NEW DETECTION SCHEMES FOR DS/CDMA WITH ANTENNA ARRAYS

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摘　　要

本文的主要目的是研究直接序列碼多分址系統抗多址接入干扰的能力. 首先, 基于非周期用戶碼的假定, 研究一种具有結构陣列天線的盲自适應線性接收机. 這种接收机收編了類似于 IS-95 標准中的 M 進制調制方案. 与周期性用戶碼的比較, 在抗多用戶干扰接收机的設計中, 非周期用戶碼序列的設計通常有一定的難度. 接著, 本文建議一种非周期和周期用戶碼的組合擴頻方案. 該方案增加了多用戶檢測和盲自适應接收. 因此, 給出了一個有效的具有陣列天線接收干扰的盲自線性接收机. 這种接收机即使在所希望接收的信號和干扰來自相同的方向也能克服多址接入干扰.

Abstract

The main objective of this work is to investigate the multiple-access interferences (MAI) rejection capabilities of receivers for direct-sequence code-division multiple-access (DS/CDMA) systems. A blind adaptive linear receiver with antenna arrays model based on the aperiodic signature sequence assumption is studied. Modification is made on the receiver structure to incorporate the use of M-ary modulated signals as in the IS-95 standard. The use of aperiodic random sequences presents some difficulties over the periodic sequence assumption usually made in the design of MAI rejecting receivers. A novel spreading scheme is proposed to combine spreading with aperiodic sequences and spreading with periodic sequences. This scheme enhances the combining of the multiuser detection (MUD) and the blind adaptive receiver. Hence, it gives rise to an effective blind linear receiver with antenna arrays which can combat MAI even in situation when the desired user and the interferers are in the same direction-of-arrival (DOA).

Contents

List of Figures

Chapter 1

Introduction

1.1 Use of Antenna Arrays in Mobile Communications

1.1.1 Overview

The demand of wireless communications is growing at an explosive rate and the provision of communication channels which can support a large number of mobile devices becomes an important issue in the development of the wireless communication systems [1]. Among the various schemes which target to increase the channel capacities of the wireless system, the application of antenna arrays provides a promising solution to overcome the problem of limited channel bandwidth [2]. Studies [3] show that when an array is appropriately used in a mobile system, it helps in improving the system performance by increasing channel capacity and spectrum efficiency, extending range coverage and steering multiple beams to track many mobiles. It also reduces multipath fading, cochannel interference and bit error rate. An array can be used in various ways to improve the performance of the wireless system and its capacity to cancel cochannel interferences is one of the most important features. Since the the desired signal and the unwanted interferences often arrive at different directions, the antenna array can adjust and combine the received signals to enhance the desired signal by using appropriate weighting in each antenna. Different schemes [4]-[6] exist to differentiate the desired signal and the interfering signals. Some requires the knowledge of a reference signal, a training sequence or the direction of the desired signal source to accomplish the task. In this thesis, we will look at a blind adaptive scheme which does not require any reference or training sequence.

1.1.2 Beamforming

In a typical adaptive antenna array system (Fig.1.1) the signals induced on different elements of an array are combined to form a single output of the array. The process of combining the signals from different elements is known as *beamforming*. Consider an array of D elements and let the complex vector $\hat{\mathbf{w}}$ represent the weights of the beamformer. A number of algorithms have been suggested to update the weights in accordance with the object for optimization. For example, in the *null beamformer*, the weights are estimated by using the directions of interfering sources in order to place nulls in these interference directions [7]. The null beamforming scheme requires knowledge of the directions of the interference sources and it becomes hard to implement if the number of interference sources grows or if the interference sources are mobile . An *optimal beamforming* scheme is proposed to overcome the limitation [7]. It is optimal

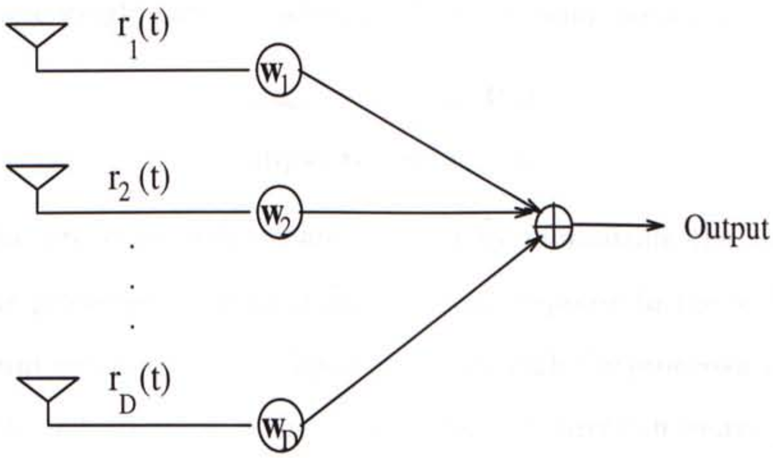

Figure 1.1: Beamformer structure

in the sense that it maximizes the output signal to noise ratio (SNR) and does not require the directions of the interference sources. For an array which is not constrained, $\hat{\mathbf{w}}$ is given by [8]

$$\hat{\mathbf{w}} = \mu \mathbf{R}_N^{-1} \mathbf{s}_0 \tag{1.1}$$

where $\mathbf{s}_0$ is the array response vector associated with the look direction, $\mathbf{R}_N$ is the array correlation matrix of the noise alone and μ is a constant. For an array constrained to have a unit response in the look direction this constant becomes

$$\mu = \frac{1}{\mathbf{s}_0^H \mathbf{R}_N^{-1} \mathbf{s}_0} \tag{1.2}$$

leading to the expression for the weight vector

$$\hat{\mathbf{w}} = \frac{\mathbf{R}_N^{-1} \mathbf{s}_0}{\mathbf{s}_0^H \mathbf{R}_N^{-1} \mathbf{s}_0} \tag{1.3}$$

In practice when the estimate of the noise alone matrix is not available, the total array correlation matrix $\mathbf{R}$ (signal plus noise) is used to estimate the weights. These weights are the solution of the following optimization problem:

$$\begin{aligned} \min_{\mathbf{w}} \quad & \mathbf{w}^H \mathbf{R} \mathbf{w} \\ \text{subject to} \quad & \mathbf{w}^H \mathbf{s}_0 = 1. \end{aligned} \tag{1.4}$$

Thus, the processor weights are selected by minimizing the mean output power of the processor while maintaining unity response in the look direction. The constraint ensures that the signal passes through the processor undistorted. Therefore, the output power is the same as the look direction source power. The minimization process then minimizes the total noise, including interferences and uncorrelated noise. Minimizing the total output noise while keeping the output signal constant is the same as maximizing the output SNR.

1.2 DS/CDMA Systems and Multiple Access Interferences

Direct sequence / coded division multiple access (DS/CDMA) system is one of the major developments in multiple access technology and the IS-95 DS/CDMA standard now plays an important role in many wireless communication systems [20]. Basically, in a DS/CDMA system, all users share a common bandwidth and the detection of the signals is achieved by differentiating the different signature sequences assigned to the users. With the use of conventional matched filter to match against the user's signature sequence, the desired signal can be demodulated but the system performance will degrade in the presence of fading, narrowband interferences and multiple access interferences (MAI) [9]. Multipath fading have typically been handled by using a RAKE receiver [10] which is a maximal-ratio linear combiner that combines the received energy from the various paths. For interference which is relatively narrowband compared with the bandwidth of the spread spectrum signal, a time domain technique with the use of notch filters often results in large improvement in system performance. Suppression can also be done with a frequency domain technique which employs the transform domain processing (excision). Both techniques were shown to have the potential of yielding a sizable improvement in system performance relative to that achievable by a conventional matched filter [11]. When the number of interferers increases, MAI will become a dominant interference source in a DS/CDMA system. In the presence of MAI, it can be difficult to recover the desired signal by simply using the matched filter since the cross correlation of the signature sequences can be significant when the number of interfering sources increases or when the interfering signals are much stronger than the desired signal.

Many methods have been developed to alleviate the problem of MAI. One way to reject MAI is by adding spatial diversity to the system and exploiting the correlation between the received signals [2]. For example, the application of antenna arrays can enhance the rejection of MAI by exploiting spatial diversity. The received signals from the antenna elements are correlated. Assuming the MAI and the desired signal come from different directions, we can filter to remove the MAI components from the desired signal component since the correlation between the MAI components is different from that between the desired signal components. With the deployment of antenna arrays, the MAI rejection capability is found to be enhanced and the system performance is greatly improved [12].

Another effective solution to the rejection of MAI is by using multiuser detection. In a conventional CDMA system, all users interfere with each other. However, in the view of multiuser detection, all user signals are considered together. They are being used for their mutual benefits by joint detection. This new point of view initiates the development of the multiuser detection and research shows that there are promising improvements in the system performance with the use of multiuser detection. The derivation and mechanism of the multiuser detection will be discussed in the next section.

The common assumption made in most MAI rejecting CDMA system models [13]-[14] is that the signature sequences are periodic. However, in the IS-95 standard, the signature sequence is so long that they can be regarded as aperiodic. With the use of long sequences most of the receivers proposed may not be able to reject MAI. To facilitate the development, we consider a linear receiver for DS/CDMA signals with aperiodic random sequence. As the signature sequences are aperiodic, it is reasonable to model them as independent random variables. This assumption greatly simplifies the analysis of the system and it is crucial in the derivation of the optimization algorithm in our work.

In resemblance to the optimal beamformer, the proposed receiver uses an antenna array. It consists of a conventional matched filter followed by a beamformer. In addition to the spatial diversity, we use M-ary orthogonal modulated signals to provide coding gain to the system. 64-ary orthogonal modulation is used as in the IS-95 CDMA standard. MAI is suppressed by choosing the optimal weights in the beamformer and a blind adaptive algorithm is used to obtain the weights which maximize the SNR.

1.3 Multiuser Detection Schemes

In the presence of MAI, the *near-far problem* is a major limiting factor in the performance of CDMA systems [15]. It arises when the powers of some of the users are much stronger than those of others and renders the reception of the weaker signal extremely difficult. As a result, a near-far resistant detector is needed so that no stringent power control is required. This leads to the development of multiuser detection (MUD) which proves to be an effective solution to the near-far problem [19].

For simplicity, we can look at the derivation of multiuser detectors for synchronous CDMA system [15]. Asynchronous case can also be found in [16]. Assume that there are K users, the received signal is

$$r(t) = \sum_{k=1}^{K} A^{(k)} b^{(k)} a_k(t) + \sigma n(t) \tag{1.5}$$

where $b^{(k)}$ is the k-th information bit which takes the value -1 or 1, $A^{(k)}$ and $a_k(t)$ is the amplitude and the signature waveform of the k-th user, and $\sigma n(t)$ is the noise contribution. We assume that $\int a_k^2(t)dt = 1$ for all k. The output for the k-th matched filter is

$$\begin{aligned} y_k &= \int r(t) a_k(t) dt && (1.6) \\ &= \int a_k(t) \left[\sum_{i=1}^{K} A^{(i)} b^{(i)} a_i(t) + \sigma n(t) \right] dt && (1.7) \\ &= A^{(k)} b^{(k)} + \sum_{i \neq k}^{K} A^{(i)} b^{(i)} \int a_k(t) a_i(t) dt + \sigma \int a_k(t) n(t) dt && (1.8) \end{aligned}$$

Note that y_k consists of three terms. The first term is the desired information bit $b^{(k)}$ and the second term is the result of the MAI and the last is due to the noise. Usually, the cross correlation between the signature sequences makes the second term the dominating noise and the cancellation of the MAI effect of one user upon another can be achieved if the cross correlation between signature sequences are known. Suppose there are only two users in the system. Let α be the cross correlation between the signature waveforms of the two users

$$\alpha = \int a_1(t)a_2(t)dt \tag{1.9}$$

the outputs of the matched filters for user 1 and 2 are

$$y_1 = A^{(1)}b^{(1)} + \alpha A^{(2)}b^{(2)} + n^{(1)} \tag{1.10}$$

$$y_2 = A^{(2)}b^{(2)} + \alpha A^{(1)}b^{(1)} + n^{(2)} \tag{1.11}$$

The MAI terms for users 1 and 2 are $\alpha A^{(2)}b^{(2)}$ and $\alpha A^{(1)}b^{(1)}$. If the signal of user 1 is much stronger than that of user 2 (near-far problem), the MAI term $\alpha A^{(1)}b^{(1)}$ present in the signal of user 2 is very large, and can significantly degrade performance of the conventional detector for that user. One way to remedy the problem is to make decision for the stronger user 1 by using the conventional detector. Since user 2 is much weaker than user 1, this decision is reliable from the point of view of user 2. So, this decision can be used to subtract the estimate of MAI from the signal of the weaker user. The decision for user 2 is given by

$$\hat{b}^{(2)} = sgn(y_2 - \alpha A^{(1)}\hat{b}^{(1)}) \tag{1.12}$$

$$= sgn\left(A^{(2)}b^{(2)} + \alpha A^{(1)}(b^{(1)} - \hat{b}^{(1)}) + n^{(2)}\right) \tag{1.13}$$

where $\hat{b}^{(1)}$ is the decision for the first user. Provided the decision for the first user is correct, all MAI can be subtracted from the signal of user 2. This simple example motivates the use of multiuser detectors for CDMA channels.

The output vector in (1.8) can be written in matrix form

$$\mathbf{y} = \mathbf{RAb} + \mathbf{n} \tag{1.14}$$

where $\mathbf{y}$ is the output vector from the matched filters, $\mathbf{b}$ is given by the information bits from the users and $\mathbf{R}$ is the cross correlation of the signature waveforms

$$\mathbf{R}_{i,j} = \int a_i(t)a_j(t)dt \tag{1.15}$$

$\mathbf{A}$ is the diagonal matrix with $\mathbf{A}_{k,k}$ given by the amplitude of the k-th user and $\mathbf{n}$ is the Gaussian noise vector. From (1.14) we can see that the information component $\mathbf{b}$ can be found by multiplying both sides of the equation by $\mathbf{R}^{-1}$, i.e.,

$$\hat{\mathbf{y}} = \mathbf{R}^{-1}\mathbf{y} = \mathbf{A}\mathbf{b} + \mathbf{R}^{-1}\hat{\mathbf{n}} \tag{1.16}$$

For very low noise level the MAI can be eliminated and the decision is

$$\hat{\mathbf{b}} = sgn(\hat{\mathbf{y}}) \tag{1.17}$$

This is the *decorrelating detector* [17]. The desirable feature of this detector is that it does not require information of the user and interferers power. Only the cross correlation between signature sequences is needed to make the decision. However in a noisy environment the detector would be erroneous since the noise vector is enhanced by the $\mathbf{R}^{-1}$ factor. With the knowledge of the received energies, an *optimal detector* [16] can be constructed by maximizing the likelihood function

$$\hat{\mathbf{b}} = arg\left(\min_{\mathbf{b}}(\int(r(t) - \sum_{k=1}^{K} A^{(k)}b^{(k)}a_k(t))^2dt)\right) \tag{1.18}$$

$$= arg(\max_{\mathbf{b}}(2\sum_{k=1}^{K} A^{(k)}b^{(k)} \int r(t)a_k(t)dt - \sum_{k_1}\sum_{k_2} A^{(k1)}A^{(k2)}b^{(k_1)}b^{(k_2)} \int a_{k_1}(t)a_{k_2}(t)dt)) \tag{1.19}$$

in matrix form the decision can be written as

$$\hat{\mathbf{b}} = arg\left(\max_{\mathbf{b}}(2\mathbf{y}^T\mathbf{Ab} - \mathbf{b}^T\mathbf{ARAb})\right) \tag{1.20}$$

Unlike the decorrelating detector, the optimal detector can obtain decisions by selecting the symbol sequences which maximizes the likelihood function without enhancing the noise component. However it is not a practical receiver since the operational complexity increases exponentially with the number of users.

Working towards practicality, the *MMSE mulituser detector* [18] is a more promising scheme which does not require the information of signature waveforms and amplitudes of the interferers. It is based on the minimization of the mean-square-error between the output and the data,

$$\min\left(E\left[\sum_{k=1}^{K}(b_k - \hat{b}_k)^2\right]\right) \tag{1.21}$$

In fact the decorrelating detector can be considered as asymptotic form of the MMSE detector as the noise level goes to zero [15].

