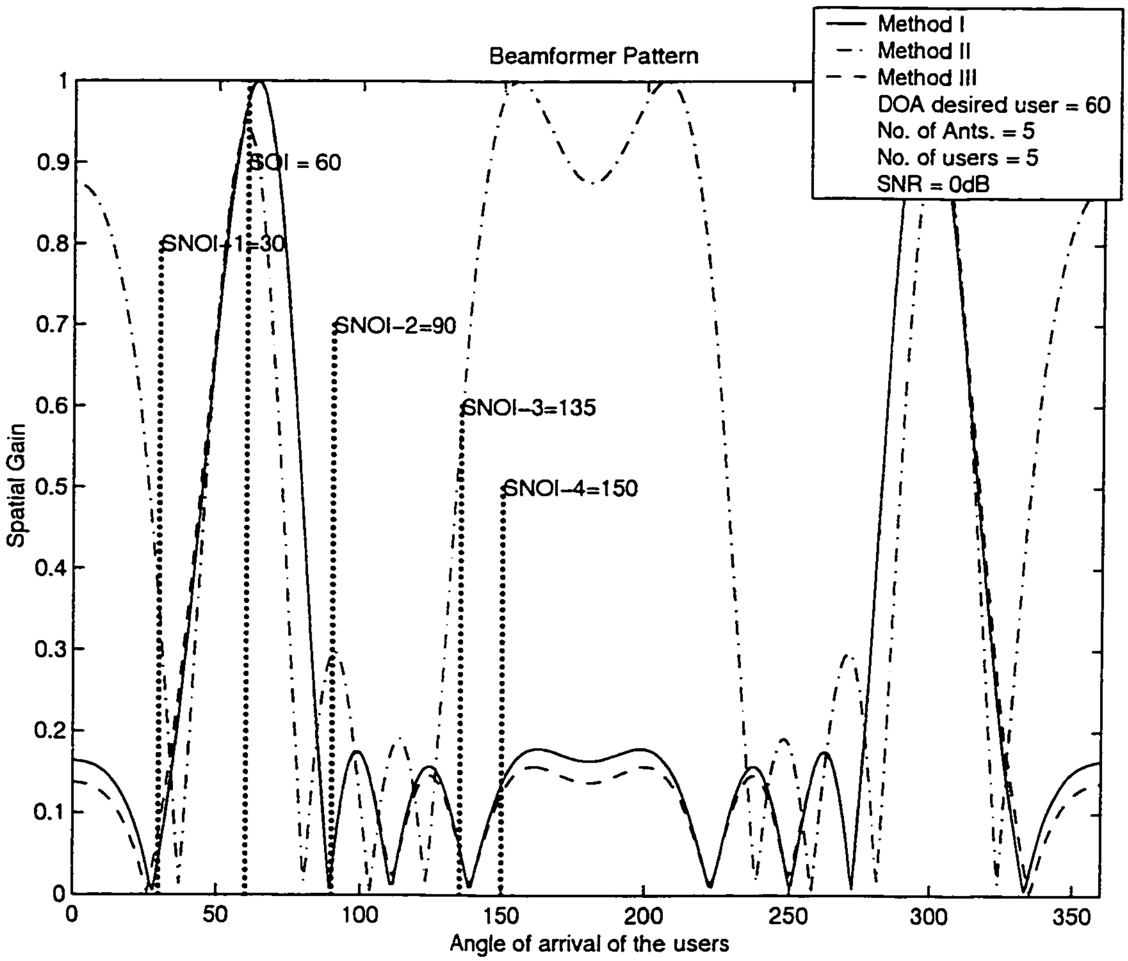


Figure 3.9: Beam-pattern for three adaptive blind algorithms.

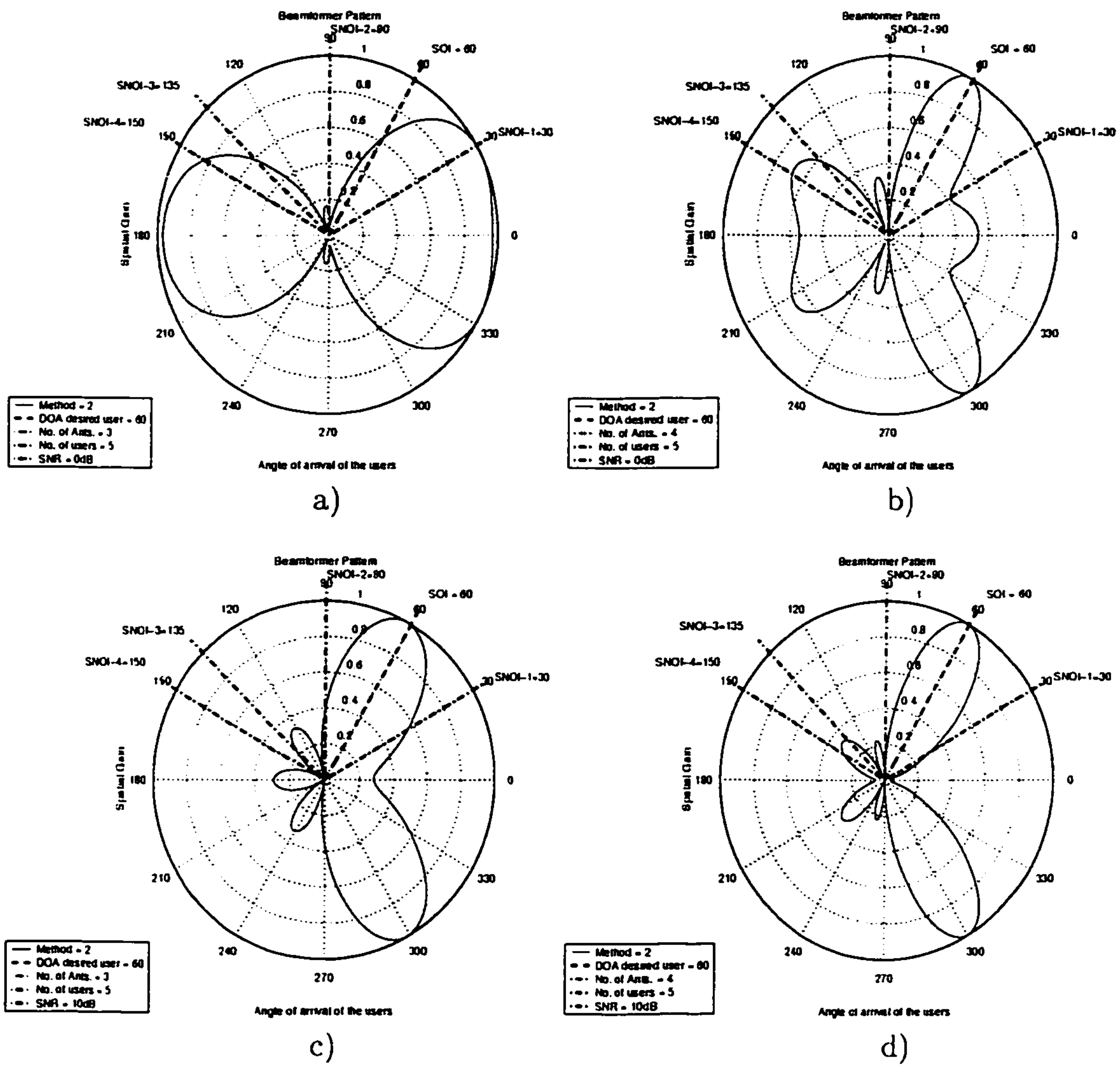


Figure 3.10: Beam-patterns with different SNR using Method II.

User #	Power (dB)	DOA (deg.)
1	0	60
2	10	55
3	10	75
4	10	100
5	10	135

Table 3.3: Signal parameters of five users transmitting signals from different directions

repeated the same simulation by only using Method III. Fig. 3.11 shows the beam-patterns of the desired user, which is assumed to be the first user. The gain achieved by this method is much better than Method II even under poor SNR situations. However, when the desired signal is much stronger than the noise (Fig. 3.11(c) and (d)), the nulls which beamformer places in the direction of the interferers, increases in depth. As we mentioned before, the extra improvement can be achieved and the nulls will become very deep when the number of antennas increases (Fig. 3.11(c) and (d)).

Example 3 Practically, in a CDMA system, we have a large number of users which are transmitting signals from different directions (over-crowded DOA case). At the receiver, the beamformer construct a narrow beam directed to the desired signal source. However, depending on the angle separation of the signals, one or more signals may fall into one main beam. In such a case, although the interference is not rejected completely due to the wide bandwidth of the main beam directed to the desired user, most of the interference coming from other directions is rejected, thus the overall interference level is reduced. The rejection of the interference will result in a low BER.

This example demonstrates a case that one of the interferers has DOA which is very close to that of the desired signal. Signal energy and angle of arrival for five users are listed in Table 3.3. Assuming a 3-element linear array, Fig. 3.12 shows the beam-patterns of the desired user, employing both Methods II and III. From Fig

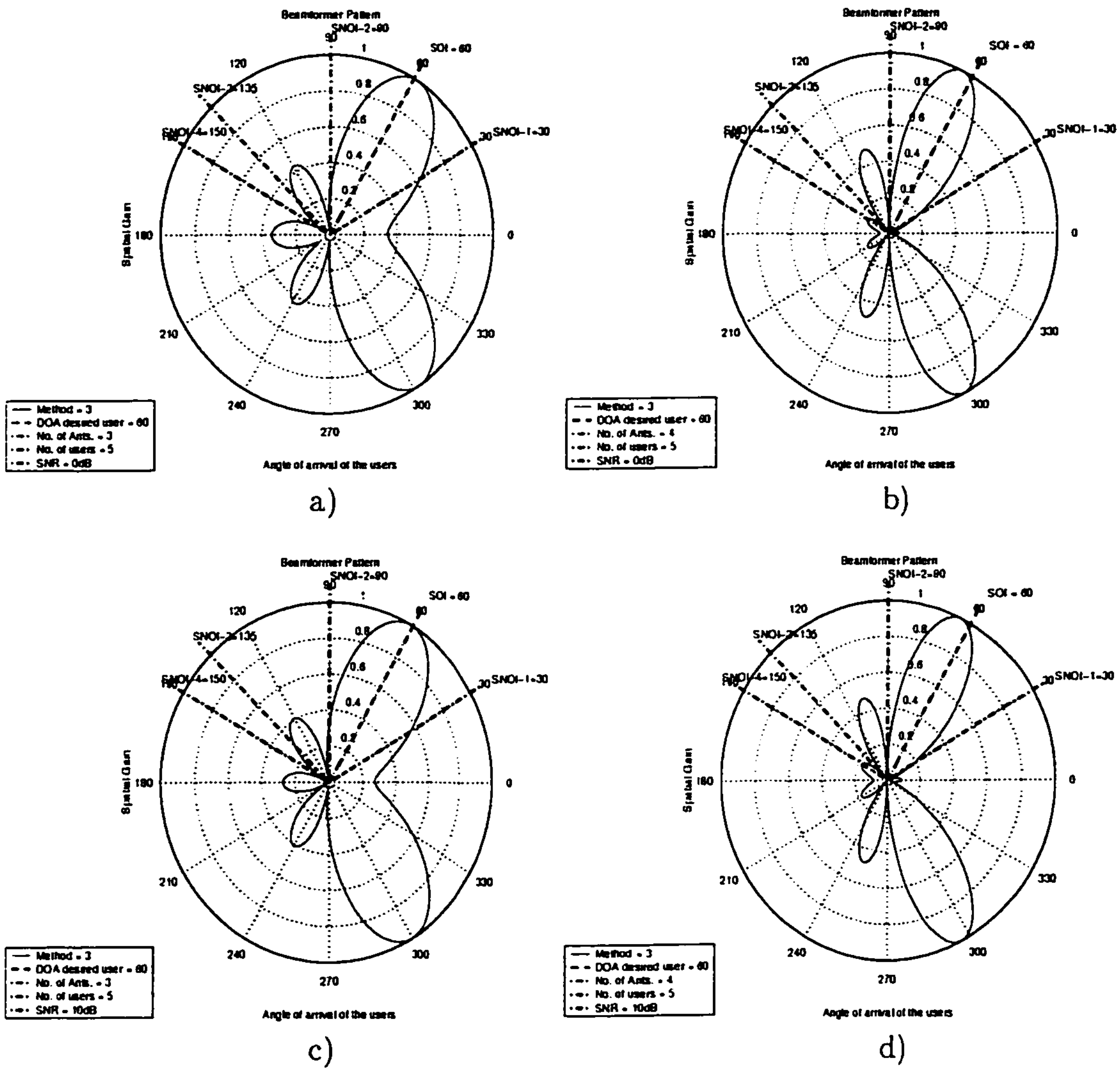


Figure 3.11: Beam-patterns with different SNR using Method III.