In general, multiuser detection is found to be very effective in the demodulation of signals in the presence of MAI, which typically occurs in the CDMA systems. There are several types of multiuser detectors which provide the near-far resistant feature. However, the complexity of the detector is another important issue for the practical implementation. In terms of the simplicity and practicality of the detector, MMSE multiuser detector seems to have more advantages. Linear multiuser receiver can be developed based on the MMSE criterion [17]. We will look at a blind adaptive multiuser detection model in chapter 3 which is derived from the MMSE detector.

1.4 Outline of Thesis

In chapter 2, we will look at a blind adaptive receiver with the antenna array and M-ary orthogonal modulation for the DS/CDMA system. The mechanism of MAI rejection of this receiver is by using spatial diversity provided by the antenna array. The received signals from the antenna elements are constructively combined by the beamformer. The optimal weights are evaluated by an adaptive algorithm which maximizes the output SNR. The major difference between our receiver and that in [25] is the addition of 64-ary orthogonal modulation in our model. Also, in our model, the demodulation is done by a pair of orthogonal matched filters instead of a single conventional matched filter. Then both the desired signal statistics and the noise statistics can be readily obtained for the adaptive algorithm.

The receiver in chapter 2 works well when the user and interferers are not too close with each other so that the added spatial diversity by the antenna array can improve the system performance. However, in realistic situation, it is possible that the interferers are in proximity to the user. The receiver may fail to detect the desired signals. Hence, we introduce the use of multiuser detector to solve this problem in chapter 3. The combined scheme of the blind adaptive receiver and the multiuser detector is realized by a novel spreading scheme. The scheme consists of two stages of spreading. For each user, the data sequence is first spread with an aperiodic random signature sequence. The resultant sequence is then spread with a periodic deterministic signature sequence. The scheme combines the advantages of the two types of spreading techniques. Signal processing algorithms developed for deterministic sequences, as well as those developed for random sequences, can be readily applied. In particular, multiuser detection and channel estimation can be easily combined in a blind adaptive fashion. Working towards practicality, we have also investigated a simplified structure of the receiver based on the adaptive algorithms.

In chapter 4, conclusions will be drawn from the work and possible extensions will be discussed.

Chapter 2

A Blind Adaptive Receiver with Antenna Arrays and M-ary Orthogonal Data Signals

2.1 Introduction

Direct Sequence / Code Division Multiple Access (DS/CDMA) systems provides improved performance in terms of capacity and coverage area [20]. However, the performance of the system degrades in the presence of multiple access interference (MAI). One approach to mitigate the effects of MAI and multipath is the use of spatial diversity. With the use of antenna arrays, spatial diversity is employed to increase the capacity of CDMA system and to suppress interference sources with arrival angles different from that of the desired user. The combining of an adaptive array antenna and a canceller of interference is found to be able to reject the cochannel interference in DS-Spread spectrum multiple access systems [21]. The effect of base station antenna arrays in cellular CDMA is also studied in [22] and it is found that there can be substantial increase in system capacity by incorporating antenna arrays at the base station.

In IS-95 CDMA standard, 64-ary orthogonal modulation is used. Analysis for DS/CDMA with M-ary orthogonal modulation but without antenna arrays has appeared in [23]-[24]. An antenna array-based receiver structure for DS/CDMA with M-ary orthogonal modulation is proposed in [12]. It uses feedback to determine the winning post-correlation signal vector which are then used to estimate the weight vector with the received signal vector. The decision feedback used in the above system requires training sequence for initialization and hence the receiver may suffer from error propagation.

Based on the need to construct a simple and practical DS/CDMA receiver, a blind adaptive linear receiver is proposed which can suppress MAI spatially and combine multipaths temporally [25] without the complexity of decision feedback. The receiver consists of the conventional matched filter followed by a tapped delay line with the provision of incorporating the use of antenna arrays. It has the ability of suppressing MAI without explicit estimation of any channel conditions. However, the receiver model is developed under the binary data assumption which differs from the orthogonal coded data assumption in IS-95 standard.

In the light of this, we consider a blind adaptive linear receiver with M-ary orthogonal modulation. The receiver has the ability of suppressing MAI in an AWGN channel with 64-ary orthogonal modulated signals. Computer simulation shows that the system performance of the proposed receiver can be maintained under a multipath fading environment. In our model, we also use two matched filters which are orthogonal to each other so that the noise and interference statistics can be collected from the orthogonal matched filter readily. Eigen-analysis and adaptive algorithms are used to obtain the optimal weight vector which maximizes the SNR.

2.2 System Model

We assume that there are K simultaneous users in the system. The kth user, for $1 \leq k \leq K$, generates a sequence of data symbols which are independent and identical distributed (iid) random variables taking values of 1 or -1. The data symbols are then grouped into groups of $\log_2 M$ bits with interleaving. Each group is mapped into one of the M orthogonal Walsh functions, forming an M-ary orthogonal coded data signal. The overall data signal $b_k(t)$ is given by

$$b_k(t) = \sum_{i=-\infty}^{\infty} b_i^{(k)} p_T(t - iT), \tag{2.1}$$

where T is the duration of each of the M Walsh symbols $b_i^{(k)}$ from each M-ary symbol and $p_T(t)$ is the unit rectangular pulse of duration T.

The kth user is provided a randomly generated signature sequence $a^{(k)} = (\ldots, a_0^{(k)}, a_1^{(k)}, \ldots, a_{N-1}^{(k)}, \ldots)$. The elements $a_i^{(k)}$ are iid random variables such that $\Pr(a_i^{(k)} = 1) = \Pr(a_i^{(k)} = -1) = 1/2$. The sequence $a^{(k)}$ is used to spectrally spread the data symbols to form the signal

$$s_k(t) = b_k(t) \sum_{i=-\infty}^{\infty} a_i^{(k)} p_{T_c}(t - iT_c), \tag{2.2}$$

where the chip duration T_c is given by $T_c = MT/N$, N is the number of chips per symbol interval, and $p_{T_c}(t)$ is the rectangular pulse given by

$$p_{T_c}(t) = \begin{cases} 1 & \text{if } 0 \le t \le T_c, \\ 0 & \text{elsewhere.} \end{cases} \tag{2.3}$$

The transmitted signal for the kth user, for $1 \le k \le K$, can be expressed as

$$\mathrm{Re}[\sqrt{2P_k} s_k(t) \exp(\mathrm{j}\omega_c t)], \tag{2.4}$$

where P_k is the power for the kth signal, and ω_c is the carrier frequency.

Without loss of generality (WLOG), we will consider the signal from the first user as the communicating signal and the signals from all other users as interfering signals throughout the chapter.

We now describe the channel model. We assume that the channel is corrupted by AWGN with two-sided power spectral density of $N_0/2$. The signals are received by an antenna array of D elements and there is no multipath fading for now. The signal vector received by the antenna array in complex baseband notation is given by

$$\mathbf{r}(t) = \mathbf{y}(t) + \mathbf{n}_I(t) + \mathbf{n}_W(t), \tag{2.5}$$

where $\mathbf{n}_W(t)$ represents AWGN. We assume that the AWGN is also spatially white. The first user signal contribution $\mathbf{y}(t)$ is given by

$$\mathbf{y}(t) = \sqrt{2P_1} s_1(t - T_1) e^{-\mathrm{j}(\omega_c T_1 + \theta_1)} \mathbf{d}_1. \tag{2.6}$$

The MAI contribution $\mathbf{n}_I(t)$ is given by

$$\mathbf{n}_I(t) = \sum_{k=2}^{K} \sqrt{2P_k} s_k(t - T_k) e^{-\mathrm{j}(\omega_c T_k + \theta_k)} \mathbf{d}_k. \tag{2.7}$$

In (2.6) and (2.7), the parameters T_k, θ_k and $\mathbf{d}_k$ represent the delay, the phase shift and the array response vector associated with the signal from the kth transmitter. For example, a typical array response vector for the k-th signal source by D antenna elements is given by

$$\mathbf{d}_k = [e^{-j2\pi f_c \tau_1(\phi_k)}, \ldots, e^{-j2\pi f \tau_D(\phi_k)}]^T, \tag{2.8}$$

where f_c is the frequency, ϕ_k is the incident angle, and $\tau_D(\phi_k)$ is the time taken by a plane wave arriving from the k-th source to the D-th antenna element. For instance, we consider a linear phase array of equispaced elements [7] with each element separated by half a wavelength ($\frac{\lambda}{2}$), the $\tau_D(\phi_k)$ becomes

$$\tau_D(\phi_k) = \frac{1}{2f_c}(D-1)\sin(\phi_k) \tag{2.9}$$

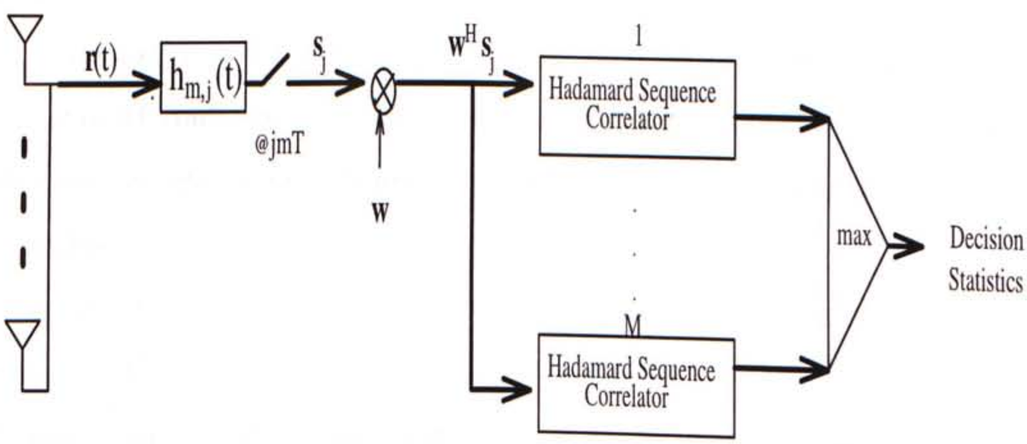

Figure 2.1: Linear receiver for the jth M-ary symbol

Consider the j-th symbol interval $[jMT, (j+1)MT)$. The signals are received at each base station by an antenna array of D elements forming a vector $\mathbf{r}(t)$ which is then passed through a matched filter with impulse response $h_{m,j}(t)$ for the m-th Walsh symbol in the j-th symbol interval.

$$h_{m,j}(t) = \sum_{i=0}^{\frac{N}{M}-1} a^{(1)}_{i+jN+(m-1)\frac{N}{M}} p_{T_c}(-t - iT_c), \quad 1 \le m \le M \tag{2.10}$$

The output of the matched filter is sampled once every T second to give the sample vectors and the matched output of the jth M-ary symbol $\mathbf{s}_j$, which consists of M vectors, is given by

$$\mathbf{s}_j = (\mathbf{s}_{1,j}, \ldots, \mathbf{s}_{M,j}) \tag{2.11}$$

where $\mathbf{s}_{i,j}$ is the corresponding $\mathbf{s}$ for the ith Walsh symbol of the jth symbol interval.

The sample vectors are passed through a beamformer to give the weighted vector $\mathbf{w}^H \mathbf{s}_j$, where $\mathbf{w}$ is a weight vector whose components remain to be determined. The decision statistic for the jth M-ary symbol is evaluated from $\mathbf{w}^H \mathbf{s}_j$.

To demodulate the signal, the weighted signal vector $\mathbf{w}^H \mathbf{s}_j$ is passed through a bank of M Hadamard sequence correlators (Fig.2.1) and the decision statistic is formed by selecting the index associated with the maximum output from the correlators.

To facilitate the derivation of the receiver, we assume that the communication channel is time-invariant. In particular, the number, the powers, the locations, the phase shifts, and the delays of the users are fixed (but unknown). Only the data, the signature sequences and the AWGN are random. It turns out that the resulting receiver is able to adapt quickly. Therefore, such an assumption does not affect the usefulness of the receiver.

We assume that we have achieved synchronization with the signal from the first user. Hence, we may assume $T_1 = 0$. For coherent detection, we may assume the phase shift $\theta_1 = 0$.

To derive the weight vector $\mathbf{w}$, we consider the time interval [0,T) without loss of generality. Equivalently, the received signal $\mathbf{r}(t)$ is passed through a correlator as shown in Fig.2.2. The output of the correlator is given by

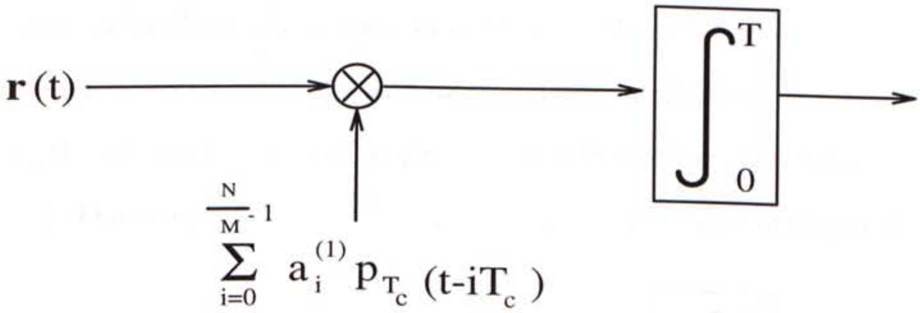

Figure 2.2: Symbol detection using an equivalent correlator

$$\mathbf{s} = \mathbf{z} + \mathbf{n} \tag{2.12}$$

where the first user contribution is given by

$$\mathbf{z} = \sqrt{2P_1}Tb_0^{(1)}\mathbf{d}_1 \tag{2.13}$$

and the overall noise and interference contribution is given by

$$\mathbf{n} = \mathbf{n}_W + \sum_{k=2}^{K} \mathbf{i}_k. \tag{2.14}$$

In (2.14), the AWGN contribution is represented by $\mathbf{n}_W$, and the interference due to the kth user is given by

$$\begin{aligned} \mathbf{i}_k &= \sqrt{2P_k} \sum_{i=0}^{\frac{N}{M}-1} a_i^{(1)} [a_{i-\gamma_k-1}^{(k)} \alpha_k + \\ & \quad a_{i-\gamma_k}^{(k)} (T_c - \alpha_k)] e^{-\mathrm{j}(\omega_c T_k + \theta_k)} \mathbf{d}_k \end{aligned} \tag{2.15}$$

where

$$\gamma_k = \lfloor \frac{T_k}{T_c} \rfloor \tag{2.16}$$

and

$$\alpha_k = T_k - \gamma_k T_c. \tag{2.17}$$

In order to facilitate the process of optimizing the weight vector, a counterpart of $\mathbf{s}$ that contains only noise and interference contributions is needed. More precisely, the received signal $\mathbf{r}(t)$ is passed through another correlator as shown in Fig.2.3. The sequence $(c_0^{(1)}, c_1^{(1)}, \ldots, c_{\frac{N}{M}-1}^{(1)})$ is chosen to be orthogonal to the

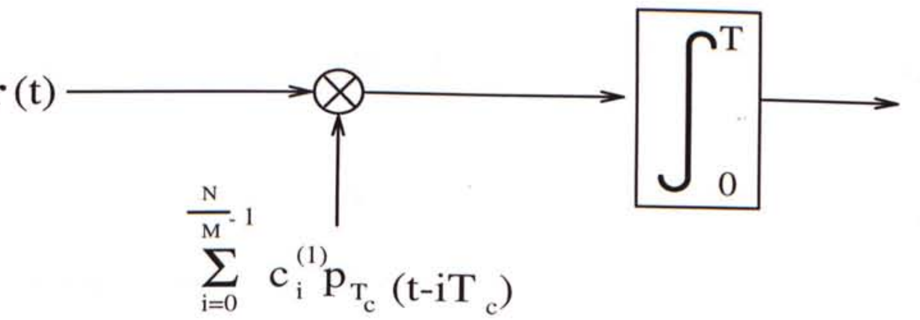

Figure 2.3: Orthogonal matched filter

sequence $(a_0^{(1)}, a_1^{(1)}, \ldots, a_{\frac{N}{M}-1}^{(1)})$, i.e.,

$$\sum_{i=0}^{\frac{N}{M}-1} a_i^{(1)} c_i^{(1)} = 0. \tag{2.18}$$

The purpose is to remove the first user signal contribution while the statistics for the noise and the interference contributions are maintained. The output is given by

$$\hat{\mathbf{s}} = \hat{\mathbf{n}} = \hat{\mathbf{n}}_W + \sum_{k=2}^{K} \hat{\mathbf{i}}_k. \tag{2.19}$$

Notice that $\hat{\mathbf{n}}_W$ is identically distributed as $\mathbf{n}_W$, and for each k, $\hat{\mathbf{i}}_k$ is identically distributed as $\mathbf{i}_k$.