3.12(a) and (c), we see that except the signals with DOAs near the desired signal, most of the signals are suppressed. On the other hand, in Fig. 3.12(b) and (d), we see that Method III (and Method I) cannot work under the situation that a powerful interferer (e. g. at least 10 times stronger than that of the desired signal), with a small angle separation from the desired signal, incident to the array.

Comparing Methods II and III, we conclude that Method II can achieve a large improvement over the other one. It is because, in Method II the blind array acts as it does when only noise and desired signal are present. Hence, Method II always attempts to point the main lobe of the adaptive array to the desired user without any interference nulling.

The disadvantage of the blind receiver using Methods I and III is that it is not robust. Under certain conditions, depending on the relative spatial locations of the interferers and their energies, the performance of the multi-element blind adaptive receiver may degrade to a point that it becomes worse than the performance of the single-element receiver (Fig. 3.12(b) and (d)). This problem is due to the fact that the blind receiver does not have the knowledge of the array response vector of the desired user. At low SNR, the dominating source of interference is the white Gaussian noise and the solution for the beamforming stage will be close to the array response vector of the desired user. At high SNR, or equivalently for low noise levels, multiple access interference becomes dominant and the beamformer performs the maximization by steering nulls in the direction of the most dominating interfering user(s). Because the receiver does not have the knowledge of the desired user's array response vector, one or more of these nulls may fall in the direction of the desired user, thereby attenuating the signal from the user of interest.

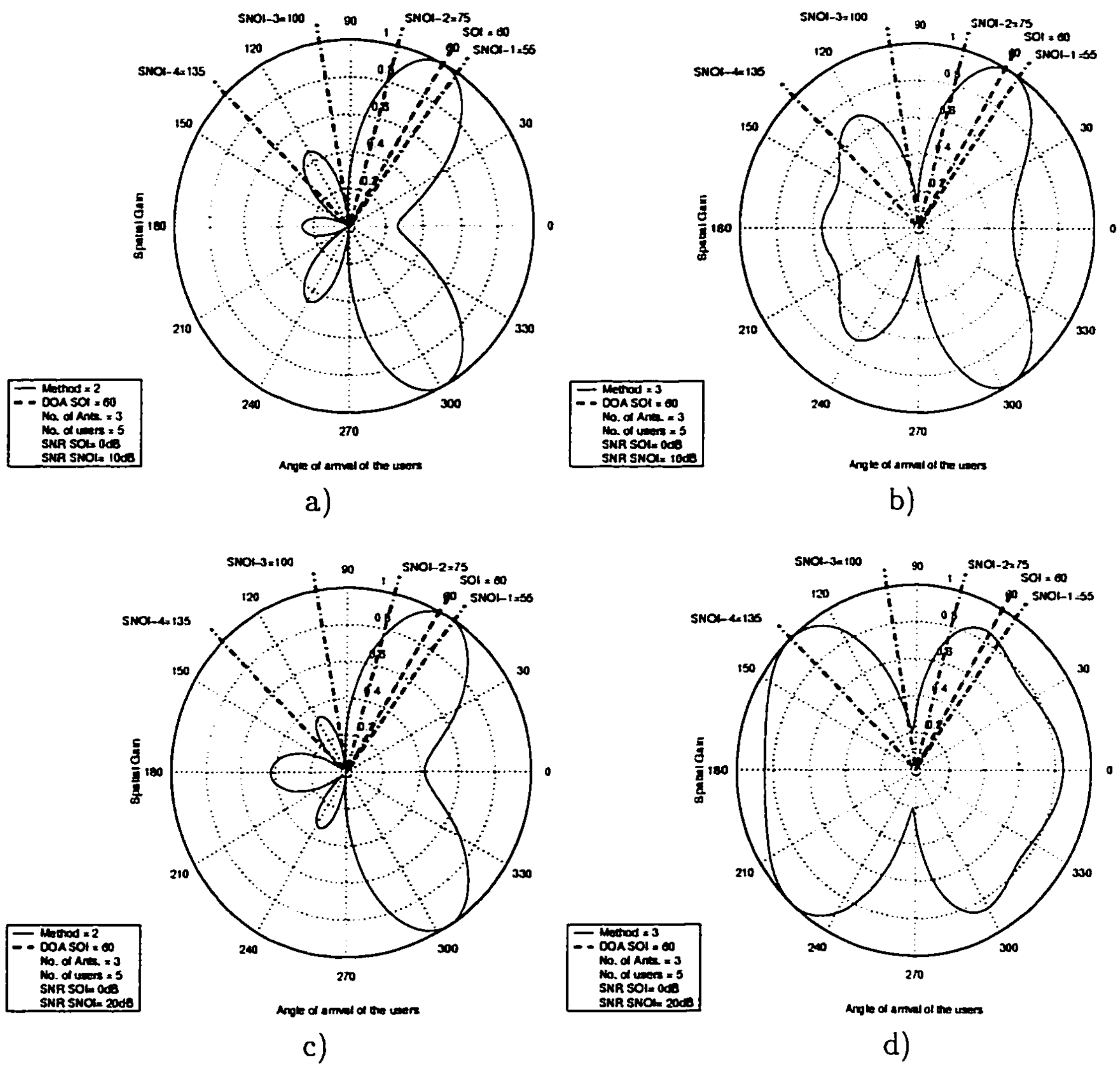


Figure 3.12: Beam-patterns for Methods II and III when in-beam interference exists.

3.4 Conclusions

In this chapter, The performance of adaptive blind arrays for WCDMA systems was presented. We have shown that a multi-element blind adaptive receiver is capable of adapting the weight vectors of the beamformer in a blind fashion to minimize the effect of multiple access interference and noise to detect the user of interest by employing spatial and temporal processing.

We have examined various optimization criteria for adaptive antenna array combining techniques and discussed their features. Specifically, we have discussed three different schemes for receivers that do not require the knowledge of the desired user's array response vector. All these receivers demonstrate improved performance compared to the single-element receiver, without requiring any extra information. It was shown that Methods I and III outperform Method II. However, in a near-far situation where the multiple access interference is large, robustness becomes an issue in Methods II. We have also concluded that the array is not capable of significantly attenuating interfering signals arriving at DOAs near the SOI.

In the next chapter, we will turn our focus back to parallel interference cancelling receiver, which was suggested as the best choice among the multiuser detection techniques. Then, we will introduce a new structure which combines multiuser detection and adaptive blind arrays. We will show that this combination scheme will be able to overcome the shortcoming of antenna arrays facing with in-beam interference.

Chapter 4

Combined Multiuser Detection and Adaptive Blind Arrays

4.1 Introduction

In the previous chapter, a multi-element blind adaptive multiuser detector was introduced and its performance was discussed. It was shown that this receiver would outperform its single-element counterpart without requiring any spatial information about the user of interest. It was also shown that in near-far situations, the performance of the receiver would degrade for some spatial distribution of the users. In addition, we mentioned that if there is a high-level interfering signal from an undesired user with the same arrival angle as that of a desired user, an antenna array cannot suppress it. Moreover, the inherent structure of the multiple access interference is not exploited, i.e., no multiuser detection is employed.

In this chapter, we will investigate the receiver structure that both multiuser detection and beamforming are employed to further increase the uplink capacity of a CDMA system. A number of combined multiuser detection and array processing techniques have been developed for enhancing the performance of CDMA systems, including a decorrelator, an MMSE detector, a maximum likelihood detector, and

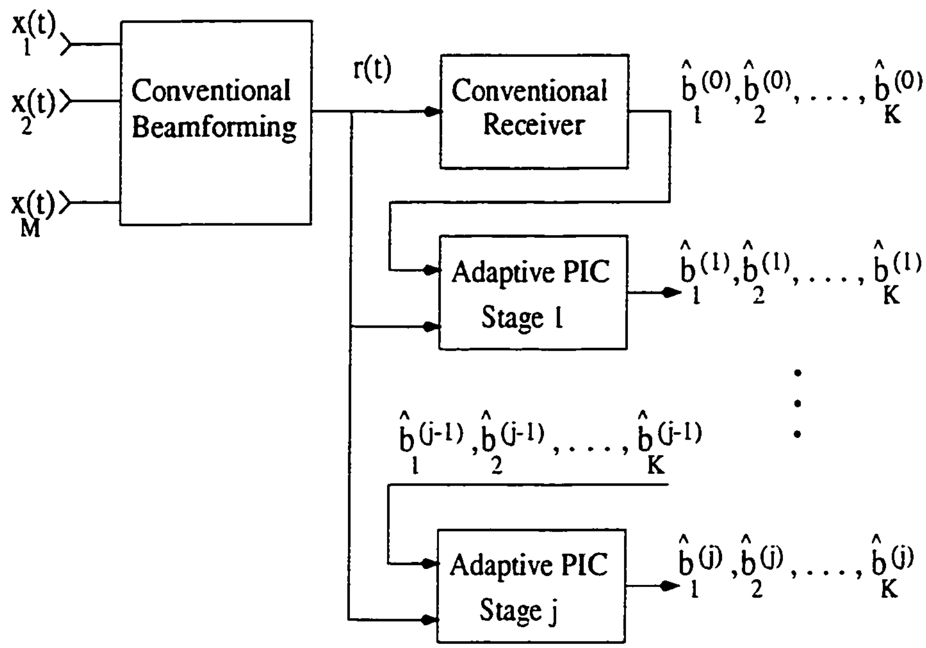


Figure 4.1: Block diagram of a multi-element adaptive parallel interference canceller.

a comprehensive treatment of space-time multiuser detection in [6]. In our work, we present a receiver structure combining an adaptive blind array with a multi-stage adaptive parallel interference cancellation receiver for CDMA communication systems [43][44]. Using antenna array, the interfering signals that are spatially separated from the desired user can be filtered out, therefore reducing the major amount of interference seen by the desired user. In addition, employing multiuser detection techniques will help the detector to remove the residual interference.