2.3 Eigen-Analysis Algorithm

We consider the correlation matrices of the output vectors. Inherent from the correlation properties (Appendix A) of the despread signal at the matched filter output, the correlation matrix obtained from $\mathbf{s}$ is given by

$$\mathbf{R}_{\mathbf{s}} = \mathrm{E}[\mathbf{s}\mathbf{s}^H] = \mathbf{R}_{\mathbf{z}} + \mathbf{R}_{\mathbf{n}} \tag{2.20}$$

where

$$\mathbf{R}_{\mathbf{z}} = \mathrm{E}[\mathbf{z}\mathbf{z}^H] \tag{2.21}$$

and

$$\mathbf{R}_{\mathbf{n}} = \mathrm{E}[\mathbf{n}\mathbf{n}^H]. \tag{2.22}$$

The correlation matrix obtained from $\hat{\mathbf{s}}$ is given by

$$\mathbf{R}_{\hat{\mathbf{s}}} = \mathbf{R}_{\mathbf{n}}. \tag{2.23}$$

We consider the weight vector that maximizes SNR defined by, for $\mathbf{w} \neq \mathbf{0}$,

$$\mathrm{SNR}(\mathbf{w}) = \frac{\mathbf{w}^H \mathbf{R}_{\mathbf{z}} \mathbf{w}}{\mathbf{w}^H \mathbf{R}_{\mathbf{n}} \mathbf{w}}. \tag{2.24}$$

It can be shown that the weight vector that maximizes the SNR is the generalized eigenvector associated with the largest generalized eigenvalue of the matrix pencil $(\mathbf{R}_{\mathbf{z}}, \mathbf{R}_{\mathbf{n}})$. Since, for $\mathbf{w} \neq \mathbf{0}$,

$$\frac{\mathbf{w}^H \mathbf{R}_{\mathbf{s}} \mathbf{w}}{\mathbf{w}^H \mathbf{R}_{\mathbf{n}} \mathbf{w}} = \mathrm{SNR}(\mathbf{w}) + 1, \tag{2.25}$$

the optimal weight vector is also the generalized eigenvector associated with the largest generalized eigenvalue of the matrix pencil $(\mathbf{R}_{\mathbf{s}}, \mathbf{R}_{\mathbf{n}})$. Since $\mathbf{R}_{\hat{\mathbf{s}}} = \mathbf{R}_{\mathbf{n}}$, the optimal weight vector may be found by the generalized eigenvector associated with the largest generalized eigenvalue of the matrix pencil $(\mathbf{R}_{\mathbf{s}}, \mathbf{R}_{\hat{\mathbf{s}}})$.

To find the optimal weight vector, we need estimates of $\mathbf{R}_{\mathbf{s}}$ and $\mathbf{R}_{\hat{\mathbf{s}}}$. Any consistent estimators of the correlation matrices $\mathbf{R}_{\mathbf{s}}$ and $\mathbf{R}_{\hat{\mathbf{s}}}$ can be used. For example, the correlation matrices $\mathbf{R}_{\mathbf{s}}, \mathbf{R}_{\hat{\mathbf{s}}}$ can be estimated by using the timing average of the M-ary symbols. For each M-ary symbol is now represented by M Walsh symbols, we can combine the M signal contributions before averaging.

$$\mathbf{R}_{\mathbf{s}} \approx \frac{1}{J}\sum_{j=0}^{J-1}\sum_{i=1}^{M}\mathbf{s}_{i,j}\mathbf{s}_{i,j}^{H}, \tag{2.26}$$

$$\mathbf{R}_{\hat{\mathbf{s}}} \approx \frac{1}{J}\sum_{j=0}^{J-1}\sum_{i=1}^{M}\hat{\mathbf{s}}_{i,j}\hat{\mathbf{s}}_{i,j}^{H}. \tag{2.27}$$

where $\mathbf{s}_{i,j}$ and $\hat{\mathbf{s}}_{i,j}$ are the corresponding $\mathbf{s}$ and $\hat{\mathbf{s}}$ for the ith bit of the jth symbol interval.

2.4 Simulation Results

In the computer simulation, we assume aperiodic signature sequence. The signature sequence employs rectangular chip waveforms. There are 256 chips per symbol, thus N=256. 64 Walsh functions are used to represent the 64-ary orthogonal modulated data as in the IS-95 CDMA standard. There are 2 users in the system. An antenna array of 5 elements is used. The power of the interferer is 20dB stronger than that of the desired user and the signal-to-white-noise ratio (SWNR) is 15dB for the desired user.

Fig.2.4 shows the average SNR obtained for different number of symbol intervals. We compare the results with the antenna array against the results when there is only one antenna element, i.e., no weighting applied. We assume that in both cases, the same amount of total energy is collected. It is clear from the figure that without weighting the average SNR maintains at a low level while in

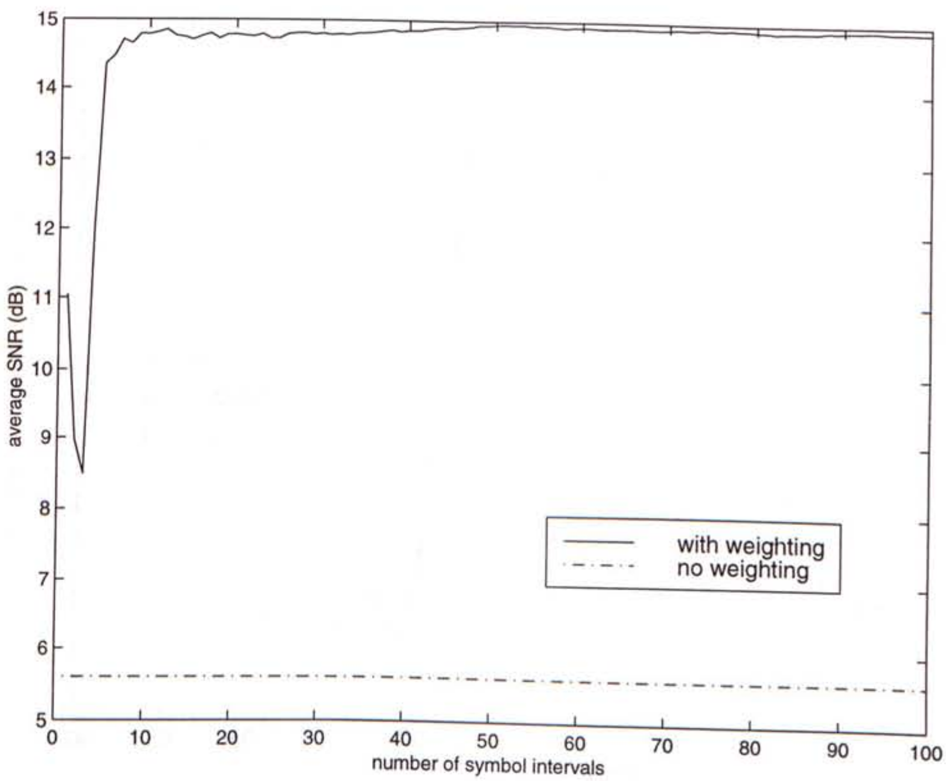

Figure 2.4: Average SNR of 64-ary orthogonal modulated signals

the weighting case the average SNR is approaching the maximum (15dB) as the number of sample vectors increases.

Next, we assume the user signal comes at 0^0 whereas the interferer comes at 60^0. The normalized directional magnitude responses of the receiver for a 5-element array and a 9-element array are shown in Fig.2.5. It shows that the receiver performs spatial selection to avoid signal in the direction of the interferer.

The average maximum SNR achievable by the receiver using antenna array with different number of elements (D) is plotted in Fig.2.6. We assume each interfering signal power is 20dB above the desired signal power and the DOA of the interfering signals are random. The advantage of using antenna arrays

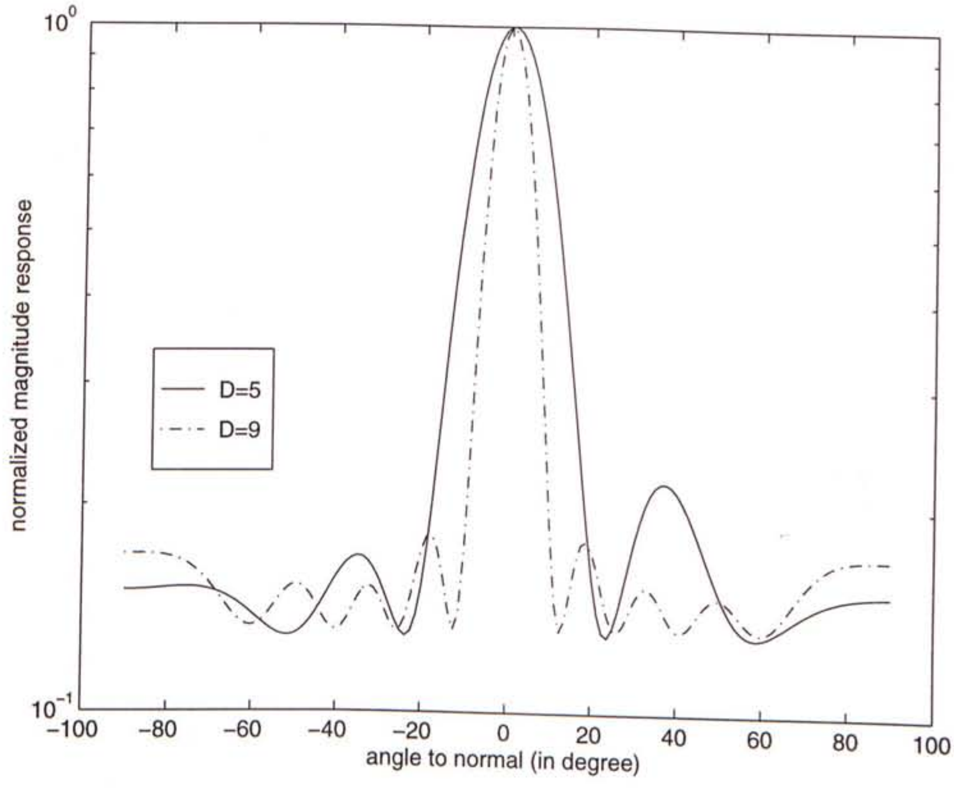

Figure 2.5: Directional magnitude response of the system

instead of a single antenna can be clearly seen from the result.

The performance of symbol error probability is shown in Fig.2.7. It can be seen that the difference between the probability of error for the weighted (D=5) and the unweighted (D=1) case becomes dramatic as E_b/N_0 value increases.

Now we consider the system under a multipath fading environment. In urban environment, the DS/CDMA system has coherence time much larger than the symbol duration T. The coherence bandwidth is much smaller than the bandwidth of the transmitted signal. Therefore, the channel can be assumed to be slow frequency-selective fading [20, Ch.8].

In the simulation, we assume that the path delay, $\tau_{k,\lambda}$, is uniformly distributed on $[0, \tau_{max})$ where $\tau_{max} = 5T_c$.

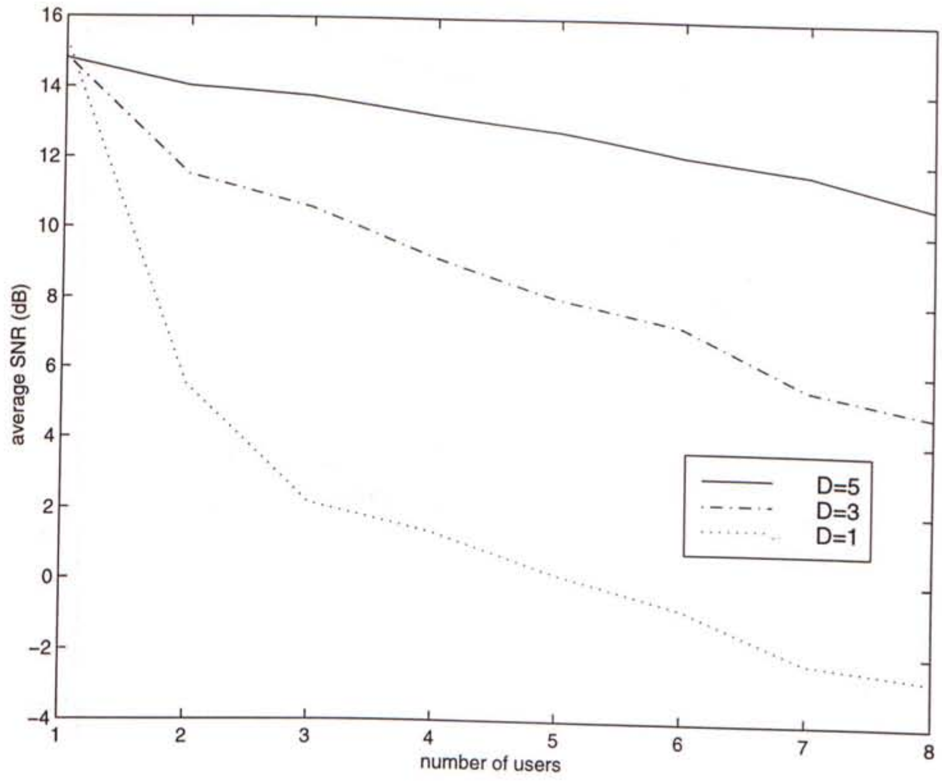

Figure 2.6: Average maximum SNR achievable vs number of users

Fig.2.8 shows the SNR achieved under multipath fading assuming that the path delays for the desired user can be correctly estimated. The optimal mean SNR can be obtained after 30 samples and the convergence rate decreases slightly comparing with the result obtained in the non-fading environment.

In order to combat multipath fading without knowledge of the path delays, we introduce a sampling scheme in the proposed receiver to catch the multipath signals. More precisely, in the previous receiver model, the matched filter output for the j-th symbol is sampled at mT for $m = 0, 1, ..., M-1$ to form $\mathbf{s}_j$ while in the new sampling scheme (Fig.2.9), we sample the matched output at $mT + T_c$ as well to form $\tilde{\mathbf{s}}_j$. The two samples are then concatenated and the same algorithm can be used to determine the weight by using the concatenated sample. The

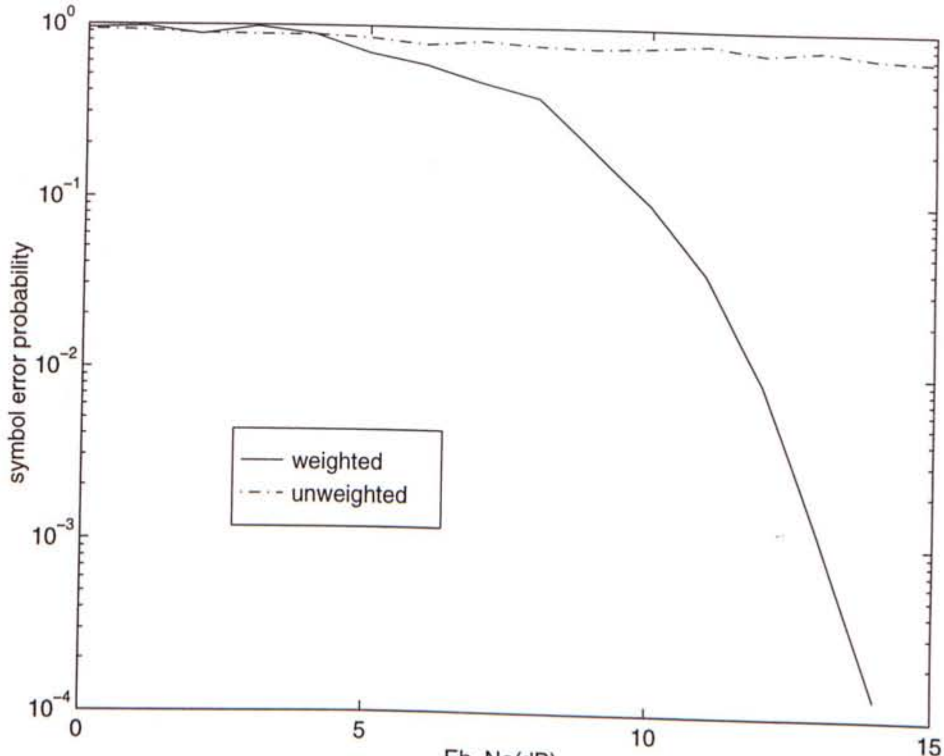

Figure 2.7: Error performance of the receiver, M=64

reason of using the new sampling scheme is that we want to catch the multipath signals by sampling at an arbitrary delay, in this case, we try to sample at a delay of one chip interval T_c. Theoretically we can have more than two samples, for example, we can add a new sample at a delay of $2T_c$ and concatenates with the previous two samples to determined the weight vector. The tradeoff is that as the number of samples increase, the complexity of the system will increase too.

Fig.2.10 shows the SNR performance of the system with the introduction of the new sampling scheme. In this scenario, we assume there are 2 users and the number of multipaths for each user is 8. The path delay is uniformly distributed on $[0,\ 3T_c)$. Two samples of the matched filter output are collected, one at

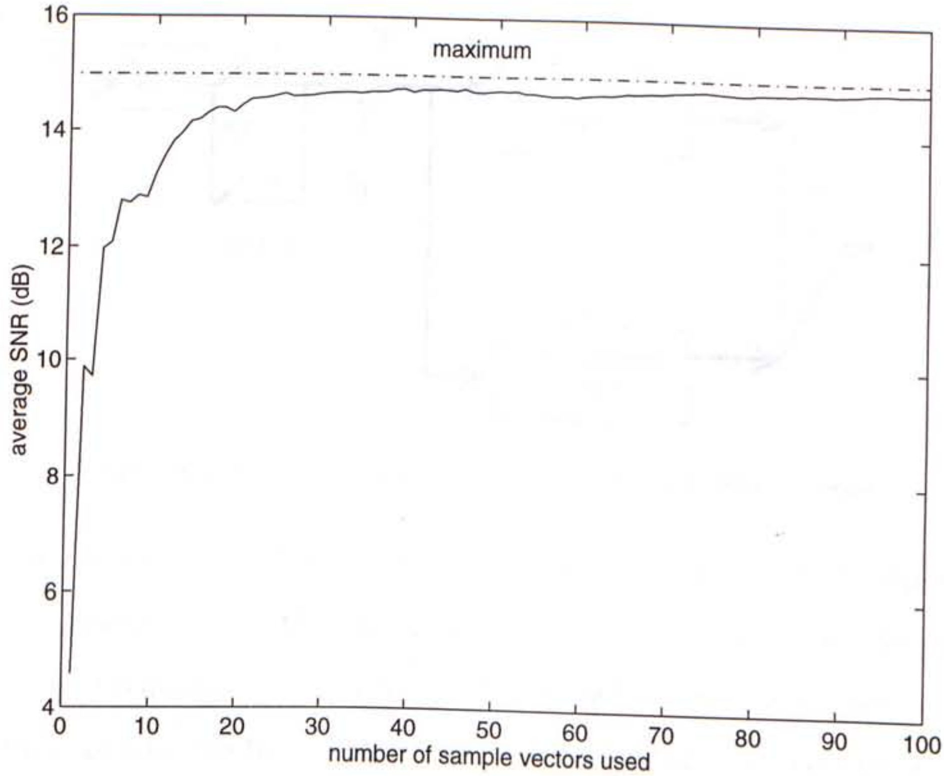

Figure 2.8: Average SNR under multipath fading, L_k=5

mT and another at $mT + T_c$. The result shows that with the use of the new sampling scheme, the SNR can converge very close to the optimal value even in the presence of a large number of multipaths with unknown delays.

2.5 Adaptive Algorithm

The major disadvantage of the eigen-analysis algorithm is the computational complexity involved in obtaining the generalized eigenvector, which limits the practicality of the system. Moreover, the convergence rate can also be limited by the accuracy in the estimation of the relevant matrices. It is possible to develop adaptive algorithms [25] to obtain the optimal weight vector for the receiver

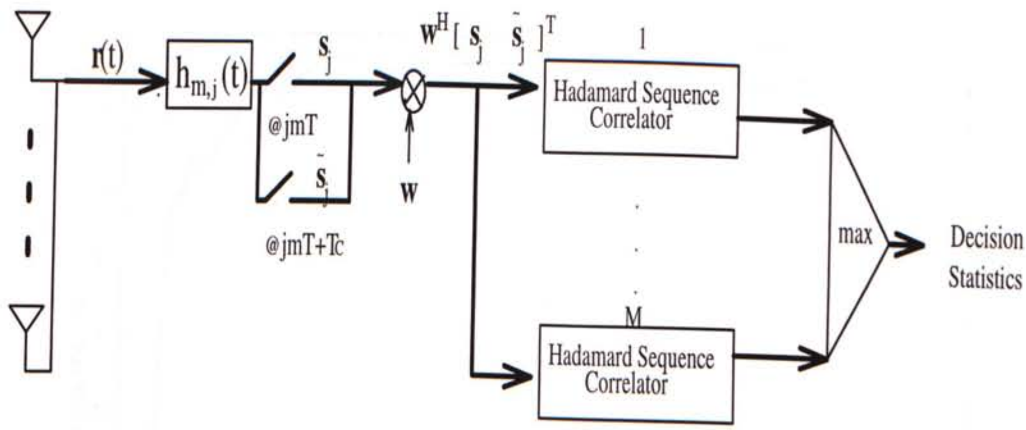

Figure 2.9: Receiver model with the new sampling scheme

based on the constrained minimization of output energy criterion (Appendix B). The algorithm solves the constrained minimization problem of the output energy and it requires the knowledge of $\mathbf{R_s}$ and $\mathbf{zz^H}$. To obtain a blind adaptive algorithm, we estimate $\mathbf{R_s}$ and $\mathbf{R_{\hat{s}}}$ by $\mathbf{s_j s_j^H}$ and $\mathbf{\hat{s}_j \hat{s}_j^H}$ where $\mathbf{s_j}$ is the j-th matched filter output vector and $\mathbf{\hat{s}_j}$ is the j-th orthogonal matched filter output vector. When N is large, it is also reasonable to estimate $\mathbf{zz^H}$ by $\mathbf{s_j s_j^H} - \mathbf{\hat{s}_j \hat{s}_j^H}$. Hence, the blind adaptive rule becomes

$$\mathbf{w}(j) = \mathbf{w}(j-1) + \delta[\mathbf{s_j^H w}(j-1)[(\mathbf{\hat{s}_j^H \hat{s}_j})\mathbf{s_j} - (\mathbf{\hat{s}_j^H s_j})\mathbf{\hat{s}_j}]] \tag{2.28}$$

The algorithm can be viewed as projecting the current weight vector to the direction of the noise and signal, then removing the noise part by orthogonal projection and changing the current weight vector by a small amount in the resulting direction.

Fig.2.11 compares the SNR performance achieved by the adaptive gradient algorithm with that of the eigen algorithm. We assume the use of antipodal data in this comparison. There are 2 users and the DOA of the interfering signal is 60 degree, with power 20dB above the desired signal. The step size (δ) used in

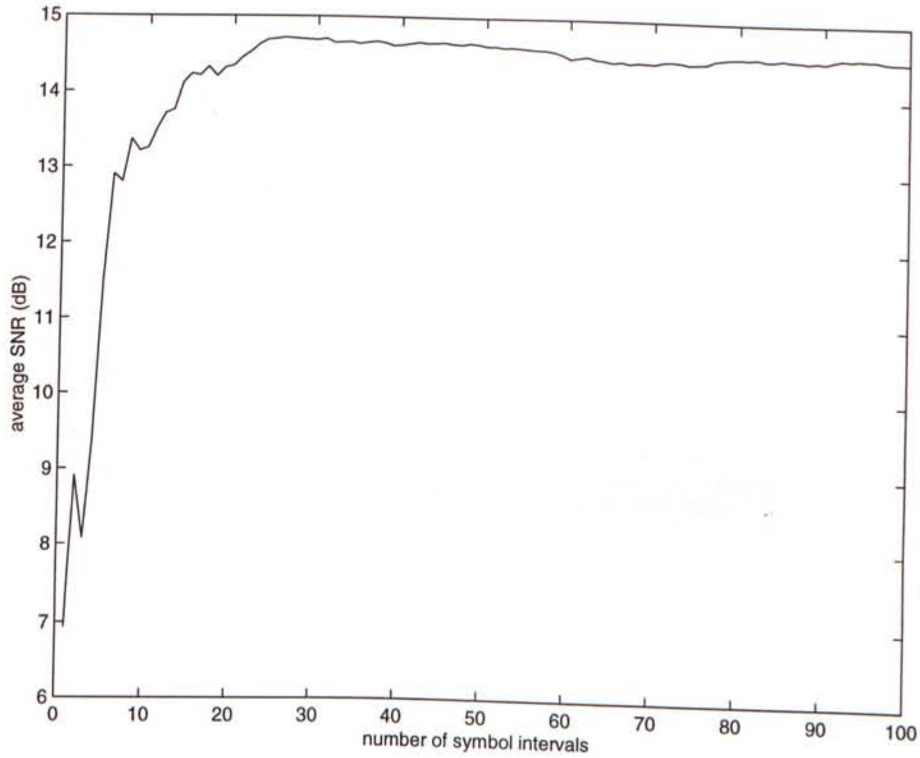

Figure 2.10: Average SNR with the new sampling scheme, D=5

this case is 0.001. It shows that the gradient algorithm settles faster than the eigen algorithm. The reason is that no estimation of matrices is required. In the gradient algorithm, only the signal vectors $\mathbf{s_j}$ and $\hat{\mathbf{s}}_\mathbf{j}$ are needed to perform iterative operation to update the weight vector.

The SNR performance of the adaptive gradient algorithm for 64-ary orthogonal data is shown in Fig.2.12. We assume that there are 2 users and the DOA of the interfering signal is random, with power 20dB above the desired signal. The step size (δ) is set to 1x10^{-6} in this scenario. Again, the result shows that with the use of M-ary orthogonal modulated signals, the gradient algorithm settles faster than the eigen algorithm.

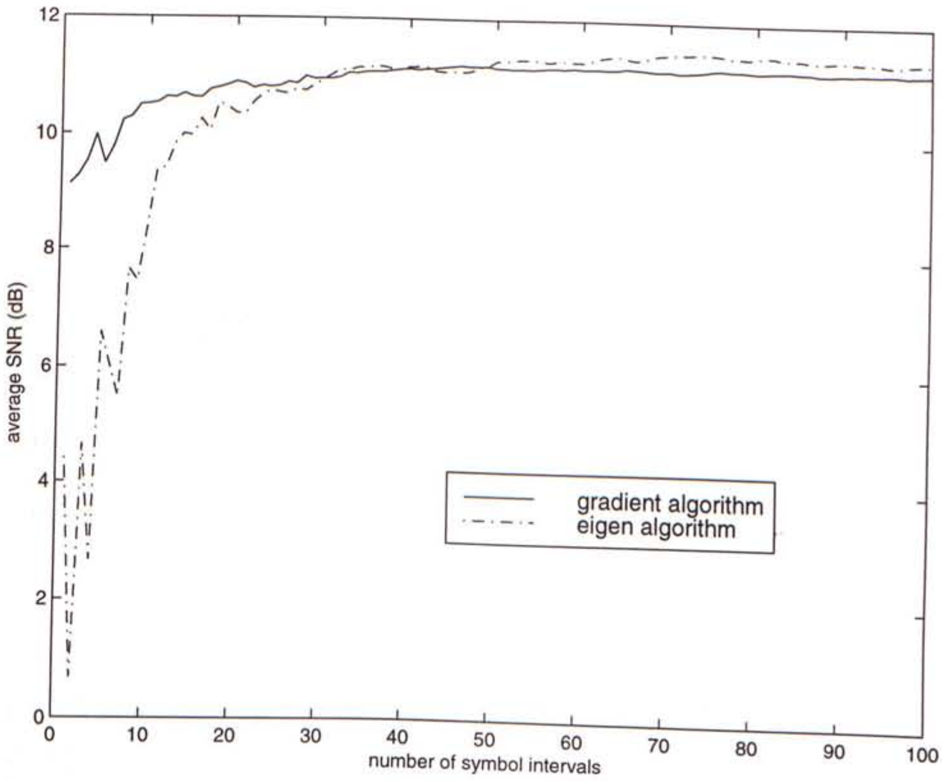

Figure 2.11: Average SNR achieved by the gradient algorithm

2.6 Summary

This scheme focuses on the suppression of multiple access interference of M-ary orthogonal-modulated signals by using a novel blind adaptive receiver. The receiver consists of a conventional matched filter followed by a beamformer. The capability of rejecting MAI is realized by choosing the optimal weights in the beamformer so as to maximize the signal-to-noise ratio. In IS-95 CDMA standard, 64-ary orthogonal modulation is used. We have incorporated the M-ary orthogonal modulated signals in our system. The proposed receiver is simple, blind adaptive and is suitable for practical implementation with the adaptive algorithm.

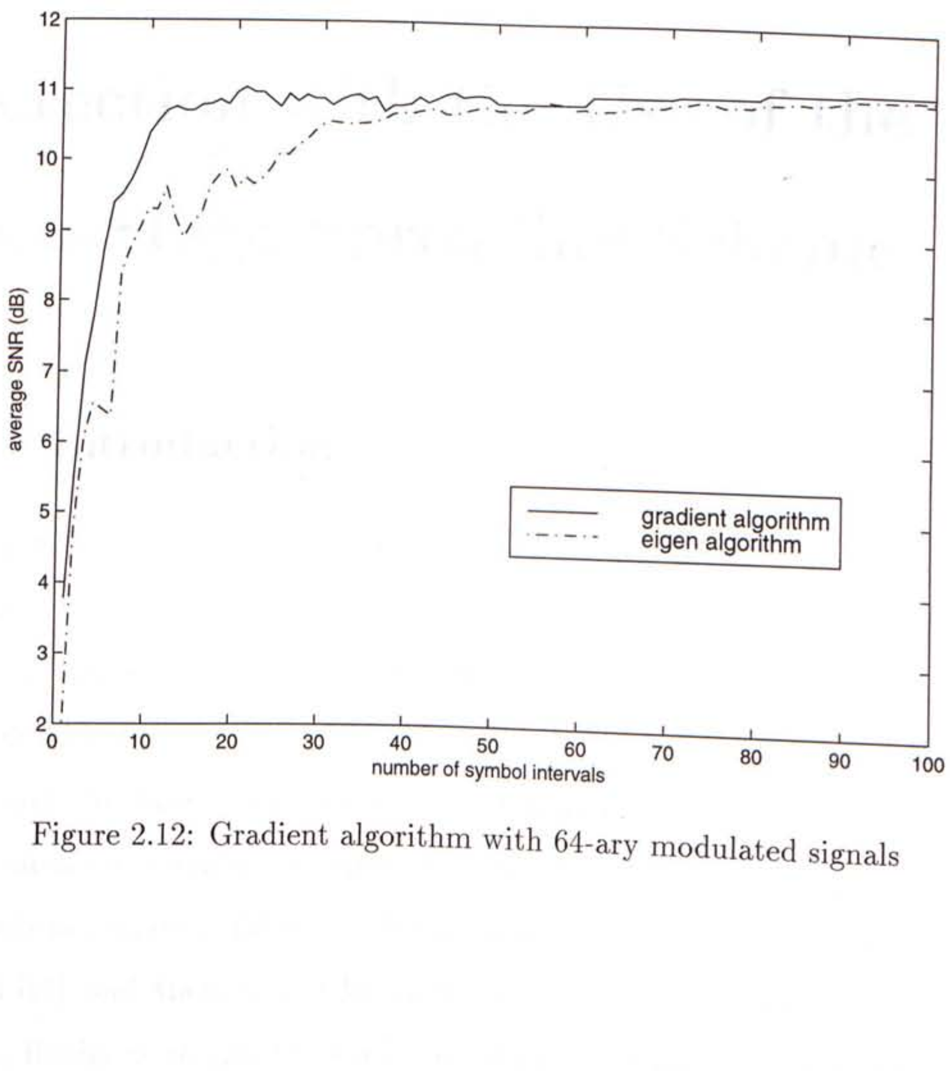

Figure 2.12: Gradient algorithm with 64-ary modulated signals

Chapter 3

Detection with the Use of the Two-Stage Spreading Scheme

3.1 Introduction

Multiple access interference (MAI) has been the key problem limiting the capacities of practical direct sequence code division multiple access (DS/CDMA) systems. To remove or reduce MAI, many signal processing algorithms have been developed.

Verdú [16] worked out the optimum multiuser detector, which was, however, often too complex to implement. Working towards practicability, many researchers proposed different suboptimal receivers. For example, Lupas and Verdú [17], and Madhow and Honig [18] considered some linear receivers. Recently, Honig, *et al.* [26] proposed a blind adaptive linear receiver which eliminated the need for training sequences. Practical implementations of these receivers with reasonable complexity rely on the use of short periodic signature sequences. However, with short periodic signature sequences, blind estimation of some channel parameters, such as the direction of arrival (DOA) of a user signal, can be quite difficult.