4.2 Combined Adaptive Parallel Interference Cancellation and Conventional Beamforming

As we indicated in Chapter 2, among the multiuser detection techniques, adaptive parallel interference cancellation can outperform some of the existing interference cancellation methods. The block diagram of the extension of an adaptive multistage

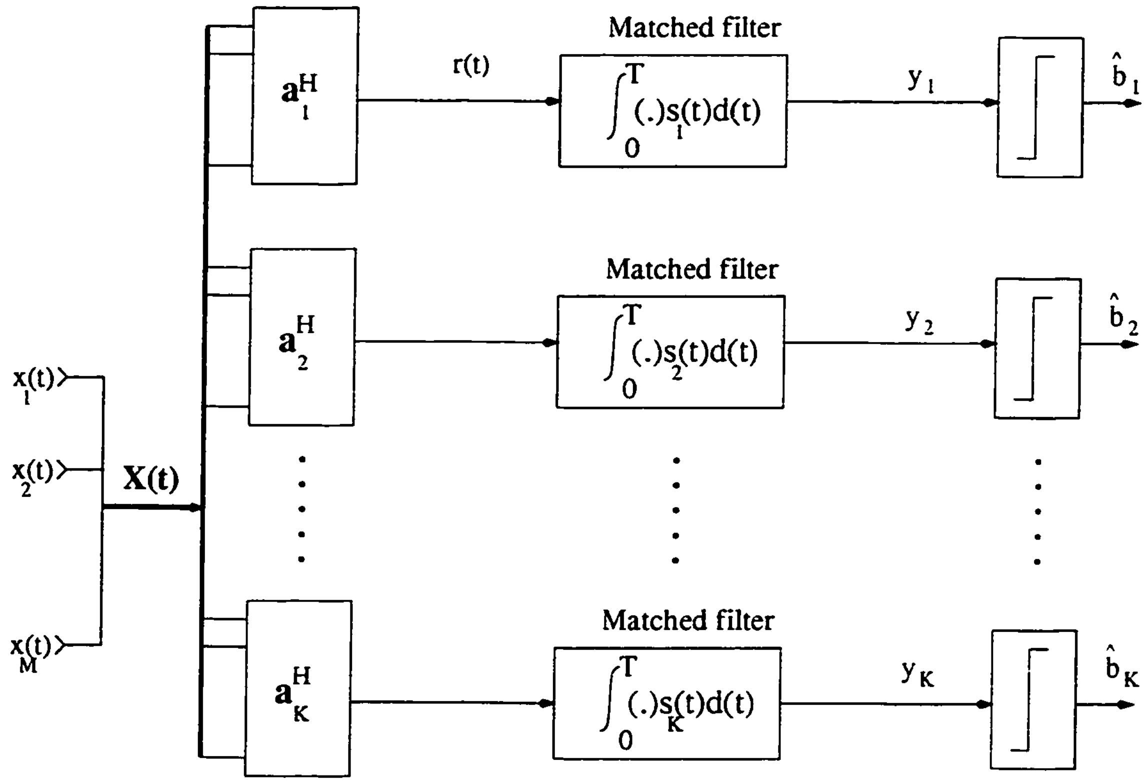


Figure 4.2: Block diagram of a DS-CDMA conventional receiver extended to antenna arrays.

parallel interference cancellation scheme to antenna array is shown in Fig. 4.1. The initial stage of this structure is a conventional single user detector and a conventional beamformer (Fig. 4.2). Decisions made at this stage are used to reconstruct MAI in the following stage for the interference cancellation. The block diagram of an LMS-based APIC scheme is depicted in Fig. 4.3. In each stage of APIC, a low-complexity normalized least mean square (LMS) algorithm is employed in searching for the optimal weights. The cost function tries 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.

Considering the same system model and notation as presented in Chapter 3, the received signal after beamforming can be expressed as

$$r(t) = \sum_{m=1}^{M} x_m(t) w_m \tag{4.1}$$

where x_m denotes the received signal at the m^{th} antenna described as

$$x_m(t) = \sum_{i=0}^{I} \sum_{k=1}^{K} \sqrt{e_k} b_k(i) s_k(t - iT_b) a_m(\theta_k) + z(t) \tag{4.2}$$

where the parameter I is used as the number of bits or packet that each user transmits, $b_k(i) \in \{-1. +1\}$ the i^{th} symbol transmitted by user k, e_k received energy of the k^{th} user at each antenna, and $z(t)$ is the additive complex white Gaussian noise. For conventional beamforming we have

$$w_m = a_m^*(\theta_1) \tag{4.3}$$

where $a_m(\theta_1)$ is the m^{th} antenna element complex array response corresponding to the desired signal with direction of arrival of θ_1. Without loss of generality, we assumed the first user as the user of interest.

The received signal is sampled at the chip rate after chip-matched filtering. The N samples of the received signal within one bit (i.e., since N is the processing gain so we have N chips for each bit) can be written as

$$r(n) = \sum_{k=1}^{K} \sum_{m=1}^{M} \sqrt{e_k} b_k s_k(n) a_m(\theta_k) a_m^*(\theta_1) + z(n) \tag{4.4}$$

where $z(n)$ is the noise sample. Next stage following beamforming is a set of conventional single-user correlators, whose outputs, $(\widehat{b}_1 \widehat{b}_2, ..., \widehat{b}_k)$, are served as the inputs of the first stage of the LMS-PIC, i.e.,

$$\widehat{b}_k = sgn(Y_k) \tag{4.5}$$

where Y_k is defined as the real part of the output of the matched filter used for despreading k^{th} user signal, i.e.

$$Y_k = Re(y_k) \tag{4.6}$$

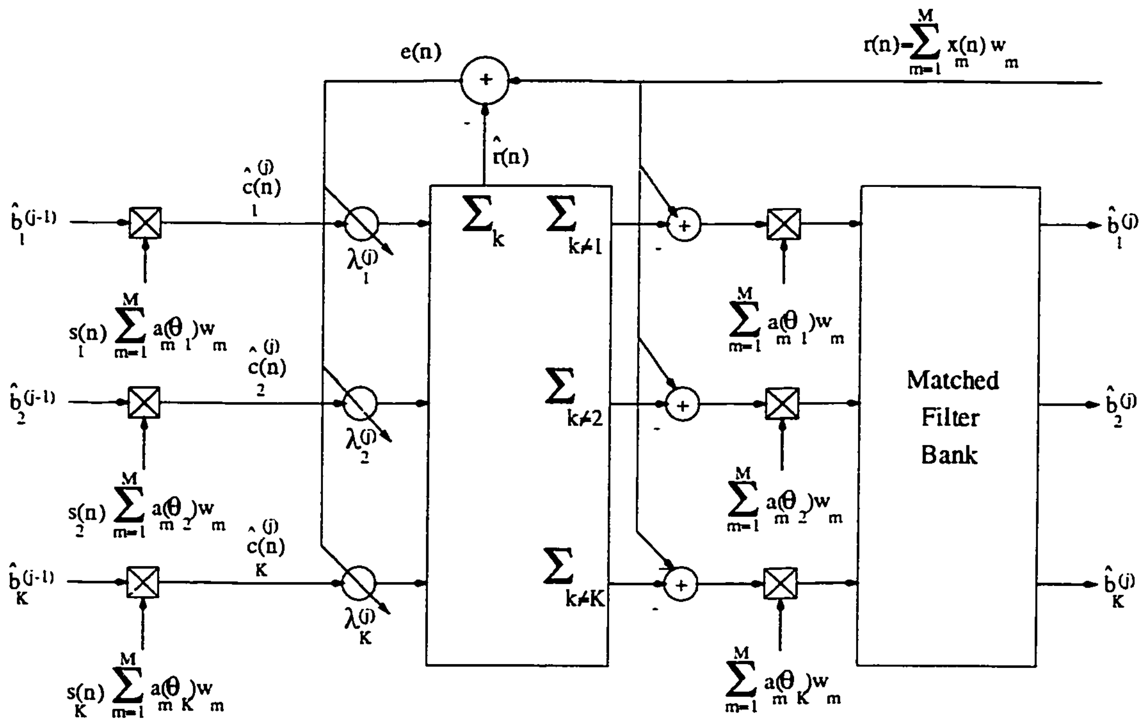


Figure 4.3: Block diagram of an LMS-based adaptive parallel interference canceller in each stage.

Employing a low-complexity normalized least mean square (LMS) algorithm in searching for the optimal weights, the cost function tries 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. Since the LMS algorithm is based on the mean-squared error (MSE) criterion, for the j^{th} stage PIC, the cost function can be formulated as

$$J = \min_{\lambda^{(j)}} E\left[|r(n) - \widehat{r}^{(j)}(n)|^2\right] \tag{4.7}$$

where $\lambda^{(j)} = (\lambda_1^{(j)}, \lambda_2^{(j)}, \ldots, \lambda_K^{(j)})^T$ is the weighting vector for the j^{th} stage adaptive PIC algorithm, and $\widehat{r}^{(j)}(n)$ the estimate of the received signal in the j^{th} stage defined as

$$\widehat{r}^{(j)}(n) = \sum_{k=1}^{K} \widehat{c}_k^{(j)}(n)\lambda_k^{(j)}(n) \tag{4.8}$$

with

$$\widehat{c}_k^{(j)}(n) = \widehat{b}_k^{(j-1)} s_k(n) \sum_{m=1}^{M} a_m(\theta_k) w_m. \tag{4.9}$$

In Eq. (4.9) $\widehat{b}_k^{(j-1)}$ is the bit estimate of the k^{th} user from the previous stage, and $s_k(n)$ denotes the PN sequence of the k^{th} user. The weighting vector is adjusted via a normalized LMS algorithm that operates in a bit interval and on a chip basis as follows:

$$\lambda^{(j)}(n+1) = \lambda^{(j)}(n) + \frac{\mu\left[\widehat{c}^{(j)}(n)\right]^*}{||\widehat{c}^{(j)}(n)||^2} e^{(j)}(n) \tag{4.10}$$

where μ is the step size and $e^{(j)}(n)$ represents the error between the desired response and its estimate, namely

$$e^{(j)}(n) = r(n) - \hat{r}^{(j)}(n) \tag{4.11}$$

For each bit, $\lambda^{(j)}(N-1)$ is used as the weight in the interference cancellation. Considering the k^{th} user in the j^{th}stage, the interference cancellation is carried out as follows:

$$\xi_k^{(j)}(n) = \left\{ r(n) - \sum_{l=1, l \neq k}^{K} \lambda_l^{(j)}(N-1)\hat{c}_l^{(j)}(n) \right\} \times \sum_{m=1}^{M} a_m(\theta_k) w_m \tag{4.12}$$

A more reliable decision is then made based on the less interfered signal $\xi_k^{(j)}(n)$, therefore

$$\hat{b}_k^{(j)} = sgn\left[Y_k^{(j)} \right] \tag{4.13}$$

where

$$Y_k^{(j)} = Re\left\{ \sum_{n=0}^{N-1} \xi_k^{(j)}(n) s_k^*(n) \right\} \tag{4.14}$$

The step size μ plays an important role in the LMS algorithm. For the normalized LMS algorithm deployed in this approach, μ must satisfy $0 < \mu < 2$ to ensure the convergence of the LMS algorithm [42]. A larger step size can result in a faster convergence, but also causes a higher excessive gradient noise due to the misadjustment of the coefficients [42]. Another important factor that affects the convergence rate of the LMS algorithm is its initial state. In fact, the LMS algorithm has a lower convergence rate as compared to the RLS algorithm because it is more sensitive to its initial state. When the perfect knowledge of all users' levels is available, the initial value of the weight for each user can be set to its corresponding amplitude. Ideally with this setting, if all bit decisions from the previous stage are correct, the LMS algorithm will just fine tune to a small error signal. For a nonideal situation, when the amplitudes of all users are unknown, the initial weights for the LMS algorithm are set to one. The values of the weights at the last iteration of the current bit are used as the initial values of the weights for the next bit. Generally, an imperfect amplitude estimation only has a little impact on the performance of the APIC. However, more accurate bit and channel estimates can lead to a faster convergence of the weights to their optimal values.The conventional multi-element receiver is the first stage of a multistage PIC if the spatial distribution of all users is known a priori. However, when there is no information about the array response vectors of the users, then a blind approach can be substituted. Despite the fact that in a multistage PIC, by increasing the number of stages, better estimates of each user are produced at each stage (i.e. allowing more effective interference cancellation). But, by employing an antenna array as the first stage, the estimates of each user will be so accurate that there is no need for several cascaded stages. As a result, the computational complexity will not be a limiting factor.