Another way to mitigate the near-far problem is to explore the spatial relationship between a user and the interferers and to utilize the steering capability of an antenna array. For example, Wong, *et al.* [25], [27], and Naguibi, *et al.* [28], [22] worked in this direction. Blind adaptive implementations of these algorithms rely on the use of aperiodic signature sequences (In practice, sequences with long periods are used). However, with aperiodic signature sequences, blind multiuser detection schemes become almost impossible.

In this chapter, we consider a novel spectral spreading scheme that combines spreading with aperiodic sequences and spreading with short periodic sequences. Aperiodic sequences are modeled as random sequences while short periodic sequences are modeled as deterministic sequences. For each user, the data sequence is first spread with an aperiodic random signature sequence. The resultant sequence is then spread with a periodic deterministic signature sequence. [1] The scheme combines the advantages of both spreading techniques. Signal processing algorithms developed for deterministic sequences, as well as those developed for random sequences, can be readily applied. The reason is that the final signal can be interpreted in two different ways – a signal spread with a deterministic sequence or a signal spread with a random sequence. To see the first interpretation, notice that the sequence after the first stage of spreading can be viewed as a sequence of coded data symbols (with a repetition code changing every symbol interval). Therefore, the final signal can be viewed as the result of spreading a

[1] In practical implementations, the two stages of spreading can be done in a single step.

coded sequence with a deterministic sequence. To see the second interpretation, notice that the second stage of spreading can be viewed as assigning a generalized chip waveform to the user. Of course, different users can now be using potentially different generalized chip waveforms. Therefore, the final signal can be viewed as the result of spreading with a random sequence.

With the simple interpretations, it can be readily seen that many algorithms for deterministic sequences or random sequences can be applied separately. However, as we will show, suitable joint applications might yield superior performance.

3.2 System Model

In this section, we describe the model of the DS/CDMA system. We assume that there are K simultaneous users in the system.

The kth user, for $1 \leq k \leq K$, generates a stream of data symbols $b^{(k)}$, given by

$$b^{(k)} = (\ldots, b_0^{(k)}, b_1^{(k)}, b_2^{(k)}, \ldots). \tag{3.1}$$

The data symbols $b_j^{(k)}$ are random variables with $E[|b_j^{(k)}|^2] = 1$.

The kth user, for $1 \leq k \leq K$, is provided an aperiodic random signature sequences $a^{(k)}$ given by

$$a^{(k)} = (\ldots, a_0^{(k)}, a_1^{(k)}, \ldots, a_{N_1-1}^{(k)}, \ldots) \tag{3.2}$$

where the elements $a_i^{(k)}$ are modeled as independent and identically distributed (iid) random variables such that $\Pr(a_i^{(k)} = 1) = \Pr(a_i^{(k)} = -1) = 1/2$. The kth user is also provided a periodic deterministic signature sequences $c^{(k)}$ of period

N_2 given by

$$c^{(k)} = (\dots, c_0^{(k)}, c_1^{(k)}, \dots, c_{N_2-1}^{(k)}, \dots). \tag{3.3}$$

The data sequence is spread with the aperiodic sequence to give the sequence

$$\begin{array}{ccccccc} \dots & b_0^{(k)}a_0^{(k)} & b_0^{(k)}a_1^{(k)} & \dots & b_0^{(k)}a_{N_1-1}^{(k)} & & \\ & b_1^{(k)}a_{N_1}^{(k)} & b_1^{(k)}a_{N_1+1}^{(k)} & \dots & b_1^{(k)}a_{2N_1}^{(k)} & \dots & \end{array} \tag{3.4}$$

The resultant sequence is then spread with the period sequence and appropriately modulated to give the following transmitted signal

$$s_k(t) = \sqrt{2P_k} \sum_{i=-\infty}^{\infty} b_{\lfloor i/N \rfloor}^{(k)} a_{\lfloor i/N_2 \rfloor}^{(k)} c_i^{(k)} \psi(t - iT_c) \cos(\omega t) \tag{3.5}$$

where the overall spreading factor $N = N_1 N_2$, T_c is the delay between consecutive chips, ω is the carrier frequency and $\psi(t)$ is the chip waveform that is normalized ($\int_{-\infty}^{\infty} |\psi(t)|^2 dt = 1$). P_k is the power for the kth user signal. Notice that (3.5) can be rewritten as

$$s_k(t) = \sqrt{2P_k} \sum_{i=-\infty}^{\infty} \tilde{b}_{\lfloor i/N_2 \rfloor}^{(k)} c_i^{(k)} \psi(t - iT_c) \cos(\omega t) \tag{3.6}$$

where $\tilde{b}_{\lfloor i/N_2 \rfloor}^{(k)} = b_{\lfloor i/N \rfloor}^{(k)} a_{\lfloor i/N_2 \rfloor}^{(k)}$. Equation (3.6) gives the first interpretation – a signal spread with a periodic deterministic signature sequence at a spreading factor of N_2. Equation (3.5) can also be rewritten as

$$s_k(t) = \sqrt{2P_k} \sum_{i=-\infty}^{\infty} b_{\lfloor i/N_1 \rfloor}^{(k)} a_i^{(k)} \Psi_k(t - iN_2T_c) \cos(\omega t) \tag{3.7}$$

where

$$\Psi_k(t) = \sum_{i=0}^{N_2-1} c_i^{(k)} \psi(t - iT_c). \tag{3.8}$$

Equation (3.7) gives the second interpretation – a signal spread with an aperiodic random signature sequence at a spreading factor of N_1 with a generalized chip waveform.

Without loss of generality, we consider the signal from the first user as the desired signal and the signals from all other users as interfering signals.

We now describe the channel model. For simplicity, we consider a multiple access channel with additive white Gaussian noise (AWGN) only. Extensions with multipath fading can be handled similarly as in [25] and [27]. An antenna array is used for signal reception. The received signal vector in complex baseband representation is given by

$$\begin{aligned}\mathbf{r}(t) = \textstyle\sum_{k=1}^{K} \sqrt{2P_k}\Big\{ \textstyle\sum_{i=-\infty}^{\infty} b_{\lfloor i/N \rfloor}^{(k)} a_{\lfloor i/N_2 \rfloor}^{(k)} c_i^{(k)} \\ \cdot\psi(t - T_k - iT_c)\Big\}\mathbf{d}_k + \mathbf{n}(t),\end{aligned} \tag{3.9}$$

where T_k represents the delay, $\mathbf{d}_k$ accounts for the overall effects of phase shift and direction of arrival (DOA) of the k-th user signal, and $\mathbf{n}(t)$ represents AWGN. We assume that synchronization has been achieved with the first user signal. Therefore, the delay of the first user signal T_1 can be taken to be zero.

3.3 Blind Beamforming

With the interpretation given by (3.7), it is possible to perform blind beamforming in way similar to those in [25] and [27].

Consider the receiver shown in Fig.3.1. The received signal vector is passed through a linear filter. Let $\hat{\Psi}_k(t)$ be the response of the linear filter to $\Psi_k(t)$. The output of the linear filter is given by

$$\begin{aligned}\hat{\mathbf{r}}(t) = \textstyle\sum_{k=1}^{K} \sqrt{2P_k}\Big\{ \textstyle\sum_{i=-\infty}^{\infty} b_{\lfloor i/N_1 \rfloor}^{(k)} a_{\lfloor i \rfloor}^{(k)} \\ \cdot\hat{\Psi}_k(t - T_k - iN_2T_c)\Big\}\mathbf{d}_k + \hat{\mathbf{n}}(t).\end{aligned} \tag{3.10}$$

The output is sampled once every N_2T_c seconds. (With suitable choices of the chip waveform $\psi(t)$ and the linear filter, it is possible to eliminate intersymbol

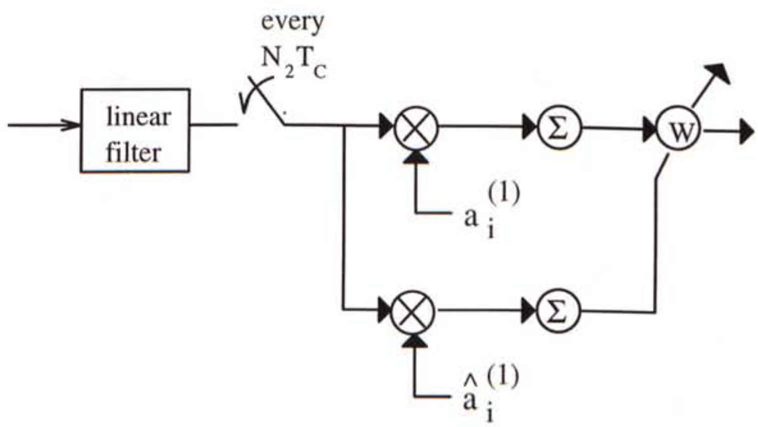

Figure 3.1: Receiver with beamforming

interference, i.e., $\hat{\Psi}_k(iN_2T_c) = 0$ for any integer $i \neq 0$ and any $1 \leq k \leq K$. We assume such choices throughout the chapter.)

The samples within a symbol interval are combined with a sequence correlator according to the sequence $a^{(1)}$. Without loss of generality, we consider the symbol interval $[0, NT_c)$. The output of the sequence correlator is given by

$$\mathbf{s} = \mathbf{z} + \mathbf{n} + \sum_{k=2}^{K} \mathbf{i}_k, \tag{3.11}$$

where the desired signal contribution is given by

$$\mathbf{z} = \sqrt{2P_1} N_1 b_0^{(1)} \hat{\Psi}_1(0) \mathbf{d}_1, \tag{3.12}$$

the interference due to the kth user is given by

$$\mathbf{i}_k = \sqrt{2P_k} \sum_{i=0}^{N_1} a_i^{(1)} \Big\{ \sum_{\lambda} b_{\lfloor \lambda/N_1 \rfloor}^{(k)} a_{\lfloor \lambda \rfloor}^{(k)} \hat{\Psi}_k((i-\lambda)N_2T_c - T_k) \Big\} \mathbf{d}_k, \tag{3.13}$$

and the AWGN contribution is represented by $\mathbf{n}$.

Finally, a weight vector $\mathbf{w} = [w_1, w_2, \ldots, w_m]^T$ combines the contributions from the output vector to give the decision statistic $Z = \mathbf{w}^H\mathbf{s}$. The same algorithms as discussed in chapter 2 can be used to find the weights. Similarly, we

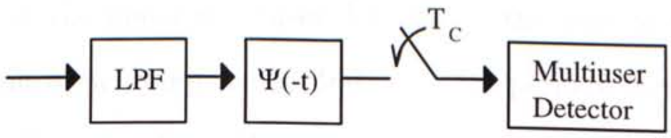

Figure 3.2: Receiver with multiuser detection

estimate the correlation matrix $\mathbf{R_s}$ and $\mathbf{R_{\hat{s}}}$ by $\mathbf{ss^H}$ and $\mathbf{\hat{s}\hat{s}^H}$, where $\mathbf{s}$ is the output from the sequence $(a^{(1)})$ correlator and $\hat{\mathbf{s}}$ is the output from the orthogonal sequence $(\hat{a}^{(1)})$ correlator. We consider the weight vector that maximizes SNR. From the formulations in section 2.3, the optimal weight vector is the largest generalized eigenvalue of the matrix pencil $(\mathbf{R_s}, \mathbf{R_{\hat{s}}})$.

3.4 Blind Adaptive Multiuser Detection without Antenna Arrays

With the interpretation given by (3.6), blind multiuser detection can be readily performed as in [26]. Consider the receiver shown in Fig.3.2. The received signal is given by

$$\begin{aligned} r(t) = \textstyle\sum_{k=1}^{K} \sqrt{2P_k}\Big\{ \textstyle\sum_{i=-\infty}^{\infty} b^{(k)}_{\lfloor i/N \rfloor} a^{(k)}_{\lfloor i/N_2 \rfloor} c^{(k)}_i \\ \cdot\psi(t - T_k - iT_c)\Big\} e^{-j\theta_k} + n(t), \end{aligned} \tag{3.14}$$

where θ_k is the phase shift and $n(t)$ represents AWGN.

It is passed through a chip matched filter, and is sampled at chip rate. Consider the interval [0, T). The input to the multiuser detector is the N_2-dimensional vector $\mathbf{r}$, which is formed by N_2 outputs of the chip matched filter. The linear multiuser detector to be considered is an N_2-dimensional vector $\mathbf{m}$, which correlates with $\mathbf{r}$ to give the output $\mathbf{m}^H\mathbf{r}$.

The Blind Multiuser Detector proposed by Honig, *et al.*[26] is based on the decomposition of the linear multiuser detector as the sum of two orthogonal components. One of the components comes from the periodic signature sequence of the desired user and is given by

$$\mathbf{c}_1 = [c_0^{(1)}, c_1^{(1)}, \ldots, c_{N_2-1}^{(1)}]^T \tag{3.15}$$

The other component $\mathbf{x}$ is orthogonal to $\mathbf{c}_1$ The canonical representation of the detector is

$$\mathbf{m} = \mathbf{c}_1 + \mathbf{x} \tag{3.16}$$

where

$$< \mathbf{c}_1, \mathbf{x} > \stackrel{\triangle}{=} \mathbf{c}_1^H \mathbf{x} = 0 \tag{3.17}$$

In order to get the adaptation rule for $\mathbf{x}$, we minimize the mean output energy $MOE(\mathbf{x})$. The reason for using MOE function in the adaptation is that it eliminates the need to know the data in order to implement a gradient descent algorithm, and the minimization of MOE is equivalent to the minimization of mean-square-error. This results from the fact that

$$MOE(\mathbf{x}) = E[| < \mathbf{r}, \mathbf{c}_1 + \mathbf{x} > |^2] \tag{3.18}$$

where $\mathbf{r}$ represents the received signal vector.

Now

$$MSE(\mathbf{x}) = E[|\sqrt{2P_1} N_2 b_0^{(1)} a_0^{(1)} b^{(1)} - < \mathbf{r}, \mathbf{c}_1 + \mathbf{x} > |^2] \tag{3.19}$$

then

$$MSE(\mathbf{x}) = 2P_1 N_2^2 + MOE(\mathbf{x}) - 2P_1 N_2 Re[< \mathbf{c}_1, \mathbf{c}_1 + \mathbf{x} >] \tag{3.20}$$

therefore

$$MSE(\mathbf{x}) = MOE(\mathbf{x}) - 2P_1 N_2^2 \tag{3.21}$$

3.4.1 Stochastic Gradient Descent Algorithm

The derivation of the adaptation rule for $\mathbf{x}$ follows from the unconstrained gradient of the MOE in (3.18) which is equal to a scaled version of the observations

$$E[< \mathbf{r}, \mathbf{c}_1 + \mathbf{x} > \mathbf{r}] \tag{3.22}$$

We consider a stochastic gradient algorithm and consider the term $< \mathbf{r}, \mathbf{c}_1 + \mathbf{x} > \mathbf{r}$. We need to find the projection of the gradient of the mean output energy $MOE(\mathbf{x})$ onto the linear subspace orthogonal to $\mathbf{c}_1$, so that the orthogonality condition (3.17) is satisfied at each step of the algorithm The component of $\mathbf{r}$ orthogonal to $\mathbf{c}_1$ is equal to

$$\mathbf{r} - < \mathbf{r}, \mathbf{c}_1 > \mathbf{c}_1 \tag{3.23}$$

Therefore, the term to update $\mathbf{x}$ becomes $< \mathbf{r}, \mathbf{c}_1 + \mathbf{x} > (\mathbf{r} - < \mathbf{r}, \mathbf{c}_1 > \mathbf{c}_1)$.
Let's denote the received waveform in the i-th interval by $\mathbf{r}[i]$, then the i-th output of the receiver is

$$\mathbf{z}[i] = < \mathbf{r}[i], \mathbf{c}_1 + \mathbf{x}[i] > \tag{3.24}$$

and the i-th output of the single matched filter be

$$\mathbf{z}_{mf}[i] = < \mathbf{r}[i], \mathbf{c}_1 > \tag{3.25}$$

so the adaptation rule can be written as

$$\mathbf{x}[i] = \mathbf{x}[i-1] - \mu \mathbf{z}[i](\mathbf{r}[i] - \mathbf{z}_{mf}[i]\mathbf{c}_1) \tag{3.26}$$

where μ is the step size.

3.4.2 Alternative Matrix Approach

As an alternative to the gradient decent approach, we could evaluate $\mathbf{m}$ by using the matrix operation. Minimization of the MOE in (3.18) can be written as

$$\min E[|\mathbf{r}^H \mathbf{m}|^2] \tag{3.27}$$

subject to

$$\mathbf{m}^H \mathbf{c}_1 = 1 \tag{3.28}$$

The solution to this optimization problem from the Lagrange method is

$$\mathbf{m} = k\mathbf{R}_\mathbf{r}^{-1}\mathbf{c}_1 \tag{3.29}$$

where k is a constant and $\mathbf{R}_\mathbf{r}$ is the average of the input vector $\mathbf{r}$, i.e.,

$$\mathbf{R}_\mathbf{r} = E[\mathbf{r}\mathbf{r}^H] \tag{3.30}$$

Hence, only $\mathbf{r}$ and $\mathbf{c}_1$ is required to work out $\mathbf{m}$ in this interpretation. However, this alternative method is not practical for actual implementation of the receiver since it is cumbersome to find the inverse of $\mathbf{R}_\mathbf{r}$. We will look into the issue of practicality for implementation in later section.

3.5 Theoretical Combined Receiver Model

The concept of the two-stage spreading of the data is essential to the development of the combined receiver model. The reason the combined scheme can be implemented is due to the fact that the transmitted data are spread by both an aperiodic random signature sequence and a periodic deterministic signature sequence as described in section 3.2. The advantage of applying the two spreading techniques is that we can combine both the multiuser detection technique using the periodic sequence and the blind beamforming technique using the aperiodic sequence. With this scheme, the problem of degradation of performance due to strong close interferers in the beamforming algorithm can be solved since the strong interfering signals are suppressed by MUD in the first stage, and the desired data can be isolated from strong interferers even in the same direction of arrival. The detected signal vector is then weighted and combined in the beamforming stage to give the decision.

Fig.3.3 shows the theoretical structure of the receiver. Firstly, we assume there is a MUD in each antenna element and the received signal r_i for the i-th antenna is detected by the corresponding MUD using the periodic signature sequence. The detected signal vector **z** from the first stage is then passed through the blind adaptive beamformer in the second stage where the aperiodic sequence is used for despreading and the despread data are constructively beamformed to give the final decision.

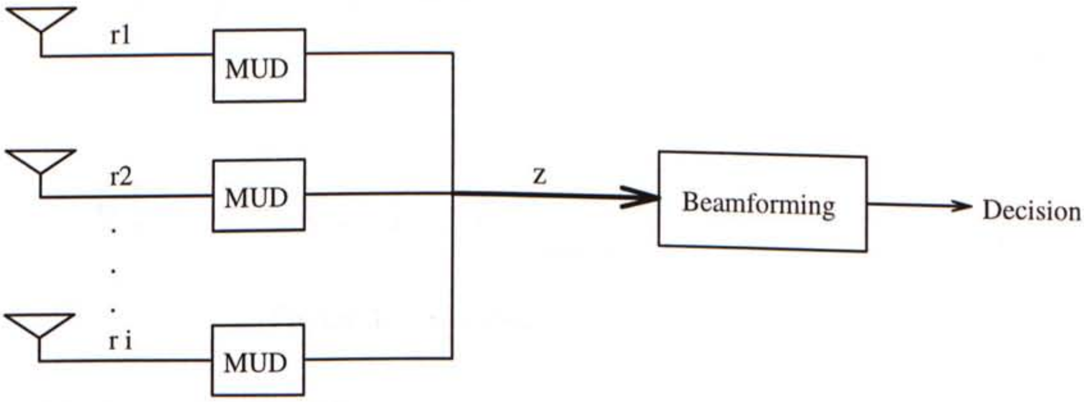

Figure 3.3: Proposed receiver structure

For theoretical comparison of the overall combined system performance, ,we use both the matrix type MUD and the eigen type blind beamformer. We consider the synchronous CDMA system where the number of rectangular spreading chips per symbol N=128. In the case of the two-stage spreading for the combined scheme, we assume the period of the periodic sequence N_2=16 and the number of the aperiodic spreading chips per symbol N_1=8, so that the overall number of spreading chips per symbol N=128. The number of antenna elements D=5.

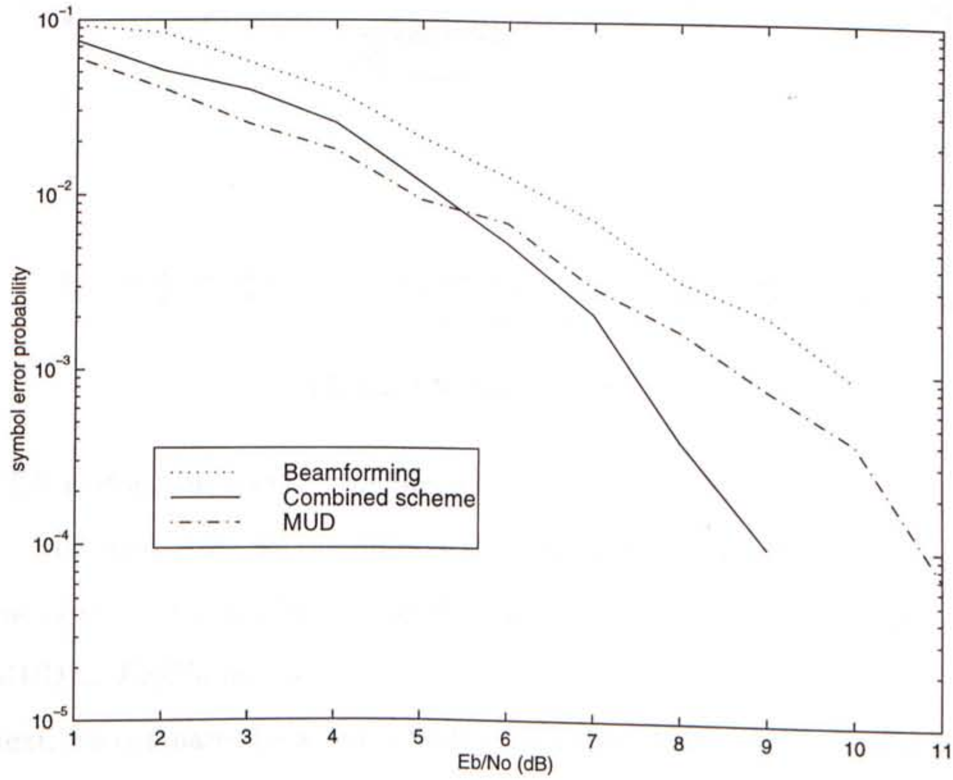

Figure 3.4: Comparison of the systems

Fig.3.4 compares BER performances of the combined receiver with the two individual components. We assume there are 2 users. The interfering signal is 20dB above the desired signal while the signal to white noise ratio for desired user from each antenna is 12dB. The DOA of the interferer is 60 degrees. Obviously,

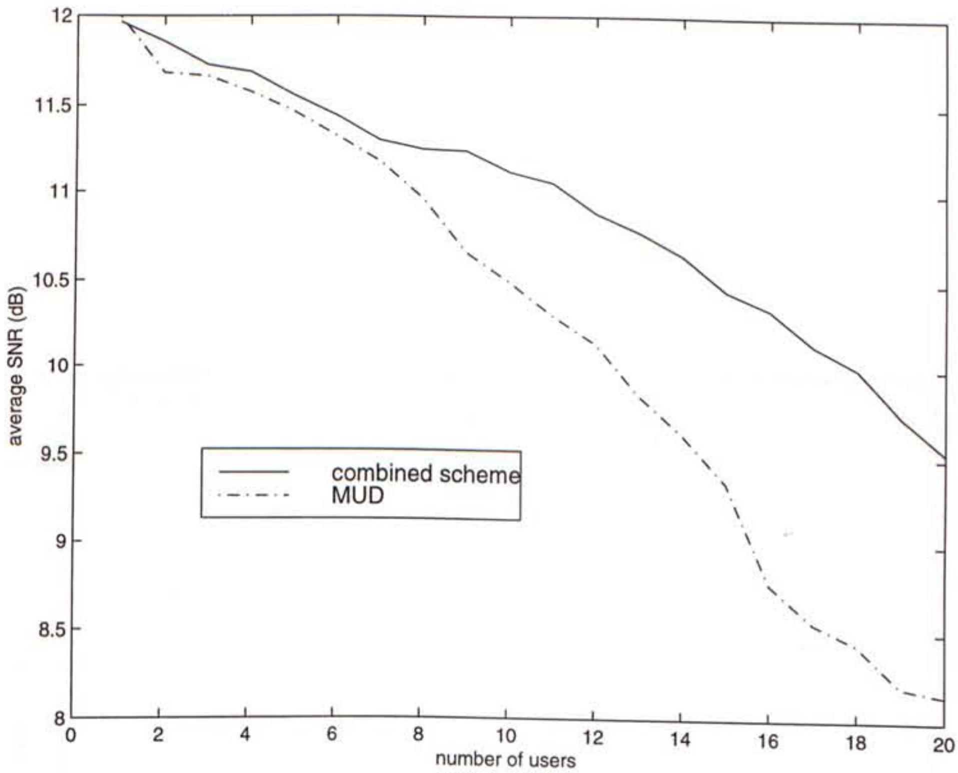

Figure 3.5: Normal case

the BER performances of the combined scheme and MUD are superior to that of the beamformer. Also, we can observe that the BER of the MUD and combined scheme is close at low Eb/No and the combined scheme starts to outperform the MUD as Eb/No increases.

Next, we compare the average SNR attained by both the combined scheme and the MUD as the number of user increases. In Fig.3.5, we assume the power of the desired and interfering signals are the same and the signal to white noise ratio is 12dB. The DOA of interferers are random. It shows that as the number of users increases, the combined scheme maintain a higher SNR over the MUD. When the number of users is small, both schemes have similar SNR performance. However, when the number of users exceeds 8, the performance of MUD starts

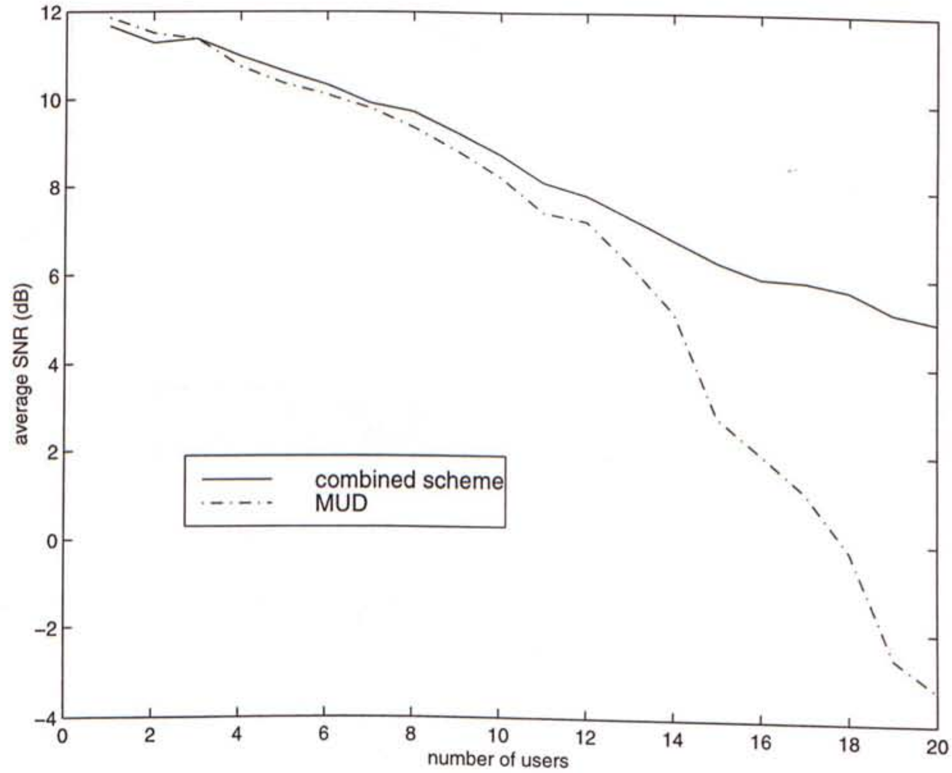

Figure 3.6: Extreme near-far situation

to drop at a faster rate. This is due to the additional spatial diversity provided by the antenna array which enhances the performance of the combined scheme, so that the combined scheme experiences a smaller drop in SNR comparing to the MUD.

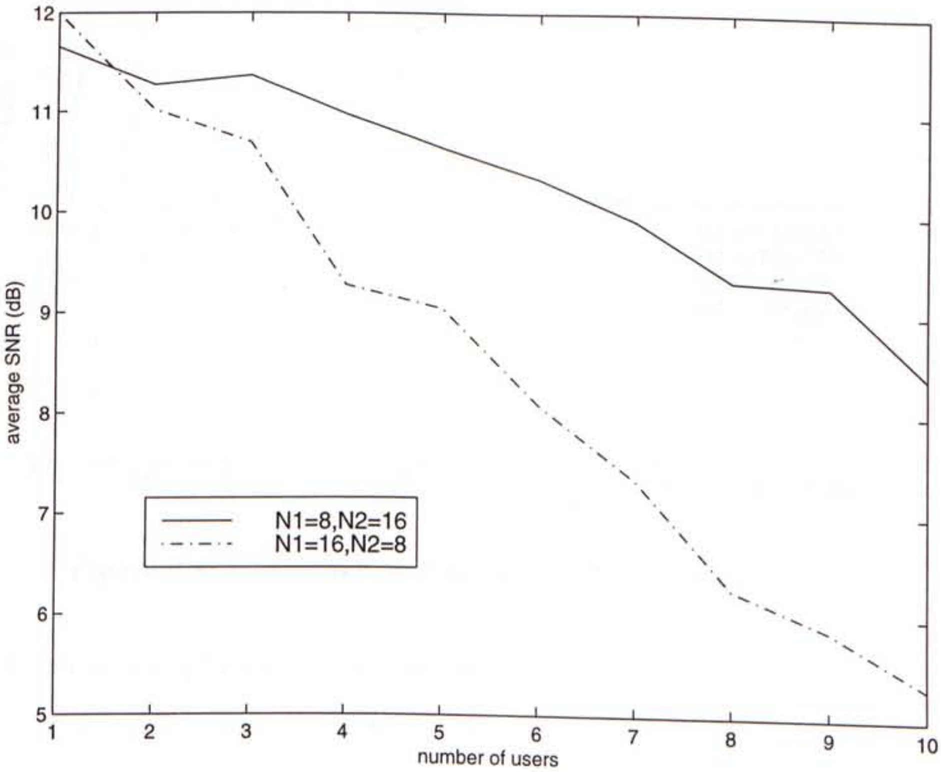

Figure 3.7: Effect of different ratios of chip lengths

Then we look at the scenario when the interfering signal power are much stronger than the desired user's. We assume the interferers are 20dB above the desired signal and the DOA are random. Fig.3.6 shows that the difference in the average SNR attained by the systems becomes significant as the number of users increases beyond 10. The SNR performance of the MUD drops drastically while the combined scheme maintains a smaller drop under this extreme near-far situation. The difference in performance can also be explained by the additional

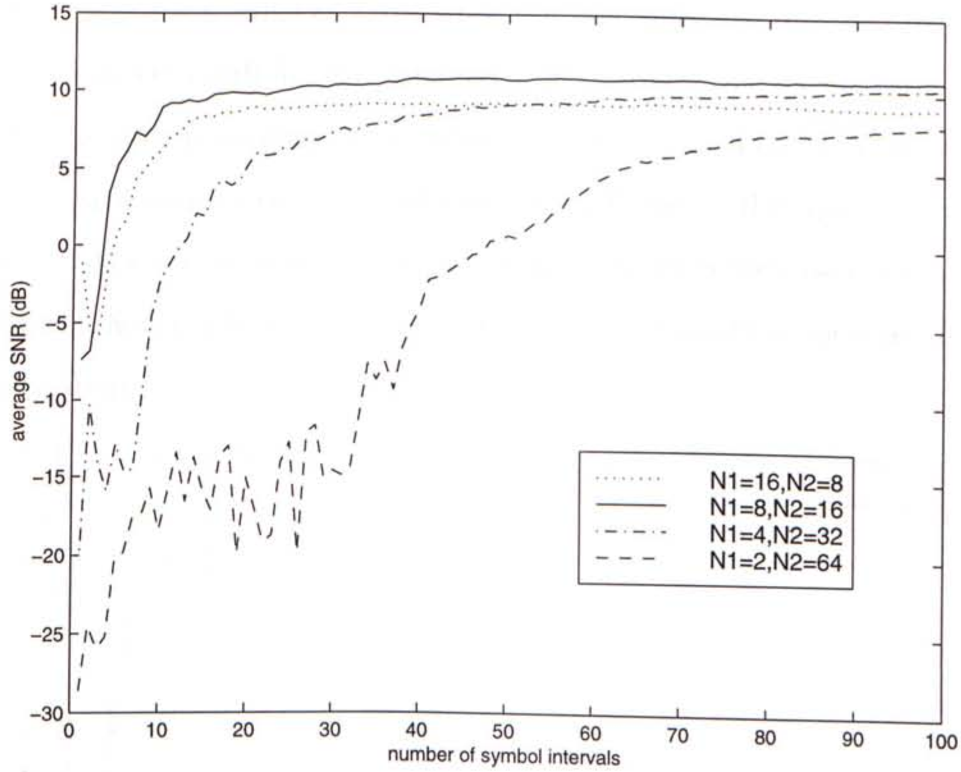

Figure 3.8: Convergence of the combined scheme (5 users)

spatial diversity exploited by the antenna array.