4.3 Combined Adaptive Parallel Interference Cancellation and Adaptive Blind Arrays

In this section, we replace the combination of the conventional beamforming and conventional receiver in the last section with a blind adaptive antenna array as the first stage. The block diagram of a combined adaptive PIC and adaptive blind array scheme is shown in Fig. 4.4. In this scheme, the adaptive blind array will estimate the array response vector needed for each user. The structure of the adaptive blind array for each user is the same as what we discussed in Chapter 3 (Fig. 3.5). Simulations are carried out and presented in the following section to verify the BER performance of this combination scheme.

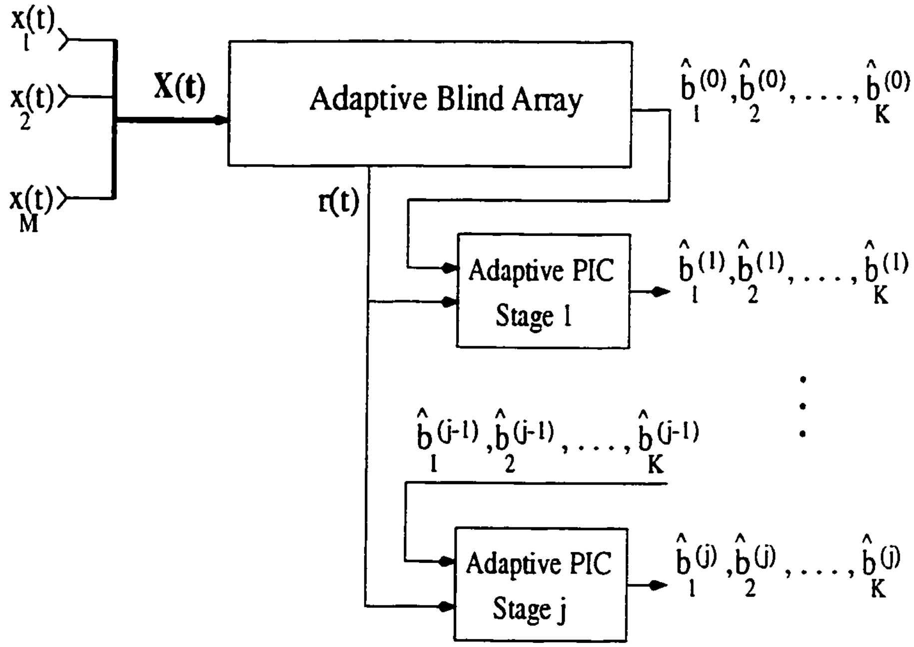


Figure 4.4: A DS-CDMA system including an adaptive blind array combined with an adaptive parallel interference canceller.

4.4 Simulation Results

To illustrate the performance of the proposed receiver and to compare it with the performance of the APIC and adaptive blind arrays, we consider a DS-CDMA system for the AWGN channel. We use the BPSK modulation and Gold codes with the length of 31, i.e., the processing gain of 31. The first user is considered as the desired one. The bit error probabilities versus the nominal signal-to-noise ratio for conventional receiver, APIC, adaptive blind arrays and the proposed scheme for five users are depicted in Fig. 4.5. Single user bounds are shown for two cases: single-element and two antennas. In this simulation study, it has been assumed that a very strong interferer with the same DOA as the desired signal exists in the system. The DOA and the power of each active user in the system are listed in Table 4.1. As we can see, the second user, which is considered to be a strong interferer, has a power which is ten times more than the desired signal. All other interferers are assumed

User #	Power 0-8 dB	DOA (deg.)
1	$\times 1$	0
2	$\times 10$	0
3	$\times 1$	30
4	$\times 1$	60
5	$\times 1$	45

Table 4.1: Signal parameters of five users transmitting signals from different directions

to have the same power as the desired one.

Fig. 4.5 shows that a conventional receiver having neither an antenna array nor an interference canceller cannot detect the desired signal by using inherent processing gain of the spread spectrum system when the desired signal is much weaker than the interfering signal. As expected, the technique of antenna array also degrades in the presence of strong interference. The poor cancellation capability is attributed to the fact that an antenna array cannot suppress the cochannel interference from an undesired user having the same direction of arrival (DOA) as that of the desired user. In this case, several signals may fall into a main beam of one output port, therefore the interference cannot be reduced to a very low level, and the BER performance is thus close to that of the conventional receiver. But, in this situation, APIC provides a better performance than antenna arrays. The reason behind this is that multiuser detectors are able to cancel the cochannel interference regardless of their arrival angles. However, shown in Fig. 4.5, it can be seen that the performance of the combination scheme is very close to the single user bound for the case of two antennas. In fact, APIC rejects the in-beam MAI and residual cochannel interference which an adaptive antenna array cannot completely suppress. This result confirms the importance of using multiuser detection for adequate interference mitigation in the design of the next generation CDMA receivers.

Fig. 4.6. illustrates a situation in which the strong interferer has a different DOA than the desired user. The result shows that by employing the technique of

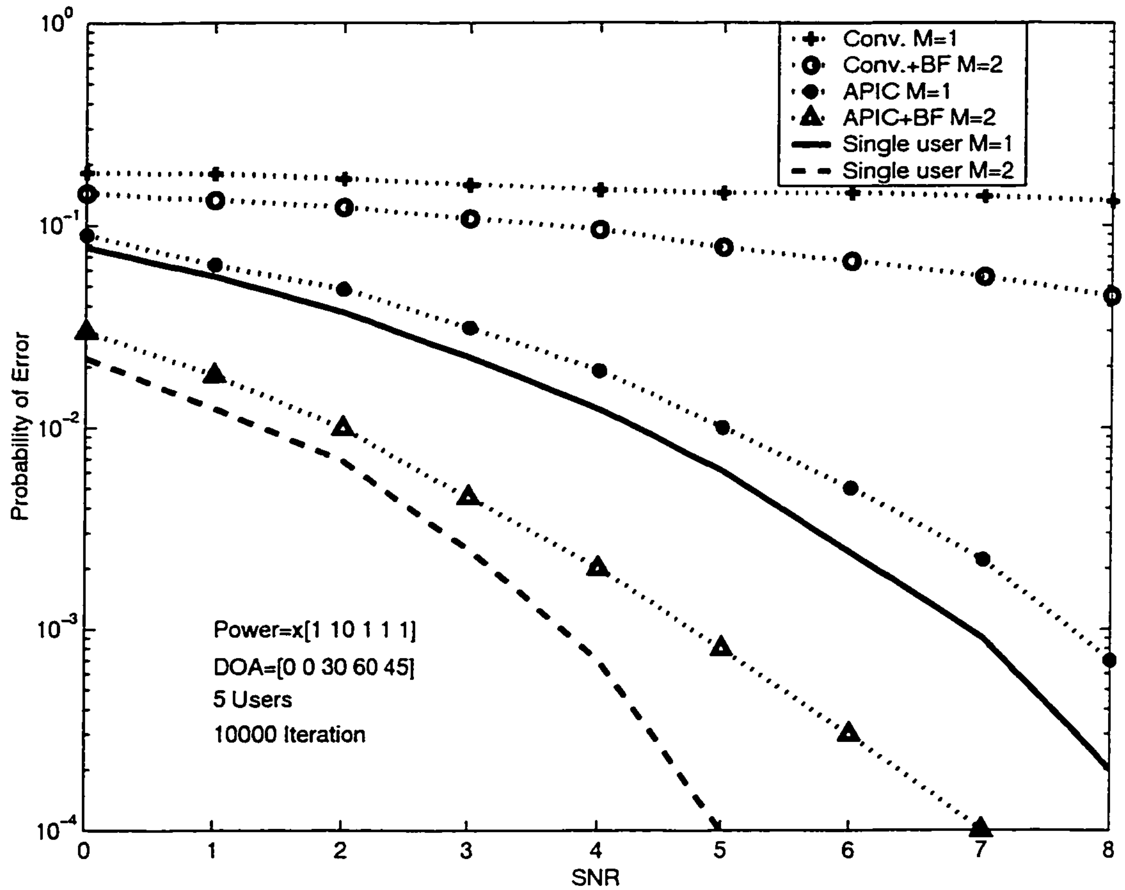


Figure 4.5: BER performance versus E_b/N_o for AWGN channel (the strong interferer has the same DOA as that of the desired signal.)

combining, the MAI arriving from directions other than that of the desired user can be significantly suppressed by using spatial filtering property of antenna arrays. Thus, in this instance, the adaptive blind receiver shows a much better performance, even though, the proposed receiver still provides a superior performance.

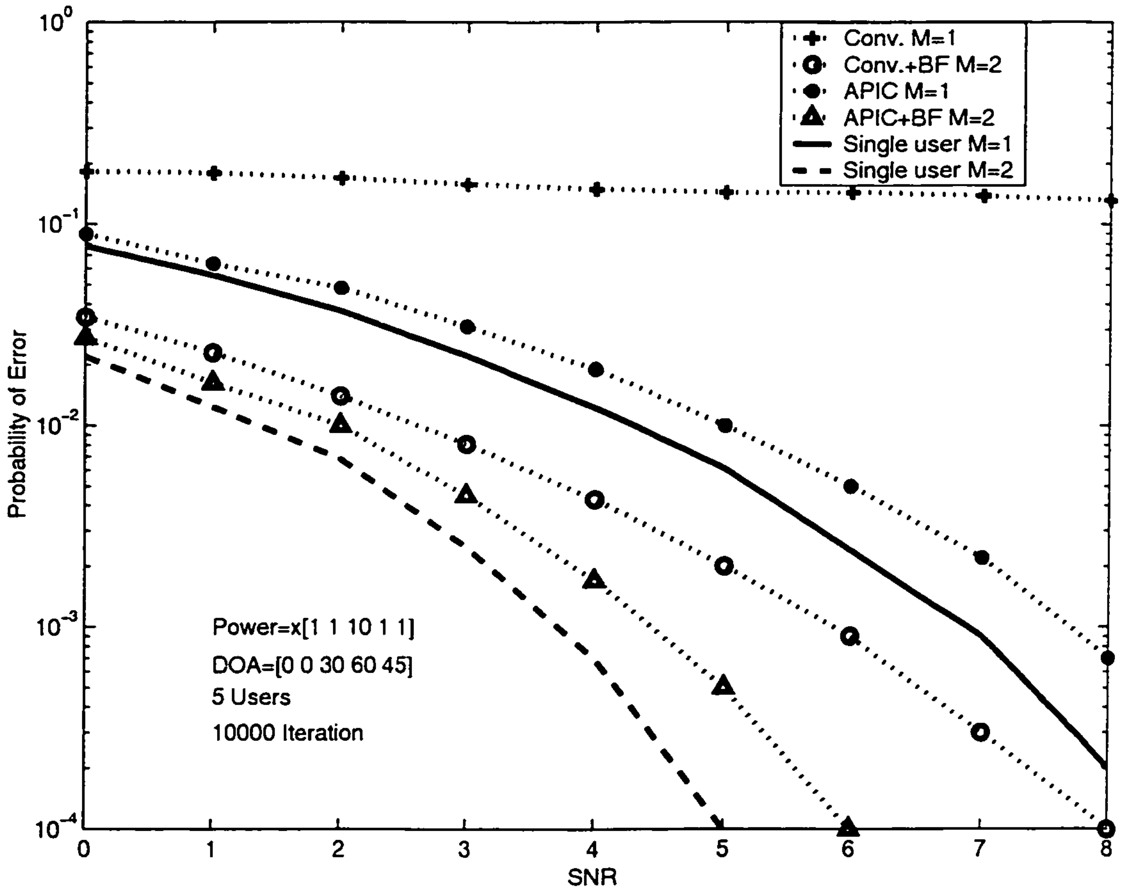


Figure 4.6: BER performance versus E_b/N_o for AWGN channel (the strong interferer has the different DOA than the desired signal.)

4.5 Conclusions

In this chapter, we have studied the combination scheme of adaptive blind arrays and multiuser detectors for CDMA communication systems over AWGN channels.

We employed adaptive blind algorithms presented in Chapter 3, which do not require the knowledge of the angles of arrival, as the first stage of a multistage detector scheme. We mentioned that since blind algorithms have been implemented on a single-user based concept using the knowledge of the desired user's code, multiuser detection schemes are needed to utilize the inherent property of the multiple access interference. We have suggested adaptive antennas for the first stage to mitigate interference which steer the main beam towards the desired user and forming nulls towards the undesired users. Then, a multistage adaptive interference canceller has been employed to improve the system performance, in which estimates of the interfering signals are constructed and subtracted from the desired signal. Simulation results also verified the performance claims for the combination scheme. It has been observed that combining the outputs of an antenna array curtails the overall MAI significantly even without multiuser detection, when the users' signals are spatially separated. On the other hand, when they are not well separated, the multiuser detection appears to be a promising technique to combat the in-beam interference.

We have illustrated that adaptive arrays are most effective when dealing with interference signals that are uncorrelated with the SOI. In the multipath case, where the interfering signal incident on the antenna element is a phase shifted version of the desired signal and thus is correlated with the SOI, the adaptive array cannot null out the multipath as effectively as it would in the presence of an uncorrelated signal. The topic of joint multiuser detection and adaptive antenna arrays for multipath channels will be discussed in Chapter 5, in which we will show that a receiver structure combining an MAI suppression receiver with an adaptive blind array is able to maintain good performance even in multipath environments.

Chapter 5

An Adaptive Blind 2D-RAKE Receiver using Parallel Interference Cancellation for Multipath CDMA Channels

5.1 Introduction

Several techniques can be used to overcome the impairment due to MAI and multipath fading; these include RAKE receivers, antenna arrays, and multiuser detectors. The popular single user RAKE receiver effectively combats multipath fading by coherently combining resolvable multipath replicas of the desired signal. Nevertheless, due to imperfect correlation properties of the spreading codes, the conventional RAKE receiver is sensitive to multipath and near-far problems. Deployment of antenna arrays is also a very promising solution to reduce the MAI from high data rate users in Wideband Code Division Multiple Access (W-CDMA) systems [30]. Combining the antenna array and a RAKE receiver, both of which exploit multipath diversity, can significantly improve the system performance. These beamformer-RAKE receivers, also known as two-dimensional (2D) RAKE receiver, provide further enhancement in the anti-fading capabilities of DS-CDMA receivers [31]. In a 2D-RAKE receiver the desired user's multipath signals, coming from different directions with different delays are combined in space, and delayed and match filtered in time with Maximum Ratio Combining to form the decision variable for the desired user. This combined spatial and temporal structure is able to cancel strong MAI, while simultaneously combat the effects of fading, thus providing an optimum output signal-to-interference-plus-noise ratio (SINR) for a desired user. Another promising approach that is applicable to DS-CDMA systems is the use of multiuser detectors. Multiuser detection techniques exploit the knowledge of the spreading waveforms of user signals to mitigate MAI. Among multiuser detection schemes, a compromise between system performance and computational complexity can be obtained by employing parallel interference cancellation [24] due to its simple structure.

In this chapter, the main objective is to investigate the integration of multiuser detection with spatial processing along with temporal diversity over frequency selective slow-fading wireless channels for the reverse link of W-CDMA systems. We propose a new structure that combines an adaptive parallel interference canceler (APIC) with an adaptive blind 2D-RAKE receiver [45][46]. The blind adaptive implementation is the same as what we discussed in Chapter 3. The interference rejection capability of the proposed receiver has been examined over frequency selective Rayleigh fading channels. Simulation results show the superior performance of the proposed structure in a severe near-far situation.

The chapter is organized as follows. Section 5.2 gives a description of the signal model. In Section 5.3, we explain the 2D-RAKE structure. Some typical spatial-temporal structures are reviewed in Section 5.4. Section 5.5 introduces the proposed 2D-RAKE receiver combined with APIC. In Section 5.6, computer simulations are conducted to verify the performance of the proposed structure.

5.2 Signal Model

Consider a direct sequence CDMA system, where K users are transmitting their own signals simultaneously and asynchronously, and each user signal propagates through L distinct paths. The channel bandwidth is assumed to be large enough so that the intersymbol interference can be ignored. The transmissions are received by an array of M elements. The received signal at the m^{th} antenna can be described as

$$x_m(t) = \sum_{i=0}^{I}\sum_{k=1}^{K}\sum_{l=1}^{L} \sqrt{e_k} b_k(i) s_k(t - \tau_{k,l} - iT_b) c_{k,l} a_m(\theta_{k,l}) + \sigma n_m(t) \qquad (5.1)$$

where the parameter I is the number of bits or packet that each user transmits, $b_k(i) \in \{-1. +1\}$ the i^{th} symbol transmitted by user k, e_k received energy of the k^{th} user at each antenna, $c_{k,l}$ the complex fading coefficient for the l^{th} path of the k^{th} user, $\tau_{k,l}$ the relative delay of the received signal from the k^{th} user on the l^{th} path. Also $a_m(\theta_{k,l})$ is the complex gain from the l^{th} path of the k^{th} user to the m^{th} antenna element, which can be written as

$$a_m(\theta_{k,l}) = e^{-j(2\pi D_m/\lambda) sin(\theta_{k,l})} \qquad (5.2)$$

where, D is the distance between the first and the m^{th} antenna element, $\theta_{k,l}$ is the arrival angle of the signal from the l^{th} path of the k^{th} user and λ is the free-space wave length. The array response vectors are normalized so that $|a_1(\theta_{k,l})| = 1 \quad for \quad k = 1, 2, \ldots, K$.

In (5.1), $n_m(t)$ is additive complex white Gaussian noise at m^{th} antenna element which is assumed to be independent of other noise elements, and the normalized signature waveform $\{s_k(t)\}$, which is of duration $T_b = NT_c$ is given by

$$s_k(t) = \sum_{n=0}^{N-1} s_{k,n} u(t - nT_c) \qquad (5.3)$$

where $s_{k,n} \in \{-1, +1\}$ is the assigned code for user k, $u(t)$ is the chip pulse waveform, and N is the *processing gain*.

As we mentioned earlier, in order to simplify the complexity of analysis, we restrict our model to the synchronous case, in which $\tau_1 = \tau_2 = \ldots = \tau_K = 0$. This simplifies the mathematical description of the blind algorithms presented here. Besides, the maximum delay spread of the channel, $T_m = \max \tau_{k,l}$, is assumed to be less than one symbol duration, T_b. Actually, the multipath spread of the channel is usually assumed to be much smaller than the spreading factor of the CDMA signal, i.e., $L \ll N$.

5.3 2D-RAKE Structure

The underlying W-CDMA signal waveforms, with a chip rate of 3.84 Mbit/s, occupy a bandwidth of about 5 MHz. The use of such a large bandwidth enables both the increase of information rate to meet the requirement of multimedia traffic, and an effective use of the multipath fading inherent in the wireless channel. Indeed, the spread bandwidth typically exceeds the coherence bandwidth of the channel, so that the multipaths would be resolved most of the time. Namely, the system experiences frequency-selective fading.

In the multipath fading channel, various diversity techniques have been introduced to improve the data detection quality, which in turn increases the system capacity. For example, the combination of beamformer and RAKE receiver [41] has been proposed to deal with spatial and temporal diversities. Antenna arrays are designed in order to utilize either spatial diversity for mitigating the effect of fading or the inherent angle diversity in the received signals for cochannel interference reduction. In addition, RAKE receivers are a very efficient way to combat multipath fading of signals; in which multipath components are added together constructively to increase the output SINR.

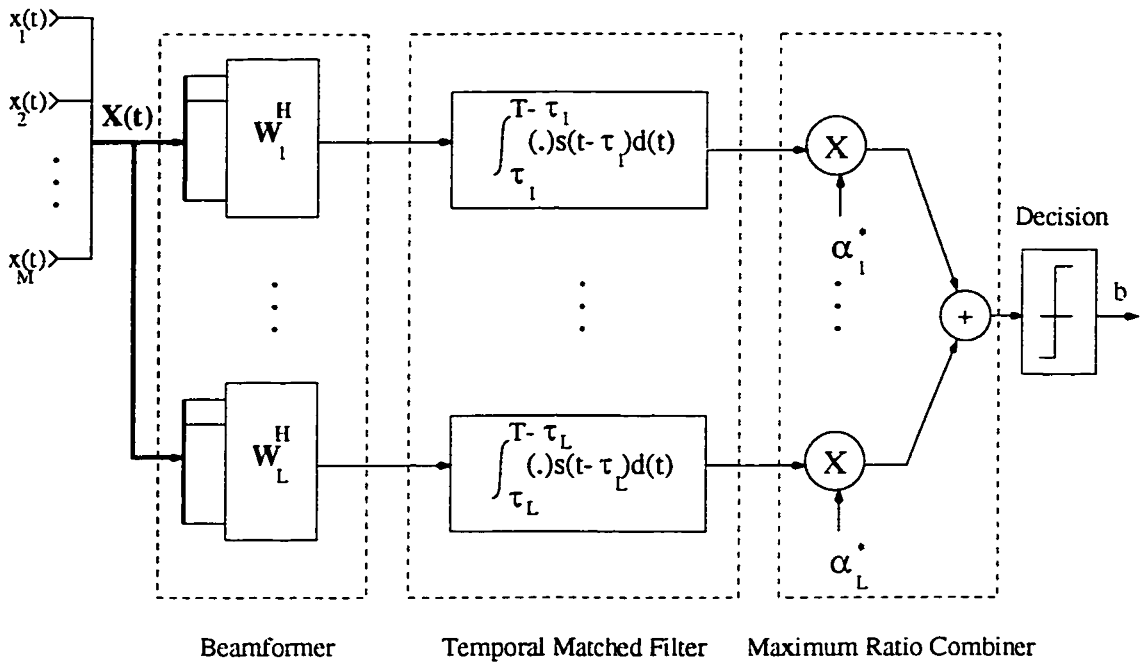


Figure 5.1: Block diagram of a conventional 2D-RAKE receiver.

Recently, there has been an increasing interest in the use of 2D-RAKE [31] which incorporates adaptive antennas into a regular RAKE receiver to simultaneously exploit space and time diversities. As a result, the 2D-RAKE receiver provides substantial improvement in user capacity, coverage and quality of service.

As shown in Figure 5.1, the traditional 2D-RAKE receiver separately tracks and coherently combines the multipath signal components of the received signal over the spatial as well as over the temporal domain. In particular, the 2D-RAKE structure consists of a bank of array combiners, followed by a bank of matched filters, whereby each delayed version of the received signal is correlated with the spreading waveform of the desired user, and then the correlators' outputs are conveniently combined in order to maximize the SINR at the receiver output.