Fig.3.7 demonstrates the fact that as the period of the periodic signature sequence N_2 increases, a larger number of users can be supported for a given average SNR level. This is because the longer the period of the periodic signature sequence, the larger the user signature subspace such that more users can be differentiated in the MUD stage. However, as N_2 increases, the convergence issue of the system becomes significant. As shown in Fig.3.8, the convergence rates of the combined scheme with different ratio of N_1/N_2 are compared. We assume that there are 5 users in the system and each interferer's power is 20 dB above the desired user's. The figure shows that at N_2=8, the system converges pretty quick to a steady SNR at around 20 symbol intervals, but it cannot reach the ideal maximum value of 12dB since the user subspace provided by N_2=8 is comparatively small for the differentiation of users. As N_2 increases to 16 and 32, the system converges to a higher SNR value since a larger N_2 provides a larger signature subspace to support more users. However, the larger the N_2, the longer it takes to converge to the steady SNR as shown in the case when N_2=64. Therefore, there is a trade-off between the length of N_2 and the convergence rate of the system.

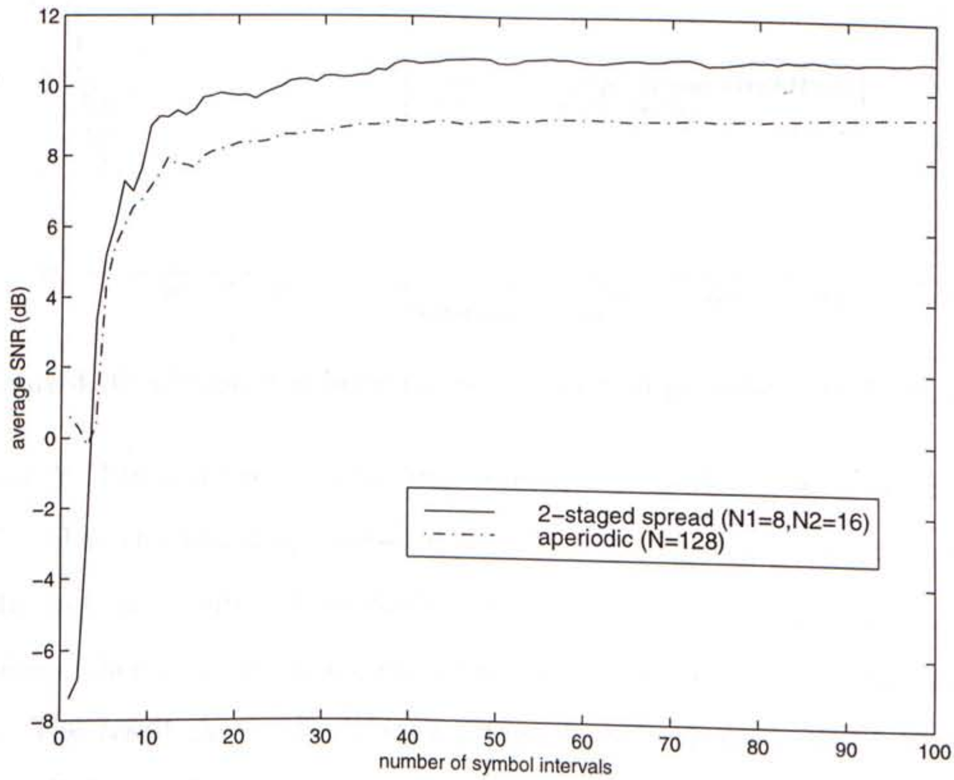

Figure 3.9: Comparison between the 2-stage and aperiodic spread scheme

Next, we compare the performance achieved by using the two-stage spread data with that achieved by using the pure aperiodic spread data (Fig.3.9). We assume that there are 5 users and 5 antenna elements in the system. The DOA's are random. For the aperiodic spread data, the number of spreading chips per

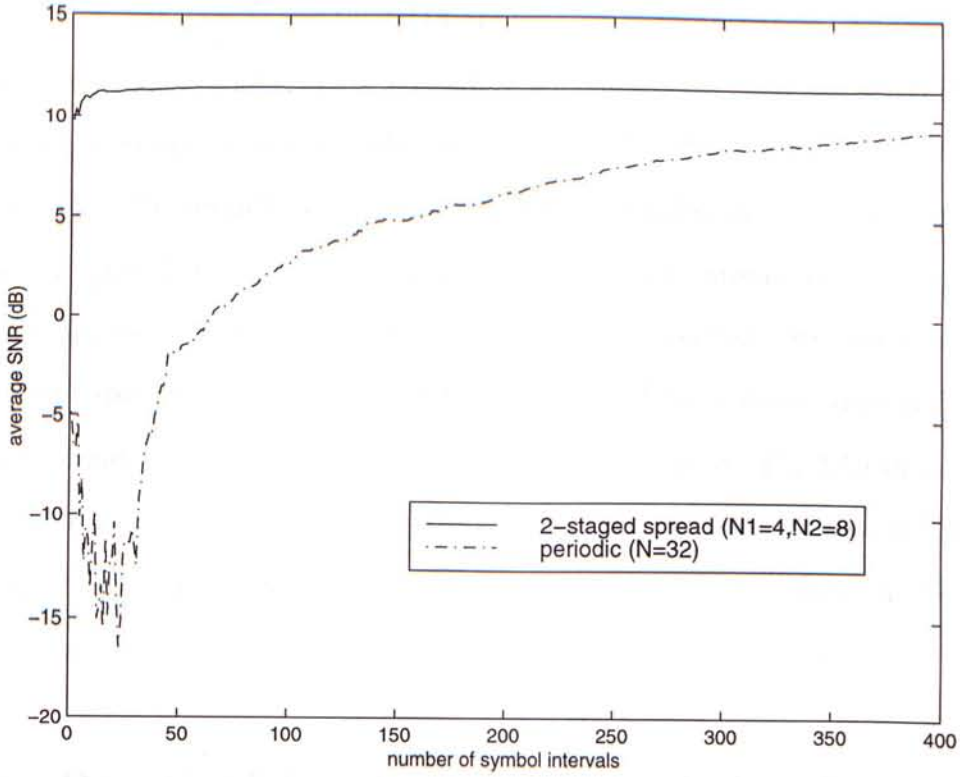

Figure 3.10: Comparison between the 2-stage and periodic spread scheme

symbol N=128 and the beamforming technique is used to obtain the output signals. For the two-stage spread data, the period of the periodic sequence N_2=16 and the number of aperiodic spreading chips per symbol N_1=8. The combined scheme is used to obtain the output signals for the two-stage spread data. The result shows that the two-stage spread scheme provides a higher average SNR over the pure aperiodic spreading scheme in the same environment. The improvement can be explained by the intrinsic periodicity embedded in the two-stage spread data which can be utilized by the multiuser detector to differentiate user signals.

Furthermore, we compare the performance achieved by using the two-stage spread data with that achieved by using the pure periodic spread data. We assume there are 2 users and the DOA are random in this scenario. The period of the randomly generated periodic spreading sequence N=32 and the MUD is used to obtain the output of the periodic spread signal. For the two-stage spread data, the period of the periodic sequence N_2=8 and the number of aperiodic spreading chips per symbol N_1=4. The combined scheme with 2 antenna elements is used for the two-stage spread data. For the ease of comparison, we use a smaller number of spreading chips since, with the use of MUD, it would take very long for the periodic spreading scheme to converge with large N. Fig.3.10 shows that the two-stage spread scheme outperforms the pure periodic spreading scheme. This is because the aperiodic sequence in the two-stage spread data can be used to perform beamforming which improves the overall performance.

3.6 Practical Implementation of the Receiver

3.6.1 Combined Scheme with Adaptive Algorithms

The matrix approach in the previous section is not a practical implementation since its complexity is high due to the matrix operations. Hence, we propose a gradient type combined scheme where the adaptive algorithm (Chapter 2) is used in the beamformer and the MUD is built upon the stochastic gradient rule described below. The gradient type combined receiver is a linear system consists of a blind linear multiuser detector followed by a blind beamforming system. The received signals (**r**) from the antenna array are first detected by the blind linear multiuser detector following the gradient descent algorithm described in the previous section. The output of the blind multiuser detector is

$$\mathbf{z}[i] = < \mathbf{r}[i], \mathbf{c}_1 + \mathbf{x}[i-1] >, \tag{3.31}$$

where $\mathbf{x}[i]$ is evaluated by the stochastic gradient adaptation rule (3.26). After the periodic sequences are detected, the aperiodic signature sequences are subsequently used to despread the output of the MUD's. The despread data are then weighted by the gradient beamforming algorithm as in chapter 2 to give the final decision.

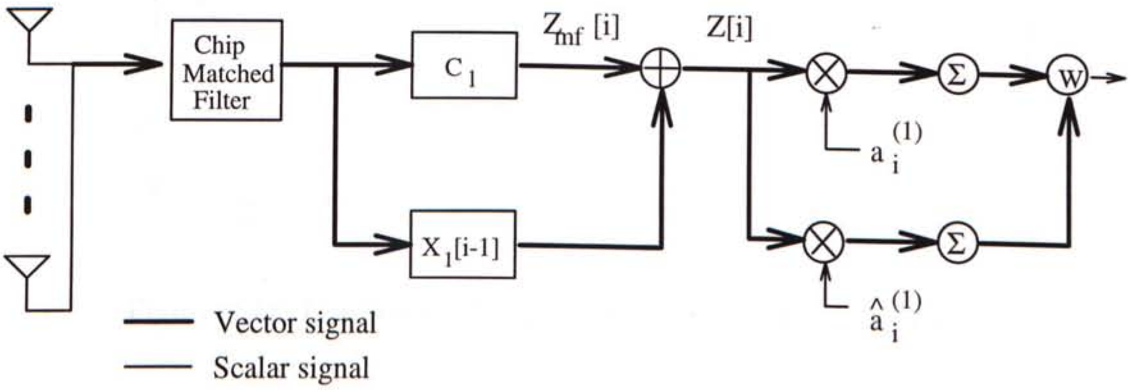

Figure 3.11: Practical receiver structure

Fig.3.12 compares the convergence of the gradient approach and the matrix approach. We assume there are 2 users where the interfering signal is 20dB stronger than the desired signal and there are 5 antenna elements with random DOA of the users. The N_1/N_2 ratio is equal to 8/16. It shows that both approaches attain roughly the same maximum SNR and the gradient approach converges to the steady SNR at a faster rate comparing to the matrix approach, with the step sizes for the MUD (μ) and the beamformer (δ) are 0.001 and 0.001 respectively in the gradient approach. The result reveals that without the presence of the complexity of the matrix operations and with suitable choices of

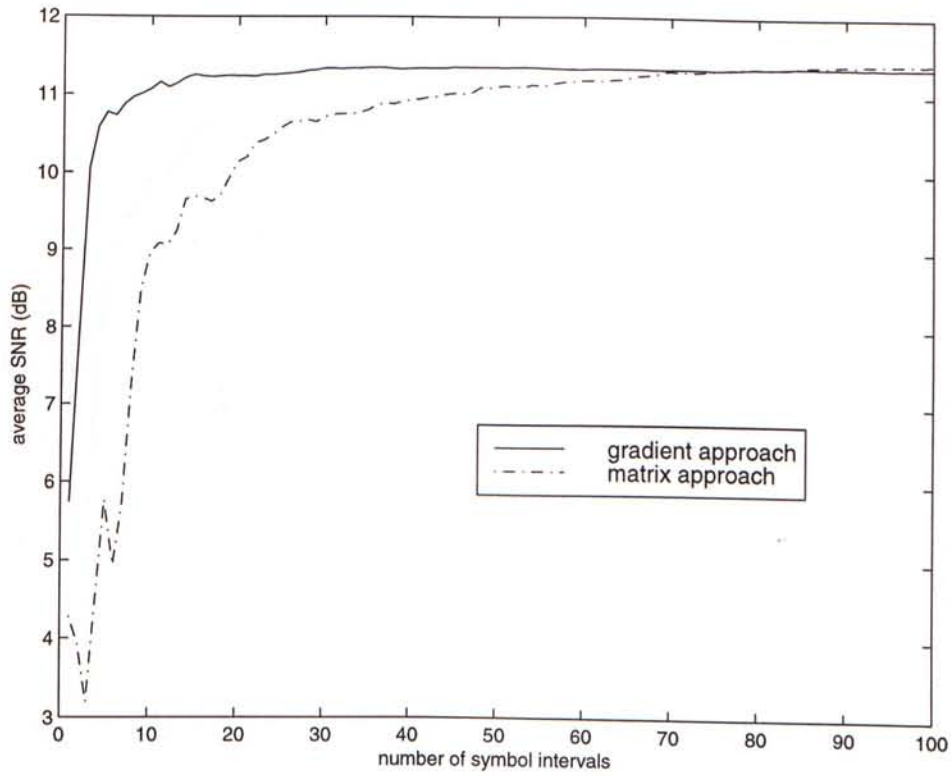

Figure 3.12: Comparison between gradient and matrix approach

the step sizes, the gradient type combined system provides a faster convergence and renders a simpler and more practical implementation of the receiver.

3.6.2 Simplified Structure

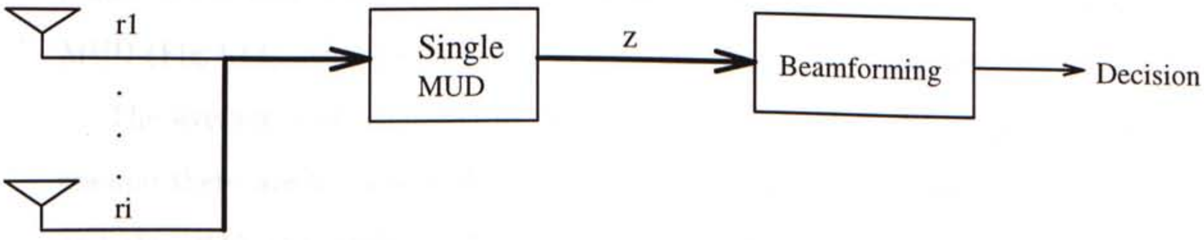

Figure 3.13: Simplified receiver structure

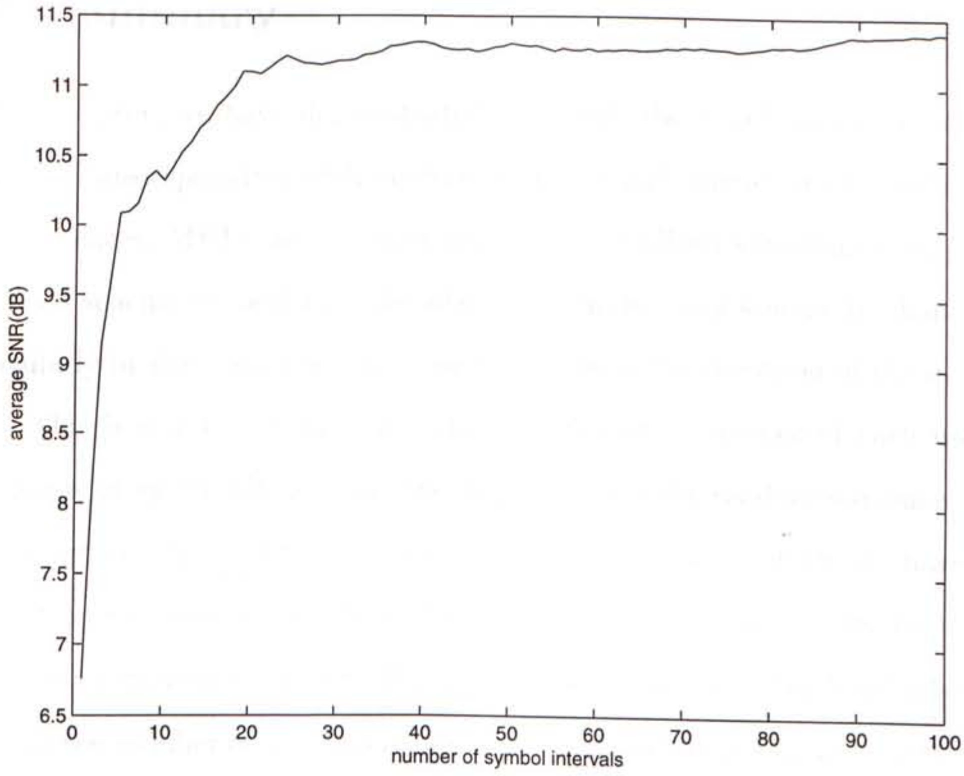

Figure 3.14: Average SNR achieved with 1 MUD

The receiver structure we discussed in the previous sections assume the use of MUD in each branch of the antenna element. However, under our antenna model, the received signals from any particular user at each branch of the antenna differs only by a phase difference. Therefore, the MUD for different antennas are linearly related and we can simplify the system by training only one MUD (Fig.3.13) instead of training every single one at each branch.