In this work, we employ the 2D-RAKE equivalent matched filter version [39], which consists of a filter matched to the channel for each antenna element followed by a combiner and a single correlator. Each filter is implemented through a tapped

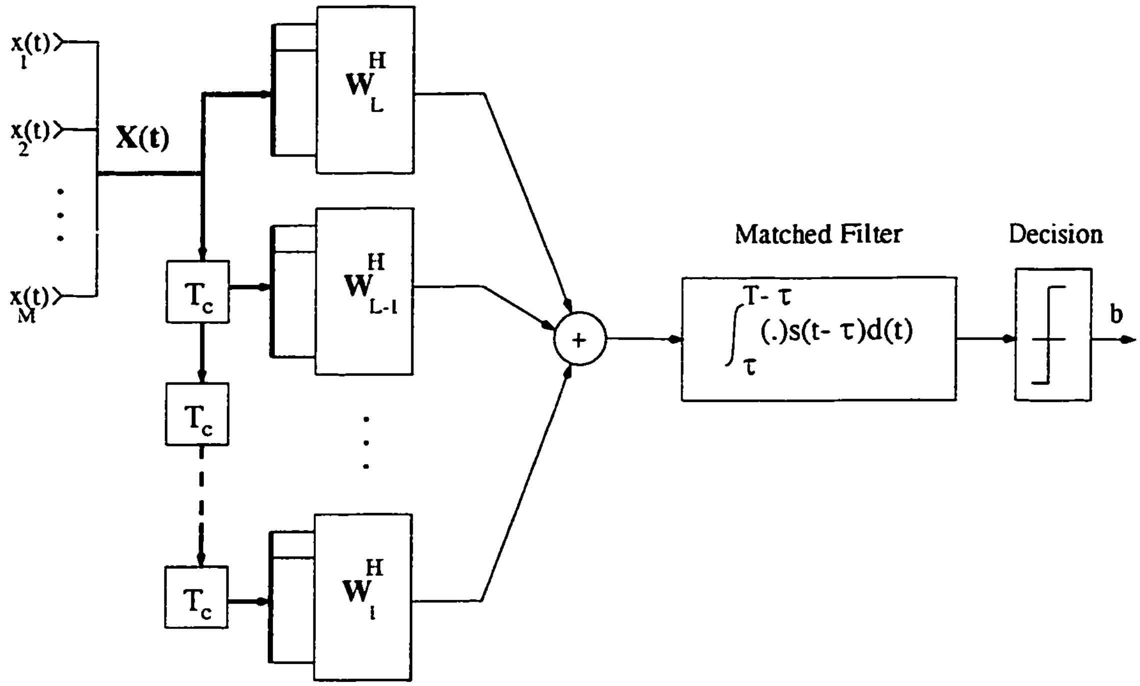


Figure 5.2: Block diagram of a 2D-RAKE equivalent matched filter version.

delay line with fixed delays which are multiple of the chip period. This structure is denoted as chip matched filter (CMF) which is suitable for the application of an optimum channel estimation method. The block diagram in Figure 5.2 depicts the typical architecture of a single-user 2D-RAKE receiver based on CMF.

5.4 Adaptive Blind 2D-RAKE Receiver

In this section, we derive an adaptive blind algorithm that computes weight vectors in order to preserve the desired signal and mitigates interference. Our assumption here is that the blind receiver has the knowledge of only the desired user's signature sequence and the timing information. This requirement is even easier than the conventional 2D-RAKE receiver, which, in addition, needs information on the multipath channel gains and the array response of the desired user.

The goal is to compute the combining weights in an optimum fashion, so

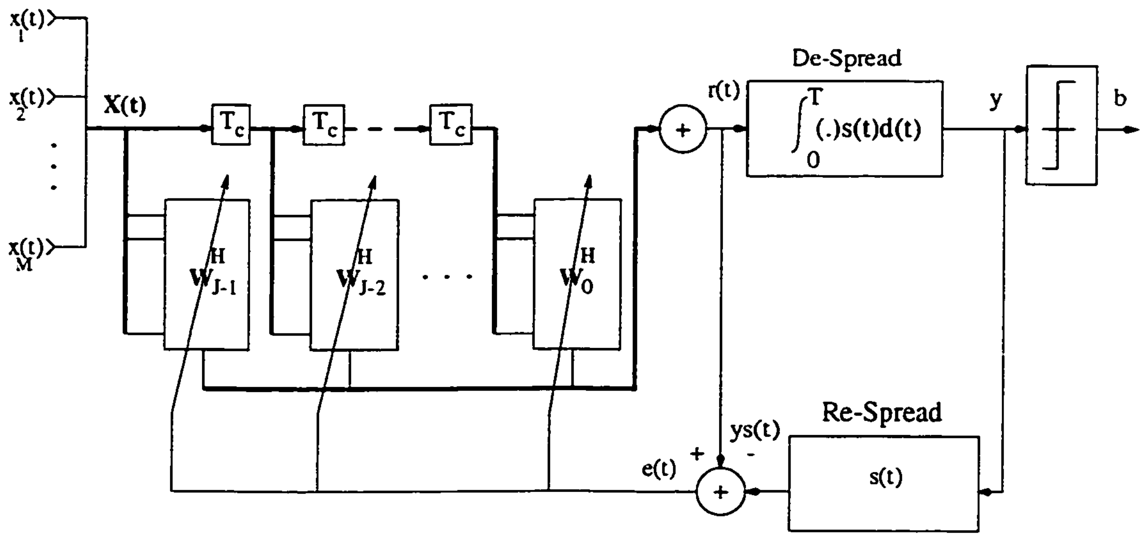


Figure 5.3: Adaptive Blind 2D-RAKE receiver

that the output of the receiver attains the maximum SINR. In this method, the desired user's signals from different paths and antennas are first combined. The combined signal, r, is then correlated with the spreading waveform of the desired user to yield decision statistic. Output of the correlator, y, is re-spread again by the signature sequence of the desired user s. This re-spread signal can then be used in the beamformer to adapt the weight vector w, and form a beam that tracks the main path of the desired user. The number of adaptive weights which should converge is given by the product of the number of resolvable paths and the number of antennas. Figure 5.3 shows the structure of an adaptive blind 2D-RAKE receiver with M antenna elements and L distinct paths.

If we set our time reference at the output of the last delay element of the tapped delay line (the indexing of the delay element outputs is done from right to left), the received signal at the output of the j^{th} delay element for a given time period can be written as

$$\mathbf{x}_j(t) = \sum_{k=1}^{K} \sum_{l=0}^{L-1} \sqrt{e_k} b_k(i) s_k(t - \tau_k - (l-j)T_c) c_{k,l} \mathbf{a}(\theta_{k,l}) + \sigma \mathbf{n}_j(t) \qquad (5.4)$$

where τ_k is the relative delay of the zeroth path of the k^{th} user so we have

$$\tau_{k,l} = \tau_k + lT_c \tag{5.5}$$

$\mathbf{x}_j(t)$ is later combined in space by the weight vector $\mathbf{w}_j = [w_{1j}\ w_{2j}\ \ldots\ w_{Mj}]^T$. If we define

$$\widetilde{\mathbf{w}} = \left[\mathbf{w}_0^T\ \mathbf{w}_1^T \ldots \mathbf{w}_{J-1}^T\right]^T \tag{5.6}$$

$$\widetilde{\mathbf{x}}(t) = \left[\mathbf{x}_0(t)^T\ \mathbf{x}_1(t)^T \ldots \mathbf{x}_{J-1}(t)^T\right]^T \tag{5.7}$$

In the synchronous case ($\tau_1 = 0$), the decision variable for user 1 can be written as

$$y = \int_0^T \left(\widetilde{\mathbf{w}}^H \widetilde{\mathbf{x}}(t)\right) s_1(t)dt \tag{5.8}$$

All three blind adaptive algorithms developed in Chapter 3 can now be extended to a multipath environment.

Method I:

$$\min_{\widetilde{\mathbf{w}}} E\left[\widetilde{\mathbf{e}}(t)^2\right] = \widetilde{\mathbf{w}}^H \widetilde{\mathbf{R}}_I \widetilde{\mathbf{w}} \qquad subject \quad to \qquad E[|y|^2] = 1 \tag{5.9}$$

where

$$\widetilde{\mathbf{e}}(t) = y s_1(t) \tag{5.10}$$

The solution to this optimization problem is given by the generalized eigenvector corresponding to the minimum eigenvalue of the matrix pencil $(\widetilde{\mathbf{R}}_I, \widetilde{\mathbf{R}}_{s_1})$ such that

$$\widetilde{\mathbf{R}_\mathbf{I}} \widetilde{\mathbf{w}} = \lambda \widetilde{\mathbf{R}}_{s_1} \widetilde{\mathbf{w}} \tag{5.11}$$

where $\widetilde{\mathbf{R}}_I$ and $\widetilde{\mathbf{R}}_{s_1}$are the extensions of $\mathbf{R}_I$ and $\mathbf{R}_s$ defined in Chapter 3.

Method II:

$$\max_{\widetilde{\mathbf{w}}} E[|y|^2] = \widetilde{\mathbf{w}}^H \widetilde{\mathbf{R}}_{s_1} \widetilde{\mathbf{w}} \quad subject \quad to \quad \widetilde{\mathbf{w}}^H \widetilde{\mathbf{w}} = 1 \tag{5.12}$$

The solution is the eigenvector corresponding to the maximum eigenvalue of $\tilde{\mathbf{R}}_{s_1}$.

Method III:

$$\min_{\tilde{\mathbf{w}}} E[\mathbf{r}^H\mathbf{r}] = \tilde{\mathbf{w}}^H\tilde{\mathbf{R}}\tilde{\mathbf{w}} \quad \textit{subject to} \quad E[|y|^2] = 1 \tag{5.13}$$

The solution to this optimization problem is given by the generalized eigenvector corresponding to the minimum eigenvalue of the matrix pencil $(\tilde{\mathbf{R}}, \tilde{\mathbf{R}}_{s_1})$. The eigenvalue problem can be written as

$$\tilde{\mathbf{R}}\tilde{\mathbf{w}} = \lambda\tilde{\mathbf{R}}_{s_1}\tilde{\mathbf{w}} \tag{5.14}$$

where $\tilde{\mathbf{R}}$ is the extension of $\mathbf{R}$.

By employing any of these methods, each stage of the RAKE receiver forms a beam toward the corresponding received multipath component, while the beams formed by methods I and III have an additional ability of setting nulls in the direction of the signals from interfering users.

5.5 2D-RAKE Receiver Combined with APIC

The adaptive blind array technique introduced in Chapter 4, has been developed for enhancing the performance of CDMA systems. However, this method is essentially a single-user-based approach as it does not exploit the inherent signal structure induced by the multiuser spreading waveforms. Furthermore, this method still suffers from the near-far problem because the degree of freedom provided by the spatial signature is limited.

In this section, we propose a blind space-time detection technique to cope with such a situation. In particular, we consider beamforming, RAKE combining and multiuser detection. The proposed system makes use of an adaptive blind 2D-RAKE receiver in conjunction with adaptive parallel interference cancellation (APIC).