The average SNR achieved by training 1 MUD is plotted in Fig.3.14. We assume there are 2 users with the interfering signal is 20dB above the user's and the DOA are random. The graph shows that with the simplified structure of training 1 MUD, the system still maintains the desired average SNR performance.

3.7 Summary

In this chapter, we have demonstrated that with the novel spreading scheme which combines spreading with random sequences and spreading with deterministic sequences, MUD and beamforming can be utilized simultaneously. The combined scheme outperforms the adaptive beamforming scheme in chapter 2, particularly in situation when the interferers are in the direction of the desired user. This is due to the fact that the deterministic sequence of each user is first despread by the MUD before the despreading of the random sequence. The desired signal can be detected even though the user and interferers have the same DOA. Simulations also show that in a near-far environment, the combined scheme can maintain a better SNR performance comparing to the blind adaptive MUD as the number of users increases. Practical and simple implementation of the receiver is realized by the use of adaptive algorithms.

Chapter 4

Conclusions and Future Work

In this work, we have investigated blind adaptive linear receivers for MAI rejection. The presence of MAI is the main obstacle in multi-access communication such as DS/CDMA systems. There are many ways to mitigate the effect of MAI and one of the effective method is to use diversities. By using the antenna arrays, we add spatial diversity to the system which enhances detection of the desired signals. In addition to the spatial diversity, 64-ary orthogonal modulation is considered as in the IS-95 standard. The MAI rejection performance is found to be improved with the use of spatial processing techniques.

One of the key issue for the design of the receiver is the implementation complexity. In most of the MAI rejection receivers for DS/CDMA, training sequences or feedback are required. The proposed receiver in this work is more practical since a blind adaptive algorithm is used to find the optimal receiver to maximize the SNR, and no prior knowledge of channel parameters are needed. Moreover, the MAI rejecting capability is realized by a linear structure. In the development of the blind adaptive algorithm, the assumption of aperiodic signature sequence is required. By doing so, we can provide a simple and computational efficient model to perform blind adaptive channel estimation. Blind channel estimation is an important research topic in detection since many receivers required some form of channel information to operate.

In order to adapt the blind algorithm for blind channel estimation to work together with multiuser detection, we have to modify the aperiodic sequences spreading scheme since most multiuser receivers are developed under the periodic sequence model. In light of this, we consider a novel spreading scheme that combines spreading with random sequences and spreading with deterministic sequences. The data sequence is first spread with an aperiodic random signature sequence. The resultant sequence is then spread with a periodic deterministic signature sequence. The advantage of the combined scheme is that the multiuser detection can be readily performed using the embedded deterministic sequence, whereas the aperiodic sequence can be used in the blind channel estimation algorithm.

In combining the multiuser receiver with the blind receiver by the novel spreading scheme, we find that there is significant improvement to the system performance, especially in the case when the interferers are in close proximity with the desired user. The original blind adaptive beamforming will fail to detect the desired signal when the interferers and user are too close to each other. However, with the use of the combined scheme, this problem can be solved since the desired signal can be isolated from the interfering signals in the same direction of arrival by MUD with the deterministic sequences. Then blind adaptive algorithm can be performed from these despread data. Overall, with the application of adaptive algorithms, the proposed receiver becomes a practical and simple solution to combat MAI.

Throughout this work we have employed the rectangular chip waveforms. As an extension to the work, we can investigate the effect of different chip waveforms on the performances of the system. Also, investigation can be done on the effect of channel coding to the system. For example, in IS-95, 64-ary orthogonal coding is used, we can modify the combined system to allow M-ary data detection.

Appendix A

Correlation Properties

We assume that the signal vector received by the antenna array in complex baseband notation is given by

$$\mathbf{r}(t) = \mathbf{y}(t) + \mathbf{n}_I(t) + \mathbf{n}_W(t) \tag{A.1}$$

where $\mathbf{n}_W(t)$ represents AWGN. The signal contribution $\mathbf{y}(t)$ is given by

$$\mathbf{y}(t) = \sqrt{2P_1}\sum_{\lambda=1}^{L_1} g_{1,\lambda}a_1(t - T_1 - \tau_{1,\lambda})e^{-j\omega_c(T_1+\tau_{1,\lambda})}\mathbf{d}_{1,\lambda} \tag{A.2}$$

The MAI contribution $\mathbf{n}_I(t)$ is given by

$$\mathbf{n}_I(t) = \sum_{k=2}^{K}\sqrt{2P_k}\sum_{\lambda=1}^{L_1} g_{k,\lambda}a_k(t - T_k - \tau_{k,\lambda})e^{-j\omega_c(T_k+\tau_{k,\lambda})}\mathbf{d}_{k,\lambda} \tag{A.3}$$

In A.2 and A.3, L_k is the number of propagation paths from the k-th transmitter to the antenna array. P_k is the power and the parameters $\tau_{k,\lambda}$, $g_{k,\lambda}$ and $\mathbf{d}_{k,\lambda}$ represent the delay, the complex gain and the array response vector associated with the λ-th path of the signal from the k-th transmitter. We assume that we have achieved synchronization with the path of the signal from the desired user that arrives earliest at the antenna array. Hence, $T_1 = 0$, $\tau_{1,1}$=0 and $\tau_{1,\lambda} > 0$ for

$2 \leq \lambda \leq L_1$.

The despread signal at the output of the matched filter $\tilde{\mathbf{r}}_0(t)$, for $t \geq 0$, is given by

$$\tilde{\mathbf{r}}_0(t) = \tilde{\mathbf{y}}(t) + \tilde{\mathbf{n}}_I(t) + \tilde{\mathbf{n}}_W(t) \tag{A.4}$$

where $\tilde{\mathbf{y}}(t), \tilde{\mathbf{n}}_I(t)$ and $\tilde{\mathbf{n}}_W(t)$ are the matched filter output due to the desired signal, the MAI, and the thermal noise components, respectively. Under the aperiodic random sequence model, the random processes $\tilde{\mathbf{y}}(t), \tilde{\mathbf{n}}_I(t)$ and $\tilde{\mathbf{n}}_W(t)$ are uncorrelated. Hence, the correlation matrix $\mathbf{R}_{\tilde{\mathbf{r}}}(t,s)$ defined as $E[\tilde{\mathbf{r}}_0(t)\tilde{\mathbf{r}}_0^H(s)]$ is given by

$$\mathbf{R}_{\tilde{\mathbf{r}}}(t,s) = \mathbf{R}_{\tilde{\mathbf{y}}}(t,s) + \mathbf{R}_{\tilde{\mathbf{n}}_\mathbf{I}}(t,s) + \mathbf{R}_{\tilde{\mathbf{n}}_\mathbf{W}}(t,s) \tag{A.5}$$

where

$$\begin{aligned}
\mathbf{R}_{\tilde{\mathbf{y}}}(t,s) &= E[\tilde{\mathbf{y}}(t)\tilde{\mathbf{y}}^H(s)] && \text{(A.6)} \\
&= 2P_1T^2 \sum_{\lambda=1}^{L_1}\sum_{\nu=1}^{L_1} g_{1,\lambda}g_{1,\nu}^* e^{-j\omega_c(\tau_{1,\lambda}-\tau_{1,\nu})}\mathbf{d}_{1,\lambda}\mathbf{d}_{1,\nu}^H \cdot \\
&\quad [\hat{\psi}(t-\tau_{1,\lambda})\hat{\psi}^*(s-\tau_{1,\nu}) \\
&\quad + \frac{1}{N}\sum_{i=-\infty,i\neq 0}^{\infty} \hat{\psi}(t-iT_c-\tau_{1,\lambda})\hat{\psi}^*(s-iT_c-\tau_{1,\nu}) \\
&\quad + \frac{1}{N}\sum_{i=-N+1,i\neq 0}^{N-1} \frac{N-|i|}{N}\hat{\psi}(t-iT_c-\tau_{1,\lambda})\hat{\psi}^*(s-iT_c-\tau_{1,\nu})] && \text{(A.7)}
\end{aligned}$$

$$\begin{aligned}
\mathbf{R}_{\tilde{\mathbf{n}}_\mathbf{I}}(t,s) &= E[\tilde{\mathbf{n}}_\mathbf{I}(t)\tilde{\mathbf{n}}_\mathbf{I}^H(s)] && \text{(A.8)} \\
&= \sum_{k=2}^{K}\frac{2P_kT^2}{N}\sum_{\lambda=1}^{L_1}\sum_{\nu=1}^{L_1} g_{k,\lambda}g_{k,\nu}^* e^{-j\omega_c(\tau_{k,\lambda}-\tau_{k,\nu})}\mathbf{d}_{k,\lambda}\mathbf{d}_{k,\nu}^H \cdot \\
&\quad \sum_{i=-\infty}^{\infty} \hat{\psi}(t-iT_c-T_k-\tau_{k,\lambda})\hat{\psi}^*(s-iT_c-T_k-\tau_{k,\nu}) && \text{(A.9)}
\end{aligned}$$

and

$$\mathbf{R}_{\tilde{\mathbf{n}}_\mathbf{I}}(t,s) = E[\tilde{\mathbf{n}}_\mathbf{W}(t)\tilde{\mathbf{n}}_\mathbf{W}^H(s)] \tag{A.10}$$
$$= N_0 T\hat{\psi}(t-s)\mathbf{I}_{D\times D} \tag{A.11}$$

In (A.7)-(A.11), the function $\hat{\psi}(\cdot)$ is the autocorrelation of the chip waveform defined by

$$\hat{\psi}(t) = \frac{1}{T_c}\int_{-\infty}^{\infty}\psi(s)\hat{\psi}(s-t)ds \tag{A.12}$$

We observe an important asymptotic property of the correlation matrix $\mathbf{R}_{\tilde{\mathbf{r}}}(t,s)$. From (A.7),

$$\lim_{N\to\infty}\mathbf{R}_{\tilde{\mathbf{y}}}(t,s) = \tilde{\mathbf{z}}(t)\tilde{\mathbf{z}}(s)^H \tag{A.13}$$

where

$$\tilde{\mathbf{z}}(t) = \sqrt{2}P_1 T\sum_{\lambda=1}^{L_1} g_{1,\lambda}e^{-j\omega_c\tau_{1,\lambda}}\hat{\psi}(t-\tau_{1,\lambda})\mathbf{d}_{1,\lambda} \tag{A.14}$$

i.e., when the number of chips per symbol is large, we can neglect the effect of interchip interference and approximate the correlation matrix of the desired signal component as an outer product of two vectors.

With $\mathbf{R}_{\tilde{\mathbf{r}}}(t,s)$, we see that the correlation matrix $\mathbf{R}_s = E[\mathbf{s}\mathbf{s}^H]$ of the sample vector $\mathbf{R}_\mathbf{s}$ can be decomposed into two parts,

$$\mathbf{R}_\mathbf{s} = \mathrm{E}[\mathbf{s}\mathbf{s}^H] = \mathbf{R}_\mathbf{z} + \mathbf{R}_\mathbf{n} \tag{A.15}$$

The first part, $\mathbf{R}_\mathbf{z}$, is due to the desired signal contribution in $\mathbf{s}$. Just as $\mathbf{R}_{\tilde{\mathbf{y}}}(t,s)$, $\mathbf{R}_\mathbf{z}$ is also asymptotic equal to an outer product of two vectors when N tends to infinity. More precisely,

$$\lim_{N\to\infty}\mathbf{R}_\mathbf{z} = \mathbf{z}\mathbf{z}^H \tag{A.16}$$

The second part, $\mathbf{R_n}$, is due to the overall noise and interference contribution in s.

Similarly, the correlation matrix $\mathbf{R}_{\hat{s}} = E[\hat{\mathbf{s}}\hat{\mathbf{s}}^H]$ of the sample vector $\hat{\mathbf{s}}$ has the same form as $\mathbf{R_s}$. It can also be decomposed into two parts. The first part, which we denote by $\hat{\mathbf{R}}_\mathbf{z}$, is due to the signal contribution in $\hat{\mathbf{s}}$. Since the output vector from the orthogonal matched filter contains mainly noise and interference contributions, so $\hat{\mathbf{R}}_\mathbf{z}$ is approximately equal to zero. The second part, which we denote by $\hat{\mathbf{R}}_\mathbf{n}$, is due to the overall interference contribution in $\hat{\mathbf{s}}$. Due to the independent random sequence assumptions, $\hat{\mathbf{R}}_\mathbf{n} = \mathbf{R_n}$. Consequently, we have

$$\lim_{N\to\infty} \mathbf{R_s} - \mathbf{R}_{\hat{s}} = \mathbf{z}\mathbf{z}^H \tag{A.17}$$

Appendix B

Adaptive Algorithm

The asymptotic equivalence of the constrained minimization of output energy (CMOE) and the minimization of signal-to-noise ratio (MSNR) [25] suggested that we can determined the optimal weight vector by constrained minimization of the output energy $\sigma(\mathbf{w})$when N is sufficiently large. Assume the matrices $\mathbf{R_s}$ and $\mathbf{zz^H}$ are given. Consider the matrix $\mathbf{P_z}$ defined by

$$\mathbf{P_z} = \frac{\mathbf{zz^H}}{\mathbf{z^Hz}} \tag{B.1}$$

It defines a projection operation onto the space spanned by the vector $\mathbf{z}$. The gradient vector of the output energy function $\sigma(\mathbf{w})$ is $\mathbf{g}_\sigma(\mathbf{w})$=$\mathbf{R_s w}$. Restricted by the constraint $\mathbf{w^H z}$=c, we cannot descend in the direction opposite to $\mathbf{g}_\sigma(\mathbf{w})$ as in the steepest descent algorithm. Let $\tilde{\mathbf{g}}_\sigma(\mathbf{w})$ be the component of $\mathbf{g}_\sigma(\mathbf{w})$ which is orthogonal to the vector $\mathbf{z}$,

$$\tilde{\mathbf{g}}_\sigma = (\mathbf{I} - \mathbf{P_z})\mathbf{R_s w} \tag{B.2}$$

Notice that the vector $\tilde{\mathbf{g}}_\sigma$ is determined directly by $\mathbf{P_z}$ and $\mathbf{R_s}$. It is easy to see that descending in the direction opposite to $\tilde{\mathbf{g}}_\sigma(\mathbf{w})$ does not violate the constraint $\mathbf{w}^{\mathbf{H}}\mathbf{z}$=c. Hence, it is possible to set up an adaptive algorithm [25] which descends in that direction to solve the constrained minimization problem.

Algorithm: for $j \geq 1$,

$$\mathbf{w}(j) = [\mathbf{I} - \delta(\mathbf{I} - \mathbf{P}_{\mathbf{z}})\mathbf{R}_{\mathbf{s}}]\mathbf{w}(j-1), \tag{B.3}$$

where $\delta > 0$ and $\mathbf{w}(\mathbf{0})^{\mathbf{H}}\mathbf{z}$=c.

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