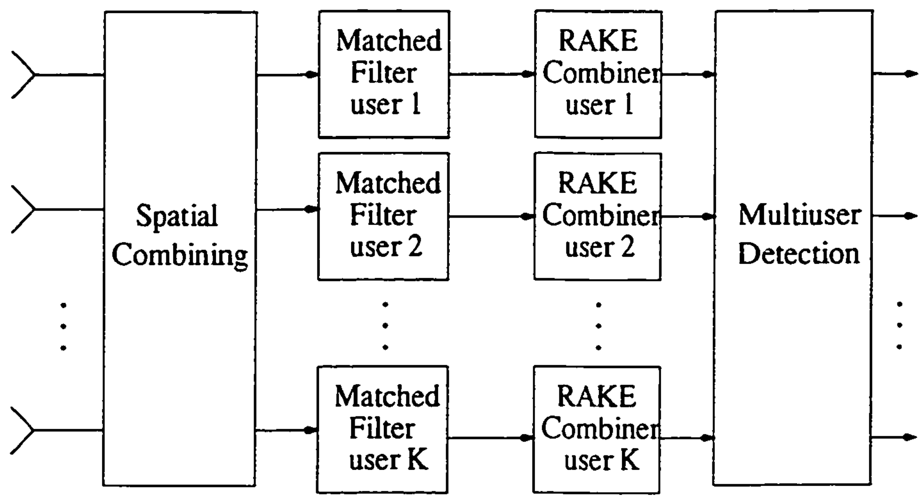


Figure 5.4: The structure of the beamformer-RAKE receiver followed by multiuser detection.

There are many different approaches to combine adaptive antennas, interference cancellation and RAKE receiver. The order of performing beamforming, interference cancellation, and maximum ratio combining affects both the performance and complexity of the system. Two possible architectures are illustrated in Figs. 5.4 and 5.5. In the receiver structure shown in Fig. 5.4, spatial and multipath combinings are performed before multiuser interference suppression. This architecture has two main advantages. First, since RAKE combining takes place before multiuser detection, the computational complexity is reduced and the multipath components corresponding to each user are exploited in a constructive fashion. Second, the receiver structure is rather practical in fading channels, since the channel estimation can be performed after suppressing strong MAI. This approach improves channel estimation accuracy significantly [40].

If multiple access and intersymbol interferences are suppressed first in each sensor followed by spatial and multipath combining, we can obtain the receiver configuration in Fig. 5.5. This connection allows the application of adaptive single-user type receivers in fast time-varying channels where within adaptive receivers often have severe convergence problems [40].

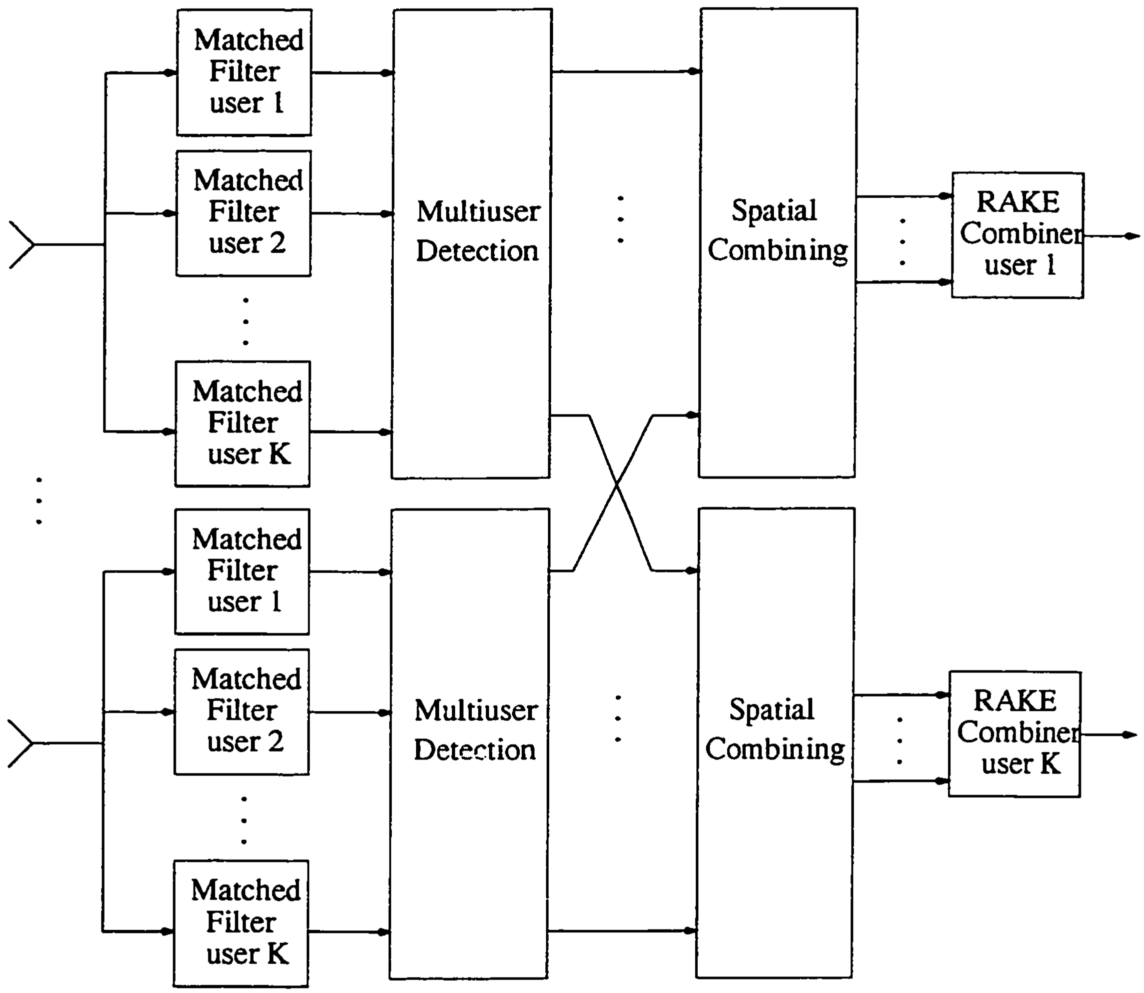


Figure 5.5: The structure of the multiuser detection combined with beamformer-RAKE receiver.

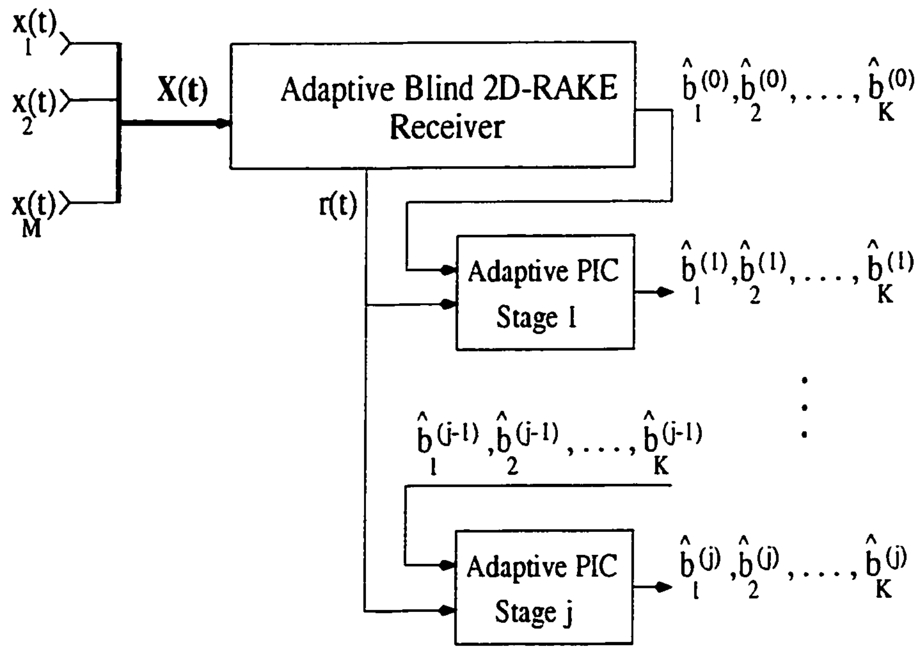


Figure 5.6: Block diagram of the combined 2D-RAKE receiver with APIC.

In our application, we first perform beamforming and RAKE combining at the same time and in a blind fashion to cancel strong MAI and combat the effects of fading and then, follow it by multiuser detection to cancel out remaining interference at the same arrival angle. Fig. 5.6 shows the block diagram of the proposed structure.

In terms of complexity, the proposed scheme is more computationally intensive than the 2D-RAKE receiver. However, both adaptive algorithms employed here, are based on the LMS algorithm which is very attractive for computation. Furthermore, since the major part of MAI is suppressed by the first stage (2D-RAKE), we don't need to have several stages for APIC. As we will show in our simulation, just one stage is enough to achieve a good performance. This approach will reduce the computational complexity. On the other hand, due to the relatively low convergence rate inherent in stochastic gradient algorithms, Least Squares (LS) algorithms can be used to achieve adequate convergence speed in the expense of higher complexity.

Path	Relative Delay (nsec)	Avg. Power (dB)	DOA
1	0	0	0
2	310	-1	5
3	710	-9	10
4	1090	-10	20

Table 5.1: Channel parameters

5.6 Simulation Results

This section presents the results of our Monte Carlo simulation for frequency selective Rayleigh fading channels. We consider a base station with a uniform linear array of M omni-directional antennas with antenna spacing $\lambda/2$. We assume BPSK Gold code spreading with processing gain $G = 31$. The input chip rate is 3.84 Mcps corresponding to a 260 ns chip-interval. We consider K active users randomly distributed in azimuth around the base station with a uniform distribution over $[-\pi/2, \pi/2]$. The system is assumed to operate in a single-cell environment with Rayleigh-fading frequency-selective channel. We also assume that four propagation paths are received from each mobile as a result of dominant reflectors and that the total received power from each user is the same for all users (perfect power control) except one interferer which has a power of 10-dB above the other users including the desired user. The desired user is denoted as user 1 and a perfect chip synchronization is assumed.

In general, three different types of multipath channel could be employed in the simulation where each of them corresponds to different environment. They are Indoor channel, Indoor to Outdoor channel, and Vehicular A Outdoor channel. In this study, we have examined the multipath profile of Vehicular A Outdoor channel. The paths' direction of arrival; time delays; and the powers are shown in Table 5.1. The power delay profile shown in Table 5.1 is taken from [32].

All the delays in the table are measured at nano-secs and the power is shown in dB scale. A mobile speed of 120 Km per hour is considered for the channel. This

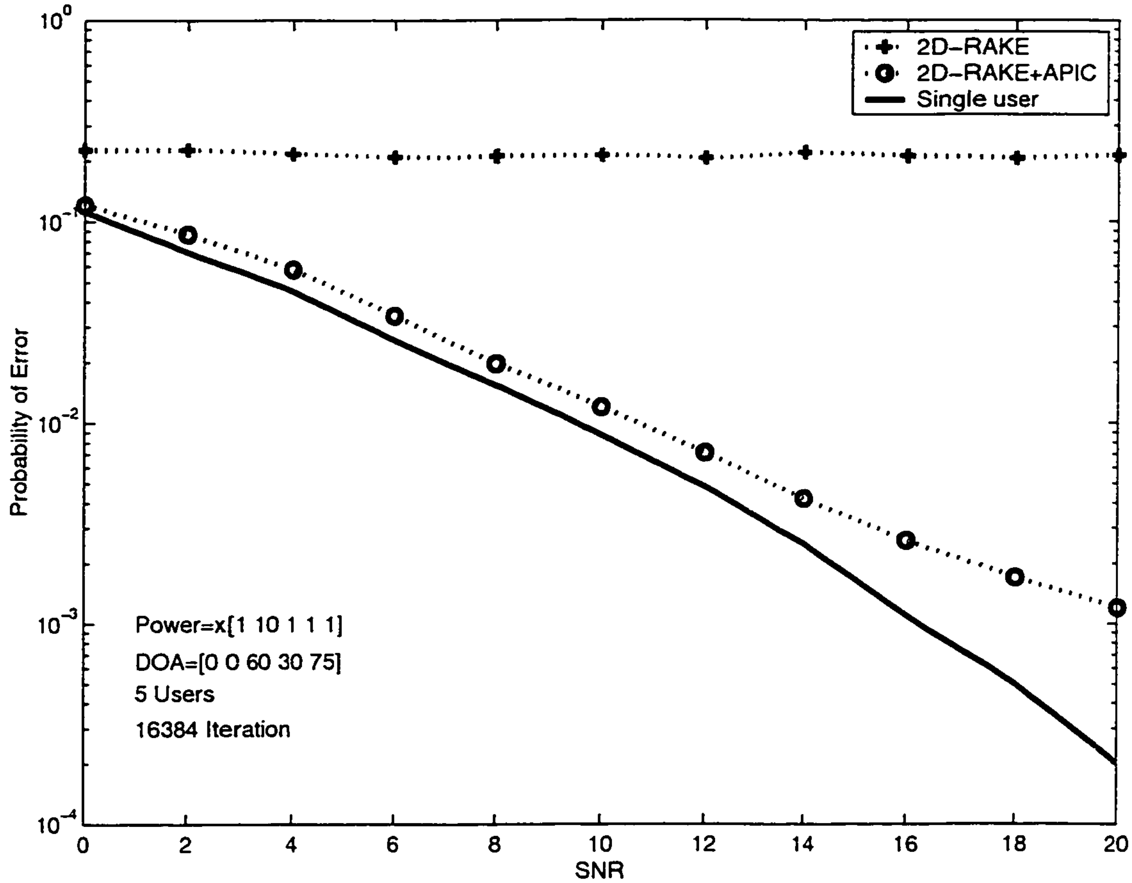


Figure 5.7: BER performance versus E_b/N_o for frequency selective Rayleigh fading channel (the strong interferer has the same DOA as that of the desired signal.)

mobile speed corresponds to a Doppler spread of 223 Hz for a carrier frequency of 2 GHz. This is very small compared to the bandwidth of the baseband signal and represents a relatively slow fading environment. The Rayleigh waveform is generated using Clarke's model and at a sampling rate equal to the chip rate.

The BER performance versus E_b/N_o of the 2D-RAKE receiver and that of the proposed combined structure are compared in Fig. 5a. In this experiment, we have assumed that the strong interferer has the same direction of arrival as that of the desired signal. As expected, the 2D-RAKE receiver degrades in the presence of strong interference. This poor cancellation is because of the fact that an antenna array can not suppress the high-level interfering signals from an undesired user with the same direction of arrival (DOA) as that of the desired user. However, it is shown that the performance of our proposed scheme is very close to single user bound. In fact, APIC rejects the MAI containing in-beam interference. This result justifies the importance of using multiuser detection for adequate interference mitigation in the next generation CDMA receivers.

Fig. 5b. illustrates a situation in which the strong interferer has a different DOA from the desired user. The result shows that the MAI and multipath components arriving from directions other than that of the desired user can be significantly suppressed by using spatial filtering property of antenna arrays. Thus, the 2D-RAKE receiver yields much better performance in this case. Although, the proposed receiver still has superior performance.

5.7 Conclusions

In this chapter, we have presented a blind adaptive technique for DS-CDMA systems over frequency selective multipath fading channels. We have also investigated a new combination scheme which is very effective in situations with severe near-far problems. The proposed structure enhances the desired signal and suppresses the cochannel interference regardless of the direction of arrival of the interferers. We have shown that the proposed scheme can improve the system bit error rate significantly.

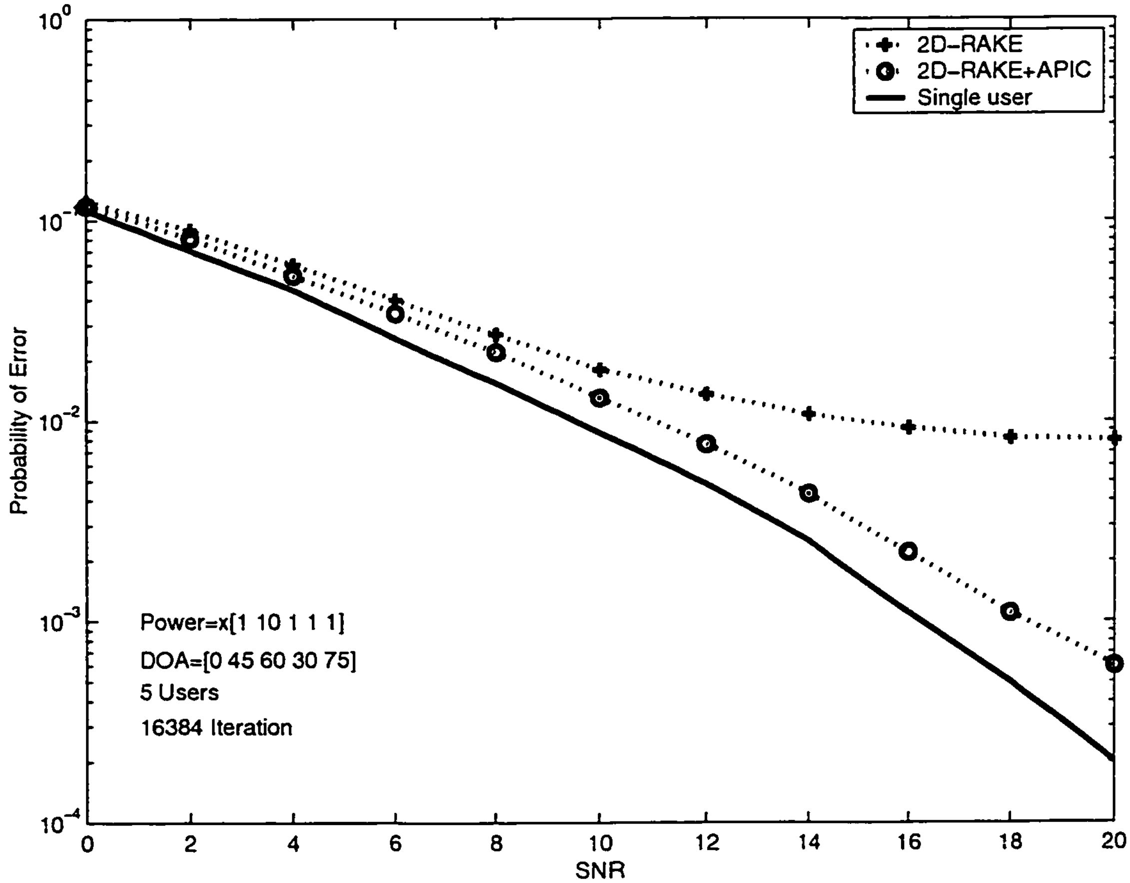


Figure 5.8: BER performance versus E_b/N_o for frequency selective Rayleigh fading channel (the strong interferer has the different DOA than the desired signal.)

Chapter 6

Conclusions and Future Research Directions

6.1 Conclusions

In this thesis, we have investigated the operation and performance of different interference cancellation techniques for CDMA systems. Specifically, we have studied how employing multiple antennas at the receiver can be used to improve the performance of the system. We showed that the spatial discrimination provided by antenna arrays can be used to reduce the considerable amount of multiple access interference, thereby decreasing the burden on the temporal processing stage of the receiver.

In Chapter 2, we reviewed and compared the performance of several multiuser detection techniques. We have shown that by employing adaptive parallel interference cancellation a compromise between system performance and computational complexity can be obtained.

Next, we studied the use of multiple receive antenna arrays in CDMA wireless communications systems. The motivation for using multiple antenna arrays was throughly discussed in Chapter 3. We pointed out that signal detection using temporal information only does not seem to be adequate to meet the performance and capacity requirements of the emerging wireless systems due to its fundamental limitation in information capacity.

Since the array response vectors of users are not available at the receiver, we turned our focus in this chapter to a multiuser receiver with an adaptive blind array. We formulated different realizations of this receiver and as a result, three adaptive blind algorithms were developed. The blind algorithms have been formulated using a constrained energy minimization criterion, and the adaptation is carried out using LMS algorithm combined with the gradient-projection algorithm to incorporate the quadratic constraint. The performances of these schemes are compared, showing that this receiver can outperform the single-element conventional receiver without requiring any additional information.

We also demonstrated that while two of them have the potential of placing spatial nulls in the direction of strong interferers, they are less robust than the other algorithm and under certain circumstances will fail to form a beam to the desired user. Also, using computer simulations, we have shown that enormous increase in traffic throughput is promised by the use of multi-element antenna arrays in wireless radio-frequency links.

In chapter 4, we applied the algorithms developed in Chapter 3 to a multiuser detector scheme. It has been demonstrated that the combination of spatial diversity and a multiuser receiver provides a significant performance improvement or system capacity gain in comparison to implementing only one of them. The interference rejection capability of the proposed receiver has been examined in situations where a single interferer dominates the received power. It was shown that this scheme of combination can significantly improve the system performance in comparison with that of using either multiuser detection or smart antennas. We concluded that when compared with classical CDMA receivers, the improvement in performance is dramatic at the expense of a practically feasible increase in complexity.

Finally in Chapter 5, we investigated the integration of multiuser detection with spatial processing along with temporal diversity over frequency selective slow-fading wireless channels. At a space-time receiver, multiple copies of the transmitting signals are received. These copies can be efficiently combined using space-time processing techniques to combat MAI interference and provide array gain. Hence, we developed a new structure that combines APIC with an adaptive blind 2D-RAKE receiver. Also, we extended the adaptive blind algorithms derived previously, for the multipath fading model which do not require knowledge of the signal waveforms and propagation channels. In the 2D-RAKE unit, the antenna array was combined with the conventional RAKE receiver. We have shown that this combined spatial and temporal structure is able to cancel strong MAI, while simultaneously combat the effects of fading. In addition, in our work, we examined the 2D-RAKE equivalent matched filter version, which consists of a filter matched to the channel for each antenna element followed by a combiner and a single correlator. Simulation results have shown that this receiver can improve the performance dramatically compared with the 2D-RAKE receiver.

6.2 Future Research Directions

The research described in this thesis leads naturally to several extensions. These extensions include:

- For a given CDMA receiver with multiple antennas, the number of users is usually larger than the number of antennas, making the spatial nulling techniques less effective. Using antenna arrays can be most effective when small number of interferers have stronger amplitude than the rest of the users, including the desired one. Future work can be done to verify the performance of the algorithms presented here for other special scenarios, including over-crowded case.

- In the adaptive algorithms developed in our work, we have not considered the speed of convergence of the weight vectors. Further work is needed to evaluate the possible delays occurred for convergence of the weights in each algorithm. In addition, the necessary and sufficient condition for the convergence or stability of the adaptive algorithm should be investigated by deriving the boundary condition of the step-size μ, which controls the size of the incremental correction applied to tap-weight vector.

- In this research, we studied the performance of the receiver in slow-fading frequency-selective channel. A possible extension of the proposed scheme to a time-varying fast-fading frequency selective channel could be investigated in future work.

- Beamforming and adaptive antenna arrays have been proposed to reduce multipath fading of the desired signal and to suppress the cochannel interference. On the other hand, the information capacity of wireless communication systems may also be increased dramatically by employing multiple transmit and receive antennas. An effective approach to increasing data rate over wireless channels is to employ space-time coding (STC) techniques in transmit antennas. Future work can be done to combine STC and antenna array signal processing with channel coding techniques to improve the transmission performance.

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